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LIGHT MODELLING IN ARCHITECTURAL SPACES

LUMINANCE-BASED METRICS OF CONTOUR, SHAPE AND DETAIL DISTINCTNESS OF DAY-LIT 3D OBJECTS

NTNU
Norwegian University of
Science and Technology

Doctoral thesis

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Thesis for the Degree of
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Abstract

Recently, the topic of lighting quality has become very significant in the lighting research community. With the dynamic exploration of the visual and non-visual effects of light on human bodies and their well-being, theories that light has a powerful impact on quality of life have become known as scientific truth.

No formal interpretation of lighting quality has been prescribed by any official source, though the most generally accepted description was published in the Lighting Handbook of Illuminating Engineering Society of North America (IESNA): *'Lighting quality: the integration of human needs, architecture, and economics and the environment'*. This description is based on Veitch (1998)'s model of lighting quality, which includes the parametres of individual well-being, architecture and economics (Veitch 1998). Each can be further broken down into other aspects: visibility, social communication, health and safety in individual well-being; form, composition, codes and standards in architecture; and maintenance, energy and environment in economy, respectively. With proper balancing of these elements, good lighting quality can be achieved.

Light modelling is a small but important part of the lighting quality concept. It determines not only the capability of the eye to detect any objects in a space but also its ability to discriminate contours, shapes and details, the most important visual characteristics of any object. These are essential and significant indicators that allow a person to analyse and ascertain another person's state of health, the freshness of food, the mood of the interlocutor and many other key characteristics of visual environments. Thus, light modelling is an essential aspect important in various architectural spaces, from museums to hospitals to offices.

To date, few studies have been dedicated to light modelling. Some basic knowledge has been achieved from studies on pedestrian visibility and road lighting. However, few investigations have been performed in day-lit interiors. Thus, the light modelling topic remains underestimated and insufficiently studied.

To address this gap, the present research aims to develop the concept of ***light modelling*** of real 3D objects in day-lit environments. The author will propose the metrics of ***contour***, ***shape*** and ***details distinctness*** of the examined units as the most critical aspects of light modelling. Based on the idea that ***light*** and ***colour*** are mentally inseparable in the human perception of visual environments, it is of great importance to

create experimental conditions that provide both of these principal concepts (light and colour). The high dynamic range (HDR) imaging technique will be used as part of the experimental research methodology, giving reliable, analysable, numerical data obtained from luminance maps.

Three experiments and their outcomes form the basis of this dissertation. Work on this dissertation began with general research questions regarding studies of chromatic interiors using HDR images, examining the possible effect of achromatic and chromatic colours and colour combinations on the perception of room illumination (***Experiment 1***). The focus then turned to the development of the appropriate luminance-based metrics of real 3D achromatic and chromatic objects placed in a room illuminated by daylight (***Experiment 2***). These metrics were then verified in a real room study and repeated through computer simulation (***Experiment 3***).

The results obtained from these experiments indicate that majority of the proposed luminance-based metrics correlate very well with subjective assessments that deem contour, shape and details to be distinguishable in different degrees. The metrics also indicate considerable variations among 3D objects with different luminance and chromatic contrasts. These luminance-based metrics outperformed currently used modelling index and cylindrical illuminance metrics. Furthermore, these luminance-based metrics can be used both in real architectural spaces and computer simulations.

Considering these advantages, the author of this dissertation proposes that luminance-based metrics should be recommended for practical use to ensure light modelling; specifically, to better guarantee the distinctness of objects’ contours, shapes and details. The metrics have some limitations dictated by existing experimental conditions and therefore require further testing if they are to be made universally applicable. These will be further discussed in the present dissertation, as will some proposals for possible future research.

Acknowledgements

First, I would like to express my sincere gratitude to my main supervisor, Dr Barbara Szybinska Matusiak, for seeing the potential of the researcher in me, for her continuous and strong support of my PhD study, for motivating me and for her immense knowledge. Her guidance helped me across all stages of my research and in the writing of this thesis. Her activities and scientific achievements served as a prime example for me, inspiring and encouraging me to strive for the best possible result in my scientific work. Dear Barbara, your advice on both research and on my career have been priceless.

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Last but not the least, I would like to thank my family: my beloved husband Leonid Zaikin, who was amazingly patient and always ready to help me during these busy four years of doctoral study, and my parents and sister for supporting me spiritually throughout this thesis and life in general.

List of appended papers

ZAIKINA, V. 2012. Light level perception in interiors with equiluminant colours. *In:* MATUSIAK, B. & FRIDELL ANTER, K. (eds.) *Nordic Light and Colour*. 2012. Trondheim: NTNU - The Faculty of Architecture and Fine Art; p. 105–122.

Status: peer reviewed, published.

ZAIKINA V, MATUSIAK BS, KLÖCKNER CA. New measures of light modelling. In: *Proceedings of CIE 2014.* Vol. 0.39. Kuala Lumpur, Malaysia: CIE Central Bureau; 2014. p. 298–305.

Status: peer reviewed, published.

Roles of the co-authors: the second co-author helped to develop the research methodology and procedure and to define the scope of the experiment; gave feedback on the article`s content; contributed by performing quality assurance and proof reading. The third co-author gave feedback on the article`s content; contributed by performing statistical analysis of the data, quality assurance and proof reading.

ZAIKINA V, MATUSIAK BS, KLÖCKNER CA (2015). Luminance-Based Measures of Contour Distinctness of 3D Objects as a Component of Light Modeling, *LEUKOS: The Journal of the Illuminating Engineering Society of North America.* Vol. 11 Issue 1. DOI: 10.1080/15502724.2014.981341

Status: peer reviewed, published.

Roles of the co-authors: the second co-author helped to develop the research methodology and procedure and to define the scope of the experiment; gave feedback on the article`s content; contributed by performing quality assurance and proof reading. The third co-author gave feedback on the article`s content; contributed by performing statistical analysis of the data, quality assurance and proof reading.

ZAIKINA V, MATUSIAK BS, KLÖCKNER CA (2015): Luminance-Based Measures of Shape and Detail Distinctness of 3D Objects as Important Predictors of Light Modeling Concept. Results of a Full-Scale Study Pairing Proposed Measures with Subjective Responses, *LEUKOS: The Journal of the Illuminating Engineering Society of North America*. Vol. 11 Issue 4. DOI: 10.1080/15502724.2015.1024848

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ZAIKINA V. MATUSIAK B S. (2016) Verification of the accuracy of luminance-based light modeling metrics by numerical comparison of photographed and simulated HDR images.

Status: under review.

Roles of the co-authors: the second co-author helped to define the scope of the experiment; gave recommendations on methodology and certain procedures of the experiment; gave feedback on the article`s content; contributed by performing quality assurance and proof reading.

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1. Introduction

1.1 Thesis outline

The body of this thesis frames the research activities performed within the current study project. The details of the methodology, results and conclusions of each conducted experiment are included in articles in Chapter 8, while the repetition of minute explanations was minimised in the thesis body. Special attention was paid to developing a structured narrative to include details concerning fulfilled works that were not included in articles or needed additional explanation. Readers can consult the following synopsis to obtain key information, but a reading of the collection of appended papers is recommended for a more extensive understanding of the experimental settings and methods, detailed results and discussions involved in this thesis. These papers serve as a basis for the current dissertation and represent the successive steps of this research project.

Chapter 1 introduces topic of the study to the reader. The five research questions are formulated here, which determine the structure and stages of the work.

The main body of the dissertation begins in ***Chapter 2*** (State of the art), where an overview of the relevant studies of ***light***[1] and ***colour***, lighting quality, luminance-based design and light modelling is provided.

Chapter 3 describes the overall project's development. Each experiment is briefly introduced, with particular attention paid to the proposed metrics. This information was not explained in the published papers and therefore required expanded commentary.

In ***Chapter 4***, a theoretical overview of the methods adapted from previous studies to explore the stated research questions is presented. The possible limitations and advantages of these methods are discussed, while detailed methodologies regarding each experiment are found in Chapter 8.

Two types of analysis of the data obtained from the experiments are provided in ***Chapter 5***: luminance maps analysis and statistical analysis. The luminance maps analysis represents the more technical approach to information processing. The statistical analysis describes the methods of data analysis used in the research project, as

[1] The text highlighted in bold, grey, italic, underlined font indicates a term defined in the Glossary.

well as work related to a questionnaire analysis that pairs data with the results of the luminance maps examination.

Results of the three experiments are discussed in ***Chapter 6***, divided into three subchapters to correspond with each experiment. All supplementary data, such as tables, graphs and metric values, can be found in Papers I–V. The study's main findings, limitations and performance of the results and metrics are described.

Finally, ***Chapter 7*** summarises the achievements of the present dissertation and discusses possible directions for future work beyond the doctoral studies.

Chapter 8 contains the papers (published or being under review) that formed the basis for this dissertation.

The most essential and frequently used terms of this dissertation are explained in the synapses text, while less important concepts, their definitions and interpretations could be found in the ***Glossary***.

1.2 Points of departure and research motivation

Daylight is a natural source of illumination that is fundamental for life. The quantity and quality of natural light varies according to time (rapidly or slowly, per day and season) and space (from different geographic regions to the local brightness variation in a room) (Tregenza & Wilson 2011).

A day-lit space at any moment in time is unique. In fact, 'the quantity and character of daylight in a space will depend on: the size, orientation and nature of the building apertures; the shape and aspect of the building and its surroundings; and, the optical (i.e. reflective and transmissive) properties of all the surfaces comprising the building and its surroundings' (Mardaljevic 2013). However, it is very important to note that people react to light in terms of what is recognized and felt, but not to measurable physical values. Therefore good lighting should be considered from different sides: from human wellbeing aspect, from the aspect of creation of interesting atmosphere at a place, and from the ability to affect architecture, surrounding and create a 'place'. (Tregenza & Wilson 2011).

At the beginning of the 20th century, recommendations on daylighting in architectural spaces were based on the illuminance levels needed for the efficient performance of typical ***visual tasks*** (Cuttle 2013). Task visibility was viewed as the primary goal of lighting. In many countries, design guides that recommended illuminance levels depended on the task and/or settings to be produced (Mardaljevic 2013). According to Mardaljevic,

> *Recommended illumination levels were conceived primarily for the purpose of designing artificial lighting systems, and not for the daylighting design of buildings because the variation in the provision of natural daylight is such that it is virtually impossible to deliver specific natural illumination levels without huge fluctuations occurring. For buildings therefore, design guidance was formulated in terms of building properties which are evaluated under a single, static "worst-case" daylight condition: an overcast sky. This is the basis of the daylight factor* (Mardaljevic 2013).

These metrics are still in active use for the following reasons: they are well defined and easy to interpret; have criterion levels for different conditions; and are simple to calculate with formulae, obtain through computer simulation or measure with a ***lux metre***.

The disadvantage of illuminance-based metrics, particularly the ***daylight factor*** (DF), is that they can only approximately predict and reflect real situations and the appearance of observed spaces, objects or tasks. This is because: i) the human eye is relatively insensitive to absolute levels of light (***illuminance***) (Tregenza & Wilson 2011); ii) the DF cannot account for prevailing climate (meaning the totality of sky and sun conditions) or building/site orientation (Mardaljevic 2013). Despite these disadvantages, however, the DF still remains the dominant metric for daylighting analysis among architects and is often the only measure of natural illumination applied in architectural daylight evaluation.

At the end of 1990s, the attention paid to the daylighting of buildings increased due to the widespread idea of energy efficiency and natural light as its key factor. Tregenza and Wilson noted: 'Lighting is a central component of sustainable architecture… The two ratios, between sunlight and skylight and between daylight and electric lighting, determine a building's sustainable performance' (Tregenza & Wilson 2011). By letting daylight into a building, windows can reduce the need for electrical light; in addition, windows may contribute positively to the energy economy if the sunlight energy will be intercepted and stored for later use for heating of the building (Matusiak 2012).

In addition to energy efficiency, the findings of different studies show that daylight exposure may have an effect on human health, state of mood, well-being and productivity (Farley & Veitch 2001; Veitch 2001; Veitch 2004; Veitch et al. 2008). Daylight supports our circadian rhythms, cures Seasonal Affective Disorder (SAD) and initiates the synthesis of vitamin D (Terman et al. 1989; Monk et al. 1997; Rastad et al. 2011; Reeves et al. 2012; Premkumar et al. 2013; Boubekri et al. 2014). Therefore daylight has become directly associated with human health, life comfort and effectiveness at work. In light of these scientific movements, increasing attention is being paid to lighting quality and visual comfort.

Peter Dehoff delivered an important manifest at the conference of The International Commission on Illumination (CIE) 2014 dedicated to lighting quality and energy efficiency:

> *Lighting quality should become the equal driver as energy efficiency. For life of humans lighting quality plays an essential role. It might be difficult to measure the benefits reached by lighting quality in the same way as savings can be calculated by using energy efficient lighting solutions. On the other hand the consequences from bad lighting might be worse than expected: lesser wellbeing, lower productivity, higher cost of labour, slower recovering and less sales in retail might be a result. Sometimes people are not even aware about these consequences. Therefore it is of higher importance to find the best way to describe what lighting quality means and how it may be achieved. It should be an essential part of standards and regulations even more than it is already incorporated* (Dehoff 2014).

Researchers seek to develop new alternative metrics to deliver better lighting quality and surpass existing methods in their predictive performance (Cantin & Dubois 2011; Leslie et al. 2012; Mardaljevic et al. 2009; Reinhart et al. 2006; Saraiji & Oommen 2014).

The fact that visual comfort metrics and others related to visibility and aesthetic judgement influence the subjective assessment of visual environment and conditions motivates some researchers to apply to ***luminance***. They estimate that luminance-based metrics may correlate with subjective acceptance and preference measures better than illuminance-based metrics, as luminance more closely relates to the human ***perception*** of brightness (Van Den Wymelenberg & Inanici 2014; Van Den Wymelenberg & Inanici 2015). In their studies, Van Den Wymelenberg and Inanici (2014; 2015) actively apply the ***High Dynamic Range (HDR) imaging*** technique. This technique is also called ***luminance mapping***, and HDR images are sometimes referred to as ***luminance maps*** when used for luminance analysis.

HDR imaging technique enables one to record a scene of wide luminance range by merging a series of photographed images at different exposures. The luminance and chromatic data of the captured scene is stored in the file from which it can be retrieved easily. According to Anaokar and Moeck, 'the true advantage of luminance maps obtained from HDR imaging is the luminance measurement of small details as well as gradients. Hence, this technique will be preferable compared to using a luminance metre to map the luminance in the scene' (Anaokar & Moeck 2005). Inanici (2006) notes,

> *It is not suggested that HDR photography is a substitute for luminance metre measurements. It requires calibration against a point or area of a reliable standard target with a reliable luminance metre to have absolute validity. Yet, it*

> *provides a measurement capability with the advantage of collecting high resolution luminance data within a large field of view quickly and efficiently, which is not possible to achieve with a luminance metre* (Inanici 2006).

The current study uses this technique as the primary method for research which allows broad comprehensive facilities. This presents a new opportunity to study the topic of interest through the examination of luminance maps (HDR images) and through the provision of reliable luminance data over each pixel of an image.

As a part of the lighting quality theory, the light modelling concept was chosen for the present study, as it seemed to be the most fascinating. Light modelling involves the ability of light to reveal a 3D object's form and characteristics (contour, shape and details). As explained by Phillips (2004), 'modelling of a shape derives from its physical form, whether round, square or otherwise, coupled with the way in which light plays on its surfaces… this provides a form which is perceived by the eye as having meaning, unambiguous' (Phillips 2004).

Good light modelling is one of the necessary conditions for lighting quality. It is essential in situations where good ***visual performance*** and communication are prioritised, but it is also significant in workplaces, museums and scenic performances. For architects, light modelling is especially valuable, as 'interior spaces are judged to be pleasant, bright or gloomy as a result of the effects of modelling and interiors are judged by the way in which the spaces and the objects within them are seen during the day to be natural, or accord to our experience of the natural world' (Phillips 2004). People need to perceive various 3D objects accurately, especially faces at the time of communication with others. The correct interpretation of human facial expressions is crucial and depends on the light distribution on the face and background (Zaikina et al. 2014). Tregenza and Wilson (2011) carefully note that,

> *Perception is, in essence, the process of linking immediate sensory information with remembered experience. The* ***distribution of the brightness and colour that constitutes our visual environment*** *is never treated as an abstract, meaningless pattern . . . our awareness of a place goes beyond mere recognition: what we see governs our expectations and our satisfaction, it affects our mood, our confidence, our approach to our activities there, and how we react with other people* (Tregenza & Wilson 2011).

It is important to pay particular attention to the above citation's mention of the ***distribution of the brightness and colour***. This is a seldom discussed topic in modern scientific works, as very few studies consider the interaction of light and colour in built spaces as a solid theme (Fridell Anter 2012). According to Klarén et al. (2013), 'colour and light in built spaces influence our experiences and feelings, our comfort and physiological well-being. Colour and light have great impact on health and can promote visual clarity, functionality, orientation and sense of security' (Klarén et al. 2013). Although these two topics are often treated as separated fields of knowledge, in the architectural context, they should be united. Humans explore space and shapes through the simultaneous perception of the colour and character of light, which helps them to understand the state of the world around them (Fridell Anter 2012). These two concepts are mentally inseparable in terms of perception, and therefore it was deemed particularly important to study both of them as a whole during this research project.

In the present study, it was decided to focus on ***luminance-based metrics of light modelling of coloured (achromatic and chromatic) 3D objects illuminated by daylight*** as the principal aim of this work.

1.3 The problem and research questions

To structure and clarify the problem, research objectives and research questions were formulated for the present study.

The first general objective was to better analyse the lighting quality topic and to single out important aspects that need improvement or have not been developed enough. This was mostly done through an initial literature review.

The second objective was to relate the aspects of lighting quality in architectural environments to the ***visual perception*** of built spaces where light and colour intrinsically exist and interact with each other. This objective also included the aim to figure out how strongly colour affects observers' process of perceiving and evaluating interiors and to examine the resources of the HDR imaging technique when studying these types of interiors. The following research questions were formulated to address the objectives:

RQ 1. How does colour affect the perception of light level in an architectural space?

RQ2. Is the HDR imaging technique a reliable tool for studying interiors with chromatic surfaces?

These questions were addressed in ***Experiment 1*** (Paper I).

The third objective was to study coloured (achromatic and chromatic) 3D objects in day-lit interiors through: i) the implementation of HDR imaging and ii) the subjective evaluation of the objects' characteristics (contour, shape and detail). This objective also aimed to develop a set of luminance-based metrics of light modelling for the studied objects and, if possible, to register their numerical values. The following question was formulated:

RQ 3. What are possible and reliable luminance-based metrics of light modelling for achromatic and chromatic 3D objects in day-lit interiors?

This question has been answered in ***Experiment 2*** (Papers II, III and IV).

The performance and precision of the proposed metrics have been verified with the help of photographed and simulated luminance maps. Suggested luminance-based metrics were also compared with the currently used illuminance-based modelling index and cylindrical illuminance. The following concluding questions were posed:

RQ 4. How effective are the suggested luminance-based metrics compared to the existing illuminance-based metrics of light modelling?

RQ5. How high are the error rates of the luminance-based metrics obtained from simulated luminance maps compared to photographed luminance maps?

These last two questions have been answered in ***Experiment 3*** (Paper V).

Together, these research questions form the consistent, logical structure of the current project and the strategy for work needed to complete the proposed study satisfactorily.

2. State of the art

Daylight is the natural source of illumination to which the human visual apparatus has adapted over millions of years. Light enables us to see and gather essential information about the physical world. It also occurs in architectural contexts, both interior and exterior (Rea 2000). Among other qualities, daylight allows us to experience the natural colours of our environments. The human visual system compensates for the natural light changes from morning to night to maintain colour constancy (Valberg 2005) in our experience of the colours we regard as 'natural' (Phillips 2004). Proper lighting can accentuate architectural form and composition, assist occupants' orientation and understanding of a space, facilitate the observation of true colours, increase the visual interest of an environment, diversify the appearance of a room by variability throughout the day and season and affect the occupant's state of mood and well-being.

Scientific interest in light and lighting has increased considerably in the past few decades. The discovery of the ganglion cell (ipRGCs) involved into the synchronisation of human circadian rhythms, a new type of electrical lighting (solid state lighting) and other achievements and events such as the proclamation of 2015 as the International Year of Light and Light-based Technology have solidified beliefs in the potential of lighting to contribute to quality of life (Boyce 2015).

In everyday architectural practice, designers follow laws and regulations pertaining to daylighting design. These laws and regulations, usually produced by governmental institutions, describe general principles and regulate important objectives from ensuring the health and safety of a building's occupants to energy saving arrangements. Regulations contain quantitative prescriptions for applying laws and can be complemented by various guides. All regulating documents are based on metrics. A metric can be interpreted as a measure applicable by the designer for (daylight) design evaluation. A metric should be quantitative, easily implemented during the design process, be calculated or verified after the completion of works and lead to desired objectives such as a good lighting quality (Boyce & Smet 2014).

However, an important question must be asked: do all the currently used metrics provide good lighting and lead to high-quality lighting? Some researchers believe that it is an unrealistic to expect to achieve good lighting quality based only on photometric quantities (Boyce 2003).

2.1 Light and colour

Before having a detailed discussion regarding lighting quality and its metrics, it is essential to have a look at light and colour correlations and the studies dedicated to their spatial interaction.

Looking at real architectural environments, many people note that these two notions—light and colour—are interdependent and inseparable (Arnkil et al. 2012). Humans intuitively perceive visual environments and the surfaces and objects within them as solid patterns of light, shadows and colours. Light enables us to see objects and their colours, and the colour of any observed surface depends on several physical factors—its structure (matte, polished, etc.), its spectral reflectance and the geometry and ***spectral distribution of the illumination*** (Valberg 2005). The human eye has adapted best to sunlight, which lends the best ability to recognise the natural colours of any surface.

However, colour and light are to a large extent treated in academic works as separate fields of knowledge, and usually those studies do not touch the topic of the spatial interaction of colour and light (Fridell Anter 2012). Fridell Anter (2012) performed a thorough literature study based on a large number of international publications, journals and conferences from 2006 to 2011, discussing the scientific works that deal with colour or light. She states,

> *Research on colour and/or light in directly architectural contexts is not common. When it occurs, it most often deals with the colouring of specific buildings, towns or time periods. Sometimes it includes also illumination and the use of daylight. The perspective is most often that of architectural history or building conservation, and the interaction between colour and light is most often not analysed* (Fridell Anter 2012).

In the past few years, researchers became increasingly interested in the topics related to colour and light in complex situations and realistic spatial contexts. Billger (2004) reported consistent results regarding the perception of a painted room and interaction of colours and light within it. One of her focuses was on how the coloured surfaces affected the perception of light and the atmosphere in the room. Among her conclusions was that daylight often dulled yellow colours but made blues more vivid; in incandescent light, however, blue colours appeared gloomy while reds and yellows became lively (Billger 2004). Hårleman (2007) investigated how windows that face north or south affect the perception of colour and the ways in which colour is experienced, causing a clear shift in ***hue*** and nuance. He aimed to develop a colour design tool based on these findings (Hårleman 2007). Other researchers have examined how the experience of colours and space can vary in rooms with different types of glazing (Pineault & Dubois 2008), how colours in interiors with modern glazing change its appearance (Angelo et al. 2012), and how the atmosphere of a room can be changed by colour, intensity and type of light source (Vogels et al. 2008).

Some studies apply 3D-vizualisations of virtual rooms to investigate how precise the appearance of colour and light in such a room will be (Stahre et al. 2007; Wästberg et al. 2015). An evaluation of a virtual room modelled in the software 3Ds Max Design 2015 and rendered using Mental Ray and Vray techniques showed incorrect reproduction of contrast effects and interreflections between angled surfaces (Wästberg et al. 2015). Another study investigated the feelings and reactions of people at a virtual railway station designed with different combinations of colour and light (Van Hagen et al. 2009). The authors concluded that even though colour and light are perceived subconsciously, the combination of the two had significant effect on people's estimates of waiting time on the platform. According to their results, respondents estimated the waiting time at the platform as shorter when warm colours in combination with dimmed lighting were used, whereas cooler colours and a more intense lighting were less preferred.

Even though interest in the field of the research regarding colour and light has increased in the past few years, Fridell Anter (2012) asserts that 'there is a great need for further research on the spatial interaction between light and colour. Initially this requires a development of methods that can include several aspects of experience at the same time' (Fridell Anter 2012).

The current research project is an architectural study that develops luminance-based metrics of light modelling in built environments and interiors; as such, it was of particular significance to include both topics (colour and light). This theme is especially important in terms of human visual perception and processing of information on the spatial interaction of light and colour. Luminance and colour, while treated independently at early stages of visual processing, begin to interact at later stages (Clery et al. 2013). This topic has not been fully investigated in previous studies, and there are still a number of ongoing projects examining the various features of simultaneous and/or separate luminance and colour stimuli. Some of these studies have shown that depth perception is directly dependent on the luminance ***contrast***, and that colours alone do not elicit any depth (Clery et al. 2013). Another study states that colour improves object recognition (Wurm et al. 1993). To conduct the current project, it was essential from the very beginning to determine whether generic interiors that normally include achromatic and coloured objects and surfaces can be examined using luminance-based techniques, as well as whether the luminance data corresponds with subjective evaluations of such interiors.

The importance of the mutual study of light and colour was the motivation to experiment with both of these quantities (colour and light) and to address to luminance quantity and subjective assessments in the observed scenes.

2.2 Lighting quality

Lighting quality is a goal of excellence, which lighting designers, architects and engineers are eager to reach in their respective practices. At present, there is no particular definition of the term ***lighting quality*** accepted by official institutions. Nevertheless, some researchers have tried to make this concept more clear and understandable through discussion in their articles (Veitch 1998; Veitch 2001, p.20; Veitch 2004; Dehoff 2014). By generalising various approaches, it can be concluded that the lighting quality concept includes several groups of parametres concerning human needs, economics, the environment and architecture (Fig. 2-1). The proper balance of these (sometimes conflicting) dimensions helps to achieve good lighting quality (Veitch 2001). This understanding of the term ***lighting quality*** has been accepted by the CIE (Veitch et al. 1998) and also represented in *The IESNA Lighting Handbook: Reference & Application* (Rea 2000).

The ***human needs*** category includes various aspects from *visibility* to health and aesthetic judgment. According to *The IESNA Lighting Handbook*, the visibility of objects and/or surroundings is one of the most important aspects that allows us to obtain

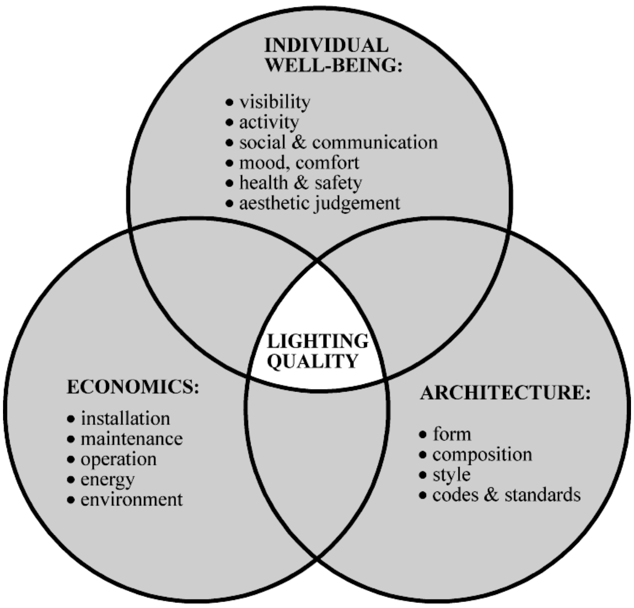


Figure 2-1. *Lighting quality: the integration of human needs, architecture, and economics and the environment.*
(c) National Research Council of Canada. Used by permission.
Adapted from Veitch, J. A. (1998). Commentary: On unanswered questions. In Proceedings of the First CIE Symposium on Lighting Quality (CIE-x015:1998, pp. 88-91). Vienna, Austria: CIE. Adapted with permission.

information from our visual environment; to be more precise, it is not only the recognition of the objects or facial expressions that is important but also the huge spectrum of related activities, even when the bright light is not needed, such as relaxation in the dim atmosphere of a café. Contrast, luminance, time and size are all crucial variables affecting the visibility of the objects around us (Rea 2000).

In terms of ***Architecture*** category, light can support a built environment, contribute to space understanding and should be applied according to specified codes and standards. Lighting may be brought into play to affect the appearance of surroundings, particularly those of indoor spaces, to create interesting variance in lighting and prevent flat, overly even or boring atmospheres. As Baker and Steemers (2002) wrote,

> *. . . the understanding and manipulation of light goes to the heart of the architectural enterprise. Vision is the primary sense through which we experience architecture, and light is the medium that reveals space, form, texture and colour to our eyes. "More and more, so it seems to me, light is the beautifier of the building" (Frank Lloyd Wright). More than that, light can be manipulated through design to evoke an emotional response—to heighten sensibilities. Thus, architecture and light are intimately bounded* (Baker & Steemers 2002).

The daylight in built environments has both aesthetic and functional purposes, and a harmonious balance between them leads to sustainable and aesthetically pleasing architecture.

Economics and the environment are additional dimensions of lighting quality. Daylighting can have significant impact on the overall energy performance of a building. To demonstrate, 'lighting accounts for between a third and a half of the energy use in commercial buildings and significant savings in energy can be obtained where the positive use of daylight has been planned' (Phillips 2004). In addition to the rigorous design of daylighting systems in a building, other aspects can also impact economics: i) lighting controls, which provide flexible use of natural and artificial light; ii) integration of lighting with heating and air-conditioning systems to save energy for cooling and heating purposes; and iii) maintenance programmes.

However, the most prioritised modern economic needs should not be the only decision-making drivers, as quality lighting, and particularly users' needs and comfort, are also important. Environmental conditions that affect the health and well-being of occupants indirectly influence their life quality, business performance and, therefore, economy (Aries et al. 2010).

Possible new metrics for the various aspects of lighting quality have been studied effectively in past years. Finding or establishing new quality lighting metrics might allow designers to identify, scale, compare and thus give priority to aspects of the quality of a luminous environment (DiLaura 2009). To make this process more successive, the lighting quality concept should be better formulated and described. Its metrics should be strongly inscribed in regulations and standards to become a clear and practically achievable goal for designers.

2.3 Visual comfort

In an effort to meet occupants' needs and study users' preferences in day-lit spaces, modern researchers focused their studies on developing the important metrics for visual comfort. Visual comfort is an essential human need frequently associated with the absence of uncomfortable elements such as ***glare***, insufficient visual contrast or disturbing sun patches within a field of view (Jakubiec & Reinhart 2013). Boyce (2003) describes the aspects that can cause visual discomfort as 'too little light, too much light, too much variation in illuminance between and across working surfaces, disability glare, discomfort glare, veiling reflections, shadows, and flicker' (Boyce 2003). In poor visual comfort conditions, a person can experience distracting symptoms such as red and itchy eyes, headache or back pain associated with bad posture trying to compensate for uncomfortable illumination. Whether any or several lighting aspects will lead to visual discomfort depends on the context in which the lighting is installed, as illumination that is undesirable in one context might be attractive in another. For instance, diffuse lighting is comfortable in an art gallery, but too even and monotonous in buildings with higher levels of activity.

Delivering lighting quality through the elimination of visual discomfort could form an effective strategy for lighting designers, but is it sufficient? Rather, removing visual discomfort is a means to prevent bad quality lighting and poor lighting conditions, but not necessarily ensure the best ones (Boyce 2003).

The importance of visual comfort in affecting occupants' satisfaction should not be underestimated. In addition, studies dedicated to this topic are particularly interesting and important because of the methodology used in many of them, namely the ***luminance-based technique***. The fundamentals of this technique will be described in sections 2.4 and 2.5 of the present paper, and examples of the most crucial studies of visual comfort using the luminance-based method will be discussed in section 2.6.

2.4 HDR imaging

HDR images store a depiction of a photographed or simulated scene in a range of intensities equal to those in the real scene. HDR imaging is referred to as ***radiance maps*** or ***luminance maps***. The conventional images suitable for representation with current display technology are called ***Low Dynamic Range*** (LDR) images. HDR images are not so inherently different from LDR images, but there are many more ways to create, store, use and display them, as well as other creative opportunities for image implementation (Reinhard et al. 2010).

It is important to explain the term ***dynamic range***. This is a dimensionless quantity that for images alludes to the ratio between the brightest and darkest pixels. The dynamic range of conventional digital cameras is limited to around two orders of magnitude (Jacobs & Wilson 2007), retained as a byte for each of the red, green and blue channels per pixel (Reinhard et al. 2010). However, it is evident that the real world produces a much larger range. For example, sunshine at noon may be 100 million times lighter than starlight. The human visual system is capable of adapting to lighting condition fluctuations of approximately 10 orders of magnitude, while within one scene it may cope with a range of around five orders of magnitude simultaneously (Reinhard et al. 2010).

Figure 2-2. *Sequence of 10 exposure-bracketed images, separated by one f-stop. These LDR images can be fused into one HDR image.*

HDR imaging adopts scientific ideas and theories related to light and colour. This type of image can be created in two different ways: with rendering algorithms (or other computer graphic techniques) or by merging a sequence of LDR images into one HDR image (see Figure 2-2) (Reinhard et al. 2010). A simple digital camera can be used to take LDR images with different exposures appropriate for further processing, either with the integrated automatic exposure bracketing function (AEB) or without it. The amount of light captured by the camera's sensor can be regulated by several methods, including setting the aperture, exposure and ISO value or using neutral density filters. However, the best option is to capture images by changing the exposure time. Altered ISO values may cause noise, whereas adjusting the aperture size will affect not only the amount of light incident upon the sensor but also depth of field, which is highly undesirable especially in terms of scientific application of HDRIs.

It is important to describe thoroughly the process of data depiction (see Figure 2-3), as this is significant for understanding the principle of HDR imaging. When the picture is just taken, the shutter remains open for a certain amount of time (depending on settings, and more precisely, the exposure time). During this moment, the light focused by the lens propagates into the objective and hits the image sensor separated into a number of small pixels the light over a small area. These records of pixels may be modelled by measurement equation, and voltages extracted from the camera sensor may therefore be related to radiance (Reinhard et al. 2010).

Because the camera records radiance, and the photometrically weighted radiance is luminance [see Equation 1], one may conclude that luminance is the most pertinent photometric unit for HDR imaging. The importance of luminance in HDR imaging lies in the fact that it provides a natural boundary for the visible wavelength; there is no need for wavelengths undetectable to the human eye to be recorded, stored or manipulated (Reinhard et al. 2010).

$$L_v = \int_{380}^{830} L_{e,\lambda}\, V(\lambda) \mathrm{d}\lambda \,, \qquad \textit{[Equation 1]}$$

where L_v is luminance value, L_e is radiance and $V(\boldsymbol{\lambda})$ is the CIE photopic luminous efficiency function.

Many programmes are available for processing LDR images into HDR ones. The three experiments performed for the current PhD research used ***Photosphere*** software (Ward 2002), created by Gregory J. Ward. In 2003, Ward proposed the use of an alignment operator on the median of the pixel values that is fairly robust against changes in exposures:

> *Input to our alignment algorithm is a series of N 8-bit grayscale images, which may be approximated using only the green channel, or better approximated from*
>
> *grey = (54*red + 183*green + 19*blue) / 256 [Equation 2].*
>
> *One of the N images is arbitrarily selected as the reference image, and the output of the algorithm is a series of N-1 (x,y) integer offsets for each of the remaining images relative to this reference. These exposures may then be recombined efficiently into an HDR image using the camera response function, which may be computed using either Debevec and Malik's original SVD technique* (Debevec & Malik 1997)*, or using the polynomial method of Mitsunaga and Nayar* (Ward 2003).

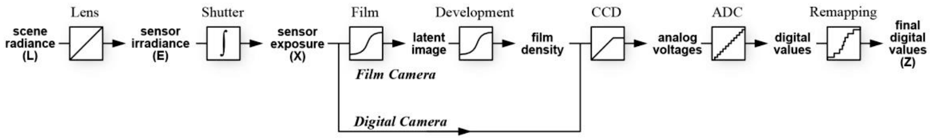


Figure 2-3. *Image Acquisition Pipeline shows how scene radiance becomes pixel value for both film and digital cameras.*
Adapted from Debevec and Malik (1997).
Adapted with permission.

This image registration works very precisely for the majority of cases and can successfully align hand-held image sequences (Jacobs 2007).

At present, three HDR image formats exists: High Dynamic Range (HDR), Tagged Image File Format (TIFF) and The EXtended Range format (EXR), of which one format can support multiple encodings. The HDR format (used in the current research project) is also known as the ***Radiance*** format (*.hdr, *.pic). It was introduced in 1989 and spread widely in the HDR photography and image-based lighting community. The RGBE (red mantissa, green, blue and exponent) components of this format—the R_M, G_M, B_M of the pixel data (also presented as XYZE, according to CIE)—are converted from the scene-referred colour by specified formulas (Reinhard et al. 2010).

The dynamic range of these encodings is larger than 76 orders of magnitude and precision is very high, making them applicable for most applications, including scientific ones.

While it might seem sufficient to combine LDR image sequences into one usable HDR image, it is obvious that some errors are present. To eliminate these errors, the image must be calibrated (see Figure 2-4). The first calibration type is called ***response curve calibration***. Combining a number of exposure-bracketed images into one HDR image involves determining the camera's response function. This automated process used to relate the pixel values to real-world luminances. Camera response curves vary considerably between different cameras, so radiometric self-calibration has to be applied to each of them. The only input to the process is a set of multiple exposure photographs, and once the camera response curve is determined, the ***Photosphere*** programme can fuse any photograph sequence taken by

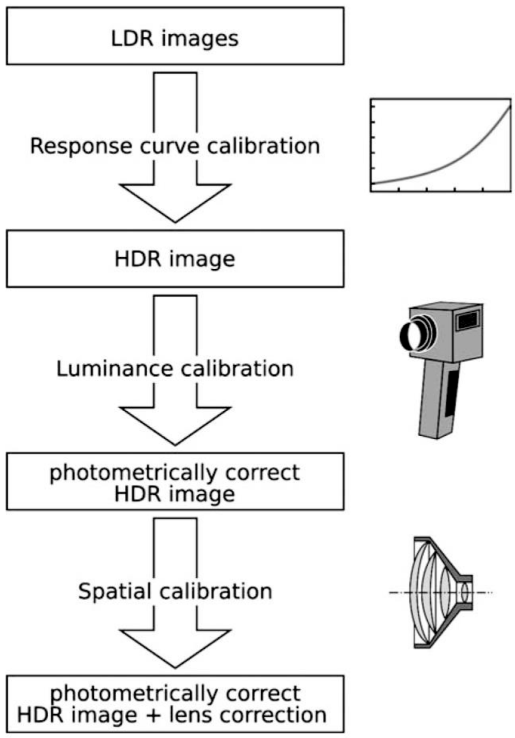


Figure 2-4. *The information that can be gained from HDR images and its accuracy depend on the level of calibration. Adapted from Jacobs A. (2007).*
Adapted with permission.

this camera into an HDR image (Inanici 2006).

The second calibration type is ***photometric calibration***. The easiest way to improve the accuracy of luminance maps is to compare the luminance reading of the photographed image with those obtained from manual measurements using spot luminance metres. The calibration factor can be implemented further in Photosphere to correct the luminance values of the photographed scene.

Some researchers go further in their attempts to improve HDR image quality by performing ***lens vignetting effect corrections***. This is an optional correction process rather than a calibration. Vignetting correction helps to eliminate the reduction of image brightness at the periphery of the image compared to its central region, which occurs due to the optical construction of the camera and the lens and strongly depends on the device's aperture size (Jacobs & Wilson 2007). Fisheye lenses usually have more noticeable vignetting, and if it is negligible in the centre of the image, the peripheral pixels can have even higher pixel errors. By capturing the set of LDR images of the scene in 5° (sometimes 10°) intervals and producing a polynomial function, it is possible to correct the image. This function can be applied to create a digital filter or mask for the image that will compensate for the luminance loss (Inanici 2010).

2.5 Luminance-based technique as a research method

Over the course of the past decades, the HDR imaging technique has been constantly developing. Now it is widely applied in different fields, including lighting design and research such as glare analysis, visual comfort studies and road and pedestrian lighting investigations. The root of the implementation of luminance maps is the fact that brightness as a human perceptual aspect closely relates to measures of luminance. As vertical visual tasks have become increasingly dominant (e.g. working with a computer or projector screen), it is assumed that luminance-based measures from the occupants' point of view may better correlate with subjective assessments of visual comfort in built spaces than illuminance-based measures (Van Den Wymelenberg & Inanici 2015).

In developing the HDR imaging technique, and because HDRI photography was not specifically developed for lighting measurements (Tyukhova & Waters 2014), researchers have shown interest in assessing the technique as a scientific method and testing its capability to capture luminance values within a scene accurately. However, this technique is still under examination as new lighting sources are being developed and new applications of luminance maps proposed.

Some of the most significant studies dedicated to HDR imaging will be discussed here. In 2005, the results of the study performed by Anaokar and Moeck were published (Anaokar & Moeck 2005). The authors investigated the impact of light spectra, spatial frequency, vignetting and thermal noise on the accuracy of luminance measurements obtained from HDR images of Munsell chips of different hues, values and chromas to determine potential errors. They found that warm hues had the least errors while cool hues resulted in larger errors. In general, saturation increment led to error increment; the error in reflectance increased as the Munsell value decreased. The error in reflectance was independent from the lighting conditions of the scene. Saturated greens and blues were found to produce the largest errors (up to 80%). The most reliable results were obtained for warm colours with high Munsell values, while high- to medium-reflectance blues and greens were shown to produce reliable readings down to Munsell value N5. The authors concluded that HDR images would be useful in most of research studies because saturated and dark hues are not frequently found in building materials and the ***error percentage would peak at around 20%***, which is acceptable as luminance metre measures can have errors of 2 to10% (Anaokar & Moeck 2005).

Inanici (2006) thoroughly studied the capacity of HDR images and the relative errors for a large number of coloured and grey targets under different lighting conditions (both day- and electrical lighting). The author found that the ***average error percentage was within 10%***; to be more precise, total, greyscale and coloured targets were 7.3%, 5.8%, and 9.3%, respectively (Inanici 2006). The previously discussed tendency when more saturated colours showed larger errors in luminance readings was noted in this study in accordance with the findings of Anaokar and Moeck (2005).

Another study investigated the HDR imaging technique in terms of variation of the calibration factor for a day-lit scene under various indoor daylight levels. Testing the HDR images of the X-Rite Colour Checker chart with 24 colour chips, no statistically significant difference in calibration factor for any colour chip of the chart or indoor vertical illuminance was found. The authors concluded that the calibration factors of each colour over the investigated range of daylight levels might be averaged, so that for any scene with dominant colour the same as one of the 24 colours of the chart, calibration from HDR luminance to real luminance can be achieved by multiplying the calibration factor of that colour (Chung & Ng 2010). These findings support the application of HDR imaging as a luminance data acquisition system.

Cai and Chung performed a study to find optimal parametres for HDR imaging dedicated to scientific use and to find error rates depending on various technical and experimental conditions (camera and lens type, colour of the surface, camera aperture size, type of illumination, etc.) (Cai & Chung 2011). Their conclusions were exclusively applied to the Canon EOS 350D fitted with the Sigma lens 10–20mm F4-5.6 EX operating under fluorescent lighting. In their study, the average error percentage of the six HDR images with the highest quality (i.e. f/5.6, *f*=10, 14 or 20 mm, with Jacobs' EV ranges, low or full ambient light) was ***2.8% ± 0.6% for grey surfaces, 10.1% ± 0.1% for colour surfaces, 1.5% ± 1.3% for black surfaces and 6.6% ± 4.0% for light-***

emitting surfaces. They also found that: i) large apertures (e.g. f/5.6) produced higher quality HDR images than small ones (e.g. f/22); ii) focal length had no significant impact on the quality of HDR images photographed at a large aperture f/5.6; iii) using more LDR images (EV steps) within the photography session significantly increased the quality of HDR images of colour, black and luminous surfaces, but not grey surfaces in the middle dynamic range (i.e. 4.8 to 212.9 cd/m^2); and iv) a higher ambient light level significantly improved the quality of HDR images of light-emitting surfaces and front grey targets.

Another study performed and presented by Cai (Cai 2011) investigated the accuracy of HDR imaging in acquiring non-uniform luminance for different types of light sources, including incandescent, tungsten halogen, fluorescent T8, CFL, mercury, MH, HPS, LPS and LED. The researcher found that ***error percentages were 29.4% +/- 28.4% if the averaged luminous pixels were larger than 500 cd/m²***, or 29.5% +/- 33.5% if manually retrieved using the provided square selection tool in the Photosphere programme. However, the error percentage between luminance values of the approximately uniform white patch of the Macbeth colour checker obtained from field measurements and those from the HDR images were found to be much smaller at 1.5% +/- 1.2%. The metal halide lamp and incandescent lamp showed the highest error level. The final conclusion was that, based on the outcomes of this pilot study, HDR images may be used to measure the luminance of light sources with enhanced accuracy.

Tyukhova and Waters (2014) continued to study the ability of HDR imaging to capture the luminance data of an electrical light source. They tested a single light-emitting diode (LED) chip using two conventional methods (the use of a luminance metre with a close-up lens, deriving luminance from illuminance measurements, source area and distance) and HDR imaging technique. Their results showed that luminance data derived from HDR images compared very well to a luminance value determined with goniophotometre measurements and calculations. This research supported confidence in the ability of HDR imaging to capture the luminance of a very small and bright light source, such as a single LED chip (Tyukhova & Waters 2014).

As a part of the experiment conducted in 2012 and the current PhD study, the capabilities of HDR images as a method for lighting studies of interiors painted in low saturated colours have been examined (Zaikina 2012). The findings showed that the luminance-based technique is a reliable method for studies of these types of interiors and can be used for further investigation of chromatic and low saturated architectural spaces and spaces that includes chromatic objects of low ***chromaticity***.

The above described studies demonstrated very thoroughly the capacity and level of precision of the HDR imaging technique (luminance mapping) for application in various lighting measurements. Not all the described studies used daylight as the main or sole light source. Moreover, in each particular situation (digital camera model, lens, experimental conditions and target position), certain camera's adjustments should be used to achieve the best possible results, while a general approach could also be derived (Cai & Chung 2011). Further studies using luminance mapping for natural light analysis might verify or assume luminance error levels individually and optionally, as was done in the study performed by Wymelenberg, Inanici and Johnson (Van Den Wymelenberg et al. 2010).

2.6 Studies applying the luminance mapping technique. Luminance-based metrics

The most common luminance-based metric referenced by design guides and reported by daylighting research is that of ***luminance ratios***, which typically occur between a task and its background or between a bright light source and the task. Patterns of light on the task plane are quite important as they can affect task visibility, visual comfort of the observer and overall perception of a space or an object. The task plane varies according to the application; it could be a desktop in an office or the floor in the corridor. Two separate phenomena are influenced by luminance ratios within a field of view: dark and ***light adaptation*** and disability glare. To limit the effects of these phenomena, luminance ratios generally should not exceed certain recommended values. However, it is not practically and aesthetically desirable to maintain these ratios throughout the entire environment, as visual interest in the space is also important (Rea 2000).

A recent study of Van Den Wymelenberg and Inanici investigated architectural spaces illuminated by daylight or a combination of daylight and electrical light. The study noted that: i) existing literature does not explicitly state how the recommended luminance ratios should be calculated in spaces with daylight; and ii) the result is strongly affected by the method (Van Den Wymelenberg & Inanici 2014). Current recommendations by the Illuminating Engineering Society (IES) list the maximum luminance ratios in daylight settings as '20:1 between daylight-media and daylight-media-adjacent-surfaces'. No specific references are offered for the IES's 20:1 recommendation, and other ratios cite the previous handbook (Rea 2000), which also lacks substantial reference to original research. The authors concluded that future research on luminance ratios in spaces with daylight is warranted to establish a consistently applicable calculation method and defensible recommended criteria (Van Den Wymelenberg & Inanici 2014).

In visual comfort-related studies, the HDR imaging technique is a frequently applied method. Visual comfort studies are also interesting and important due to the frequent goal of researchers to find and develop new metrics or even sets of the metrics of visual comfort, including those based on luminance data.

Recently, new studies have been performed to examine the relationship between scene luminance and occupant assessments of visual comfort using HDR images. One such study was done by Konis (Konis 2014). The goal of the research project was to develop and test 15 visual discomfort predictors. These were: interior vertical illuminance, interior global horizontal daylight illuminance, the Daylight Factor, average luminance and maximum luminance of an upper two rows of windows, average luminance and maximum luminance of lower rows of windows, the Daylight Glare Index, Daylight Glare Index of a glare source seven times greater than the average scene luminance, Daylight Glare Index of a glare source greater than 2000 cd/m^2, the Unified Glare Rating, the CIE Glare Index developed by Einhorn, the ratio of maximum window luminance to a vertical visual task of 200 cd/m^2, the ratio of average window luminance to task luminance and the ratio between the window region and some interior surfaces. According to the results of this study, the models developed from discomfort indicators based on ***luminance contrast ratio limits*** and from ***absolute measures of vertical luminance*** were found to be the most accurate in predicting discomfort responses. However, contrast ratios based on maximum values of a region were more effective compared with ratios based on averaged luminances. In addition, the horizontal daylight illuminance and the daylight factor were found to be two of the least effective predictors of visual discomfort.

Another convincing study was performed by Van Den Wymelenberg, Inanici and Johnson (2010) and was dedicated to the ability of common illuminance and advanced luminance-based measures to differentiate between participants' 'most preferred' luminous environment and those with 'just disturbing' glare (Van Den Wymelenberg et al. 2010). Over 150 different illuminance and luminance metrics were tested in this research. The most meaningful finding was that ***mean luminance of glare sources metrics*** based on various task and scene mean luminance multipliers consistently emerged within the top 10 metric rankings for the Likert items. Moreover, the ***standard deviation of the entire scene luminance*** was proven as a good predictor of satisfaction with general visual appearance.

In the recent study performed by Van Den Wymelenberg and Inanici (2014), existing visual comfort metrics were reviewed and criticized based on their ability to explain the variability in human subjective responses in a day-lit private office laboratory environment. Luminance-based metrics were also included in the scope of the study. The authors provided the results of a six-month human factor research project replete with extensive lighting data collection in an office space with daylight only and with both daylight and electric light (integrated lighting). The results showed that vertical illuminance and simple luminance metrics (mean and standard deviation of scene luminance) outperformed more complex metrics (such as DGP and DGI, or luminance ratios) for inquiry on subjective satisfaction with the amount of light for computer work. The authors concluded that establishing reliable vertical illuminance- and luminance-based metrics and design criteria that can be referenced in design stages, through additional research, should lead to improved occupant satisfaction in spaces adhering to these criteria. However, the luminance ratio between the mean luminance of the daylight source and the mean luminance of the circular task did not yield squared correlation coefficients as high as other existing metrics with regard to the subjective visual comfort ratings. This metric was even recommended by the authors to be entirely dismissed. The authors concluded that commonly reported luminance-based metrics do not appear to have greater predictive ability than common illuminance-based metrics. Even if luminance measures closely relate to human perceptions of brightness, it is probable that luminance-based metrics will correlate with subjective acceptance and preference ratings more closely than illuminance-based measures. Therefore, the authors illustrated the necessity to develop a new luminance-based analysis metrics in the future (Van Den Wymelenberg & Inanici 2014).

These authors took the results of the 2014 experiment even further. In 2015, their article was published with new findings. Here, they asserted that despite previous conclusions, luminance-based metrics outperformed illuminance-based metrics (Van Den Wymelenberg & Inanici 2015). Namely, luminance-based metrics had higher squared correlation coefficients (r^2 = 0.425 for ***standard deviation of the window luminance*** metric) than illuminance-based metrics (r^2 = 0.298 $\boldsymbol{E_{vertical}}$ ***at the top of the monitor measured in the participants' viewing direction***) for all subjective questionnaire items. The authors particularly emphasised three the most promising metrics that, with additional research, may support lighting design recommendations aimed at improving visual comfort in spaces with daylight. These metrics were: standard deviation of window luminance, 50th percentile luminance value from the lower window and mean luminance of the 40° horizontal band.

The authors of another study (Piccablotto, et al. 2011) described the results of an experiment on lighting quality assessment in a museum (museum showcases). Lighting and visibility conditions were estimated with the help of luminance-based lighting quality metrics, an evaluation of the light distribution in exhibits and showcases and through assessing discomfort glare for visitors. A luminance-based analysis of the three LED fittings layouts showed the usefulness of luminance contrast images (the images that showed the ratio between each image's pixel luminance and the average target luminance) as the first step to estimate visibility conditions, rather than a borderline between discomfort glare caused by primary sources and distracting or annoying glare caused by reflections (Piccablotto, et al. 2011).

All the above mentioned studies prove the suitability of the luminance-based technique and demonstrate appropriate luminance-based metrics to be highly consistent and precise in the research studies related to subjective assessment of lit environments, visual appearance of spaces and visual comfort of occupants. However, the use of luminance does not guarantee the assured success of any luminance-based metric (Van Den Wymelenberg & Inanici 2014). This methodology is also actively applied in glare studies, which is not in the scope of current thesis.

The application of luminance-based techniques remains primarily within the research community, and it has not gained popularity among design practitioners (Van Den Wymelenberg & Inanici 2014). Like the illuminance-based method, the luminance-based technique suffers from an established lack of confidence or consensus by the research and design communities regarding what metrics should be implemented and what criteria are recommended. At present, there is a lack of sufficient and adequate research to support consensus-based design recommendations (Van Den Wymelenberg & Inanici 2014). Thus, it is very important to identify the strengths and limitations of existing and newly proposed metrics, and to the continue research process to develop a new set of luminance-based metrics.

2.7 Light modelling

Living in a 3D world, humans obtain the majority of their information about the surrounding world through vision, constantly detecting objects and people and discriminating their qualities. ***Discrimination*** is the ability to identify an object or image after distinguishing it from its background, and this process usually requires more contrast than detection (Valberg 2005). The basic purpose of visual perception is to enable the recognition of object attributes, such as to judge whether fruit is in a good state to eat or whether a child is sick. The light that we require in our everyday lives has to provide not only for discriminating detail and colour but also object characteristics (Cuttle 2008).

By changing the directivity, eliminating or accentuating of shadows and contrast, light reveals or conceals the depth, shape and texture of an object. Usually this phenomenon is called ***light modelling***. Appropriate light modelling is critical in various types of buildings. In hospitals, it is crucial to correctly determine the health status of patients; in industrial applications, modelling is essential for assessing material and finish quality and consistency; in museums it is needed to address visitors' attention towards the displayed objects; in offices it is important for pleasant communication and productive cooperation. When we communicate with each other at work and at home, a high percentage of communication is nonverbal; it is especially important that the pattern of light on faces enables clear recognition and interpretation of expressions (Rea 2000).

It was discussed earlier that the concept of lighting quality proposed by Veitch (Veitch et al. 1998) include several groups of parametres concerning individual well-being, economics and architecture. There are a great number of particular parametres and measures that can be analysed and applied to obtain the best lighting solution for a particular building, room or situation. Light modelling (telling how well the light describes a 3D object in a given place) is one of the lighting quality parametres that might be related to both individual well-being and a functional requirement of an architectural space (Zaikina et al. 2015b).

In the European Standard EN 12464-1:2011 *Lighting of Workplaces*, light modelling is defined as ‘the ratio between cylindrical and horizontal illuminance at a specific point and should be between 0.3 and 0.6’ (CEN 2011). Useful as this definition may be, the current study did not rely on this light modelling index because it is based on illuminance values. Though commonly used metrics for daylight design are based on horizontal illuminance, and some researchers state that the daylight factor (as a ratio of the simultaneously measured horizontal illuminance inside and outside the building) can be applied as a predictor of the appearance of a space (Cuttle 2008), methods based on luminance values might be more reliable and useful, as was described in the previous chapter.

In the current study, the term ***light modelling*** represents the degree to which light describes 3D objects so their contours, shapes and details are clearly visible. The better the light modelling, the easier 3D objects can be discriminated from the background and the more correctly their 3D shapes and specific characteristics read.

It is necessary to discuss here the most significant studies related to light modelling. In the book *Human Factors in Lighting*, studies on face recognition from various distances were presented (Boyce 2003). Studies from the 1980s were based on semi-cylindrical illuminance that later became a basis for the modelling index used in the European Standard EN 12464-1:2011. Following the work of Caminada and van Bommel (Caminada & van Bommel 1980), semi-cylindrical illuminance was used as a measure of the lighting conditions required for easy visual recognition of distant pedestrians. Rombauts et al. (Rombauts et al. 1989) identified a minimum semi-cylindrical illuminance of 0.6 lx on the face as necessary to ensure confident identification at 4m (4m is the so-called public space surrounding an individual). Other authors found that people considered the lighting of facial features to be well balanced when the vertical/semi-cylindrical illuminance ratio was in the range 1.1–1.5. Assuming a desirable vertical/semi-cylindrical illuminance ratio of 1.3, the results convert to a vertical illuminance of 33 lx for confident face recognition at 17 m and 0.8 lx at 4 m (Boyce 2003).

Figure 2-5. Vertical axis cubic illumination metre. Six silicon photodiodes are aligned on the faces of a cube and tilted so that one long axis is vertical.
Adapted from Cuttle (2008).
Adapted with permission.

Another example of the study on light modelling was performed by Cuttle (2008), based on illuminance measurements using a six-sided illumination metre (Figure 2-5) (Cuttle 2008). The author proposed a theory of cubic illumination at a point in space that could be defined by six measured or predicted illuminance values on the facets of a small cube centred at the point. This method enabled the estimation of a range of spatial illumination metrics, including the illumination vector, and scalar and mean cylindrical illuminance values. According to the author, this method could also be used to predict the shading patterns of various objects or the distribution of eye illuminance at a given point (Cuttle 2008; Cuttle 2014). However, although this technique was reliable for outdoor applications, its reliance on calculations of direct illuminances of the cube sides made it insufficient for indoor lighting, especially where indirect light was dominant and directional.

A different method suggests using a modelling sensor to predict light distribution on a 3D object, the occurrence of light spots, cast shadows and register light direction (Matusiak 2002). The modelling sensor is a comprehensive instrument consisting of three elements: the matte white sphere that shows an illumination pattern revealed by the variation of illuminance over its surface; the black glossy sphere that reveals the highlight pattern; and the open lattice-like cube that generates the shadow pattern on the

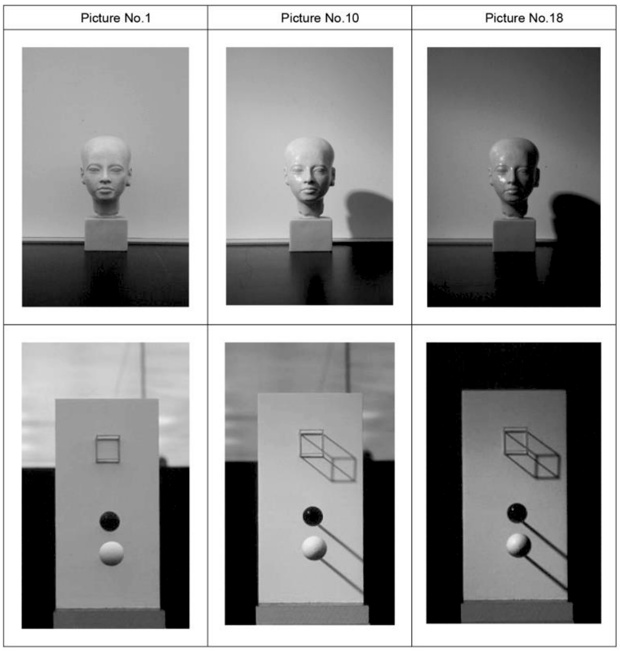


Figure 2-6. *Photos of the sculpture and the modelling sensor taken in the artificial sky. Adapted from Matusiak (2002). Adapted with permission.*

white vertical partition (Figure 2-6). The shadow pattern made by the open cube reveals information about the number of light sources, the angle of incidence of light from the respective sources and how concentrated and how strong the light from the respective light sources is. In most cases, the way in which light describes the appearance of illuminated opaque objects exposed on a vertical background should be examined; the modelling sensor is supposed to be used in places where light falls preferably on the front of the shape (as seen by the observer) (Matusiak 2002).

The approaches described by Cuttle and Matusiak are very interesting because they represent two different methodologies: the numeric illuminance-based method and another more visually or perception-oriented method (Zaikina et al. 2015b)

The authors of a recent article used the luminance-based design method to develop new metrics for the lighting of pedestrians (Saraiji & Oommen 2014). They studied the target's (pedestrian) visibility at night on an unlit street and developed the concept of ***dominant contrast*** (Figure 2-7). Dominant contrast is the contrast of any part of the target that provides the highest target visibility and is considered a useful measure for visibility models. Therefore, understanding the usability of luminance-based measures related to object distinctness and detail discrimination could be important and useful both for science and practice in the field. Interestingly, the researchers also tested semi-cylindrical illuminance and vertical illuminance metrics to compare driver's detection distance and reaction time in the presence of pedestrians. Despite the common use of vertical illuminance as a design target for pedestrians, Saraiji (2014) found the 'vertical illuminances to be minimal in significant portions of the street that satisfy the IESNA horizontal illuminance requirement (Illuminating Engineering Society of North America. Roadway Lighting. ANSI/IESNA RP-8.00. New York: IESNA, 2005)'. In other words, the minimum vertical illuminance ($E_{v(min)}$ 1.5m above ground) can be zero even if the horizontal illuminance on the street satisfies IESNA recommendations (Saraiji 2009a; Saraiji 2009b). This study on dominant contrast is highly significant because luminance contrast values were proposed here as a basic for the dominant contrast metric, namely ***luminance contrast values associated with object visibility and object distinctness from its background***.

The small number of existing studies on light modelling in built environments (and especially under the real daylight conditions) leaves the topic open for further research. Light modelling is an important attribute of quality lighting and comfortable visual communication, naturalness of observed objects and faces in a surrounding space. The understanding that light modelling is a basic need for convenient visual communication with humans and objects in the real world and the consistency of current metrics (modelling index) demonstrates the need for new light modelling metric investigations.

2.8 Summary

This chapter provided an overview of the existing studies relevant to the current research project. Despite the number of studies that investigated the various aspects of lighting quality over the past few decades, this topic remains insufficiently studied.

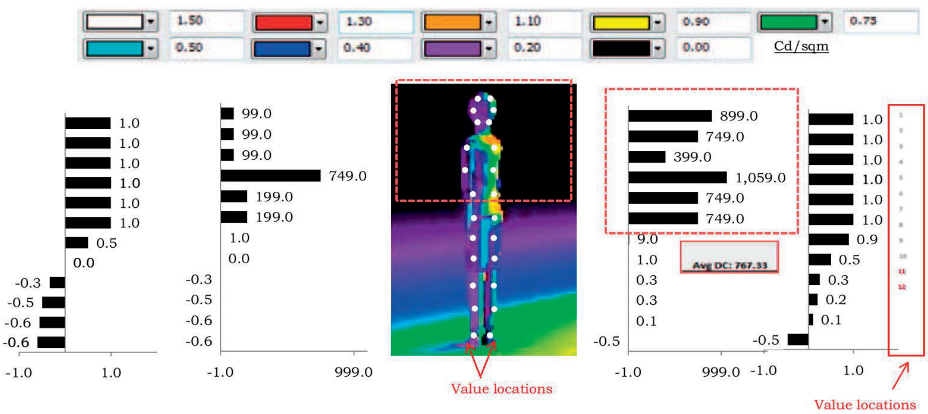


Figure 2-7. *Average dominant contrast of the left pedestrian at grid 42.5 and D=10 m. Adapted from Saraiji and Oommen (2014). Adapted with permission.*

Modern advanced and rapidly developing technologies and computer programmes now facilitate the innovative study of these issues. Many of the examples reviewed in this chapter, especially the studies on visual comfort, successfully applied HDR imaging as their source of luminance data. This technique is well-studied, with comprehensive and available user recommendations and possible error descriptions. Although the various luminance-based metrics proposed by researchers were actively examined in a relatively short period of time, they have already proven themselves as promising tools that outperform some illuminance-based metrics.

The topic of light modelling remains an open question despite the importance of the issue for most day-lit spaces. The studies that proposed illuminance-based metrics of light modelling could not effectively predict the appearance of 3D objects in a space or account for certain qualities of the objects and their backgrounds. Quantification of the amount of light at a point in space, even when captured from different directions (as cylindrical illuminance or cubic illumination), is a useful method that had been used for decades. Still, this absolute value of light falling on a point or object in space is unlikely to correlate with subjective observer assessments of the object’s visibility. Thus, luminance-based metrics could become very useful, serving as a simple tool to achieve better light modelling prediction results.

3. Project development

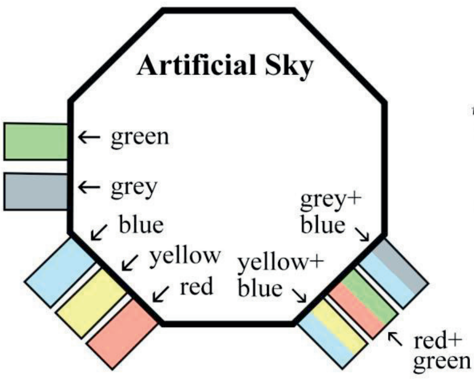
Before starting the discussion of methods, results and conclusions, a short overview of the overall project's development will be presented in this chapter. The most significant points include the choice of the metrics, and important findings will be described in detail (though a thorough review will be provided in Chapter 6).

This thesis is based on three empirical investigations described in the dissertation as ***Experiments 1***, ***2*** and ***3***. Since the major goal was to develop appropriate and verified luminance-based metrics of light modelling in architectural spaces, each performed experiment represents a significant step towards the main objective.

3.1 Experiment 1

The current project is an architectural study wherein both colour and light are examined. It was important to figure out how the chromatic properties of the interiors painted in low saturated equiluminant (***isoluminant***) colours and colour combinations affect the perception of light levels in the spacce. It was also important to examine whether the luminance maps of chromatic and achromatic interiors would reflect similarly (in numeric values) those tendencies particular to observers' subjective assessments of the interiors.

The experiment conducted in the Daylight Laboratory under the Artificial Sky included



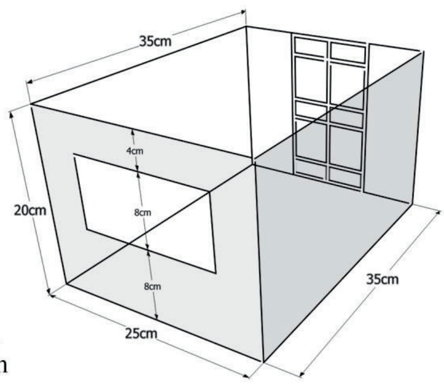


Figure 3-1. *To the left: arrangement of the models in the laboratory under Artificial Sky during the experiment, photographing and measuring illuminance. To the right: form and sizes of scale models*

Figure 3-2. The observation of the scale models placed in the laboratory under the Artificial Sky by one of the participants.

Figure 3-3. Appearance of the striped scale model photographed through the opening for observation.

the careful observation by 32 participants of eight scale models and answering a questionnaire form. Also a single photographing session of each of the observed scale models was done. The scale models were divided into two groups according to their colouration: one-coloured models (yellow, green, grey, blue, pink) and striped models (striped patterns of various colour contrasts: yellow/blue, red/green, grey/blue) (see Figure 3-1).

Participants were asked to evaluate light levels in the models by placing them in descending order from bright to dark. Three questions in the questionnaire form addressed perceptions of comfortable lighting, personal preferences of the respondents and self-reporting on colour's degree of influence on the perception of light levels. The questionnaire answers were analysed using the Fridman test. A series of LDR images of each scale model was processed into eight HDR images, respectively. The results showed that ***the differences in the perceived light levels among five one-coloured rooms were not statistically significant***. The respondents admitted in their comments the difficulties in the evaluation of these models as the light levels seemed almost identical. ***The differences in the perceived light levels among the striped models were statistically significant. Similarly to those of subjective evaluation, the quantitative results obtained from luminance maps of striped models were also different***. In general, even poorly saturated colours had an impact on the subjective perception of light levels in the observed spaces. However, ***the difference in the perceived level of illumination that was statistically significant was also detectable in luminance maps***.

These findings form an essential basis for further research, as they support the evidence needed to study the architectural spaces and objects of various low saturated colours with the help of HDR imaging.

A detailed description of ***Experiment 1*** and its results can be found in Paper I, Chapter 8.

3.2 Experiment 2

After finishing the first experiment, focus turned to possible new luminance-based metrics of light modelling as part of the lighting quality concept. A new experiment was performed under overcast daylight conditions in the mock-up room built in the Room Laboratory. The interior resembled a generic room with one window shielded from the participants' view and two shelves with 18 randomly painted Venetian masks (see Figure 3-4). The colouration of those masks was identical to the colours used and tested in Experiment 1. Two types of coating were used (glossy and matte). Thirty-two participants observed the Venetian masks and evaluated the distinctness of their contours, shapes and details using the provided questionnaire form. For each pair of subjects, a set of 11 LDR images of the scene was taken.

The data from the questionnaire forms were statistically analysed, and 18 HDR images were generated for further examination. Numerical values of the proposed luminance-based metrics were paired with the subjective assessments of the visibility of the contours, shapes and details of the masks. Certain reliable metrics were revealed.

Figure 3-4. *The experimental room from the observers' point of view.*

Figure 3-5. *Two participants of the experiment observing the masks and answering the questionnaires.*

3.2.1 Proposed luminance-based metrics

It is important to elaborate on the choice of appropriate light modelling luminance-based metrics. The metrics based on ***luminance contrast*** were considered the departing point in the study. Contrast perception is a fundamental ability of our visual system that enables us to discriminate, among other things, a target from its background (Valberg 2005). Perception of contrast depends on the size of the observed object, its form and temporal variation. In good illumination, ***sensitivity*** to static contrasts with sharp borders is greatest for objects that are larger than 0.2° in ***visual angle***. If the borders are less distinct (as is often the case of shadows), sensitivity for larger areas is reduced. The sensitivity for pure chrominance contrast, however, still increases for objects larger than 0.2º. It is also not affected by blurred or sharp borders. Thus, chromatic and achromatic objects were included in the present study as examples of luminance and chromatic (chrominance) contrasts.

Numerous scientific investigations of luminance and chrominance contrasts and their ***threshold*** values have been carried out in fully controlled conditions in research laboratories for decades (Watson et al. 1983; Mullen 1985; Kelly 1994; Edwards et al. 1995; Valberg et al. 1997). However, it is not known what contrast threshold values are necessary for the detection of the contour of objects—for example, human faces—in real full-scale rooms illuminated by daylight with its typical gradation of illuminance, and how those threshold values may differ depending on the optical characteristics of both object and background surfaces (Zaikina et al. 2015a). These questions arose in the current study and were examined in Experiment 2.

Regarding thresholds, it is needed to note that subjective impressions are always qualitative and it is simpler to measure a magnitude of the physical stimulus that gives rise to the smallest subjective impression (threshold) in order to quantify perceived value (Valberg 2005). The minimum numerical values of the metrics tested previously by researchers and then possibly subscribed by norms and regulations helped only to prevent poor or unwanted lighting conditions. In the case of Experiment 2, low illumination was used to create conditions with hardly visible objects to help detect the luminance values corresponding to their contour, shape and details discrimination.

Any stimulus to the visual system can be described by five parametres: its ***visual size*** (appropriate angular measure), ***luminance contrast***, ***colour difference***, ***retinal image quality***, and ***retinal illumination***. These parametres commonly determine the extent to which the visual system will be able to detect and identify the stimulus (Boyce 2003). In Experiment 2, lighting was kept at a relatively low level (thus creating a low retinal illumination), so the contours of the masks, their shapes and details were hardly visible. Therefore, ***luminance-*** and ***chrominance contrasts*** were the major factors affecting objects' distinctness, and these factors were adapted as predictors of contour and shape distinctness in the statistical analysis. Thus, luminance- and chrominance contrasts were chosen as possible luminance-based metrics.

The angular size of the objects observed from the observer's point of view was almost equal, varying only from 2.7º to 3.6º vertically and 1.5º to 2.1º horizontally. Therefore, the differences in the masks' angular size were not taken into account.

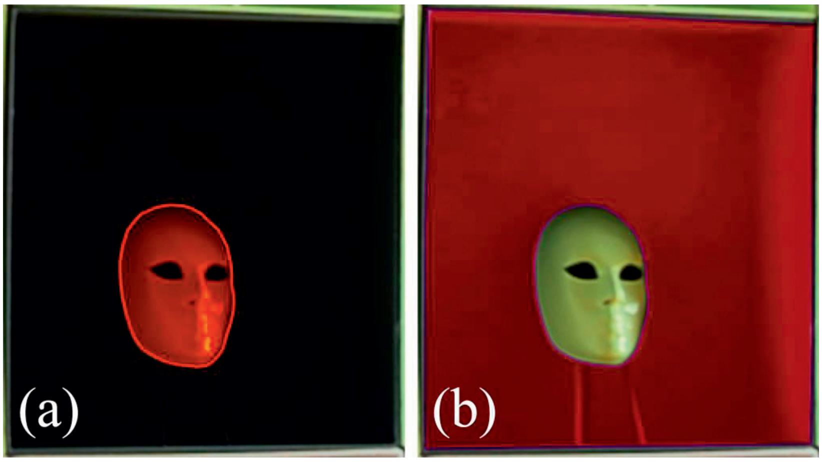


Figure 3-6. *Example of the selection for the analysis regions at the HDR image of the mask, in red colour: foreground or object (a), background (b).*

The possible choice of metrics was also limited by the technical options of the software used for image analysis, which provided only a few tools for selecting areas of interests in the images and obtaining their luminance values.

Two sets of four metrics each were proposed to perform the contour, shape and details distinctness analysis. The contour distinctness metrics were:

- *Contrast (Luminance contrast calculated as the Weber ratio)*
- *Luminance ratio (Luminance$_{(foreground)}$/Luminance$_{(background)}$)*
- *Percentage of the invisible part of the contour*
- *Mean point luminance ratio (LR)*

The shape and detail distinctness metrics were:

- *Luminance of the foreground*
- *Luminance ratio (Luminance$_{(foreground)}$/Luminance$_{(background)}$)*
- *Ratio between the maximum luminance value of the mask and the mean luminance*
- *Standard deviation of the foreground luminances*

The choice of metrics based on luminance contrast has already been discussed in this section.

The 'percentage of the invisible part of the contour' metric and 'mean point luminance ratio (LR)' were founded on 12 paired point luminance measurements around the contour of the mask. The first point of the pair was measured at the mask, and the second point was measured at the background. The percentage of the invisible part of the contour was also based on the analysis of the participant's drawings (i.e. relative length of the outlined invisible part of the contour of the mask to the total length of its contour), which was contrasted with luminance measurements of the 12 paired points. It was assumed that because this metric was based on the pixels close to the border between the mask and its background, and because it took into account the subjective assessments of the participants, it might better reflect the contour distinctness of the observed masks.

The mean point LR was based on 12 paired point luminance measurements around the contour of the mask; simply put, it was the arithmetic mean of those measurements. It was recommended because reducing the measurements up to 12 pairs was beneficial and time-saving.

The luminance of the foreground (the Venetian mask) metric was chosen as the simplest possible measure of shape and detail distinctness and was imposed under the logical assumption that shadows that reveal the visibility of various forms are more visible on lighter objects.

The ratio between the maximum luminance value of the mask and the mean luminance of the mask was chosen due to the presumption that higher ratios of this metric might reflect better detail visibility of the observed object. Similar arguments were applied to the 'standard deviation of the luminances of the foreground' metric for shape and detail distinctness.

The additional factors considered during the statistical analysis of the results included ***lightness of the background***, ***type of colouration of the object*** (chromatic/acromatic), and ***type of surface*** (matte/glossy).

The analytical comparison of the questionnaire data with numerical values of examined luminance-based metrics showed that the ***contrast metric, luminance ratio between the average luminance of the object and average luminance of the background, mean of the paired point luminance ratio (mean point LR) measurements around the contour of the object and the percentage of the invisible part of the contour were good predictors of contour distinctness in the observed 3D objects. The luminance ratio, mean luminance of the object and standard deviation of the object's luminances exhibited the strongest correlations with the subjective perceptions of the 3D objects' shapes and detail distinctness***. The proposed metrics expressed in numerical values are comprehensive, easy to obtain and could be practically applicable after further development.

3.3 Experiment 3

As discussed in section 2.4, HDR images can also be obtained through computer simulation tools. Light transport and reflection/refraction/transmission algorithms implemented in modern, physically based rendering tools (e.g. Radiance) simulate the properties of light in complex environments with reasonable accuracy (M. N. Inanici 2004). This computational method enables the completion of lighting calculations and analysis that are too complex to be carried out manually, or which are required for already designed but not yet constructed buildings. This method is popular among architects, lighting designers and consultants.

As noted previously, luminance-based metrics studied in Experiment 2 were acquired from photographed HDR images. As such, it was important to figure out if those metrics would be consistent with the metrics obtained from simulated images. This information would support or reject the idea of using the proposed metrics with simulated luminance maps.

A new experiment was set up in an existing meeting room in one of the university buildings in Trondheim. The same Venetian masks as used in Experiment 2 were used here as well. The masks were placed at certain points in the room one by one. A set of 11 LDR images was taken for each mask to total eight HDR images. The same real-world scene was replicated in the 3D computer model (see Figure 3-7) using Rhinoceros and DIVA software (DIVA-for-Rhino 2014). The hypothesis assumed that the numerical differences of the luminance-based metrics of contour, shape and detail distinctness of the 3D objects obtained from photographs versus simulated luminance maps would remain within the permissible range. Authors of previous studies that compared photographed HDR images with physical instrumented measurements of the chromatic and achromatic targets reported the following possible average error levels: up to 5.8% for grey surfaces, 1.5% for black surfaces, 10.1% for colour surfaces and 6.6% for light emitting surfaces (Anaokar & Moeck 2005; Inanici 2006; Cai & Chung

Figure 3-7. *Experiment 3 with achromatic and coloured 3D objects (Venetian masks) presented in real room and simulated in Rhinoceros and DIVA programmes.*

2011).

The luminance-based metrics obtained from both the photographed and simulated images were compared with currently used illuminance-based metrics (cylindrical illuminance and modelling index). The luminance-based metrics (consequently colour and specularity dependent) showed considerable variation among the examined masks, verifying the impact of colour and specularity on the visibility of contour, shape and detail.

The analysis of the results showed that the ***mean value of the relative error of all the luminance-based metrics tested for the set of eight masks (four glossy and four matte masks) was 14.78%***. Only one metric exhibited a high relative error rate at 27.75% (percentage of the invisible part of the contour); the average error rate was not higher than 16.6%, and the minimum error rate was 7.91% (ratio between mean luminance of the mask and mean luminance of the background). Of all the average errors among the metrics obtained from simulated and photographed images, 42.86% stayed under the 10% error limit, and 71.4% of them stayed within the 20% error limit. In general, ***glossy objects had higher error rates than matte objects***.

These results confirm that luminance-based metrics tested as predictors of light modelling, and in particular of the contour, shape and detail distinctness of day-lit 3D objects can be successfully used with simulated luminance maps.

4. Methodology

In this chapter, the methodology applied in the three fulfilled experiments will be discussed so as to evaluate the reliability of the final findings and results. The research questions that were raised for investigation required several approaches. Experimental, simulation and modelling research were combined. Multiple experiments were performed to provide mutual support to the final results. The experiments included simulation studies with scale models, mock-ups, computer simulations, real room studies and surveys. The simulation methodology was used first to validate the ability of the luminance maps in application for lighting studies of the chromatic interiors (Experiment 1). Then, the luminance-based metrics of contour, shape and detail distinctness for real 3D objects (Venetian masks) were investigated (Experiment 2). In the final phase, these metrics were verified with the help of simulated luminance maps, then compared with illuminance-based metrics currently prescribed by lighting guidance (Experiment 3).

4.1 Experimental research

Experimental research is widely used in various scientific fields and can be applied in architectural research. It allows researchers to credibly establish a cause-effect relationship. In some literature, experimental research is also called stimulus/response relationships (Boyce 2003). This method measures the subject's response to the stimulus under certain controlled conditions. There are ***independent***, ***dependent*** and ***control/intervening*** variables. ***Independent variables*** are manipulated by the researcher define the conditions of the experiment. A ***dependent variable*** is a measure of the response to those conditions. ***Control*** or ***intervening variables*** are all those factors that can influence the relationships between the independent and dependent variables and that are possible to register.

Experimental research can involve a wide variety of tactics, from strongly controlled laboratory experiments to field site studies, from firmly adjusted physical manipulations to less controlled nonphysical conditions. In the current research project, laboratory settings were combined with exclusively instrumented measures of physical outcome variables (both manual instrument measurements and HDR photography). Thus, the outcome variables included both technically obtained readings and subjective ratings of 3D objects' contour, shape and detail distinctness.

The experimental design method is frequently criticised due to its possible shortcomings, such as its efficacy and validity, misapplication of experimental procedures and ethical concerns (Groat & Wang 2002). Validity—particularly external validity—concerns the assumption that the most real-life settings are too complex to be reduced to a small setting with controlled variables. This concern cannot be ignored; however, a solution may be possible, such as repeating the experiment under slightly different conditions to lend additional valuable results. This method is even more useful in situations when the complexity of experimenting in real environments can lead to failure.

Despite the weaknesses of experimental research, it is especially useful in technical areas. Combining the strength of the experimental method with the advantages of other research methods (in the present case, those of simulations) is the best strategy to avoid the described limitations while accessing all the method's benefits (Groat & Wang 2002).

4.2 Simulation research

Simulation research originates from human curiosity and the fascination with replicating real-world conditions. Simulation research is characterised by the generation of data that can be analysed, manipulated or rectified, then returned to the real world in an improved state. Simulation studies may be performed in scale modelling, mock-up constructions, computer simulations and any other kind of reproduction of environments, conditions or situations. This research method is useful when researchers are dealing with issues of scale or complexity, is cost effective, provides an safe alternative when studying harmful or dangerous constructions or conditions, and finally, it is useful for developing and testing theories (Groat & Wang 2002).

4.2.1 Scale model studies

Scale model studies were performed in ***Experiment 1: Light level perception in interiors with equiluminant colours*** (see Paper I). Scale model studies allow the investigation of spaces and fenestration systems that are more complex than can be evaluated using simplified computational methods (formulas). Scale models provide a simple means of changing one variable at a time (e.g. window geometry, shading systems or surface reflectance), allowing the designer to easily manipulate variables and select optimum conditions. The models' performance may be evaluated outside or in a laboratory, under artificial or ***overcast sky*** conditions.

In the experiment on light level perception (see Paper I), the scale models were tested under a simulated overcast sky (see Figure 4-1). The testing model was 1:20 in scale at

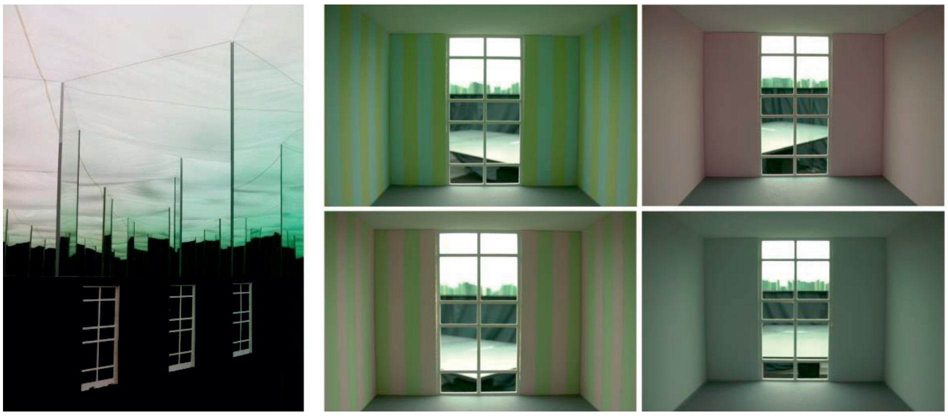


Figure 4-1. *Experiment 1 with scale models inside the Artificial Sky (to the left). Example of the room interiors (one-coloured and striped).*

25cm × 35cm × 20cm, which represented a room of 5m × 7m × 4m. The size was chosen to be large enough for comfortable observation and to facilitate good conditions for taking photos of the interior. All eight scale models of the rooms were placed under the Artificial Sky installation (see http://www.ntnu.edu/bff/laboratories; http://www.ntnu.no/ab/dagslyslab), which reproduced the luminance distribution of the CIE standard overcast sky. The equality of the illumination (that simulated overcast sky light) was a necessary condition that allowed equivalent comparison of the perceived light levels in the rooms. The scale model simulation enabled repeated access to the observed rooms if needed and saved costs and time.

The scale model studies (Experiment 1) examined three main issues—the degree to which colour affected perceived light levels in the scale models; the ability of luminance maps to adequately represent chromatic interiors and/or objects; and the ability of the luminance maps to reflect in numerical values the difference in light levels similar to those registered by the observers. The results of these scale model studies adequately represented or equalled real room studies; as such, the findings of this stage were very valuable to the future research phases.

4.2.2 Full-scale mock-up room study

The main advantage of this type of study was its ability to recreate the conditions maximally close to the real world while enabling relatively easy control over the independent and intervening variables. The aim of the experiment in the mock-up rooms (Experiment 2) was to investigate day-lit 3D objects and their luminance maps and to propose appropriate luminance-based metrics of contour, shape and details distinctness for those objects by pairing luminance values of the metrics with subjective assessments of the participants.

In the experimental-simulation research performed in the mock-up room in the Room Laboratory (see Papers II, III, IV and Figure 4-2), a certain degree of abstraction was created deliberately. This included the choice of the 3D objects presented for observation and the environment in which participants observed them. Let us suppose that participants were to observe realistic objects that resembled human faces (e.g. head sculptures) even more than abstract masks. In a real room, these realistic 3D objects would be presented on shelves of realistic design and in different painted cells. These conditions may have an unpredictable effect on subjective responses: participants might like or dislike the head sculptures; some might prefer female heads more than male ones and vice versa; they might also react to certain attributes of those faces (e.g. facial expressions, attractiveness or the presence of other elements). Further, observation of the heads painted in different colours, sometimes in unnatural hues, presented at first sight on the randomly painted shelves would likely cause abruption and negative reactions among the respondents. Therefore, experimentation in a mock-up space with a relatively realistic design was deemed a more suitable option for the experiment than real environment settings.

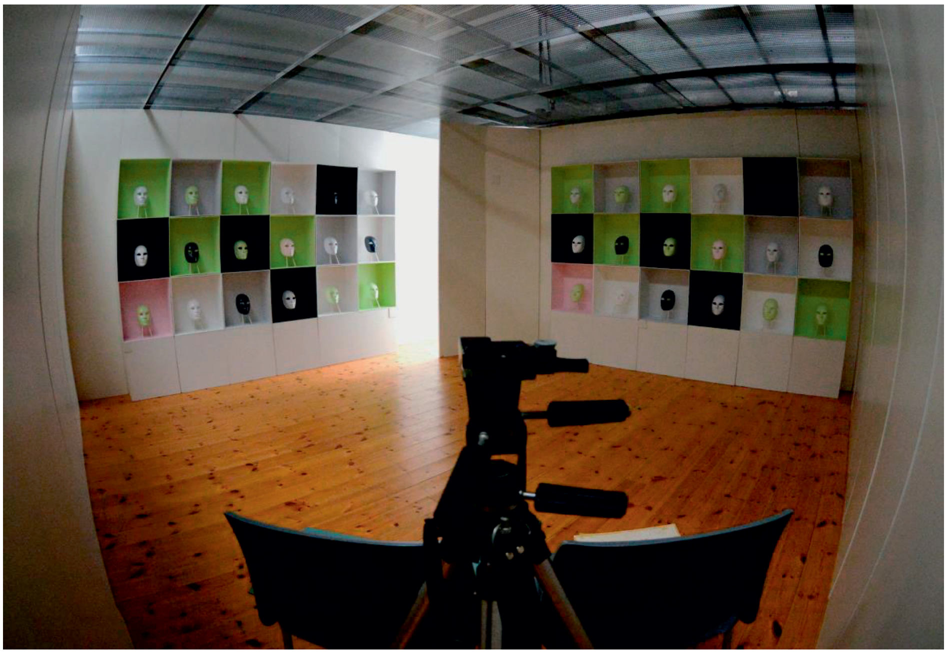


Figure 4-2. *Experiment 2 with achromatic and coloured 3D objects (Venetian masks) presented in a full-scale mock-up room (Room Laboratory).*

4.2.3 Computer simulations

Computer-based simulation methods offer flexibility that scale-model studies and manual methods sometimes cannot. They are especially valuable when the complexity of a building would make a scale model too costly and complicated to construct, or when there is a need to evaluate several proposed design alternatives. Computer-based simulations provide a convenient means to parametrically evaluate designs against other design alternatives (Rea 2000). Another undoubted advantage of computer simulations is their high performance speed and the easiness of modelling complex objects with small details.

Modern software packages allow simulations to be performed with daylight and electrical lighting, usually using ***radiative transfer*** and/or ***ray tracing*** approaches. The utility of these computational techniques is usually dictated by the nature of the information required. Ray tracing is an advanced approach capable of handling almost unlimited geometric complexities to produce realistic images. It is 'based on following one-dimensional rays, where each ray is defined by an origin point and a vector direction. In a rendering algorithm, each ray is followed until it intersects a visible surface, where new rays may be spawned in a recursive process. In light-backwards ray tracing (as in Radiance), each view ray is traced from the point of measurement to the contributing light sources' (Larson & Shakespeare 1998). Ray tracing produces reasonably accurate renderings of environments and surfaces with a wide variety of optical effects, such as reflection and refraction, scattering and dispersion phenomena (e.g. chromatic aberration).

The computer simulation approach was used in the verification study of the proposed luminance-based metrics of contour, shape and detail distinctness (Experiment 3) (see Paper V and Figure 4-3). In this computer simulation, the real-world context of the experiment performed in a real meeting room at a university building in Trondheim was replicated by 3D computer model. Through the creation of the virtual room and most of its characteristics, the research issues was examined. Thus, the hypothetical metrics proposed for application in lighting analysis and design that may be performed both in real spaces and in computer programmes were verified. The 3D model was built with the help of the ***Rhinoceros*** software. The lighting analysis was performed using ***DIVA 2.0*** (Jakubiec & Reinhart 2011).

The DIVA is a highly optimised, sustainable analysis plugin for the Rhinoceros 3D Nurbs modelling programme for integrating detailed daylighting analysis using ***Radiance/DAYSIM*** with thermal load simulations using EnergyPlus (Jakubiec & Reinhart 2011). DIVA allows the automatic coupling and visualisation of daylight and

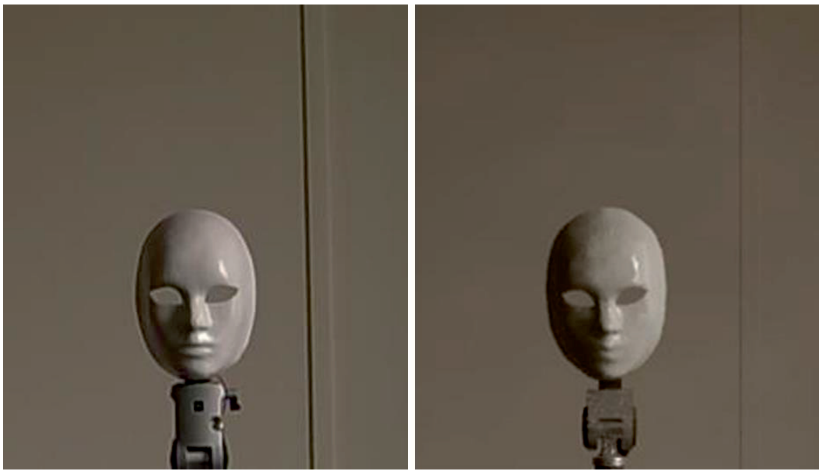


Figure 4-3. *Two HDR images of the grey glossy mask. To the left: photographed image; to the right: simulated image*

energy consequences as peak loads, and the amount of heating, cooling and lighting necessary each year in a space can be changed by designers through formal decisions, the design of shading systems, the amount of glazed area and the choice of materials. All can be analysed visually, photometrically and energetically from within DIVA (Jakubiec & Reinhart 2011).

It is also important to note the advantages of the integration of the Radiance programme for daylight simulation. Radiance is a physically-based rendering system tailored to the demands of lighting design and architecture. The programme uses a light-backwards ray-tracing method with extensions to efficiently solve rendering equations under the most conditions, namely specular, diffuse and directional-diffuse reflection and transmission in any combination to any level in any geometry. The fusion of deterministic and stochastic ray-tracing techniques facilitates the best balance between speed and accuracy in its local and global illumination methods (Ward 1994). Therefore, the use of the simulation programme with integrated Radiance and the 3D model of optimal geometry ensures the best possible outcomes.

4.2.4 Other activities within the simulation research

Simulation research often requires activities from the researcher that are not directly related to the simulation itself (Groat & Wang 2002). These could be interviews, checking records or documents or other qualitative field work. All three simulations for the experiments in the present study, whether they involved scale models, masks in mock-up rooms or computer modelling research, included some preparatory work.

For the experiment with scale models, paints were manually mixed and checked in the laboratory. Their luminance values were measured under Artificial Sky to calculate their *reflectance factors* and ensure the equiluminance of the paints (see Figure 4-4). Also the illuminance values were measured at the central point on the floor inside each scale model, arranged under the Artificial Sky installation (see Figure 4-5). This not only enabled access to the existing illuminance readings inside the models but also allowed the researcher to check and analyse differences in light levels inside the models.

Before the second experiment was started, thorough preparations were conducted, including weather monitoring and testing of the participants with the following: *visual acuity* test using a Snellen chart; Ishihara test for color vision; and a *contrast sensitivity* test (*Vigra* programme, see Glossary). Normality of 3D vision was self-reported by the respondents (according to their ability to see the depth of the space and stereoscopic videos using 3D glasses).

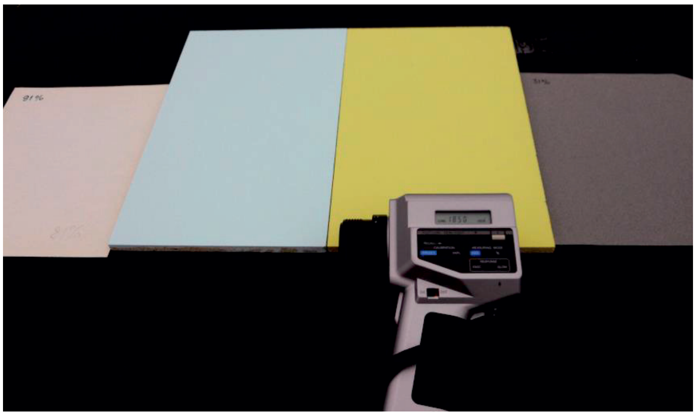


Figure 4-4. *Example of the luminance measurements of two samples of the paints used in scale models.*

The 3D computer simulation of the masks placed in the meeting room model required thorough preliminary measurements to be taken in the real room. These measured the size of the room, the objects within it and the facilities; the luminance of most of the surfaces in the real room respective to the grey and white reference cards (for further reflectance calculations); and colour registration of all the achromatic and chromatic colours of the real room with help of NCS COLOUR SCAN 2.0. In addition, simulation on the investigation of the specularity and roughness values of the glossy masks' material was performed (see Paper V).

The simulation research method served as the core element of the current doctoral study. The complete methodology includes other strategies, such as surveys (questionnaires), luminance mapping and some manual instrumented measurements, which will be discussed in greater detail in the sections below. Simulation research enables researchers to capture the complexity of real-world behaviors without reducing them to a limited number of discrete variables; it is often able to reveal unexpected results useful for analysis (either to be taken into account or not) and for future work (Groat & Wang 2002).

Figure 4-5. *Measurement of illuminance inside the yellow scale model at floor level.*

4.3 Questionnaire survey

Questionnaire surveys were used in two of the performed experiments: the scale model experiment and the full-scale mock-up room experiment with Venetian masks. In the full scale mock-up room experiment, the simulation method was combined with correlational research, allowing the researcher to seek and predict the relationships among several variables. A questionnaire was used for data collection in addition to luminance mapping. To conduct statistical analysis of correlation research, the regression method is frequently employed (Groat & Wang 2002). The current experiment used ordinal regression analysis, which is explained in greater detail in section 5.2.

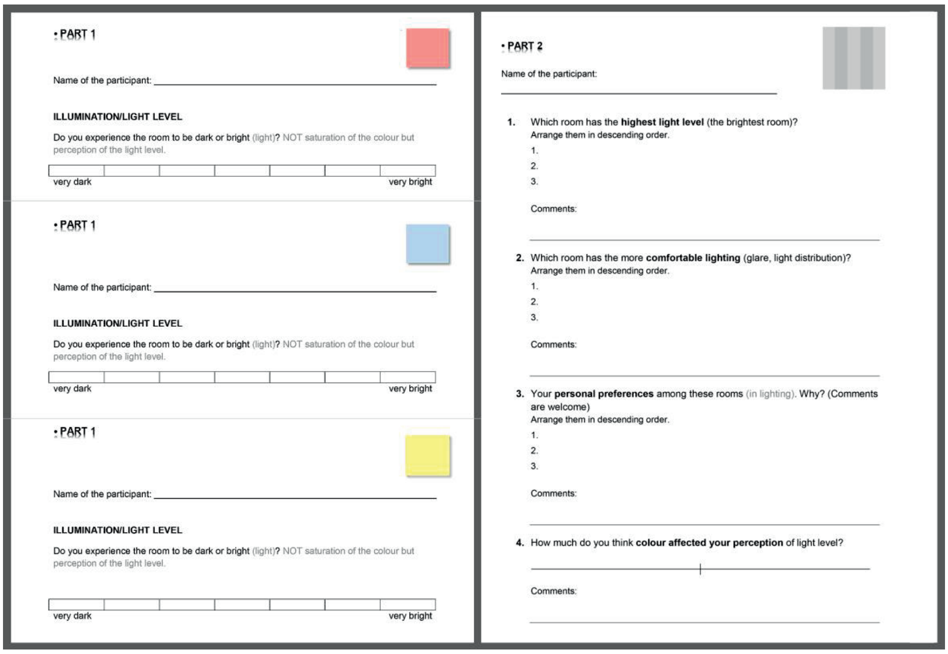
The structure and design of the questionnaire was crucial, as these factors can determine the range of the responses toward a pre-selected area of interest. The questionnaire needed to be easy to understand, simple to fill out and elicit honest answers (Stamatis 2012). It could also be administrated differently, such as by paper and pencil, by computer or by phone. Several advantages of the questionnaire, particularly the on-the-spot questionnaire used in the current research project, may be noted; these include the immediate collection of information from respondents, the possibility to ask questions from the survey manager as they are raised and the ability to survey groups of people at a time.

4.3.1 Questionnaire survey: Experiment 1

Thirty-two respondents participated in ***Experiment 1*** regarding light level perception in interiors with equiluminant colours. Participants were master's students of architecture (14), physicists (5), PhD candidates in architecture (5), engineers in computer science (3) and a few people from other academic fields (5). The ages of participants varied from 21 to 42 years, and all of them had normal colour vision.

As the respondents observed two different groups of scale models (one-coloured models and models painted in striped patterns) (see Paper I), two similar but separate questionnaires were distributed (Figure 4-6). Each consisted of two parts. The first contained one question from the Perceptive Spatial Analysis of Colour and Light (PERCIFAL) questionnaire (Arnkil et al. 2011; Fridell Anter, Häggström, et al. 2012; Matusiak et al. 2011). The intention was to elicit spontaneous answers to the question: *do you experience the room to be dark or bright?* The participants made a mark on a seven-step scale that ranged from very dark to very bright. The second part included four more questions about lighting in the scale models and demanded more conscientious answers. Answering the questions from this part of the questionnaire, observers had to arrange the rooms into descending order. The questions were:

1. *Which room has the highest light level (the brightest room)*?
   Arrangement had to be from the brightest to the darkest.
2. *Which room has more comfortable lighting?*
   Arrangement had to be from the most to the least comfortable.
3. *Indicate your personal preferences among these rooms (in lighting).Why?*
   Arrangement had to be from most to least preferable room.
4. *How much do you think colour affects your perception of light levels?*
   The subject had to mark the level of the influence of colour and colour compositions (in the case of the striped rooms) on light level perception on the proposed scale (see Figure 3-4).



• PART 1

Name of the participant: ______

ILLUMINATION/LIGHT LEVEL

Do you experience the room to be dark or bright (light)? NOT saturation of the colour but perception of the light level.

very dark | very bright

• PART 1

Name of the participant: ______

ILLUMINATION/LIGHT LEVEL

Do you experience the room to be dark or bright (light)? NOT saturation of the colour but perception of the light level.

very dark | very bright

• PART 1

Name of the participant: ______

ILLUMINATION/LIGHT LEVEL

Do you experience the room to be dark or bright (light)? NOT saturation of the colour but perception of the light level.

very dark | very bright

• PART 2

Name of the participant: ______

1. Which room has the **highest light level** (the brightest room)?
Arrange them in descending order.
1.
2.
3.
Comments:

2. Which room has the more **comfortable lighting** (glare, light distribution)?
Arrange them in descending order.
1.
2.
3.
Comments:

3. Your **personal preferences** among these rooms (in lighting). Why? (Comments are welcome)
Arrange them in descending order.
1.
2.
3.
Comments:

4. How much do you think **colour affected your perception** of light level?
Comments:

Figure 4-6. *Questionnaire from Experiment 1 on light level perception in interiors with equiluminant colours*

The first question of the second part of the questionnaire was the main source of the necessary data. The two questions concerning comfortable lighting and personal preferences in lighting among the rooms served to verify the reliability of the results by comparing answers. The overall design of the questionnaire form was effective; participants easily understood the questions they had to answer. The obtained data provided significant results, mostly due to the questions asked in the questionnaire, which have been discussed in the article *Light level perception in interiors with equiluminant colours* (Zaikina 2012) (see Paper I).

4.3.2 Questionnaire survey: Experiment 2

The experimental design and research questions used in the study on the contour, shape and detail distinctness of the Venetian masks required a modified form of the questionnaire. It had to be very simple, because respondents placed in relatively dark lighting conditions were observing 36 separate masks painted in different colours and presented in differently coloured boxes. It was expected that these conditions might tire the observers, which was highly undesirable. Thus, only one simple question was asked about the distinctness of the contour of each mask, and a similar question made up the second part of the questionnaire concerning the masks' distinctness of shape and detail (see Figure 4-7 and Papers II, III and IV). This allowed participants to answer the questions quickly using a four-point ordinal scale to indicate the range of contour, shape and detail distinctness.

Participants chose from the following options:

• *Indistinguishable* (invisible contour/shape and details)
• *Just distinguishable* (barely visible contour/shape and details or some details)
• *Well distinguishable* (well-visible contour/shape and details except some parts or elements)
• *Perfectly distinguishable* (the whole contour/mask is well visible)

Participants were allowed to start their evaluation from any mask presented on the shelf, although this was not systematically implemented as participants chose themselves. To collect more information on the visibility of particular areas of the masks, the respondents were asked to specify indistinguishable and perfectly distinguishable zones of the contour or the whole mask (in the cases of shape and detail distinctness) in the form of drawings included in the questionnaire form. These drawings consisted of a simple, not too small outline graph of the mask, convenient for the participants to draw upon. The graphical information obtained from the participant's drawings was then used

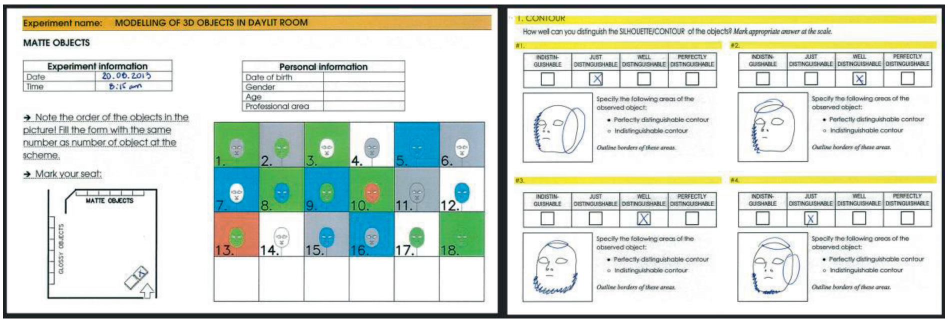


Figure 4-7. Questionnaire form from Experiment 2

during the luminance measuring and analysis process.

This type of the questionnaire worked well in the present experiment, as most of the participants were able to complete the experimental session (including other parts such as an explanation of the terms and a photographing session) within one hour, through there was no time limit. Very few answers were missed and the proposed questions were answered.

Questionnaires are a very important part of the present experiments related to human perception of visual environments as they provided the necessary empirical data. The questionnaires used in this research project were closely related to the purpose of each particular study and provided consistent information.

4.4 Luminance mapping

Luminance mapping was used as a specific technique in all the experiments performed during the current research project (see Papers I through V). Luminance maps obtained through HDR photography (luminance mapping) were one of the main data sources intended for further statistical analysis. The theoretical background of this technique has already been discussed in section 2.3. Here, the way the luminance mapping was performed in each separate case will be discussed and an outline of the general rules, advantages and weaknesses of this method will be presented.

Thorough and useful guidance on how to perform HDR photography was developed by Reinhard (2010). Reinhard's strategy is applicable to most cases, though it may vary a bit depending on target, illumination or camera type. This technique was indispensably used in all three experiments according to the following directions:

> ***1.*** *Use aperture priority or manual exposure mode so that only the exposure time is allowed to vary. This reduces problems associated with vignetting (light fall-off toward the edge of the image).*
> ***2.*** *Fix the camera's white balance on a specific setting for the entire sequence—preferably daylight (a.k.a. D_{65}).*
> ***3.*** *If the camera offers an "optimised colour and contrast" mode, switch it off. The more settings you can fix manually, the less likely the camera will alter the expose function between exposures. This especially goes for automatic ISO/ASA and programmed exposure modes.*
> ***4.*** *Use a tripod if possible, and control your camera via a tether to a laptop computed if this option is available. The less touching of the camera during a sequence, the fewer alignment problems will be experienced.*
>
> *It is helpful to calibrate the camera's response one time, and then reuse this calibration for later exposure sequences. In this way, the scene and exposure sequence may be optimized for camera response recovery. For such a sequence:*
>
> - *Set the camera on a tripod and use a tether if available.*
> - *Choose a scene with large, grey or white surfaces that provide continuous gradients for sampling. The closer your scene is to a neutral colour, the less likely colour transforms will undermine the response recovery process.*
> - *Choose a scene with very bright and very dark areas, then take a long sequence of exposures separated by 1 EV (a factor of two in exposure*

time). The darkest RGB values should have no RGB values greater than 200 or so, and the lightest exposure should have no RGB values less than 20 of so. Do not include an excess of exposures beyond this range, as it will do nothing to help with response recovery and may hurt.

- *If you have access to a luminance metre, take a reading on a grey card or uniform area in your scene to provide absolute response calibration.*

> *Once a camera has been characterised in this way, it is possible to combine hand-held bracketed sequences that are too short to reliably recover the response function* (Reinhard et al. 2010).

The stable lighting conditions provided by the Artificial Sky installation used in Experiment 1 (see Paper I) allowed the set of the images of the scale models to be taken at any suitable moment during the experiment. The sets of 13 low-dynamic images for each room were made with a Canon EOS300D digital camera, which was mounted on a tripod and situated in the plane of the subject's eye to simulate the viewing position of the observers. Changes of exposure were made manually due to a lack of other suitable controlling devices; as such, some blurry after-effects may have occurred after image alignment. The luminance readings were taken with a calibrated handheld luminance metre. The readings were used for absolute response calibration of the luminance maps as recommended in the literature.

Experiment 2 took place in a full-scale mock-up room built in the Room Laboratory (see Papers II - IV) under the real daylight conditions. One daylight opening in the room provided soft illumination from an overcast sky. It was absolutely necessary to operate the process under a stable overcast sky with preferably minimal fluctuations in the light level; only eight days within two weeks in August 2013 met these conditions. The photographing session had to be done with minimal differences in time with the answering of the questionnaire in order to reduce the risk of possible light fluctuation and distinctions of illumination/light distribution on the photo and during the observation process. Sets of 11 LDR images were done before the respondents (two persons at a time) started to fill in the questionnaire. Luminance measurements were then taken manually, and the terms used in the questionnaire were orally explained. The low dynamic images were taken within a period of 1–2 min, and the manual luminance measurements were conducted immediately after. The whole process (photographing, measuring and explanating) took approximately 10–15 min, depending on the respondents' questions. During this time, participants were able to adapt to the lighting conditions in the room. The survey itself took 1 hour for each pair of respondents. The Nikon D600 digital camera and a full-frame (AF DX Fisheye-Nikkor 10.5mm f/2.8G ED) lens providing 180° diagonal angle of view were used. To ensure sharpness, the camera was mounted on a tripod and situated between the participants' chairs. All camera settings were adjusted virtually via Nikon Camera Control Pro software, which prevented luminance maps from developing unwanted fuzziness.

Experiment 3 was fulfilled in the real meeting room on the 8th floor of Sentralbygg 1, Gløshaugen campus, Norwegian University of Science and Technology. As in the previous experiment, overcast sky conditions were chosen, and fluctuations in the light level stayed within 17.3%. The settings of the experiment enabled very short pauses between photographing sessions for each of the eight studied masks. First, the point illuminance measurements and manual luminance measurements were taken (1–2 minutes). Next, the masks were placed one-by-one on the tripod at a height of 1.2 metres, and photographing session was performed (1–2 min each). Short pause followed while the masks were changed, and then the procedure was repeated. The whole experiment in the real room took only 50 min in total, of which approximately 6.5 minutes were used for the work with each mask. The same equipment (camera, lens and software) as in the previous experiment was used; all the recommendations for successful application of the luminance mapping technique were followed.

The HDR imaging procedure was developed and tested previously, and useful recommendations for its application were suggested. The alignment of the low dynamic images is an automatic process that can be performed using a number of free computer programmes, including ***Photosphere*** (Ward 2002), ***hdrscope*** (Kumaragurubaran & Inanici 2013) and ***WebHDR*** (Jacobs 2007; Jacobs n.d.). HDR photography has some weaknesses and limitations that the user should be aware of. Two such limitations are the ability to capture images of static scenes only (at least during the photographing sequence) and the need for calibration against the luminance metre reading of a reliable standard target. Nevertheless, the luminance mapping method provides a measurement capability that has the advantage of collecting high resolution luminance data within a large field of view quickly and efficiently, which is not possible to achieve with a luminance metre. The method uses equipment at reasonable prices that both practitioners and researchers may purchase. Moreover, the self-calibration algorithm in Photosphere provides quick and easy camera response functions. Though not a substitute for any currently used instrument, this method is still a useful tool for capturing luminance values over a wide range within 10% accuracy (Inanici 2006).

4.5 Manual quantitative instrumented measurements

Instrumented measurements are usually used to quantify a luminous environment and thereby indirectly measure or monitor stimuli to the visual system (Boyce 2003). They are also frequently used to establish relationships between the physical measure of lighting and subjective judgment of the lighting.

As discussed in section 4.4, photographing the sequence of LDR images to be used for luminance map creation required instrumented luminance measurements to provide absolute response calibration of the HDR images. This procedure was performed using a Minolta LS-100 luminance metre. In Experiment 1, which involved scale models, a single measurement in six pre-defined points inside each of the eight scale models was used. In Experiment 2 (with the Venetian masks), 17 luminance measurements were performed accordingly to 17 sets of images for luminance maps. Luminance was measured at four target points in the mock-up room, and the procedure was repeated for each new photographing session. In the real room experiment (Experiment 3), the luminance measurements were done twice (before and after the photographing session). This procedure was repeated with each of the tested masks (i.e. eight times). In addition to the photometric calibration of HDR images, taking the measurement before and after the photographing process enabled the researcher to monitor light changes during the experiment. The luminance of all surfaces in the experimental room was measured in reference to Kodak grey and white cards. Based on these measurements, the reflectance factors of those surfaces were calculated.

In addition to luminance measurements, illuminance levels were also important in the conducted experiments. Illuminance measurement is the most widely used quantifier of light, and it is usually measured on a horizontal plane at the point of interest, frequently at the ***working plane*** level. In the experiment with scale models, illuminance was measured using a lux metre with a small, detached photocell. It was convenient to put this photocell into the scale models through small openings for observation. The illuminance was measured in the centre of the room at floor level. These measurements were needed to estimate the equality of the illumination inside all the scale models under the Artificial Sky installation.

For the experiment in real meeting room, more instrumental measurements were taken. First, the outside illuminance values were registered before each new photographing session. These outside illuminance values were used later in computer simulations (replicating existing lighting conditions) and allowed the researcher to track internal and external illuminance fluctuations. Simultaneous to the outside illuminance registration, the internal horizontal illuminance measurement was conducted as well. This was a point in the room where each mask was mounted and the photocell was fixed to the horizontal element of the tripod. Exactly after this measurement, two semi-cylindrical illuminance measurements (with a difference of 180°) were performed at the same point. Based on these horizontal and semi-cylindrical illuminance measurements, the modelling indeces at this point in the room were calculated.

The instrumented measurement is an inherent and necessary technique in various experimental studies. This method does the following:

i) ensuring of good experimental conditions through monitoring of changes in light levels that could lead to error if not recorded;
ii) correction or adjustment of the generated HDR images according to the instrumental readings for more reliable luminance values;
iii) measurement of the illuminance values for illuminance-based metrics calculations needed for their further comparison with luminance-based metrics;
iv) measurement of luminance of the various surfaces (relatively to reference grey and white Kodak cards) of experimental spaces used for reflectance factor calculations.

All these instrumented measurements improved the quality of the results of all three experiments through the supplement of additional verifying data.

5. Analysis

Several statistical methods were used to analyse the data obtained from the three experiments. The analyses were determined by the data type and the research questions raised in each particular case. As luminance maps were one of the main data sources in all the studies performed, their analysis method will be explained separately in section 5.1 of this dissertation. A brief description of the statistical analysis methods will be provided, as these methods were systematically implemented for data analysis.

5.1 Analysis of the luminance maps

The low dynamic images taken of the scene were generically aligned into one HDR image file, after which the photometric calibration could be performed in any HDR image analysis and processing programme. The current study used the Photosphere programme (Ward 2002). After calibration, the image data was analysed, again with the help of the chosen programme. The Photosphere software was rather limited in its choice of tools for image examination; options included measurements of the whole area of the picture, squared areas of interest and point luminance measurements. These tools were actively used in the experiment with scale models where the luminance readings were taken in six pre-determined points in the interior, and in selected rectangular regions of walls (see Paper I).

Another valuable option provided by Photosphere (and most other programmes for HDR imaging) is the ***false colour picture*** tool. In this particular case, the false-colour picture was an image that displayed the existing luminance values in specific colours. In other words, it was a graph in which each newly assigned colour signified a particular luminance value. This was a helpful analytical tool that facilitated image study, especially in terms of visual representation for observation. The distribution of luminance values in the image were more clearly displayed here, which was useful for analysing the single-coloured and striped rooms. The scales of the luminance values from maximum to minimum (the luminance ranges) were equally set in the compared pictures. Luminance distribution patterns depicted in false colours allowed comparison among images (Paper I). Overall, this method is highly useful when the objects in a luminance map are not clearly visible, or generic pictures do not satisfactorily represent light distribution (bright or dark spots) on the surface and visual investigation is of critical importance.

In other experiments (with masks in the full-scale mock-up room and real meeting room) the ***hdrscope*** programme was used alongside Photosphere. In addition to the simple functions provided by Photosphere, hdrscope enables the user to examine multiple selected regions of interest and figures of complex geometry (Kumaragurubaran & Inanici 2013). Moreover, this programme allows the user to obtain and save raw luminance data from any selected region (in this case, the information regarding each pixel in the scene or selected zone, its luminance values, the number of pixels with equal luminance, et cetera). Those data may be operated and manipulated further in any programme intended for statistical analysis. All these options were adopted for luminance data collection used for proposed ***luminance-based metric*** test and for the ***histogram*** analysis of specific chosen masks (see Papers II-V).

5.2 Statistical analysis

In the experiments that included surveys, the data outcome was ***ordinal data***, meaning that possible responses could be arranged in order. The numbers assigned to the responses facilitated this organisation, but the actual distances between the numeric codes were not interpretable (Stamatis 2012), as there was no fixed pitch between values. When the differences between the ranks of the scale are not equal (or unknown), means and variances are in error and nonparametric procedures may be used to test hypotheses (Sheldon et al. 1996). Thus, the ***Friedman test*** served as the main tool for statistical analysis of the results from ***Experiment 1*** (with scale models).

The Friedman test is a nonparametric statistical procedure for comparing more than two related samples. The parametric equivalent to the Friedman test is the repeated measures analysis of variance (ANOVA) (Corder & Foreman 2009). Results obtained through Friedman testing usually show that at least one sample is different from the others, but do not identify where the difference(s) occurs or how many are present. To determine such information, other tests (sample contrast, or post hoc tests) among specific sample pairs are necessary (Corder & Foreman 2009).

In ***Experiment 1***, the stated null hypothesis suggested that all one-colour rooms (5 scale models) and striped rooms (3 scale models) had the same distribution of scores on the different measures represented by the conditions. Namely, there was no difference in perceived light level scores among the different one-colour rooms and striped rooms. According to the statistical analysis of the one-colour rooms, differences were small and not statistically significant. Analysis of the striped rooms showed a highly significant difference in perceived light level scores in the different striped rooms. More detailed information can be found in Paper I.

In ***Experiment 2***, which used Venetian masks in a mock-up room, respondents evaluated contour, shape and detail distinctness of the masks using a four-point ordinal scale in the provided questionnaire. The categories were the following:

• *Indistinguishable* (invisible contour/shape and details).
• *Just distinguishable* (barely visible contour/shape and details or some detail)
• *Well distinguishable* (well-visible contour/shape and details except some parts or elements)
• *Perfectly distinguishable* (the whole mask and its contour are well visible)

The ***ordinal regression analysis*** was chosen as the main statistical method. Regression analysis is a technique that provides many individual ways to identify variation and relationships. Specifically, regression analysis finds an equation that relates a variable of interest (the dependent variable) to one or more other variables (the independent or predictor variables). To clarify, the ***independent variable*** is a quantity that can be manipulated within the experiment and cause change in the ***dependent variable***, which represents output. A regression analysis estimates the strength of relations between the dependent variable and the independent variables (controlled for each other). Ordinal regression is a technique that is used to predict ordinal level dependent variables' behaviour with a set of independent variables. The dependent variable is the order response category variable, and the independent variable may be categorical (label or means of identification) or continuous (it can assume any of a range of values).

For the experiment with Venetian masks in the mock-up room, the experimental design involving 32 participants who assessed 36 masks each resulted in a data structure wherein 36 evaluations were nested with each respondent. This means that the personal characteristics of each person affected their ratings of all 36 masks. This led to a dependency of the ratings of each person, violating the assumption of unrelated residuals in a normal regression analysis. Therefore, a multilevel regression analysis was used instead of single-level one. The main analysis was conducted at the object level, but the person-specific variance in the evaluations across all masks was modelled simultaneously and taken out of the regression equation at the mask level.

This statistical technique enabled the researchers to identify relationships between the visual distinctness of contour/shape and details, proposing seven luminance-based metrics or predictors. Some factors, such as surface type (glossy or matte), colouration (chromatic or achromatic), background lightness (white, medium dark and dark) and the order of observation of the shelves, were included in the analysis as additional control variables. Detailed results can be found in Papers II, III and IV.

Besides this analysis, probability calculations were performed. Probability plots are presented in Papers II, III and IV. Probability theory provides a mathematical model for the study of randomness and uncertainty, referring to the likelihood of occurrence. By informally defining the probability, it can be said that the probability of an event is a measure (number) of the chance with which one can expect the event to occur. A number between 0 and 1 is assigned inclusive to the probability of an event. A probability of 1 means that one is 100% sure of the occurrence of an event, and a probability of 0 means that one is 100% sure of the non-occurrence of the event. The probability of any event (A) in the sample space (S) is denoted by P(A) (Ramachandran & Tsokos 2015). In order to express regression analysis results in terms of probability, the dependent variable (probability) must be transformed into a quantity (logit) ranging from $-\infty$ (when P=0) to ∞ (when P=1). Logit transformation consists of two steps: i) conversion of the observed probabilities into odds and ii) obtaining logits by taking the logarithm of the odds (which is given by the ratio P/[1-P]).

In the present study, the probability plots displayed the probability of four types of observed Venetian masks (matte/achromatic, matte/chromatic, glossy/achromatic, glossy/chromatic) being evaluated as proposed in the questionnaire (indistinguishable, just distinguishable, well distinguishable or perfectly distinguishable contour/shape and details) and corresponding values of the main predictor (proposed luminance-based metrics). Using this result, it was possible to specify threshold values for most of the predictors and metrics, allowing the worst-case scenarios (when the object was invisible or hardly visible) to be eliminated. Several tables were created based on an 80% probability for some of the tested predictors that were statistically significant. These comprehensive tables indicated clear values of the tested measures that were also applied as numeric reference points, ensuring perfect visibility of the contour/shape and details of the 3D objects. Additional details are provided in Papers III and IV.

Within the analysis of the observed Venetian masks' contour distinctness, a ***cross-classified regression analysis*** was performed. The cross-classified regression has as a single data point, an observation on a particular individual's assessment of the masks' contour, shape and detail distinctness, as well as other variables such as the peculiarities of each mask. Cross-classification allowed the researchers to control the variance components from two nesting levels (masks and people) that were parallel to each other.

In the current study, the cross-classified regression analysis for a binary dependent variable (0 = the contour in this part of the mask is visible; 1 = the contour in this part of the mask is invisible) tested the relationship between the individual point measures of the luminance ratios and the subjective rating if the area was visible. The cross-classified analysis controlled the ***people factor*** and ***mask factor***, which both impact the results on their second levels, respectively. This allowed the correlation between each individual pair of luminance readings and indistinguishable contour to be tested as being marked by the participants.

Results showed a high statistical significance (see Paper IV) for both sides of the contrast with medium to strong correlations, which can be interpreted as an indication that the data regarding areas of invisible contours obtained from the questionnaire matched with the luminance ratios closest to 1 measured in the pairs of points belonging to these areas. This shows that the participants were able to reliably report the invisibility of the contour in certain areas of the masks.

In ***Experiment 3***, which used a real room, the main focus was on the verification of the proposed luminance-based metrics of contour, shape and detail distinctness through a comparison of those obtained from photographed HDR images with simulated luminance maps. The indicator used for analysis and comparison of the data from simulated and photographed luminance maps was ***relative error***, given by:

$$Relative\ error = \left|\frac{M_{sim} - M_{photo}}{M_{photo}}\right| * 100\%, \qquad \textit{[Equation 3]},$$

where M_{sim} is the value of a certain metric of simulated luminance maps and M_{photo} is the value of the same metric obtained from the photographed luminance map.

The relative error indicator is a simple method by which to evaluate the difference between two quantities. It expresses the ***relative size of the error*** of the measurement in relation to the measurement itself.

The variation of luminance-based metric values obtained from simulated and photographed HDR images were compared with variations in the illuminance-based modelling index. However, no statistical method was implemented for this purpose.

When planning the experiment to investigate the present research questions, it was necessary to ensure that the measurement process was simple, that the study could be concluded in a reasonable time frame and that it would produce reliable data. The experimental design determined the basic characteristics of the data collected. These data were then processed using statistical analysis techniques, with goals being determined by the experimental objectives. Conclusions were obtained by looking at the results of the statistical analyses (Ramachandran & Tsokos 2015). In summary, it may be concluded that the multiple methods used to collect the empirical material increased the credibility of the present study, and the statistical analysis adopted at all the stages of the research project and in all the experiments produced reliable results.

6. Discussion of the results

In this chapter, the results from three experiments (and appended papers) are summarised. The main results and contributions of each experiment have been compiled into several articles that form the basis for this thesis will be described further in sections 6.1, 6.2 and 6.3.

The general direction of the study was towards the new possible luminance-based metrics of lighting quality. To compensate for the broadness of the topic, the research began with general questions first, progressing to the more particular and detailed ones as the study went on. The more extensive topics were investigated in Experiment 1, including: i) the influence of colour/colour combinations on the perception of light levels in interiors painted in equiluminanat colours/colour combinations; and ii) the capabilities of HDR images to depict correctly the luminance data in photographed luminance maps of coloured interiors. These questions are addressed in Paper I.

The primary interest of the research project was that of the light modelling topic, particularly the contour, shape and detail distinctness of observed 3D objects. This problem was investigated in Experiment 2. Here, several luminance-based metrics of light modelling were proposed, tested and paired with subjective responses. The results are reported in Papers II, III and IV.

Finally, all the proposed luminance-based metrics obtained from the photographed HDR images were verified against the simulated HDR images. The metrics were then compared with currently used cylindrical illuminance and modelling index metrics (CEN 2011). Experiment 3, performed in a real room under real daylight conditions and replicated in computer model, facilitated a more thorough verification of the metrics (explained in Paper V).

6.1 Findings from Experiment 1 'Light level perception in interiors with equiluminant colours'

As discussed in Chapter 2, light and colour in architectural spaces should not be studied separately. Colour and light are tightly interconnected concepts in our experience of the world and together form our visual experience of space (Fridell Anter, Arnkil, et al. 2012). The current study's hypothesis assumed that the perceived light level in a room is affected not only by luminance but also the chromatic properties and contrasts of wall colours. This was tested in model studies using low saturated equiluminant colours normally used in interiors and combinations of equiluminant colours of contrasting hues. In addition, an examination of the capabilities of HDR images as a method for lighting studies of interiors painted in low saturated colours was performed.

Through this experiment with scale models, it was determined that even poorly saturated colours have a qualitative impact on the human perception of light levels in spaces. This impact can be strong, as with colour contrast (in striped rooms) when higher hue contrast can affect perception, or it can be weak, as with one-coloured models wherein the differences among the ratings on perceived light levels in the differently painted rooms were not statistically significant. Regardless, this impact should be taken into consideration when using the luminance-based method for lighting design analysis.

According to the statistical analysis, the interiors of three striped models were perceived by the participants as rooms with different levels of illumination. The model painted in the blue/yellow striped pattern was evaluated as the brightest one, and the blue/grey model the darkest. Similar to subjective evaluation, significant differences were registered among the luminance maps of the striped models. Differences were noted through both visual examination of false-colour images of the interiors and numerical analysis of the luminance values within the selected regions at the HDR images. Results for the one-coloured models were not so straightforward, showing insignificant differences in subjective evaluations of the light levels among five one-coloured rooms, similar to the results of the examined luminance maps of those models.

In general, the results have not contradicted the stated hypothesis and appear to prove the reliability of luminance maps in capturing luminance data of chromatic interiors painted in low saturated colours.

6.2 Findings from Experiment 2 'Luminance-based metrics of contour, shape and detail distinctness of 3D objects as important predictors of light modelling: A full-scale study pairing proposed metrics with subjective responses'

The second experiment was performed in a mock-up room under real daylight conditions. It was possible to propose a set of several luminance-based metrics predicting a large gradation in the distinctness of contours, shapes and details of the observed 3D objects (Venetian masks). The hypothesis stated that certain numerical luminance values or luminance ratios obtained from HDR images might adequately describe the distinctness of contour, shape and details of day-lit 3D objects as being observed by subjects, thus forming the metrics of contour, shape and detail visibility (light modelling). Results showed that all the tested metrics of contour distinctness (contrast, luminance ratio, percentage of the invisible part of the contour and mean point LR) were significant (p-values) and almost equally strong predictors (due to β values). For shape and detail distinctness, the analysis showed that some of the proposed metrics—such as the mean luminance of the masks, standard deviation of the luminances of the masks and luminance ratio between mean luminances of the object and its background—correlated very well with subjective assessments of the masks' shape and detail distinctness. The luminance ratio between the highest luminance value of the masks and their mean luminances showed rather weak and limited results applicable only to matte objects on darker backgrounds.

Based on the obtained numerical values of the proposed metrics, it was possible also to create tables showing the threshold values formed by an 80% probability for tested predictors (metrics) that are statistically significant (see Tables 1 and 2). These comprehensive tables clearly indicate certain values of the tested metrics that may also be applied as numeric reference points to ensure perfect visibility of contour, shape and details of 3D objects. These tables are very useful and easy to apply, especially taking into account the optical characteristic of the object's surface (glossiness and chromaticity).

	Perfectly distinguishable contour, 80% probability			
	Matte/achromatic combination	**Matte/chromatic combination**	**Glossy/achromatic combination**	**Glossy/chromatic combination**
Luminance Ratio ≤ 1	0.49	0.42	0.59	0.52
Luminance Ratio ≥ 1	13	14	13	14
Contrast ≤ 0	-0.5	-0.57	-0.4	-0.47
Contrast ≥ 0	11.5	12.5	11.5	12.5
Mean Point LR ≤ 1	0.46	0.44	0.6	0.59
Mean Point LR ≥ 1	23	22.5	23	22.5

TABLE 1. *Threshold values for luminance ratio, contrast and mean point LR measures of contour visibility*

	Perfectly distinguishable shape and details, 80% probability			
	Matte/ achromatic combination	**Matte/ chromatic combination**	**Glossy/ achromatic combination**	**Glossy/ chromatic combination**
Mean luminance of the mask, (cd/m^2)	49	52	43	46
Luminance ratio between maximum luminance of the mask and mean luminance of the mask (excl. masks # 5, 8, 12, 15)	3.55	3.65	-	-
Standard Deviation of the luminances of the mask	30	32.5	26	28.5

TABLE 2. *Threshold values for masks' mean luminance, luminance ratio between maximum luminance of the mask and mean luminance of the mask (excluding situations with the strong negative contrast, namely masks #5, 8, 12, 15) and standard deviation of the luminances of the mask metrics of shape and detail distinctness*

Despite the fact that the metrics for contour and metrics of shape and details were analysed separately, some similar tendencies were observed in both groups of metrics. First, due to the mathematical properties of the measures based on luminance contrast (luminance ratio, Weber contrast, mean point LR and ratio between the highest luminance of the mask and its mean luminance), the two basic types of the object/background combinations (light on darker background, conditionally positive contrast and dark on lighter background, conditionally negative contrast) should be studied separately, regardless of whether they are chromatic or achromatic, matte or glossy. Their values below and above a certain contrast point cannot be equally compared; whereas negative contrast can only vary between 0 and −1, positive contrast can vary between 0 and positive infinity.

The next issue was that of factor ***glossiness***. The appearance of objects is fundamentally affected by the bidirectional reflection distribution function, or the BRDF. One type of BRDF is known as Lambertian reflectance, when the incoming light is scattered in all directions to the same degree. The orientation of view is therefore irrelevant for luminance as long as the surface patch is not obstructed from sight. Such surfaces are usually called matte surfaces. By adding a specular lobe to the Lambertian reflectance the BRDF will be changed and the object will look glossy instead of matte. Specular highlights are found at those points on the surface where the illumination direction mirrors the viewing direction in the surface normal (Nefs et al. 2006). According to Nefs et al. (2006),

> *The intensity of specular highlights is usually higher than the maximum intensity in Lambertian shading. This increases the luminance contrast, and possibly also the colour contrast in the image. Finally, specular highlights are not point-like but are of finite size and therefore have shape. Highlight shape might be useful for the perception of surface relief, although no one has yet investigated how the highlight shape is related to the object shape* (Nefs et al. 2006).

In terms of spatial appearance, two identical shapes of matte and glossy surfaces look slightly different. Qualitatively, the glossy object looks more convincingly three-dimensional than the matte one. Some recent research findings (Norman et al. 2004; Nefs et al. 2006) indicate that highlights sometimes help and, in worst cases, do not counteract quantitative shape perception while observing fine (with defined borders) 3D shapes.

Empirical research on the visual perception of 3D shape has generally adopted the same modular approach as in theoretical analyses, using stimuli that contain a single type of visual feature presented in isolation (Norman et al. 2004). In our study, the masks were observed in natural daylight conditions and the stimuli was relatively complex. However, the tendency described in previous studies of glossiness (or highlights existed on the observed surfaces) to improve shape perception was also registered in the current research. Thus, glossiness was added into the statistical analysis as an additional variable affecting shape and details distinctness; it was a statistically significant extra factor for mean luminance of the mask, luminance ratio and standard deviation metrics, and all types of the masks tested. Glossiness slightly enhanced the visibility of objects' shape and details in comparison to matte objects, which corresponds to previous results described in the literature (Norman et al. 2004; Nefs et al. 2006). In terms of contour distinctness, glossiness was a significant factor only for the mean point LR metric and only for dark objects on lighter backgrounds. For the luminance ratio metric of contour distinctness, glossiness was barely significant $p=0.049$), though it still improved the contour visibility of the dark masks on light backgrounds.

Chromaticness was significant for all metrics except luminance ratio as a metric of shape and detail distinctness. As in the previous experiment with scale models, this one showed that low saturated colours in a room interior influence light level perception; here, similar chromatic colours had a significant effect on the discrimination of contour, shape and detail of the Venetian masks.

It is known through several neurophysiological experiments that colour and shape information interacts in object recognition, and colour facilitates object recognition (Wurm et al. 1993). At small *spatial frequencies*, human chrominance contrast sensitivity is higher than luminance contrast sensitivity (see Figure 6-1) (Valberg 2005). Thus, colour improves object recognition more when spatial resolution is low (blurred) or when shape information is less specific (fruits and vegetables vs man-made objects) (Wurm et al. 1993). If to express the size of the mask used in the experiments in terms of spatial frequency, it would be equal to about 0.42 cycles per degree (Figure 6-1). From first sight, the fact that colour makes the object recognition better seems contradictory to the results obtained from our experiment. The ordinal regression analysis results showing that ratings of contour, shape and detail distinctness of the masks with chromatic combinations (either object or background was chromatic, or both of them were chromatic) had lower rates. Simply put, it was more difficult for participants to distinguish contour, shape and detail when the objects were of chromatic combinations. However, the measurement of respondent reaction time in naming a type of object as seen in psychophysical experiments, which produces a contrast sensitivity function (see Figure 6-1), is different from the evaluation of the visibility of contour, clarity of shape and object detail conducted in the present experiment; the two different

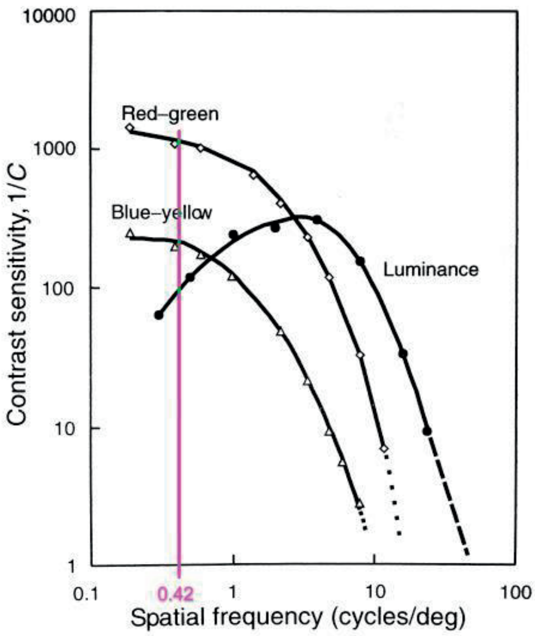


Figure 6-1. *Spatial contrast sensitivity for luminance and isoluminant chrominance ratings*
Adapted from Valberg A. Light, vision, colour. 2005.
Adapted with permission.
The approximate spatial frequency of the mask is represented by the violet colour.

assignments and procedures seek distinct results. This allows us to conclude that in terms of evaluating the shape and detail visibility of 3D objects under real daylight conditions, chromaticness slightly complicated the process of shape and detail distinctness assessment.

There is a theory speculating that contours defined by colour differences may provide more reliable information about object shape in the natural world than luminance contours because shadows and occlusion boundaries also produce luminance contours (De Valois & Switkes 1983). However, such a tendency has not been observed here due to the low saturation of the used colours.

An interesting inference could be done through observation of the probability plots of tested metrics of shape and detail distinctness. Here, glossy/chromatic and glossy/achromatic objects required slightly lower values of the proposed luminance-based metrics (for all categories, from not distinguishable to perfectly distinguishable) than did the matte/chromatic and matte/achromatic objects. It may be concluded that for shape and detail distinctness, glossiness has a higher effect than chromaticity. However, for contour distinctness, this tendency is not that straightforward, as it is similar to the above noted tendency among dark objects on lighter backgrounds and almost diminished by chromaticity for light objects on darker backgrounds.

Another significant observation that should be described here concerns the distinctness of the shapes and details of the Venetian masks in terms of histogram analysis. While a detailed explanation of the processing of HDR image luminance data can be found in Paper IV, the important conclusions are presented here. The histogram shows at one graph the two regions of interest selected at the HDR image (foreground and background), specifying the distribution and frequency of luminance values of the selected mask and its background. This may be a useful tool for predicting objects' shape and detail distinctness. Excluding overlapping areas or areas with equal luminance values (based on certain threshold values that can be determined by the researcher in each particular case), it is practicable to interconnect the remaining areas with a subjective evaluation of shape and detail visibility. In other words, certain remaining areas of the luminance values on the histogram may indicate the determined degree of shape and detail distinctness of the observed object. Through application of more advanced tools (e.g. MATLAB software), these histograms may become a new tool for predicting a real 3D object's visibility.

The proposed luminance-based metrics showed high consistency with subjective visual perception of the contour, shape and detail distinctness of the observed 3D objects and were expressed numerically to reflect several levels of visibility. Although the obtained results were restricted by experimental conditions such as illumination, type of object and coloration, further development might result in a simple and useful tool for light modelling prediction. These metrics are basic and simple to obtain; they complement each other and are good instruments for analysing and predicting 3D objects' visibility. In addition, their threshold values might be useful and promising for further research and practical use.

6.3 Findings from Experiment 3 'Verification of the accuracy of luminance-based light modelling metrics by numerical comparison of photographed and simulated HDR images'

In the third experiment, the previously proposed luminance-based metrics of contour, shape and detail distinctness of day-lit 3D objects were examined with the help of photographed and simulated HDR images. This experiment was set up in a real room where a scene with the Venetian masks (previously used and placed one by one) was photographed with different exposures. To verify the reliability of the proposed luminance-based metrics obtained through simulated HDR images, an identical scene was simulated using a 3D-modelling programme (Rhinoceros). The lighting renderings were performed using the Radiance-based software, DIVA. In addition, semi-cylindrical illuminance (in two opposite directions) and horizontal illuminance measurements were taken in the real room for further calculation of cylindrical illuminance values and modelling indices of the masks. Variations in the numerical values of luminance-based metrics obtained from the simulated and photographed HDR images occurred because of contrast between objects and their backgrounds were compared to the variations observed in the illuminance-based modelling index.

The results revealed a mean relative error between all the metrics obtained from the photographed and simulated luminance maps at 14.78%. Of these errors, 71.4% were below the 20% border, and 42.9% were below 10%. The minimum and maximum mean error values varied from 7.91% (ratio between mean luminance of the mask and mean luminance of the background) to 27.75% (percentage of the invisible part of the contour). The high relative error of this metric could be explained by the method of its calculation. The metric is based on 12 paired point luminance measurements taken with equal steps around the contour of the mask, close to its border. This means that each point and area between the measured points is equal to 8.33% of the whole contour length. The estimation of possible belonging of the points to invisible or visible parts of the contour was performed by the author according to the data from Experiment 2 (namely, based on the maximum, minimum and standard deviation of luminance values that were specified and registered in the invisible part of the contour of the masks). However, even a single point difference between the invisible contours of the simulated and photographed masks will produce a significant error. Also, due to the mathematical properties of the relative error formula, it is clear that the fewer points an invisible part of the contour has, the higher the error level will be, even if the actual difference is only one point of 12. A possible solution in this case could be to increase of the number of measured points around the contour of the object.

It is important to note that the numerical parametres for outside illuminance values were set in the DIVA programme accordingly to the instrumented readings measured during the experiment. The photographing session took approximately two minutes and, with additional instrumented measurements and mask changes, the time period between each photographing session totalled five to six minutes. The illumination may have changed a bit within this short time span, even though the weather status was an overcast sky, the registered maximum light change (between maximum and minimum registered values) was 17.3% and the coefficient of variation (relative standard deviation) was only 6.33 %. This indicates that any difference in illumination that could have occurred during the five to six minute period was very low, but still might have introduced minor error to the final simulation results.

Glossy masks showed slightly higher error rates in comparison to matte masks. The difference in errors of metrics between achromatic and chromatic masks was not

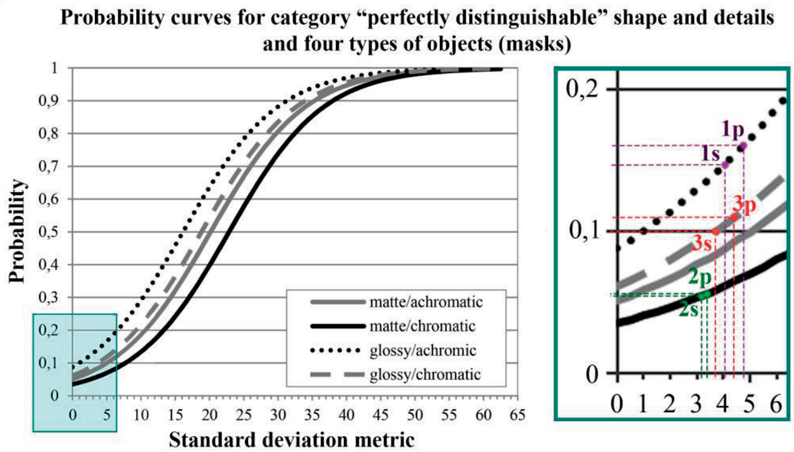


Figure 6-2. *Probability plot with curves for 'perfectly distinguishable' shape and details category, standard deviation metric and four types of the 3D objects (specified in the legend). At the enlarged area of the plot, three pairs of points are indicated:*

1p - value of the standard deviation metric (SD=4,79) obtained from photographed HDR image of white glossy mask;
1s - value of the standard deviation metric (SD=4,02) obtained from simulated HDR image of white glossy mask;
2p - value of the standard deviation metric (SD=3,31) obtained from photographed HDR image of pink matte mask;
2s - value of the standard deviation metric (SD=3,08) obtained from simulated HDR image of pink matte mask;
3p - value of the standard deviation metric (SD=4,39) obtained from photographed HDR image of pink glossy mask;
3s - value of the standard deviation metric (SD=3,38) obtained from simulated HDR image of pink glossy mask.

examined, as only two of the eight masks were chromatic (pink glossy and pink matte).

The higher errors in luminance-based metrics between the photographed glossy and simulated glossy masks may be explained by the numerical characteristics describing the materials used for the simulation. In the Radiance programme, the necessary variables describing opaque material properties are ***reflectivity*** (defined through the amount of red, green and blue), ***specularity*** and ***roughness*** (Larson & Shakespeare 1998). For glossy masks, the specularity and roughness parametres were found by trial and error simulations of one glossy mask placed in a black box, and by visual comparison of the simulated and photographed HDR image of this scene (see Paper V). Through multiple repetitions of the visualizations and adjustments of the specularity and roughness parametres, the most reliable parametres were found (e.g. when the simulated mask closely resembled the real one) (see Figure 3). These parametres were then applied to the main simulations of the glossy masks. This method facilitated the identification of important parameters needed for further simulations of glossy masks in the experimental model of the room when more reliable methods of instrumented measurements were unavailable. Although these numbers were obtained through repeated simulations, they are not as precise as advanced instrumented measurements could be; this can explain the higher error rates observed among the glossy masks. If all

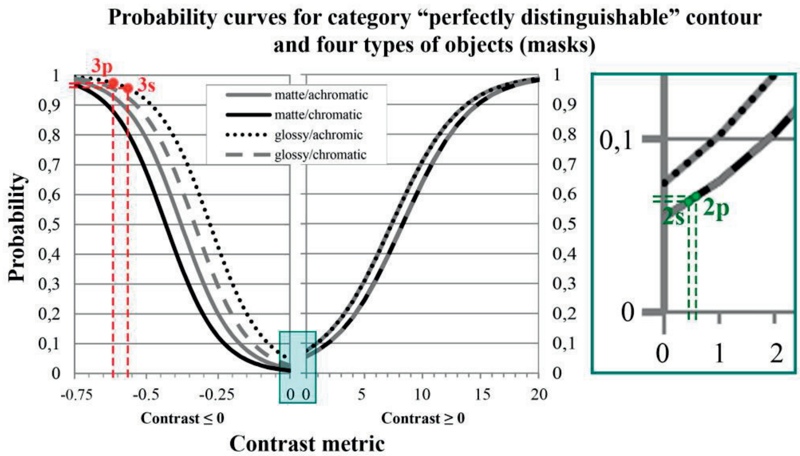


Figure 6-3*. Probability plot with curves for 'perfectly distinguishable' contour category, contrast (Weber ratio) metric and four types of 3D objects (specified in the legend).*
At the left part of the graph, a pair of points is indicated where:
3p - value of the contrast metric (-0,616) obtained from photographed HDR image of dark grey glossy mask
3s - value of the contrast metric (-0,5688) obtained from simulated HDR image of dark grey glossy mask
At the enlarged area of the plot, another pair of the points is shown, where:
2p - value of the contrast metric (0,606) obtained from photographed HDR image of pink glossy mask
2s - value of the contrast metric (0,462) obtained from simulated HDR image of pink glossy mask.

the characteristics of the surfaces of the real scene could be measured instrumentally with the highest possible precision (i.e. RGB colour coordinates, reflectance and specularity), the error level would be lower. As this was not possible in our case and only the *Natural Colour System* (NCS) colour coordinates and reflection factors were measured, certain errors related to specularity and roughness values in the simulation occurred.

Other factors resulting in higher error values among glossy masks could be: i) inaccurate matching of shapes between the simulated and real masks (even if the simulated mask looked very similar to original one, small differences may exist); and ii) small deviations in the masks' positioning, as each of the eight masks were manually changed with every photographing session while the simulated masks remained as modelled. The presence of one person performing the measuring and photographing operations, the laptop and some other instruments in the room during the real time experiment may have affected the final readings as well.

By transferring the results of the luminance-based metrics obtained from photographed and simulated images to probability plots generated in Experiment 2 in similar daylight conditions, even errors within a 20% span were relatively small (see Figures 6-2 and 6-3).

It is also interesting to examine the modelling index values in comparison to the proposed luminance-based metrics. The results of the analysis of all the metrics are presented in Table 1. It is easily noticeable that the numerical values of cylindrical illuminance and modelling index had little variance among the different masks, and the modelling index stayed within the range recommended by CEN (CEN 2011). According to these recommendations, values higher than 0.3 provide adequate modelling of an observed object. The masks examined in Experiment 3 had values from 0.482 to 0.552, demonstrating that they all had good modelling.

However, luminance-based metrics provide much higher variability and precision. For instance, both ***mean luminance of the mask*** metrics and ***standard deviation*** metrics reflected low values for the dark grey masks (glossy and matte) and significantly higher levels for the light masks. Values of the glossy masks were slightly larger than the corresponding values of matte masks, proving again the previous finding that glossiness

as a factor enhances the shape and detail distinctness of 3D objects. Through estimating L_{mean} (mask) and SD values of the eight masks, it became clear that their shapes and details will likely be only just distinguishable (poor light modelling due to the low numerical values of the metrics) compared to conclusions based on modelling index results.

Notably, ***contrast*** (Weber ratio) and ***mean point LR*** as metrics of contour distinctness also demonstrated compelling output. The contrast and mean point LR values of the dark grey masks equalled -0.616 (glossy)/-0.615 (matte) and 0.475 (glossy)/0.35 (matte), respectively, indicating very good contour distinctness in these masks. This would be impossible to evaluate using the standard modelling index.

The response of the visual system in terms of perception is related to the stimulus received, but not the stimulus alone. Perception also depends on the state of ***adaptation*** of the visual system, and it is influenced by the way the luminous environment is organised into patterns (types of foreground and background). Finally, perception is guided by our present knowledge and past experience of the luminous environment, which determines the assumptions we make about objects and the ways they are usually lit (Boyce 2003). Thus, it is possible to conclude that the proposed luminance-based metrics of contour, shape and detail distinctness have significant advantages over the existing illuminance-based measures. These metrics take into account essential characteristics of the observed object: its background, coloration and surface/coating. However, it must be noted that the proposed metrics were only studied in certain lighting conditions with particular types of object and backgrounds, even if these combinations were the most typical in real life conditions. This represents a respectively restricted stimulus, thus limiting possible conclusions regarding the proposed metrics. For these reasons, further studies should be conducted.

	GLOSSY MASKS				**MATTE MASKS**				**Avr. relative error, %**
	Dark grey	**White**	**Pink**	**Light grey**	**Dark grey**	**White**	**Pink**	**Light grey**	
L_{mean}(mask), cd/m^2 photographed	1.32	7.1	6.36	5.54	1.35	6.16	5.16	4.96	**14.25**
L_{mean}(mask), cd/m^2 simulated	1.41	5.81	4.9	4.75	1.25	4.96	4.54	4.32	
Relative error, %	6.818	18.169	22.956	14.26	7.407	19.48	12.016	12.903	
SD (mask), photographed	1.14	4.79	4.39	3.74	0.97	3.96	3.31	3.21	**11.62**
SD (mask), simulated	1.11	4.02	3.38	3.28	0.89	3.39	3.08	2.91	
Relative error, %	2.632	16.075	23.006	12.299	8.247	14.39	6.95	9.346	
L_{mean}(mask)/L_{mean}(bkgr), photographed	0.384	1.797	1.606	1.505	0.385	1.755	1.564	1.585	**7.91**
L_{mean}(mask)/L_{mean}(bkgr), simulated	0.431	1.609	1.463	1.471	0.394	1.595	1.450	1.421	
Relative error, %	12.37	10.462	8.927	2.315	2.524	9.124	7.237	10,325	
Contrast (Weber), photographed	-0.616	0.798	0.606	0.505	-0.615	0.755	0.564	0.585	**16.59**
Contrast (Weber), simulated	-0.569	0.609	0.463	0.471	-0.606	0.595	0.450	0.421	
Relative error, %	7.703	23.58	23.657	6.894	1.577	21.21	20.076	27.984	
Mean point LR, photographed	0.475	1.479	1.761	1.621	0.35	1.756	1.415	1.570	**11.89**
Mean point LR, simulated	0.416	1.571	1.342	1.382	0.379	1.531	1.372	1.354	
Relative error, %	12.303	6.22	23.816	14.731	8.454	12.823	3.054	13.75	
L_{max}/ L_{mean}(mask), photographed	6.545	3.597	4.383	4.598	3.659	2.32	2.376	2.476	**13.45**
L_{max}/ L_{mean}(mask), simulated	7.972	3.411	3.651	3.577	2.84	2.256	2.216	2.231	
Relative error, %	21.789	5.166	16.713	22.2	22.39	2.748	6.739	9.869	
Percentage of the inv. part of the contour, phot.	50.0	16.67	33.33	33.33	75	33.33	33.33	33.33	**27.75**
Percentage of the inv. part of the contour, sim.	50.0	25.0	16.67	8.33	91.67	41.61	33.33	33.33	
Relative error, %	0	49.97	49.985	75.008	22.23	24.84	0	0	

TABLE 3. *Numerical values of the metrics obtained from photographed and simulated luminance maps and their relative errors.*

7. Conclusions and ideas for future research

From a design perspective, architectural lighting is a decision-making process that affects lighting quality and, consequently, occupants' visual comfort and performance. Various lighting design options cannot be evaluated or compared through a single quantity or performance indicator. Lighting design is a 'multitasking' process, and it is impossible to have a universal recipe for choosing the best solution to fulfil different criteria and goals. Satisfying set codes, recommendations and legislations are but a few of many requirements (M. Inanici 2004). Eventually, it could be possible for many inputs to be set together to form one composite performance metric, but at present, studying the separate dimensions of day-lit environments independently is likely to be more informative (Mardaljevic et al. 2009). Thus, lighting quality may be described by different criteria, of which light modelling is one. Light modelling can be also measured using diverse metrics; illuminance- or luminance-based, quantitative or qualitative, research grade (advanced) or professional grade (officially accepted and used by practitioners). Yet, the most useful metrics have an intuitive meaning so they can be easily understood or interpreted, and should also be measured directly for validation. Previously known measures for light modelling in general have been based on illuminance. The present research project, however, used a method based on luminance and HDR imaging because luminance, in forming what our eyes see, correlates better than illuminance with the subjective perception of a visual environment.

From the information presented above, it can be concluded that the luminance-based metrics of contour, shape and detail distinctness of 3D objects are important predictors of the light modelling concept, and thus are good instruments for analysing and predicting a 3D object`s visibility. They demonstrate higher precision, variability and consistency than the currently used illuminance-based metrics. Luminance-based metrics can be used to predict the distinctness of various 3D objects and their attributes (details) object and background colours and types of surfaces. These measures are simple to obtain from photographed or simulated images, and HDR images offer huge amounts of information that can be processed in a variety of ways. The existing limitations of the available tools of the programmes dedicated to luminance maps' analysis could be overcome through the creation and integration of comprehensive algorithms into existing computer programmes, which would allow the automatic performance of simple calculations, similar to how hdrscope programme easily acquire the contrast value of selected regions of an image. Another possibility is to use more advanced software—such as Matlab—for luminance maps analysis (M. Inanici 2004; Inanici 2006; Lu et al. 2014; Araji & Boubekri 2011).

Luminance imaging (and therefore the use of luminance-based metrics) is also beneficial in terms of economic cost, as consumer-grade digital cameras and free software can be used instead of the expensive professional equipment needed for advanced illuminance-based measurements. Moreover, simulated luminance maps can be used for image analysis and to obtain the numerical values of luminance-based metrics, as demonstrated in the previous chapter of the current dissertation. Simulations may help because architectural spaces often need to be examined at different periods throughout the year, when different sky conditions and different times of the day/year have to be considered. The temporal dynamics of daylight also influence daylight design, while the usual approach is to select critical situations, prioritise and/or optimise objectives and assess performance accordingly (M. Inanici 2004). Simulations using modern software may be extremely helpful, save time and allow the testing of numerous alternatives in terms of temporal light variation.

Complementing each other and other existing useful metrics, the proposed luminance-based metrics are a promising and useful tool for analysing and predicting 3D objects' contour, shape and detail distinctness, and their threshold values may be utilised for further development and practical use. These metrics have greater predictive ability than the cylindrical illuminance and modelling index. As this is a new approach, the present study represents the first step towards finding reliable luminance-based measures for light modelling. It is thus too early to claim that the suggested tested metrics are all-sufficient and ready for practical use.

A suggestion for future research would be not to change the methodology, but to test the metrics under other experimental conditions and with different objects' qualities. Certainly, objects with other chromaticity types could be studied (e.g. hue and saturation), as the current experiments tested only those with low saturation. Colour can be an important factor for enhancing visual search. Lighting can alter the colour difference between an object and its background when light sources with different spectral contents are used (Boyce 2003). Even though previous studies showed higher error among saturated colour chips (Anaokar & Moeck 2005), it would be interesting to examine how distinctive the contours, shapes and details of these objects will be, what values the luminance-based metrics will have, how different will they be in comparison to previously found numbers related to low saturated masks' colours and how substantial the errors will be. This will supplement previous findings and, hopefully, increase the reliability of the suggested metrics.

Another possibility is to test the proposed metrics under different lighting conditions (e.g. light level variation or directivity). In the second experiment of the present study, two kinds of light directions were mixed with the surface type factor; in the future, these variables could be divided to form several separate groups: light directivity, light level in the room and type of surfaces of the observed object. Overall, the addition of light directionality as a separate complementing factor by which to analyse the suggested metrics could be exceptionally beneficial. Adequate directionality might distinguish the details of an observed object, reveal surface textures and model the 3D surfaces (Inanici & Navvab 2006). Directionality might also be solely evaluated, such as using the directional-to-diffuse luminance ratio proposed earlier by Inanici and Navvab (Inanici & Navvab 2006; M. Inanici 2004). They suggested that the diffuse and directional components of light be separated via the image subtraction method, and the ratio between directional and diffuse components be calculated using average luminance values.

Even more beneficial may be to study elderly observers or people with poor vision. Older people tend to show reduced ***visual field*** size, increased absolute threshold luminance, reduced visual acuity, reduced contrast sensitivity, increased sensitivity to glare and poorer colour discrimination (Boyce 2003). In certain settings, such as in hospitals, the number of people with reduced vision is likely to be higher. In such conditions, the modelling of faces is important, and the numerical values of the suggested luminance-based metrics will probably be much higher.

Finally, the histogram analysis technique might be developed further. Pairing histogram analysis results with subjective assessments of a masks' shape and detail visibility could lead to useful results, enabling the thorough utilisation of this vast luminance information and possibly leading to the development of new metrics for 3D objects' shape and detail distinctness.

In the future, when luminance-based metrics are thoroughly studied and correct numerical values applicable to various situations are prescribed, their integration into computer programmes that perform advanced lighting design analysis will open up new opportunities for the researchers and professionals to understand, predict and design object light modelling.

References

Anaokar S, Moeck M. Validation of high dynamic range imaging to luminance measurement. *LEUKOS*. 2005; 2:133–144.

Angelo K, Matusiak B, Fridell Anter K. Colour shift behind modern glazing. In: *Interim Meet Int Color Assoc Proc.* 2012; Taipei, Taiwan; p. 22–25.

Araji M, Boubekri M. A novel way of utilising Radiance-Matlab visualisation for facade design optimisation. *Light Res Technol*. 2011; 43:103–118.

Aries MBC, Veitch JA, Newsham GR. Windows, view, and office characteristics predict physical and psychological discomfort. *J Environ Psychol.* 2010; 30:533–541.

Arnkil H, Anter KF, Klarén U, Matusiak B. PERCIFAL: Visual analysis of space, light and colour. In*: AIC 2011 Interact Colour Light Arts Sci Midterm Meet Int Colour Assoc.* 2011; Zurich, Sweitzerland; p. 229–232.

Arnkil H, Anter KF, Klarén U. *Colour and light: concepts and confusions.* Unigrafia Oy, Helsinki, Finland: Aalto University; 2012.

Baker N, Steemers K. *Daylight design of buildings.* Hong Kong: James & James (Science Publishers) Ltd; 2002.

Billger M. The experience of the painted room: the significance of light and colour combinations. In: *Interim Meet Int Color Assoc.* 2004; [place unknown]; p. 219.

Boubekri M, Cheung IN, Reid KJ, Wang C-H, Zee PC. Impact of windows and daylight exposure on overall health and sleep quality of office workers: a case-control pilot study. *J Clin Sleep Med.* 2014.

Boyce P. Editorial: recognition and opportunity. *Light Res Technol.* 2015; 47:3–3.

Boyce PR. *Human factors in lighting.* London; New York: Taylor & Francis; 2003.

Boyce P, Smet K. LRT symposium 'better metrics for better lighting': a summary. *Light Res Technol.* 2014; 46:619–636.

Cai H. Camera aided luminance measurement of the luminous surfaces of different light sources. In: *AEI 2011 Build Integr Solut.* Vol. 30. 2011; Oakland, California; p. 272–279.

Cai H, Chung T. Improving the quality of high dynamic range images. *Light Res Technol.* 2011; 43:87–102.

Caminada JF, van Bommel WJM. New lighting considerations for residential areas. *Int Light Rev.* 1980; 3:69–75.

Cantin F, Dubois M-C. Daylighting metrics based on illuminance, distribution, glare and directivity. *Light Res Technol.* 2011; 43:291–307.

CEN. Light and lighting: lighting of workplaces. *EN 12464-1*. 2011

Chung T, Ng R. Variation of calibration factor over time for high dynamic range photography in a single daylit interior scene. *J Light Vis Environ*. 2010; 34:87–93.

Clery S, Bloj M, Harris JM. Interactions between luminance and color signals: effects on shape. *J Vis*. 2013; 13:1–23.

Corder GW, Foreman DI. *Nonparametric statistics for non-statisticians: a step-by-step approach.* Wiley; 2009.

Cuttle C. *Lighting by design*. 2nd ed. Elsevier; 2008.

Cuttle C. A new direction for general lighting practice. *Light Res Technol*. 2013; 45:22–39.

Cuttle C. Research note: a practical approach to cubic illuminance measurement. *Light Res Technol.* 2014; 46:31–34.

Debevec PE, Malik J. Recovering high dynamic range radiance maps from photographs. In: *Proc Siggraph.* 1997; ACM; p. 369–378.

Dehoff P. Measures for a better quality in lighting. a journey through recent activities in applications and standards. In: *CIE 2014*. Vol. 0.39. 2014; Kuala Lumpur, Malaysia: CIE Central Bureau; p. 348–356.

De Valois KK, Switkes E. Simultaneous masking interactions between chromatic and luminance gratings. *JOSA*. 1983; 73:11–18.

DIVA-for-Rhino. Solemma LLC. Available from: http://www.solemma.net/DIVA-for-Rhino/DIVA-for-Rhino. Accessed 2014 Nov.

Edwards DP, Purpura KP, Kaplan E. Contrast sensitivity and spatial frequency response of primate cortical neurons in and around the cytochrome oxidase blobs. *Vision Res.* 1995; 1501–1523.

Farley KM, Veitch JA. *A room with a view: a review of the effects of windows on work and well-being.* Institute for Research in Construction, National Research Council Canada; 2001.

Fridell Anter K. Spatial interaction between light and colour: an overview over current international research. In: *Nord Light Colour.* Trondheim, Norway: NTNU - The Faculty of Architecture and Fine Art; 2012.

Fridell Anter K, Arnkil H, Berggren L, Billger M, Duwe P, Enger J, Gustafsson A, Häggström C, Karlsson Y, Klarén U. SYN-TES: interdisciplinary research on colour and light. In: *Color We Live Color Environ.* 2012; Taipei, Taiwan; p. 80–83.

Fridell Anter K, Häggström C, Klarén U, Matusiak B. A trans-disciplinary approach to the spatial interaction of light and colour. In: *Proc CIE 2012 Light Qual Energy Effic.* 2012; Hangzhou, China; p. 264–275.

Groat L, Wang D. *Architectural research methods.* Wiley; 2002.

Hårleman M. Daylight influence on colour design: empirical study on perceived colour and colour experience indoors. Stockholm: Axl Books; 2007.

Inanici M. Transformations in architectural lighting analysis: virtual lighting laboratory. The University of Michigan; 2004. Available from: http://faculty.washington.edu/inanici/Publications/Inanici-Dissertation.pdf

Inanici M. Evaluation of high dynamic range photography as a luminance data acquisition system. *Light Res Technol.* 2006; 38:123–136.

Inanici M. evalution of high dynamic range image-based sky models in lighting simulation. *LEUKOS*. 2010; 7:69–84.

Inanici MN, Navvab M. The virtual lighting laboratory: per-pixel luminance data analysis. *LEUKOS*. 2006; 3:89–104.

Jacobs A. High dynamic range imaging and its application in building research. *Adv Build Energy Res*. 2007; 1:177–202.

Jacobs A. WebHDR Roll-Your-Own . Available from: http://www.jaloxa.eu/webhdr/roll-your-own.shtml. Accessed 2014 Nov.

Jacobs A, Wilson M. Determining lens vignetting with HDR techniques. In: *Bulg Natl Light Conf.* 2007; Varna, Bulgaria.

Jakubiec JA, Reinhart CF. DIVA 2.0: Integrating daylight and thermal simulations using Rhinoceros 3D, Daysim and EnergyPlus. In: *12th Conf Int Build Perform*

Simul Assoc. 2011; Sydney; . Available from: http://www.jakubiec.net/papers/bs2011_diva20_jakubiec,reinhart.pdf

Jakubiec JA, Reinhart CF. Predicting visual comfort conditions in a large daylit space based on long-term occupant evaluations: a field study. In: *Proc 13th Int Conf Int Build Perform Simul Assoc.* International Building Performance Simulation Association. 2013; Aix-les-Bains, France.; p. 3408–3415.

Kelly DH. In: *Eye Mov Contrast Sensit*. New York: Marcel Dekker; 1994. p. 93–114.

Klarén U, Arnkil H, Fridell Anter K. Colour and light in design: levels of experiencing colour and light. In: *2nd International Conference for Design Education Researchers*; 2013 May 14–17, Oslo, Norway.

Konis K. Predicting visual comfort in side-lit open-plan core zones: results of a field study pairing high dynamic range images with subjective responses. *Energy Build*. 2014; 77:67–79.

Kumaragurubaran V, Inanici M. Hdrscope: high dynamic range image processing toolkit for lighting simulations and analysis. In: *Int Build Perform Simul Assoc IBPSA.* 2013, Chambery, France. p. 3400–3407.

Larson GW, Shakespeare R. *Rendering with Radiance: the art and science of lighting visualization.* San Francisco, California: Morgan Kaufman Publishers; 1998.

Leslie R, Radetsky L, Smith A. Conceptual design metrics for daylighting. *Light Res Technol*. 2012; 44:277–290.

Lu J, Sang N, Hu Y, Fu H. Detecting citrus fruits with highlight on tree based on fusion of multi-map. *Opt - Int J Light Electron Opt*. 2014; 125:1903–1907.

Mardaljevic J. Daylighting science: a brief survey and suggestions for inclusion in the architectural curriculum. In: *Nord Light Colour*. Trondheim: NTNU - The Faculty of Architecture and Fine Art; 2013. p. 73–94.

Mardaljevic J, Heschong L, Lee E. Daylight metrics and energy savings. *Light Res Technol*. 2009; 41:261–283.

Matusiak B. Low-energy house, back to the “årestue”: a thought experiment about low-energy houses. *Archit Sci Rev*. 2012; 55:86–91.

Matusiak B, Anter KF, Arnkil H, Klarén U. PERCIFAL method in use: visual evaluation of three spaces. In: AIC 2011 *Interact Colour Light Arts Sci Midterm Meet Int Colour Assoc*. 2011; Zurich, Switzerland: Zurich: 2011.

Matusiak BS. A modelling sensor designed to be used in the lighting practise in cases where there it is essential to compare the modelling ability of light in an important point in a room for different lighting alternatives. In: *CIE 2002*. CIE Central Bureau; 2002.

Monk T, Buysse D, Billy B, Kennedy K, Kupfer D. The effects on human sleep and circadian rhythms of 17 days of continuous bedrest in the absence of daylight. *Sleep*. 1997; 20:858—864.

Mullen KT. The contrast sensitivity of human colour vision to red-green and blue-yellow chromatic gratings. *J Physiol*. 1985; 381–400.

Nefs HT, Koenderink JJ, Kappers AML. Shape-from-shading for matte and glossy objects. *Acta Psychol (Amst)*. 2006; 121:297–316.

Norman JF, Todd JT, Orban GA. Perception of three-dimensional shape from specular highlights, deformations of shading, and other types of visual information. *Psychol Sci.* 2004; 15:565–570.

Phillips D. *Daylighting: natural light in architecture*. New York: McGraw-Hill; 2004.

Piccablotto, G, Aghemo C, Pellegrino A. LED lighting quality assessment for museum showcases. In: *Proc 27th Sess CIE.* Vol. 1. South Africa: Sun City; 2011. p. 294–304.

Pineault N, Dubois M-C. Effect of window glazing type on daylight quality: scale model study of a living room under natural sky. *LEUKOS*. 2008; 5:83–99.

Premkumar M, Sable T, Dhanwal D, Dewan R. Vitamin D homeostasis, bone mineral metabolism, and seasonal affective disorder during 1 year of Antarctic residence. *Arch Osteoporos.* 2013; 8.

Ramachandran KM, Tsokos CP. *Mathematical statistics with applications in R*. 2nd ed. Elsevier Inc.; 2015.

Rastad C, Ulfberg J, Lindberg P. Improvement in fatigue, sleepiness, and health-related quality of life with bright light treatment in persons with seasonal affective disorder and subsyndromal sad. *Depress Res Treat.* 2011; 1–10.

Rea MS, editor. *The IESNA lighting handbook: reference & application*. New York: Iluminating Engineering Society of North America; 2000.

Reeves GM, Nijjar GV, Langenberg P, Johnson MA, Khabazghazvini B, Sleemi A, Vaswani D, Lapidus M, Manalai P, Tariq M. Improvement in depression scores after 1 hour of light therapy treatment in patients with seasonal affective disorder. *J Nerv Ment Dis.* 2012; 200:51–55.

Reinhard E, Heidrich W, Debevec P, Pattanaik S, Ward G, Myszkowski K. *High dynamic range imaging: acquisition, display, and image-based lighting.* Elsevier Science; 2010.

Reinhart CF, Mardaljevic J, Rogers Z. Dynamic daylight performance metrics for sustainable building design. *LEUKOS.* 2006; 3:7–31.

Rombauts P, Vandewyngaerde H, Maggetto G. Minimum semicylindrical illuminance and modelling in residential area lighting. *Light Res Technol*. 1989; 21:49–55.

Saraiji R. A methodology for locating the maximum vertical illuminance in street lighting. *LEUKOS*. 2009a; 6:139–152.

Saraiji R. Vertical illuminance based crosswalk illumination. *LEUKOS*. 2009b; 6:153–167.

Saraiji R, Oommen MS. Dominant contrast as a metric for the lighting of pedestrians. *Light Res Technol*. 2014.

Sheldon MR, Fillyaw MJ, Thompson WD. The use and interpretation of the Friedman test in the analysis of ordinal-scale data in repeated measures designs. *Physiother Res Int.* 1996; 1:221–228.

Stahre B, Billger M, Anter KF. To colour the virtual world-difficulties in visualizing spatial colour appearance in virtual environments. *Int J Archit Comput.* 2007; 7:289–308.

Stamatis DH. *Essential statistical concepts for the quality professional.* Taylor & Francis Group, LLC.; 2012.

Terman M, Terman J, Quitkin F, McGrath P, Stewart J, Rafferty B. Light therapy for Seasonal Affective Disorder. *Neuropsychopharmacology*. 1989; 2:1–21.

Tregenza P, Wilson M. *Daylighting: architecture and lighting design*. New York, NY: Routledge; 2011.

Tyukhova Y, Waters C. An assessment of high dynamic range luminance measurements with LED lighting. *LEUKOS*. 2014; 10:87–99.

Valberg A. *Light, vision, color.* Wiley; 2005.

Valberg A, Fosse P, Gjerde T. Chromatic contrast sensitivity without correction for chromatic aberration. *Invest Ophthalmol Vis Sci.* 1997; 38:S893.

Van Den Wymelenberg K, Inanici M. A critical investigation of common lighting design metrics for predicting human visual comfort in offices with daylight. *LEUKOS*. 2014; 10:145–164.

Van Den Wymelenberg K, Inanici M. Evaluating a new suite of luminance-based design metrics for predicting human visual comfort in offices with daylight. *LEUKOS*. 2015; 1–26.

Van Den Wymelenberg K, Inanici M, Johnson P. The effect of luminance distribution patterns on occupant preference in a daylit office environment. *LEUKOS*. 2010; 7:103–122.

Van Hagen M, Galetzka M, Pruyn A, Peters J. *Effects of colour and light on customer experience and time perception at a virtual railway station.* Eindhoven, The Netherlands: Eindhoven University of Technology; 2009. p. 137–145.

Veitch JA. *Commentary: on unanswered questions.* Vienna, Austria: CIE Central Bureau; 1998. p. 88–91.

Veitch JA. Psychological processes influencing lighting quality. *J Illum Eng Soc.* 2001; 30:124–140.

Veitch JA. *Principles of healthy lighting: highlights of IE TC6-11's forthcoming report.* Institute for Research in Construction; 2004.

Veitch JA, Julian W, Slater AI. A framework for understanding and promoting lighting quality. *Commission Internationale de L'eclairage CIE Central Bureau.* 1998; 15:237–241.

Veitch J, Newsham G, Boyce P, Jones C. Lighting appraisal, well-being and performance in open-plan offices: a linked mechanisms approach. *Light Res Technol.* 2008; 40:133–151.

Vogels I, De Vries M, Van Erp T. Effect of coloured light on atmosphere perception. In: *Association Internationale de la Couleur (AIC)*; 2008; Stockholm, Sweden.

Ward G. Photosphere. Anyhere Software; 2002. Available from: http://www.anyhere.com/ Accessed 2014 Nov.

Ward G. Fast, robust image registration for compositing high dynamic range photographs from hand-held exposures. *J Graph Tools*. 2003; 8:17–30.

Ward GJ. *The Radiance lighting simulation and rendering system*. Orlando, Florida: ACM; 1994. p. 459–472.

Wästberg BS, Forzelius J, Billger M. To predict reality in virtual environments: exploring the reliability of colour and light appearance in 3D-models. In: *Color and Image, Midterm Meeting of the International Colour Association (AIC)*; 2015 May 19–22; Tokyo, Japan. p. 1301–1306.

Watson A, Barlow HB, Robson JG. What does the eye see best? *Nature.* 1983; 419–422.

Wurm LH, Legge GE, Isenberg LM, Luebker A. Color improves object recognition in normal and low vision. *J Exp Psychol Hum Percept Perform.* 1993; 19:899.

Zaikina V. Light level perception in interiors with equiluminant colours. In: *Nord Light Colour*. Trondheim: NTNU - The Faculty of Architecture and Fine Art; 2012. p. 105–122.

Zaikina V, Matusiak BS, Klöckner CA. New measures of light modelling. In: *Proceedings of CIE 2014*. Vol. 0.39. Kuala Lumpur, Malaysia: CIE Central Bureau; 2014. p. 298–305.

Zaikina V, Matusiak BS, Klöckner CA. Luminance-based measures of shape and detail distinctness of 3d objects as important predictors of light modeling concept: results of a full-scale study pairing proposed measures with subjective responses. *LEUKOS.* 2015a; 1–15.

Zaikina V, Matusiak BS, Klöckner CA. Luminance-based measures of contour distinctness of 3d objects as a component of light modeling. *LEUKOS*. 2015b; 11:31–45.

Other literature

Ashdown, I. & Eng, P. The virtual photometer: modeling the flow of light. In *IESNA 1998 Annual Conference Technical Papers*. Canada; 1998.

Bellia, L., Spada, G. & Pedace, A. Lit environments quality: A software for the analysis of luminance maps obtained with the HDR imaging technique. *Energy Build*. 2013. 67, pp.143–152.

Van Bommel, W. Visual, biological and emotional aspects of lighting: Recent new findings and their meaning for lighting practice. *LEUKOS*, 2005. 2(1), pp.7–11.

Boyce, P. Editorial: Light distribution - a missing variable. *Light Res Technol*, 2014a. 46(6), pp.617–617.

Boyce, P. Editorial: What does it take to change a metric? *Light Res Technol*, 2014b. 46(5), pp.491–491.

Boyce, P.R. et al. Lighting quality and office work: two field simulation experiments. *Light Res Technol*, 2006. 38(3), pp.191–223.

Bullough, J., Radetsky, L. & Rea, M. Testing a provisional model of scene brightness with and without objects of different colours. *Light Res Technol*, 2011. 43(2), pp.173–184.

Cai, H. High dynamic range photogrammetry for synchronous luminance and geometry measurement. *Light Res Technol*, 2013a. 45(2), pp.230–257.

Cai, H. Luminance gradient for lighting evaluation. *Light Res Technol*. 2013b. 0: pp. 1–21.

DiLaura, D.L. Why we need lighting quality metrics. *LEUKOS*, 2009. 6(1), pp.4–6.

Duff, J.T. The 2012 SLL Code for Lighting: the Impact on Design and Commissioning. *SDAR- J Sust Des Appl Res*, 2012. 1(2), p.4.

Falissard, B. *Analysis of Questionnaire Data with R*, Taylor & Francis Group, LLC. 2012.

Gilchrist, A.L. Lightness and brightness. *Current Biol*, 2007. 17(8), pp. 267–269.

Hayman, S. Daylight measurement error. *Light Res Technol*, 2003. 35(2), pp.101–110.

Hirning, M.B. et al. Post occupancy evaluations relating to discomfort glare: A study of green buildings in Brisbane. *Building Envir*, 2013. 59, pp.349–357.

Hirning, M.B., Isoardi, G.L. & Cowling, I. Discomfort glare in open plan green buildings. *Energy Build*, 2014. 70, pp.427–440.

Hopkinson, R.G., Petherbridge, P. & Longmore, J. *Daylighting*, Heinmann. 1966.

Ibarra, D. & Reinhart, C.F. Teaching daylight simulations – improving modeling workflows for simulation novices. In: *Building Simulation Conference 2013*. Chambery, France. 2013.

Inanici, M. Computational approach for determining the directionality of light: directional-to-diffuse ratio. In: *Building Simulation 2007*. 2007. pp. 1182–1188.

Inanici, M. Dynamic daylighting simulations from static high dynamic range imagery using extrapolation and daylight coefficient methodologies. In *Proceedings of BS2013.* 13th Conference of International Building Performance Simulation Association. Chambéry, France. 2013. pp. 3392–3399.

Isoardi, G., Garcia-Hansen, V.R. & Hirning, M. Evaluation of the luminous environment in open-plan offices with skylights. In: *Proceedings of WREF 2012*, 2012. pp.1–8.

Kumaragurubaran, V. & Inanici, M. *hdrscope*, Seattle: University of Washington. 2012. Accessed 2014 Sep.

Lynn, A.C. & Reitherman, R. In: *AEI 2011: Building Integration Solutions*, American Society of Civil Engineers. 2011.

Mardaljevic, J. Validation of a lighting simulation program under real sky conditions. *Light Res Technol*, 1995. 27(4), pp.181–188.

Mardaljevic, J. Verification of program accuracy for illuminance modelling: assumptions, methodology and an examination of conflicting findings. *Light Res Technol*, 2004. 36(3), pp.217–239.

Mardaljevic, J., Painter, B. & Andersen, M. Transmission illuminance proxy HDR imaging: A new technique to quantify luminous flux. *Light Res Technol*, 2009. 41(1), pp.27–49.

Mishima, K. et al. Morning bright light therapy for sleep and behavior disorders in elderly patients with dementia. *Acta Psychiatrica Scandinavica*, 1994. 89(1), pp.1–7.

Montgomery, P. & Dennis, J.A. Bright light therapy for sleep problems in adults aged 60+. In The Cochrane Collaboration, ed. *Cochrane Database of Systematic Reviews*. Chichester, UK: John Wiley & Sons, Ltd. 2002.

Nakamura, Y., Suzui, S. & Aoki, T. Lighting design method applicable both to day lighting and to electric lighting using luminance image. In *27th Session of the CIE*. CIE 2011. Sun Sity, South Africa. 2011. CIE Central Bureau, pp. 398–403.

Navvab, M. Opinion: Simulation in lighting design and research. *Light Res Technol*, 2014. 46(2), pp.92–92.

Newsham, G. et al. Lighting quality research using rendered images of offices. *Light Res Technol*, 2005. 37(2), pp.93–115.

Newsham, G.R. et al. Comparing lighting quality evaluations of real scenes with those from high dynamic range and conventional images. *ACM Trans. Appl. Percept.*, 2010. 7(2), pp.1–26.

Panitz, K. & Garcia-Hansen, V.R. Daylighting Design and Simulation: Ease of use analysis of digital tools for architects. In: *Proceedings of the 19th CIB World Building Congress, Brisbane 2013: Construction and Society*. 2013. Queensland University of Technology (QUT), pp. 1–13.

Parpairi, K. et al. The Luminance Differences index: a new indicator of user preferences in daylit spaces. *Light Res Technol*, 2002. 34(1), pp.53–68.

Reinhart, C. & Fitz, A. Findings from a survey on the current use of daylight simulations in building design. *Energy Build*, 2006. 38(7), pp.824–835.

Reinhart, C.F. & Walkenhorst, O. Validation of dynamic RADIANCE-based daylight simulations for a test office with external blinds. *Energy Build*, 2001. 33(7), pp.683–697.

Rockcastle, S. & Andersen, M. Measuring the dynamics of contrast & daylight variability in architecture: A proof-of-concept methodology. *Build Env*, 2014. 81, pp.320–333.

Ruppertsberg, A.I., Bloj, M. & Hurlbert, A. Sensitivity to luminance and chromaticity gradients in a complex scene. *J. Vis*, 2008. 8(9), pp.1–16.

Schielke, T. Tutorial: Rationale, Concepts, and Techniques for Lighting Vertical Surfaces. *LEUKOS*, 2013. 9(4), pp.223–243.

Tai, N.-C. & Inanici, M. Space perception and luminance contrast: investigation and design applications through perceptually based computer simulations. In: *Proceedings of the 2010 Spring Simulation Multiconference*. 2010. International Society for Computer Simulation, p. 185.

Tamrat, R., Huynh-Le, M.-P. & Goyal, M. Non-Pharmacologic Interventions to Improve the Sleep of Hospitalized Patients: A Systematic Review. *J. Gen. Intern. Med.*, 2014. 29(5), pp.788–795.

Taylor, P.C. & Medina, M.N.D. Educational research paradigms: From positivism to multiparadigmatic. *J. Mean.-Centered Educ.*, 2013. 1(3).

Veitch, J.A. Lighting Quality Contributions from Biopsychological Processes. *J. Illum. Eng. Soc.*, 2001. 30(1), pp.3–16.

Ward, G. Invited Paper: The Hopeful Future of High Dynamic Range Imaging. In: *SID Symposium Digest of Technical Papers*. 2007. Wiley Online Library, pp. 1046–1048.

8. Appended papers

Paper I.

Light level perception in interiors with equiluminant colours

Veronika Zaikina

In: *Nord Light and Colour.* 2012. Trondheim: NTNU - The Faculty of Architecture and Fine Art; p. 105–122.

ABSTRACT

The visual experience of indoor environment depends on both colour and light. Usually these two concepts are studied separately although they are tightly intertwined. Luminance distribution in visual field is assumed to be crucial for perception of light level in space. Taking into consideration the fact that colours of surfaces may also affect light level perception, an impact of low saturated interior colors on light level perception was examined. The luminance-based approach as a perception-oriented method for lighting design was a complementary part of the study.

Findings showed that even low saturated colours influence light level perception although magnitude can vary. From an architectural perspective it is important to note that the brightness of the visual environment is a perceptual phenomenon and not just a direct mapping of a light stimuli or linear function of the luminance. Nevertheless, luminance, as a basis for vision, can greatly develop lighting design methods as an applicable and effective tool.

BACKGROUND

Humans get the major part of information about the world through vision. Our visual perception is based on a continuous stream of changing pictures created by light at the retina. We can see objects and colours because of light. Colour and light are inseparable. However, the established classical scientific tradition prevailing to date separates these concepts. In this essay we will show how strongly interdependent they are.

It is important to specify particular definitions of concepts used in this paper. Thus, *equiluminant* (or isoluminant) *colours* are the colours equal in luminance (Valberg 2005), which implies they may be chromatically different. *Brightness* is the perceptual dimension that runs from dim to bright. The physical counterpart of brightness is luminance, or put simply, brightness is perceived luminance (Gilchrist 2007). Perceptual attribute *light level* represents the appearance of the room as a whole as bright or dark. At the same time light level does not refer to how well or bad a person can see in the room or in a special place of the room (Liljefors 2003:13; 32-33). The appearance of the observed room (or its light level) was registered with the help of the *PERCIFAL* questionnaire (Matusiak et al. 2011), (Arnkil et al. 2011), (Fridell Anter, Haggstrom et al. 2012). Answers are marked on a scale ranging from very dark to very bright. The PERCIFAL method was developed by scientists from the SYN-TES group and is now recommended as a good analytical tool for professional application (Fridell Anter, Arnkil et al. 2012). This method is based on direct observations of the space and recording of these observations by verbal-semantic descriptions.

Our visual apparatus is an intricate and complex system with amazing abilities such as luminance and colour adaptation and colour constancy. Furthermore, the Helmholtz-Kohlrausch phenomenon is a visual effect, showing that more saturated colours appear brighter than less saturated colours at equiluminance. This may be explained by the fact that the human brain adds the information from the chromatic channel to the brightness channel. The Helmholtz-Kohlrausch phenomenon appears both in selfluminous and surface colours (Valberg 2005: 178-178), (DeCusatis et al. 1997: 338).

Chromatic contrast is another strong effect that may influence brightness of surfaces, e.g. in interiors. At low spatial frequencies our sensitivity to chromatic contrasts is significantly higher than for achromatic contrasts (see Figure 1). In this context it is necessary to define the term spatial frequency. It represents a measure of numbers of periods per degree of a repetitive pattern (Valberg 2005: 432). Following the above, we can say that equiluminant chromatic pattern of colours with distinctly contrasting hues is the best representation of chromatic contrast effects. The perception of the contrast depends on the size and form of the observed objects, its temporal variation. The visual system deals with chromatic contrast in distinctly different ways than with luminance contrast (Valberg 2005: 182).

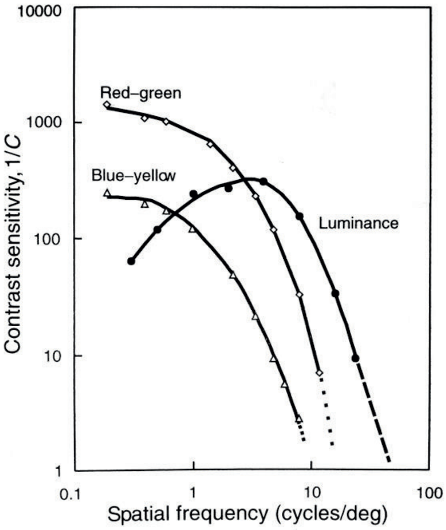


Figure 1. *Spatial contrast sensitivity for luminance and isoluminant chrominance gratings. The sensitivity curves for pure color differences resemble low-pass filters, while the curve for luminance contrast sensitivity corresponds to a band-pass filter. When using a common cone contrast measure for luminance and chrominance, the results can be compared, and we see that contrast sensitivity is best for a red-green sinusoidal grating of low spatial frequency. Resolution is best for luminance contrast. The data are averages of 10 subjects (Valberg, 2005): 260).*

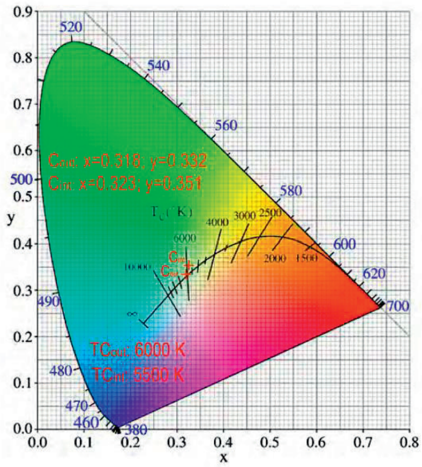


Figure 2. *Correlated colour temperature of the Artificial Sky.*

Aims and hypothesis

In this study we pursued two main objectives. The first question deals with the perception of the interior light level in relation to the colours of the room surfaces. We have formulated the hypothesis that the perceived light level is affected by not only the luminance but also the chromatic properties and chromatic contrasts of wall colours. This was tested in model studies using low saturated equiluminant colours that are normally used in interiors, and combinations of equiluminant colours of contrasting hues. The way that subjects responded to these stimuli is discussed in relationship to other scientists` previously published psychophysical experiments dealing with human response to chromatic contrast stimuli (Valberg 2005).

The second objective was to examine the capabilities of high dynamic range (HDR) images as a method for lighting studies of interiors painted in low saturated colours. The High dynamic range image is a merged image of several conventional low range images taken with different exposures. In photography, the term dynamic range is a dimensionless quantity. It is a ratio of the lightest and darkest pixel (Reinhard et al. 2010: 4). We can also use the term "luminance map" instead of HDR images, to accentuate that the picture has been used generally for the luminance values measurements. *Luminance-based design* is a new approach to lighting design using such pictures. It is currently being promoted by a number of scientists (Y. Nakamura, J. P. Skar, M. Fontoynont, and others – CIE TC 3-45) as a perception-oriented method for lighting design (Nakamura et al. 2011). The prime advantage of this method is that luminance is a basis that forms perception of the visual environment and its brightness.

It is known from previous studies (Anaokar & Moeck 2005) that warm and low saturated colours has the highest accuracy in luminance representation at HDR images while cool and saturated colours have a higher level of errors. Therefore it is supposed that in the current experiment, the luminance of the surfaces painted in chosen low saturated colours will be represented with high precision.

METHOD

Experiment design

The experiment was conducted in the Daylight Laboratory, under Artificial Sky, at the Department of Architectural Design, Form and Colour Studies, NTNU. It enabled us to get stable lighting conditions and equal illumination for all scale models (Matusiak & Arnesen 2005). The experiments could be carried out independent of weather conditions and time of the day. The Artificial Sky installation simulates a standard model of a perfectly cloudy sky, the CIE Overcast Sky in which the horizon luminance is equal to 1/3 of the zenith luminance. The light is produced by fluorescent light tubes of the Cool Daylight type (PHILIPS MASTER TL5 HE 28W) (Matusiak & Arnesen 2005). According to measurements conducted by architect Julie Guichard in 2010 using "Spectra Scan 650", the Correlated Colour Temperature inside the Artificial Sky is 5500

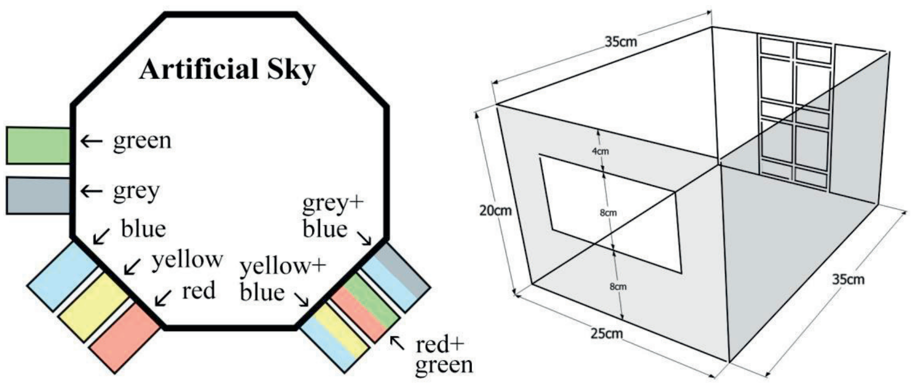


Figure 3. *To the left: arrangement of the models in the laboratory under Artificial Sky during experiment, photographing and measuring illuminance. To the right: form and sizes of scale models*

(Salvesen et al. 2012) (see Figure 2).

Eight scale models of the rooms were prepared. The 1:20 scale model 25cm × 35cm × 20cm represented a room 5m × 7m × 4m, see Figure 3. The size was chosen to be large enough for a comfortable observation as well as enable good conditions for taking photos of the interior. The walls, ceiling and floor were constructed using 1cm MDF boards. From the outside, the models were painted in black colour which helps to avoid light penetration from the Artificial Sky through splices of the boards. The window frame was made of opaque white cardboard. The models were also covered externally by black textiles to eliminate light penetration from the outside during the observation.

The colouration of the walls in models was of two types, while colours of the ceiling and floor were identical for each model (see Figure 4, 5 and Table 1). The first type was striped pattern, i.e. a combination of low saturated equiluminant colours representing the chromatic contrast: red and green, yellow and blue, blue and grey (see Figure 4). The width of the stripes was 19 mm and according to the distance from the walls to the observers` eyes (35 cm), this pattern has a spatial frequency 0.161 c/deg.

The second type of wall colouration was uniform, one-coloured, with the use of the same colours as in striped patterns, i.e. red, green, grey, yellow, and blue (see Figure 5). All the paints were matte. It was decided to paint the ceiling of the models in white colour and the floor in dark grey colour (see Table 1), similarly to many real rooms. Moreover, these colours are achromatic, which is an advantage in terms of studying the effects of chromatic colours of the walls. First, orientation colours with similar luminous reflectance factor (Y_1) were chosen from the samples of the NCS Colour Atlas. Then paints were mixed manually and wooden pieces were painted. After drying, the luminance of each of them was measured using the MINOLTA Luminance meter. The process was repeated until equiluminance of the paints was reached, see Figure 6.

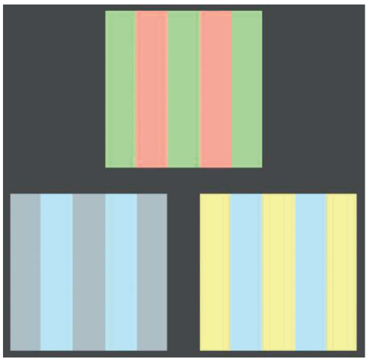


Figure 4. *The first type of the scale models` colouration – striped patterns:1-Yellow/blue; 2-Red/green; 3-Blue/grey.*
The width of the bars is 19mm.

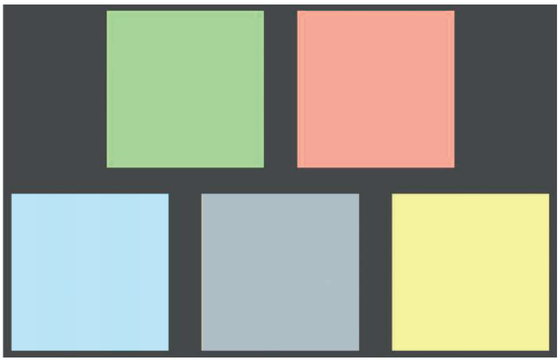


Figure 5. *Second type of the scale models` colouration – one-coloured:1-Blue; 2-Grey; 3-Yellow; 4-Red; 5-Green*

The final colours were matched with the NCS colour samples again by two persons independently. In Table 1 you can find all the colour notations according to the NCS system (NCS samples that were the most approximate to used paints). Finally, all the models were properly painted and prepared for the experiment.

Name of the colour will be used in the paper	Linguistic description of the colour	Nominal colour nearest NCS sample	Approx. luminous reflectance factor according to NCS atlas (Y1) (nearest 5)	NCS chromaticness as derived directly from NCS code
Red	Pink	S 0515-R20B	75	15
Green	Yellowish green	S 0520-G40Y	80	20
Blue	Greenish blue	S 0510-B10G	80	10
Yellow	Greenish yellow	S 0520-G90Y	85	20
Grey	Grey	S 1000-N	75	0
White	White	S 0300-N	90	0
Black	Black	S 9000-N	5	0
Dark grey	Bluish grey	S 5005-R80B	25	5

Table 1. *Information about NCS colour samples consistent to coloures used in scale models.*

Lighting measurements and reflectance calculations

Painted wooden samples were placed one by one in the center of the Artificial Sky together with grey and white reference cards for luminance measurements. Luminance, at the central point of each sample and grey and white cards were measured (see Figure 6). Afterwards the reflectance of each sample was calculated according to the luminance readings of the reference cards. The illuminance was measured at the central point on the floor inside each scale model when it was arranged under the Artificial Sky (see Figure 3; 7; 12 and 13). It enabled us to not only to get illuminance values in models, but also to check and analyze differences of the lighting in terms of the models` arrangement.

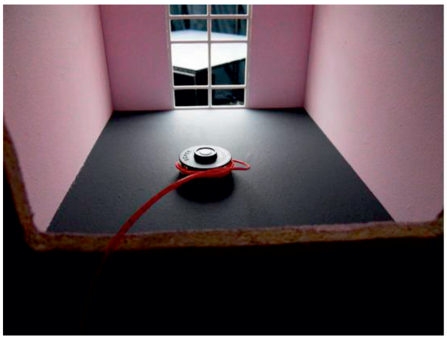


Figure 7. *Measuring illuminance in a central point of scale model. During measuring process the scale model was covered with black fabric to stop light penetration from the outside.*

Figure 8. *The view of the scale model; the photo was taken through the opening for the observation.*

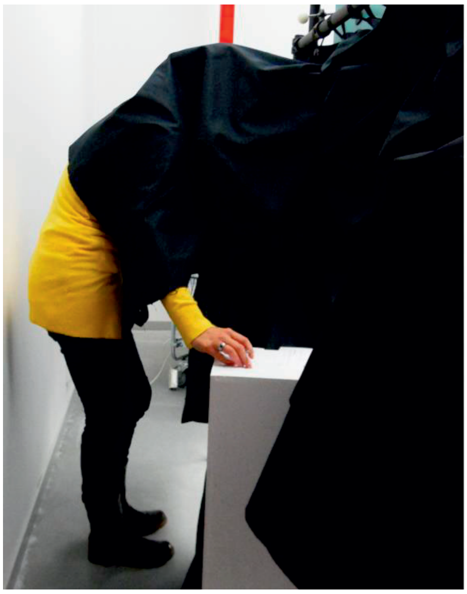


Figure 9. *The observation of the scale models placed in the laboratory under the Artificial Sky by one of the participants.*

Figure 10. *Scale models lit through the windows faced Artificial Sky.*

Survey and questionnaires

The experiment was conducted in September 2012 in the Daylight Lab at the Gløshaugen campus of the Norwegian University of Science and Technology. All the scale models were placed in the laboratory under the Artificial Sky, see Figure 3. In total 32 observers were involved in the experiment. The subjects were mostly master students of architecture (14), a group of physicists (5), PhD Candidates in architecture (5), a group of engineers in computer science (3) and few people from other academic fields (5). The age of participants varied from 21 to 42 years, all of whom have normal colour vision. The models were lit through a window facing the Artificial Sky. The interiors of the models were observed through an opening made in the wall opposite the window; see Figures 2, 9 and 10. Each subject observed both groups of scale models (striped and one-coloured models) and answered the questionnaires. The order of the observation of one-coloured and striped models were random. Therefore one group of subjects started with striped models, while another part observed one-coloured models. This provided the necessary conditions for randomization. Randomized design allows the experimenter to avoid statistical errors and increase the chances of detecting differences among reactions (Stamatis 2012: 114-115).

There were similar but separate questionnaires for each group of models. Each form consisted of two parts.

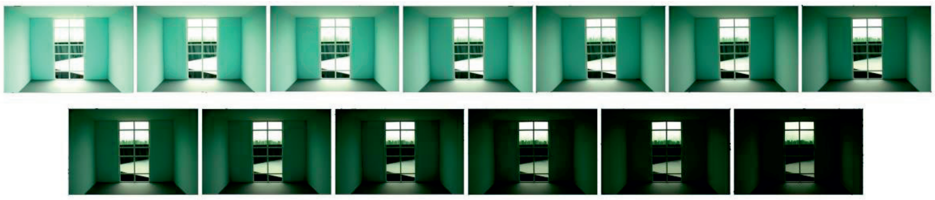


Figure 11. *The set of 13 low dynamic (LD) images of the Blue room, taken with different exposures, the step is 1 EV.*

The first part contained one question from the PERCIFAL (Perceptive Spatial Analysis of Colour and Light) questionnaire (Arnkil et al. 2011), (Matusiak et al. 2011), (Fridell Anter, Haggstrom et al. 2012). The intention was to get spontaneous answers to the question: ***Do you experience the room to be dark or bright?*** The participant made a mark on a 7-step scale from very dark to very bright. The number of marks for each step and for each room was calculated, see Figure 15 and 19.

The second part included four more questions about lighting in the scale models and needed more conscientious answers. In answering the questions from this part of the questionnaire, observers had to arrange rooms into descending order. The first question from this part was: ***Which room has the highest light level (the brightest room)?*** Arrangement had to be from the brightest to the darkest. All the answers (for each particular group of scale models) were calculated as a percentage of the total number of participants. Results are represented in Figures 16 and 20.

The second question of the second part was: ***Which room has the more comfortable lighting?*** Answers were arranged from the most comfortable to the least comfortable. Results are presented in Figure17 and 21.

The third question: ***Your personal preferences among these rooms (in lighting).Why?*** Results represented in Figure 18 and 22.

These two questions (about comfortable lighting and personal preferences in lighting among the rooms) were needed to verify reliability of the results by help of comparison of the answers.

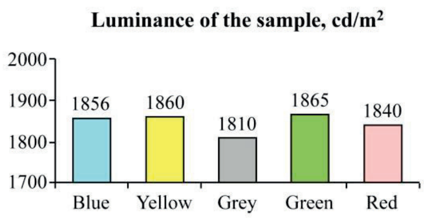


Figure 12. *Luminance values of the painted wooden samples, measured at the middle point of each sample in the center of Artificial Sky.*

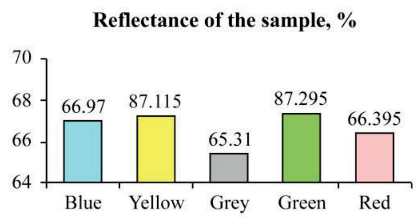


Figure 13. *Reflectance of the painted wooden samples calculated according to measured luminances.*

The last question in the questionnaire was: ***How much do you think colour affects your perception of light level?*** The subject had to mark the level of the influence of colour/colour compositions on the light level perception on the proposed scale.

High dynamic range imaging (luminance maps)

HDR images of all the interiors of the models were created. Afterward, 13 sets of low-dynamic images for each room were made with a Canon EOS300D digital camera (see Figure 11). The camera was mounted on a tripod and situated in the plane of subject`s eyes to simulate the viewing position of the observers. The following camera settings were used: White balance – Daylight, Auto-Bracketing – off, Sensitivity – 100 ISO, Auto Focus – off, Aperture – fixed, f/4. Exposure variations mode with step 1 EV.

In addition to the photos, references to physical measurements have been made with a calibrated hand held Luminance meter. The readings were used for further calibration of the HDR images. All the low dynamic range images were processed and combined into HDR images with the help of Photosphere software and were calibrated according to the measured luminance readings.

Statistical analysis

For the statistical analysis of the survey results, mode values were calculated as most representative in the experiment with ordinal data. Percentages represented on the graphs were calculated relative to the total number of participants. As a main tool for the statistical analysis the Friedman test was used. This is a nonparametric statistical procedure for comparing more than two samples that are related. The parametric equivalent to the Friedman test is the repeated measures analysis of variance (ANOVA) (Corder & Foreman 2011).

RESULTS

Measurements

According to the manual measurements and further calculations, the difference in luminance values, measured in a central point of the painted wooden pieces under the Artificial Sky, is 3% (see Figure 12). Therefore, the difference in the reflectance of these samples is also 3% (Figure 13). Based on these data we can conclude that the colours of the walls in the scale models were equiluminant.

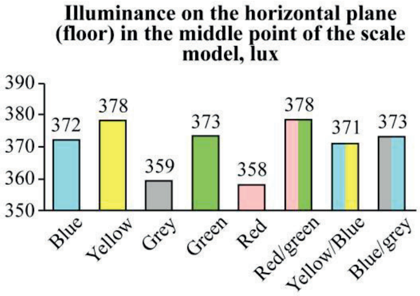


Figure 14. Illuminance in a central point inside the scale models. During the measurement process, models were arranged under the Artificial Sky as in Figure 3, the illuminance were measured at the floor level.

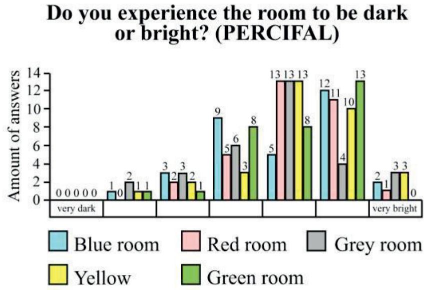


Figure 15. Answers to the questionnaire about one-coloured models - Part 1 - "Do you experience the room to be dark or bright?" The unit of measurements is the amount of answers (mark at a certain cell of a scale from very dark to very bright. Total amount of the observers: 32.

Illuminance values have a higher difference – 5.3% (Figure 14). However, these measurements are not comparable to luminance readings due to different measuring conditions.

Perception of the light level in one-coloured models

Part 1. The subjects were asked to evaluate the light level in models using a scale from dark to bright. It was not allowed to compare the rooms. The answer to the question had

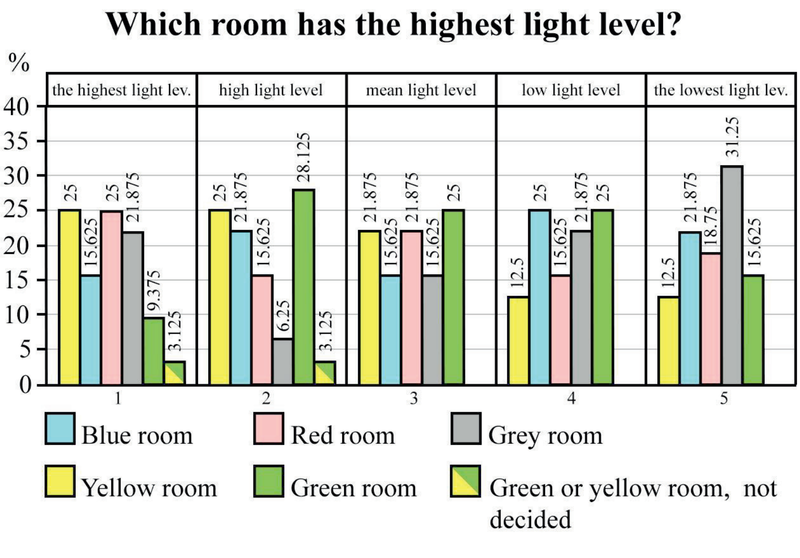


Figure 16. Answers to the questionnaire about one-coloured models- Part 2 - "Which room has the highest light level? (Put them into descending order)" The unit of measurement is a percentage relative to the total number of observers (32). 1: room with highest light level, 5: room with lowest light level.

to be done immediately and spontaneously.

Results showed that the Yellow room was perceived as brightest, the Grey room as darkest, and the rest of the rooms were placed in medium positions, Figure 15.

Part 2. In the second part of the questionnaire subjects compared appearances of observed rooms and made a deliberate ranking of the scale models.

Which room has the highest light level (from brightest to darkest, in descending order)?

Yellow and Red rooms were evaluated equally bright (25% correspondingly), see Figure 16. The Grey room was chosen as the darkest (31.25%). The rest of the rooms were placed in medium positions. However, according to the statistical analysis the differences were small and not statistically significant (Fr = 3.9612, critical value = 9.49, $\partial = 0.05$, df = 4).

Which room has the more comfortable lighting (from the most comfortable to the least comfortable)?

According to evaluation, the Blue room has the most comfortable lighting (28.13%), the Green room has less comfortable lighting (28.13%), the Red room has the least comfortable lighting (31.25%), Figure 17. Other rooms were placed in medium

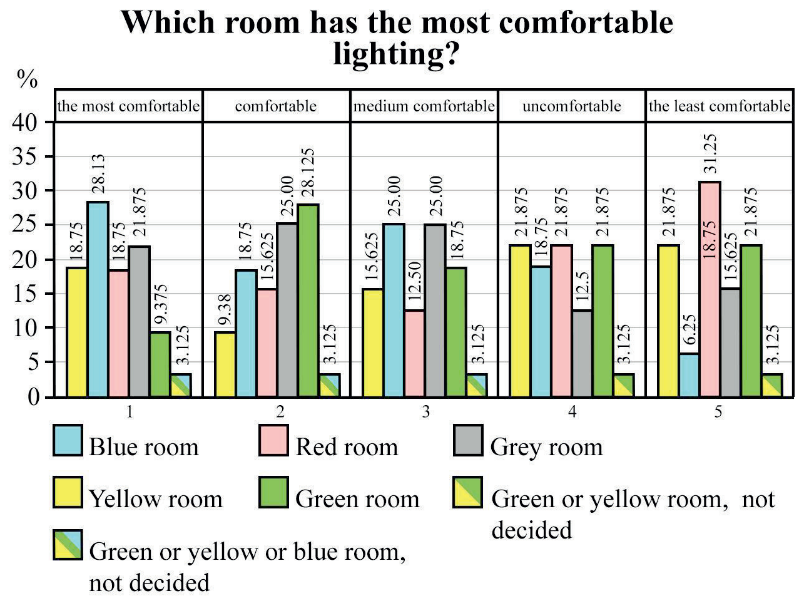


Figure 17. *Answers to the questionnaire about one-coloured models- Part 2 - "Which room has the most comfortable lighting? (Put them into descending order)" The unit of measurement is a percentage relative to the total number of observers (32). 1: room with the most comfortable lighting, 5: room with the least comfortable lighting.*

positions. Results showed no significant differences between the rooms (Fr = 6.648, critical value = 9.49, a = 0.05, df = 4).

Your personal preferences among these rooms (in lighting). Why?

Results are shown in Figure 18. According to statistical analysis there was no significant difference between the rooms.(Fr = 3.5986, critical value = 9.49, a = 0.05, df = 4).

However, it is interesting to analyze the subjects` spontaneous explanations which supported their decisions. Even if the question was about preferences in lighting, most of the people commented the colour of the room (examples of the explanations: grey is boring; I prefer non-chromatic interiors; red is not suitable for the walls). Others were not concentrated on colour itself but still estimated the atmosphere in the room as cold or warm (examples of the comments: colour affected the temperature of the room, but not light level; I prefer warm interiors). This observation illustrates how strongly one`s perception of the interiors depends on colour.

How much colour affected your perception of light level?

The last question about power of influence of colour on light level perception also showed interesting results: 87.5% of the participants considered that colour affected their perception of the light level. This effect was stronger for one-coloured models than for striped rooms.

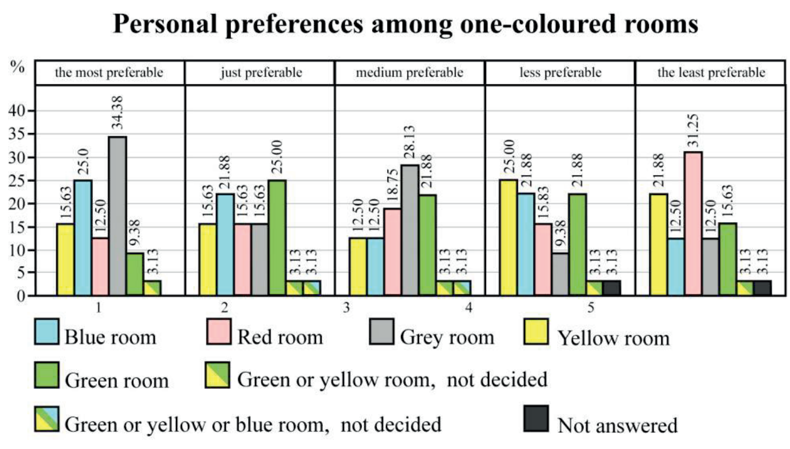


Figure 18. *Answers to the questionnaire about one-coloured models - Part 2 - "Your personal preferences among these rooms (in lighting) Why? (Put them into descending order)" The unit of measurement is a percentage relative to the total number of observers (32). 1: the most preferable room, 5: the least preferable room.*

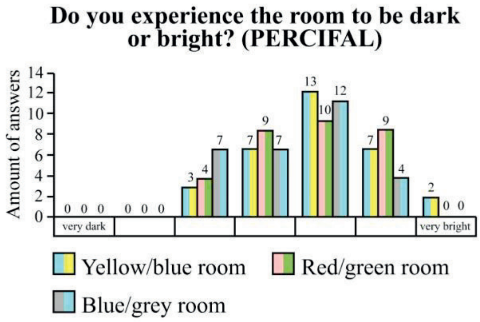


Figure 19. Answers to the questionnaire about striped models - Part 1- "Do you experience the room to be dark or bright?" Unit of measurements is the amount of answers (mark at a certain cell of a scale from very dark to very bright. Total amount of the observers: 32.

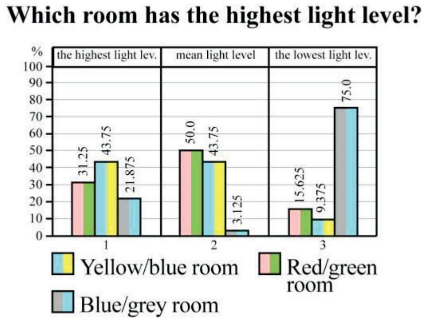


Figure 20. Answers to the questionnaire about striped models – Part 2 - "Which room has the highest light level? (Put them into descending order)" The unit of measurement is a percentage relative to the total number of observers (32). 1: the room with the highest light level, 3: the room with the lowest light level.

Perception of the light level in the striped models

Part 1. Spontaneous answers to question about the light level in the scale model showed that the Yellow/Blue model was perceived as the brightest room, the Red/Green as medium-bright and the Grey/Blue as the darkest one, see Figure 19.

Part 2.

Which room has the highest light level (from brightest to darkest, in descending order)?

The Yellow/Blue model was evaluated as the brightest room by 43.75% of the participants, the Red/Green model was rated as the medium-bright room (50%) and the Grey/ Blue model was rated as the darkest room (75%), see Figure 20. Results showed a highly significant difference between the rooms (Fr = 12.9677, critical value = 5.99, a =0.05, df = 2).

Which room has the more comfortable lighting?

According to evaluation, the Red/Green room was chosen as a model with the most comfortable lighting by 56.25% of the participants. The Yellow/Blue room was evaluated as the room with medium-comfortable lighting (50%). The least comfortable lighting had the Grey/Blue model (50%), see Figure 21. Furthermore, there was a statistically significant difference between the rooms (Fr = 7.4666, critical value = 5.99, a = 0.05, df = 2).

Your personal preferences among these rooms (in lighting).Why?

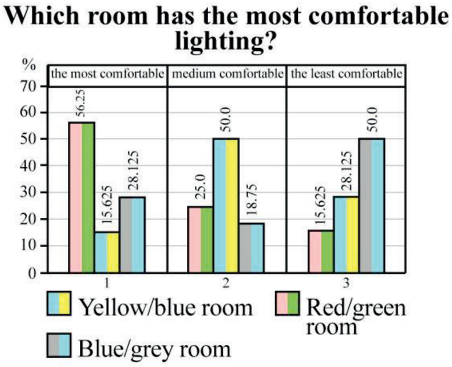


Figure 21. *Answers to the questionnaire about striped models - Part 2 - "Which room has the most comfortable lighting? (Put them into descending order)" The unit of measurement is a percentage relative to the total number of observers (32). 1: room with the most comfortable lighting, 3: room with the least comfortable lighting.*

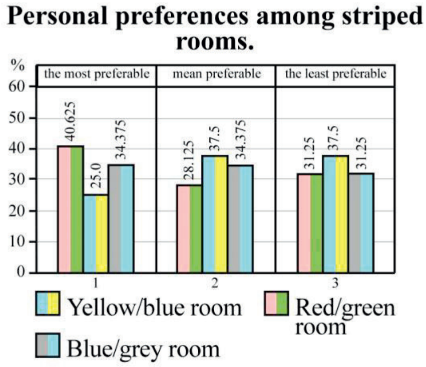


Figure 22. *Answers to the questionnaire about striped models - Part 2 - "Your personal preferences among these rooms (in lighting) Why? (Put them into descending order)" The unit of measurement is a percentage relative to the total number of observers (32). 1: the most preferable room, 3: the least preferable room.*

Results are shown in Figure 22. According to statistical analysis there was no significant difference in preferences between the rooms (Fr = 0.8125, critical value = 5.99, $\partial = 0.05$, df = 2). It is also important to note here that in striped models the same tendency in room appearance evaluation was observed.

However, the subjects were more concerned with colour rather than the light in the rooms (example of the comments: Red/Green reminds me of Christmas, Yellow/Blue reminds me of summer). The subjects tended to observe the room as a whole rather by colour or light specifically (example of the notes: the high contrast between green and pink made the room feel darker; if the colour feels uncomfortable, the lighting also feels uncomfortable).

How much colour affected your perception of light level?

Answering the last question 81.25% of the participants considered that colour affected their perception of the light level.

Luminance maps vs. questionnaires

First, the obtained luminance maps of the scale models were converted using Photosphere software into false-colour pictures. In this particular case, the false-colour picture is a picture that shows specific representation of luminance values. In other words, the picture becomes a graph where newly assigned colours are not important themselves, but each of these colours pertains to particular luminance values. Furthermore, all the false-colour pictures were calibrated. The range of the luminance

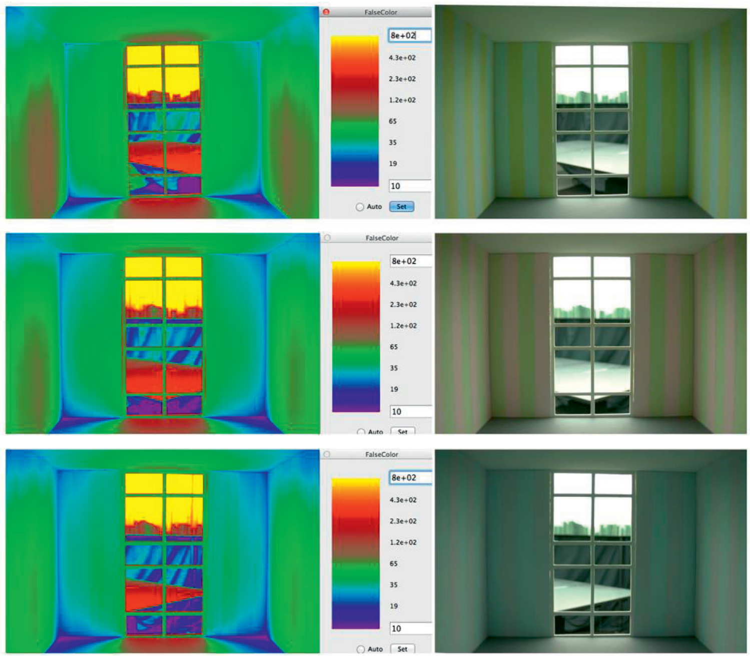


Figure 23. *Images of striped models created using Photosphere software. To the right: HDR images of the rooms. To the left: false-colour pictures of respective photos.*

was set from 10 cd/m^2 to 800 cd/m^2. It was an important action to be able to compare luminance patterns of the images and parallel photos of the rooms.

Significant differences between the luminance pictures of the striped models can be observed. Obviously, the Yellow/Blue room is the brightest one according to the luminance pattern of the false-colour picture as well as the luminance values (44.7/46.9 cd/m^2 on the window wall and 61.7/65.4 cd/m^2 on the side walls). There is also a noticeable striped pattern on the walls here, see Figure 23. In the Red/Green room the pattern is less visible and luminance values are lower according to the graph (37.1/38.6 cd/m^2 on the window wall and 53.8/57.6 cd/m^2 on the side walls). The darkest room is Grey/Blue, where the pattern is almost invisible and the luminance values are even lower (34/35.4 cd/m^2 on the window wall and 49.3/50.8 cd/m^2 on the side walls). This is consistent with the the test results from the experiment respondents.

Results for the one-coloured models are not so evident, Figure 25. According to the luminance patterns on the false-colour pictures, two rooms have quite dark frontal window walls – Yellow (37.2/38.2 cd/m^2) and Grey (35.4/37.7 cd/m^2). At the same time, the side walls in the Yellow room are brighter (55.7/57.9 cd/m^2) than in the Grey room (51.5/54.9 cd/m^2). Therefore the Grey room can be considered the darkest model. This is consistent with the subject`s answers. The brightest room, according to the luminance patterns and values of false-colour pictures, is the Red model (40.7/41.4

Figure 24. *Measurements of luminance on the walls were done in Photosphere and represent an average luminance of the selected areas (highlighted in orange rectangles). It means that program performed luminance calculations for the selected zones. For all the scale models these zones were similar.*

cd/m^2 on the window wall and 65.1/63.5 cd/m^2 on the side walls). According to these results, the Red room, scored by 25% of the subjects, was the brightest room. This was equivalent to the Yellow room (25%).

DISCUSSION

This paper investigates the dependence of the perceived light level of space on unsaturated equiluminant colours and its combinations (colour contrast). The capability of luminance maps (as a possible method for lighting design) to reproduce this information is also a subject of interest.

During the above described experiment eight scale models of the rooms were studied. All the scale models were identical except for the hue of the colours of the walls and a slight difference in saturation of these colours (see Table 1). Geometry, openings, types of surfaces, luminance and reflectance were equal for all the models. Nevertheless, some differences in light level perception of the scale models were found. Consequently, for the models painted in a striped pattern, the observed and subsequently statistically calculated difference was considerably significant ($Fr = 12.9677$, critical value = 5.99, $a = 0.05$, $df = 2$). Here, the room painted in a striped Yellow/Blue pattern was chosen as the brightest one, the room painted in a striped Red/Green pattern was chosen as the medium-bright room, and the room painted in a striped Blue/Grey pattern was ascertained as the darkest model. This outcome can be partly explained by chosen colour composition of the patterns. Yellow/Blue and Red/Green patterns are examples of strong colour contrast, while Blue/Grey is a composition of achromatic grey colour and poorly saturated blue colour. The derived NCS chromaticness is 10. Chromaticness of Yellow/Blue is 20/10 and Red/Green is

15/20. Chromaticness, as one of the variables of the colour in the NCS system, defines the portion of the chroma relative to white and black components of the chosen colour (Arnkil et al. 2012). It means that Yellow/Blue high chromaticness makes the hue difference more visible. It leads to a higher hue contrast that can also be a factor which affects perception. It should be noted that illuminance measured inside the Yellow/Blue model (see Figure 23) was the lowest among the striped models and therefore hardly had an impact on the subjective light level perception. Meanwhile, it was expected that the Red/Green room would be chosen as the brightest room but the final results were different. The reason that the Yellow/Blue model rather than the Red/Green model was scored as the room with highest light level could be the highest contrast in chromaticness of blue and yellow colour. At the same time, the size of the stripes of the patterns can play a great role in brightness evaluation due to fact that at high spatial frequencies the luminance contrast is prevailing (Valberg 2005). Luminance maps of the striped models corresponded with measured results (see Figure 23).

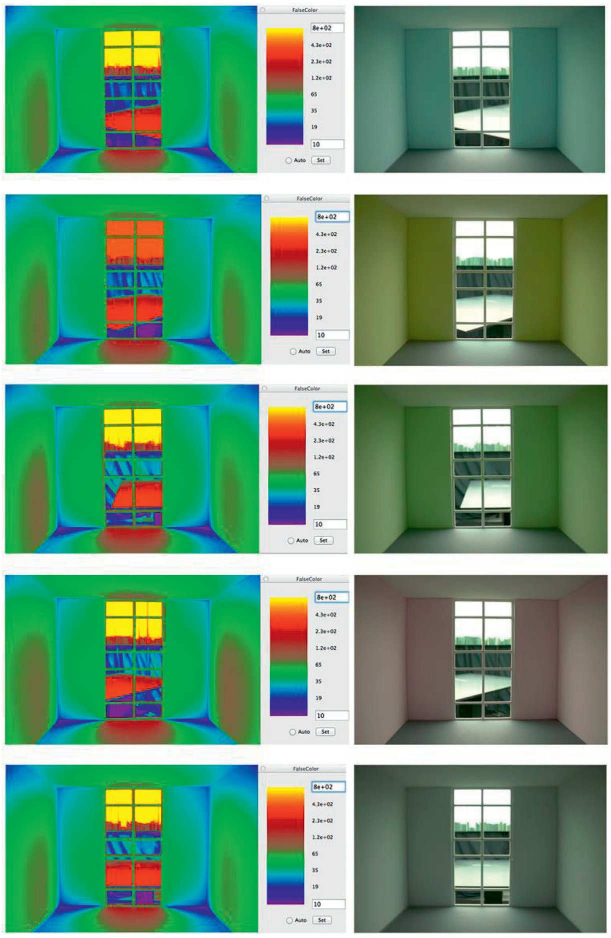


Figure 25. *Images of one-coloured models created using Photosphere software. To the right: HDR images of the rooms. To the left: false-colour pictures of respective photos.*

However, for the one-coloured models, the situation is more complicated. The difference in the perception of the light level was observed indeed, but it was not statistically significant. Participants also commented verbally on the difficulties in ranking one-coloured scale models. Luminance maps observation of these models do not contradict the survey results. However, it was problematic for the subjects to point out the most bright or least bright rooms due to the minimal differences in luminance values. . Perhaps, in this case, the difference in stimuli was too low, almost at the threshold. According to luminance values obtained from luminance maps (see Figure 25), the Red room has the highest luminance values on the side walls (63.5/65.1 cd/m^2) and this room was scored by 25% of the subjects as the brightest room, which is equivalent to the Yellow room. Meanwhile, the Yellow room has lower luminance values – 55.7/57.9 cd/m^2 on the side walls and 37.2/38.2 cd/m^2 on the window wall. Even the Blue room has higher luminance values – 55/58.7 cd/m^2 on the side walls and 40.4/43.3 cd/m^2 on the window wall, but it was scored as a relatively dark room. It can be explained for two reasons. First, there is a possible error of luminance values in representation of the cool hue of blue colour (Anaokar & Moeck 2005) For low saturated colours of cool hues, errors can be up to 20 percent. The second reason is the fact that the blue paint used in the scale models has very low NCS chromaticness – 10. The rest of the chromatic colours used in the models, e.g. Red, Green, Yellow and Blue have equal blackness (05), see Table 1. This means that the Blue colour has low saturation and therefore the Blue model has been perceived as quite a dark room. A Grey room has the lowest luminance values according to the HDR image – 35.4/37.7 cd/m^2 on the window wall, 51.5-54.9 cd/m^2 on the side walls. This was also scored by subjects as the darkest room. We can conclude that, because of the low saturation of the colours, it was difficult for respondents to place the models in order. Still, the results were compatible with luminance maps that accurately replicated obtained data.

The consistency between the answers to the question about light level from Part 2 (Which room has the highest light level?) and to the question from Part 1 ("Do you experience the room to be dark or bright?") helps to conclude that the results are quite reliable. Moreover, the participants' responses to the questions about rooms with the most comfortable lighting and about their personal preferences varied. This means that the subjects were guided not by predilections, but by the subjective perception that was very similar to their responses to their first impression of the rooms.

CONCLUSION

A colour contrast and the Helmholtz-Kohlrausch phenomenon have been investigated and described in literature previously (Valberg 2005). In this experiment we transfer these phenomena into the field of architectural design and the perception of the visual environment. From an architectural perspective it is important to note that even poorly saturated colours have an impact on the human perception of light level in spaces. This impact can be strong, as with color contrast, or weak, as with one-coloured models. Nevertheless, this impact can be taken into consideration when using the luminance-based method in lighting design.

REFERENCES

Anaokar, S. & Moeck, M., 2005. Validation of High Dynamic Range imaging to luminance measurements. *Leukos*, 2(2), 133-144.

Arnkil, H. et al., 2011. PERCIFAL: Visual analysis of space, light and colour. In V. Schindler & S. Cuber *AIC 2011 Midterm meeting. Conference Proceedings.* pp 229-232.

Arnkil, H., Fridell Anter, K. & Klaren, U., 2012. *Colour and light: concepts and confusions*, Helsinki, Aalto University.

Corder, G. & Foreman, D., 2011. *Nonparametric Statistics for Non-Statisticians : A Step-by-Step Approach*, Wiley.

DeCusatis, C. et al., 1997. *Handbook of applied photometry* C. DeCusatis, Springer.

Fridell Anter, K., Haggstrom, C. et al., 2012. A trans-disciplinary approach to the spatial interaction oflight and colour. In *Proceedings of CIE 2012 „Lighting quality and energy efficiency"*. pp 280-291.

Fridell Anter, K., Arnkil, H. et al., 2012. SYN-TES. Interdisciplinary research on colour and light. In T. Lee & J. Shyu *AIC 2012 Interim Meeting of theInternational Colour Association (AIC)*. pp 80-83.

Gilchrist, A., 2007. Lightness and brightness. *Current Biology*, 17(8), 267-269.

Liljefors, A., 2003. *Seende och ljusstralning*, Jonkoping, Belysningslara, Ljushogskolan, Hogskolan i Jonkoping.

Matusiak, B. et al., 2011. Percifal method in use: visual evaluation of three spaces. In V. Schindler & S. Cuber *AIC 2011 Conference Proceedings*. pp 568-571.

Matusiak, B. & Arnesen, H., 2005. The limits of the mirror box concept as an overcastsky simulator. *Lighting research and technology*, 37(4), 313-328.

Nakamura, Y., Suzuo, S. & Aoki, T., 2011. Lighting design method applicable both to day lighting and to electric lighting using luminance image. *27th session of the CIE*, Volume 1, Part 1, 398-403.

Reinhard, E. et al., 2010. *High dynamic range imaging: acquisition, display, and image-based lighting*, 2nd., Elsevier, Morgan Kaufmann.

Salvesen, F. et al., 2012. *Veileder for bruk av translusente fasader*, Oslo: Asplan Viak.

Stamatis, D., 2012. *Essential statistical concepts for the quality professional*, Taylor & Francis Group, LLC.

Valberg, A., 2005. *Light, vision, color*, Wiley.

Paper II

New measures of light modelling

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ABSTRACT

Most of the current lighting recommendations aim at ensuring a minimum quantity of light needed to see objects in the surrounding environment and to enable work or other activities.

Authors believe that these recommendations and measures are not a guarantee for the lighting quality. The qualitative aspects of lighting are frequently discussed topics in the lighting community. One of the issues that the currently used measures touch only sporadically is e.g. light modelling. We set up an experiment where different measures of light modelling were studied with help of High Dynamic Range Imaging technique. The analytical comparison of survey results from 32 subjects and measures obtained from luminance maps showed that the Contrast measurement (calculated with the Weber formula) and the Ratio between average luminance of the object and average luminance of the background are both good predictors for contour distinctness of the observed objects.

Keywords: *Luminance maps, light modelling, luminance measurements, HDR images*

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1 Introduction

We live in a three dimensional space and have a fantastic aptitude for constant perception of different qualities of objects i.e. size, shape and colour, depending on the way they are viewed (Boyce, 2003). Is an adequate visibility of 3D objects important for us? Apparently yes, and moreover, it is a vital ability that enables us to see the world around and to communicate with other human beings. The current building codes for daylighting design in buildings are very simplified and use, in most countries, the daylight factor as the fundamental measure (Mardaljevic et al., 2009); other recommendations are sparse and tell very little about qualitative aspects of lighting. On the other side, research tells us that providing better recommendations is crucial because creating a comfortable and pleasant environment for occupants may increase productivity and health, may indirectly improve their home life by reducing job related stressors, and thus indirectly increase economic benefits of the companies (Aries et al., 2010).

During the past few years, researchers tried to investigate new daylighting metrics. Some studies suggest particular techniques based on standardised climate datasets, so called Climate-based daylight modelling (CBDM) and development of certain luminous quantities associated with factors related to visual comfort and quality (Mardaljevic et al., 2009). Another study dedicated to assessing of the set of metrics based on illuminance, distribution, glare and directivity and suggested that these are the most useful measures for the determination of the daylighting quality of architectural spaces (Cantin and Dubois, 2011). In both these investigations luminance measurements were included to some extent. A “Daylighting dashboard” approach was suggested in another study where eight particular daylighting metrics were analysed. The main goal was to use average illuminance, coverage, diffuse daylight, daylight autonomy, circadian stimulus, glazing area, view and solar heat gain, as a determinant measures during the conceptual phase of architectural design (Leslie et al., 2012).

The light modelling is one of several lighting quality characteristics, deprived of the attention of the researchers. With light modelling we mean the degree to which the light describes 3D-objects, so both the contour and shape are clearly visible. The better the light modelling is, the easier we distinguish 3D-objects from the background, and the more correctly we perceive its 3D-shape and their specific characteristics. A good light modelling is important in different spheres: from hospital lighting to museum or commercial lighting. The possibility to predict light modelling in particular rooms and spaces would be an undoubted advantage for architects and designers.

Some researchers tried to shed light onto the topic of light modelling earlier. Different approaches were used. One of them is illuminance measurement using a six-sided illumination meter for prediction of shading pattern of various objects or the distribution of eye illuminance at a given point (Cuttle, 2008). Another approach suggests using a particular instrument, a modelling sensor, to predict light distribution on a 3D-object, occurrence of light spots, cast shadows and to register the light direction (Matusiak, 2002).

Another rather new technique offers new options in studying light modelling characteristics, namely High Dynamic Range Imaging (HDRI). The High Dynamic Range image is a merged image of several conventional low range images taken with different exposures that contains full luminance information of the photographed region. The term “luminance map” can also be used instead of HDR images, to accentuate that the picture has been utilized specifically for the luminance measurements. The luminance-based design is a new approach to lighting design applying such pictures. It is currently being promoted by number of scientists and by CIE Technical Committee 3-45 as a perception-oriented method for lighting design (Nakamura et al., 2011). The prime advantage of this method is that the luminance is the measure that the visual perception can be most correctly described by, e.g. the perception of brightness as a function of luminance (Gilchrist, 2007).

The aim of the current study was to develop measures of light modelling by exploration of a daylit environment (the full-scale mock-up room) furnished with achromatic and chromatic 3D objects with the help of luminance mapping technique.

The hypothesis asserts that certain numerical luminance values or luminance ratios obtained from HDR images may adequately describe the modelling of daylit 3D objects as being observed by subjects.

2 Methodology

The real-life experiment consisted of the observation of 3D achromatic and chromatic objects placed in the full-scale mock-up room and simultaneous photographing of the observed environment. A previous experiment conducted by the authors showed that low saturated colours and interiors containing this type of colours could be successfully studied using luminance mapping technique (Zaikina, 2012). Therefore, it was decided to include coloured objects into the new experiment. The main data sources were subjective ratings of contour and shape visibility provided by participants in a quantitative questionnaire, graphical information i.e. drawings made by participants, and subsequently generated HDR images. In this case taking 180° HDR images or luminance maps was a method that enabled the technical-instrumental recording of the observed visual scene under the real conditions concurrently with surveying the subjects. The method of HDR Imaging is now well established and its reliability was previously tested regarding accuracy in different lighting conditions, different times of the day and representations of the different colours by a number of researchers (Inanici, 2006; Anaokar and Moeck, 2005; Chung and Ng, 2010; Cai, 2011). The experiment was conducted under the real daylight conditions, on several days, from 09:00 to 13:00. A number of female Venetian masks were chosen as 3D objects for observation. On the one hand, they are realistic enough to remind of a real human face and thus carry semantic importance for people, but nevertheless simplified and stylized so that no unnecessary noise is added to the data. On the other hand, masks possess the qualities typical for other non-face-like 3D objects: they have a well distinguishable convex shape and contain a number of small elements and details.

2.1 Experiment design

The experiment was performed in the Room Laboratory, the laboratory for construction of small full-scale spaces at the Faculty of architecture, Norwegian University of Science and Technology, Trondheim, Norway (http://www.ntnu.edu/bff/laboratories). Data was collected during eight days under stable overcast sky conditions within two weeks of August 2013. The experimental space was a full scale mock-up room with no particular function. It was a non-specific room with one daylit opening and walls made of portable wall elements. The size of the room was 4,8 m ×4,8 m, height was 2,5 m. Two shelves were placed in the room at two different but adjacent walls. One shelf was illuminated by reflected daylight and the other shelf was illuminated by side-light from the window. The glare was avoided with the help of a partition wall constructed in front of the window. The shelves were made of box-like cells 0,5 m × 0,5 m in size, that were painted in different achromatic and equiluminanat chromatic colours. The 3D objects (Venetian masks) were also painted in the same colours as the cells. Most of the colours were low saturated: grey, pink, green; additionally white and dark grey were used. Notations of the colours according to NCS colour system can be found in Table 1.

Name of the colour used in paper	**Dark grey**	**White**	**Green**	**Pink**	**Grey**
Nominal colour nearest NCS sample	S 6005-R80B	S 0300-N	S 0520-G40Y	S 0510-R20B	S 1002-B50G

Table 1 – *Notations of the colours used in the experiment, according to NCS Colour System*

The combination of colours of the objects and colours of the cells (namely colour of the object and colour of the background) was different and unique for each cell; totally it was 18 different combinations. Positive and negative contrasts were provided for observation. The composition of the coloured objects and backgrounds was the same for both shelves, but the textures of the masks were different. The shelf with mostly diffuse lighting presented matte objects, while the shelf illuminated from the side presented glossy objects, see Figure 1. The light level in the experimental room was kept low, as it was of importance to create a situation with hardly visible objects. Two subjects observed the objects in the room and answered the questionnaires at the same time. They were sitting on adjoining chairs. The camera was placed between them at eye-level, namely at a height of 1,2 m. A set of 11 low dynamic images were taken immediately before the participants started to answer the questions. During this

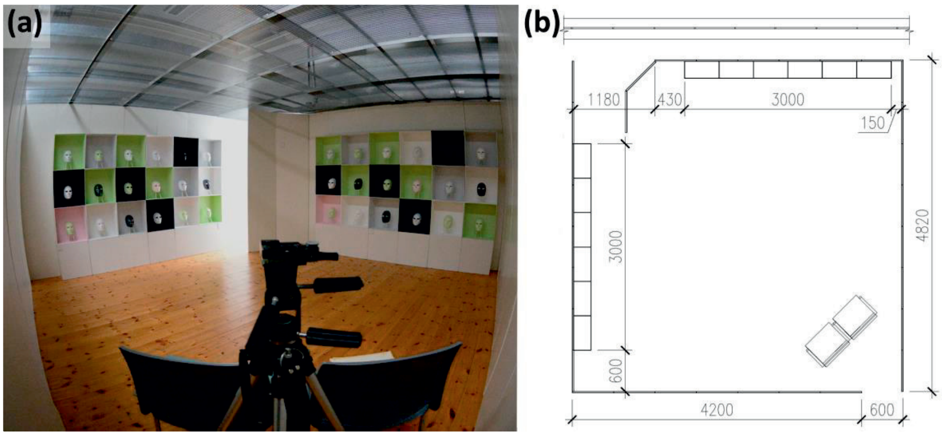

Figure 1 – Picture showing (a) an overview of the experimental room, and (b) the plan of the experimental room

photographing session that lasted approximately 10 minutes, participants were able to adapt to the lighting conditions in the room.

2.2 Participants

In total 32 subjects participated in the experiment. Age of the participant varied from 14 to 74, the average age was 32 years, standard deviation was 10,76. Most of the respondents were naïve with such a type of experiment; they had a different educational background and professions. Before staring the experiment, the vision of the participants was tested with the following vision tests: the visual acuity test using a Snellen chart, the Ishihara test for colour vision, a contrast sensitivity test (Vigra program); normality of 3D-vision was self-reported. According to these vision controls all the respondents had normal or corrected to normal vision and were allowed to participate in the experiment.

2.3 Questionnaire

The questionnaire consisted of two main questions:

1. How well can you distinguish the contour of the object?
2. How well can you distinguish shape and details of the object?

Both questions were asked about each of the 36 objects. The subjects were requested to mark their answers on a four-point ordinal scale with the following options:

- indistinguishable
- just distinguishable

- well distinguishable
- perfectly distinguishable

In addition, subjects specified indistinguishable and perfectly distinguishable zones at a drawing of the mask included in the questionnaire. When two participants simultaneously started the observation, one of them started with the evaluation of glossy masks while the other evaluated the matte objects first. After finishing the evaluation of one shelf with masks, they started to evaluate the second shelf without changing their position in the room. The whole procedure with one pair of the participants took approximately 1 hour.

2.4 Camera settings and manual measurements

Totally, 17 sets of 11 low-dynamic images of the observed scene were made with a Nikon D600 digital camera. To ensure of sharpness the camera was mounted on a tripod and situated between participants' chairs. The following camera settings were used: white balance – Cloudy, Auto-Bracketing – off, sensitivity – 200 ISO, auto focus – Auto, aperture – fixed, f/4. Exposure variations were achieved by varying the shutter speed in manual exposure mode with step 1 EV. All the camera settings were adjusted by dint of a computer and with the Nikon Camera Control Pro software.

For further calibration of the HDR images the manual luminance measurements were taken in four specially marked points at the observed scene. For these purposes a Minolta LS-100 luminance meter was used. Manual measurements were repeated with each new photographing session and each new pair of respondents.

All the low dynamic range images were processed and combined into HDR images with the help of the Photosphere software (Ward, 2005). After this step a calibration was applied according to the readings from the manual luminance measurements.

2.5 Measurements from luminance maps

Luminance measurements were done using two programs: the Photosphere (that was used during the preparation phase for merging of low dynamic images and calibration) and hdrscope (Kumaragurubaran and Inanici, 2013). In this particular case, both the general and the point measurements were taken in Photosphere program. Luminance measurements of multiple selected regions, complex figures and Contrast values were obtained from hdrscope software. The contrast is calculated in this program as the Weber ratio, i.e. the difference of the mean luminances of chosen foreground and background regions divided by the mean luminance of the background (Valberg, 2005), see equations 1 and 3. For convenience, we shell use the term Contrast further in this article. As a background the whole area of the cell were selected for analysis. Another measure of interest was ratio between mean luminance of the mask and mean luminance of the background (see equation 2 and 3), further will be called Ratio. The Ratio was calculated, but not generated by any of the used programs.

$$C_W = \frac{L_o - L_b}{L_b} \tag{1}$$

where

L_o is the luminance of the object;

L_b is the luminance of the background.

$$C_R = \frac{L_o}{L_b} \tag{2}$$

where

L_o is the luminance of the object;

L_b is the luminance of the background.

$$C_W = C_R - 1 \tag{3}$$

where

C_R is the luminance ratio.

To the authors' opinion, this method provides a great opportunity of getting rich information based on luminance readings from different regions at the luminance maps.

3 Statistical analysis and results

In this paper the authors present the earliest results related to the first question i.e. contour distinctness.

For the statistical analysis of the data a two-level ordinal regression analysis was chosen. The experimental design with 32 participants evaluating 36 masks each resulted in a data structure where 36 evaluations were nested within each participant. To eliminate the noise that each participants' general answering patterns contributed to the data, the main analysis was conducted at the object level, but the person specific variance in the evaluations across all masks was modelled simultaneously (listed as Level 2 variance in Table 2 and 3). The regression analysis was conducted as an ordinal (and not linear) regression because the dependent variable "distinctness of the contour" had neither equidistant nor normally distributed answers across the categories.

In two separate analyses (Table 2 and Table 3) the Contrast and the Ratio were assessed as main predictors of contour distinctness and as the dependent variable, while type of

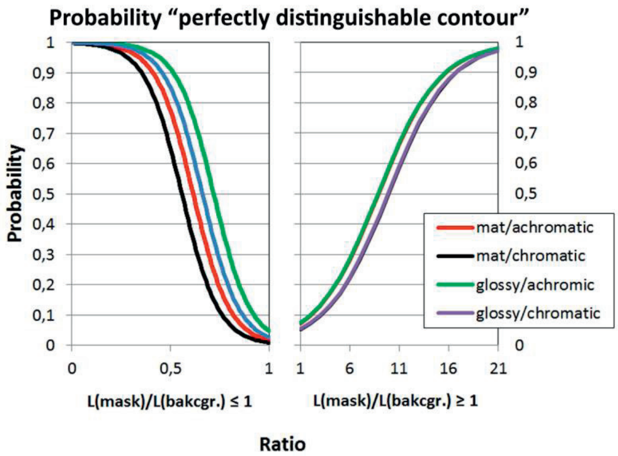

***Figure 2** – Probability curve for the „perfectly distinguishable" category of the questionnaire, four combinations of control variables, and Ratio as a main predictor*

the surfaces (glossy or matte), coloration (chromatic or achromatic) and order of observation were assessed as additional independent control variables. Because the characteristics of both main predictors are different below and above the zero contrast point (which is 0 for the Contrast and 1 for the Ratio) within each analysis to separate sub-analyses were conducted (left and right half of the table).

Results show that both measures (Contrast and Ratio) are equally good predictors of

	Ratio ≤ 1				Ratio ≥ 1			
	B	SE	β	p	B	SE	β	p
Ratio	-10,775	1,270	-0,803	< 0,001	0,322	0,022	0,577	< 0,001
Glossiness (0=matte, 1=glossy)	1,123	0,572	0,146	0,049	0,021	0,129	0,005	0,870
Chromaticness (0=achromatic, 1=chromatic)	-0,615	0,406	-0,080	0,130	-0,324	0,134	-0,073	0,016
Order of observation (0=matte masks first, 1=glossy masks first)	-1,589	0,661	-0,213	0,016	-0,533	0,280	-0,120	0,057
Level 2 variance "contour"	1,978	0,970		0,041	0,495	0,161		0,002
$R^2_{level\ 1}$	0,764				0,332			
$N_{level\ 1}$	255				897			
$N_{level\ 2}$	32				32			

***Table 2** – Regression analysis results: corellation between contour distinctness and Ratio.*

	Contrast ≤ 0				Contrast ≥ 0			
	B	SE	β	p	B	SE	β	p
Contrast	-10,781	1,271	-0,803	< 0,001	0,341	0,023	0,569	< 0,001
Glossiness (0=matte, 1=glossy)	1,081	0,570	0,141	0,058	-0,004	0,129	-0,001	0,975
Chromaticness (0=achromatic, 1=chromatic)	-0,579	0,404	-0,076	0,152	-0,323	0,134	-0,073	0,016
Order of observation (0=matte masks first, 1=glossy masks first)	-1,572	0,657	-0,212	0,017	-0,531	0,281	-0,120	0,058
Level 2 variance "contour"	1,952	0,959		0,042	0,496	0,162		0,002
$R^2_{level\ 1}$	0,761				0,323			
$N_{level\ 1}$	255				897			
$N_{level\ 2}$	32				32			

***Table 2** – Regression analysis results: corellation between contour distinctness and Contrast.*

the distinctness of the contour of the observed masks (see Table 2 and 3).

As can be seen in Table 3 and Figure 3 the results are almost identical when the luminance ratio is substituted by the Contrast as main predictor. Here the cut-off for the zero Contrast is “0”. The Contrast is a highly significant and strong negative predictor for negative contrasts (better visibility the more negative the Contrast below 0 get) and it is a highly significant, strong positive predictor the more positive the Contrast is. The

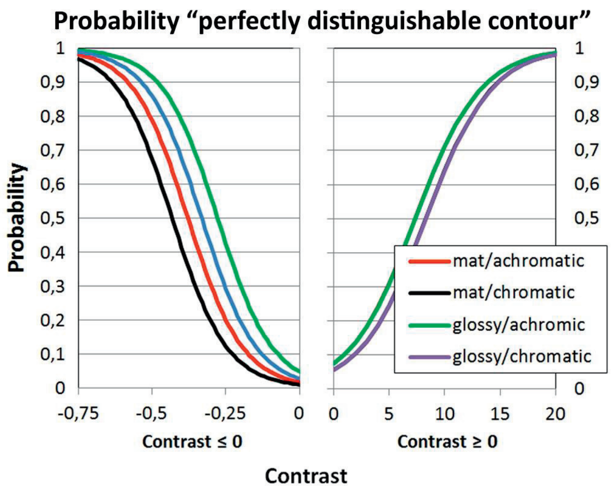

***Figure 3** – Probability curve for the „perfectly distinguishable“ category of the questionnaire, four combinations of control variables, and Contrast as a main predictor*

closer to 0, the more difficult is it to perceive the contour. Again, glossiness and order of observation have a small but significant impact for dark masks on light backgrounds, and chromaticness has a small effect for light masks on dark backgrounds.

4 Discussion and conclusion

High quality lighting becomes an especially important issue in a time dominated by a dynamic technical development of new light sources and daylighting techniques. A good light modelling is one of the necessary conditions for lighting quality. It is essential both at workplaces and at homes. When we communicate with other people we need to accurately perceive various 3D-objects, especially faces; and we know that the correct interpretation of the human face expression depends on the light distribution on the face and the background.

This experiment has shown that luminance measurements could be promising predictors of light modelling. In this particular case the Contrast and the Ratio were studied as predictors of contour distinctness of the observed Venetian masks. These are measurements that are easy to perform with help of computer software, which is why they became departing point of the current experiment. Correlation of the physical luminance measurements and peoples' perceptions are complex and usually nonlinear, so they should be studied carefully. For this purposes we used a two-level ordinal regression analysis that took into account various interconnections between factors and was able to control for a number of variables, including answering style and other person related factors of the participants. The analysis shows clearly that easily measurable luminance values can predict a large amount of variance in the distinctness of the contours of the 3D objects. However, the conclusions should be tested by other researchers under other lighting conditions and/or with other objects to verify the relations with higher precision.

This article presents only the first step in the whole study. We intend to extend the testing of the different luminance measurements in terms of contour and shape visibility and distinctness. We believe the findings will provide new and useful information helping to develop modern techniques for designing qualitatively comfortable lighting.

References

ANAOKAR, S., MOECK, M. 2005. Validation of high dynamic range imaging to luminance measurements. Leukos, 2(2), 133-144.

ARIES, M., VEITCH, J., NEWSHAM, G. 2010. Windows, view, and office characteristics predict physical and psychological discomfort. Journal of Environmental Psychology, (30), 533-541.

BOYCE, P. R. 2003. Human factors in lighting, 2nd ed. London: Taylor & Francis.

CAI, H. 2011. Camera aided luminance measurement of the luminous surfaces of different light sources. AEI 2011: Building Integration Solutions. American Society of Civil Engineers, pp 272-279.

CANTIN, F., DUBOIS, M.C. 2011. Daylighting metrics based on illuminance, distribution, glare and directivity. Lighting research and technology, 43, 291-307.

CHUNG, T., NG, R. 2010. Variation of calibration factor over time for High Dynamic Range Photography in a single daylit interior scene. Light and Visual Environment, 34(2), 87-93.

CUTTLE, C. 2008. Lighting by design 2nd ed., Elsevier.

GILCHRIST, A. 2007. Lightness and brightness. Current Biology, 17(8), 267-269.

INANICI, M. 2006. Evaluation of high dynamic range photography as a luminance data acquisition system. Lighting Research and Technology, 38(2),123-136.

KUMARAGURUBARAN, V., INANICI, M. 2013. Hdrscope: high dynamic range image processing toolkit for lighting simulations and analysis. In BS2013: 13th Conference of International Building Performance Simulation Association. 3400-3407. Available at: http://courses.washington.edu/hdrscope/index.html

LESLIE. R., RADETSKY, L., SMITH, A. 2012. Conceptual design metrics for daylighting. Lighting Research and Technology, (44), 277-290.

MARDALJEVIC, J., HESCHONG, L., LEE, E. 2009. Daylight metrics and energy savings. Lighting Research and Technology, 41, 261-283.

MATUSIAK, B. 2002. A modelling sensor designed to be used in the lighting practise in cases where there it is essential to compare the modelling ability of light in an important point in a room for different lighting alternatives. Proceeding of CIE 2002, London.

VALBERG, A. 2005. Light, vision, color, Wiley.

WARD, G. 2005. Photosphere, Available at: http://www.anyhere.com.

ZAIKINA, V. 2012. Light level perception in interiors with equiluminant colours. In B. Matusiak & K. Fridell Anter Nordic light and colour. Trondheim: NTNU - The Faculty of Architecture and Fine Art, 105-122.

Paper III

Luminance-based measures of contour distinctness of 3D objects as a component of light modeling

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ABSTRACT

This article presents possible luminance-based measures of contour distinctness of 3D objects observed under real daylight conditions. Contour distinctness is considered here as a component of the broader concept of light modeling and is a significant metric of quality lighting. We set up an experiment where different measures of contour distinctness were studied with the help of high dynamic range imaging techniques. Measures obtained from the luminance maps were brought into correlation with survey results from 32 subjects. The analytical comparison showed that the contrast measurement (calculated with the Weber formula), luminance ratio between average luminance of the object and average luminance of the background, mean of paired point luminance ratio (mean point LR) measurements around the contour of the object, and percentage of the invisible part of the contour are good predictors for contour distinctness of the observed 3D objects. The proposed measures expressed in numerical values are comprehensive and easy to obtain and can be practically applicable after the further development.

KEYWORDS *contour distinctness, high dynamic range images, luminance-based measurements, luminance maps*

1. INTRODUCTION

Most of the current lighting recommendations aim at ensuring a minimum quantity of light needed to see objects in the surrounding environment and to enable work or other activities. Nevertheless, this is not a guarantee for lighting quality or the occupants' comfort. The present building codes for daylighting design in buildings are very simplified and use, in most countries, the daylight factor as the fundamental measure; other recommendations are sparse and give scant information about qualitative aspects of lighting. On the other hand, research tells us that providing better recommendations is crucial because creating a comfortable and pleasant environment for occupants may increase productivity and health and may indirectly improve their life at home by reducing job-related stressors, thus indirectly increasing economic benefits of the companies [Aries and others 2010].

Based on such considerations, researchers have recently pointed out that lighting quality should become equally important as energy-efficiency aspects in lighting design [Dehoff 2014]. The qualitative aspects of lighting are frequently discussed topics in the lighting community but less frequent among laypeople. Often laymen are even unaware of consequences of low-quality lighting. One of the issues that the currently used measures touch only sporadicallyn is light modeling, which is one of the lighting quality characteristics deprived of the attention of researchers.

In the European Standard EN 12464-1:2011 "Lighting ofWorkplaces" the modeling term is explained as "the ratio between cylindrical and horizontal illuminance at a specific point and should be between 0.3 and 0.6 in. [European Committee for Standardization (CEN) 2011].

In the current study dedicated to measures of light modeling quality, we define the term "light modeling" as the degree to which the light describes 3D objects, so both the contour and shape are clearly visible. The better the light modeling is, the easier we distinguish 3D objects from the background and the more correctly we perceive their 3D shape and their specific characteristics. A good light model is important in different spheres, from hospital lighting to museum or commercial lighting. The possibility to predict light modeling in particular rooms and spaces would be an undoubted advantage for architects and designers [Zaikina and others 2014].

2. BACKGROUND

During the past few years, a number of researchers conducted studies on new daylighting metrics. One of them suggested particular techniques based on standardized climate data sets, so called climate-based daylight modeling, and development of certain luminous quantities associated with factors related to visual comfort and quality [Mardaljevic and others 2009]. Another study focusing on assessing a set of metrics based on illuminance, distribution, glare, and directivity implied that these are the most useful measures for the determination of the daylighting quality of architectural spaces [Cantin and Dubois 2011]. In both studies, luminance measurements were included to some extent. A “daylighting dashboard” approach was proposed in another study where eight particular daylighting metrics were analyzed. The main goal was to use average illuminance, coverage, diffuse daylight, daylight autonomy, circadian stimulus, glazing area, view, and solar heat gain as determinants during the conceptual phase of architectural design [Leslie and others 2012].

Other researchers tried to shed light particularly onto the topic of light modeling. Different approaches were used. One of them is illuminance measurement using a six sided illumination meter for prediction of shading patterns of various objects or the distribution of eye illuminance at a given point [Cuttle 2008]. Another approach suggests using a particular instrument, a modeling sensor, to predict light distribution on a 3D object or the occurrence of light spots, cast shadows, and register the light direction [Matusiak 2002].

An original technique called high dynamic range (HDR) imaging offers new options in studying light modeling characteristics. The HDR image is a merged image of several conventional low-range images taken with different exposures that contains full luminance information of the photographed region. The term “luminance map” can also be used instead of HDR images to accentuate that the picture has been utilized specifically for the luminance measurements. The luminance-based design is a new approach to lighting design applying such pictures. It is increasingly used in the field of architectural daylight studies [Bellia and others 2013; Konis 2014; Van DenWymelenberg and others 2010]. Moreover, it is being promoted by a number of scientists and CIE Technical Committee 3-45 as a perception-oriented method for lighting design [Nakamura and others 2011]. The prime advantage of this method is that the luminance is the currently known measure that describes visual perception most correctly; for example, the perception of brightness as a function of luminance [Gilchrist 2007].

The aim of the study is to develop and compare simple, precise, and perception-oriented measures of light modeling by investigation of a daylit environment (a full-scale mock-up room) furnished with achromatic and chromatic 3D objects by help of a luminance mapping technique.

According to the stated provisional hypothesis, certain numerical luminance values or luminance ratios obtained from HDR images may adequately describe the distinctness of contour of daylit 3D objects as being observed by subjects and form possible measures for contour visibility.

It is important to note that measures based on luminance contrast were considered as a departing point in the current study. Contrast perception is a fundamental ability of our visual system that enables us to discriminate, among other things, a target from its background [Valberg 2005]. Numerous scientific studies of the luminance contrast and its threshold values have been carried out in fully controlled conditions in research laboratories for decades. However, we do not know what the threshold values of contrast are that are necessary for the detection of the contour of objects—for example, human faces—in real full-scale rooms illuminated by daylight with its typical gradation of illuminance and how those threshold values may differ depending on the optical characteristics of both object and background surfaces. By addressing these questions, this study presents a new angle.

3. METHODOLOGY

The real-life experiment consisted of the respondents' observation of the contours of 3D objects placed in a full-scale mock-up room, answers to surveys, and photographing sessions of the observed scene.

Although the visual system handles chromatic and achromatic contrast in different ways [Valberg 2005], 3D objects of both types were presented in the experiment because it is rare to see them completely separated from one another in real life. The effect of chromaticity was analyzed specifically. Moreover, a previous experiment conducted by the authors showed that low saturated colors and interiors containing the same type of colors could be successfully studied using the luminance mapping technique [Zaikina 2012]. The main data sources for the current study were subjective ratings of contour and shape visibility provided by participants in a quantitative questionnaire, graphical information—that is, drawings made by participants—and subsequently generated HDR images. In this case, taking 180° HDR images or luminance maps was a method that enabled the technical–instrumental recording of the observed visual scene under real conditions concurrently with surveying the subjects. The method of HDR imaging is now well established, and its reliability was previously tested regarding accuracy in different lighting conditions, different times of the day, and representations of the different colors by a number of researchers [Anaokar and Moeck 2005; Cai 2011; Chung and Ng 2010; Inanici 2006; Tyukhova and Waters 2014].

The experiment was conducted under real daylight conditions, on several days, from 9:00 AM to 1:00 PM. A number of female Venetian masks were chosen as 3D objects for observation. On the one hand, they are realistic enough to be reminiscent of a real human face and thus carry semantic importance for people; nevertheless, they are simplified and stylized so that no unnecessary noise is added to the data. On the other hand, masks possess the qualities typical for other non-face-like 3D objects: they have a well-distinguishable convex shape and contain a number of small elements and details.

3.1. Experiment Design

The experimental room was built in the Room Laboratory, the laboratory for construction of small full-scale spaces at the Faculty of Architecture, Norwegian University of Science and Technology, Trondheim, Norway (http://www.ntnu.edu/bff/laboratories). Data were collected during 8 days under stable overcast sky conditions within 2 weeks of August 2013. The experimental space was a nonspecific room with one daylit opening and walls made of portable wall elements of half-matte white coat; see Fig. 1a. The size of the room was 4.8 m × 4.8 m, and the height was 2.5 m. Glare was avoided with the help of a partition wall constructed of the wall elements in front of the window. Two shelves were placed in the room at two different but adjacent walls. They were made of box-like cells 0.5 m × 0.5 m in size that were painted in different achromatic and equiluminant chromatic colors. The 3D objects (Venetian masks) were painted the same colors as the cells. Most of the colors were low saturated: grey, pink, and green; additionally, white and dark grey were used. Notations of all of the colors used, correspondingly to the Natural Color System (NCS) widely used in Scandinavian countries, can be found in Table 1.

The shelves were identical in construction, size, and color combination of the cells. Nevertheless, they were lit diversely and contained objects with different types of surfaces (matte and glossy). One shelf was shielded by a partition wall and therefore illuminated by reflected and evenly distributed daylight; see Fig. 1a. It contained masks with matte coat. Another shelf was illuminated mostly by sidelight from the window and partly by the reflected light. Thus, shadow patterns were more strongly pronounced due to the side illumination. This shelf contained only glossy masks. The combination of colors of the objects and colors of the cells (that is, color of the object and color of the background) was unique for each cell of the shelf. The setup resulted in 18 different

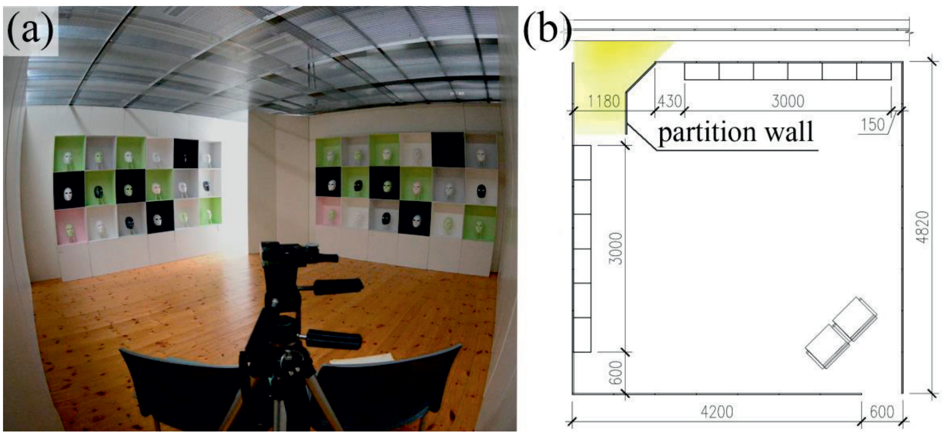


Fig. 1 (a) *Overview of the experimental room and (b) plan of the experimental room.*

combinations that were duplicated on both shelves.

The light level in the experimental room was kept low, because it was important to create a situation with hardly visible objects. Even in similar overcast weather conditions that prevailed during all experimental days, light levels in the rooms fluctuated; vertical illuminance at the plane of the eye was calculated from the luminance readings of the luminance maps varied in the range from 3 lx (minimum value in the darkest lighting conditions) to 167 lx (maximum value in the brightest lighting conditions). Although the eye-illuminance variance is high, no significant difference in answers between participants who answered under the brightest lighting conditions and those in the darkest condition was found.

Name of the colour used in the paper	**Dark grey**	**White**	**Green**	**Pink**	**Grey**
Nominal colour nearest NCS sample	S 6005-R80B	S 0300-N	S 0520-G40Y	S 0510-R20B	S 1002-B50G

TABLE 1. *Notations of the colors used in the experiment, according to NCS*

During the experiment, no particular registration of the light changes over a single observation session was performed. However, the author monitored light changes visually and kept a diary of observations where the noticeable changes of the light level were marked. Visually noticeable light level fluctuations were detected only twice. However, it was decided to include the data from these two cases in the analysis because the participants claimed that those fluctuations did not affect their answers. Because the experimental room has a northeast orientation and translucent curtains were used on the windows, no direct sunlight or sunlight reflected from other buildings could penetrate into the room.

In each session, two respondents observed the objects in the room and answered the questionnaires at the same time. This helped to reduce the time of the experiment by half, which was highly desirable considering changeable weather conditions, where only a cloudy state was acceptable. Participants were sitting on adjoining chairs. The camera was placed between them at eye level; that is, at a height of 1.2 m and with the angle of view oriented toward the window, capturing both shelves with the masks. This was done to get simultaneous results for two participants and to do it as quickly and as accurately as possible. Because the distance between the viewpoint of camera and the viewpoint of each participant was only 35 cm and the distance from each of those viewpoints to the objects was minimum 3.6 m, the difference in the view angle between the camera and a participant was maximum 4.63° and thus was negligible. This allows us to assume that the directivity of specular reflections that appeared on the glossy objects registered by the camera was similar to the participants' vision. However, because a digital camera still is not an eye and human perception includes various complex processes, it would be incorrect to state that images captured by the camera are completely equivalent to human perception, even in terms of the directivity of the specular reflections.

Before respondents started to fill in the questionnaire, photographing of the set of 11 low dynamic images, manual luminance measurements, and oral explanation of the terms used in the questionnaire were performed. The low dynamic images were taken within a period of 1–2 min and the manual luminance measurements were conducted immediately after. The whole process (photographing, measuring, and explanation) took approximately 10–15 min, depending on the respondents' questions. During this time, they were able to adapt to the lighting conditions in the room. The survey itself took 1 h for each pair of the respondents, and they were not allowed to communicate with each other during this process.

3.2. Participants

Thirty-two subjects participated in the experiment. Their ages varied from 14 to 74; the average age was 32.1 years, the mode was 26 years, and the standard deviation was 10.9 years. There were 20 female and 12 male participants of different nationalities. Most of them were naïve regarding such experiments and all had different educational backgrounds and professions.

Before staring the experiment, the vision of each participant was tested with the following tests: the visual acuity test using a Snellen chart, the Ishihara test for color vision, and a contrast sensitivity test (Vigra program). Normality of 3D vision was self-reported by the respondents due to unavailability of an appropriate test. According to the vision controls, all of the respondents had normal or corrected to normal vision (with the help of glasses or contact lenses). Therefore, all were allowed to participate in the experiment.

3.3. Questionnaire

The questionnaire was divided into two parts; each part dealt with one of two shelves with 3D objects. Every part included only two simple questions per object:

1. How well can you distinguish the contour of the object # N?
2. How well can you distinguish shape and details of the object # N?

Both questions were asked about each individual mask; thus, 18 matte and 18 glossy masks were evaluated according to their contour and shape/details. The subjects were requested to mark their answers on a 4-point ordinal scale with the following options:

- *indistinguishable* (invisible contour),

- *just distinguishable* (barely visible contour or parts of the contour),
- *well distinguishable* (well visible contour except some parts or areas),
- *perfectly distinguishable* (the whole contour is very well visible).

The meaning of the each term used was explained to all of the respondents before they started to answer the questions. They were allowed to begin the evaluation from any mask presented on the observed shelf, which provided a partial randomization of mask observation, although this was not systematically implemented because participants chose themselves. Participants had no time limits for the observation process, though most kept it within one hour without any haste.

Respondents specified indistinguishable and perfectly distinguishable areas at a drawing of the mask included in the questionnaire. These graphical drawings were an important part of the survey needed for the further luminance measurements and statistical analysis. When two participants simultaneously started the observation, one of them began with the evaluation of glossy masks and the other evaluated the matte objects first. After finishing the evaluation of the first shelf and answering the questions for the first part of the questionnaire, they changed the shelf of observation without changing their position in the room. This alternating order was accomplished to prevent disturbance by the other respondent and was controlled during the statistical analysis.

3.4. Camera Settings and Manual Measurements

For luminance measurements and analysis of the observed scene, 17 sets of 11 low dynamic range images were made with a Nikon D600 digital camera and a full-frame (AF DX Fisheye-Nikkor 10.5mm f/2.8G ED) lens (Japan Photo Trondheim, Munkegaten 35, 7011 Trondheim, Norway) that provides 180° diagonal angle of view. To ensure sharpness, the camera was mounted on a tripod and situated between the participants' chairs. The following camera settings were used: white balance, cloudy; auto-bracketing, off; sensitivity, 200 ISO; auto focus, auto; and aperture, fixed, f/4. Exposure variations were achieved by varying the shutter speed in manual exposure mode with step 1 EV. All camera settings were adjusted by dint of a computer using Nikon Camera Control Pro software (Japan Photo Trondheim, Munkegaten 35, 7011 Trondheim, Norway).

For further calibration of the HDR images, manual luminance measurements were taken at four specially marked points of the observed scene. These areas were matte white surfaces placed in different parts of the experimental room and at various distances from the window. This helped to minimize error between manual luminance measurements and reading from luminance maps. Manual luminance measurements were performed using a Minolta LS-100 luminance meter and repeated with each new photographing session and each new pair of respondents.

All of the low dynamic range images were processed and combined into 17 HDR images using Photosphere software [Ward 2005] at a resolution of 3936 × 2624 pixels. After this step a calibration was applied in the same program, according to the metrics obtained by the luminance meter.

3.5. Measurements from Luminance Maps

Although two topics were investigated in this study—that is, *contour distinctness* and *shape and details distinctness* - this article presents the luminance measures for evaluation of contour distinctness only. These measures are luminance ratio, contrast, percentage of the invisible part of the contour of the observed mask, and mean point luminance ratio (LR). These measures are easy to perform because they are based on the luminance values obtained from selected regions of luminance maps.

Luminance measurements were done using two programs: Photosphere (which was used during the preparation phase for merging of low dynamic images and calibration) and hdrscope [Kumaragurubaran and Inanici 2013]. In this particular case, the general measurements of the whole area of the image, measurements of squared areas of interest, and the point measurements were conducted in Photosphere. Luminance measurements of multiple selected regions, figures of complex geometry, and contrast values were obtained from hdrscope software.

It is important to specify that selection of the regions of interest, namely, an object and its background, was performed by hand. Firstly, the mask intended for analysis was cropped from the HDR image. The background selected was the whole box or the cell where the mask was placed. The foreground area was selected as the whole mask including the eye areas. This was done for two reasons: the first one was caused by limitations of the applicable tools in the program (hdrscope), and the second was provoked by time constraints; exclusion of the eye area might make the time-consuming procedure even longer and more complicated. However, considering that the eye area constitutes at maximum 2.5% of the whole mask area (depending on the each mask placement; each mask was seen slightly differently due to its position on the shelf and distance from the observer), the possible error will not be high.

The contrast (contrast measure) is calculated in hdrscope as the Weber ratio; that is, the difference of the mean luminance of the chosen foreground and background regions divided by the mean luminance of the background [Valberg 2005]; see (1) and (3). As a background the whole area of the cell was selected for analysis.

Another measure of interest was the luminance ratio, which is the ratio between the mean luminance of the mask and the mean luminance of the background; see (2) and (3). The luminance ratio was calculated by the authors based on the luminance metrics from HDR images but not generated by any of the programs. It was expected before the statistical analysis was performed that luminance ratio and contrast should lead to very similar results due to their straight mathematical interconnection. Nevertheless, during the working process both were tested, because they were acquired by different methods. hdrscope generated negative contrast values without the minus sign so that all data had to be checked thoroughly and the luminance ratio was used as a backup.

$$C_W = \frac{L_o - L_b}{L_b} \tag{1}$$

where

L_o is the luminance of the object;

L_b is the luminance of the background.

$$C_R = \frac{L_o}{L_b} \tag{2}$$

where

L_o is the luminance of the object;

L_b is the luminance of the background.

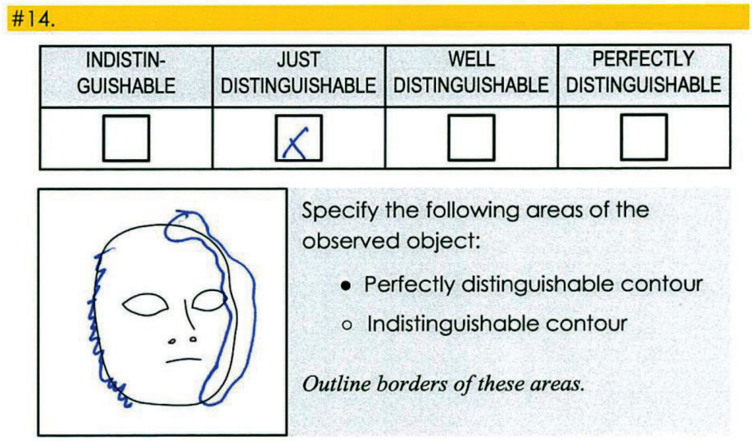
$$C_W = C_R - 1 \tag{3}$$

where

C_R is the luminance ratio.

Respondents specified in their questionnaires the areas where mask contours were indistinguishable as well as perfectly distinguishable; see Fig. 2. This information was used to test the validity of the interconnection between the invisible part of the contour marked by the participants, luminance values measured in 12 paired points around the contour of the mask, and evaluations of contour distinctness. This measure will be referred to as the percentage of the invisible part of the contour in the following sections. It was calculated as a relative area of the indistinguishable contour marked by the participant to the length of the whole contour of the observed mask and tested in comparison to obtained luminance readings. The results from each mask with the graphics from each participant were registered.

Point luminance values were measured in 12 paired points around the contour of the mask; see Fig. 3. The first luminance reading in this pair was measured on the object


#14.

INDISTIN-GUISHABLE	JUST DISTINGUISHABLE	WELL DISTINGUISHABLE	PERFECTLY DISTINGUISHABLE
☐	☒	☐	☐

Specify the following areas of the observed object:

- Perfectly distinguishable contour
- Indistinguishable contour

Outline borders of these areas.

Fig. 2 *Example of the questionnaire answer and participant's drawing.*

(numerator in the equation) and the second point measurement was taken from the background (denominator in the equation). Pairs of these point luminance measurements were within 30◦ of each other, so the pattern of the couple of points was reminiscent of a clock dial. We decided to make 12 pairs of measurements because this allowed measurement of four main positions (top, down, left, and right) and measurements between these main four spots. Analysis of luminance fluctuations around the contours of the masks, easily noticeable as false color images, helped us to conclude that two additional intermediate points supplementing the main four points would be enough to predict the distinctness of the mask's contour.

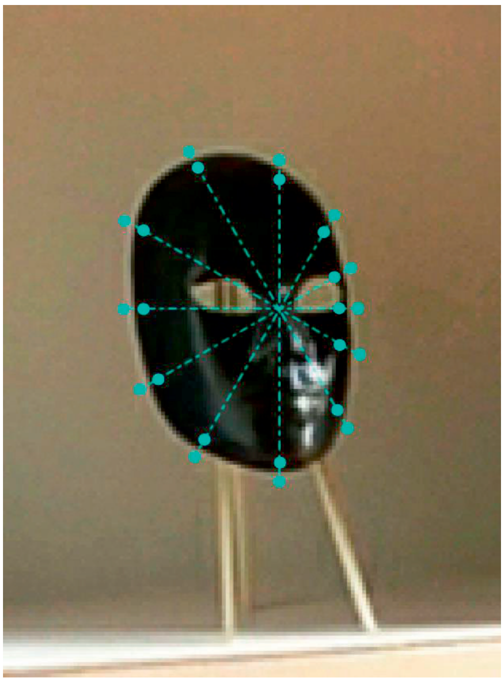


Fig. 3 *Twelve paired points around the contour of the mask where luminance was measured.*

The last measure of contour distinctness tested in this study was the mean ratio of the 12 paired point luminance measurements, which will be referred to as mean point LR. Mean point LR was based on the previously described measurements and was important because it allowed us to reduce the measured area from the whole mask and its background as for ratio and contrast to 12 pairs of points.

Thus, this could be a beneficial and time-saving quality of the measure.

4. STATISTICAL ANALYSIS AND RESULTS

As stated prevously, this article presents results related to analysis, detection, and prediction of contour visibility.

For statistical analysis of the data, a two-level ordinal regression analysis was chosen. As an additional method for testing the correlation between mean point LR and indistinctness of the contour in a given point, a cross-classified analysis controlling for individual participant effects and mask effects was used.

The experimental design with 32 participants evaluating 36 masks each resulted in a data structure where 36 evaluations were nested within each participant. To eliminate the noise that each participant's general answering patterns contributed to the data, the main analysis was conducted at the object level, but the person-specific variance in the evaluations across all masks was modeled simultaneously (listed as Level 2 variance in Tables 2–5). The regression analysis was conducted as an ordinal (and not linear) regression because the dependent variable "distinctness of the contour" had neither equidistant nor normally distributed answers across the categories.

In four separate analyses (Tables 2–5), the contrast, luminanceratio, percentage of the indistinguishable part of the contour of the mask, and mean point LR were assessed as main predictors of contour distinctness and as the dependent variable, and type of surface (glossy or matte), coloration (chromatic or achromatic), and order of

	Luminance Ratio ≤ 1				**Luminance Ratio ≥ 1**			
	B	**SE**	**β**	**p**	**B**	**SE**	**β**	**p**
Luminance Ratio	-10.775	1.270	-0.803	< 0.001	0.322	0.022	0.577	< 0.001
Glossiness (0=matte, 1=glossy)	1.123	0.572	0.146	0.049	0.021	0.129	0.005	0.870
Chromaticness (0=achromatic, 1=chromatic)	-0.615	0.406	-0.080	0.130	-0.324	0.134	-0.073	0.016
Order of observation (0=matte masks first, 1=glossy masks first)	-1.589	0.661	-0.213	0.016	-0.533	0.280	-0.120	0.057
Level 2 variance "contour"	1.978	0.970		0.041	0.495	0.161		0.002
$R^2_{level\ 1}$	0.764				0.332			
$N_{level\ 1}$	255				897			
$N_{level\ 2}$	32				32			

TABLE 2 *Regression analysis results: luminance ratio as a predictor of contour distinctness*

observation of the shelves were assessed as additional independent control variables. The characteristics of some main predictors are different below and above a certain contrast point (0 for contrast and 1 for luminance ratio and mean point LR), as can be seen from the formulas to calculate them: whereas negative contrast, for example, can only vary between 0 and −1, positive contrast varies between 0 and positive infinity. This means that values below the zero contrast point cannot be compared to values above it. Therefore, two separate subanalyses were conducted (left and right half of the table).

Results show that all the tested measures (contrast, luminance ratio, percentage of the invisible part of the contour, and mean point LP) are good predictors of the distinctness of the contour of the observed masks (see Tables 2–5).

	Contrast ≤ 0				**Contrast ≥ 0**			
	B	**SE**	**β**	**p**	**B**	**SE**	**β**	**p**
Contrast	-10.781	1.271	-0.803	< 0.001	0.341	0.023	0.569	< 0.001
Glossiness (0=matte, 1=glossy)	1.081	0.570	0.141	0.058	-0.004	0.129	-0.001	0.975
Chromaticness (0=achromatic, 1=chromatic)	-0.579	0.404	-0.076	0.152	-0.323	0.134	-0.073	0.016
Order of observation (0=matte masks first, 1=glossy masks first)	-1.572	0.657	-0.212	0.017	-0.531	0.281	-0.120	0.058
Level 2 variance "contour"	1.952	0.959		0.042	0.496	0.162		0.002
$R^2_{level\ 1}$	0.761				0.323			
$N_{level\ 1}$	255				897			
$N_{level\ 2}$	32				32			

TABLE 3 *Regression analysis results: contrast as a predictor of contour distinctness*

Table 2 presents the results for the ratio of the mean luminance of the mask and the mean luminance of the background. The luminance ratio has a highly significant and strong negative impact on the visibility of the contour in the area of negative contrast, which means the closer the ratio approaches 1 the more difficult it is to see the contour. For positive contrasts, the luminance ratio has a highly significant and strong positive impact, which means that the higher the luminance ratio value, the better the visibility of the contours. The type of surface has an impact on the visibility of the contour only for dark masks on light backgrounds, but the impact is small. This means that the factor "glossiness" enhances the visibility of the contour of dark masks (negative contrast). In addition, the order of observation (which shelf was attended first) had a small impact for dark masks on light backgrounds. Chromaticity had a small but significant impact for

	B	SE	β	p
Percentage of the invisible contour of the mask as being marked by the respondents	-0.128	0.005	-0.890	<0.001
Glossiness (0=matte, 1=glossy)	0.051	0.133	0.006	0.700
Chromaticness (0=achromatic, 1=chromatic)	0.304	0.133	0.037	0.023
Order of observation (0=matte masks first, 1=glossy masks first)	-0.145	0.282	-0.018	0.606
Level 2 variance "contour"	0.494	0.167		0.003
$R^2_{level\ 1}$	0.802			
$N_{level\ 1}$	1148			
$N_{level\ 2}$	32			

TABLE 4 *Regression analysis results: percentage of the invisible part of the contour as a predictor of contour distinctness*

light masks on dark backgrounds, where contours were slightly more difficult to see if the combination was chromatic. In these combinations, either both the mask and the cell or only one of them were chromatic. Figure 4 presents the probability plots for the each of the four categories (perfectly distinguishable, well distinguishable, just distinguishable, and indistinguishable contour) in the questionnaire depending on the

	Mean Point LP ≤ 1				Mean Point LP ≥ 1			
	B	SE	β	p	B	SE	β	p
Contrast	-9.666	1.418	-0.705	<0.001	0.555	0.039	0.572	<0.001
Glossiness (0=matte, 1=glossy)	1.450	0.583	0.234	0.013	0.009	0.127	0.002	0.944
Chromaticness (0=achromatic, 1=chromatic)	0.249	0.572	0.040	0.664	-0.467	0.131	-0.105	<0.001
Order of observation (0=matte masks first, 1=glossy masks first)	-1.116	0.718	-0.182	0.120	-0.551	0.273	-0.125	0.043
Level 2 variance "contour"	2.283	1.110		0.041	0.467	0.153		0.002
$R^2_{level\ 1}$	0.648				0.327			
$N_{level\ 1}$	225				923			
$N_{level\ 2}$	32				32			

TABLE 5 *Regression analysis results: mean point LR as a predictor of contour distinctness*

four combinations of the control variables glossiness and chromaticity. The order of the shelves' observation effect was controlled when calculating the probabilities.

As can be seen in Table 3 and Fig. 5, the results are almost identical when the luminance ratio is substituted by contrast as the main predictor. Here the cutoff for zero contrast is 0. Contrast is a highly significant and strong negative predictor for negative contrasts (the better the visibility the more negative the contrast is below 0) and it is a highly significant, strong positive predictor the more positive the contrast is. The closer to 0, the more difficult is it to perceive the contour. Again, the order of observation has a small but significant impact for dark masks on light backgrounds, and chromaticity has a small effect for light masks on dark backgrounds.

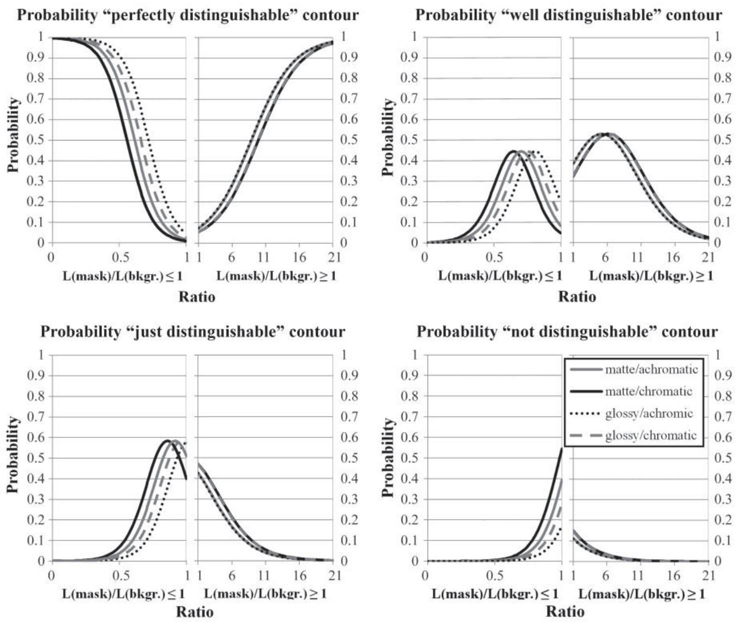


Fig. 4 *Probability curve for the four categories of the questionnaire, four combinations of control variables, and luminance ratio as a main predictor.*

The next measure of interest that was statistically tested was percentage of the invisible part of the contour marked by the respondents. In fact, it is not an entirely independent measure based only on luminance measurements. In this study it was based on the analysis of the drawings of the participant and contrasted with luminance measurements of 12 paired points set close to the border between the object and background (Fig. 3). Nevertheless, the authors believe that a correct interpretation of this information allows us to make some significant conclusions that will be discussed further in the article. Therefore, percentage of the invisible part of the contour is a statistically significant measure of the 3D object's contour distinctness. It also signifies that people were consistent and specified those contours' parts that are really characterized by low luminance. Glossiness has no impact here, which indicates that irrespective of the type of surface and light directivity, respondents marked similar parts of the invisible contour of the same glossy and matte masks. Chromaticity remains statistically significant but has a positive effect, which indicates that for chromatic masks/backgrounds the visibility is rated higher when the effects of the other predictors in the equation (especially percentage of visible contour) are controlled for.

Looking at the probability plots we can see some interesting and quite consistent results (Fig. 6). For illustrative purposes, let us take a look at the probability of 60% for each category of the subjective distinctiveness. The value of 60% probability was chosen as being represented by measure percentage of the invisible contour of the mask at each particular category. The mask is evaluated as perfectly distinguishable by more than 60% of the respondents if the percentage of the invisible part of the contour is less than 4% for chromatic contributions and 2% for achromatic combinations. The invisible area of the contour of a mask evaluated as well distinguishable by more than 60% of the participants lies in the interval from 10% to 25% for achromatic combinations and from 14% to 27% for chromatic combinations with peaks at 18% and 19%, respectively. When the contour of the mask is rated as just distinguishable by 60% or more, the invisible area lies between 34% and 64% for achromatic combinations and between 37% and 66% for chromatic combinations. If the invisible part of the contour of the

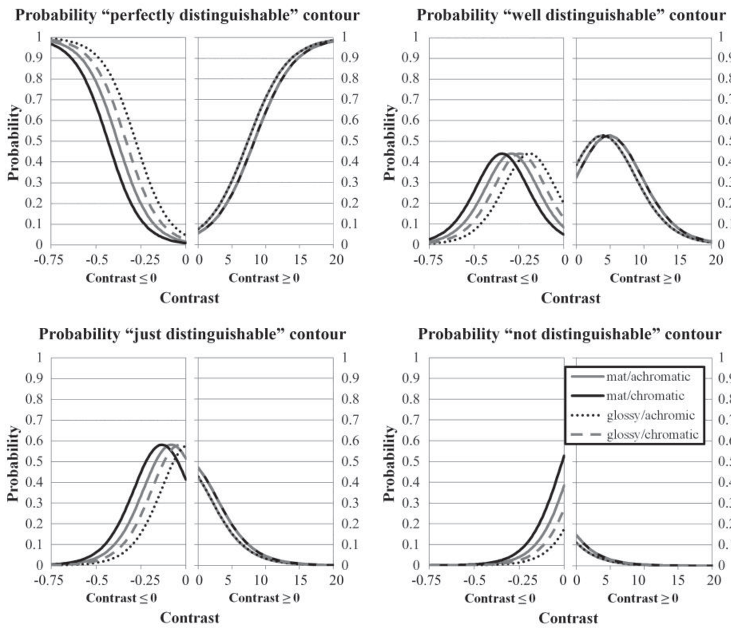


Fig. 5 *Probability curve for the four categories of the questionnaire, four combinations of control variables, and contrast as a main predictor.*

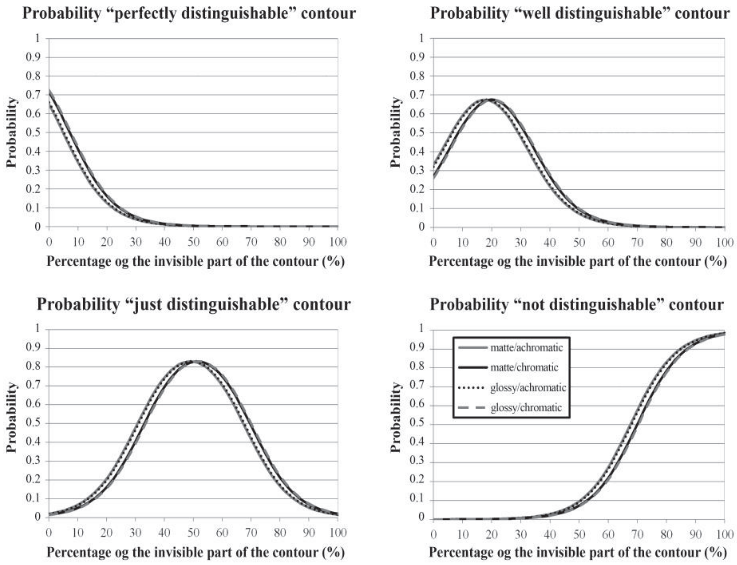


Fig. 6 *Probability curve for the four categories of the questionnaire, four combinations of control variables, and percentage of the invisible part of the contour as a main predictor.*

observed mask is more than 71% (achromatic) and 73% (chromatic), it is evaluated as indistinguishable.

Considering the results of general descriptive statistics of the areas of the invisible contours of all 36 masks specified by respondents and further measured at luminance maps, we can conclude that the mean point LR in these areas was 1.449. The median, as a measure less sensitive to extreme values, was 1.05, and the standard deviation was 0.728. If we compare these results to those taken from several particular masks that were evaluated by participants as having a just distinguishable contour with highest consistency, the values would be mean point luminance ratio = 1.026, median = 1.02, and standard deviation = 0.059. These results conform to each other and help us to conclude that part of the contour of 3D object could be evaluated as indistinguishable if the point luminance ratio is between 1 and 1.449. It could be below 1 and still perceived as indistinguishable, but for more precise conclusions further studies are required.

The last measure that was investigated is the mean point LR, which is an averaged measure obtained from the 12 pairs of luminance measurements all over the contour of the mask. Results show that it is a statistically significant predictor of distinctness both for the light and dark masks (Table 5, Fig. 7). Glossiness has an impact on contour visibility for the negative contrast combination, again improving to a small degree contour distinctness of dark masks. Chromaticity has an opposite effect to light masks on dark background, decreasing visibility of the contours in chromatic combinations; that is, combinations where either object or cell was chromatic.

Finally, a cross-classified regression analysis for a binary dependent variable (0 = the contour in this part of the mask is visible; 1 = the contour in this part of the mask is invisible) was performed to test the relation between the individual point measures of the luminance ratios and the subjective rating if the area was visible. The cross-classified analysis controls the "people factor" and "mask factor," which both impact the results on each their second level. This helped us to test the correlation between each individual pair of luminance readings and indistinguishable contour as being marked by the participants. Results show a high statistical significance (Table 6) for both sides of the contrast and medium to strong correlations, which can be interpreted as an indication that the data regarding areas of invisible contours obtained from the questionnaire matched with the luminance ratios closest to 1 measured in the pairs of points that belonged to these areas. This shows that the participants were able to reliably report the invisibility of the contour in certain areas of the masks.

	Correlation	**SE**	**p**
Ratio of paired luminance measurements ≤ 1 (if belongs to indistinguishable area = 1, if belongs to visible area = 0)	0.554	0.051	<0.001
Ratio of paired luminance measurements ≥ 1 (if belongs to indistinguishable area = 1, if belongs to visible area = 0)	-0.391	0.024	<0.001

TABLE 6 *Cross-classified data analysis results*

5. DISCUSSION

The experiment reported in this article has shown that luminance measurements can be promising predictors of light modeling. In this particular case, the contrast, luminance ratio, percentage of the invisible part of the contour, and mean point LR were studied as predictors of contour distinctness of the observed Venetian masks. Correlation of the physical luminance measurements and participants' perceptions are complex and usually nonlinear, so they should be studied carefully. For this purpose, we used a two-level ordinal regression analysis that took into account various interconnections between factors and was able to control for a number of variables, including answering style and other individual factors of the participants. The analysis shows clearly that easily measurable luminance values can predict a large amount of variance in the distinctness of the contours of the 3D objects. However, the investigated measures gave partly identical and partly different results.

	Perfectly distinguishable contour, PROBABILITY 80%			
	matte/achr. combination	matte/chr. combination	glossy/achr. combination	glossy/chr. combination
Luminance Ratio ≤ 1	0.49	0.42	0.59	0.52
Luminance Ratio ≥ 1	13	14	13	14
Contrast ≤ 0	-0.5	-0.57	-0.4	-0.47
Contrast ≥ 0	11.5	12.5	11.5	12.5
Mean Point LR ≤ 1	0.46	0.44	0.6	0.59
Mean Point LR ≥ 1	23	22.5	23	22.5

***TABLE** 7 Threshold values for Luminance Ratio, Contrast and Mean Point LR measures of contour visibility*

First, let us compare the results when using luminance ratio and contrast. These measures are simple and are based only on average luminance values of selected regions, namely, foreground and background. Their results are almost identical as expected at the beginning of the study. The only difference is the glossiness factor. For the luminance ratio, glossiness has an additional significant impact, whereas for contrast this effect does not show. However, both P values are quite close to 0.05, so this result is most likely random. The glossiness factor in fact combines two different conditions of the observed shelf with 3D objects that distinguishes it from the shelf with matte

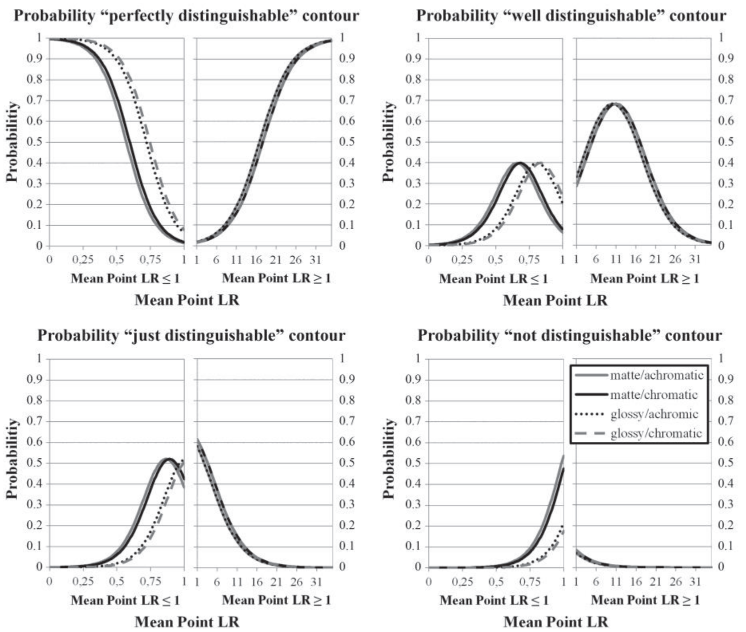


***Fig.** 7 Probability curve for the four categories of the questionnaire, four combinations of control variables, and mean point LR as a main predictor.*

mask: type or directivity of the lighting and type of surface of the mask. To generalize the significance of glossiness to all of the measures, we found that it affected only perception of the contour of the dark masks on the light background, slightly enhancing it. This can be explained by the appearance of a dark glossy object in a lighter environment. In this situation, the observer easily notices that not only do highlights and reflections appear brighter at the dark object but that the overall treatment of light and shade all over the object is more noticeable, which can indirectly affect contour visibility. Nonetheless, the influence of the glossiness factor always had a positive effect, slightly enhancing contour visibility, and therefore it is not a factor that should be avoided in studies of contour distinctness of various 3D objects.

Chromaticity is a factor that affected the discrimination of the contours of all of the light masks on the dark background and appears in the results of all of the measures. For luminance ratio, contrast, and mean point LR, this influence is strongly negative (reduces visibility), whereas for percentage of the invisible part of the contour it is positive. This contradiction can be explained by the fact that the measure percentage was calculated for all of the masks irrespective of whether it was positive or negative contrast. Surely this factor should be taken into account during the process of contour distinctness analysis. Although it is important to emphasize that chromaticity slightly deteriorates contour detection, high consistency between measures and observations shows that chromatic objects can be studied using luminance maps considering the colors' saturation.

For a better understanding of the results, it should be noted that a comparison and examination of the probability plots can be done for any of the four measures. They express the probability of the evaluation of the contour of the mask as perfectly distinguishable, well distinguishable, just distinguishable, or indistinguishable. We can look at luminance ratio or contrast, mean point LP, or percentage of the invisible part of the contour and figure out which values of the particular measure the contour of the mask will be assigned to any of the represented categories. Another advantage of these plots is that threshold values of the proposed measures representative of each of the four categories can be found; see Table 7. We may find threshold values of the measures that guarantee perfect visibility of contour by 80% of observers. We may also find out how the threshold values differ depending on the optical characteristic of the object surface; that is, glossiness and chromaticity. Additionally, we may compare luminance ratio thresholds with the mean point LR. Interestingly, the thresholds of mean point LR ≥ 1 are always higher than the thresholds for all object categories of luminance ratio ≥ 1.

6. VALIDATION ISSUES AND FUTURE WORK

High-quality lighting becomes an especially important issue in a time dominated by a dynamic technical development of new light sources and daylighting techniques. A good light model is one of the necessary conditions for lighting quality. It is essential both in workplaces and in homes. When we communicate with other people we need to accurately perceive various 3D objects, especially faces, and we know that the correct interpretation of human facial expressions depends on the light distribution on the face and the background [Zaikina and others 2014].

We believe that the findings presented in this study will provide new and useful information to help develop modern techniques for designing qualitatively comfortable lighting. It is economically beneficial among designers today to shift to various computer simulation tools that allow them to simulate, test, and visualize different lighting scenarios and conditions. The measures from the current study can be useful not only for analysis of objects' contour visibility in a real environment using HDR imaging techniques but also in simulated or virtual environments. Indeed, these measures should be tested with other objects and in different conditions to provide reliability of their use. However, the results show that measures of light modeling based on luminance mapping are promising tools that should be further developed to help lighting designers to create quality lighting in the future.

7. CONCLUSION

The aim of the current study was to study and propose some possible measures of light modeling, particularly distinctness of the contour of the 3D objects illuminated by daylight. These measures had to be reliable, easy to obtain, and reconciled with the perception of the real daylit environment and objects in it. The results of the current experiment showed that proposed luminance-based measures of the contour distinctness correlate well with subjective visual perception and expressed numerically reflect several levels of contour visibility. Although the obtained results are restricted by conditions such as illumination, type of object, its coloration, and others, further development can nevertheless form a simple and useful tool for contour visibility prediction.

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REFERENCES

Anaokar S, Moeck M. 2005. Validation of high dynamic range imaging to luminance measurement. LEUKOS. 2(2):133-144.

Aries MBC, Veitch JA, Newsham GR. 2010. Windows, view, and office characteristics predict physical and psychological discomfort. J Environ Psychol. 30(4):533-541.

Bellia L, Spada G, Pedace A. 2013. Lit environments quality: a software for the analysis of luminance maps obtained with the HDR imaging technique. Energ Build. 67:143-152.

Cai H. 2011. Camera aided luminance measurement of the luminous surfaces of different light sources. Proceedings of the 2011 Architectural Engineering Conference; 2011 March 30-April 2; Oakland, CA. p. 272-279.

Cantin F, Dubois MC. 2011. Daylighting metrics based on illuminance, distribution, glare and directivity. Lighting Res Technol. 43(3): 291-307.

[CEN] European Committee for Standardization. 2011. Light and lighting—lighting of work places. Vienna, Austria: The European Committee for Standardization. EN 12464-1:2011.

Chung T, Ng R. 2010. Variation of calibration factor over time for high dynamic range photography in a single daylit interior scene. J Light Vis Environ. 34(2):87-93.

Cuttle C. 2008. Lighting by design. 2nd ed. Burlington (MA): Elsevier. 247 p.

Dehoff P. 2014. Measures for a better quality in lighting. A journey through recent activities in applications and standards. Proceedings of CIE 2014: Lighting Quality and Energy Efficiency; 2014 Apr 23- 26; Kuala Lumpur, Malaysia. Vienna, Austria: CIE Central Bureau. p. 348-356.

Gilchrist AL. 2007. Lightness and brightness. Curr Biol. 17(8): R267-R269.

Inanici M. 2006. Evaluation of high dynamic range photography as a luminance data acquisition system. Lighting Res Technol. 38(2):123-136.

Konis K. 2014. Predicting visual comfort in side-lit open-plan core zones: results of a field study pairing high dynamic range images with subjective responses. Energ Buildings. 77:67-79.

Kumaragurubaran V, Inanici M. 2013. Hdrscope: high dynamic range image processing toolkit for lighting simulations and analysis. Proceedings of the BS2013: 13th

Conference of International Building Performance Simulation Association; 2013 Aug 25-28; Chambery, France.

Leslie R, Radetsky L, Smith A. 2012. Conceptual design metrics for daylighting. Lighting Res Technol. 44(3):277-290.

Mardaljevic J, Heschong L, Lee E. 2009. Daylight metrics and energy savings. Lighting Res Technol. 41(3):261-283.

Matusiak BS. 2002. A modelling sensor designed to be used in the lighting practise in cases where there it is essential to compare the modelling ability of light in an important point in a room for different lighting alternatives. Proceedings of CIE 2002; 2012; London. CIE Central Bureau: Vienna, Austria.

Nakamura Y, Suzui S, Aoki T. 2011. Lighting design method applicable both to day lighting and to electric lighting using luminance image. Proceedings of the 27th Session of the CIE; 2011 July 9-16; Sun City, South Africa; Vienna, Austria: CIE Central Bureau. p. 398-403.

Tyukhova Y, Waters C. 2014. An assessment of high dynamic range luminance measurements with LED lighting. LEUKOS. 10(2):87-99.

Valberg A. 2005. Light, vision, color. Chichester, UK: JohnWiley and Sons. 474 p.

Van Den Wymelenberg K, Inanici M, Johnson P. 2010. The effect of luminance distribution patterns on occupant preference in a daylit office environment. LEUKOS. 7(2):103-122.

Ward G. Photosphere. Anyhere Software. http://www.anyhere.com/ Accessed 2013 Aug.

Zaikina V. 2012. Light level perception in interiors with equiluminant colours. In Matusiak B, Fridell Anter, K editors. Nordic light and colour. NTNU - The Faculty of Architecture and Fine Art: Trondheim. 148 p.

Zaikina V, Matusiak BS, Klöckner CA. 2014. New measures of light modelling. Proceedings of CIE 2014: Lighting Quality and Energy Efficiency; 2014 Apr 23-26; Kuala Lumpur, Malaysia. Vienna, Austria: CIE Central Bureau. p. 298-305.

Paper IV

Luminance-based measures of shape and detail distinctness of 3D objects as important predictors of light modeling concept. Results of a full-scale study pairing proposed measures with subjective responses

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ABSTRACT

Nowadays it is very common to discuss the various aspects of lighting within a framework of energy efficiency. In addition, the questions concerning lighting quality and occupants' comfort are another topic for active studies and debates. In the current investigation we tested one aspect of lighting quality—that is, light modeling—with the help of a luminance mapping technique. Here the degree of a 3D object's shape and detail distinctness are associated with modeling quality; that is, directly related to the light modeling concept. The aim of the study was to comprehend whether luminance-based design as a method, most perception oriented among others, could be applicable for the evaluation and prediction of the visibility of the shape and details of real 3D objects observed by people under daylight conditions and, further, to suggest luminance-based measures that can be developed into indicators of shape and details distinctness. Ordinal regression analysis of the survey results paired with several measures based on luminance values was performed. The tested measures were luminance ratio, mean luminance of the object, standard deviation of the luminances of the object, and the ratio between the highest luminance value of the object and mean luminance of the object. Among all of these measures the first three have the strongest correlations with subjective perception of 3D objects' shape and detail distinctness.

KEYWORDS: *high dynamic range images, luminance-based measurements, luminance maps, light modeling, shape and detail distinctness*

1. INTRODUCTION

Lighting quality is a goal of excellence, which lighting designers, architects, and engineers are eager to reach. However, there is no particular definition of the term "lighting quality" that is accepted by official institutions. Some researchers have tried to make this concept clearer and more easily understood by discussion in their articles [Dehoff 2014; Veitch 2004]. By generalizing various approaches, it can be concluded that lighting quality includes several groups of parameters concerning individual well-being, economics, and architecture. Such understanding of the term lighting quality has been accepted by the CIE [Veitch and others 1998]. There are a great number of particular parameters and measures that can be analyzed and applied to obtain the best lighting solution for a certain building/room/situation. Light modeling (telling how well the light describes a 3D object in a given place) is one of the lighting quality parameters that might be both individual well-being and a functional requirement of the architectural space.

In the European Standard EN 12464-1:2011 Lighting of Workplaces, light modeling is defined as "the ratio between cylindrical and horizontal illuminance at a specific point and should be between 0.3 and 0.6" [European Committee for Standardization 2011]. Useful as this definition may be, we did not rely on this light modeling index because it is based on illuminance values. Though currently used metrics for daylight design are based on horizontal illuminance and some researcher state that the daylight factor (as a ratio of the simultaneously measured horizontal illuminance inside and outside the building) can be applied as a predictor of the appearance of the space [Cuttle 2008], methods based on luminance values might be more reliable and useful, especially for estimation of light modeling, as more perception-oriented.

Luminance is a measure of the amount of light reflected from the surfaces that forms an image on the eye's retina that is then processed by the brain. The human eye is sensitive to luminance and adapts to different luminance levels quickly and precisely. The perception of brightness of the surrounding surfaces and objects is also based on the luminance levels and may be interpreted as a function of luminance levels of an object and a background observed simultaneously by an observer [Hopkinson and others 1966].

2. BACKGROUND

The fact that the occupants' requirements should be in agreement with the lighting solutions being applied in a building is widely discussed nowadays. Lighting quality is a broad concept consisting of various factors, and it may have serious consequences if not reached, among which are low productivity, fatigue, depression and slower recovery, decreased well-being, higher cost of labor, lower sales in retail, and many others [Dehoff 2014]. Therefore, different aspect-oriented measures should be equally considered during the lighting and architectural design process or according to reasonable allocation of priorities.

Modeling as a factor closely interconnected with the subjective perception of objects in space could be important in different spheres: from hospital lighting to museum or commercial lighting. The possibility to predict light modeling in particular rooms and spaces could be beneficial for lighting experts.

In the current study the term “light modelling” represents the degree to which the light describes 3D objects so the contour, shape, and details are clearly visible. The better the light modeling is, the easier we discriminate 3D objects from the background and the more correctly we read their 3D shape and their specific characteristics.

It is important to mention previous studies dedicated to light modeling. One of them was based on illuminance measurements using a six-sided illumination meter for prediction of shading patterns of various objects or the distribution of eye illuminance at a given point [Cuttle 2008]. Another suggests using a particular instrument, a modeling sensor, to predict light distribution on a 3D object, predict the occurrence of light spots, cast shadows, and register the light direction [Matusiak 2002]. Both approaches are highly interesting because they represent two different methodologies: numeric illuminance-based method and another more visually or perception-oriented method. As further evidence of the value of vertical surface illumination, Schielke [2013] recently reviewed and outlined the rationale and methods for lighting vertical surfaces.

However, the methodology used in the current study combines advantages of numeric measures with visual assessment of the observed objects in terms of their shape and detail distinctness. This method, called high dynamic range imaging, and its prime advantage is that it is based on luminance values, and luminance is the currently known measure that describes visual perception most correctly; for example, the perception of brightness as a function of luminance [Gilchrist 2007]. The term “luminance map” will also be used further instead of high dynamic range image to accentuate that the picture was used for the luminance measurements.

It is noteworthy that authors of one recent article focused on metrics for the lighting of pedestrians [Saraiji and Oommen 2014] also used luminance-based design as a method. They studied the target (pedestrian) visibility during the night time at the unlit street and developed the concept of dominant contrast. The dominant contrast is the contrast of any part of the pedestrian that provides the highest pedestrian visibility and is considered a useful measure for visibility models. Therefore, understanding of usability of luminance-based measures related to objects' distinctness and its detail discrimination can be important and useful both for science and practice in this field.

The authors were eager to identify luminance-based measures that will enable evaluation and prediction of light modeling. We assume that a good light modeling is achieved only if both the contour of the object and the shape and details on the object surface are well visible. The results connected to the contour visibility have been published in Leukos [Zaikina and others 2015]. The four proposed measures were contrast (calculated with the Weber formula), the luminance ratio between the mean luminance of the object and mean luminance of the background, the mean of paired point luminance ratio measurements around the contour of the object, and the percentage of the invisible part of the contour. The ordinal regression analysis performed showed that those measures are good predictors for contour distinctness of the observed 3D objects; because they are expressed numerically, they are comprehensive and easy to obtain and can be practically applicable after the further development in other lighting conditions.

In this article we focus at the object's shape and detail visibility. The hypothesis is that certain luminance-based predictors of shape and detail visibility of real daylit 3D objects correlate very well with the human visual evaluation of shape and detail distinctness and might become important measures of light modeling. These will be four possible luminance-based measures for shape and detail distinctness of real daylit 3D objects, namely, luminance ratio (object–background), mean luminance of the object, standard deviation of the luminances of the object, and the ratio between highest luminance value of the object and mean luminance of the object.

3. METHODOLOGY

A real-life experiment was set up and conducted for this study in August 2013. It consisted of the respondents' observations of daylit 3D objects placed in a full-scale mock-up room, survey answering using provided scale for the evaluation, and photographing sessions of the observed scene [Zaikina and others 2015].

Despite the fact that the visual system handles chromatic and achromatic contrast in different ways [Valberg 2005], 3D objects of both types were presented in the experiment to reconstruct a realistic real-life situation. Moreover, a previous experiment conducted by the authors showed that low saturated colors and interiors containing the same type of colors could be successfully studied using the luminance mapping technique [Zaikina 2012]. In addition the precision of the luminance maps of the scenes containing surfaces of various hue and color saturation were taken into account according the results of the study conducted by Anaokar and Moeck [2005].

The main data sources for the present study were subjective ratings of shape and detail visibility provided by participants in a quantitative questionnaire, graphical information—that is, drawings made by participants— and subsequently generated high dynamic range images [Zaikina and others 2015]. High dynamic range imaging is a well-established method and its accuracy and reliability were tested by a number of researchers in different lighting conditions, at differenttimes of the day, and using different colors of light sources and surfaces in the interiors [Anaokar and Moeck 2005; Cai 2011; Chung and Ng 2010; Inanici 2006; Tyukhova and Waters 2014].

3.1. Experiment Design

The experiment took place in the Room Laboratory at the Faculty of Architecture, Norwegian University of Science and Technology, Trondheim, Norway (http://www.ntnu.edu/bff/laboratories). A full-scale mock-up room 4.8 m × 4.8 m × 2.5 m in size was built (Fig. 1). Daylight was provided through one daylight opening that was shielded by a partition wall constructed in front of the window. This construction prevented possible glare in the visual field of the participants.

The experimental space contained two shelves (shelf A and shelf B) that were placed at two adjacent walls. They were made of box-like cells, 0.5 m × 0.5 m in size, which were painted in different achromatic and equiluminanat chromatic colors. 3D objects (Venetian masks) provided for observation during the experiment were placed in the middle of each cell. All of the cells and masks were painted in following low saturated colors: grey, pink, and green; additionally, white and dark grey were used. Notations of these colors, corresponding to the Natural Colour System®© (NCS) widely used in Scandinavian countries, can be found in Table 1.

Two shelves were identical in construction, size, and color combinations of the masks and cells, whereas they were lit diversely and contained objects with different type of the surface (coating). Shelf A was illuminated mostly by sidelight from the window and partly by the reflected light; it contained masks with glossy coating. Due to dominant side illumination from the window, a shadow pattern was strongly pronounced on the masks presented here. Glossiness of the masks also created interplay of bright highlights and reflections that were quite easily noticeable. Shelf B was shielded from the window by a partition wall and therefore illuminated by reflected and evenly distributed daylight (Fig. 1a). It contained matte masks. Color combination of the object and its background was unique for each box of the shelf; therefore, the setup resulted in 18 particular combinations (chromatic and achromatic) that were duplicated on shelves A and B.

From the observer's point of view the vertical angular size of the observed Venetian masks varied from 2.7 to 3.63°, and the horizontal angular size varied from 1.5 to 2.1°.

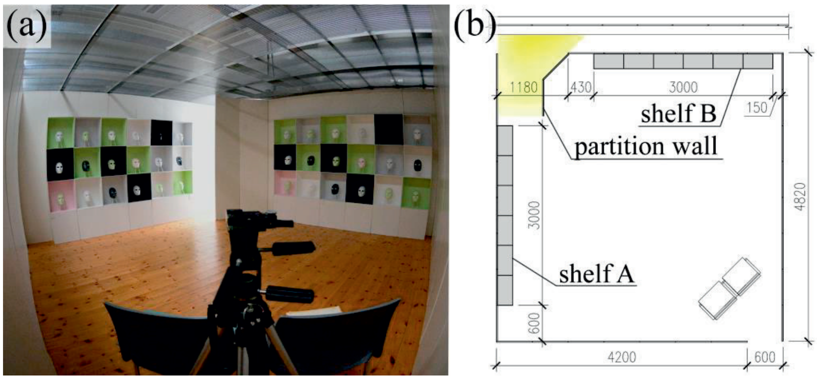

Fig. 1 Picture showing (a) an overview of the experimental room and (b) the plan of the experimental room.

Name of the colour used in the paper	Dark grey	White	Green	Pink	Grey
Nominal colour nearest NCS sample	S 6005-R80B	S 0300-N	S 0520-G40Y	S 0510-R20B	S 1002-B50G

TABLE 1. *Notations of the colours used in the experiment, according to NCS Colour System.*

The light level in the experimental room was kept low, because it was necessary to create a situation with hardly visible objects and their details. The orientation of the room was northeast and translucent curtains were used on the windows; therefore, no direct or reflected sunlight could penetrate into the room.

Although the experiment was conducted in overcast weather conditions, the light level in the room fluctuated; eye illuminance calculated from the readings of the luminance maps varied in the range from 3 lx (minimum value in the darkest lighting conditions) to 167 lx (maximum value in the brightest lighting conditions). During the single experimental session no particular registration of the light level and its changes was performed. The noticeable light fluctuations were monitored visually and noted in the diary of the experiment. Only two cases had noticeable changes of light level within the experimental session. Because the participants claimed that those changes did not affect their answers, the above-described cases were included in the scope of the data for analysis.

Data were collected during 8 days in August 2013. In each session two subjects observed the Venetian masks and answered the questionnaires. Participation of two people simultaneously helped to reduce the time of the experiment by half, which was highly desirable considering changeable weather conditions, where only a cloudy state was acceptable. Respondents were sitting on adjoining chairs and a digital camera was mounted between them at eye level (1.2 m). The camera was oriented toward the window and captured the scene with both shelves. This was done to get angle of view approximated to the participants' angles of view and reduce the complexity of the experiment but still photograph as quickly and as accurately as possible. Because the distance between the viewpoint of camera and the viewpoint of each participant was only 35 cm and the distance from each of those viewpoints to the objects was a minimum of 3.6 m, the largest difference in the view angle between the camera and a participant was 4.63° and thus negligible. This allows us to assume that directivity of specular reflections appearing on the glossy objects was registered by the camera similar to the participants' vision but not equal to it because a camera is not a physical equivalent to the human eye.

At the beginning of each experimental session the following procedure was performed: photographing of the set of 11 low dynamic range images that lasted one or two minutes, manual measuring of luminance in certain points of the observed scene (1–2 minutes), and explanation of the terms used in the questionnaire and answering the participants' questions. Normally it took approximately 15 minutes and allowed participants to adapt to the existing lighting conditions. The survey answering took no more than 1 hour, although the time was not limited. Participants were asked not to communicate with each other during this time.

3.2. Participants

Thirty-two subjects participated in the experiment (20 female, 12 male). Subjects were of different nationalities, had various educational and professional backgrounds, and were naïve to this type of experiment. Their ages varied from 14 to 74, with an average age was 32.1 years, mode of 26 years, and standard deviation of 10.9 years.

To ensure normality of the respondents' vision they were tested using a Snellen chart, the Ishihara test for color vision, and a contrast sensitivity test (Vigra program); normality of 3D vision was self-reported. According to performed controls all participants were allowed to participate in the experiment who had normal or corrected-to-normal vision.

3.3. Questionnaire

A two-part questionnaire was provided for the survey. Each part was dedicated to one of the two shelves with the 3D objects and included two simple questions concerning contour distinctness of the observed object and its shape and detail distinctness.

According to the short explanation given to the participants, the contour was associated with the border between the object and background; the shape represented the form of the object being concave or convex; and all face parts such as nose, eyebrows, cheeks, mouth, and forehead were related to the details of the mask. A four-point ordinal scale for the range of the contour, shape, and detail distinctness was provided in the questionnaire and contained following options:

- Indistinguishable (invisible shape and details)
- Just distinguishable (barely visible shape and details or some of the details of the mask)
- Well distinguishable (well-visible shape and details of the mask except some parts or elements)
- Perfectly distinguishable (the whole mask is well visible)

Participants were allowed to start their evaluation from any mask presented on the particular shelf, which helped to provide randomization of mask observation, although this was not systematically implemented because participants chose themselves.

Because the authors were eager to obtain more information on visibility of particular areas of the masks, the respondents were asked to specify indistinguishable and perfectly distinguishable zones as drawings included in the questionnaire form. This graphical information was considered during the luminance measuring and analysis process. An example from the participants' questionnaire with outlined perfectly distinguishable and indistinguishable zones of the observed mask is presented in the last figure.

During the experimental session, an alternating order of shelf observation was maintained. This means that participants observed different shelves during the first half of the experiment and others during the second part without changing their sitting position. This order was accomplished to prevent disturbance of one respondent by another and was controlled for during the statistical analysis (specified as "order" factor in Tables 2–5).

3.4. Camera Settings and Manual Measurements

A Nikon D600 digital camera fitted with a full-frame (AF DX Fisheye-Nikkor 10.5mm f/2.8G ED) lens was used for taking 17 sets of low dynamic range images assigned for further luminance measurements. The camera was mounted on a tripod to ensure sharpness of the photographs. It remained untouched during the experiment and was controlled by a computer with Nikon Camera Control Pro software. The following camera settings were used: white balance, cloudy; auto-bracketing, off; sensitivity, 200 ISO; auto focus, auto; and aperture, fixed, f/4. Exposure variations were achieved by varying the shutter speed in manual exposure mode with step 1 EV.

Calibration of the assembled HDR images requires manually measured luminance values as the reference; measuring was performed using a Minolta LS-100 luminance meter. The four specific points were targeted in the scene and the procedure was repeated for each new photographing session. Merging low dynamic range images into high dynamic range images and calibration were performed using Photosphere software [Ward 2005]. The resolution of the final luminance maps was 3936 × 2624 pixels.

3.5. Proposed Luminance-Based Measures

An important task after finishing data collection was to determine the luminance-based measures that would be tested as predictors of shape and detail visibility of the observed 3D objects. These should be easy to obtain, simple to interpret, precise, and universal for various objects and lighting situations. The possible choice of measures was limited by technical options of the software.

Luminance measurements were performed using two programs: Photosphere [Ward 2005] and hdrscope [Kumaragurubaran and Inanici 2013]. In particular, the measurements of the whole area of the image, squared areas of interest, and point measurements were conducted in the Photosphere program. Luminance measurements of multiple selected regions and figures of complex geometry were carried out using the hdrscope software.

Due to technical restrictions of the currently available programs for analysis of luminance maps, which provide simple basic tools for area selection by outlining particular zones, the process of selection of various regions of interest was performed manually. Therefore, while selecting the foreground or mask area, the eyes were included in the whole outline. Considering that the eye area constitutes at maximum

	Mean luminance of the mask			
	B	**SE**	**β**	**p**
Mean luminance of the mask	0.092	0.012	0.419	< 0.001
Background colour (white backgrounds = 0, the medium dark bkgr. = 1, the dark bkgr. = 2)	0.455	0.089	0.143	< 0.001
Glossiness (0=matte, 1=glossy)	0.594	0.124	0.140	< 0.001
Chromaticness (0=achromatic, 1=chromatic)	-0.293	0.113	-0.069	0.010
Order of observation (0=matte masks first, 1=glossy masks first)	-0.723	0.367	-0.170	0.049
Level 2 variance "shape and details"	0.975	0.278		< 0.001
$\mathbf{R^2_{level\ 1}}$	0.270			
$\mathbf{N_{level\ 1}}$	1145			
$\mathbf{N_{level\ 2}}$	32			

TABLE 2. *Regression analysis results: mean luminance of the mask as a predictor of shape and details distinctness (controlled for background colour, glossiness, chromaticness order of observation, and person effects).*

2.5% of the total mask area (depending on the placement of each mask because they were seen slightly differently due to position on the shelf and distance from the observer), the possible error will not be high.

The first measure used in the subsequent analyses was the mean luminance of the foreground (the Venetian mask). This measure was chosen as the simplest possible measure and was imposed by the logical assumption that shadows revealing visibility of the various forms are more visible on lighter objects. However, the kind of background can be a factor affecting perception and influencing adaptation of the visual system; therefore, the background factor was controlled for during the statistical analysis.

The second measure tested was the luminance ratio; that is, the ratio between the mean luminance of the mask and the mean luminance of the background. This measure relates to the contrast, which might be significant factor for an object's shape and detail distinctness.

The third measure was the ratio between the maximum luminance value of the mask and the mean luminance of the mask, because it was presumed that higher ratios might reflect better detail visibility. Similar assumptions concerned the last measure of shape and detail distinctness, which was standard deviation of the luminances of the foreground.

Additionally histograms and false color images of the obtained luminance maps were examined using hdrscope [Kumaragurubaran and Inanici 2013]. The program enables obtaining and saving the raw luminance data of the selected regions of interest, namely,

	Luminance ratio ≤ 1				**Luminance ratio ≥ 1**			
	B	**SE**	**β**	**p**	**B**	**SE**	**β**	**p**
Luminance ratio	1.978	0.501	0.259	< 0.001	0.075	0.017	0.156	< 0.001
Glossiness (0=matte, 1=glossy)	2.343	0.304	0.531	< 0.001	0.576	0.130	0.150	< 0.001
Chromaticness (0=achromatic, 1=chromatic)	-0.112	0.258	-0.025	0.664	-0.258	0.133	-0.067	0.052
Order of observation (0=matte masks first, 1=glossy masks first)	-0.493	0.446	-0.115	0.270	-0.858	0.339	-0.224	0.011
Level 2 variance "shape and details"	1.091	0.463		0.019	0.780	0.236		0.001
$R^2_{level\ 1}$	0.278				0.102			
$N_{level\ 1}$	256				893			
$N_{level\ 2}$	32				32			

TABLE 3. *Regression analysis results: luminance ratio as a predictor of shape and details distinctness (controlled for glossiness, chromaticness, order of observation, and person effects).*

the information according to each pixel in the scene or selected zone, its luminance values, the number of pixels with equal luminance, et cetera. Results acquired from the analysis of this information will be discussed further.

4. STATISTICAL ANALYSIS AND RESULTS

To process the data that might be affected by a wide spectrum of factors of a real daylit environment, a two-level ordinal regression analysis was chosen. The analysis was conducted as an ordinal (and not linear) regression because the dependent variable "distinctness of the shape and details" had neither equidistant nor normally distributed answers across the categories.

The independent variables for statistical analysis were as follows:

1. Mean luminance of the mask
2. Luminance ratio
3. Ratio between the maximum luminance value of the mask and the mean luminance of the mask
4. Standard deviation of the luminance of the foreground

The additional independent control variables were as follows:

1. Type of surface (glossy or matte)
2. Coloration (chromatic or achromatic)

	Matte masks				**Glossy masks**			
	B	**SE**	**β**	**p**	**B**	**SE**	**β**	**p**
Ratio between maximum luminance value on the mask and mean luminance of the mask, L_{max}/L_{mean}	-0.681	0.091	-0.338	<0.001	0.030	0.022	0.061	0.179
Chromaticness (0=achromatic, 1=chromatic)	-0.393	0.165	-0.098	0.017	-0.026	0.164	-0.007	0.872
Order of observation (0=matte masks first, 1=glossy masks first)	-0.859	0.406	-0.214	0.034	-0.631	0.325	-0.171	0.052
Level 2 variance "details"	1.103	0.346		0.001	0.639	0.218		0.003
$R^2_{level\ 1}$	0.183				0.033			
$N_{level\ 1}$	571				574			
$N_{level\ 2}$	32				32			

TABLE 4. *Regression analysis results: luminance ratio between maximum luminance of the mask and mean luminance of the mask as a predictor of shape and details distinctness separated for matte and glossy masks (controlled for chromaticness, order of observation and person effects).*

3. Lightness of the background (white, medium dark, and dark)
4. Order of observation of the shelves

These variables were controlled for by entering them as additional predictors in the regression analyses, which adjusts the regression weight for the main independent variables accordingly. The regression weights for the control variables are reported in the results tables (Tables 2–5).

The dependent variable was shape and detail distinctness.

The experimental design with 32 participants who assessed 36 masks each resulted in a data structure where 36 evaluations were nested within each respondent. This means that the personal characteristics of each person will affect the ratings for all 36 masks each person rated and so on. This leads to a dependency of the ratings of each person, which violates the assumption of unrelated residuals in a normal regression analysis. Therefore, a multilevel regression analysis was used instead. The main analysis was conducted at the object level, but the person-specific variance in the evaluations across all masks was modeled simultaneously and taken out of the regression equation at the mask level. For information purposes, the amount of variance located at the person level is listed as level 2 variance in Tables 2–5.

The characteristics of the luminance ratio are different below and above the zero contrast point 1, because the values below this contrast point cannot be equally compared to values above it. Therefore, two separate subanalyses were conducted (left and right half of Table 3).

Results show that three of the tested measures are good predictors of the distinctness of the shape and details of the observed masks. These measures are the luminance ratio,

	All masks			
	B	**SE**	**β**	**p**
Standard Deviation of the luminances of the mask	0.145	0.020	0.372	< 0.001
Glossiness (0=matte, 1=glossy)	0.585	0.126	0.141	< 0.001
Chromaticness (0=achromatic, 1=chromatic)	-0.391	0.114	-0.094	0.001
Order of observation (0=matte masks first, 1=glossy masks first)	-0.756	0.346	-0.183	0.029
Level 2 variance "details"	0.853	0.246		0.001
$\mathbf{R^2_{level\ 1}}$	0.232			
$\mathbf{N_{level\ 1}}$	1143			
$\mathbf{N_{level\ 2}}$	32			

TABLE 5. *Regression analysis results: standard deviation of the luminances of the mask as a predictor of shape and details distinctness (controlled for glossiness, chromaticness, order of observation and person effects).*

mean luminance of the observed object, and standard deviation of the luminances of the object. The ratio between maximum luminance of the mask and the mean luminance of the mask appeared to be the least precise measure and suitable only for matte objects.

Table 2 presents the results f or the mean luminance of the mask being the main predictor of the object's shape and detail distinctness. It has a highly significant and strong positive impact for all masks, both glossy and matte. Background color was added here as an additional factor influencing perception. Background color has an impact on visibility of shape and details, showing that the darker the background, the better the visibility. The words "visibility" and "distinctness" will be used as synonyms defining the clarity and ease of an object being seen by subjects. The factor "glossiness" included not only the type of coating on the masks but also the kind of illumination because both aspects were confounded; that is, sidelit glossy masks on shelf A and diffusely illuminated matte masks on shelf B. This factor has a weak but still statistically significant impact on shape and detail distinctness. This means that glossiness slightly enhanced visibility; in other words, glossy sidelit masks received slightly higher distinctness ratings than matte objects. "Chromaticness" expresses the state of the mask being chromatic or achromatic and had a rather low impact, making the object's shape and details a bit less visible in comparison to situations with achromatic color combinations. Order of observation is the factor that controlled the potential effect of the order of observation of the shelves, because it was noted already that two people started observation from different shelves—one from sidelit shelf A and another one from the diffusely illuminated shelf B. In this analysis the order is just a significant factor.

Probability plots (Fig. 2) show the probability of four types of observed objects (matte/achromatic, matte/ chromatic, glossy/achromatic, glossy/chromatic) being evaluated as proposed in the questionnaire and corresponding values of the main

	Perfectly distinguishable shape and details, 80% probability			
	Matte/ achromatic combination	**Matte/ chromatic combination**	**Glossy/ achromatic combination**	**Glossy/ chromatic combination**
Mean luminance of the mask, (cd/m^2)	49	52	43	46
Luminance ratio between maximum luminance of the mask and mean luminance of the mask (excl. masks # 5, 8, 12, 15)	3.55	3.65	-	-
Standard Deviation of the luminances of the mask	30	32.5	26	28.5

TABLE 6. *Threshold values for mean luminance of the mask, luminance ratio between maximum luminance of the mask and mean luminance of the mask (excluding situations with the strong negative contrast, namely masks # 5, 8, 12, 15), and standard deviation of the luminances of the mask measures of shape and details distinctness.*

predictor. By using this result it is possible to specify threshold values for mean luminance (and other predictors tested) that will allow avoiding worst-case scenarios when the object is invisible or hardly visible.

Table 3 represents the results for luminance ratio between the object and its background. This is a statistically highly significant predictor of shape and details visibility of masks, with a positive effect for both dark objects on a light background and light objects with a darker background. The results show that for dark masks on light backgrounds the closer the ratio is to one (which is the zero contrast point), the better the shape and detail distinction is. For light masks on dark backgrounds, the distinctness value increases as the distance from the zero contrast point increases. The control variables that are significantly influential include glossiness, which again has a positive effect, enhancing objects' shape and detail discrimination, and order of observation.

The luminance ratio between maximum luminance of the mask and mean luminance of the mask was proposed as a possible measure because it was assumed that the light areas on the mask could be anchoring elements for vision, which can affect mask

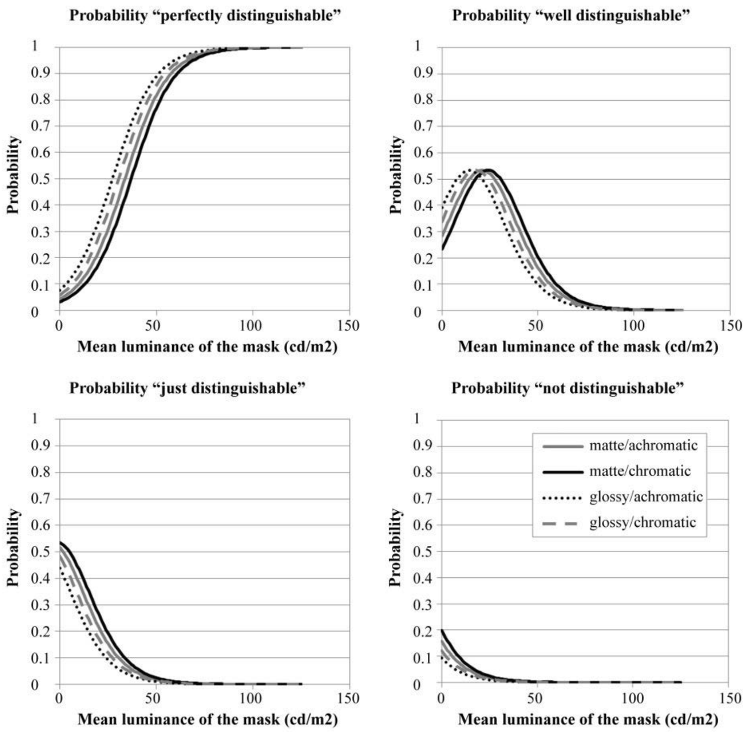

Fig. 2 *Probability curves for the four categories of the questionnaire, four combinations of control variables, and mean luminance of the mask as a main predictor.*

perception.

In Table 4 the results are displayed separately for two types of objects—glossy and matte masks. This was done because the predictor luminance ratio between the maximum luminance of the mask and mean luminance of the mask is significant only for matte masks. The other factors are insignificant for matte masks. Further, we performed another version of this regression analysis and narrowed down the types of matte masks excluding four masks that had a strong negative contrast (dark mask on light background). Although it refined the results, it did not lead to fundamental changes. In the Figure 3 the probability plots referring to these results can be observed.

The last predictor tested was the standard deviation of luminance values of the mask. This predictor is statistically significant and one of the most powerful. All of the other factors are also significant: glossiness has a highly significant and positive effect, making discrimination of the shape and details of the object a little easier; chromaticness complicates shape and detail discrimination; and order of observation has a rather low negative impact.

Following the results from the probability plots it is possible to determine the threshold values for this predictor. Thus, the shape and details of the masks will be likely

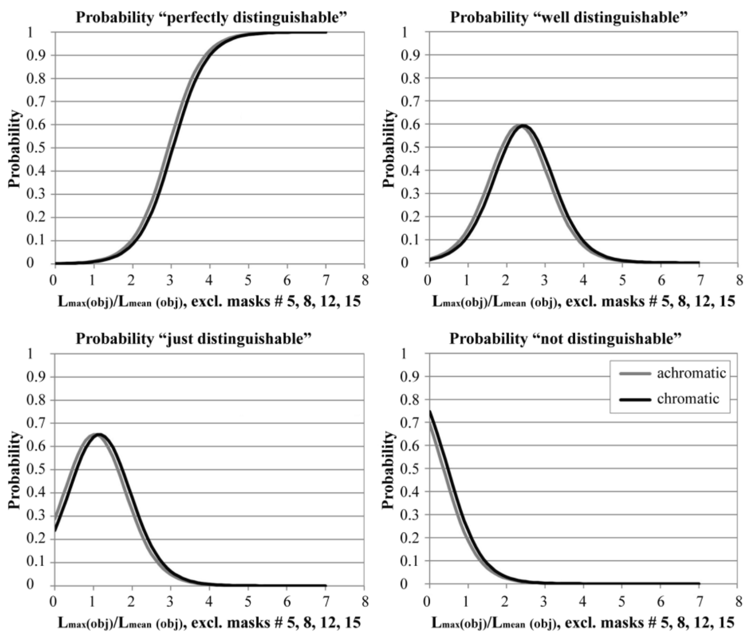

Fig. 3 *Probability curves for the four categories of the questionnaire, two types of control variables, and luminance ratio between maximum luminance and mean luminance of the object as a main predictor.*

evaluated as perfectly distinguishable by 80% of the observers if the standard deviation of the luminances of the object are not lower than 26 for glossy achromatic objects, 28.5 for glossy chromatic objects, 30 for matte achromatic objects, and 32.5 for matte chromatic objects (Fig. 4, Table 6).

Table 6 shows the threshold values based on an 80% probability for three of the four tested predictors that are statistically significant. This comprehensive table indicates clearly certain values of the tested measures that may also be applied as numeric reference points ensuring perfect visibility of shape and details of the 3D objects.

Additional to the luminance-based measures testing, a histogram analysis of the masks and their backgrounds was performed. Unfortunately, due to restrictions in technical methods that could be used for histogram analysis, this analysis resulted only in general observations. In Fig. 5 the most explicit examples of the observation are presented. Four masks that were rated on average as "indistinguishable" to "perfectly distinguishable" are presented (matte mask #4, glossy mask #14, glossy mask #3, and glossy mask #17). These are the masks that were evaluated by most of the participants as belonging to each of the categories. Histograms of the images that were chosen for this example belong to a person who evaluated the masks in accordance with the majority of participants.

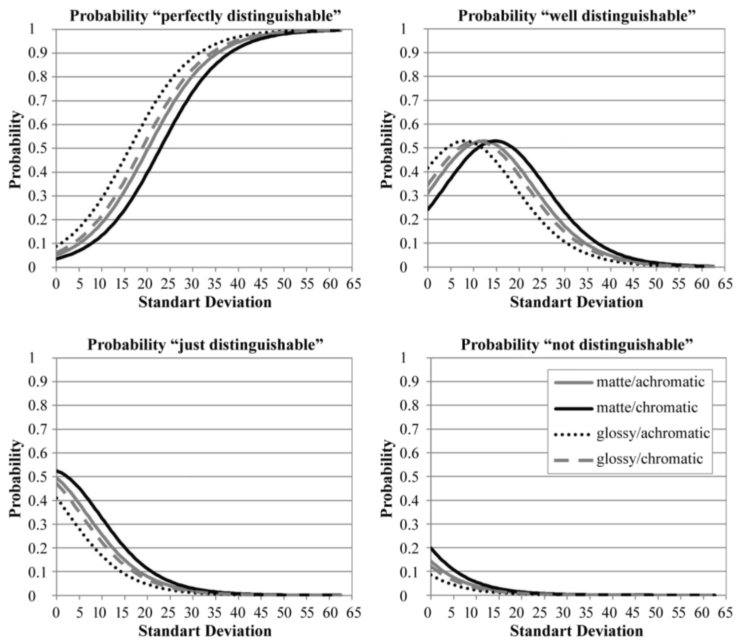

Fig. 4 *Probability curves for the four categories of the questionnaire, four combinations of control variables, and standard deviation of the luminance values of the object as a main predictor.*

The statistical data of the selected regions of the masks (matte mask #4, glossy mask #14, glossy mask #3, and glossy mask #17, Fig. 5) was obtained using hdrscope [Kumaragurubaran and Inanici 2013]. The program allows saving the data from the whole luminance maps or selected regions of an image as an MS Excel file that can be analyzed in more detail. Thus, the information contained in the file consist of the type of region selected (circle/square/polygon), number of vertices of these regions, X and Y coordinates of each pixel of the selected regions, and their luminance values. Therefore, it is possible to perform analysis regarding the luminances of the background and foreground of the particular high dynamic range image. In our case, the graph was

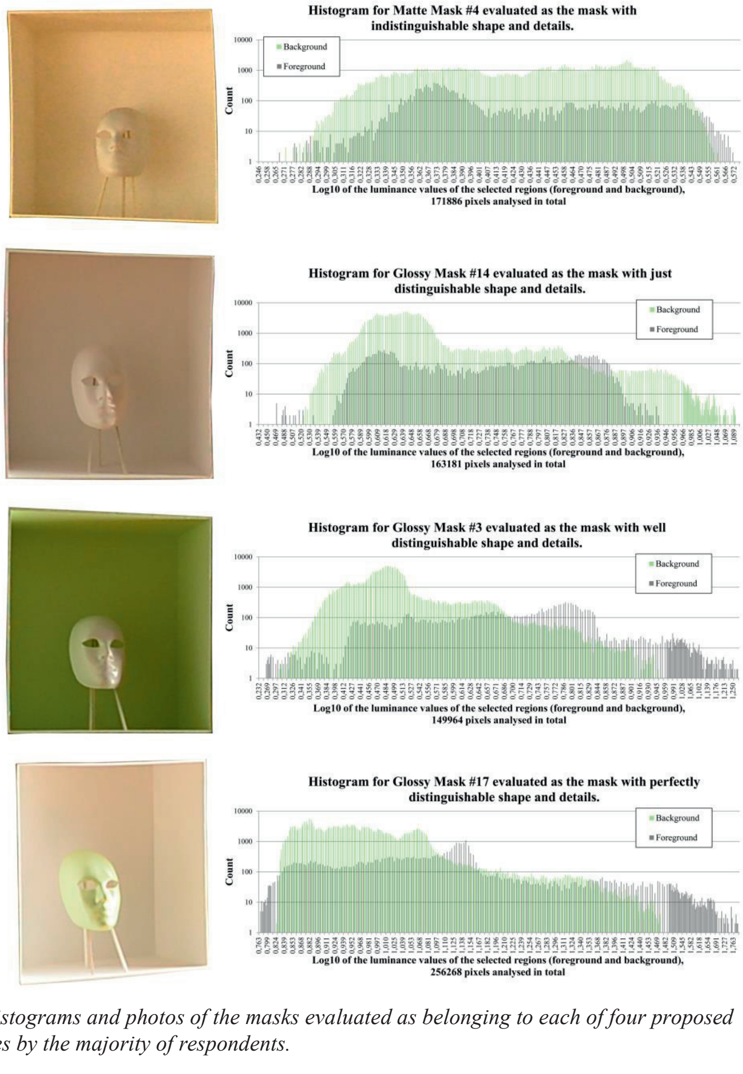

Fig. 5 *Histograms and photos of the masks evaluated as belonging to each of four proposed categories by the majority of respondents.*

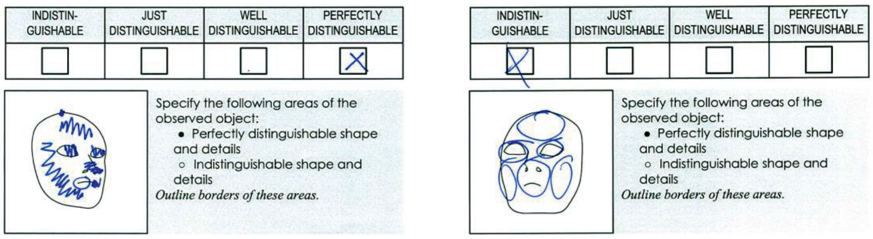

Fig. 6 *Drawing from the questionnaire of one of the participants. On the left side (a) the mask with perfectly distinguishable shape and details is presented, with perfectly visible areas specified by the dark hatching. On the right side (b) the mask with indistinguishable shape and details is presented. Invisible areas are outlined without any hatching.*

created where common logarithms of luminances of both selected mask and background were represented on the X axis, and the count (Y axis) represented the frequency of certain luminance values that appeared on the background or foreground in logarithmic scale. This means that the graphs produced show the distribution and frequency of luminance values of the selected mask and its background. Therefore, it is easy to observe some important effects here.

As can be seen in Fig. 5, the histograms for the two regions of interest (foreground and background) almost fully overlap for the mask with indistinguishable shape and details. The histograms of glossy mask #14 (just distinguishable) include more divergent zones of the object's luminances and background luminances, although their peaks are still in a similar region of the histogram. The third histogram of glossy mask #3 with a well-visible shape and details includes even more divergent zones with a less uniform distribution of the luminance values along the X axis and more prominent peaks for both regions of interest tending in opposite directions from each other. The last histogram for the "perfectly distinguishable" category shows a tendency similar to those from the "well distinguishable" category. The difference between foreground and background regions is a little more explicit here, although it could be challenging to compare these two histograms (well- and perfectly distinguishable shape and details) based only on general visual observation.

However, excluding overlapping areas or areas with equal luminance values (based on certain threshold values that can be determined by the researcher in each particular case) from the high dynamic range image, it is practicable to interconnect the remaining areas with a subjective evaluation of their shape and detail visibility. In other words, certain remaining areas of the luminance values on the graph may indicate the determined degree of shape and detail distinctness of the observed object.

In our case, the respondents' drawings of masks evaluated as objects with perfectly visible shape and details showed clearly that all of the elements except the smallest are easily distinguishable (Fig. 6a), whereas the drawings from the "indistinguishable" category indicate that in most of the drawings only peculiar convex elements such as the nose were visible (Fig. 6b). These data can be analyzed using other currently available methods (but not included in the scope of the current study) as in a paper by Lu and others [2014] and could lead to interesting conclusions in the future, even if it is difficult to perform this kind of analysis using the current tools for high dynamic range image processing. After development of this method in terms of ease of use it could become a new tool for predicting a real 3D object's visibility.

Processing of the histograms of the selected foreground and background as described earlier seems to us as a tool with good perspectives. With the numerous options of image processing developed today, it could be possible to analyze and predict an object's visibility based on its high dynamic range image.

5. DISCUSSION

Statistical analysis of the results demonstrated that luminance-based measures of 3D objects' shape and detail visibility can be regarded as useful and promising measures of light modeling. Not all of the measures are equally precise and applicable for all types of the objects (glossy or matte, chromatic or achromatic, dark or light). However, finding the best possible measures, used separately or complementing other measures and methods, can provide an advantage for architects and lighting designers in predicting light modeling in real environments.

In this article we focused on four possible measures: the mean luminance of the mask, luminance ratio between the mean luminance of the object and mean luminance of the background, luminance ratio between the highest luminance value of the mask and its mean luminance, and standard deviation of the luminance point measures of the mask.

The mean luminance of the mask as a separate measure could be assessed as an uninformative measure as is. The main information that it provides is confirmation of the fact that the lighter the object is, the better its shape and detail visibility. At certain values of mean luminance of the mask (numbers obtained from the probability plots), the object's shape and details are likely evaluated as perfectly visible. In our case, an 80% probability that the masks' shape and details are perfectly visible is reached at an average luminance of 43–52 cd/m2 depending on the type of mask (Table 6). However, an application of this measure alone could be problematic because the mean luminance value of the object itself seen in different lighting conditions and various surroundings theoretically may be interpreted differently, whereas in a similar lighting situation as was during the experiment, threshold values may be a rather useful tool. This means that below certain threshold values, determined according to probability plots, an object's shape and details will be hardly visible.

The tests of the measure luminance ratio also yield contradictory results, because it is basically the lightness of the object (as in the first measure) that has an impact here. However, an interesting conclusion can be made based on the results that glossiness of the object also had a strong influence on perception, especially for situations where the object was dark. However, for light objects this factor was also important. Glossiness intensifies reflections on the masks and improves visibility of its shape and details.

The next predictor tested was the luminance ratio between the highest luminance value of the mask and its mean luminance. Surprisingly, this measure showed rather weak or limited results in comparison to the other measures. It is applicable only for matte objects on a darker background.

The standard deviation as a measure reflecting the variability of luminances at different points across the object showed promising results and high consistency with survey results. This measure is applicable for any of the tested objects, namely, glossy or matte, chromatic or achromatic, light or dark. Yet glossiness has an independent additional effect on shape and detail distinctness, again slightly enhancing its visibility. Chromaticity influenced in the other direction, reducing the visibility of details of the masks.

It is necessary to point out that R2 values of the proposed predictors of shape and detail distinctness are slightly lower than those of contour distinctness described in a previous article [Zaikina and others 2015]. This is because shape and detail visibility is a more complex stimulus that is highly affected by other factors—for example, angular size of the object—that were not included in the analysis. In other words, more (unmeasured) factors seem to affect shape and detail distinctness than contour distinctness.

6. FUTURE VALIDATION

Light modeling is an important attribute of quality lighting and comfortable visual communication, naturalness of the observed objects, and faces in the surrounding space. New methods and fast developing technologies provide opportunities to study important aspects of lighting differently than it has been done before, and high dynamic range imaging is one of these new methods.

A great number of lighting designers, architects, and engineers actively use computer simulation tools that enable modeling, testing, and visualization of architectural objects with various possible lighting solutions. Therefore, the luminance images obtained from the simulations as well as real high dynamic range images can become a rich source of data, and proposed luminance-based measures could be used as a tool for visibility prediction of 3D objects. Results described in this article are restricted by the existing conditions of the experiment and therefore they should be replicated with other objects and under different conditions to confirm reliability of their use. However, the results show that luminance-based measures are highly correlated with subjective assessment of the objects' visibility and therefore they are substantially useful instruments for light modeling in the near future.

7. CONCLUSION

The aim of the current study was to propose and test some possible luminance-based measures of 3D objects' shape and detail distinctness as a component of the light modeling concept. Previously known measures for light modeling are based on illuminance, whereas we turned to a method based on high dynamic range imaging because luminance forms what our eyes see and therefore is closer to human perception. This is a new method and the article is a first step toward finding more reliable measures for light modeling.

The analysis showed that some of the proposed measures such as the mean luminance of the mask, standard deviation of the luminances of the mask, and luminance ratio between an object and its background correlate very well with subjective assessment of the shape and detail distinctness of the masks. As simple-to-obtain and basic measures, they complementing each other and are good instruments for analysis and prediction of the 3D objects' visibility; in addition, their threshold values might be useful and promising for further development and practical use.

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REFERENCES

Anaokar S, Moeck M. 2005. Validation of high dynamic range imaging to luminance measurement. LEUKOS. 2(2):133-144.

Cai H. 2011. Camera aided luminance measurement of the luminous surfaces of different light sources. In: Proceedings of the 2011 Architectural Engineering Conference; 2011 March 30-April 2; Oakland, California. Editors: Abraham C. Lynn, Robert Reitherman. p. 272-279.

Chung T, Ng R. 2010. Variation of calibration factor over time for high dynamic range photography in a single daylit interior scene. Journal of Light & Visual Environment. 34(2):87-93.

Cuttle C. 2008. Lighting by design. Amsterdam: Elsevier. 247 p.

Dehoff P. 2014. Measures for a better quality in lighting. A journey through recent activities in applications and standards. In: Proceedings of CIE 2014, Lighting Quality and Energy Efficiency; 2014 April 23-26; Kuala Lumpur, Malaysia. p. 348-356.

European Committee for Standardization. 2011. Light and lighting— lighting of work places. European Committee for Standardization. EN 12464-1.

Gilchrist AL. 2007. Lightness and brightness. Curr Biol. 17(8):R267-R269.

Hopkinson RG, Petherbridge P, Longmore J. 1966. Daylighting. Heinmann. 606 p.

Inanici M. 2006. Evaluation of high dynamic range photography as a luminance data acquisition system. Lighting Res Technol. 38(2):123-136.

Kumaragurubaran V, Inanici M. 2013. Hdrscope: high dynamic range image processing toolkit for lighting simulations and analysis. In: International building performance simulation association (IBPSA) 2013 conference; 2013 Aug. 25-28; Chambery, France. p. 3400-3407.

Lu J, Sang N, Hu Y, Fu H. 2014. Detecting citrus fruits with highlight on tree based on fusion of multi-map. Optik. 125(8):1903-1907.

Matusiak BS. 2002. A modelling sensor designed to be used in the lighting practise in cases where there it is essential to compare the modelling ability of light in an important point in a room for different lighting alternatives. CIE Central Bureau.

Saraiji R, Oommen MS. 2014. Dominant contrast as a metric for the lighting of pedestrians. Lighting Res Technol. 0:1-15.

Schielke T. 2013. Tutorial: rationale, concepts, and techniques for lighting vertical surfaces. LEUKOS. 9(4):223-243.

Tyukhova Y, Waters C. 2014. An assessment of high dynamic range luminance measurements with LED lighting. LEUKOS. 10(2): 87-99.

Valberg A. 2005. Light, vision, color. UK: Wiley. 462 p.

Veitch JA. 2004. Principles of healthy lighting: highlights of IE TC6-11's. Canada: Institute for Research in Construction. No. 1009370. 8 p.

Veitch JA, Julian W, Slater AI. 1998. A framework for understanding and promoting lighting quality. J. A. Veitch, Ed. Proceedings of the First CIE Symposium on Lighting Quality. Vol. CIE-x015-1998. Vienna, Austria: Commission Internationale de l'Eclairage Central Bureau. p. 237-241.

Ward G. 2005. Photosphere. Anyhere software. <http://www.anyhere.com/> Accessed 2013 Aug.

Zaikina V. 2012. Light level perception in interiors with equiluminanat colours. In: Nordic light and colour. Trondheim (Norway): NTNU–The Faculty of Architecture and Fine Art. Barbara S. Matusiak, Karin F. Anter, Eds. p. 105-122.

Zaikina V, Matusiak BS, Klöckner CA. 2015. Luminance-based measures of contour distinctness of 3D objects as a component of light modeling. LEUKOS. 11(1):31-45.

Paper V

Verification of the accuracy of luminance-based light modeling metrics by numerical comparison of photographed and simulated HDR images

Veronika Zaikina, Barbara Szybinska Matusiak

Submitted paper, under review. Updated with minor changes on 19.04.2015.

ABSTRACT

The study verifies the accuracy of previously developed luminance-based metrics 1,2 of light modelling (i.e. the distinctness of contour, shape and details of daylit 3D objects) trough comparison of numerical values of the metrics obtained from photographed and simulated HDR images. The analysis of the luminance data of eight photographed and eight simulated HDR images of Venetian masks showed that the mean relative error of all the tested metrics was 14.78%. The minimum average relative error was 7.91 %, and the maximum error (found for only one metric) was 27.75 %. The glossy objects had higher error rates than matte objects tested within the experiment. Additionally, the variation of luminance-based metric values obtained from simulated and photographed HDR images due to the colour of the mask versus the colour of the background was compared with variation of illuminance-based modelling index. It became evident that luminance-based metric showed larger variability of the numerical values and higher consistency with subjective perception of objects. It is remarkable since the set-up had low light level resulting with hardly visible shape and details of the objects. The results of this study makes an important contribution confirming that the developed metrics, if used in lighting simulations made with the advanced computer programs, will give results close to real room-real time study obtained with the help of HDR imaging technology. This confirms robustness of the metrics and encourages use of the luminance-based light modeling metrics also in computer lighting simulations.

Keywords: *luminance-based metrics, light modelling, photographed and simulated HDR images, modelling index, cylindrical illuminance.*

Is not included due to copyright

Other contributions not included in the scope of this thesis

Zaikina, Veronika; Matusiak, Barbara Szybinska. Nye Luminansbaserte Målinger For Lysmodelleringsanalyse. *Lys, magasin for belysning og lysdesign.* 2014 (4): 36-38

Orleanski, Krzysztof; Angelo, Kine; Matusiak, Barbara; Zaikina, Veronika; Booker, Charles Alexander; Moscoso, Claudia; Valberg, Arne. *Synergy of music and stereoscopic images and sequences. Meta.morf Biennale.* 2012.

Zaikina, Veronika; Matusiak, Barbara Szybinska. Brightness Perception And Equiluminant Colours In Interiors. *Nordic Lighting Conference*; 2012 (Poster presentation)

Glossary

This chapter contains terminology used in current thesis and the articles presented in ***Chapter 8* - *Appended papers***. All terms are presented in alphabetical order and are followed by their standard symbols or abbreviations, their defining equations, and their definitions.

Most of the definitions in this glossary have been adapted from:

[1] – Light, vision, color book written by Arne Valberg (Valberg 2005)

[2] - The IESNA LIGHTING HANDBOOK, Ninth Edition (Rea 2000)

***Achromatic colours*[1]** colours with no chroma, i.e. black, grey and white.

***Adaptation*[1]** the ability of the visual organ to adjust its sensitivity and function to the prevailing light level and colour. The term can be used for the process itself or for the final state. The retina is said to be light adapted (corresponding to photopic vision) or dark-adapted (scotopic vision). The size of the pupil plays only a minor role in adaptation.

***Chromatic adaptation*[2]** the process by which the chromatic properties of the visual system are modified by the observation of stimuli of various chromaticities and luminances.

***Chromatic color*[2]** perceived color possessing a hue. In everyday speech, the word color is often used in this sense in contradistinction to white, gray, or black.

***Chromaticity*[1]** two-dimensional colour coordinates (r,g) in a unit colour triangle $R + G + B = 1$, or the (x,y)-coordinates in the CIE system for colour measurement, in a plane where the sum of tristimulus values $X + Y + Z = 1$.

***Chromaticness*[2]** the attribute of a visual sensation according to which the (perceived) color of an area appears to be more or less chromatic.

***Color*[2]** the characteristic of light by which a human observer can distinguish between two structure-free patches of light of the same size and shape. See light source color and object color.

***Contrast*[1]** Michelson contrast, $C_{Mich} = (L_{max} - L_{min})/(L_{max} + L_{min})$, is commonly used for periodic stimuli. Weber contrast, $C_{Web} = (L - L_b)/L_b = \Delta L/L_b$, where L stands for stimulus luminance and L_b for background luminance. Combined cone contrast, $C_{LMS} = [(1/3)(C_L^{\,2} + C_M^2 + C_S^2)]^{1/2}$, where C_L, C_M and C_S are the individual cone contrast for the absorptions (excitations) in L-, M- and S-cones.

***Contrast sensitivity*[2]** the ability to detect the presence of luminance differences. Quantitatively, it is equal to the reciprocal of the brightness contrast threshold.

Daylight factor[2] a measure of daylight illuminance at a point on a given plane, expressed as the ratio of the illuminance on the given plane at that point to the simultaneous exterior illuminance on a horizontal plane from the whole of an unobstructed sky of assumed or known luminance distribution. Direct sunlight is excluded from both interior and exterior values of illuminance.

Discrimination[1] the ability to identify an object or an image after distinguishing it from the background. Discrimination usually requires a larger contrast than detection. One talks about colour discrimination when one sees a qualitative difference between two colour stimuli.

Glare[2] the sensation produced by luminances within the visual field that are sufficiently greater than the luminance to which the eyes are adapted, which causes annoyance, discomfort, or loss in visual performance and visibility. See blinding glare, direct glare, disability glare, and discomfort glare.

Note The magnitude of the sensation of glare depends on such factors as the size, position, and luminance of a source; the number of sources; and the luminance to which the eyes are adapted.

Hue[1] the hue of the colour can be characterized by relative proportions of the closest elementary hues yellow, red, blue and green. They can be ordered in a hue circle.

Illuminance[2], $E = d\Phi/dA$ the areal density of the luminous flux incident at a point on a surface.

Isoluminance[1] a situation where different colour stimuli have the same luminance.

Light[2] radiant energy that is capable of exciting the retina and producing a visual sensation. The visible portion of the electromagnetic spectrum extends from about 380 to 770 nm.

Note The subjective impression produced by stimulating the retina is sometimes designated as light. Visual sensations are sometimes arbitrarily defined as sensations of light, and in line with this concept, it is sometimes said that light cannot exist until an eye has been stimulated. Electrical stimulation of the retina or the visual cortex is described as producing flashes of light. In illuminating engineering, however, light is a physical entity--radiant energy weighted by the luminous efficiency function. It is a physical stimulus that can be applied to the retina. See spectral luminous efficacy of radiant flux and values of spectral luminous efficiency for photopic vision.

Light adaptation[2] the process by which the retina becomes adapted to a luminance greater than about 3,4 cd/m^2.

Illuminance (footcandle or lux) ***meter***[2] an instrument for measuring illuminance on a plane. Instruments that accurately respond to more than one spectral distribution are color-corrected, that is, the spectral response is balanced to $V(\lambda)$ or $V'(\lambda)$. Instruments that accurately respond to more than one spatial distribution of incident flux are cosine-corrected, that is, the response to a source of unit luminous intensity, illuminating the detector from a fixed distance and from different directions, decreases as the cosine of the angle between the incident direction and the normal to the detector surface. The instrument is comprised of some form of photodetector with or without a filter driving a digital or analog readout through appropriate circuitry.

Lambertian surface[2] a surface that emits or reflects light in accordance with Lambert's cosine law. A lambertian surface has the same luminance regardless of viewing angle.

Lambert's cosine law[2], $I_\theta = I_0 \cos\theta$ the law stating that the luminous intensity in any direction from an element of a perfectly diffusing surface varies as the cosine of the angle between that direction and the perpendicular to the surface element.

***Luminance*[2]**, $L = d^2\varphi/(d\omega\ dA\ \cos\theta)$ (in a direction and at a point of a real or imaginary surface) the quotient of the luminous flux at an element of the surface surrounding the point, and propagated in directions defined by an elementary cone containing the given direction, by the product of the solid angle of the cone and the area of the orthogonal projection of the element of the surface on a plane perpendicular to the given direction. The luminous flux can be leaving, passing through, and/or arriving at the surface.

By introducing the concept of luminous intensity, luminance can be expressed as $L = dI/(dA \cos\theta)$. Here, luminance at a point on a surface in a direction is interpreted as the quotient of luminous intensity in the given direction, produced by an element of the surface surrounding the point, by the area of the orthogonal projection of the element of surface on a plane, perpendicular to the given direction. Luminance can be measured at a receiving surface by using $L = dE/(dA \cos\theta)$.

Note In common usage the term brightness usually refers to the strength of sensation that results from viewing surfaces or spaces from which light comes to the eye. This sensation is determined in part by the definitely measurable luminance defined above and in part by conditions of observation such as the state of adaptation of the eye. In much of the literature, brightness, when used alone, refers to both luminance and sensation. The context usually indicates which meaning is intended. Previous usage not withstanding, neither the term brightness nor the term photometric brightness should be used to denote the concept of luminance (IESNA).

***Luminance contrast*[2]** the relationship between the luminances of an object and its immediate background. It is equal to $(L_1 - L_2)/L_1$ or $(L_2 - L_1)/L_1 = |\Delta L/L1|$, where L_1 and L_2 are the luminances of the background and object, respectively. The form of the equation must be specified. The ratio L/L1 is known as Weber's fraction.

Note See note under luminance. Because of the relationship among luminance, illuminance, and reflectance, contrast often is expressed in terms of reflectance when only reflecting surfaces are involved. Thus, contrast is equal to $(\rho_1 - \rho_2)/\rho_1$, or $(\rho_2 - \rho_1)/\rho_1$, where ρ_1 and ρ_2 are the reflectances of the background and object, respectively. This method of computing contrast holds only for perfectly diffusing surfaces; for other surfaces it is only an approximation unless the angles of incidence and view are taken into consideration.

***Luminance ratio*[2]** the ratio between the luminances of any two areas in the visual field.

***Luminance threshold*[2]** the minimum perceptible difference in luminance for a given state of adaptation of the eye.

***Modeling light*[2]** illumination that reveals the depth, shape, and texture of a subject; key light, cross lighting, counter-key light, side light, back light, and eye light are types of modeling light.

***Munsell color system*[2]** a system of surface-color specification based on perceptually uniform color scales for the three variables: Munsell hue, Munsell value, and Munsell chroma. For an observer of normal color vision, adapted to daylight and viewing a specimen when illuminated by daylight and surrounded with a middle-gray to white background, the Munsell hue, value, and chroma of the color correlate well with the hue, lightness, and perceived chroma.

***Munsell chroma*[2]**, C an index of perceived chroma of the object color defined in terms of the luminance factor (Y) and chromaticity coordinates (x, y) for CIE Standard Illuminant C and the CIE 1931 Standard Observer.

Natural Colour System[1] uses a perceptual scaling based on the relative proportions of unique colours. Colour differences are therefore not equal everywhere in the NCS colour space (as in the Munsell system). The coordinates are *hue*, *chromaticness* and black content.

Overcast sky[2] one that has 100% cloud cover; the sun is not visible.

Perception[1] subjective qualitative experience or impression of some sensory input (internal representation). Can also be used for our understanding, comprehension and ideas, and is therefore sometimes linked to hypothesis and interpretations of sensory information about the environment.

Reflectance factor, ***R***[2] the ratio of the flux actually reflected by a sample surface to that which would be reflected into the same reflected-beam geometry by an ideal (glossless), perfectly diffuse (lambertian), completely reflecting standard surface irradiated in exactly the same way as the sample. Note the analogies to reflectance in the fact that nine canonical forms are possible that "spectral" can be applied as a modifier, that it can be luminous or radiant reflectance factor, and so on. Note that reflectance cannot exceed unity, but reflectance factor can have any value from zero to values approaching infinity.

Saturation (colour vision)[1] apparent amount of chromatic colour relative to achromatic colour of the same lightness.

Saturation of a perceived color[2] the attribute according to which it appears to exhibit more or less chromatic color judged in proportion to its brightness. In a given set of viewing conditions, and at luminance levels that result in photopic vision, a stimulus of a given chromaticity exhibits approximately constant saturation for all luminances.

Sensitivity, s[1] sensitivity (s) = criterion response (R)/physical stimulation (I), or $s = \Delta R/\Delta I$ at threshold (ΔR being constant).

Spatial frequency[1] number of periods per degree of a repetitive pattern, for example a sinusoidal grating.

Threshold[1] the lowest intensity or energy of a stimulus that can be detected or discriminated in a given situation. The threshold value will depend on the task, the threshold criterion, the physical conditions, and on physiological and psychological states.

VIGRA[1] a specific 3×10 bit computer display system (videographic system) for the presentation and manipulation of a variety of visual stimuli on a colour monitor.

Visibility[2] the quality or state of being perceivable by the eye. In many outdoor applications, visibility is defined in terms of the distance at which an object can be just perceived by the eye. In indoor applications it usually is defined in terms of the contrast or size of a standard test object, observed under standardized viewing conditions, having the same threshold as the given object. See visibility (meteorological).

Visual acuity[1] a measure for the ability to resolve of small details of maximum contrast, often assessed by means of a letter chart (e.g. Snellen chart). Decimal acuity = $1/\alpha$, where α is the minimum angle of resolution (MAR), expressed in minutes of arc (1 arcmin = 1/60°). Foveal acuity of 1.0 or better is regarded as normal. Another measure is log MAR = log α. Resolution improves as luminance increases, and it decreases with the distance from the fovea.

Visual angle[2] the angle that an object or detail subtends at the point of observation. It usually is measured in minutes of arc.

Visual field[2] the locus of objects or points in space that can be perceived when the head and eyes are kept fixed. Separate monocular fields for the two eyes can be specified or the combination of the two. See binocular portion of the visual field, central visual field, monocular visual field, and peripheral visual field.

Visual perception[2] the interpretation of impressions transmitted from the retina to the brain in terms of information about a physical world displayed before the eye.

Note Visual perception involves any one or more of the following recognizing the presence of something (object, aperture, or medium); identifying it; locating it in space; noting its relation to other things; and identifying its movement, color, brightness, or form.

Visual performance[2] the quantitative assessment of the performance of a visual task, taking into consideration speed and accuracy.

Visual task[2] conventionally designates those details and objects that must be seen for the performance of a given activity, and includes the immediate background of the details or objects.

Note The term visual task as used is a misnomer because it refers to the visual display itself and not the task of extracting information from it. The task of extracting information also has to be differentiated from the overall task performed by the observer.

Workplane[2] the plane on which a visual task is usually done, and on which the illuminance is specified and measured. Unless otherwise indicated, this is assumed to be a horizontal plane 0,76 m (30 in.) above the floor.