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Gjøvik Color Imaging Symposium 2005

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Preface

For the third consecutive year Gjøvik University College and The Norwegian Color Research Laboratory organised an international symposium on colour imaging. Gjøvik Color Imaging Symposium 2005 took place November 30 and December 1, 2005, at Gjøvik University College in Gjøvik, Norway.

The first day of the conference focused mainly on applied colour management, whereas the second day was devoted to current topics in colour imaging research, such as advanced colour management, spatial colour imaging, colour vision and colour constancy.

In these proceedings you will find short abstracts of the presentations, as well as copies of the presentation foils for selected presentations. For more information about the conference, please refer to http://www.colorlab.no.

Gjøvik, September 2006

Prof. Jon Y. Hardeberg, Conference Chair

Advances in Colour Management

Phil Green

Colour management has moved from concept to everyday application over the last ten years or so. With increasing adoption of version 4 of the ICC profile specification, colour processing can give consistent, reliable and accurate results across a range of different media. This is an opportunity to consider the challenges for colour management in the forthcoming period.

Methods of modelling colour imaging devices are well-established, and can provide good levels of accuracy. With good modelling techniques, poor profile performance can be traced to two main areas:

- a lack of correspondence between methods of measurement and methods of viewing
- characterisation data which lends itself poorly to modelling.

Colorimetric accuracy alone does not give assurance of a good colour reproduction. Even where accurate colour matching is required, In particular, the smoothness of a transform has a significant effect on perceived image reproduction quality.

While the ICC profile format meets many of the current needs of the graphic arts, there are new challenges for colour management which arise from emerging needs in graphic arts and in other application areas.

In digital photography and digital motion picture, the output-referred PCS is less relevant to the optimum colour processing of scene originals.

Colour profiles have typically been used to define a static transform with a fixed rendering. However, Version 4 of the ICC profile specification permits colour transform possibilities over a continuum which ranges from static to dynamic. In the latter case, colour appearance transforms, gamut mapping, and image state changes can be configured dynamically at run time.

For home users, colour management appears over-complex. The need for different profiles for each media type imposes complex profile selection choices and may even require such users to have the capability to create their own profiles. They are also sometimes uncertain how profiles should be applied in a particular colour reproduction task.

With the move to more automated colour reproduction workflows, formats such as PDF/X acts as containers for both image data and metadata. The latter can include colour processing models and rendering choices. In order to support automated selection of output profiles, there is a need to provide additional metadata about the printing condition for which the profile is made. This will also aid users in the manual selection of profiles.

Biography

Phil Green worked in the printing industry for 13 years before joining the London College of Communication (then known as the London College of Printing) as a lecturer in 1986. He is Course Director of the Postgraduate Programme in Colour Imaging. He received an MSc from the University of Surrey in 1995 and a PhD from the Colour and Imaging Institute at the University of Derby in 2003. He is currently technical Secretary of the International Color Consortium.

WebICC – Colour Management in Heatset

Tom E. Johansen

Do the customers have to have knowledge of print media and the local print house to obtain colour control of their magazines when they colour convert to CMYK? Local, regional and European aspects of ICC use seen from a Norwegian heatset perspective.

Biography

Tom E. Johansen, project manager quality assurance at the Norwegian Institute of Graphic Media, is a printer by profession with a Bachelor from University of Oslo in media esthetics and media science. He has also been working with the KDI project the last three years, with special attention to JDF standardisation and colour management questions.

Factors Affecting the Appearance of Print

Peter Nussbaum

This study aims to investigate factors affecting the appearance of print. In particular it looks at factors from five categories: the digital input, the printing system, the print, the illumination under which the print is viewed and the viewing environment in which it is viewed. The key method underlying the work described here relies on identifying a range of factors in these categories and having alternative states for each factor, e.g., the substrate factor can be plain paper , glossy paper or newsprint . A reference state is then defined for each factor and alternative states are compared with the reference one factor at a time. The comparison is in terms of colour differences between patches of a test chart obtained in the reference and an alternative state. The results for factors are then viewed both individually and by grouping all factors of a given category together. Finally the results indicate the magnitude of the change that can be expected due to a given factor or category and this makes it possible to order factors in terms of the magnitude of visual difference they can cause when altered. Having such an ordered list is then of use both in improving printing systems and in dealing with customer service queries.

Biography

Peter Nussbaum obtained his MSc in imaging science from the Colour & Imaging Institute, University of Derby, GB in 2002. Currently he is in process to enrol as a PhD part time student at the Oslo University but located at Gjøvik University College in the field of colour science. The area of study will be Colour Image Quality Assessment. He is also a lecturer at Gjøvik University College within the Department of Computer Science and Media Technology where he is teaching digital image reproduction. Moreover he is a member of the Norwegian Colour Research Laboratory. Before joining Gjøvik University College in September 2000, Peter Nussbaum was an Application Engineer for Colour Management and consultant for GretagMacbeth, Switzerland. His professional memberships include IS&T, TAGA and IFRA Colour Management Working Group.

Proof-to-print tolerances in contract proofing

Olli Nurmi

In this study the acceptability of color differences between the proof and print were studied. Psychometric scaling techniques were used to build numerical scales for the perceived similarity of proof samples, as compared to reference prints in visual experiments. Approximately 30 graphic arts professionals took part in the visual experiments, in which they rank ordered and categorized proofs according to how we well their colors matched the reference print. The results of the categorization study allowed the limit of acceptable contract proof to be specified in the interval scale resulting from the analysis of the rank order data. The visual scaling results were further compared to deltaE color difference metrics measured from the Fogra Media wedge, in an effort to give an objective definition to acceptable contract proof. The results suggests that the average deltaE between contract proof and the prints, as measured from the media wedge, should be no higher approximately 4 to 5 deltaE.

Biography

Senior Research Scientist, VTT Information Technology, FIN

Olli is working in the research area of Media and Interner as Research Group Manager. Working within media logistics and colour imaging systems his group is developing new systems for integrated electronic and print media, digital printing and media conversion of information.

Olli graduated from Helsinki University of Technology. He is a member of the Graphic Arts Industry´s Education Committee of National Board of Education and was also teaching in Espoo-Vantaa Institute of Technology.

Olli has about 50 publications, including original research papers in printing technology and paper technology, project reports, articles, TAGA Proceedings, etc. He has also about 30 presentations at conferences and seminars, such as IFRA, NATS, INSKO, VTT, HKK.

Making and Applying ICC Profiles with Matlab

Phil Green

Matlab's Image Processing Toolbox provides a wide range of functions which use ICC profiles. This session will focus on the mechanics of constructing, testing and applying ICC profiles using Matlab. We will look at the requirements of the data structure and the encoding of colour transforms using matrix, curves and LUTs.

We will review methods of evaluating the profiles for accuracy, invertibility and conformance to the ICC specification.

We will also explore methods of applying ICC profiles in Matlab, together with other functions in the Image Processing Toolbox and the Colour Engineering Toolbox.

Biography

Phil Green worked in the printing industry for 13 years before joining the London College of Communication (then known as the London College of Printing) as a lecturer in 1986. He is Course Director of the Postgraduate Programme in Colour Imaging. He received an MSc from the University of Surrey in 1995 and a PhD from the Colour and Imaging Institute at the University of Derby in 2003. He is currently technical Secretary of the International Color Consortium.

Spatial Colour Imaging – From Retinex to ACE

Alessandro Rizzi

What gives us the final sensation of colour is not only the colour signal. The appearance of colour in real scenes can vary widely according to several factors. The two major of them are illuminant and context. These two factors seem to “pull” our vision system in two different directions. From one side colour constancy mechanisms make the object colour more stable under the changes of light sources spectral composition while, from the other side the effect of the context makes the object colour depending on the scene spatial composition and consequently less stable in itself.

These two apparently contradicting phenomena are based on the same principle: the spatial recomputation of the colour signal. It produces the final overall appearance of the scene content.

So far, several algorithms have tried to simulate this visual normalisation mechanism. Their two main basic macro behaviours are Gray World and White Patch, which are considered alternatives. Considering them separately, they produce two different normalisation mechanisms. Lightness Constancy and Colour Constancy. Gray World approach goes in the Lightness Constancy direction: it centres the histogram dynamic, working in the same way as a camera exposure control. White Patch approach goes in the Colour Constancy direction, searching for the lightest patch to use as a sort of illuminant reference.

Retinex algorithm basically belongs to the White Patch family due to its reset mechanism. Searching a way to merge these two components, we developed a chromatic correction algorithm, called Automatic Colour Equalisation (ACE), which is based on both. It maintains the main Retinex idea that colour sensation derives from a local comparison of the spectral lightness values across the image. We present the common ground of the two algorithms, their differences and their results.

Biography

He took the degree in Computer Science at University of Milano and received a PhD in Information Engineering at University of Brescia (Italy). He taught Information Systems and Computer Graphics at University of Brescia and at Politecnico di Milano. Now he is assistant professor at University of Milano teaching Multimedia and Human-Computer Interaction. Since 1990 he is researching in the field of digital imaging and vision. His main research topic is colour perception.

Spatial Colour Gamut Mapping

Ivar Farup, Alessandro Rizzi and Carlo Gatta

A colour gamut of a device is the set of all colours reproducible by the given device. Similarly, the colour gamut of an image, is the set of all colours present in that image. Upon reproduction of colour images, one usually encounters colours in the image that are not within the colour gamut of the reproduction device, thus the need for colour gamut mapping. Conventional colour gamut mapping algorithms operates as mappings in colour space, thus not taking the image content into account.

We have investigated various techniques for performing spatial colour gamut mapping, including multi-level recursive techniques, as well as techniques based upon the Retinex and ACE models. The results are promising, and show that spatial gamut mapping algorithms preserve local contrast better than conventional gamut mapping algorithms.

Biography

Ivar Farup received a M.Sc. in theoretical physics from NTNU, Trondheim, Norway, in 1994, and a Ph.D. in applied mathematics from UiO, Oslo, 2000. He is currently with Gjøvik University College, mainly focusing on colour science and colour imaging.

Texture Analysis – From Grayscale to Colour

Fritz Albregtsen

Statistical texture analysis methods extract a number of pre-defined often ad hoc features, resulting in a very large number of possible feature combinations. Several sophisticated schemes have been developed to select a suboptimal feature set of lower dimensionality, often using resubstitution (leave-one-out) techniques instead of separate training and test data sets to estimate the texture classification error. Still, this leads to too optimistic results.

It is well known that the number of training samples affects the feature selection and the error estimation. However, the effect of the number of feature candidates analysed is not much discussed. In simulation experiments it turns out that the number of feature candidates is critical for small data sets. It is also found that to avoid biased error estimates, feature selection should be performed for each cycle of the leave-one-out procedure.

The most common statistical texture analysis methods have been developed for gray level images. Now, most images that are candidates for statistical texture analysis are actually colour images. In some applications, colour and texture are treated as separate entities. However, during the last decade, a variety of colour-texture descriptors have been proposed, exploiting both the intra- and inter-channel textural information. One of the consequences is a potential explosion in the dimensionality of the feature vectors used.

The Local Binary Pattern approach is an example of this. Ojala et al. (1996) proposed a binary version of the Wang and He (1990) texture spectrum approach, thresholding each 3×3 neighbourhood by the centre pixel value. Binomial position weights are then put on the eight binary pixel values, so that a weighted summation gives a unique local binary pattern (LBP) index to each such binary pattern. There are $2^8 = 256$ possible LBP values within a 3×3 neighbourhood. In the Opponent Colour extension, the LBP operator is applied on each channel and each channel pair, giving 2304 or 4608 features, depending on whether a contrast measure is used! The approach is simple, but is colour texture really that complex?

About a decade ago, high dimensionality problems would have been solved by neural nets, doing a recomputation of the network coefficients together with a pruning of the net and its input. Today, there is again the notion that high dimensionality is not a problem, as Support Vector Machines and Genetic Algorithms are available, and the minimum complexity principle used in most natural sciences seems to be forgotten by many practitioners.

Using a matrix description of textural parameters where neighbouring cells have a meaningful relation (neighbouring graylevels, interpixel distances, runlengths, etc), we have extracted low dimensional feature vectors from high dimensional matrices, based on class distance and class difference matrices. It turns out that such class distance matrices contain localised areas of consistently high values. The same approach can be used if chromaticity is added to the texture description, giving adaptive low dimensional feature vectors.

Colorimetric Characterisation of Digital Cameras Preserving Hue Planes

Casper Andersen and Jon Yngve Hardeberg

In this paper we present a colorimetric characterisation method for digital colour cameras, based on hue plane and white point preservation. The present implementation of the method incorporates a series of 3 by 3 matrices, each responsible for the transformation of a subset of camera RGB values to colorimetric values. The method is compared to a choice of other common characterisation methods based on least squares fitting. These other methods are an unconstrained 3 by 3 matrix, a white point preserving 3 by 3 matrix, a second order and a third order polynomial. The methods have been evaluated on real camera signals coming from an Imacon Ixpress professional digital CCD camera, under flash light. The Gretag MacBeth Color Checker and the Color Checker DC charts have been used as test set, and training set, alternately. The method is evaluated in combination with a noise susceptibility estimation of the training set samples that reduces the amount of test samples needed in the characterisation. The noise estimation is based on a geometric analysis in camera chromaticity space.

Biography

Casper Find Andersen; M.Sc. 1993 from the Danish Technical University DTU. Specialised in Computational Fluid Dynamics and descriptive geometry. Employed by DTU as research assistant specialising in colour theory and colour management until 1998. From 1998 to 2001 senior researcher at r&d department Phase One dealing with colour management and image manipulation. From 2001 working as teacher, consultant and researcher at the Graphic Arts Institute of Denmark. At the moment working on a phd-project about "characterisation of digital colour cameras" with Prof. Jon Yngve Hardeberg, Gjøvik University College, Norway, as de facto supervisor.

Gamut Intersection for Image Retrieval

Andrei Ouglov

Colour is agreed to be one of the most important and widely used features in image indexing and retrieval. Colour histograms are the most dominate technique for image indexing based the image colour content. Colour histogram relies on both the colour gamut and density information. In this paper we propose a new method that retains and improves upon the advantages of colour histograms while not requiring quantisation hence keeping the number of colour combinations intact. The method is based on describing the shape of the colour gamut rather than the colour density information. To achieve that, the introduced method projects the image colour data onto two orthogonal planes resulting in two 0 1 binary images which we use as our image descriptors. The most important motivation for choosing the projection planes , is that the planes should be orthogonal to ensure that the projects are linearly independent and that both planes should contain the grey-axis since the colour distributions are elongated along this axis, as it is shown in the paper by applying PCA on the MPEG7 image database. Our experiments performed on MPEG7 image database show that the Gamut intersection approach performs favourably or equally good for almost all the test images when compared with histogram.

Biography

Andrei Ouglov received his B. Eng. and M. Eng. degrees in Electrical Engineering and Information and Communication Technology in 2001 and 2003 from Narvik University College and Agder University College, Norway. In 2003 he joined Gjovik University College where he is currently focusing on the colour image processing and engaged in research on image indexing and retrieval.

Colour Differences Introduced by Pixel Format Conversions

Øyvind Kolås

Pixel format conversions introduce errors, and occur in many imaging workflows. Errors are due to a combination of unaligned quantisations and non linear transforms between colour models. This poster documents average colour differences for all conversions possible within a set of pixel formats.

Robustness of Texture Parameters for Colour Texture Analysis

Ambroise Marin, Audrey Minghelli-Roman, Jon Y. Hardeberg, Pierre Gouton

Texture analysis is a large field of investigation in pattern recognition area. Several articles compare texture parameters using blind classification algorithms [5]. Considering that all these parameters should be used out of laboratory with non perfect texture pictures, it is interesting to quantify the impact of perturbation on these parameters. Hence, as a first step, a method for comparison of texture parameters to perturbations is presented. Three texture characterisation parameters are considered, the cooccurrence [2] matrices, the auto-correlation [3] matrix and the local-extrema function [4] [7]. The behaviour of these three texture characterisation parameters will be investigated when perturbations such as Gaussian noise, salt and pepper noise or re-scaling are applied to original texture. To achieve the comparison of these parameters, a set of coloured textures from the free texture database "absolute background texture" was selected. Perturbations were applied to this set of textures and then a k-NN classification was performed to determine relative perturbation sensitivity.

Keywords: Texture, Colour, Cooccurrence, Auto-correlation, oriented local extrema

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Biography

Ambroise Marin obtained his master degree in computer science at Burgundy university in 2004. He is currently a PhD student from the LE2I and the Norwegian color research laboratory. His PhD thesis is about multispectral imagery and artificial vision.

Spectral Reproduction by Vector Error Diffusion

Jeremie Gerhardt

In the context of spectral colour reproduction, the goal is typically to reproduce a given target, i.e. a multispectral image, so that the spectral reflectance of every pixel is reproduced as accurately as possible.

To achieve this using ink-jet print technology, a multi-ink (N>4) system is needed, first to increase the spectral gamut of the device and secondly to allow to find a colorant combinations close to the reflectance to reproduce. The limitation on total ink coverage reduces the possibility of spectral reproduction and a larger choice of colorants deals with this problem.

This paper demonstrates the feasibility of vector error diffusion for spectral colour reproduction using a multi-channel printing device. Using a simplified 7-channel spectral printer model we demonstrate that spectral Vector Error Diffusion is able to produce a good spectral match, implicitly solves the problem of printer model inversion, and achieves reduced noise (stochastic moiré) compared to when using standard channel-independent error diffusion.

Biography

Jérémie received his Bachelor degree in Electronic in 2000 and his Master degree in Image Processing in 2002 from University Pierre and Marie Curie in France. His master thesis project was on wide format ink-jet printing with the use of diluted inks, this project was made part time in the printing company Océ PLT in Créteil. He started his PhD in the field of spectral colour reproduction last September at Gjøvik University College in the Norwegian Research Color Laboratory, he is involved as a PhD student from Ecole Nationale Supérieure des Télécommunictions in Paris. He took part in the second European Conference CGIV 2004 in Aachen and the AIC 2005 in Granada.

Effect of Spatial Structure on Visual Tolerance

Vien Cheung

It is known that the reflectance spectra of both natural and man-made surfaces may be represented efficiently using linear models. A key question, however, is how many basis functions of a linear model are necessary for a given accuracy of representation. Many studies have been carried out to estimate the minimum number of basis functions for spectral reproduction. The question is ill-posed, however, since it is understood that the number of basis functions required depends to a great extent on the intended application of the linear model. However, in one study it was shown that more than six basis functions were required so that the worst colour difference in the set of spectra was less than 1.0 CIELAB unit and therefore it is reasonable to assume that, for many applications where relatively large patches of spatially uniform colour are present, six of basis functions will be required since CIELAB colour differences of unity or more in such circumstances are known to be noticeable. However, the magnitude of colour difference that would be visible in a complex or natural image is not so well established. A recent psychophysical study demonstrated that although five basis functions produced on average unit error in CIELAB space, original natural images were psychophysically indistinguishable from their linear-model approximations only if there were at least 8 basis functions. The aim of this study is to psychophysically investigate the effect of spatial structure on the number of basis functions required to reproduce spectral images.

Biography

Vien Cheung graduated from The Hong Kong Polytechnic University (Hong Kong) in 1999 with a BSc degree in Textile Chemistry, and obtained an MSc degree in Colour Imaging at University of Derby (UK) in 2000. She then moved to the Institute of Textiles and Clothing at The Hong Kong Polytechnic University, for a research assistantship, to work on a project investigating digital camera fidelity for colour management. In 2004 Vien completed her PhD research under the supervision of Professor Stephen Westland at University of Leeds (UK), and since then has worked as a Research Fellow at School of Design in University of Leeds.

Implementing Colour Managed Workflow in a Professional Printing Lab

Håkon Grønning

An open standard for colour management is well defined by the International Color Consortium. One of its components is the ICC profile format, and is supported by most vendors of platforms for image and graphics colour workflow. The ICC standard is also adapted as an international standard, ISO 15076. However, even if this standard is widely supported, the understanding and proper use of a colour managed workflow is still a very complex issue for most end users.

In this paper we focus on implementing colour managed workflow in a professional printing lab based on ICC profiles.

As the actual printing lab had a tight schedule for finishing output prints for its customers, it was most important not to disturb the production too heavily. The work was planed and divided into a few separate tasks to meet this constraint. The company itself was most interested in the output profiles for their Epson printers, therefore we decided first to build output profiles for two paper qualities for each of their Epson 6400 and Epson 9600 printers. Next we should make profiles for the two CRTs in their dual monitor setup. The lab gets images as digital files as well as doing in house scanning of film and reflex originals. The last optional step was to profile theirs scanners. The order of the tasks was chosen because the only disturbance in the production in the first task was printing the TC 9.18 test chart four times. Then the rest of the profiling could be done at our colour lab. The strategy was that if the new printer profiles could help to achieve better prints, it would increase the confidence to our work. Then it would be easier to argue for the need for the rest of the tasks.

The paper describes the results that were achieved. Further we also discus the need for education of the users. It seems to be very important that the user understand the principles of an ICC colour managed workflow. The user must have a certain level of insight to be motivated to take the necessary steps to really achieve that colour managed workflow.

We conclude that educating the users in the workflow chain definitely is as important as the calibration and profiling of the different hardware devices.

Biography

Håkon Grønning received his sivilingeniør (M.Sc.) degree in telecommunications and signal processing from the Norwegian Institute of Technology in Trondheim, Norway in 1981. He obtained his Ph.D. in image processing / compression, also from the Norwegian Institute of Technology, in 1996. Since then he has worked at Sør-Trøndelag University College in Trondheim as an Associate Professor. He teaches subjects in the field of digital signal processing, from general, fundamental topics to magnetic resonance imaging. Signal processing in general and image processing in particular has always been his main interests. During the last years his growing interest for colour imaging science has resulted in a few colour science projects. (`http:/www.iet.hist.no/ hakon/`)

High Resolution, High Speed Hyperspectral Cameras for Laboratory, Industrial and Airborne Applications

Ivar Baarstad

Hyperspectral imaging can be defined as the combination of imaging and spectrometry. Norsk Elektro Optikk AS (NEO) has over the last years developed a series of compact, high performance imaging spectrometer systems (hyperspectral cameras).

The instrument concept is based on the results of the HISS definition study (Hyperspectral Imager for Small Satellites), performed by NEO for ESA in 1996–97.

The development is currently (2003–2006) partly funded by the French and Norwegian Ministries of Defence, within the context of the EUCLID-project HYPOLAC (Hyperspectral Polarimetric Active and Passive Imaging). This project is undertaken by a French–Norwegian consortium consisting of NEO, Thales Research and Technology, Thales Optronique SA and the Fresnel Institute – University of Marseille. Within the HYPOLAC project, high resolution hyperspectral data from the developed imaging spectrometer has been used in order to select the appropriate wavelengths for a laser based active polarimetric multispectral camera. Additionally, the receiver unit of the active instrument has been built around the imaging spectrometer developed by NEO.

The unique hyperspectral camera concept has also demonstrated significant potential for use in civilian airborne, laboratory and industrial applications of imaging spectrometry. Four different versions of the instrument have been realized so far, with the following main specifications:

Module	VNIR-640	VNIR-1600	SWIR-1.7	SWIR-2.5
Detector	Si CCD 640*480	Si CCD 1600*1200	InGaAs 320*256	CdHgTe 320*256
Spectral range	0.4-1μm	0.4-1μm	0.9-1.7μm	0.8-2.5μm
Spatial pixels	640	1600	320	320
FOV across track	18.4°	17°	14°	14°
Pixel FOV across track/ along track	~0.5mrad/ 0.5mrad	~0.2mrad/ 0.4mrad	0.75mrad/ 0.75mrad	~0.75mrad/ 0.75mrad
Spectral sampling	5nm/10nm*	3.7nm	5nm	5nm
# spectral bands	128/64	160	160	256
Digitization	12bit	12bit	12bit	14bit
Frame rate to HD	500/850fps*	>120fps	>100fps	>100fps

The instrument design is flexible, and the specifications can be tailored to individual users and applications. All instruments employ the pushbroom scanning principle, acquiring one spatial line of the scene at a time. The unique and compact mirror based fore optics minimises spherical and chromatic aberrations. A slit defines the instantaneous field of view, and a transmission grating disperses the light spectrally before it is focused by a lens system onto the focal plane array detector. The lens system has been carefully optimised for minimisation and equalisation of the point spread function across the FOV and spectral range, as well as for minimisation of distortions such as spectral keystone and smile effect. The high performance demonstrated in the optical simulations has been verified experimentally.

All instruments are being calibrated spectrally and radiometrically, using several narrow band sources and a calibrated integrating sphere in order to produce absolute radiance spectra (in W/m^2 nm sr) for each pixel in the image.

The VNIR and SWIR-1.7 modules have been integrated into an aircraft, where GPS and inertial navigation system data are logged continuously to provide geometric correction and georeferencing of the images. Airborne images have been acquired for several military and civilian research institutions in 2003, 2004 and 2005.

The VNIR-640 module, being capable of continuous acquisition of more than 850fps with a window of 640 spatial pixels by 64 spectral bands, can be adapted to various industrial applications. As an example, when mounted ∼1m above a conveyer belt, a belt speed of ∼1m/s is feasible with 1mm spatial resolution and 64 bands. One such system has been delivered to the Norwegian Institute for Fish Research (Fiskeriforskning) for development of an on-line quality control system in the fish fillet industry.

A tripod mountable rotation stage has been designed, providing synchronous operation of the spectrometer with the scanning platform. This setup can be used to acquire lab or field measurements of stationary scenes, and has been employed for data acquisition for several different users and applications.

The key features of the instrument concept will be presented, along with sample images and results from applications such as target detection, agriculture and quality control.

Colour, Constancy, Invariance and the Chromagenic Constraint

Graham Finlayson

In this talk I will take a wide ranging view of colour constancy. In a simple sense colour constancy comprises both the estimation of the prevailing light and the removal of colour bias due to the light (the colour cast in images). This problem is introduced and I show how light colour can be estimated using the tools of probability theory. However, despite deriving an 'optimal' solution, current colour constancy algorithms do not always work very well.

I then show how a restricted constancy problem is easier to solve. Namely, it is easy to find a single 'grey-scale' image that is independent of the light colour. Moreover, this grey scale can be used to better understand the illumination in images. Specifically, by looking for edges in colour images that do not appear in the invariant grey scale we can find and then remove shadows from images. This said, we still cannot uniquely estimate and remove the colour cast.

In the last part of the talk we show that a special 'chromagenic' camera that takes 6 as oppose to 3 measurements of a scene is able to more easily and more accurately solve for colour constancy. Moreover, we speculate that this multispectral view of constancy computation may play could plausibly play a role in our own vision.

Ability of Red-Green Colour Deficient Observers to Judge Natural and Munsell Surface Colours under Different Illuminants

Rigmor Baraas

In man, normal trichromatic vision is based on three different types of retinal cone pigments with peak spectral sensitivities lying close to 420, 530 and 560 nm, termed the short-wavelength (S), the medium-wavelength (M), and the long-wavelength (L) cone pigments respectively. The L and the M pigments are genetically coded for on the X-chromosome, and about 8% of the male population are missing either the L or the M pigment and are therefore red green colour deficient. They are classified in terms of the pigment that is absent; protan deficiencies relate to a missing L pigment and deutan deficiencies relates to a missing M pigment. About 2% of the male population has only two pigments; the S- and either the M- or the L- pigment, these individuals are dichromatic. A further 6% of the male population is anomalous trichromats. These individuals have three pigments; the S- pigment and two narrowly separated pigments either in the medium-wavelength (M) region or in the long-wavelength (L) region.

A variety of studies have shown that normal trichromatic observers can make reliable surface-colour judgements under changing illumination with coloured geometric Mondrian-like patterns (Arend et al. 1991; Foster et al. 2001), and with natural scenes (Amano et al. 2003, 2004) presented on a CRT display. Protanopes are also able to judge surface colour under different illuminants with Mondrians, but they have proved to be less colour constant than normal trichromats when the patterns are made up of Munsell spectra (Munsell Color Corporation, 1976), or natural spectra drawn at random from a range of hyperspectral images of urban and rural scenes (Nascimento et al., 2002). Protanopes ability to judge surface colour under different illuminants, however, is more accurate with Mondrians of natural spectra (Baraas et al., 2004). How well do other red-green colour deficient observers judge surface colour under different illuminants, and will their performance improve with surfaces drawn from natural scenes?

Stimuli were simulations of Mondrian-like coloured patterns, presented on a computer-controlled monitor. The DeMarco-Pokorny-Smith cone fundamentals for anomalous trichromats (DeMarco et al., 1992) were used to calibrate a colour monitor for deuteranomalous and protanomalous observers, and the Smith- Pokorny cone fundamentals (Smith and Pokorny, 1975) were used for dichromatic and normal trichromatic observers. The patterns consisted of 49 abutting 1.0-deg-square uniform surfaces with spectral reflectances drawn at random from natural scenes or, as a control, from the Munsell set. The illuminants were drawn from the daylight locus. In each trial, two images of a pattern were presented in sequence, each for 1 s, with no interval: in the first image, the correlated colour temperature of the illuminant was 25000 K or 4000 K, in the second, it was 6700 K. The spectral reflectance of the central square in the second image changed randomly from trial to trial. Observers reported whether there was an illuminant change or a surface reflectance change. Nine deuteranomalous, five protanomalous, five deuteranopes, five protanopes, and nine normal trichromatic observers participated in the study.

Anomalous trichromats ability to judge surface colours was no different from that of normal trichromats with the two illuminant changes tested here. The ability of both protanopes and deuteranopes, however, was poorer than that of normal trichromats.

Normal trichromats and deuteranopes ability to judge surface colours was the same with Munsell and natural spectra regardless of illuminant change. Anomalous trichromats, however, performed better with natural spectra than with Munsell spectra for the 4000 K to 6700 K illuminant change, but not for the 25000 K to 6700 K illuminant change.

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Calibrating Colour Cameras Using Metameric Black

Ali Alsam

Spectral calibration of digital cameras based on the spectral data of commercially available calibration charts is an ill-conditioned problem which has an infinite number of solutions. To improve upon the estimate, different constraints are commonly employed. Traditionally such constraints include: non-negativity, smoothness, uni-modality and that the estimated sensors results in as good as possible response fit.

In this work, we introduce a novel method to solve a general ill-conditioned linear system with special focus on the solution of spectral calibration. We introduce a new constraint based on metamerism where we show that: Given two metamers which integrate to the same sensor response, the difference between them is in the null-space of the sensor. This approach allows us to robustly estimate the sensor's null-space. Having done that, we derive projection operators to solve for the range of the unknown sensor. Our new approach has a number of advantages over standard techniques: It involves no minimisation which means that the solution is robust to outliers and is not dominated by larger response values and it offers the ability to evaluate the goodness of the solution where it is possible to show that the solution is optimal, given the data, if the calculated range is one dimensional.

Appendix: Program and Foils from Selected Presentations

1. Program
2. *Green*: Advances in Colour Management
3. *Johansen*: WebICC – Colour Management in Heatset
4. *Nussbaum*: Factors Affecting the Appearance of Print
5. *Nurmi*: Proof-to-print tolerances in contract proofing
6. *Green*: Making and Applying ICC Profiles with Matlab
7. *Rizzi*: Spatial Colour Imaging – From Retinex to ACE
8. *Farup*: Spatial Colour Gamut Mapping
9. *Finlayson*: Colour, Constancy, Invariance and the Chromagenic Constraint
10. *Alsam*: Calibrating Colour Cameras Using Metameric Black

Gjøvik Color Imaging Symposium 2005

November 30 - December 1, 2005
The Norwegian Color Research Laboratory
Gjøvik University College

Day 1 (30.11): Color management

	09:00 - 09:30	***K102***	***Registration, with coffee and sandwiches***		
Session 1: Introduction					
	09:30 - 09:35	K102	Symposium welcome and general introduction	Jon Y. Hardeberg	Gjøvik University College
	09:35 - 10:20	K102	Advances in colour management	Phil Green	London College of Communications
Session 2: Introductory tutorials and workshops (Parallel tracks)					
2A	10:30 - 12:00	A012	Color Management Workshop 1	Peter Nussbaum & Casper F. Andersen	Gjøvik University College, Graphic Arts Inst. of Denmark
2B	10:30 - 12:00	A007	Color Phenomenology tutorial and demonstrations	Jan H. Wold	Gjøvik University College
2C	10:30 - 12:00	A204	Introduction to Matlab for Color Imaging	Andrei Ouglov and Jeremie Gerhardt	Gjøvik University College
	12:00 - 13:00		***Lunch***		
Session 3: Graphic Arts					
	13:00 - 13:30	K102	WebICC - Color Management in Heatset	Tom E. Johansen	Norwegian Institute of Graphic
	14:00 - 14:30	K102	Factors affecting the appearance of print	Peter Nussbaum	Gjøvik University College
	14:30 - 15:00	K102	Proof-to-print tolerances in contract proofing	Olli Nurmi	VTT Media Technology, Finland
	15:00 - 15:30		***Coffee break (with preview of tomorrow's posters)***		
Session 4: Advanced tutorials (Parallel tracks)					
4A	15:30 - 16:30	A012	Color Management Workshop 2	Peter Nussbaum	Gjøvik University College
4B	15:30 - 16:30	K102	Spectral device characterization	Ali Alsam	Gjøvik University College
4C	15:30 - 16:30	A204	Gamut visualization and mapping using ICC3D	Ivar Farup and Arne Magnus Bakke	Gjøvik University College
	19:00 - 19:45		***Visit to Gjøvik Olympic Mountain Hall (http://www.fjellhallen.no/)***		
	20:00 - 23:00		***Dinner at Belvedere Restaurant (http://www.belvedere.as/)***		

Day 2 (1.12): Current topics in color imaging research

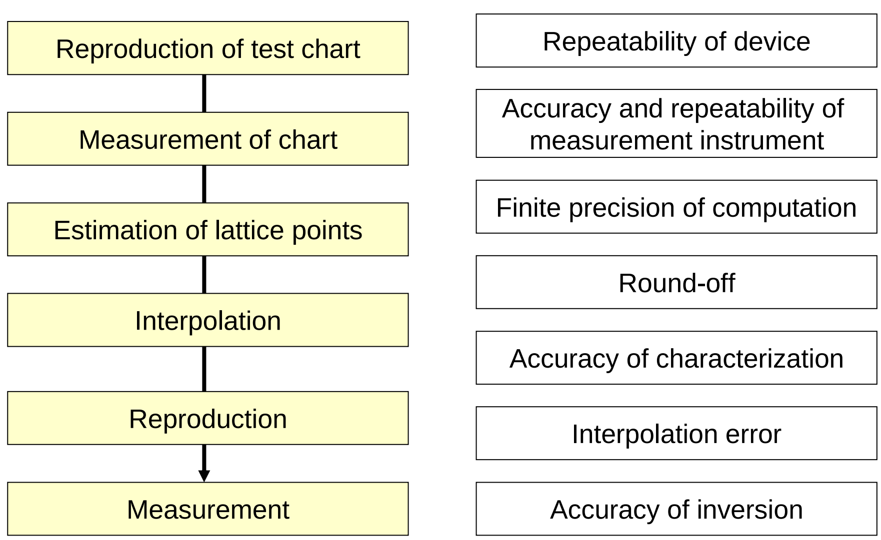
Session 5: Advanced Color Management					
	08:30 - 09:15	K102	Making, editing and applying ICC profiles with Matlab	Phil Green	London College of Communications
	09:15 - 09:45		***Coffee break***		
Session 6: Spatial Color Imaging					
	09:45 - 10:30	K102	Spatial Color Imaging - from Retinex to ACE	Alessandro Rizzi	University of Milano, Crema
	10:30 - 11:00	K102	Spatial Gamut Mapping	Ivar Farup	Gjøvik University College
	11:00 - 11:45	K102	Texture analysis - from grayscale to color	Fritz Albregtsen	University of Oslo
Session 7: Posters and interactive presentations					
	11:45 - 13:30	***A006***	***Posters and lunch buffet***		
			Colorimetric characterization of digital cameras preserving hue planes	Casper Andersen	Graphic Arts Institute of Denmark
			Content based image retrieval by gamut intersection	Andrei Ouglov	Gjøvik University College
			Investigating color errors due to conversion between different image representations	Øyvind Kolås	Gjøvik University College
			Robustness of texture parameters for color texture analysis	Jon Y. Hardeberg	Gjøvik University College
			Spectral reproduction by vector error diffusion	Jeremie Gerhardt	Gjøvik University College
			Effect of spatial structure on visual tolerance	Vien Cheung	University of Leeds
			Implementing color managed workflow in a professional printing lab	Håkon Grønning	Sør-Trøndelag University College, Trondheim, Norway
			High resolution, high speed hyperspectral cameras for laboratory, industrial and airborne applications	Ivar Baarstad	Norsk Elektro Optikk A/S, Lørenskog, Norway
Session 8: Color Vision and Color Constancy					
	13:30 - 14:15	K102	Computational colour constancy	Graham Finlayson	University of East Anglia, UK
	14:15 - 14:45	K102	Ability of red-green colour deficient observers to judge natural and Munsell surface colors under different illuminants	Rigmor Baraas	Buskerud University College, Kongsberg, Norway
	14:45 - 15:30	K102	Calibrating color cameras using metameric black	Ali Alsam	Gjøvik University College

Final program (28.11.05)
Conference venue: Gjøvik University College, Gjøvik, Norway, K102 (A building)
Conference chair: Professor Jon Y. Hardeberg
Conference committee: J. Y. Hardeberg, P. Nussbaum, A. Alsam, S. E. Skarsbø, I. Farup
For more information and registration, see http://www.colorlab.no or http://www.hig.no

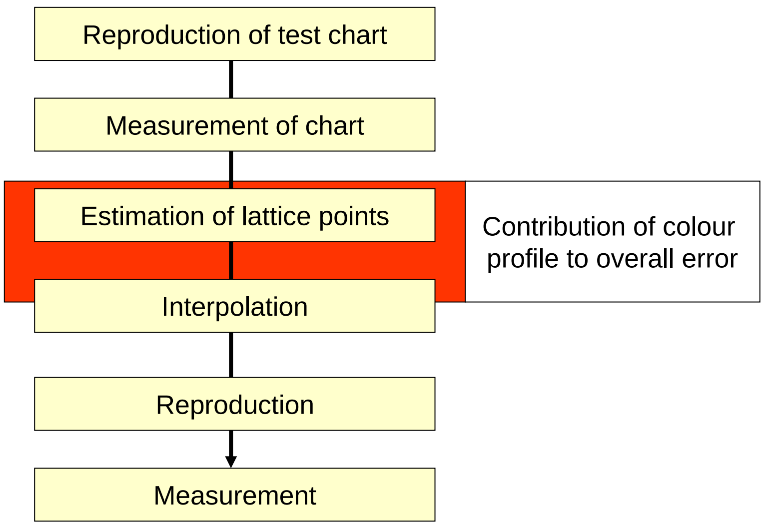
Advances in Colour Management

Phil Green
Colour Imaging Group
London College of Communication

Sources of error during colour transformation workflow



Sources of error during colour transformation workflow



Error propagation

Assuming that errors are randomly distributed and not systematic, the effect of a series of errors can be calculated by the method of combined uncertainty:

$$u_c = \sqrt{u_r^2 + u_{CRM}^2 + u_{x_1}^2 + u_{x_2}^2 + u_{x_3}^2 \ldots + u_{x_n}^2}$$

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Characterization errors: Neugebauer equations

	ΔE_{avg}	ΔE_{max}	**Source**
Basic	**8.70**		Johnson, Luo, Li, Xin and Rhodes
Basic	**7.41**	**15.52**	Rolleston and Bala
Y-N modified	**4.98**		Johnson, Luo, Li, Xin and Rhodes
Cellular	**2.85**	**8.76**	Rolleston and Bala
Cellular spectral Y-N modified	**2.62**	**8.71**	Rolleston and Bala

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Characterization errors: regression

	2nd order ΔE_{avg}	3rd order ΔE_{avg}	**Source**
Proofing systems	**2.14**	**1.25**	Johnson, Luo, Li, Xin and Rhodes
Digital printers	**3.22**	**2.17**	Johnson, Luo, Li, Xin and Rhodes
News presses		**2.32**	Green

Accuracy of the characterization model in predicting CIELAB values of test colours not in the training set.

© Phil Green 2004

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LUT and interpolation errors

	ΔE_{avg}	ΔE_{max}	Source
Trilinear	**0.75**	**3.14**	Singh
Prism	**0.97**	**7.74**	Singh
Pyramid	**1.38**	**8.70**	Singh
Tetrahedral	**1.37**	**9.44**	Singh
Max error for 17-point lattice, trilinear interpolation		**17.20**	
Max error for 33-point lattice, trilinear interpolation		**8.86**	

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Profile accuracy

	ΔE_{avg}	ΔE_{max}	Source
Profile based on FOGRA1 data set	**0.77**	**2.11**	Green
Profile based on IFRA02 data set	**0.54**	**1.12**	Green
Ink jet proofer	**1.88**	**4.01**	Green

Numerical accuracy of profiles in predicting a test set of in-gamut colours in the AToB0 intent (device space to CIELAB)

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Round-off

	ΔE_{avg}
Round CIELAB to nearest 8-bit integer	0.857
Round CIELAB to 8-bit integer floor	1.722

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White point

The D50 illuminant ‘white point’ varies widely

	X	Y	Z
Calculated at double precision according to CIE 15.3 (and 15.2)	0.9641986 5576090	1.00	0.8251164 8322104
Specified by CIE 15.2 (and ICC)	0.9642	1.00	0.8249
Specified by CIE 15.3	0.9642	1.00	0.8251
16-bit fractional approximation of CIE 15.2	0.9642028 8085938	1.00	0.8248901 3671875
Calculated by summation of ISO 13655 weightings	0.96423	1.02	0.82522
Specified by ISO 13655	0.96422	1.00	0.82521

The difference between CIE 15.2 and the double precision calculation according to CIE 15.3 is ΔE_{ab} 0.018

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Accuracy in colour management

Methods for accurate device characterisation are largely established and ICC profiles can produce satisfactory levels of accuracy for most applications.

Given a well-formed characterisation data set, a transform accuracy of $1\Delta E^*_{ab}$ is possible.

Four areas where further work is needed are:

1. Agreement between viewing and measurement conditions
2. Defining the smoothness of a colour transform and the effect on visual performance
3. Improving metameric matches across different illuminants
4. Limitations to the scope of media-relative colorimetry

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Agreement between viewing and measurement

Methods for accurate device characterisation are largely established and ICC profiles can produce satisfactory levels of accuracy for most applications.

Examples of cases where measurement and viewing conditions may be different :

1. Samples with highly directional reflection properties, such as metallics
2. Samples which fluoresce
3. Measurement backing differs from viewing backing

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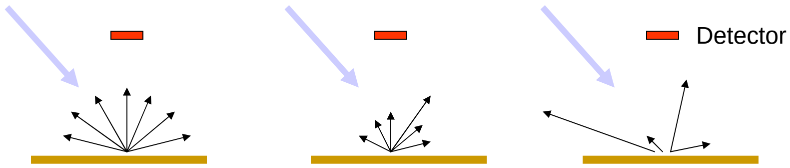
Viewing and measuring metallics

1. Samples with highly directional reflection properties, such as metallics



The reflection seen by the detector may not be consistent with the mode of viewing. Some metallic samples reflect close to zero at the angle of the detector.

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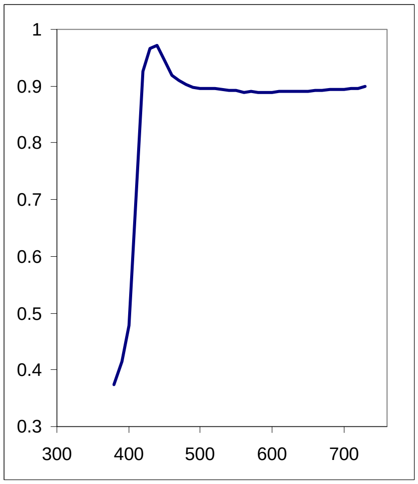
Fluorescence

A fluorescing sample has an emission at approx 430nm which arises from incident light in the excitation spectrum which peaks at approximately 350nm.

This effect is seen when there is some UV content in the illuminating source.

The problem is that incandescent sources used in instruments have little UV content, and don't 'see' the sample in the same way as an observer.

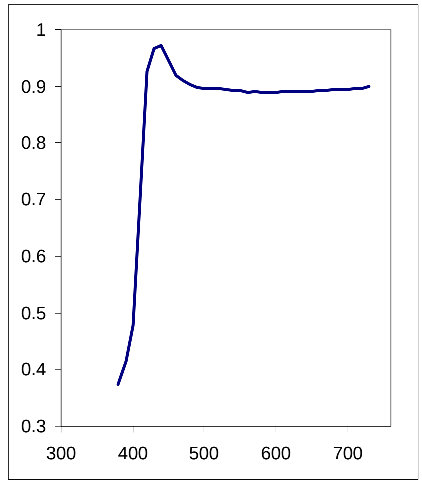


Epson Photo ink-jet paper

Fluorescence

The problem can be addressed by:

1. Eliminating UV from both measurement and viewing
2. Reproducing the UV content of the D50 viewing source in the instrument source
3. Estimating the effect of UV under the viewing condition and incorporating this into the measurement.



Smoothness of colour transforms

Transform smoothness is important to avoid contouring in images.

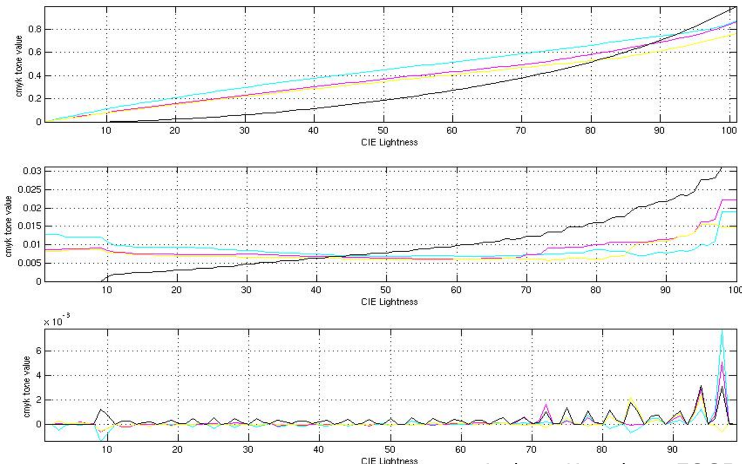
LUT-based profiles use discrete data points which are interpolated

As a result, a transform can have local non-smoothness

Various methods have been proposed for the evaluation of the smoothness of a function, but these methods have still to be tested for their ability to predict observer judgements

Smoothness of colour transforms

Example metric: device values against L* in a smooth ramp



Andreas Kraushaar, FOGRA

Improving metameric matches

Trichromatic matches are only valid for the illumination for which they were defined

Hence a match can be difficult to predict when colours are reproduced by different processes, when the illumination conditions vary

To improve metameric matches across different illumination conditions it is necessary to be able to construct matches in the spectral domain

This is not directly supported by the ICC architecture, although a profile can act as a container for spectral characterization data.

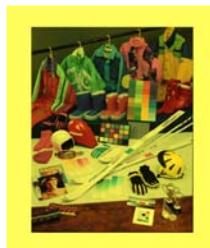
Limitations of media-relative colorimetry

The ICC architecture uses media-relative colorimetry as a default.

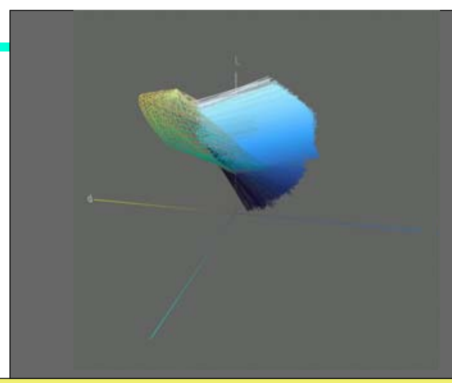
This assumes that the observer is completely adapted to the media white point

In reality, adaptation is partial – approximately 66%

This becomes a problem when the substrate colour deviates significantly from neutral



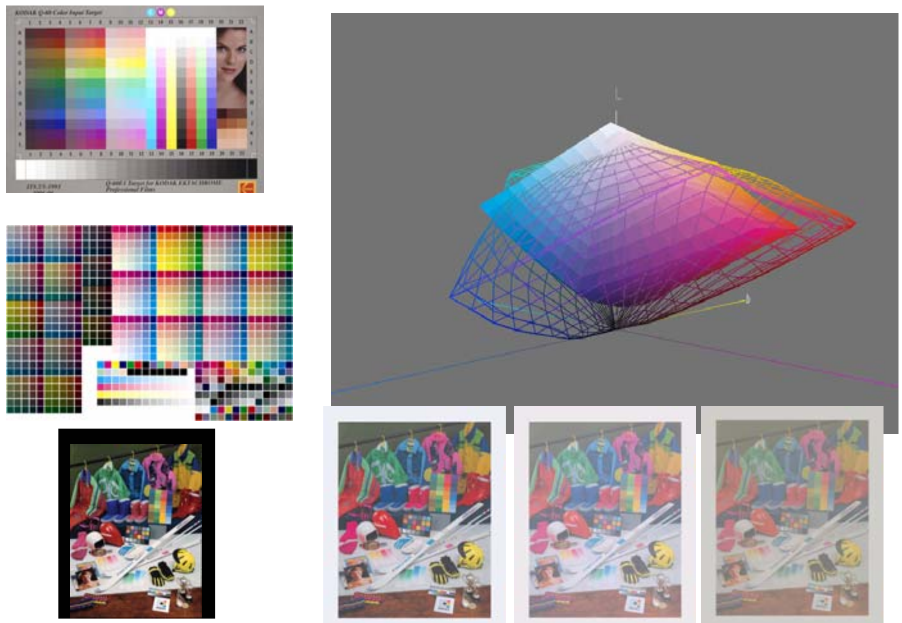
Original DSC image



Printed using colorant amounts correct for a white substrate

ICC profile for substrate, relative colorimetric intent

ICC profile for substrate, perceptual intent



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Why should the relative volume of the media gamut affect the performance of gamut mapping algorithms?

Algorithms that are clipping or strongly chroma-preserving generate contouring in high-chroma colours

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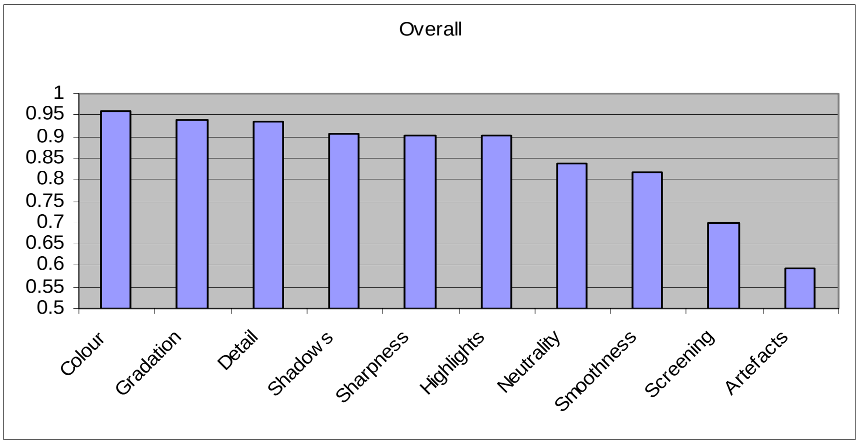
Correlation from INCQC 2002 visual assessment



Correlation between overall quality judgement and individual criteria in INCQC subjective image evaluation

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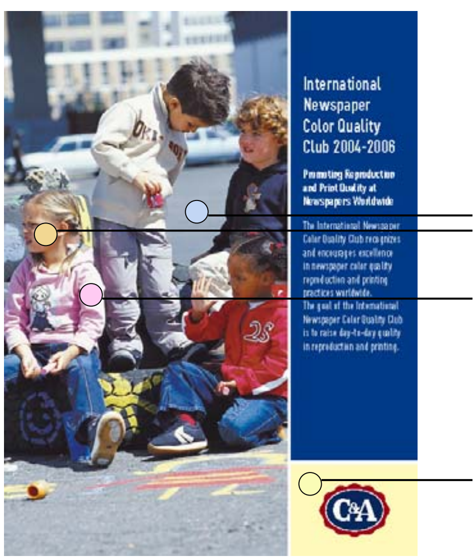
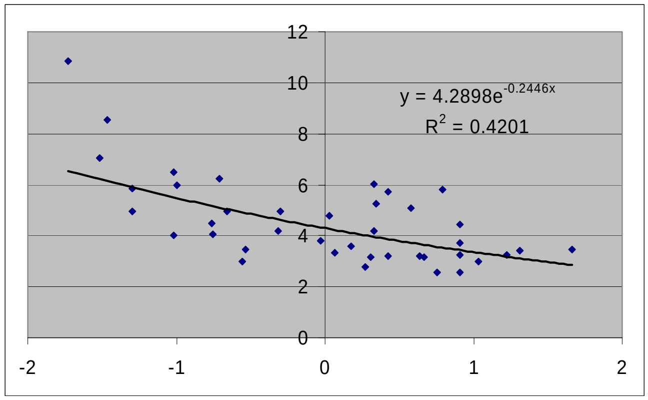


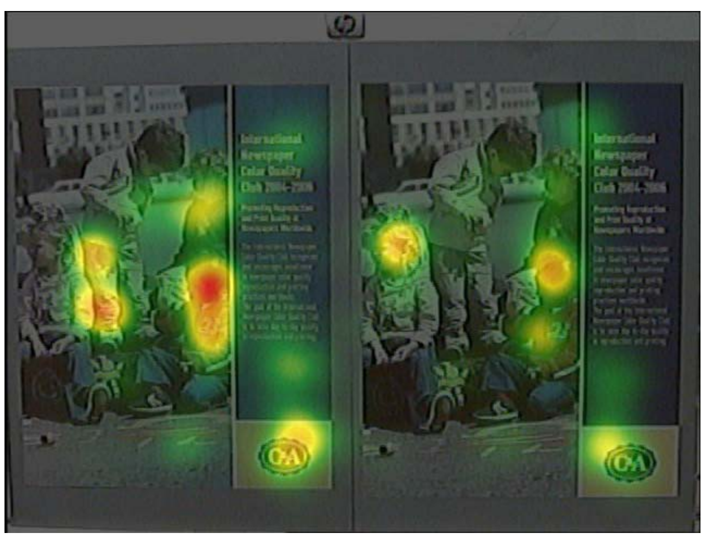
- 26 measurement locations
- Measurement using Spectrolino/Spectrascan xy table with punch registration of images
- Repeatability of registration and measurement technique established
- Prints from 40 sites measured

$\overline{\Delta E^*_{ab}}$



INCQC Visual evaluation score for 'Colour' attribute

Early results from eye tracker, showing observer fixation points.



Observer 1 Observer 2

Standard printing conditions

For all exchanges of colour data it is necessary to:

- Define relationship between data encoding and colour appearance
  - to ensure unambiguous interpretation of colour data
- Define processes and/or control procedures
  - to obtain predictable or consistent colour on various devices
- Define image, device and process assessment procedures - metrology, test images and viewing conditions
  - to ensure consistency of assessment

Printing Definition

Based on standard metrology (ISO 13655)

Ink colour and transparency

- Colour of the ink used for printing (ISO 2846)

Printing specifications using standard ink (ISO 12647)

- Colour to be obtained on a defined range of substrates - which represent all substrates
- 'Colour' for various halftone values - sufficient to define whole range
- Tolerances for process control
- Other parameters important for production (GCR, maximum/minimum dot %, etc)

ICC Characterization Data Registry

- The ICC hosts a Characterization Data Registry for reference printing conditions conforming to ISO 12647.
- Characterization data sets created by FOGRA, CGATS/SWOP, IFRA and JapanColor are registered.
- The Characterization Data Registry includes information about the printing condition and method of measurement for each registered data set.
- This information enables an application or a user to determine which is the appropriate data set for a particular printing process
- Profiles have been published by other bodies for many of the data sets registered.

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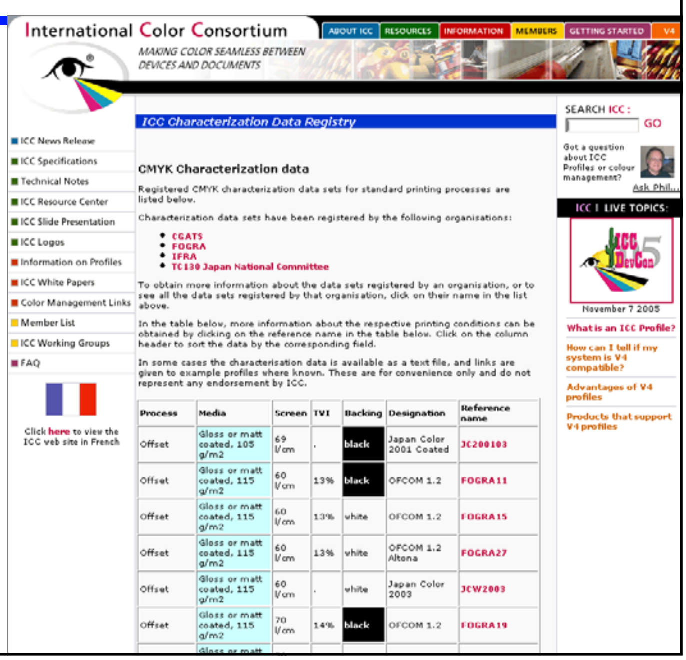
ICC Characterization Data Registry

- Reference name links to detailed page which includes process definition and source of data.
- Where available, detail page links to actual characterization data and profile.

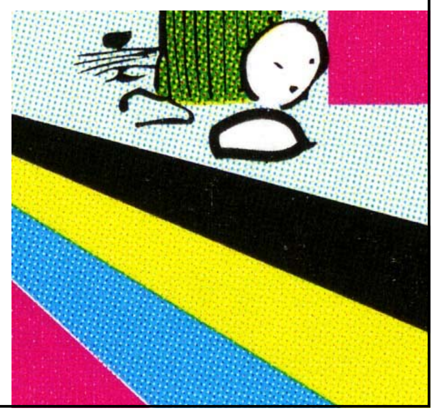


ICC Device Link profile

In many situations it is desirable to preserve the information in CMYK and xCLR separations. This information is lost when transforming between devices via the 3-component PCS.

The DeviceLink profile type provides an alternative method of transforming between devices.

A DeviceLink profile has device data as both source and destination.



ICC Device Link profile

One-way transform between devices

A single AToB transform is defined in a DeviceLink profile. Any (one) rendering intent can be used

Cannot be embedded

Does not represent device model (i.e. no Device ⟷ CIE transform)

Data Color Space is that of the first profile in the transform sequence.

As well as RGB and CMYK, xCLR spaces can be used.

If the Data Colour Space is xCLR, the colorants are defined in a colorantTableTag which specifies the colorants and their CIELAB values

Multiple profiles can be used to create a DeviceLink profiles. Information from the header of each contributing profile is stored in a profileSequenceDescTag.

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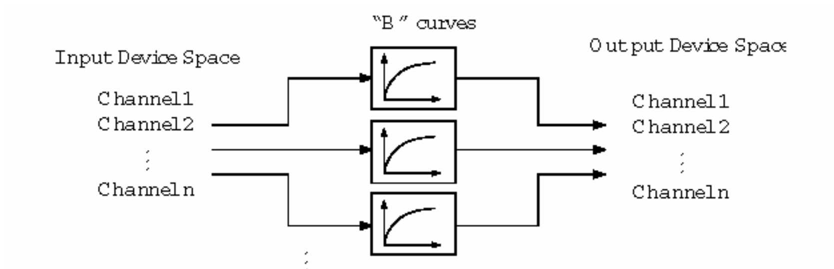
DeviceLink profile

Processing model (1) TRC



Simple tone curve adjustment of input channels, no channel mixing

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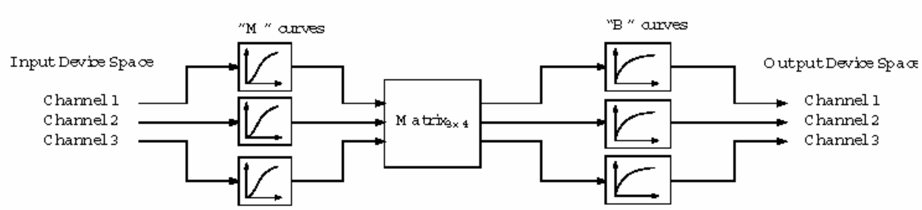
DeviceLink profile

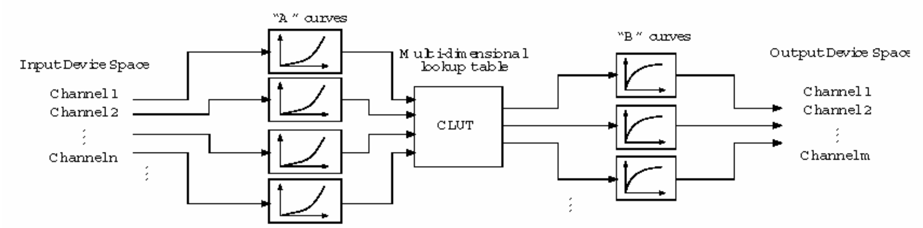
Processing model (2) Matrix + TRC



Matrix for linear mixing of channels where both input and output device spaces are 3-component spaces

DeviceLink profile

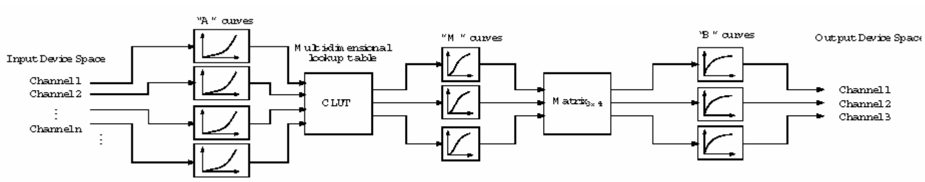
Processing model (3) CLUT + TRC



Multi-dimensional CLUT for non-linear transform between two device spaces where the number of input and output channels is 3 or more.

DeviceLink profile

Processing model (4) CLUT + Matrix + TRC



Combined CLUT ,matrix and TRC for transforms where at least one device colour space has three components

Automation of colour transforms

Graphic arts workflows are increasingly automated

PDF/X-3 files containing embedded source profiles and output intent profiles are queued for processing by a RIP

Users may receive a PDF/X-1a file with a reference printing condition but no embedded profile and need an automated method of selecting a suitable profile for this printing condition in order to make a proof

ISO TC130 is planning a version of PDF/X that allows users to include links to profiles rather than the profile itself

The ICC is considering proposals for a Profile Registry which would hold details of registered profiles for reference printing conditions – on similar lines to the Characterization Data Registry

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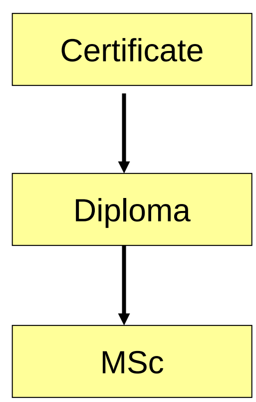
Colour imaging at LCC

Postgraduate Programme in Digital Colour Imaging



12-month full-time course beginning January

3 phases: Certificate, Diploma and MSc

Certificate and Diploma phases each comprise 3 x 30-credit taught modules

After completion of Certificate/Diploma phases, students undertake a research-based project for the MSc phase

Do the customers have to have knowledge of print media and the local printhouse to optain colour control of their magazines when, and if, they colour convert to CMYK?

Local, regional and European aspects of ICC use seen from a Norwegian heatset perspective.

References:
The *webICC.no!* project test print
Measurement and analyses:
Colorlab at GUC by Peter Nussbaum

Tom E. Johansen
Project manager quality assurance

igm

DESIGNSKOLEN
kompetanse gir overskudd

KDI project and *webICC.no!*-project

- KDI: 3 years research into quality assured content management (JDF and ICC) - amongst 3 research partners and 11 firms in the graphic arts industry
- *webICC.no!* 1 year project: "Can the customers use only one ICC profile irrespective of which print house that will execute the job?"
  - The customer do not need to know in detail the processes and media beeing used

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Goals of the ***webICC.no!***-project

- 1. Test print in 5 heatset print houses to assess present situation - by printing 16 pages with pictures profiled with their own local colour profile and one international reference profile
- Measure and generate one average profile from the 1. test print, and evaluate that in comparison with an international profile
- 2. Test print (some of the same pictures - repeatability) by using average, new local and international profiles
- Dissemination of results to customers, the graphic art industry and in seminars

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16 page signature
A 4

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Prima


Sekunda

5 firms

webcoatedISO

ICC profile

5 firms

local

ICC profile

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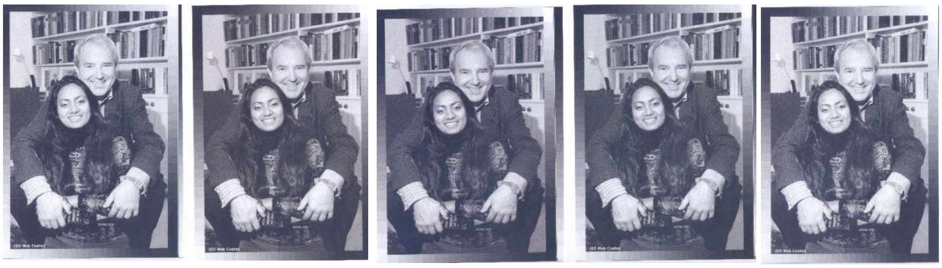
5 firms

webcoatedISO

ICC profile



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5 firms

local

ICC profile

DESIGNSKOLEN

kompetanse gir overskudd

5 firms

webcoatedISO

ICC profile

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5 firms

local

ICC profile

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7. september 2005

WEBICC

Testmålinger ved Fargelaboratoriet HIG

Peter Nussbaum, Gjøvik University College

colorlab.no

The Norwegian Color Research Laboratory

HØGSKOLEN I GJØVIK

The goals of the test printing

- Testing of the heatset offset printing capabilities of each **webICC.no!** member
- What could be the differences between these capabilities, each press compared to the average of these presses, the average of the 5 and the ISOwebcoated
- Evaluation, by Peter Nussbaum, is based on objective colorometric measurements

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Measurements

- For every printhouse 6 **ECI**2002V CMYK test charts have been measured, representing the printrun
  - 1. Measurement: print no 1 Schön - prima
  - 2. Measurement: print no 1 Wider - sekunda
  - 3. Measurement: print no 10 Schön - prima
  - 4. Measurement: print no 10 Wider - sekunda
  - 5. Measurement: print no 21 Schön - prima
  - 6. Measurement: print no 21 Wider - sekunda
- **ECI**2002V CMYK test chart were chosen since this chart were used by **ECI** to generate the ISOwebcoated.icc profile

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Measurement equipment

- Spectrophotometer, Spectrolino.
- Spectral measurements giving data.
- XYZ conversions based on 2° and D50 lightsource.
- CIELAB data is based on D50 white
- ΔE^*ab is the basis for calculation of all coulor differences.

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Measurements and evaluation

- 1. Repeatability for each printing press
- 2. Differences between these presses
- 3. Differences between each press and ISOwebcoated
- 4. Difference between **webICC** (average of the 5 presses/printhouses) and ISOwebcoated

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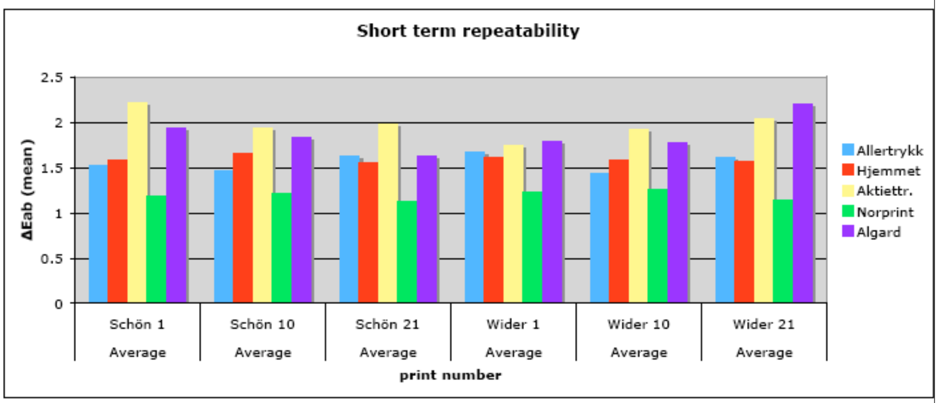
Repeatability for each printing press

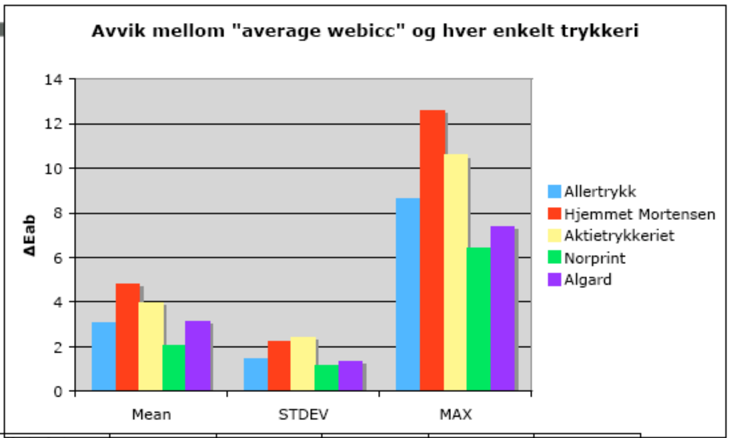
1. Repeterbarhet fra hver enkelt trykkpresse



Forholdet mellom gjennomsnittet av alle fem presser og hver enkelt kandidat.

Difference between 5 print houses

2. Avvik mellom de 5 trykkpresser



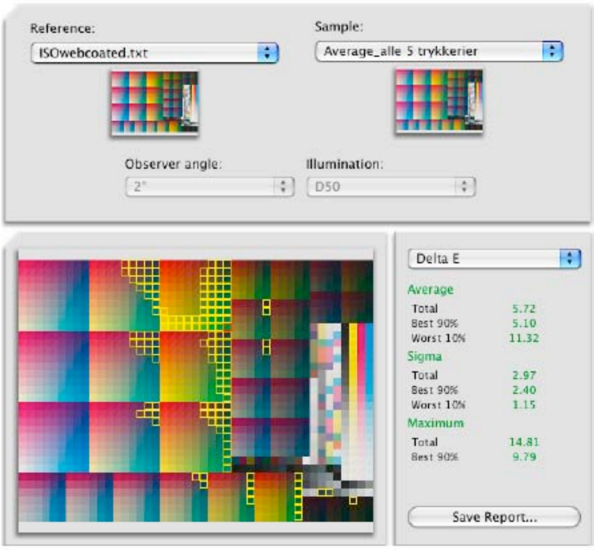
Bestrøket					
	Average webicc AllerTrykk	Average webicc Hjemmet M	Average webicc Aktietrykkeriet	Average webicc Norprint	Average webicc Ålgård
ΔEab					
Mean	3.09	4.83	3.96	2.06	3.12
STDEV	1.47	2.24	2.41	1.16	1.35
MAX	8.65	12.58	10.58	6.42	7.41

Difference between **webICC** and ISOwebcoated

4. Avvik mellom webicc og «ISOwebcoated»

Difference between **webICC** (average of 5 print houses) and ISOwebcoated

Avvik mellom webicc (gjennomsnitt av alle 5 trykkerier) og «ISOwebcoated»

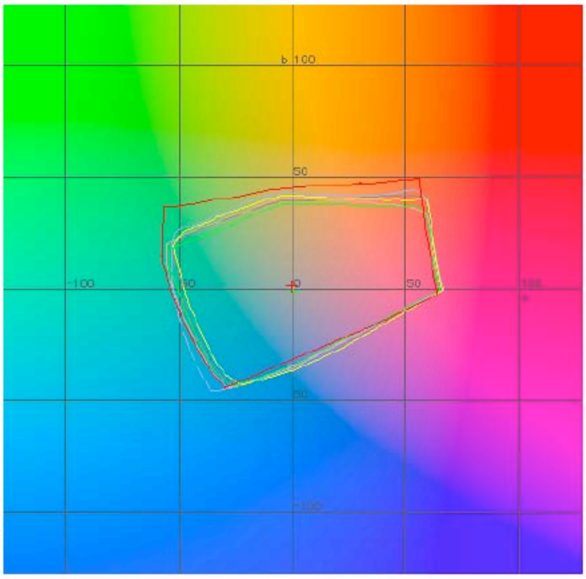


Difference between **webICC** and ISOwebcoated

4. Avvik mellom webicc og «ISOwebcoated»

Fargeomfang (Colour Gamut)

- webAktirtrykkeri (CMYK)
- webAlgard (CMYK)
- webHjemmet (CMYK)
- webAller (CMYK)
- webNorprint (CMYK)
- ISOwebcoated.icc (CMYK)



2D (ab) diagrammet (på L*=50) med colour gamut av de 5 trykk inklusive «ISOwebcoated»

Difference between **webICC** and ISOwebcoated

4. Avvik mellom webicc og «ISOwebcoated»

Fargeomfang Colour Gamut)

- webAktirtrykkeri (CMYK)
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- webHjemmet (CMYK)
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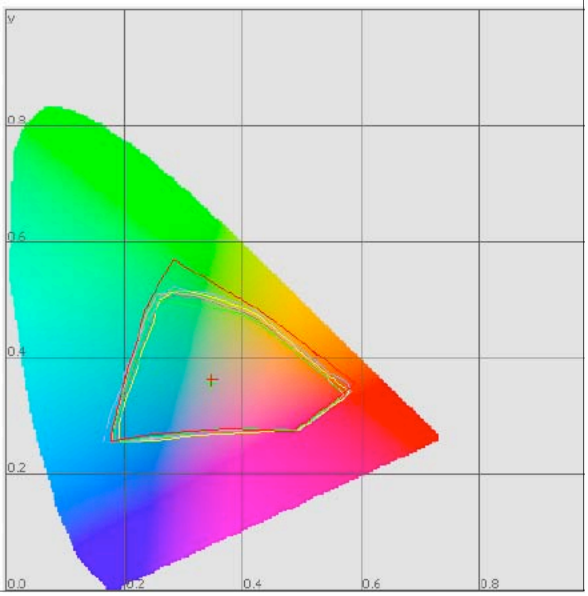

2D (xy) diagrammet (på L*=50) med colour gamut av de 5 trykk inklusive «ISOwebcoated»

Difference between **webICC** and ISOwebcoated

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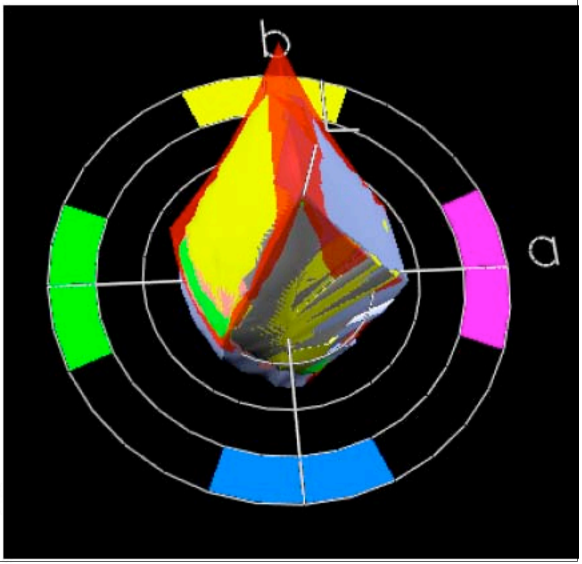

3D (Lab) diagrammet (på L*=50) med colour gamut av de 5 trykk inklusive «ISOwebcoated»

What could possibly this imply?

- Is there a need for local ICC profiles?
  - Definately, since we use different machines and paper media
- Is there a need and place for regional ICC profiles for defined processes?
  - SWOP, EuroCMYK
  - Regoinal standards ISO
  - Sheet fed: coated, silk and uncoated
  - Heatset: coated, silk and uncoated
  - Coldset: white newsprint, coloured newsprint

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Which is the most benefactor?

- The quality assured print house that can say to its customers:
- "You just send us the taged RGB, we know how to handel the rest of the process!"
  - Meaning: they know their CMYK-conversion schemas, CTP rendering and compensations, defined and controlled print process and media capabilities!

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Gjøvik Color Imaging Symposium 2005

November 30th 2005

Factors Affecting the Appearance of Print

Peter Nussbaum

colorlab.no

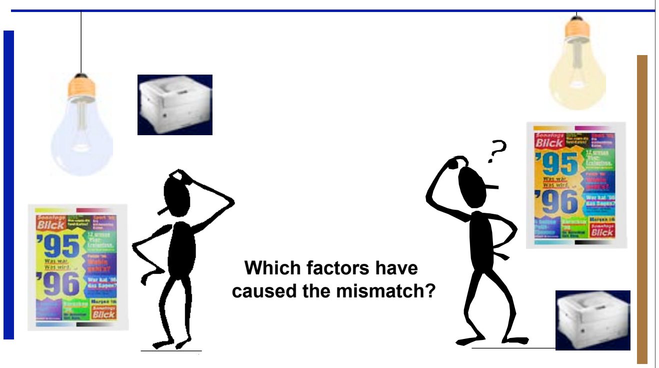
The Norwegian Color Research Laboratory

Outline

- Introduction
- Experimental method
- Data analysis
- Results
- Further research

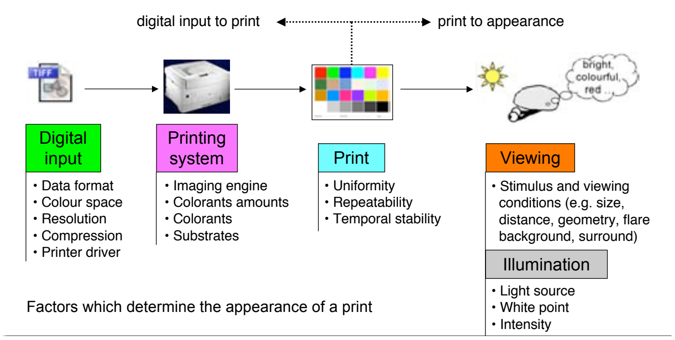
Introduction:

Typical practical scenario



Introduction:

Generic digital printing workflow



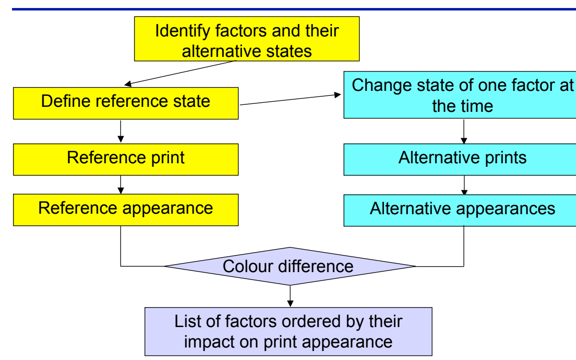
Introduction:

Aims of the project

- **To develop a list of factors ordered in terms of the magnitude of their potential impact on print appearance.**
- **The final result will be a list of factors ordered in such a way and it could be used as a checklist for those involved in the making and servicing of printing systems.**

Experimental methods:

Overview over method

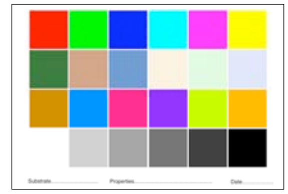


Experimental methods:
Resources

- Printer
- Substrates
- Computer for controlling printer
- Tele-spectroradiometer
- Viewing booth
- Application for data analysis

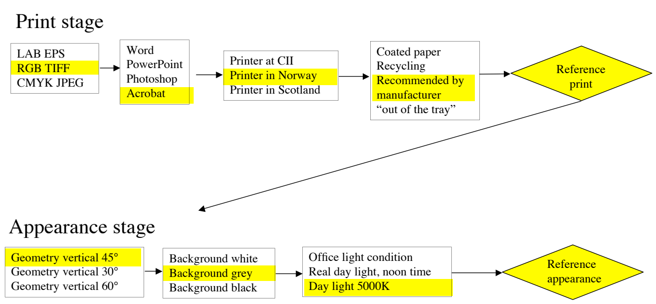
Experimental methods:
Digital test chart

- 24 colour patches in RGB colour space.
- Memory colours: skin, grass and sky.
- Pastel colours
- Colours from the RGB-cube's surface give information about the print's colour gamut.
- The last row contains a grey scale colours which will show how tone rendering is affected by various factors.



Digital RGB test image

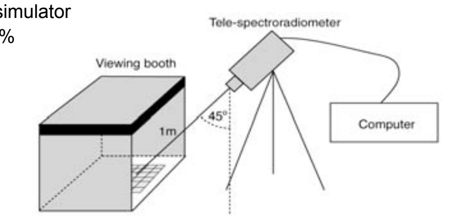
Experimental methods:
Reference setting



Experimental methods:
Measuring set-up

Viewing set-up for the reference is based on the standard condition of the graphic art industry (ISO 3664, viewing condition)

- Vertical geometry 45°
- Background grey
- Light source D50 simulator
- Light intensity 100%



Experimental methods:
Potential factors

Factors and their alternative states:

Factors	Alternative state	Alternative state	Alternative state
Digital input			
Printer setting	Visual calibration	mis-calibr. 1	mis-calibr. 2
		extr. magenta	extr. blue
Printer driver setting PPD	Color Control	Image color matching	Black Finish
Application used for printing	Adobe Photoshop	MS PowerPoint	MS Word
Application printing menu	Individual ICC	Standard OKI ICC	Newspaper ICC
Printing system			
Various printing system	C7400 Oki Scottland	C7400 Oki CII	
Substrate properties	"out of the tray"	Silk 250g	Carton 250g
Print			
Printers repeatability	2. Week	3. Week	4. Week
MTS in dark condition	2. Week	3. Week	4. Week
MTS in day light condition	2. Week	3. Week	4. Week

Requires both new prints and new measurements

Experimental methods:
Potential factors

Factors and their alternative states:

Factors	Alternative state	Alternative state	Alternative state	Alternative state
Viewing				
Geometry vertical	60°	30°		
Geometry horizontal	45°			
Background	white	black		
Surround	Ambient light on			
Illumination conditions				
Light source	CWF 4150K	A 2856K	normal office light condition	real daylight
Intensity	75 %	50 %	25 %	

Requires only new measurements

One factor at the time only has been changed

Experimental methods:

Colour measurement

- The aim of the present project has been achieved on the basis of data gathered in an experiment involving colour measurement.
- **Repeatability of the measuring instrument**
  - Short-term repeatability performance of the measuring instrument has a mean ΔE^*_{ab} of 0,05 and 95th percentile of 0,11.
- **Repeatability of the reference measuring set-up**
  - The mean repeatability error was ΔE^*_{ab} of 0,4 and 95th percentile of 0,83.

Data analysis:

Measurement data

- From measured spectral radiance data X, Y and Z tristimulus values have been calculated (observer angle 2°).
- L*a*b* values have been computed from each set with the reference white from the calibration tile.
- CIE94 colour-difference calculated between reference and alternative states.
- Arithmetic mean, maximum and 95th percentile indicate the resulting colour difference distribution.

Data analysis:

CIECAM97s

- Colour Appearance Model CAM takes the intensity of illumination and light source into account.
  - CIECAM97s applied to predict XYZ values for factors:
    - Light source conditions
    - Intensity conditions
    - Background
  - Firstly the forward model has been used to predict Jab from XYZ and then the reverse model to predict XYZ from Jab under the reference conditions.

Data analysis:

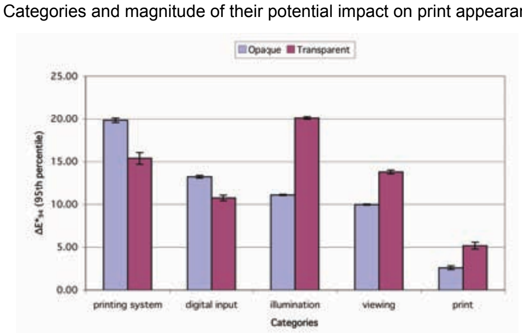
Perceptibility threshold

- Considering the colour difference in relationship to perceptibility threshold, which indicates the colour difference area where differences are just noticeable (JND).
- Perceptibility threshold in complex images.
- Perceptibility threshold for single colours.
  - Due to the nature of the targets content and texture.
- High percentile correlates better with the perceptibility threshold than by mean colour differences (Uroz *et* al. (2002).

Results:

Categories

Categories and magnitude of their potential impact on print appearance.



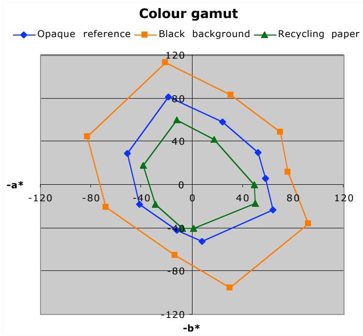
Results:

Factors

List sorted by 95th percentile of ΔE^*_{94} distributions between reference state and alternative states of individual factors (Opaque substrate).

Category	Factors	ΔE*94 95th perc	
Printing system	Various printer	25,12	
Digital input	Application printing menu (Profile)	16,20	
Digital input	Printer setting (Calibration)	15,93	
Viewing	Background	12,87	
Illumination	Light source	11,42	
Printing system	Substrate	9,98	
Digital input	Printer driver setting	8,00	
Viewing	Geometry	3,62	
Illumination	Intensity	3,57	
Print	Repeatability	3,22	perceptibility threshold
Digital input	Application used for printing	2,96	in complex images
Print	MTS light	1,41	
Print	MTS dark	0,59	perceptibility threshold
Viewing	Surround	0,47	for single colours

Results:
Effect on colour gamut



Effect of changes to Factors considered in terms of the colour gamut

Comparison of smallest, largest and reference 2D colour gamuts

Results:
Relative gamut volumes

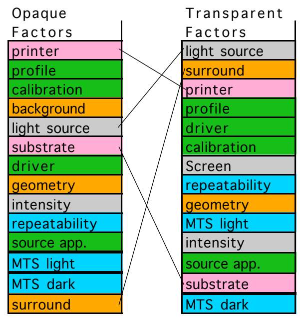
RANKING	%
Background black	224
Office light condition	117
Printer driver "Color Control"	105
Opaque reference	100
Mis-calibration	99
Individual ICC profile	72
Printer system CII	71
Recycling paper	39

Alternative states ordered by relative gamut volumes.

Effect of changes to factors considered in terms of their relative colour gamut.

Results:
Correlation between substrates

List of factors ordered in terms of their impact on print appearance.



Results:
Implementation of the results

- Application for printer manufacturer
  - Check list for technical support
  - Recommendation for customers
  - Training
  - Printer quality control

Further research:
Further research areas

- More then one factor at the time could be changed simultaneously.
- Further data analysis to investigate alternative states and their impact on memory colours and tone reproduction curve.
- More research on alternative states (e.g. printer driver).
- Help desk system (artificial intelligence system).
- Extension to other media (e.g. factors affecting the appearance of display, digital projector).

Summary

- Evaluating the magnitude of visual differences in prints caused by changes in various factors and ordered in a list in terms of the size of their potential impact on print appearance.
- The colour differences were compared to perceptibility thresholds both in complex images and for single colours.
- Factor “Printing system” affect most the print appearance whereas the factor “Surround” condition did not cause any change.
- Illustrates the impact of the factors in terms of variation in colour gamut.
- Basis for developing more robust printing solutions and for troubleshooting current printing system.

Thank you for your attention...

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colorlab.no

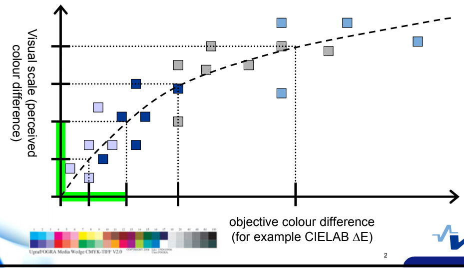
The Norwegian Color Research Laboratory

Proof-to-print tolerances in contract proofing

Gjovik Color Imaging Symposium 2005
30.11 - 1.12 .2005, Gjovik
Olli Nurmi, Janne Laine, Kaisa Koivumäki

The target of the study

Define an objective tolerance for the contract proofing



Implementation of the study

- 20 proofing systems with ICC-workflow made proofs with coated/uncoated paper
- 33 persons* made following visual test:
  1. **Rank order experiment**: eight pictures were compared to reference
  2. **Category scaling experiment**: proofs were compared one by one to the reference

•*colour vision was tested with the Ishihara test.

Viewing conditions

- ISO 3664:2000: Viewing conditions—Graphic technology and photography
- Conditions for critical comparison of prints (P1)
  - Illuminance ≈ 2000 lux
  - ≈ standard illuminant D_{50}
  - neutral gray background

Rank order experiment

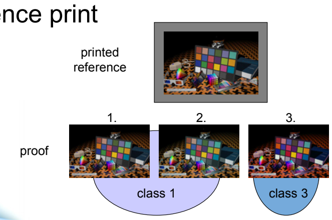
- Observers were asked to choose from 8 samples the proof that best matched the reference print (center)
- Repeat for remaining proof samples

Interval scale from rank order data

- Experimental rank order data was transformed into form of paired comparison data
- Thurstone's Law of Comparative Judgement was applied to data to calculate interval scale values for each proof sample
- The proofs with the highest interval scale values (z-score) are visually closest to the reference print

Category scaling experiment

- Observers were asked to place each proof sample into 1 of 3 categories according to how well the proof matched the colors of the reference print



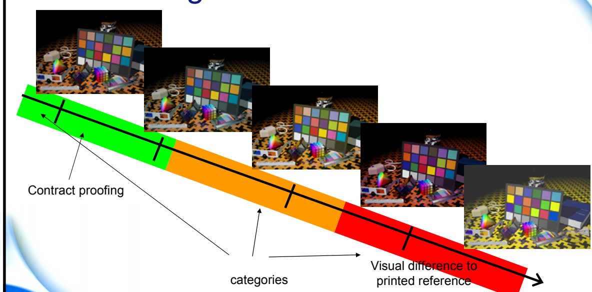
the original version of the example image: ©Bruce Lindbloom (www.brucelindbloom.com)

Category definitions*

- Category 1—Excellent proof: The difference between the colors of the reference print and the proof is not noticeable or is just noticeable.
- Category 2—Acceptable contract proof: There is a noticeable difference between the reference print and the proof, but the difference is small enough to be still acceptable for a contract proof.
- Category 3—Not acceptable as a contract proof: The proof differs significantly from the the reference print, and is not acceptable as a contract proof.

*translations from Finnish observer instructions

Categories in interval scale



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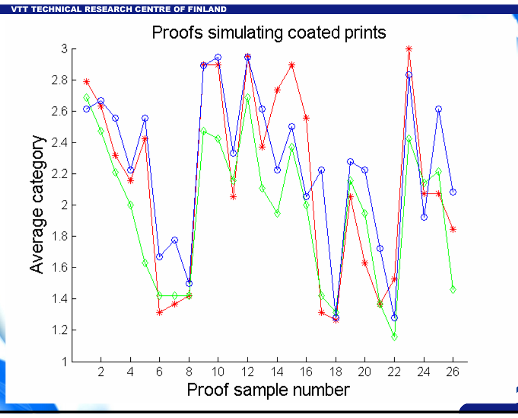

Average categories of the proofs, coated paper

	KuvaA (ka)	KuvaB (ka)	KuvaC (ka)	ABC (ka)	ABC (hajonta)
A-C018	1,26	1,32	1,28	1,29	0,46
A-C022	1,53	1,16	1,28	1,32	0,51
A-C008	1,42	1,42	1,50	1,45	0,54
A-C006	1,32	1,42	1,67	1,47	0,54
A-C021	1,37	1,37	1,72	1,49	0,57
A-C007	1,37	1,42	1,78	1,52	0,60
A-C017	1,32	1,42	2,22	1,65	0,64
A-C026	1,85	1,46	2,08	1,80	0,58
A-C020	1,63	1,95	2,22	1,93	0,60
A-C024	2,07	2,14	1,92	2,05	0,67
A-C004	2,16	2,00	2,22	2,13	0,51
A-C019	2,05	2,16	2,28	2,16	0,63
A-C011	2,05	2,16	2,33	2,18	0,61
A-C005	2,42	1,63	2,56	2,20	0,72
A-C016	2,56	2,00	2,06	2,20	0,68
A-C025	2,07	2,21	2,62	2,30	0,56
A-C014	2,74	1,95	2,22	2,30	0,60
A-C003	2,32	2,21	2,56	2,36	0,62
A-C013	2,37	2,11	2,61	2,36	0,52
A-C015	2,89	2,37	2,50	2,59	0,56
A-C002	2,63	2,47	2,67	2,59	0,53
A-C001	2,79	2,68	2,61	2,69	0,46
A-C023	3,00	2,42	2,83	2,75	0,44
A-C009	2,89	2,47	2,89	2,75	0,48
A-C010	2,89	2,42	2,94	2,75	0,48
A-C012	2,95	2,68	2,94	2,86	0,35

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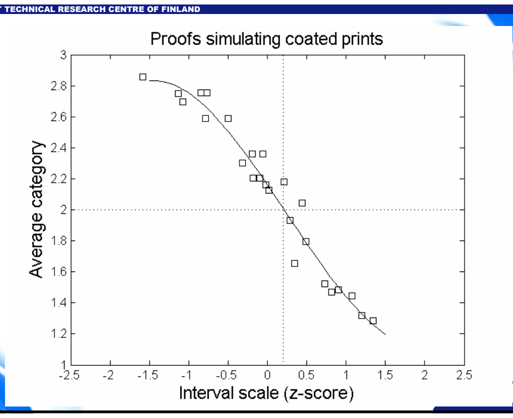
Z-scores, 95% confidence intervals, and ranks (coated paper)

Kuva	Z-arvo	95% LV	Järjestys
ABC018	1,34	0,17	1
ABC022	1,20	0,18	2
ABC008	1,07	0,15	3
ABC021	0,90	0,16	4
ABC006	0,82	0,17	5
ABC007	0,73	0,15	6
ABC026	0,49	0,17	7
ABC024	0,44	0,16	8
ABC017	0,35	0,15	9
ABC020	0,29	0,16	10
ABC011	0,21	0,16	11
ABC004	0,02	0,16	12
ABC019	-0,02	0,14	13
ABC013	-0,06	0,15	14
ABC016	-0,09	0,16	15
ABC005	-0,18	0,16	16
ABC003	-0,19	0,15	17
ABC025	-0,32	0,16	18
ABC014	-0,32	0,16	19
ABC015	-0,50	0,17	20
ABC010	-0,77	0,16	21
ABC002	-0,78	0,15	22
ABC009	-0,84	0,15	23
ABC001	-1,08	0,15	24
ABC023	-1,13	0,17	25
ABC012	-1,58	0,17	26

VTT TECHNICAL RESEARCH CENTRE OF FINLAND



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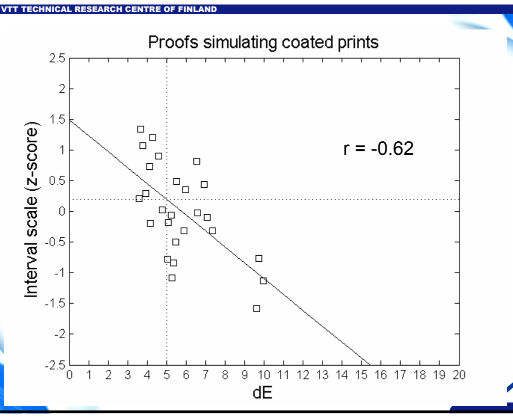
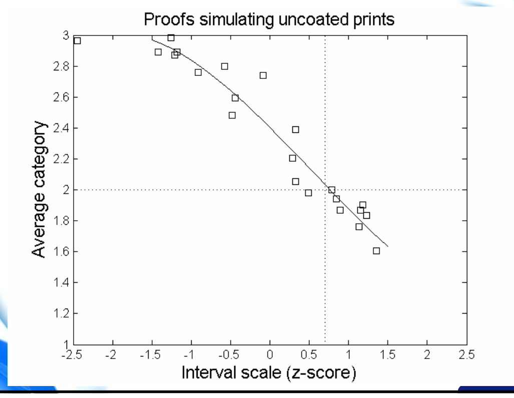
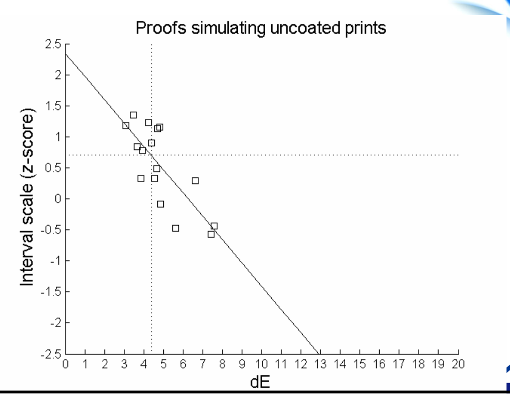


VTT TECHNICAL RESEARCH CENTRE OF FINLAND



VTT TECHNICAL RESEARCH CENTRE OF FINLAND



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Summary of results

- Maximum aceptable color difference for a contract proof ~4-5 ΔE
- CIE94 and CIEDE2000 equations did not perform better than the classic ΔE in predicting perceived color differences in complex images between print and proof
- ΔE's measured from the Media wedge give only appr. indication of perceived color difference
  - ΔE metrics designed for uniform color patches not perfectly suited for predicting perceived color differences between complex images
  - memory colors, sensitive grays

Making and using ICC profiles with Matlab

Support for ICC profiles in Matlab
Reading and writing profiles
Shaper/matrix profiles
Interpolation and table look-up
LUT-based profiles

Phil Green
Colour Imaging Group, LCC

Why use Matlab for ICC transforms?

Double precision calculation, no rounding
- (LUTs limited to 8 or 16 bit precision by ICC spec)

Can evaluate individual elements of a transform

Can apply profile classes such as Abstract and Link which are not supported by some other programs

Can script complex sequences of actions and loop through lists of images or profiles

General support for ICC profiles

Matlab Image Processing Toobox support for ICC profiles

P=ICCREAD(profilename)
• Reads an icc profile and stores the result as a structure in p

C = MAKECFORM('icc', SRC_PROFILE, DEST_PROFILE)
• Creates a colour transformation using the source and destination profile specified

B = APPLYCFORM(A, C)
• Converts the color values in A using the colour transformation specified in C

P_NEW = ICCWRITE(P, newprofilename)
Writes the structure P to an ICC profile with the filename specified

Reading ICC profiles

Output of iccread

P=iccread('ProPhoto.icm')

Header: [1x1 struct]
TagTable: {12x3 cell}
Copyright: [1x63 char]
Description: [1x1 struct]
MediaWhitePoint: [0.9642 1 0.8249]
DeviceMfgDesc: [1x1 struct]
DeviceModelDesc: [1x1 struct]
MatTRC: [1x1 struct]
PrivateTags: {'mmod' [1x40 uint8]}
Filename: 'ProPhoto.icm'

Reading ICC profiles

Output of iccread: Header

P=iccread('ProPhoto.icm'); P.Header

Size: 940
CMMType: 'KCMS'
Version: '2.1.0'
DeviceClass: 'display'
ColorSpace: 'RGB'
ConnectionSpace: 'XYZ'
CreationDate: '01-Dec-1998 18:58:21'
Signature: 'acsp'
PrimaryPlatform: 'Microsoft'
DeviceManufacturer: 'KODA'
DeviceModel: 'ROMM'
RenderingIntent: 'perceptual'
Illuminant: [0.9642 1 0.8249]
Creator: 'KODA'

Reading ICC profiles

Output of iccread: Tag Table

P=iccread('ProPhoto.icm'); P.TagTable

'cprt'	[276]	[72]
'desc'	[348]	[131]
'wtpt'	[480]	[20]
'rTRC'	[500]	[14]
'gTRC'	[500]	[14]
'bTRC'	[500]	[14]
'rXYZ'	[516]	[20]
'gXYZ'	[536]	[20]
'bXYZ'	[556]	[20]
'dmnd'	[576]	[110]
'dmdd'	[688]	[209]
'mmod'	[900]	[40]

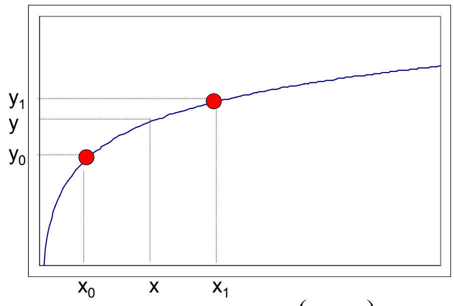
Reading ICC profiles

Output of iccread: Matrix and tone curve

P=iccread('ProPhoto.icm'); P.MatTRC

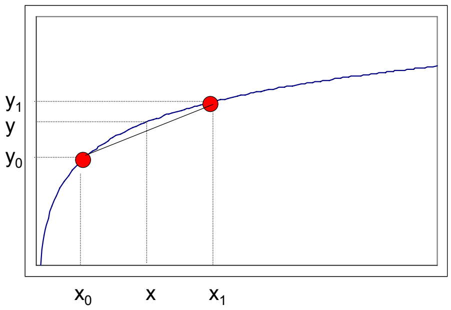
```
RedTRC:    461
GreenTRC: 461
BlueTRC:    461
RedColorant:    [0.7977  0.2880  0]
GreenColorant: [0.1352  0.7119  0]
BlueColorant:    [0.0313  0.0001  0.8249]
```


1-D Interpolation



$$y = y_0 + (y_1 - y_0)\frac{(x - x_0)}{(x_1 - x_0)}$$

1-D Interpolation

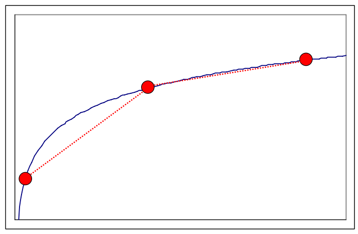


Interpolation error = y_{est} - y

1-D Interpolation

To smooth a curve by adding new points by cubic spline interpolation:

```
xfine=linspace(x(1),x(end));
yfine=interp1(x,y,xfine,'cubic');
plot(xfine,yfine)
```



Creating shaper/matrix tables

Steps in creating a Matrix/TRC profile

1. **Determine Colorant values**
2. **Determine TRC values**
3. **Convert to encoding**
4. **Add to profile structure**

Determine colorant values

```
rColorant=[0.4124,0.3576,0.1805];
gColorant=[0.2126,0.7152,0.0722];
bColorant=[0.0193,0.1192,0.9505];
```

Determine TRC values

```
in=linspace(0,1,1024);
out=in.^2.4;

rTRC=out*65535;
gTRC=out*65535;
bTRC=out*65535;

%  OR

rTRC=2.4*255
```

this ranges the values

we then need to type as uint8 values

We can also encode as an exponent

Add to profile structure

```
P=iccread('SMPTE-C.icc.m');
```

Use an existing profile as a template for convenience

```
P.RedTRC = rTRC;
P.GreenTRC = gTRC
P.BlueTRC = bTRC

P.RedColorant = rColorant
P.GreenColorant = rColorant
P.BlueColorant = rColorant
```


Write the new profile

```
P.Copyright='Phil Green';
P.Description.String='philicc';
```

Note that the description field is what is usually displayed in a list of profiles.

Now we're ready to write the new profile

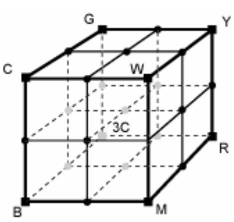
```
P2=iccwrite(P,'phils_profile.icc');
```


Table look-up and 3-D interpolation

Three steps in using look-up tables:

1. Packing
2. Extraction
3. Interpolation

Table look-up: packing



3x3x3 LUT

Each node stores an input value and a corresponding output value.

The input space should be uniformly spaced.

In practice, LUT dimension is often either n^2 or n^2+1, where n is a multiple of 2

This allows computationally simple methods of extraction or interpolation to be used

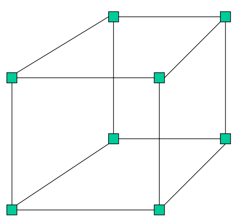


Table look-up: extraction

Given a colour P , whose input value is bounded at the lower corner by $[c_1\ c_2\ c_3]$ where $c_{1:3}$ are the indices of the entries in the uniform 3D table T of size n

i.e. $p_1 = T(c_1\ c_2\ c_3)$

$p_{1\,(1)} < P(1)$

$p_{1\,(2)} < P(2)$

$p_{1\,(3)} < P(3)$

LUT row of lower corner of bounding cube is given by:

$p_1 = c_1.n^2 + c_2.n + c_3$

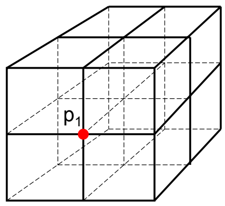


Table look-up: extraction

If the LUT row of lower corner of bounding cube is given by:

$p_1 = c_1.n^2 + c_2.n + c_3$

LUT row numbers of the bounding cube are then given by:

p_1 + [0 1 n n+1 n^2 n^2+1 n^2+n n^2+n+1]

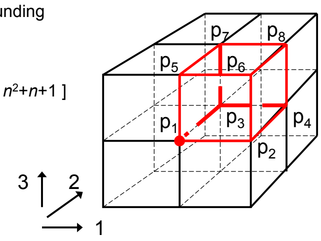
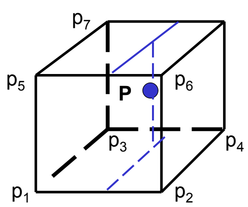
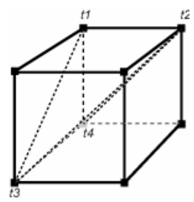


Table look-up: 3-D interpolation



Bounding cube: tri-linear interpolation or sequential linear interpolation



Bounding tetrahedron: tetrahedral or barycentric interpolation

Table look-up: interpolation

Trilinear interpolation

$$P(x,y,z)= c_1+c_2\Delta x+c_3\Delta y+c_4\Delta z +c_5\Delta x\Delta y+c_6\Delta x\Delta z +c_7\Delta y\Delta z + c_8\Delta x\Delta y\Delta z$$

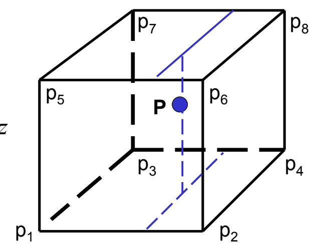


Table look-up: interpolation

P(xyz) = c(1) + c(2)Δx + c(3)Δy + c(4)Δz + c(5)ΔxΔy + c(6) ΔxΔz + c(7)ΔyΔz + c(8)ΔxΔyΔz

where:

c(1)=p1

c(2)=(p5-p1)/Δx

c(3)=(p3-p1)/Δy

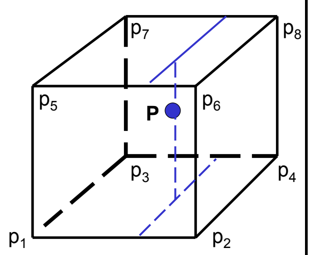
c(4)=(p2-p1)/Δz

c(5)=(p7-p3-p5+p1)/(ΔxΔy)

c(6)=(p6-p2-p3+p1)/(ΔxΔz)

c(7)=(p4-p2-p3+p1)/(ΔyΔz)

c(8)=(p8-p4-p6-p7+p5+p2+p3-p1)/(ΔxΔyΔz)



Creating output tables

Steps in creating a 3-D LUT for an ICC profile

1. **Generate input table**
2. **Calculate output values**
3. **Convert to encoding**
4. **Reshape dimensions if necessary**
5. **Add to profile structure**

Table look-up: packing

Rules for input table formation:

- 1 column per colour component
- Normalise input table entries to fixed range (conventionally 0-1)
- Equal intervals between entries
- First column varies least rapidly, last column varies most rapidly.

E.g. for a simple RGB cube:

R	G	B	
0	0	0	(black)
0	0	1	(blue)
0	1	0	(green)
0	1	1	(cyan)
1	0	0	(red)
1	0	1	(magenta)
1	1	0	(yellow)
1	1	1	(white)

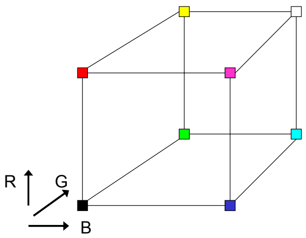


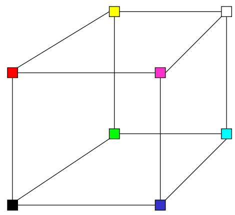
Table look-up: packing

Output table

- Output table consists of the output values corresponding to each entry in the input table

Index	R	G	B	L*	a*	b*
1	0	0	0	0	0	0
2	0	0	1	40	0	-50
3	0	1	0	55	-60	20
4	0	1	1	50	-55	-45
5	1	0	0	60	60	40
6	1	0	1	50	55	-10
7	1	1	0	90	5	80
8	1	1	1	100	0	0

Only the output table is stored in the profile



Input table

```
% BToA0 structure
% generate input table
t=[0:1:255];

% convert to encoding
t_in1=uint16(t*257);
```


LUT

```
% generate lut
n=32;
lut=create3dlut(n);
B(:,1)=lut(:,1)*100;
B(:,2:3)=lut(:,2:3)*255-128;

% calculate output values
a=xyz2srgb(lab2xyz(B));

% convert to encoding
A=uint16(a*257);
```


LUT

```
% reshape to dimensions required by profile-
  writing library
for i=1:3
   cubeB(:,:,:,i)=reshape(A(:,i),n,n,n);
end
```


Add to profile structure

```
% generate profile structure array
P=iccread('ICCtemplate.icc');

% add BToA0 tables to profile structure array
P.BToA0.InputTables{1}=t_in1;
P.BToA0.InputTables{2}=t_in1;
P.BToA0.InputTables{3}=t_in1;

P.BToA0.CLUT=cubeB;
```

Write profile

```
% update filename and write profile
newfilename='fred0010.icc';
P.Filename=newfilename;
iccwrite(P,newfilename);
```


Writing ICC profiles with Profiler

Colour Engineering Toobox ICC Profiler function

```
load iccprofilestructure
% .......
% add fields to profile structure in Mprofile as required
% ......
MAKEPROFILE(mProfile, profilename)
```

- uses C++ wrapper for lcms library
- accepts LUT grid in nx3 structure
- accepts private tag for storing parameter information
- accepts profile structure from iccread

Other Matlab resources

Colour Engineering Toobox

3D LUT
`ndlut`
`extract3d`
`lookup3d`

Characterization
`charac3`
`polyconvert3`

Colour conversions
Most colour conversions supported
All functions fully vectorized for performance

Other resources

Other third party Matlab functions

- **Stephen Westland's Computational Colour Science**
- **Harold Boll's profile test**

C++ resources

- **SampleICC**
- **Argyll**
- **Lcms**
- **ICC header file**

Spatial color imaging: from retinex to ACE

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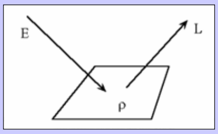
Outline

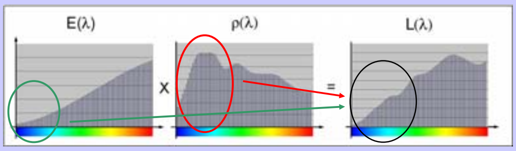
- pixel colorimetry
- HVS adaptational properties
- color in context and appearance
- global vs local
- Retinex
- ACE
- application for tone reproduction
- Conclusion and perspectives

What is color

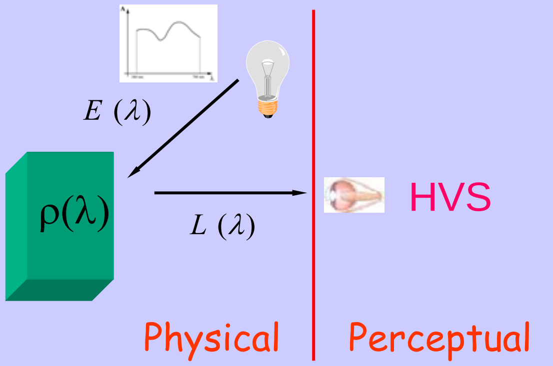
- Only exists spectral power distributions in the visible range (380-780nm)



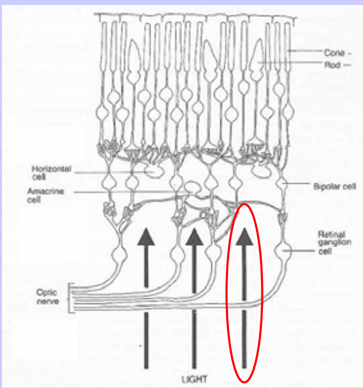
$$L(\lambda) = E(\lambda)\rho(\lambda)$$



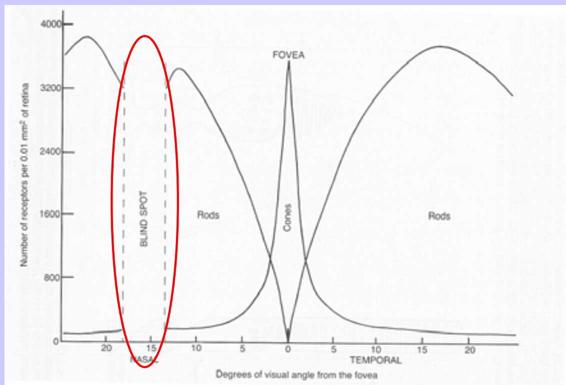
Vision Process

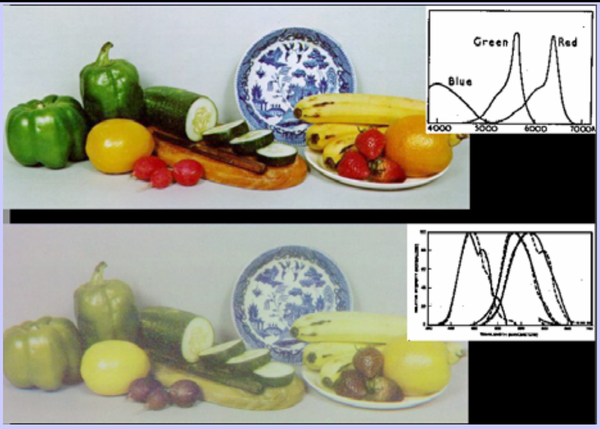


Light direction towards retina



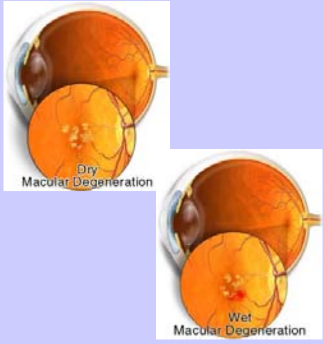
Rods/cones distribution in the retina



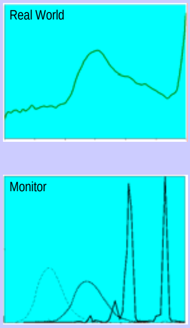


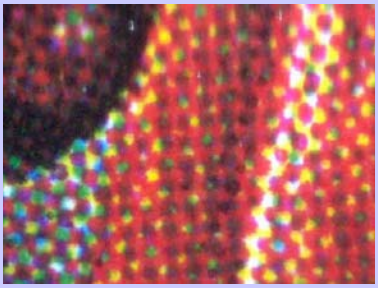
by Land and McCann

Macula degeneration



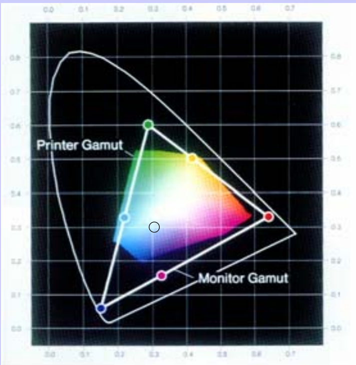
Metamerism



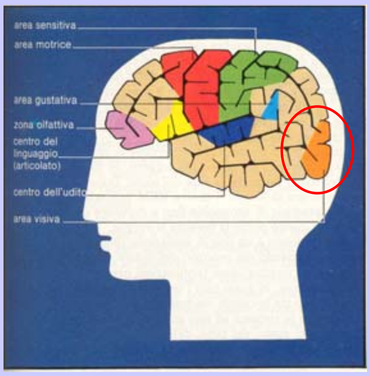


Gaze and attention

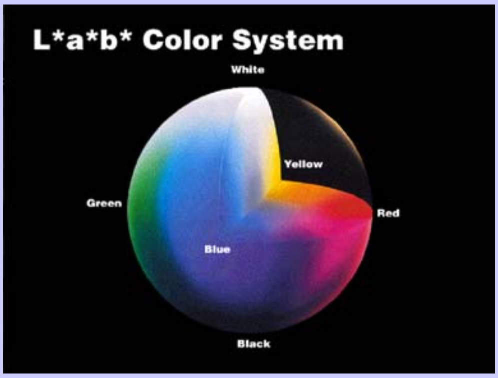
Device gamuts

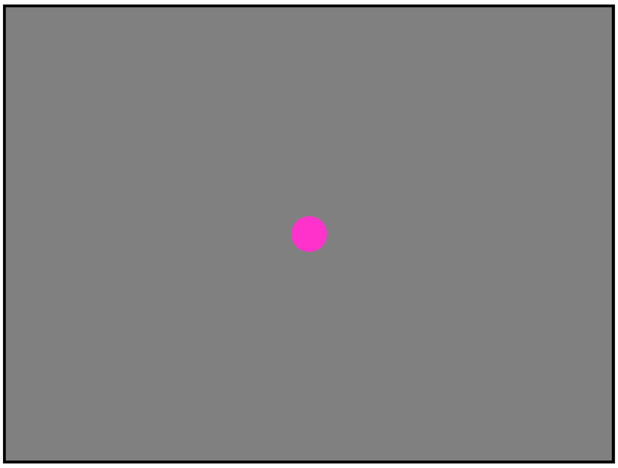


Color sensation



CIELab space





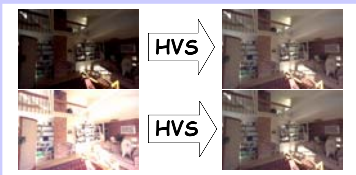
Color depends on context

color is subject to several computations that depend on context

HVS adaptational mechanisms

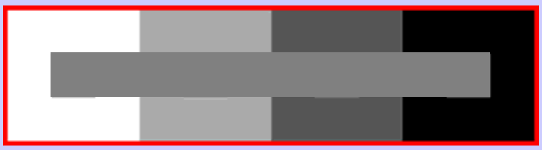
Lightness constancy

GW



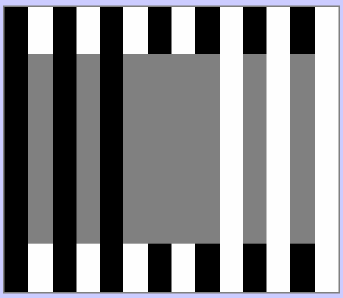
Never completely

Lightness perception



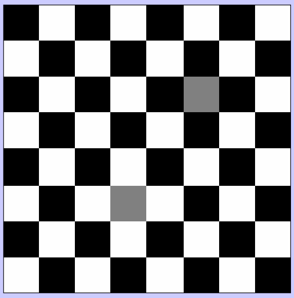
Simultaneous contrast

Lightness perception



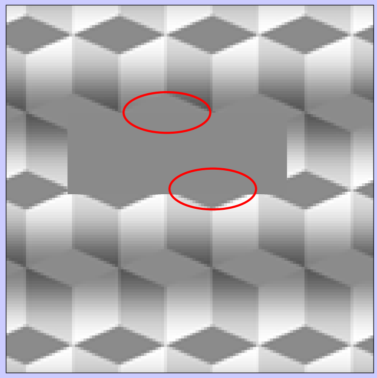
ASSIMILATION: White's Effect

Lightness perception

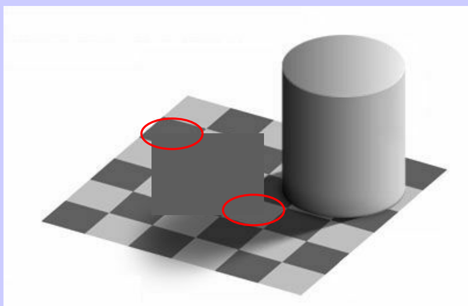


ASSIMILATION: De Valois

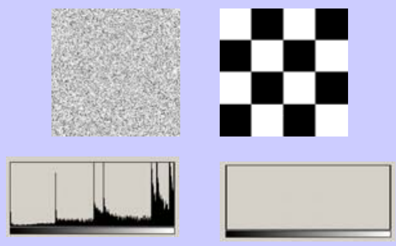
High vs low level



High vs low level

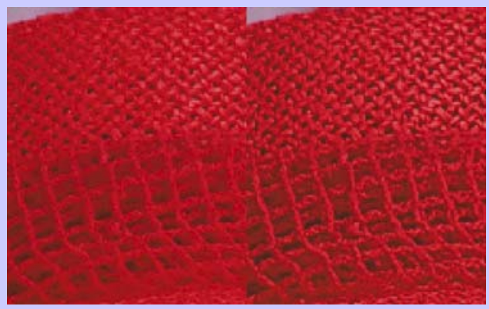


Local contrast and visual information

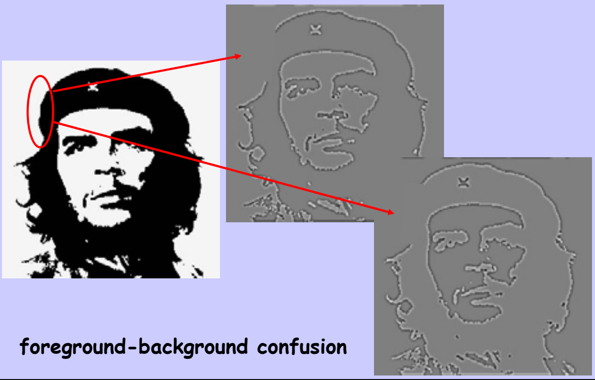


Contrast and appearance

Contrast and appearance



Edge effect

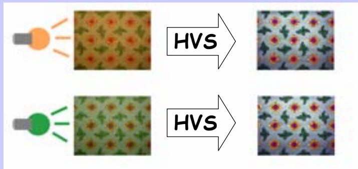


foreground-background confusion

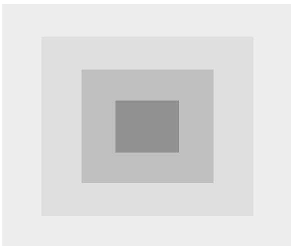
HVS adaptational mechanisms

Color constancy

WP

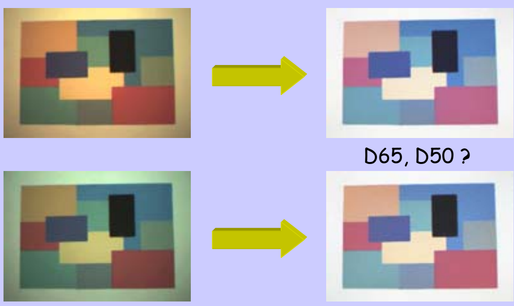


Never completely



Different illuminants

Which reference ?



which is the "real color" ?

HVS spatial computation

never adapts completely
does not estimate illuminant
change according to image content

STABLE ⟷ UNSTABLE

STABLE	UNSTABLE
Colour Constancy	Simoultaneous Contrast
Lightness Constancy	Assimilation
	Edge effects

ROBUSTNESS

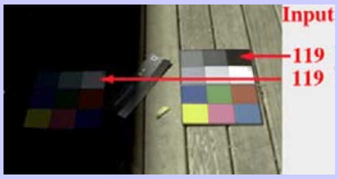
Global vs local

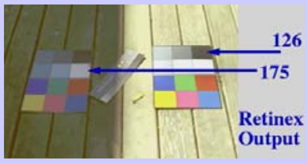
global

original

local

Acquisition and perception





Computing the appearance

From pixelwise colorimetry to
SPATIAL COLOR COMPUTATION

Retinex

ACE
(Automatic Color Equalization)

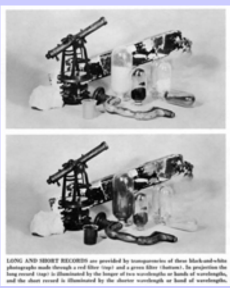
… many more

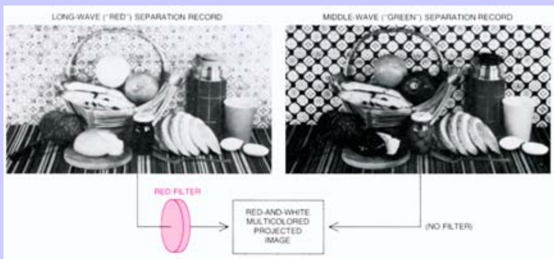
Retinex Theory

Edwin Land

John McCann

SCIENTIFIC AMERICAN 1959

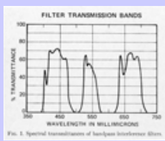


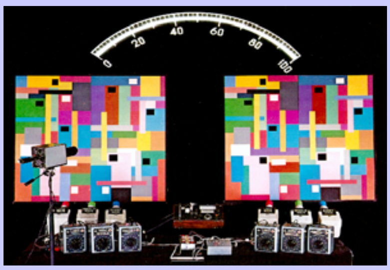


G channel

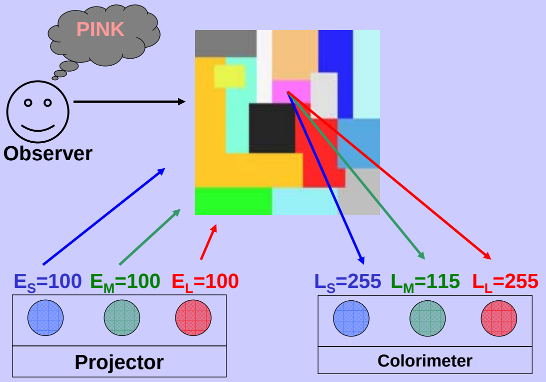
R channel

Edwin Land original projection

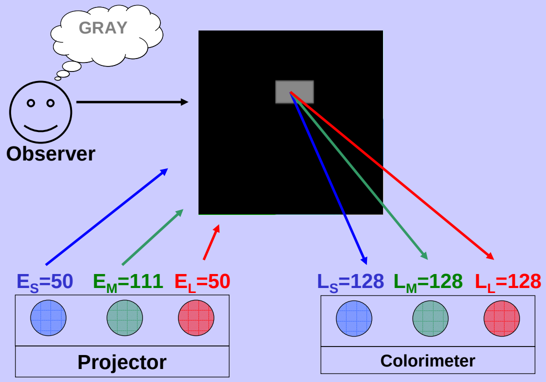




Land's experiment



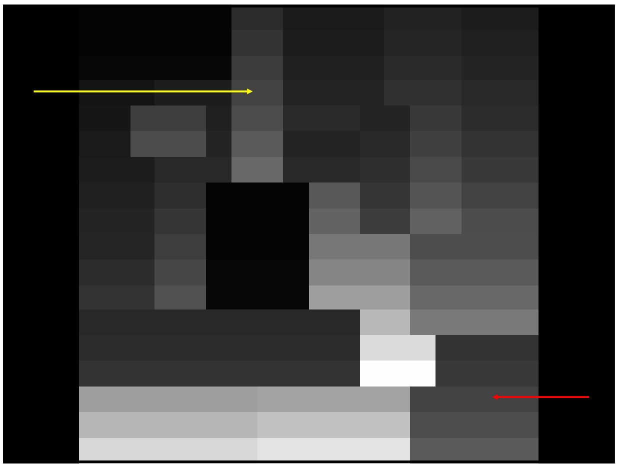
Land's experiment



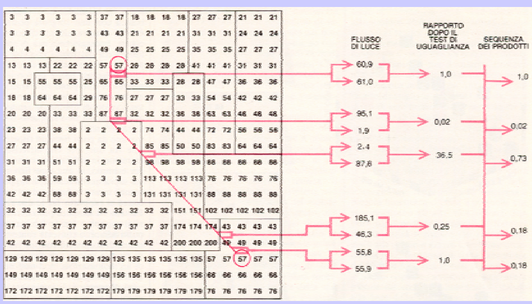
The Retinex model

Retinex is a local model:

three "lightness" stimuli are produced by taking the ratio of luminance from near and far areas



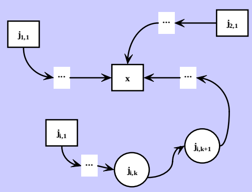
Retinex paths



The Retinex Algorithm (1)

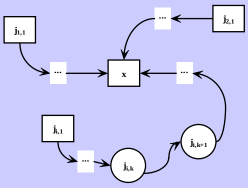
Relative lightness at a pixel *x* is the mean value of the relative lightness (*RL*) computed along *N* random paths to the pixel, for each chromatic band *c* :

$$\overline{L}_c^x = \frac{1}{N}\sum_{i=1}^{N} RL_c^{i,x}$$



The Retinex Algorithm (2)

Relative lightness is the product of the lightness ratios along a path *i*:



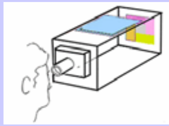
$$RL_c^{i,k} = RL_c^{i,k-1}\delta_c^{i,k}$$

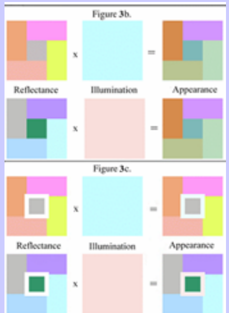
$$\delta_c^{i,k} = \begin{cases} \dfrac{L_c^{j_{i,k}}}{L_c^{j_{i,k-1}}} & if \quad \left|L_c^{j_{i,k}} - L_c^{j_{i,k-1}}\right| > threshold \\ 1 & otherwise \end{cases}$$

Reset mechanism WP

Retinex WP behaviour

Maximov shoeboxes





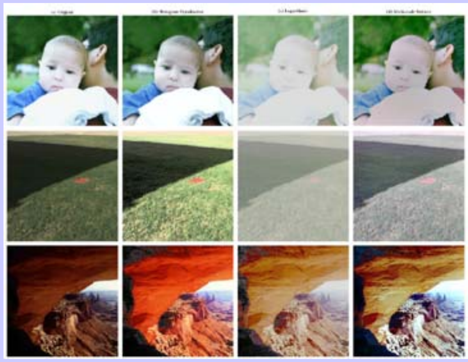
McCann

2000

Figure 5: A: Input with blue color cast created by scene illumination for which the camera was not balanced. The image also has extended dynamic range obtained by frame averaging. B: Output from the McCann99 4-iteration. C: Output from the Frankle-McCann 4-iteration. The results here can be compared with those of Barnard [1]. Note that both the input and output images have been adjusted with postfuts for printing. The actual retinex input image is in log space.

Rahaman

1996



Marini - Rizzi

1999

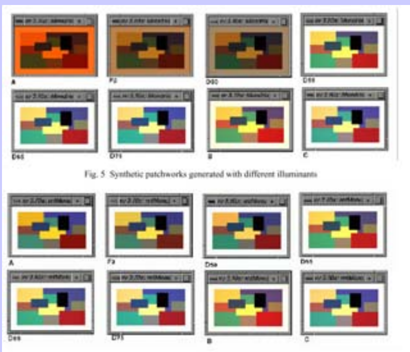
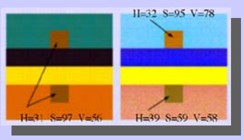


Fig. 5 Synthetic patchworks generated with different illuminants

Fig. 6 The same patchworks after the Retinex filtering

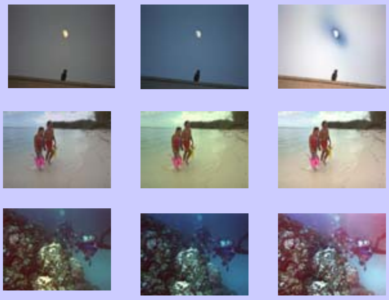
Retinex simulates color adaptation

Retinex can be used to equalize color or to simulate color illusions



Retinex can fail

Gray World | White Balance | Retinex



BEST METHOD
White Balance
WORST METHOD
Retinex

BEST METHOD
Retinex
WORST METHOD
White Balance

BEST METHOD
Original !!
WORST METHOD
Retinex

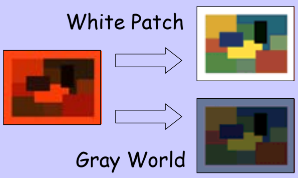
Computing the appearance

Retinex

ACE
(Automatic Color Equalization)

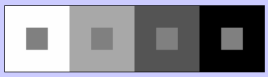
Modelling HVS (1)

- **Independent adaptation**
  on RGB (short, middle and long waves) [McCann 1999]
- **White Patch** [Von Kries 1902]
- **Gray World** [Buchsabum 1980]



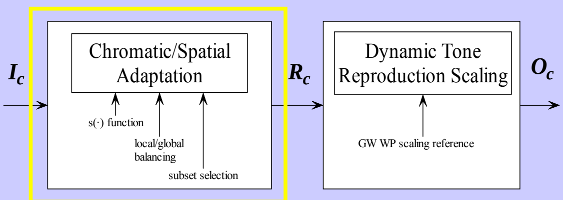
Modelling HVS (2)

- **Non-linearity** [Weber 1832]
- **Lateral Inhibition** [Hartline et al. 1956]



- **Local/global adaptation** [McCann 1987]

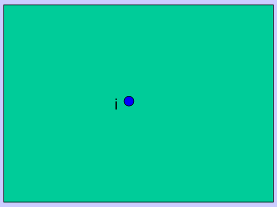
ACE structure



The basic formula

For each channel C

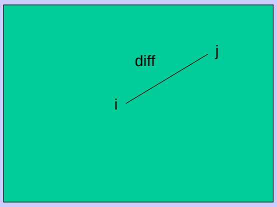
The basic formula



For each channel C

$$R_c(i) =$$

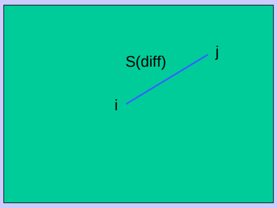
The basic formula



For each channel C

$$R_c(i) = \qquad I_c(i) - I_c(j)$$

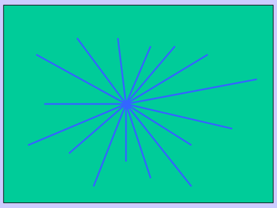
The basic formula



For each channel C

$$R_c(i) = \qquad s(I_c(i) - I_c(j))$$

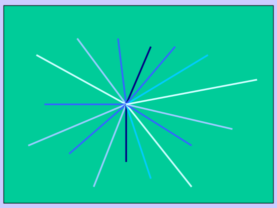
The basic formula



For each channel C

$$R_c(i) = \underset{j \in subset, j \neq i}{} \qquad s(I_c(i) - I_c(j))$$

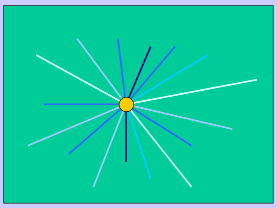
The basic formula



For each channel C

$$R_c(i) = \underset{j \in subset, j \neq i}{} \qquad \frac{s(I_c(i) - I_c(j))}{d(i,j)}$$

The basic formula



For each channel C

$$R_c(i) = \sum_{j \in subset, j \neq i} \frac{s(I_c(i) - I_c(j))}{d(i,j)}$$

Spatial computation

$$R_c(i) = \sum_{j \in subset, j \neq i} \frac{s(I_c(i) - I_c(j))}{d(i,j)}$$

$I_c(i)$-$I_c(j)$ ⇒ **lateral inhibition mechanism**

ACE

Retinex

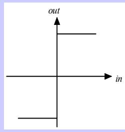
$\frac{L_c^{j,k}}{L_c^{j,k-1}}$ ⇒ **ratio product**

$$\delta_c^{i,k} = \begin{cases} \frac{L_c^{j,k}}{L_c^{j,k-1}} & \text{if } \left| L_c^{j,k} - L_c^{j,k-1} \right| > \text{threshold} \\ 1 & \text{otherwise} \end{cases}$$

Spatial computation

$$R_c(i) = \sum_{j \in subset, j \neq i} \frac{s(I_c(i) - I_c(j))}{d(i,j)}$$

$s(\cdot)$ ⇒ **non-linearity, WP, GW**

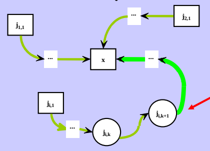


Signum

ACE

Retinex

Reset ⇒ **non-linearity, WP**

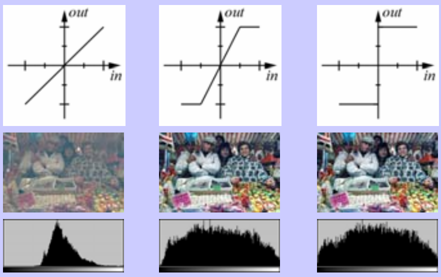


Reset mechanism

Tested s(·) function

ACE

Linear | Saturation | Signum



Contrast tuning

Spatial computation

$$R_c(i) = \sum_{j \in subset, j \neq i} \frac{s(I_c(i) - I_c(j))}{d(i,j)}$$

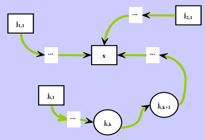
$d(\cdot)$ ⇒ **local/global balancing**

Euclidean distance

ACE

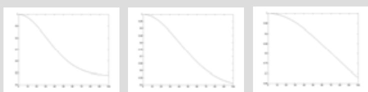
Retinex

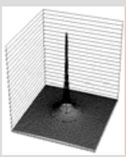
Random paths ⇒ **local/global balancing**



Tested distances

local/global balancing

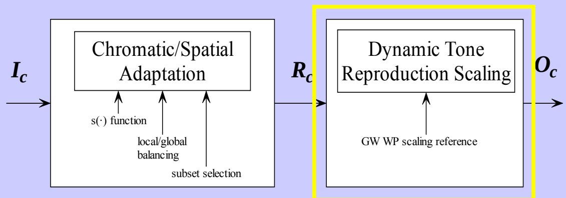




$$1/d = \frac{e^{-\alpha x} + e^{-\alpha x^2}}{2}$$

$\frac{1}{d}$ = euclidean distance

ACE structure



Dynamic tone reproduction scaling

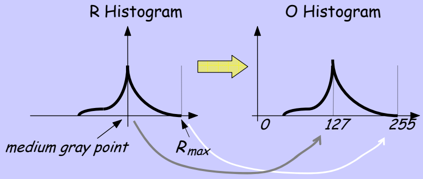
ACE

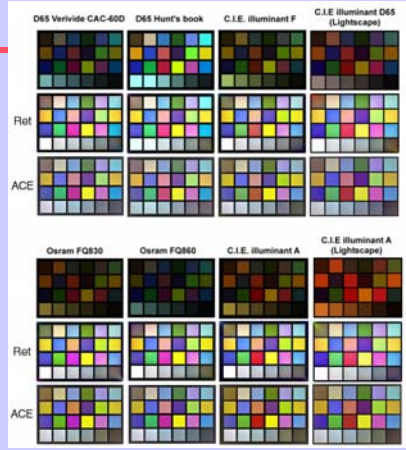
WP/GW scaling:

Estimated "white" ⇨ White Patch

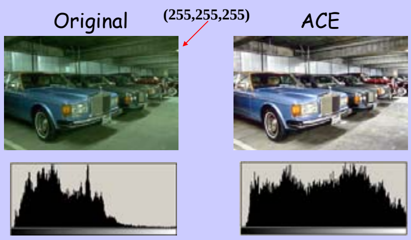
Estimated "*gray*" ⇨ Gray World

$$O_c(i) = round[127.5 + \frac{R_{max}}{127.5} R_c(i)]$$

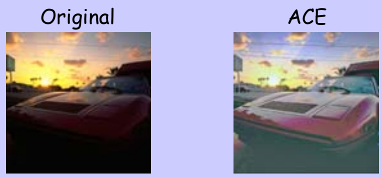




Color Constancy

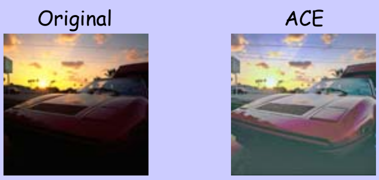


Local filtering effect



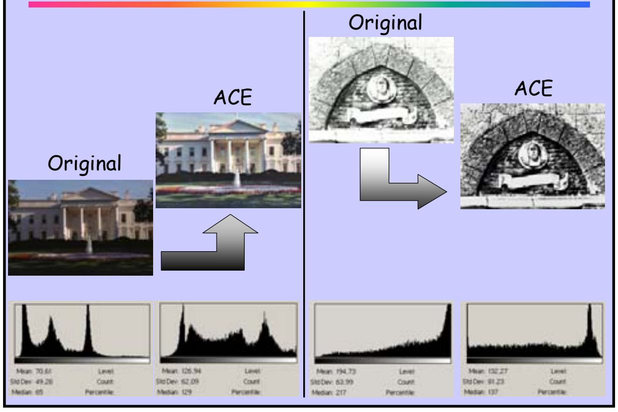
RGB differences ACE-Original around "128" gray

Local filtering effect



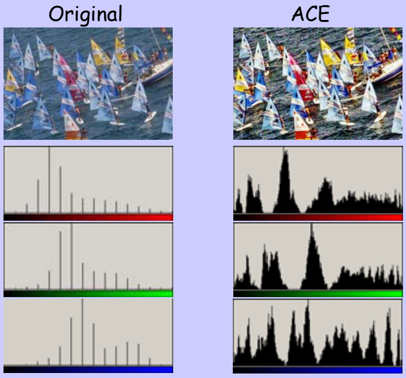
Difference ACE-Original around "128" gray

Tone remapping (LC)

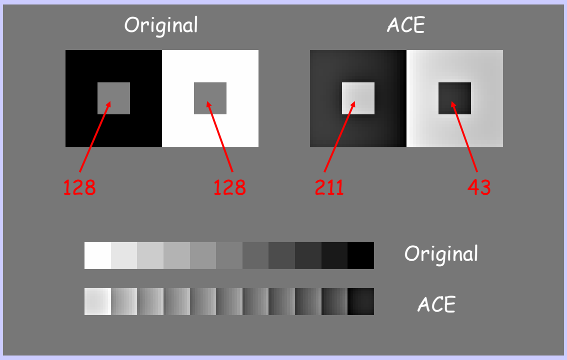


Contrast correction

Data driven color dequantization



Computing visual illusion



Computational cost

ACE

$O(N^2)$

AMD K6 II@350Mhz, 128Mb Win98

39sec for a 100x75 pixels

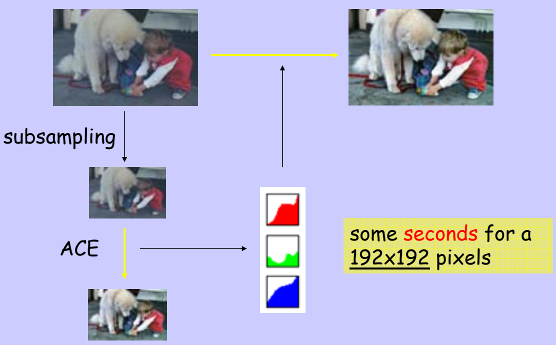
about 12min for a 192x192 pixels

BRW Retinex

$O(N\sqrt{N})$

640x480 on a PII @333Mhz under Linux in about 10 minutes

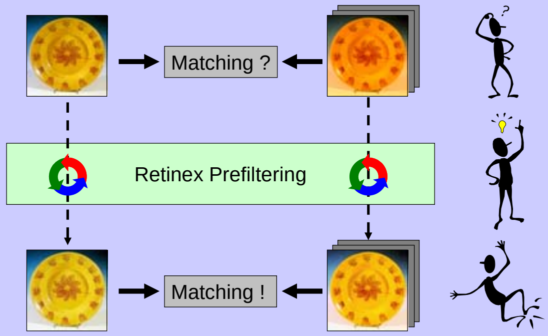
ACE Local LUT



Spatial colour application

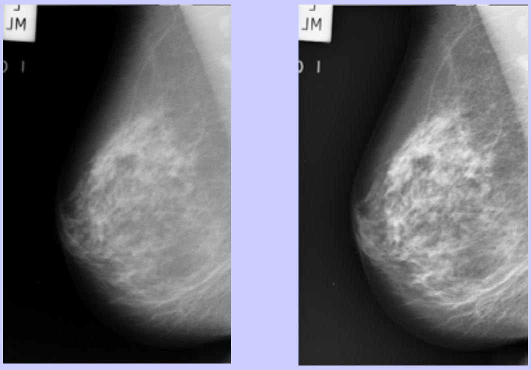
Digital flash (HP)

Image DB color normalization



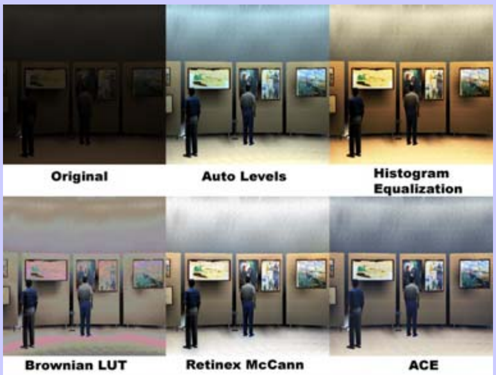
Prefiltering

for computer vision or medical imaging

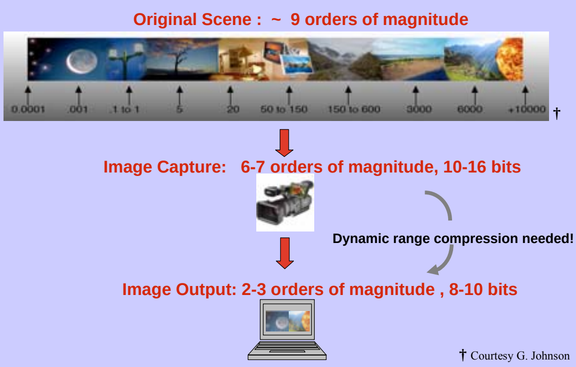


LDR and HDR images
tone mapping

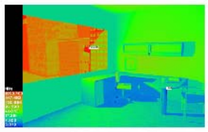
Low dynamic range images



High Dynamic Range (HDR) imaging



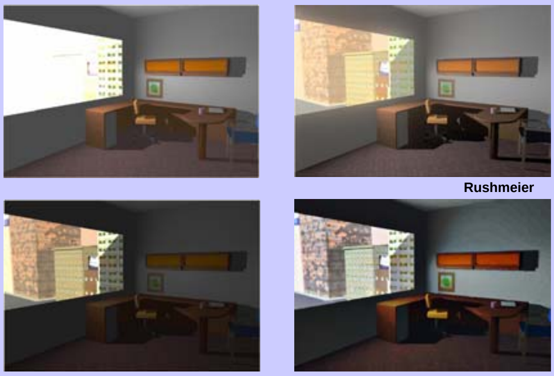
Tone mapping problem



Overexposed mapping of original luminance gamma.

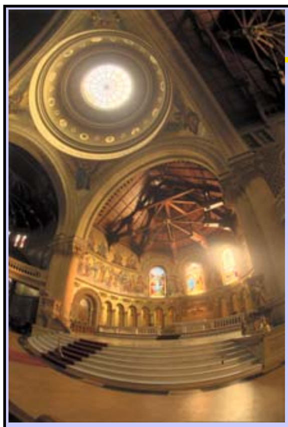
Underexposed mapping of original luminance gamma.

Visual comparison



Rushmeier

ACE for HDR

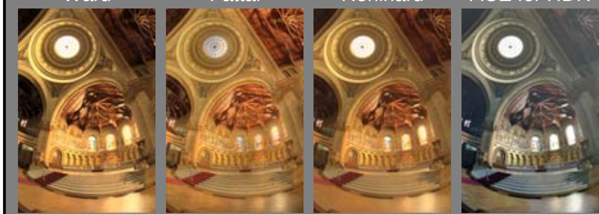


Ward

Retinex

Visual comparison

Ward | Fattal | Rehinard | ACE for HDR



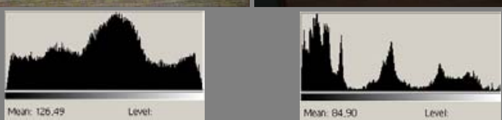
Colour correction

[Debevec]

Brightness/Luminance Match

(max lum=3.5 cd/m²)

[Gatta]



ACE "basic version" | **ACE for HDR**

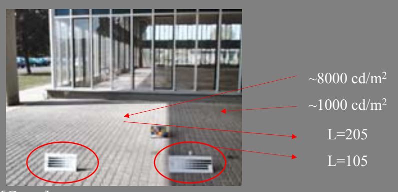
Noise enhancement

ACE "basic version" | **ACE for HDR**

[Ward]

Results on real HDR images

(input in cd/m²)



[Gatta]

8:1 → 2:1

Visual comparison

[Tumblin]

Which is the best ?

- a unique measure is missing
- the available measures depend on the approach of the tone reproduction
- work towards a unified test framework should be done

ACE for film restoration

Another example

Original image

After ACE

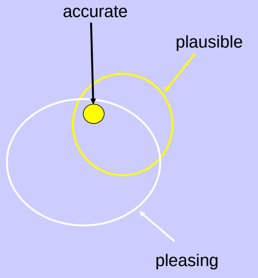
Hue histogram original image

Hue histogram result image

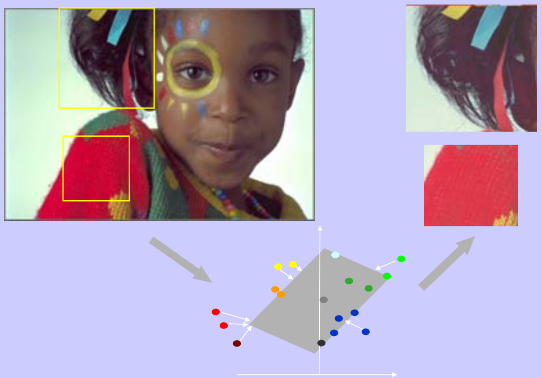
Spatial gamut mapping

Definitions of color reproduction

- Accurate reproduction
  - Spectral / colorimetric match
- Plausible reproduction
  - Convey a realistic experience
- Pleasing reproduction
  - Image "looks good"
  - May not match original
  - Original may not exist
    - "match what's in my head !"

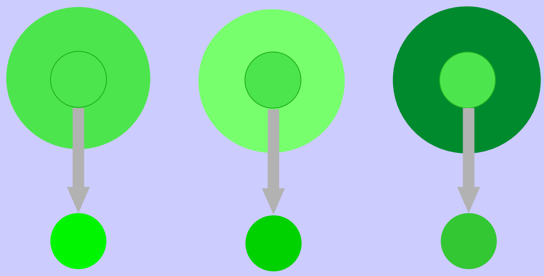


Colorimetric Gamut Mapping

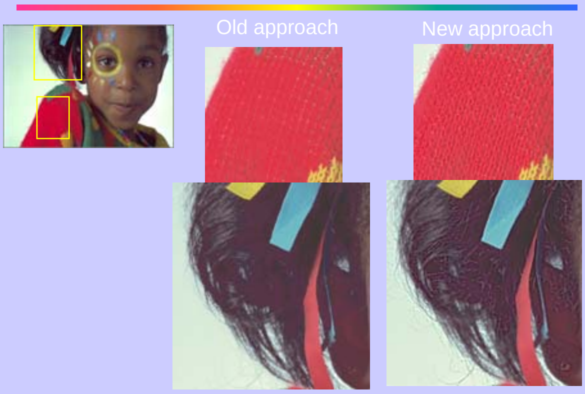


Effect of context

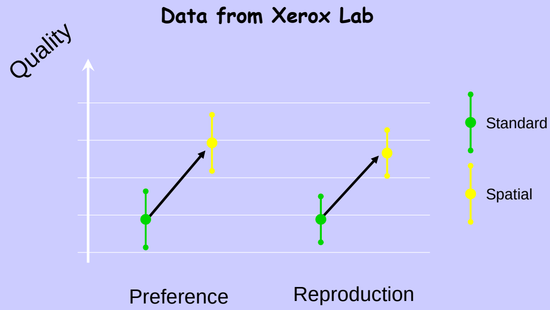
Spatial Gamut Mapping



The Result...



User Rating



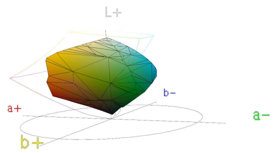
Conclusions and perspectives

- limits of the pixel colorimetry
- towards appearance
- local and global adaptations
- Retinex and ACE as synthetic "observers"

Thanks

rizzi@dti.unimi.it

Spatial Colour Gamut Mapping



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Gjøvik University College, Norway

[2]Dipartimento di Technologie Dell'Informazione
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Outline of the Presentation

- Colour image reproduction
- Traditional colour gamut mapping
- Spatial colour gamut mapping
  - the idea
  - implementation
  - results
- Problems with the multilevel approach
- Ideas for improvement
- Ideas on 'perceptual gamut mapping'
- Conclusion

Colour Image Reproduction – Image Capture

- Most often RGB
  - Scanner
  - Camera
  - CRT
  - LCD
  - Computer generated
- Needs colorimetric calibration, i.e., a transformation RGB $\longrightarrow$ XYZ.
  - LUT
  - Regression
  - Physical models

Colour Image Reproduction – Printing/Display

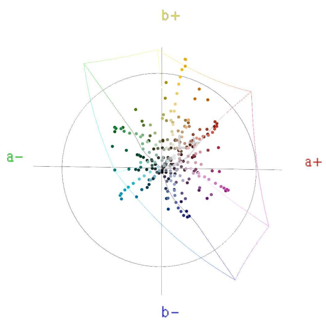
- RGB
  - CRT
  - LCD
  - LCD projector
  - LDP projector
- CMYK
  - Printer
- Needs colorimetric calibration, i.e., a transformation XYZ $\longrightarrow$ RGB/CMYK.
  - LUT
  - Regression
  - Physical models
- and determination of the colour gamut. . .

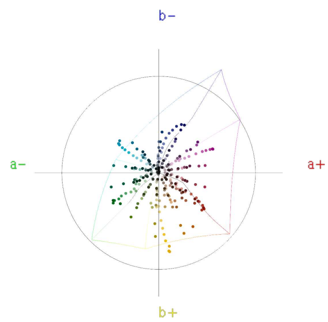
Colour Image Reproduction – Intermediate Colour Space

Reduce the number of transforms ($M + N$ instead of $M \times N$)

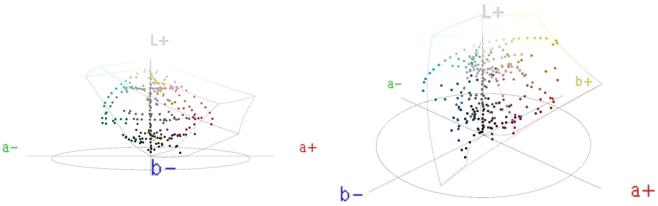
- Should be colorimetric to be meaningful
- Should in some way reflect the human concepts of colours
  - lightness
  - hue
  - saturation
- Should be perceptually as homogeneous and isotropic as possible
  - CIELAB
  - CIECAM97s
  - CIECAM02

Traditional Colour Gamut Mapping – Non-Matching Colour Gamuts (1)





Traditional Colour Gamut Mapping – Non-Matching Colour Gamuts (2)



Traditional Colour Gamut Mapping – Objectives (Hunt 1995)

Spectral: Spectral power distributions
Exact: Chromaticities, relative luminances and absolute luminances
Colorimetric: Chromaticities and relative luminances
Equivalent: Apparent chromaticities and relative and absolute luminances
Corresponding: Apparent chromaticities and relative luminances
Preferred: Apparent match should be sacrificed to achieve a more pleasing result

Traditional Colour Gamut Mapping – Type of Mapping

Clipping

- Preserves vividness/saturation
- Destroys detail

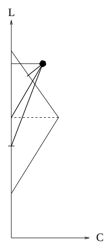
Compression

- Destroys vividness/saturation
- Preserves detail

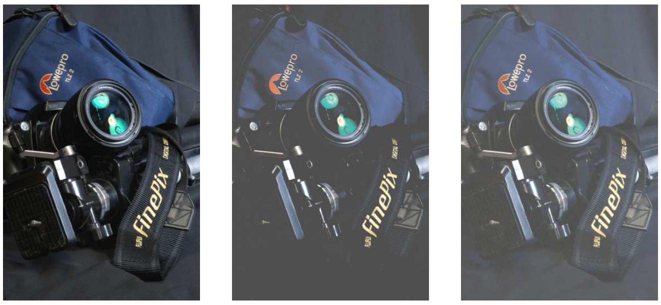
Traditional Colour Gamut Mapping – Direction of Mapping

The direction in the colour space in which the colours are changed, strongly affects the result:

- Constant hue
- Constant lightness
- Towards centre of colour space
- Towards centre of gravity
- Towards cusp
- Closest

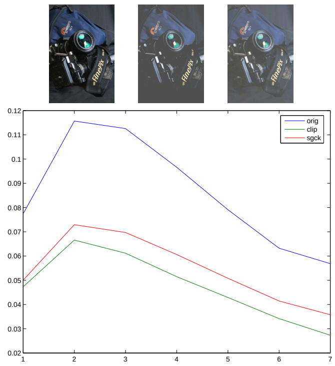


Traditional Gamut Mapping – Reproduction of Contrast (1)



Original Clipping SGCK

Traditional Gamut Mapping – Reproduction of Contrast



Colour Constancy Type Observations

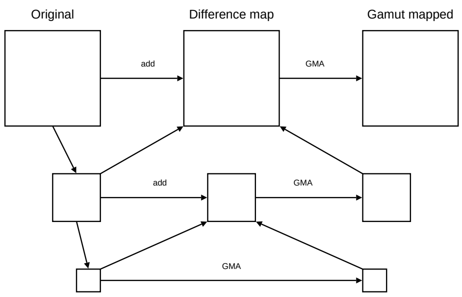
- Colour constancy: overall colour casts ‘removed’ by the human visual system
- Land: *Ratio* between colours that is important for the appearance (retinex)
- McCann: Better if all colours are changed in the same direction than if the colours are changed independently.
- ACE by Rizzi et al.: The closer pixels are more important for the perceived lightness of a pixel
- Similar results in colour appearance and image colour appearance (Fairchild et al.)

The Idea of Spatial Gamut Mapping

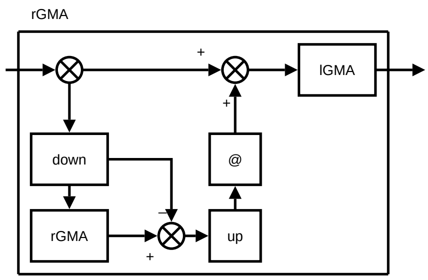
- Traditional colour gamut mapping:
  - Map the colours of the individual image pixels independently.
- Idea based upon previous foil:
  - Make colour shifts on as large image areas as possible in order to maintain the local ratios as much as possible

Realisation: Multilevel Gamut Mapping

- Scale down image with low-pass filtering, perform gamut mapping, upscale and apply differences at next level.

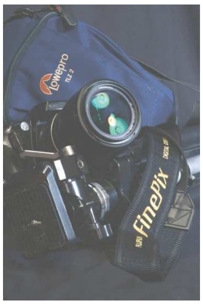


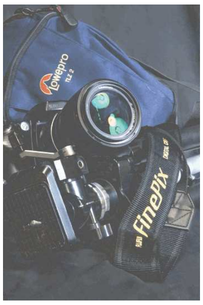
Implementation: Recursive Gamut Mapping



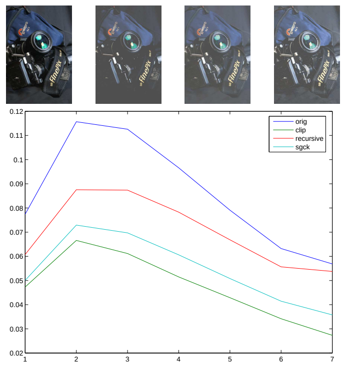
Some Results (1)


Original

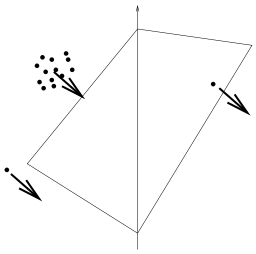

SGCK


Spatial

Some Results (2)

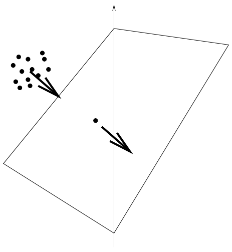


Problems (1): Direction of mapping



- Halos and hue shifts near sharp edges.

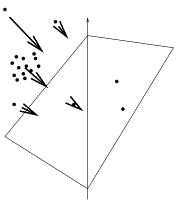
Problems (2): Magnitude of mapping



- Hue shifts near neutrals, too much compression in some regions

Solution

- Bilateral filtering: the mapping of the individual pixel is dependent on both the mapping of the region and its position in colour space
- Local in both colour space and image plane simultaneously
- Promising results
  - reduces the problems
  - (and the local contrast . . .)



Further improvement: Perceptual Gamut Mapping

- Instead of using the multilevel approach to keep local ratios, calculated perceived ratios using, e.g., ACE (or Retinex or iCAM or . . .)
- McCann patent: Retinex for spatial gamut mapping
- Combine multilevel and perceptual gamut mapping using ACE at each step
- Again: promising results

Conclusion

- New spatial gamut mapping technique
- Improved reproduction of contrast, particularly at high frequencies
- Ideas for further improvement

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Texture analysis - from grayscale to color

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Outline

- On feature selection strategies
  – the dangers of many feature candidates
- Gray level texture analysis
  – a brief review
- Color and texture
  – or textured color
- A case study
  – Local Binary Patterns, in graylevel and color
- A possible low dimensional strategy
  – Class Distance Matrix features including color

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Many are called …

- Statistical texture analysis methods extract a large number of pre-defined – often ad hoc –features.
- This gives a much larger number of combinations.
- Several sophisticated schemes developed to select a suboptimal feature set of lower dimensionality.
- Resubstitution instead of separate training and test data sets to estimate the texture classification error.
- Still, this leads to optimistically biased results.

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– but few should be chosen

- The number of training samples affects the feature selection and the error estimation.
- The effect of the number of feature candidates analyzed is not much discussed.
- The number of feature candidates is critical for small data sets.
- Feature selection should be performed for each cycle of the leave-one-out procedure.

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Feature selection

- The goal is to find the subset of features which
  – best characterizes the differences between groups
  – is similar within the groups
  – **Maximize ratio of between-class and within-class variance.**
- Exhaustive search finds the optimal feature set.
- The number of possible sets grows exponentially, particularly if we do not know *a priori* the maximum number of features (up to m out of D) to select:

$$n = \sum_{d=1}^{m} \frac{D!}{(D-d)!\,d!}$$

- Impractical even for a moderate number of features!
  – M=5, D=100 => n = 79.374.995

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Feature selection strategies

- Best features are often correlated and thus may give a suboptimal discrimination.
- Sequential forward selection (SFS) adds one feature per step.
- Sequential backward selection (SBS) discards one at a time.
- When a feature is selected or removed, this decision can not be changed (nesting problem).
- Stepwise forward/backward (SFB) selection overcomes nesting problem.
- A special case of *"plus l - take away r"*.
- Floating Search allows *l* and *r* to change in each step.

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Background

- Feature selection and error estimation
  - often discussed independently.
- Small sample size effects are well known
  - Raudys and Jain, PAMI 1991
- Feature selection and small sample performance
  - Jain and Zongker, PAMI 1997
- Estimation of error rates with feature selection
  - Well known in theoretical statistics:
  - Snapinn and Knoke, Biometrics 1989,
  - Rutter, Flach and Lachenbruch, Comm.Stat.Sim 1991
- The effects of the number of feature candidates analyzed initially is rarely discussed.

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A simulation study design

- H. Schulerud and F.Albregtsen,
  CMPB,73, 1061-1073, 2004.

- Monte Carlo study, 100 simulations
- 2 classes, normal distributed, common Covar = I
- 5 features separating the classes, the rest is noise
- 10 to 200 feature candidates
- Mahalanobis distance equal 0, 1, 4
- 20 - 1000 training samples
- 20 - 1000 test samples

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Study design cont.

- Feature selection methods:
  - Plus -1-Minus -1 (SFB)
  - Sequential Forward Floating Selection (SFFS)
- Bayesian classification with equal class a priori probability and common unknown covariance matrix
- Error estimation
  - Leave-one-out (P_L), feature selection on all data and error estimation on the same data
  - Leave-one-out (P_L2), Feature selection and error estimation in one step
  - Holdout (P_H), 50 % training, 50 % testing

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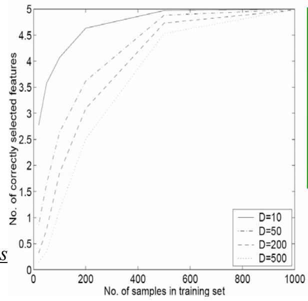
Simulation results - Feature selection I

- The number of correctly selected features increases when
  - **The number of training samples increase**
  - **The Mahalanobis distance increase**
  - **The number of feature candidates decrease**
- For small sample sizes the number of feature *candidates* is of great importance



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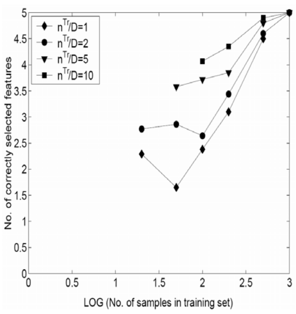
Simulation results – Sample / feature ratio

- The sample/feature ratio depends on
  - **Mahalanobis distance**
  - **Sample size**
  - **Feature candidates**
- Recommending an optimal ratio is not advisable.



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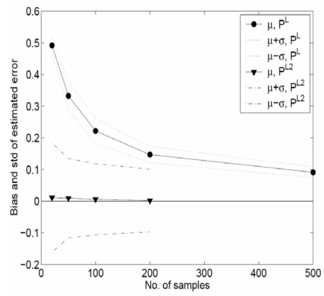
Results - Performance estimation I

- The Leave-one-out estimate after feature selection (P_L) may be highly biased.
- The Leave-one-out estimate including feature selection (P_L2) is unbiased, but has some variance.



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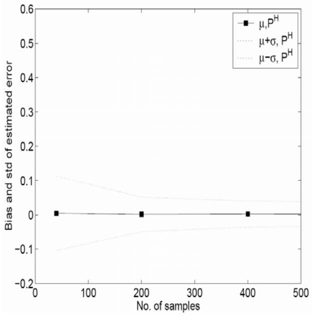
Results - Performance estimation II

- Holdout estimate is unbiased and the variance depends on the test sample size.



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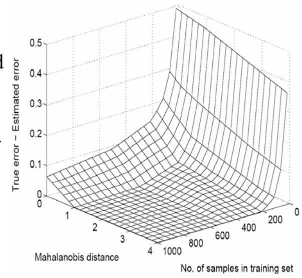
Results - Performance estimation III

- Bias of the P_L error estimate as a function of Mahalanobis distance and number of training samples, selecting 5 out of 200 feature candidates.
- For n^{Tr} <200, the P_L error estimate is significantly biased, even for high class distances.



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Conclusions of simulation study

- The number of feature *candidates* is critical for small data sets.
- Perform feature selection and error estimation on separate data for small sample sizes.
- In order to find the correct features the feature/sample ratio is not constant.
- The SFB and SFFS feature selection methods gave the same results.

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Reliable comparisons?

- The most common statistical texture analysis methods have been developed for gray level images.
- Over the years, several surveys have been written.
- Conclusions often depend on parameter settings.
- Small data sets have been used for training.
- Resubstitution has been used to estimate errors.
- Remember our simulation results ???
- Brodatz textures
  - too easy to segment and classify
  - Subimages are highly correlated

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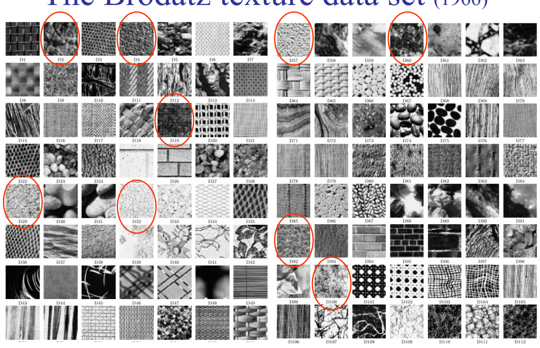
The Brodatz texture data set (1966)



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Most challenging Brodatz textures

The 10 most stochastic, isotropic, homogeneous and fine-grained textures, giving 45 possible texture pairs for testing.

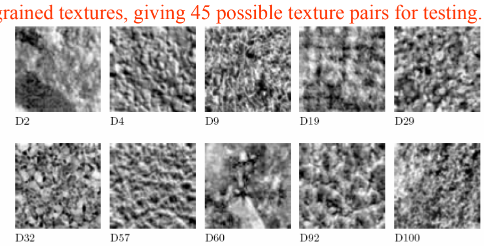

Figure 1: One 75 × 75 sample from each of the selected Brodatz textures after histogram normalization (D2: Fieldstone, D4: Pressed cork, D9: Grass lawn, D19: Woolen cloth, D29: Beach sand, D32: Pressed cork, D57: Handmade paper, D60: European marble, D92: Pigskin, D100: Ice crystals).

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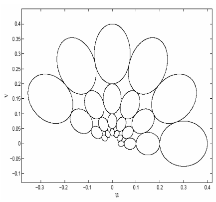
Gabor filter bank



- Locally dominating frequency and orientation are very powerful texture features
  - Quadrature filters
  - (Knutsson & Granlund).
- Gabor (1946) filtering
  - first used in image analysis by Granlund (1978)
  - although many cite Daugman (1988)
  - One of the most commonly used texture analysis methods in the research community
    - Jain & Farrokhnia 1991
    - Manjunath & Ma 1996
    - Randen & Husøy (1999).

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Gray level cooccurrence matrix

- One of the most frequently used methods of extracting second order statistical features from digital images.
- Matrix element ***P(i,j|d,θ)*** gives estimate of second order probability of transition between gray levels ***i*** and ***j*** at an inter-pixel distance ***d*** at an angle ***θ***.
- Related to sum and difference histograms.
- Alternative: Gray level run length matrix.
- Also:
  - Cooccurrence of gray level run length matrix
  - Gray level variance matrix
  - Gray level entropy matrix

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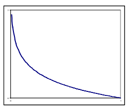
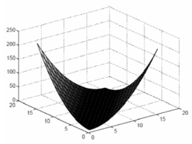
Non-adaptive GLCM features

- Features are weighted sum of the matrix element values.
- Two general categories of weighting functions:
  - weighting based on the element value
  - e.g. "Entropy"



$$H = -\sum_{i=0}^{G-1}\sum_{j=0}^{G-1} P(i,j)\log_2[P(i,j)], \qquad W(i,j) = -\log_2[P(i,j)]$$



  - weighting based on the element position.
  - e.g. "Inertia"

$$I = \sum_{i=0}^{G-1}\sum_{j=0}^{G-1} (i-j)^2 P(i,j), \qquad W(i,j) = (i-j)^2$$

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Color and texture

- Most statistical texture analysis methods have been developed for gray level images.
- Most images that are candidates for statistical texture analysis are actually color images.
- Intuitively, color and texture are separate phenomena.
- In some applications, color and texture are treated as separate entities.
- A variety of color-texture descriptors have been proposed, using both the intra- and inter-channel textural information.
- Potential "explosion" in dimensionality of feature vector.

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Color and texture

- In our visual system, color is treated at a lower spatial frequency than intensity.
- This is exploited in image compression and in image sensors.
- Several CBIR systems use
  - texture descriptors (e.g. Gabor filters) and
  - color histograms (e.g. Cb Cr)
- True color texture analysis use both intra-channel and inter-channel textural information.
  - Wavelet correlation signatures
  - Color wavelet covariance
  - Chromaticity moments
  - Opponent color LBP

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Local Binary Pattern

- Ojala et al. (1996) proposed a binary version of the Wang and He (1990) texture spectrum approach, thresholding each 3 x 3 neighborhood by the center pixel value.
- Binomial position weights are then put on the eight binary pixel values, so that a weighted summation gives a unique local binary pattern (LBP) index to each such binary pattern.
- There are $2^8 = 256$ possible LBP values within a 3 x 3 neighborhood.

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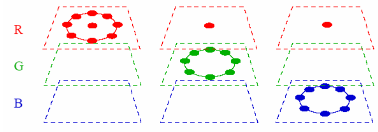
Opponent Color LBP

- OC-LBP is a joint color-texture operator.
- Jain and Healey (1998) used OC as all pairs perceived as opposing pairs by humans (red-green, yellow-blue).
- In OC-LBP, the LBP operator is used within each channel, and on each possible pair of channels.



Creating opponent color LBP codes with a red center.

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LBP complexity

- The Opponent Color extension of the LBP operator gives 2304 or 4608 features, depending on whether a local contrast measure is used!
- The approach is simple, but does color texture really need to be that complex?
- Would you use hierarchies of simple circles to describe planetary motion?

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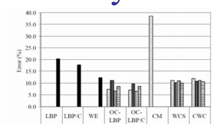
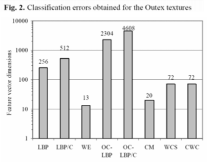
Error and dimensionality

- A recent comparison of methods favours OC-LBP/C.
- Is OC-LBP/C really better than Wavelet Energy (graylevel) or Wavelet Correlations, given the difference in dimensionality?
- Note the small difference between graylevel and color results !



	LBP	LBP/C	WE	OC-LBP	OC-LBP/C	CM	WCS	CWC
RGB				7.3	6.9	38.5	11.1	11.9
I1I2I3				11.0	9.6		10.1	10.8
HSV				6.6	6.5		10.9	11.1
CIE-Lab				8.4	8.5		10.0	10.6
Gray Level	20.3	17.6	12.2					

Fig. 2. Classification errors obtained for the Outex textures



Feature vector dimensions produced by the corresponding descriptors

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"Optimal Brain Damage"

- 15 years ago, high dimensionality problems would have been "solved" by neural networks, doing a recomputation of the network coefficients together with a pruning of the net and its input.
  - LeCun, Denker, and Solla: "Optimal Brain Damage", Advances in Neural Information Processing Systems 2, 598-605, 1990.
- Today, "high dimensionality is not a problem"
  - Support Vector Machines and Genetic Algorithms are available.
  - The minimum complexity principle used in most natural sciences seems to be forgotten by many practitioners.
  - Vapnik never stated that SVM is tolerant to input dimensionality.

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Aristotle and Occam

- Our search for models or hypotheses that describe the laws of nature is based on a "minimum complexity principle".
- Aristotle (384-322 BC), Physics, book I, chapter VI:
  'The more limited, if adequate, is always preferable'.
- William of Occam (1285-1349):
  'Pluralitas non est ponenda sine necessitate'.
- The simplest model that explains the data is the best.
- So far, this principle (also called Occam's Razor) has generally motivated the search for reduced feature sets.
- It should also motivate us to generate only a few but powerful features.

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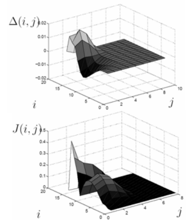
The class distance matrix

- For a given texture analysis method (e.g. GLCM or GLRLM), we get one probability $P(i,j|\omega_c)$ matrix per image.
- For each element (i,j) of the matrix, we estimate the class conditional probability distribution of the normalized matrix value.
- From this distribution, we compute
  - The average matrix for each class
  - The class variance matrix
  - The class difference matrix
  - The Mahalanobis class distance matrix between class pairs.
- Class distance matrices contain localized areas of high values.



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From texture to class distance

- The computation of class difference and class distance matrices is quite simple:

$$\hat{P}(i,j\,|\,\omega_c)=\frac{1}{N(\omega_c)}\sum_{n=1}^{n(\omega_c)}P(i,j\,|\,\omega_c)$$

$$\sigma_P^2(i,j\,|\,\omega_c)=\frac{1}{N(\omega_c)}\sum_{n=1}^{n(\omega_c)}[P_n(i,j\,|\,\omega_c)-\hat{P}(i,j\,|\,\omega_c)]^2$$

$$\Delta(i,j\,|\,\omega_1,\omega_2)=\hat{P}(i,j\,|\,\omega_1)-\hat{P}(i,j\,|\,\omega_2)$$

$$J_P(i,j\,|\,\omega_1,\omega_2)=2\frac{\left[\hat{P}(i,j\,|\,\omega_1)-\hat{P}(i,j\,|\,\omega_2)\right]^2}{\sigma_P^2(i,j\,|\,\omega_1)-\sigma_P^2(i,j\,|\,\omega_2)}$$

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Adaptive feature extraction

- The squared class distance is used as a weighting function when summing probability matrix elements that contribute most to class separability.
- We use the disjoint positive and negative parts of the class difference matrix as the domains of the weighted summation.
- We get only two adaptive feature values:

$$F_+=\sum_{\Delta_P(i,j|\omega_1,\omega_2)\geq 0}P_k(i,j\,|\,\omega_c)[J_P(i,j\,|\,\omega_1,\omega_2)]^2$$

$$F_-=\sum_{\Delta_P(i,j|\omega_1,\omega_2)<0}P_k(i,j\,|\,\omega_c)[J_P(i,j\,|\,\omega_1,\omega_2)]^2$$

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Local Binary Pattern Matrix

- Nielsen, Albregtsen, Danielsen (2004) introduced a local binary pattern matrix in ovarian cancer prognostics.
- A mapping of all 256 possible 8-bit patterns to the 30 possible rotation and mirroring invariant patterns is simply stored in a look-up-table.
- The LBPM element ***P(i,j|ω)*** gives the probability of having a LBP index ***j*** around a pixel having gray level ***i***.
- The 9 most uniform LBP's contributed 89% of patterns.
  - 00000000 00000111 00111111
  - 00000001 00001111 01111111
  - 00000011 00011111 11111111
- Uniform patterns with high center pixel value carried almost all of the discriminative information.
- Low dimensional (***d=2***) feature extraction is very easy.

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A possible solution

- Using a matrix description of textural parameters where neighboring cells have a meaningful relation (neighboring graylevels, interpixel distances, runlengths, etc), we have extracted low dimensional feature vectors from high dimensional matrices, based on class distance and class difference matrices.
- It turns out that such class distance matrices contain localized areas of consistently high values.
- The same approach can be used if chromaticity is added to the texture matrix description: a 4-D matrix, e.g.
  - (LBP index, gray level, Cb, Cr)
- The dimensionality of the feature vector is not increased!

Colour, constancy, invariance and the Chromagenic Constraint

Graham D. Finlayson
School of Computing Sciences
University of East Anglia

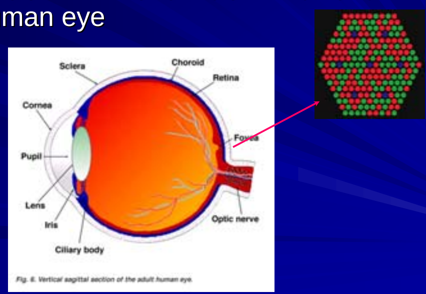
Overview

1. Digital Photography
2. Colour Constancy
3. Invariance
4. Shadow Removal
5. Chromagenic Camera
6. The Human Vision system (Chromagenic?)

1. Digital Photography

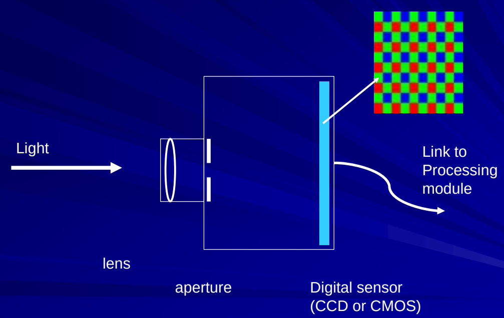
Measuring Light

- Starting point for (digital) photography is the human eye

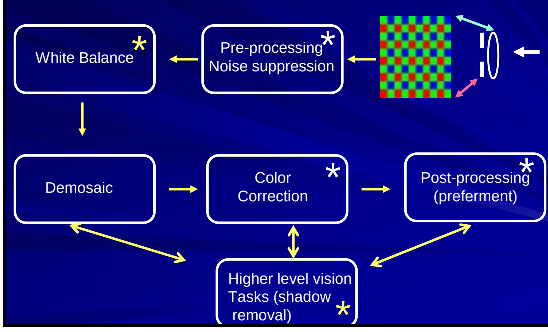


http://webvision.med.utah.edu/imageswv/sagitta2.jpeg

Basic Camera Design



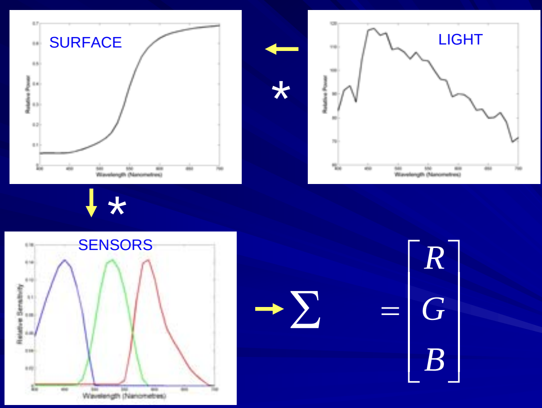
Processing Pipeline

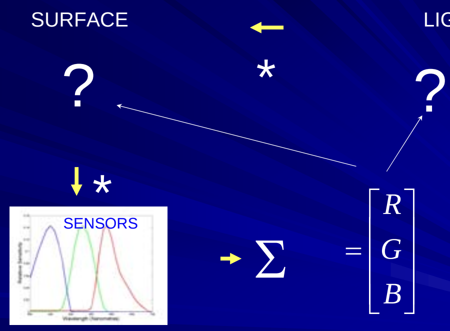


2. White Balance/Colour Constancy

White Balance/colour constancy

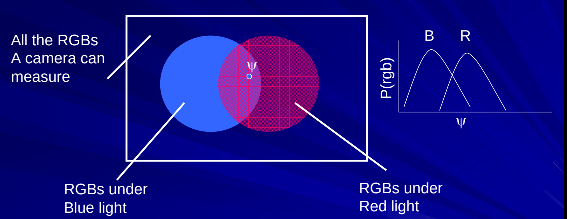
Estimate colour cast and remove





If we can estimate the light we can solve for the surface (colour constancy is illuminant estimation)

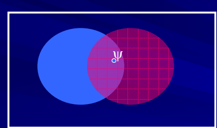
The Bayesian Approach to estimating the light



What is the probability of observing an RGB in Ψ given that we know the light colour is red?

The Bayesian Approach

What is the probability of observing an RGB in Ψ Given that we know the light colour is red?



$$p(\psi \mid red) = \frac{p(\psi \,\&\, red)}{p(red)} \qquad (1)$$

$$p(red \mid \psi) = \frac{p(\psi \,\&\, red)}{p(\psi)} \qquad (2)$$

(1) + (2) combined:

$$p(red \mid \psi) = \frac{p(\psi \mid red)\, p(red)}{p(\psi)} \qquad (3)$$

$$p(red \mid \psi) = \frac{p(\psi \mid red)\, p(red)}{p(\psi)} \quad (3)$$

$$p(blue \mid \psi) = \frac{p(\psi \mid blue)\, p(blue)}{p(\psi)} \quad (4)$$

Of course there is no reason to assume *p(red)* is different from *p(blue)* and *p(Ψ)* is a constant so, it is common to write:

$$p(red \mid \psi) \propto p(\psi \mid red) \quad (5)$$

$$p(blue \mid \psi) \propto p(\psi \mid blue) \quad (6)$$

$$p(\psi \mid i)$$

Denotes RGBs observed in an image

i denotes the ith Illuminant

$i \in \{red, blue\}$

Under independence assumption

$$p(\psi \mid i) \propto \prod_{\underline{v} \in \psi} p(\underline{v} \mid i)$$

$$p(\psi \mid i) \propto \sum_{\underline{v} \in \psi} \log[p(\underline{v} \mid i)]$$

The most likely light:

$$\max_i \sum_{\underline{v} \in \psi} \log[p(\underline{v} \mid i)] \qquad \min_i - \sum_{\underline{v} \in \psi} \log[p(\underline{v} \mid i)]$$

Maximum likelihood white point estimation

$$\max_i \sum_{\underline{v} \in \psi} \log[p(\underline{v} \mid i)]$$

The probability Is found by indexing a precomputed histogram

$\underline{v}$ is an RGB image

Many probabilistic algorithms exist and at least one[1] is implemented an a commercial digital camera

[1] G. Finlayson, S. Hordley and P.Hubel. Color by Correlation: a simple unifying concept for color constancy. *IEEE transactions on Pattern Analysis and Machine Intelligence*, 1209-1221, 2001.

[2] D. Brainard and W. Freeman. Bayesian Color Constancy. *Journal of the Optical Society of America A*, 1393-1411, 1997

[3] C. Rosenberg, M. Herbert and S. Thurn. Color constancy Using KL-divergence. *International Conference on Computer Vision*, Vancouver, 239-246, 2001

Algorithm Performance: Real Images

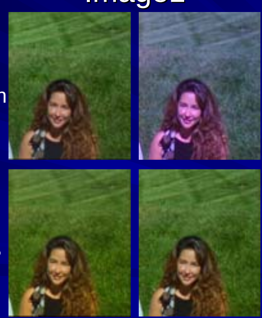
Raw Image data

Colour Correction: Full Image

Perfect Correction | Grey World | Max RGB | Bayesian

Colour Correction: Cropped Image1

Perfect Correction | Grey World | Max RGB | Bayesian



Colour Correction:Cropped Image 2

Perfect Correction

Grey World

Max RGB

Bayesian

Grey World Failure

Raw Image Data

Perfect Correction

Grey World

Max RGB

Bayesian

When does constancy fail?

- When there are few surface colours
  - A pink image is evidence of a pink surface under a white light
- When there are multiple lights
  - E.g. Sun and Shadow (yellow and blue light)
- When a calibration is assumed and the calibration is incorrect
- Can anything be done?

3. Pixel constancy (and shadow removal)

Pixel Invariants (pixel constancy)

- Intensity is a one dimensional variable (light is brighter or dimmer)
- Light colour (for photographers) is also 1 dimensional)
  - A colour temperature is specified: 2500K, 5000K, 10000K is repsectively reddish, whitish and bluish
- It is thus plausible that given 3 measurements we might find one quantity that is independent of light intensity and colour

Pixel Invariants (pixel constancy)

- Theoretically, the sensitivities of a camera might be designed so they filter out light variation [Brainard]
  - In practice these sensors just measure noise
- Under strong assumptions about image formation (dimensionality of light and surface), pixel invariants exist [Yuille]
  - Again doesn't work in practice
- The key to useful pixel invariance is looking at non linear aspects of image formation

Let us rederive the chromaticity transform in Log space

1. Shading is a scalar multiplier in colour images

$$\begin{bmatrix} R \\ G \\ B \end{bmatrix} \rightarrow \begin{bmatrix} kR \\ kG \\ kB \end{bmatrix}$$

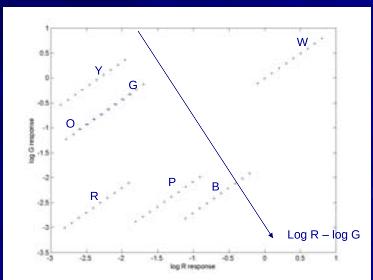
2. Taking logarithms makes multiplication additive

$$\begin{bmatrix} R' \\ G' \\ B' \end{bmatrix} \rightarrow \begin{bmatrix} k' \\ k' \\ k' \end{bmatrix} + \begin{bmatrix} R' \\ G' \\ 'B' \end{bmatrix}$$

3. There are two coordinates orthogonal to intensity change

$$\begin{bmatrix} R'-G' \\ B'-G' \end{bmatrix} = \begin{bmatrix} R'+k'-G'-k' \\ B'+k'-G'-k' \end{bmatrix}$$

Log differences are intensity independent



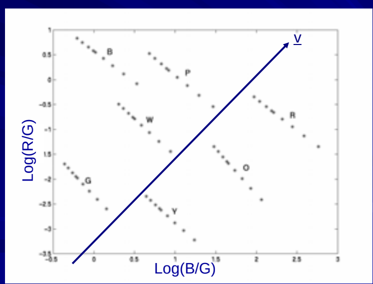
So what have we learned

- If we project orthogonal to translational direction of intensity change then we arrive at an intensity invariant
- What if illumination change was equally simple?
  - What if as we change light colour the chromaticty coordinates always translated in the same direction?
- Then projecting orthogonal to this direction of variation would suffice to remove light colour

Experiment

- For many coloured surfaces and a single light
  - Calculate logR-logG and logB-logG
  - Remember these are already intensity invariants
- Now repeat for many different colours of light
- Examine how the log chromaticities change with light colour
- If the variation is linear with fixed direction there exists a light colour invariant

Differences of log differences are light colour independent



The intrinsic invariant

4. Color change is a translation
Log cromaticity space

$$\begin{bmatrix} R'-G' \\ B'-G' \end{bmatrix} = \begin{bmatrix} R'-G' \\ B'-G' \end{bmatrix} + \frac{1}{T}\begin{bmatrix} a \\ b \end{bmatrix}$$

5. The translation cancels
for one color space direction

$$R' - (1-\alpha)G' - \alpha B'$$

$$\boxed{I' = \underline{x}.\underline{v}}$$

Log chromaticity — Projection direction

Examples

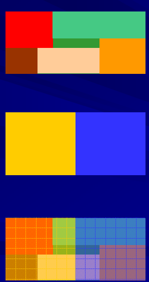
When does an intrinsic invariant exist

- Narrow-band sensors + Planckian Light (or Planckian-like light)
  - [Finlayson et al. Colour Invariance at a pixel. BMVC 2000]
- Broad-band sensors + Planckian Light + constraint on surfaces
  - [Brill+Finlayson. Illuminant Invariance from a single reflected light. CRA 2002]
- Empirically, for all typical colour cameras

Note that almost all lights are Planckian in terms of how they Integrate to form RGBS

Shadow Removal

Image Formation

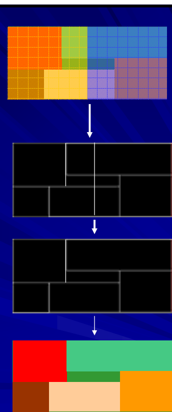


Reflectances
(Mondrian World)

Light
(sun +shadow)

Image RGBs
Light * surface

Recovering Shadow-free Full Colour Images



1. Calculate edges

2. Identify and remove Edges due to light change

3. Reintegrate the image

Lightness Algorithms & Shadow Removal

Calculate Edges

log R then **log** G then **log** B

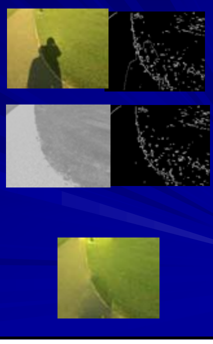
↓

Find+remove shadow Edges by looking at invariant

↓

Re-integrate the thresholded edge map to give

Log RGB image. Then exponentiate



Reintegration Details

- Involves solving a PDE: Poisson Equation. These can be solved efficiently:
  - Fourier methods [Chellapa '91, Weiss, '01, Borenstein '99]
  - Gauss Siedel Iteration, Multigrid methods e.g. [Press et al. '93]
- Care must be taken at the Boundary
  - We use Neumann Conditions [Blake '85] (much less artifacts than Dirichlet)
- Large regions are masked by shadow edges
  - Apply an iterative diffusion process to infill local edges
  - The diffusion enforces integrability at each step
- Observation: reintegration within all shadow or non shadow regions should be perfect (Poisson reintegration propagates error)
- Recently proposed path based re-integration delivers superior results [Fredembach and Finlayson, '05]

4. Chromagenic colour constancy

The Chromagenic Approach

The basic idea

- Take a second picture through a coloured filter
- Compute colour constancy with 2 images (filtered+unfiltered)

Original image

2nd image (scene view Though a reddish filter)

Is it easier to solve The colour constancy Problem with 2 images?

Filters and Lights

- a filter can be thought of as a light

$$X_1 = \int_\omega x(\lambda)S(\lambda)E(\lambda)F_1(\lambda)d\lambda$$

$$E_1(\lambda) = E(\lambda)F(\lambda)$$

$$X_1 = \int_\omega x(\lambda)S(\lambda)E_1(\lambda)d\lambda$$

- So, if we have two lights we have 6 measurements per pixels and colour constancy must be easier?

Unfortuately, Multi-light constancy is hard

- There is a substantial literature on the 2 (or generally N) light constancy problem
- Dzmura and Iverson (series of papers in JOSA, 1993) have shown that only poor constancy is possible
  - Why? Because the new measurements are not independent!

- Chomagenic approach is based on 2 new ideas
  - 1) filtered RGBs are not independent
  - 2) a filter can be chosen so the redundancy correlates strongly with light colour

Suppose reflectances are 3D

$$S(\lambda) = \sum_{i=1}^{N} \sigma_i S(\lambda)$$

(1) A reflectance is a weighted sum of 3 basis vectors

$$\begin{bmatrix} R \\ G \\ B \end{bmatrix} = \begin{bmatrix} R_1 & R_2 & R_3 \\ G_1 & G_2 & G_3 \\ B_1 & B_2 & B_3 \end{bmatrix} \begin{bmatrix} \sigma_1 \\ \sigma_2 \\ \sigma_3 \end{bmatrix} = \Lambda \underline{\rho}$$

(2) It follows (by linearity of integration) that RGBs are a linear sum of basic RGBs

RGBs related linear across Lights/filters

$$\underline{\rho}^1 = \Lambda^1 \underline{\sigma} \qquad \underline{\rho}^2 = \Lambda^2 \underline{\sigma}$$

$$\Rightarrow \underline{\rho}^2 = \Lambda^2 [\Lambda^1]^{-1} \underline{\rho}^1$$

When does a filtered images help

Theorem:

assuming 3 dimensional reflectance and 3 dimensional illumination then and RGB plus filtered RGB image will nearly always uniquely identify the viewing illuminant

(the best map taking RGBs to filtered counterparts changes with and depends on illumination)

Chromagenic Colour Constancy

1. Preprocessing: calculate the best Ti for a large set of training lights and surfaces
   - T based on good data
2. Given pairs of RGBs (filtered and unfiltered)
   - Test each Ti in turn
   - Choose the one that works best
3. In principle constancy becomes possible in ‘deficient scenes’
   - Because Ts not determined based on image data

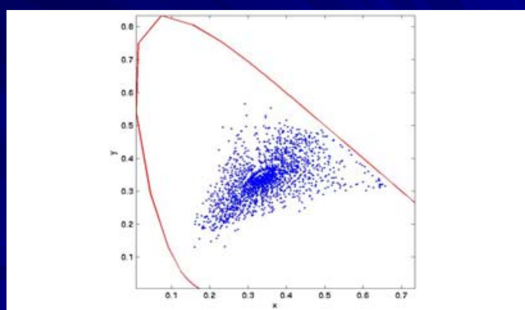
Choosing a good filter

- A neutral density filter would give the same transform for all lights
  - Very poor choice
- A good (chromagenic) filter
  - Induces different Ts for different lights
  - But, each Ti accurately maps RGBs to filtered counterparts

5. Experiments Chromagenic vs other methods

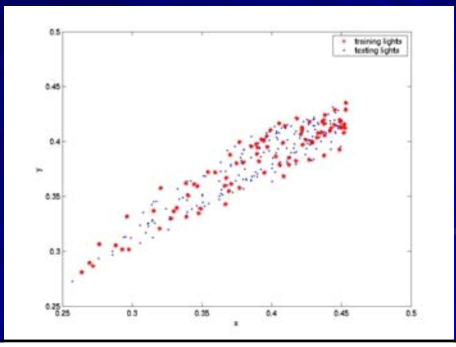
Experiments: the Simon Fraser protocol

1995 Reflectances

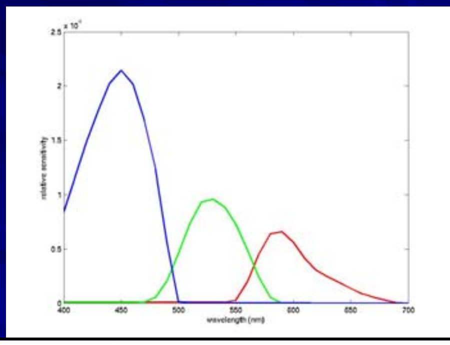


Reflectance chromaticities for equi-energy light source.

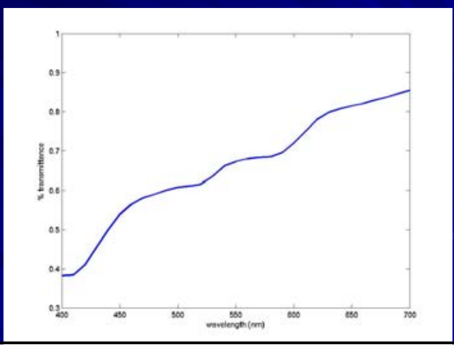
Training and Testing Lights



SONY DXC-930 Sensors



Chromagenic Filter: Wratten gelatin filter



Measuring Algorithm Performance

Estimate the RGB of the light colour: **w**

Measure the RGB of a white surface: **v**

$$error = ang(\underline{v}, \underline{w})$$

How to evaluate performance

How good is colour constancy?

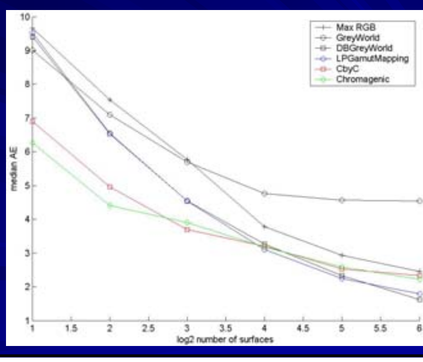
1 = great performance: the correct answer

2-3 = acceptable performance: for digital photography

4-5 = ok, so long as images do not have strong reference colors (e.g. faces)

>5 = may not acceptable (>7 not acceptable)

Chromagenic Results



Statistical Testing

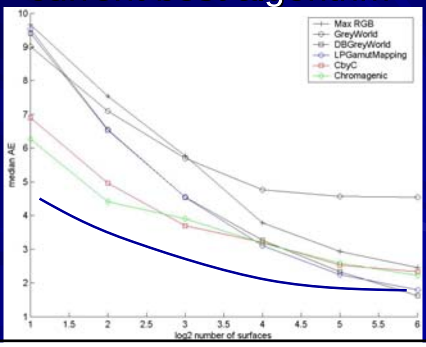
	MxRGB	GW	DBGW	LPGM	CbyC	CanCG
MxRGB		+	-	-	-	-
GW	-		-	-	-	-
DBGW	+	+		-		-
LPGM	+	+			-	-
CbyC	+	+	+	+		
CanCG	+	+	+	+		

Wilcoxon Sign Test (0.01 significance level). A plus sign (+) in the *ij*th entry implies that the algorithm in row *i* is better than the algorithm in column *j*. A minus (-) means it's worse and no sign means that the two algorithms are statistically equivalent.

Results summary

- Chromagenic works as well as the best known algorithms
- But, is much simpler
- Results have been corroborated on real images
- However,
  - The approach does have significant outliers
  - Can we engineer a stable soln?
  - Or combine with conventional approach?

A hybrid chromagenic + gamut mapping algorithm is the current best algorithm

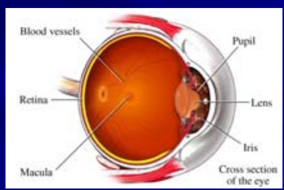


6. Human vision: beyond 3 sensors

Relevance to human vision

- We have good colour constancy
- If chromagenic is a good solution would we expect nature to have evolved a similar soln?
- Remarkably it is plausible we are chromagenic!
- Completely new observation

The Human Eye

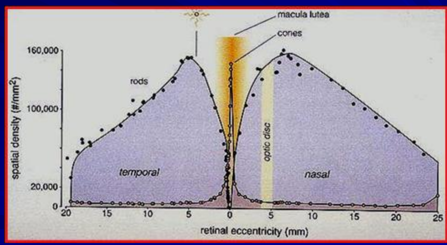


The Macula

- The *Macula Lutea* is a small central region of the Retina (Fovea)
- characteristically yellow pigmentation

Macula

Spatial Density of Macula Lutea



[Rodiek, R. W., The First Steps in Seeing, Sinauer, 1998]

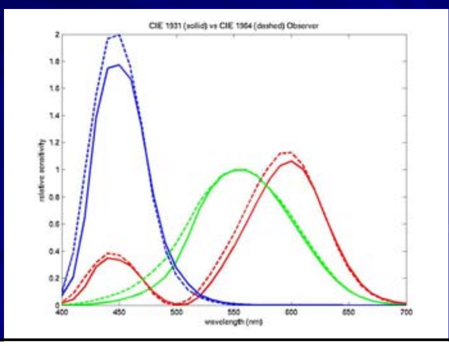
Purpose of the Macula

- The ***macula lutea*** is thought to act as a short wavelength filter, additional to that provided by the lens [Rodieck, 1973]
- As the fovea is the most essential part of the retina for human vision, protective mechanisms for avoiding bright light and especially ultraviolet irradiation damage are essential

But, how big is the effect of the Macular pigment?

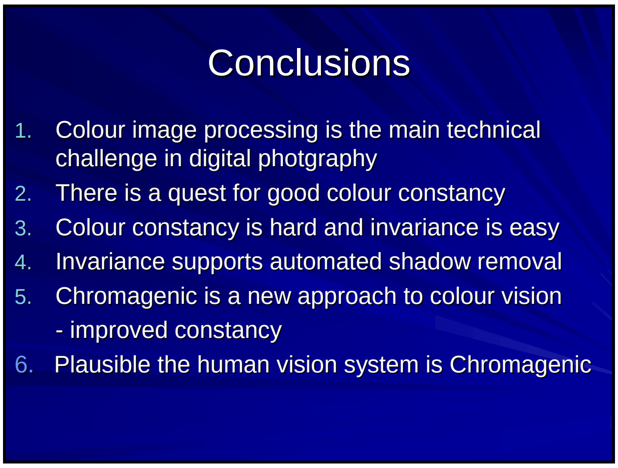
- When matching small field colours vs large field it is recommended that different matching functions are used
- The CIE recommends two different standards called the 2-degree and 10 degree observers
- In some matching experiments the Macular pigment (or Maxwell's spot) is visible to observers

CIE XYZ 2˚ and 10˚ Observer



How could the visual system take two pictures?

- The chromagenic approach requires filtered and unfiltered RGBs
  - But though there is the macular pigment we see one picture
- But, the visual system fixates at around 3 locations per second
  - In principle the different fixation points allow the visual system to build a pair of images
- Initial experiments indicate good chromagenic constancy is plausible using 2 and 10 degree matching curves


Conclusions
1. Colour image processing is the main technical challenge in digital photgraphy
2. There is a quest for good colour constancy
3. Colour constancy is hard and invariance is easy
4. Invariance supports automated shadow removal
5. Chromagenic is a new approach to colour vision
- improved constancy
6. Plausible the human vision system is Chromagenic

Calibrating Color Cameras Using Metameric Blacks

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Linköping University Sweden

1

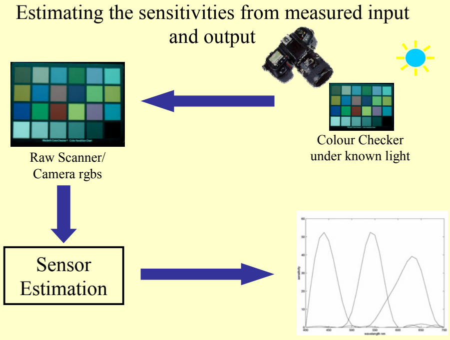
Outline

- The camera, light and colour,
- The camera calibration experiment,
- Camera calibration is an ill-posed problem,
- Metamerism is device dependent,
- Different devices result in different metamers,
- Estimating metamers without sensor calibration,
- Metamer based camera calibration,
- Results.

2

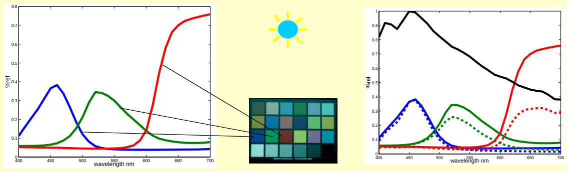
The camera calibration experiment

Estimating the sensitivities from measured input and output



3

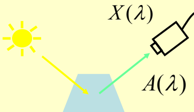
A colour signal is the product of light and surface



A colour signal is a physical property which can be measured using a spectrophotometer

4

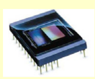
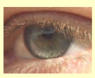
Understanding how a device sees colour



$$b = \int_{\omega} X(\lambda)A(\lambda)d\lambda$$

Device sensitivities are not colour matching functions

⇒ Devices see colour differently to humans

 ≠ 

5

Why we need the device sensitivities

To understand how a device sees colour
- to predict device rgbs

To relate device colours to colorimetric colours
- relate rgbs to XYZs

To enable colour correction
- map device colours to a colorimetric space

For physics-based vision algorithms
- for example colour constancy algorithms

And most importantly because it is a difficult and interesting problem to solve.

6

How can we get the device sensitivities?

Measure them

- *monochromator/narrow-band filters [Hubel,Farell et al] – expensive and doesn't solve the problem.*

Estimate them

- *by unconstrained regression [Sharma]*
- *by constrained regression [Finlayson et al, Barnard, Dyas, Alsam]*

7

Sensor estimation as regression

$$b = \int_{400}^{700} X(\lambda)A(\lambda)d\lambda \quad (1)$$

We want to solve (1) for $X(\lambda)$

Represent spectral functions as discrete approximations [Nyquist]:

$$X(\lambda) \cong [X(400), \quad X(410), \quad X(420), \quad \cdots, \quad X(700)] = x$$

$$A(\lambda) \cong [A(400), \quad A(410), \quad A(420), \quad \cdots, \quad A(700)] = a$$

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Simplifying the integration

Replace the integral by a summation

$$b = \int_{400}^{700} X(\lambda)A(\lambda)d\lambda \quad \approx \quad \sum_{i=1}^{31} x(\lambda_i)a(\lambda_i)$$

$$b \quad = \quad x.a$$ Summation is the vector dot product

$$b \quad = \quad a^T x$$ Dot product is a matrix multiplication

We have 1 equation and 31 unknowns $\Rightarrow$ Need more equations

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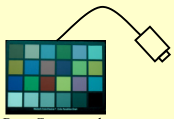
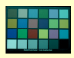
The camera response to N colour signals



Raw Camera rgbs (unrendered)

Measure illuminant with a spectroradiometer: $E(\lambda)$



Measure surface reflectances with a spectrophotometer: $S_i(\lambda)$

$$\begin{array}{ccc} b_1 & = & a_1^T x \\ b_2 & = & a_2^T x \\ \vdots & \vdots & \vdots \\ b_N & = & a_N^T x \end{array} \qquad a_i(\lambda) = E(\lambda)S_i(\lambda)$$

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Solving for *x*

Place all N colour signals in a matrix **A**:

$$b = A^T x$$

Nx1 vector of red camera responses — Nx31 colour signals — 31x1 vector: red camera sensor

We now have N equations and 31 unknowns ...

*... if we know **A** and b, we can solve for x*

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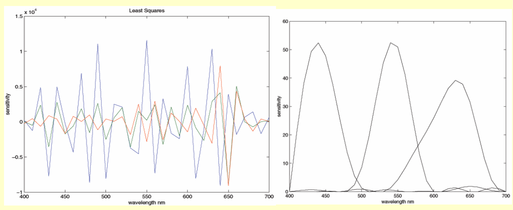
Unconstrained regression

Find x which minimises: $\left\| A^T x - b \right\|$ (least-squares regression)



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Problems with least-squares regression

- The colour signal matrix is rank deficient:

$$A(\lambda) \approx \sum_{i=1}^{m} w_i W_i(\lambda) \quad m = 6,7$$

$\Rightarrow$ *unconstrained regression is sensitive to noise*

- Note that the sensor is in a 31 dimensional space while the colour signal matrix has only 6 to 7 dimensions.

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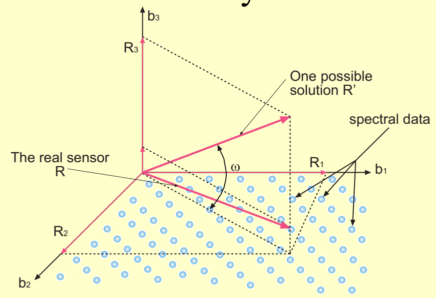
A geometric example of a rank deficient system



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Summary

- We have learned that colour formation can be described using a linear system of the form:

$$Ax = b$$

where A contains the spectral data and b is a vector of responses.
- The linear system is rank deficient, i.e. $(A^TA)^{-1}$ doesn't exists.

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Regularization

- To solve the problem regularization methods such as the Truncated Singular Value Decomposition and Tikhonov regularization are normally used. For $Ax=b$ this means:

$$x = \left(\hat{A}^T \hat{A}\right)^{-1} \hat{A}^T b$$

where

$$A = \sum_{i=1}^{n} u_i \sigma_i v_i \text{ and } \hat{A} = \sum_{i=1}^{r} u_i \sigma_i v_i$$

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Tikhonov Regularization

- Or using Tikhonov regularization:

$$x = \left(A^T A + \lambda^2 I\right)^{-1} A^T x$$

- Regularization is needed because we are trying to estimate a point x in the ill defined space of A.

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Vision Science For Solving Ill-posed Linear Systems

- Metamerism offers the means to divide the space of A into two parts: one which is orthogonal to the sensor and another which is in its range.

1. A definition of metamerism,
2. The use of metamerism to solve ill-posed inverse problems.

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Metamerism

- Two or more colour signals which integrate to the same device response are known as metamers, i.e. if:

$$b = a_1^T x = a_2^T x$$

and

$$a_1 \neq a_2$$

Then a_1 and a_2 are metamers.

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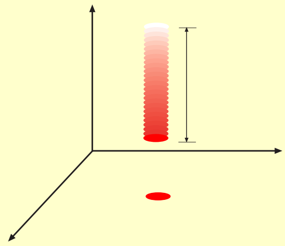
Metamerism a geometric example

- More than one spectrum are likely to integrate to the same response.

$$b = a^T x$$



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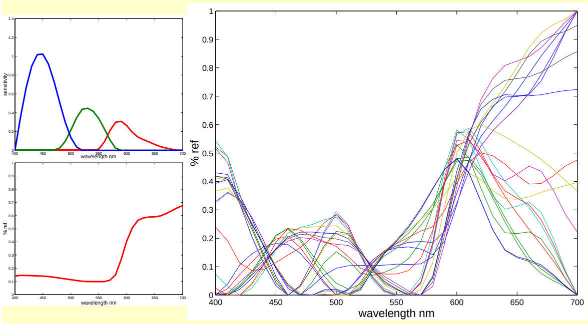
An example



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Different devices result in different metamers

- Horn proved that two sets of sensors result in the same metamers *if and only if* they are within a linear transform from each other.
- The question which we asked ourselves is: given the metamers of a device, is it possible to estimate the sensors? The answer is yes.

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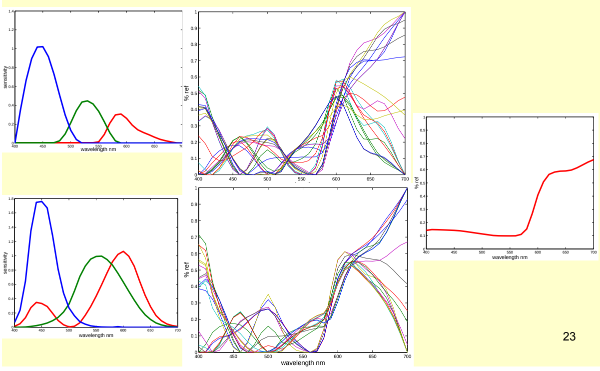
The metamers of different devices are different



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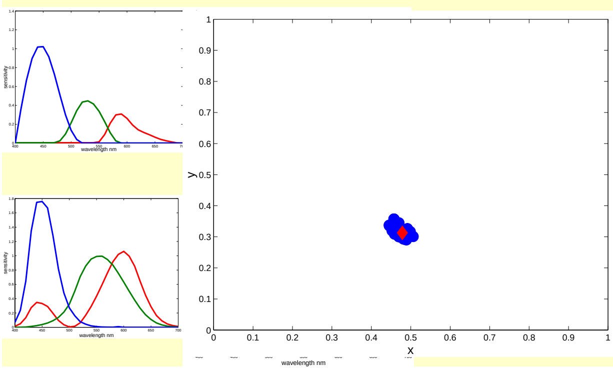
In the Chromaticity diagram



The chicken and egg

- To calculate the sensor we would like a set of metamers but to get the metamers we need a sensor.
- We show that it is possible to calculate metamers without sensor knowledge [Alsam and Finlayson 2005].
- Having calculated the metamers, we show that it is possible to estimate the sensor without minimisation.

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Linear systems and convexity

- The colour formation equation is linear:

$$b = a^T x$$

- Linear systems are homogenous:

$\lambda b_1 = \lambda a_1^T x$ subject to $0 \le \lambda \le 1$

$(1-\lambda) b_2 = (1-\lambda) a_2^T x$ subject to $0 \le \lambda \le 1$

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Linear systems are additive

- Considering the sum of two colour signals a_1 and a_2 the system's response can be written as:

$$\lambda b_1 + (1-\lambda) b_2 = \left(\lambda a_1^T + (1-\lambda) a_2^T\right) x$$

subject to $0 \le \lambda \le 1$

- Convexity is preserved in the response space:

$$\lambda b_1 + (1-\lambda) b_2 \Rightarrow \left(\lambda a_1^T + (1-\lambda) a_2^T\right)$$

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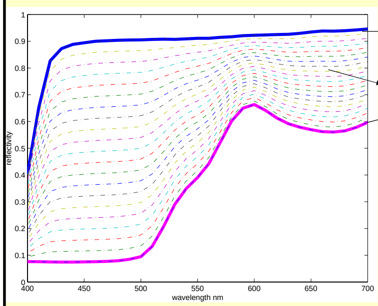
Solving for metamers by convexity



$a = \lambda a_1 + (1-\lambda) a_2$

subject to,

$\lambda \ge 0$,

$\lambda \le 1$.

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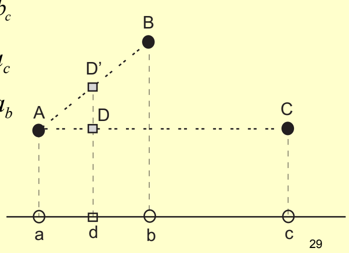
Calculating the metamers without sensor knowledge

$$\lambda b_1 + (1-\lambda) b_2 \Rightarrow \left(\lambda a_1^T + (1-\lambda) a_2^T\right)$$

Given that $b_a \le b_d \le b_c$

$a_d = \lambda a_a + (1-\lambda) a_c$

$a_d = \tilde{\lambda} a_a + (1-\tilde{\lambda}) a_b$



D and D' are metamers

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Calculating the black space of an unknown sensor

- Let us consider two metamers a_1 and a_2:

$$b = a_1^T x = a_2^T x$$

hence

$$(a_1 - a_2)^T x = 0$$

In other words: the difference between two metamers is in the null space of the unknown senor.

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For a single response *b*

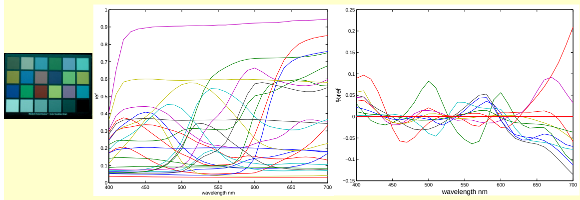
- We have two metameric colour signals, a_m and a_n where a_m is the measured, physical, signal and a_n is the calculated signal, numerical. The calculation is:

$$\lambda = \frac{b_m - b_1}{b_2 - b_1}$$

where: $b_1 \le b_m \le b_2$

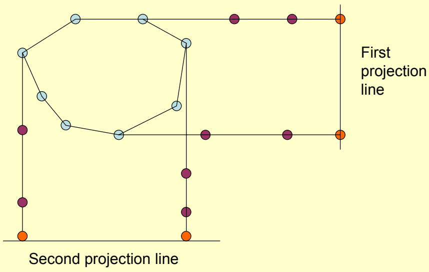
- We have $a_n = \lambda a_1 + (1-\lambda)a_2$

Given a set of calibration surfaces we can estimate the black space of an unknown sensor



Knowledge of the black space is equivalent to knowledge of the range

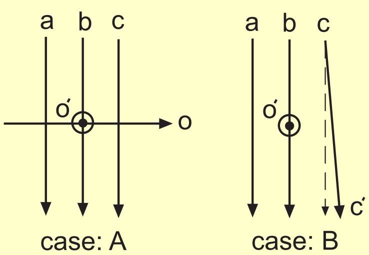
- The solution is based on taking an image of a three dimensional object.



If we are able to construct the black perfectly the range is the orthogonal complement

- In the noise free case the black can be estimated perfectly using metamerism.
- Noise changes the direction of the black vectors making it impossible to estimate the range.

The effect of noise on sensor estimation



To counteract the noise we need to reduce the dimensions

- Instead of estimating the orthogonal to the full dimensional black space we estimate the orthogonal to the main bases functions.

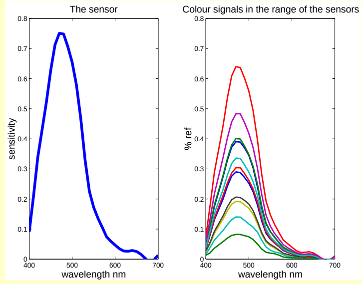
Estimating the range of the sensor

- Having calculated the null space using convexity and metamerism, the range is defined as:

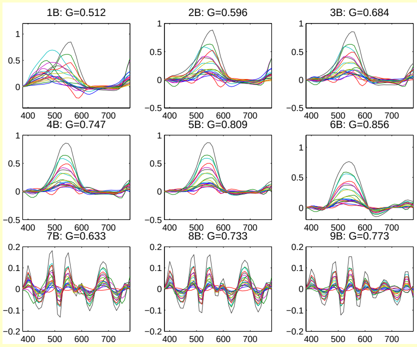
$$R = A - ABB^T$$

The noise free case

- Results in a 1-D range where any colour signal is represented as a scalar multiple of the sensor.



When noise is present the range and thus the sensor are an estimate

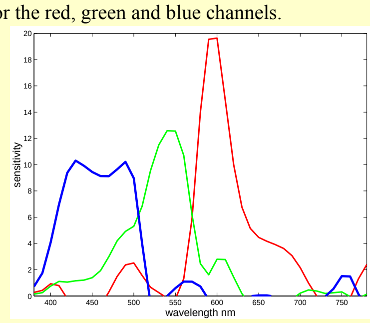


Experiment

- A Nikon D70,
- The calibration target used was the Esser chart with 264 colour patches and 22 greyscale,
- The images where captured in the Nikon D70 raw format and the data was checked for linearity,
- The spectral data was measured under a daylight simulator using a Minolta CS-1000 spectroradiometer.

Nikon D70

- The recovered sensor set was used to estimate the absolute error for the red, green and blue channels.



Absolute error based on the training set

method	Abs-Error		
TSVD	**Red**	**Green**	**Blue**
Mean	1.34	1.00	0.96
Median	0.94	0.62	0.75
Max	8.40	8.08	6.61
TR	**Red**	**Green**	**Blue**
Mean	1.82	1.26	1.53
Median	1.35	0.83	1.07
Max	8.92	5.75	6.13
MB	**Red**	**Green**	**Blue**
Mean	1.31	0.95	0.67
Median	0.82	0.66	0.51
Max	8.63	6.73	4.39

Absolute error based on the test set.

method	Abs-Error		
TSVD	Red	Green	Blue
Mean	2.64	2.58	2.74
Median	1.66	2.34	2.04
Max	9.21	8.34	8.84
TR	Red	Green	Blue
Mean	2.07	2.49	2.80
Median	1.54	1.45	1.77
Max	8.09	8.61	10.49
MB	Red	Green	Blue
Mean	1.87	1.36	0.94
Median	1.44	0.95	0.79
Max	7.01	4.74	2.97

Conclusions

- We introduced a method to solve an ill-posed linear system using metamerism.
- The approach is based on characterising the null space of the sensor by defining it as the difference between two metamers.
- The approach doesn't require optimisation.
- Our experiments indicate that the method is more robust to noise than TSVD and Tikhonov regularization with improvements of up to a 100% depending on the noise statistics and data dimesnionality.

Questions

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