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Computational Color Constancy using a Stereo Camera

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Abstract

Chromagenic color constancy is one of the promising solutions to the color constancy problem. However, this technique requires two shots of a scene: a conventional RGB image and an additional image that is optically pre-filtered using a chromagenic filter. This severely limits the usefulness of chromagenic based color constancy algorithms to static scenes only. In this paper we propose a solution to this with the use of a digital stereo camera, where we place the chromagenic filter in front of one of the lenses of the stereo camera. This allows capturing two images of a scene, one unfiltered and one filtered, in one shot. An illuminant can then be estimated using chromagenic based illumination estimation methods. Since more and more digital stereo cameras are being commercially available, the system can be built quite easily, and being a one shot solution, it is a practical computational color constancy method that could be useful in many applications. Experiments with a modern commercial digital stereo camera show promising results.

Introduction

Human vision has a natural tendency to correct for the effects of the color of the light source [1–3], allowing us to see the color of an object more or less the same under different lighting conditions. This is why, for example, a red apple appears red, no matter under which illuminant we observe it. This ability to account for the color of the light source is called color constancy. Computational color constancy is to emulate this ability in color imaging, and this is one of the fundamental requirements in many color imaging and computer vision applications. A significant volume of research work has been carried out in this area; however, they are still far from the capability of color constancy of human vision.

The primary task in a computational color constancy algorithm is to estimate the illuminant. The effects of the color of the illuminant are then corrected to obtain the desired color constancy. Since the latter part is relatively easy, most color constancy algorithms focus mainly on the illuminant estimation problem. Many methods have been proposed for the illuminant estimation, and these methods are based on the assumption of spatially uniform color of the light source across the scene. Some example methods are gray-world [4], max-RGB [5], a gamut based algorithm [6], neural networks [7], color-by-correlation [8], Bayesian method [9]. Yet another color constancy algorithm, known as the chromagenic color constancy, has been proposed by Finlayson et al. [10], and it uses a special color filter which they named as chromagenic. Fredembach and Finlayson [11] claimed to improve this further with their bright-chromagenic algorithm. Both the chromagenic and the bright-chromagenic algorithms take two pictures of a scene: a normal one and one with a specially chosen color filter placed in front of the camera. These methods have inherent weaknesses, namely, a need for perfectly registered images, occasional large errors in illuminant estimation, and a necessity of two shots. Even though Fredembach and Finlayson [11] claimed to remedy the large error problem and relax the registration constraint, the two shot requirement still severely limit its applicability to static scenes only.

We propose here an extension to the chromagenic based color constancy algorithms aiming to avoid their shortcomings and at the same time have comparable results. In order to avoid both registration as well as two shot constraints, we propose to use a digital stereo camera, or alternatively two commercial digital cameras joined together in a stereoscopic configuration, with the chromagenic filter in front of one of its lenses. This allows us to capture two images of the same scene: an unfiltered and a filtered version, in one shot. The illuminant can then be estimated based on the chromagenic [10] or the bright-chromagenic [11] algorithm. A custom designed chromagenic filter or an appropriate filter selected from a set of filters can be used. Since we are using a stereo camera, it is also possible to acquire 3D stereo images at the same time. However, this is outside the scope of the paper. Moreover, the additional color information obtained with the normal and the filtered images of a scene could also be used to increase both the colorimetric and spectral accuracy of the scene, and this has been investigated extensively by Shrestha et al. [12, 13].

We have performed experiments with the proposed stereo based chromagenic color constancy method using synthetic images, and also validated on real images using a set of hyperspectral images of natural scenes.

In the next section, we discuss the chromagenic and the bright-chromagenic algorithms. We then present the proposed stereo based chromagenic color constancy. Experiments and results are presented next. The results from the experiments are then discussed, and finally we conclude the paper.

Chromagenic and Bright-Chromagenic Color Constancy

The chromagenic color constancy algorithm was proposed by Finlayson et al. [10]. They aimed to make the multiple light approach initially proposed by D'Zmura and Iverson [14] plausible. According to D'Zmura and Iverson, if we had p measurements per pixel and s surfaces, l light sources, and the light and the surfaces were described by M and N dimensional linear models then color constancy could be solved (in many cases) so long as $pse >= sM + lN - 1$. But the approach works poorly in practice because the proposed method is highly nonlinear and numerically unstable. In order to make the idea of multiple lights a more plausible starting premise for illuminant estimation, they began with a first approximation that the image formed by placing a colored filter in front of the camera is the same as changing the illumination incident on the scene. So, two images of a scene are captured: one unfiltered and one filtered through a special filter. They called the specially chosen filter as chromagenic, if it makes the relationship between filtered and unfiltered RGBs depend more strongly on the illumination. We discuss the chromagenic illuminant estimation next.

Chromagenic Illuminant Estimation

The responses of the camera with and without the filter can be considered as the responses of a single surface under two different illuminants. When the same surfaces are viewed under two light sources, the corresponding camera responses, to a good approximation, can be related by a linear transform [14, 15]. Therefore, if C and C^F denote the unfiltered and filtered camera responses, then these responses can be related by the following equation:

$$C^F = MC, \tag{1}$$

where M is a 3×3 linear transformation matrix. M depends on both the illuminant and the filter used, and it can be computed as:

$$M = C^F C^+, \tag{2}$$

where C^+ denotes the pseudo-inverse of C. The transformation matrix M can be described as the transform that maps, in a least square sense, unfiltered to filtered responses of the camera under a given illuminant.

The chromagenic illuminant estimation method is based on the assumption that we know all possible illuminants a priori. The transforms M_i are different for different illuminants l_i; the matrix M_i is determined for each of these illuminants. This property of chromagenic camera responses is used to identify the illuminant in a scene, i.e., to solve the color constancy problem. Let $l_i(\lambda)$, $i = 1,...,m$ be the spectral power distributions (SPD) of the possible known illuminants, and $r_j(\lambda)$, $j = 1,...,n$ the reflectances of the n representative real world surfaces. For each illuminant l_i, we determine the camera responses without and with the chromagenic filter: C_i, and C_i^F respectively, which are $3 \times n$ matrices whose j^{th} column contains the camera responses of the j^{th} surface under the i^{th} illuminant. The transformation matrix M_i for the i^{th} illuminant is obtained using Equation 2.

For a given test illuminant, we select an illuminant $l_{\text{est}}(\lambda)$ from all plausible illuminants l_i as the estimated illuminant, which gives the minimum error:

$$\text{est} = \underset{i}{\text{argmin}}(e_i),\ i = 1,...,m \tag{3}$$

where e_i is the fitting error that can be calculated as:

$$e_i = \|M_i C - C^F\|,\ i = 1,...,m. \tag{4}$$

Bright-Chromagenic Algorithm

Fredembach and Finlayson [11] proposed the bright-chromagenic algorithm with the aim to improve the two major limitations of the chromagenic algorithm: possible large estimation errors and the need for perfectly registered images. They did extensive analysis on the influences of the illuminants and the reflectances on the transformation matrix M_i. These influences have been quantified with the variability measures. They found that the linear transforms used in the chromagenic algorithm vary significantly with the reflectances used in both training and testing. They tried to find a subset of the reflectance which is better suited to illuminant estimation. It has been found that low errors correlate with fairly de-saturated RGBs whereas high errors correlate with dark and saturated RGBs. Based on three criteria: easy to pick out, reliably present in natural images and avoiding dark colors because of the lower signal-to-noise ratio, they came up with the conclusion to use bright-achromatic reflectances. They proposed to use a certain percentage of the brightest pixels (typically 1-3%) in an image instead of all the pixels as in the chromagenic algorithm, and they named the proposed approach as the bright-chromagenic algorithm. Brightest pixels are defined as the ones with the largest sum of the squares of the RGB values.

They argued that the bright-chromagenic algorithm is robust since it does not make assumptions about which reflectances might or might not be present in the scene, i.e. if there are no bright reflectances, it will still have an equivalent performance to the chromagenic algorithm. Moreover, if the filter does not vary too drastically across the spectrum, the brightest unfiltered RGBs will be mapped on the brightest filtered RGBs, and by limiting the number of brightest pixels (typically top 1-3%), the algorithm has been expected to estimate illuminants even when the images are not registered.

Figure 1. *Illustration of a stereo based chromagenic camera*

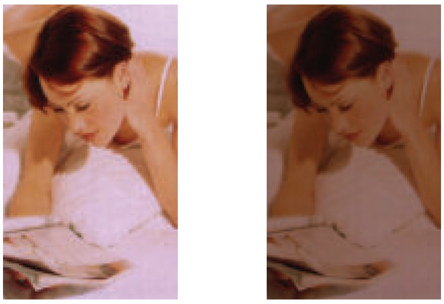
Stereo based Chromagenic Color Constancy

Even though the bright-chromagenic algorithm tries to address the two inherent weaknesses of the chromagenic algorithm, namely, a need for perfectly registered images, and occasional large errors in the illuminant estimation, the usefulness of the algorithm is still severely limited to static scenes only because of the need of two shots of an image. Furthermore, the solution proposed by the bright-chromagenic algorithm for the registration problem is rather weak. It may even fail, i.e. mapping of the bright pixels in the filtered and unfiltered images may fall off widely, if we use a filter that varies bit drastically across the spectrum.

In our proposed technique, a chromagenic filter is placed in front of one of the lenses of a digital stereo camera, and the system captures a normal unfiltered and a filtered versions of a scene, in a single shot. Furthermore, knowing the geometry of the stereo camera, not only the two images can be registered rather more precisely but also 3D information of the scene can be obtained. Among the many registration techniques [16–18], the Phase-Only Correlation (POC) method [19] could be the one for precision registration. Figure 1 illustrates a stereo based chromagenic camera. A simulated sample pair of unfiltered and filtered images produced from a spectral image (woman reading) from the University of Eastern Finland [20] with the stereo camera under one of the test illuminants is shown in Figure 2. In the next sub-section we present the system model and discuss how we estimate illuminant with the proposed system.

System Model

Let $l(\lambda)$ be the spectral power distribution of the light incident on a surface whose spectral reflectance is given by $r(\lambda)$. λ is the wavelength of the electromagnetic radiation, and here we will be interested in the visible range of the spectrum (from $\lambda_{\text{min}} = 380\text{nm}$ to $\lambda_{\text{max}} = 780\text{nm}$). Let $t(\lambda)$ be the spectral transmittance of the chromagenic filter. If $s_k(\lambda)$ denotes the sensitivities of the one side of the stereo camera without the filter, and $s_k^F(\lambda)$ denotes the sensitivities of the other side of the stereo



(a) Unfiltered (b) Filtered

Figure 2. *A sample pair of unfiltered and filtered images produced by the chromagenic stereo camera with the Kodak Wratten 81B filter*

camera with the filter, $k = \{R, G, B\}$, then the responses of these cameras: c_k and c_k^F are given by:

$$c_k = \int_{\lambda_{\min}}^{\lambda_{\max}} l(\lambda) r(\lambda) s_k(\lambda) d\lambda, \tag{5}$$

and

$$c_k^F = \int_{\lambda_{\min}}^{\lambda_{\max}} l(\lambda) r(\lambda) t(\lambda) s_k^F(\lambda) d\lambda. \tag{6}$$

Let us denote the unfiltered and the filtered camera responses in vector forms as: $C = [c_R, c_G, c_B]^T$ and $C^F = [c_R^F, c_G^F, c_B^F]^T$, where x^T denotes the transpose of x. With these responses which are related by the Equation 1, an illuminant can be estimated with the chromagenic or the bright-chromagenic algorithm discussed above.

It is to be noted that the choice of the chromagenic filter has a significant effect on all chromagenic based color constancy algorithms, as the transformation matrices depend on both the illuminant and the filter. A chromagenic filter can either be custom designed or selected from a set of filters available. We discuss this in the following sub-section.

Selection of the Chromagenic Filter

Choice of the filter and the camera sensors greatly influence the performance of the chromagenic based algorithms. A rank-deficient filter produces poor chromagenic color constancy as significant information is lost. With some of the filters and/or sensors, the chromagenic color constancy may not even be possible. Two typical examples are: the filter having a neutral density and the camera sensors behaving like Dirac delta functions [11]. Given a camera, the camera sensitivities are fixed and the only controllable parameter will be the filter. The selection of the filter is therefore vital in a chromagenic based algorithms. The goal is to select a filter that produces transformation matrices M_i that depend more strongly on illuminants and less on the surface reflectance, and such a filter has been termed as chromagenic by Finlayson et al. [10].

One approach of filter selection would be to select an optimal filter from a given set of filters through exhaustive search. Fredembach and Finlayson [11] selected the Kodak Wratten 81B filter from a set of 53 Kodak Wratten filters. If there is a considerably large number of filters, computational complexity with the exhaustive search could be improved by introducing a secondary criterion [12, 21] which excludes all infeasible filters from computations. This criterion states that filter pairs that result in a maximum transmission factor of less than forty percent and less than ten percent of the maximum transmission factor in one or more channels are excluded. Alternative approach would be to design a custom filter for a given camera, specifically for chromagenic processing. Finlayson et al. [22] reported, through simulation, that such a filter produces better results.

Experiments

Experiments have been carried out with two different sets of data: synthetic and real reflectances, and the estimation results are compared with the chromagenic and the bright-chromagenic algorithms along with the gray-world and the max-RGB methods. Before presenting the experiments, we first discuss the experimental setup used to carry out the experiments.

Experimental Setup

We discuss here the experimental setup used in the experiments. The same setup and framework as followed in the bright-chromagenic algorithm by Fredembach and Finlayson [11] have been used in the experiments. A modern digital stereo camera from Fujifilm: the *Fujifilm FinePix REAL 3D W1* (we call here after, Fujifilm 3D, in short) has been used. The sensitivities of this camera measured by Shrestha et al. [21] have been used. The sensitivities of its left and right cameras are shown in Figure 3. The experiments are carried out first with the same filter used by Fredembach and Finlayson [11] in their bright-chromagenic algorithm: the Kodak Wratten 81B (KW81B) filter whose spectral transmittance are shown in Figure 4.

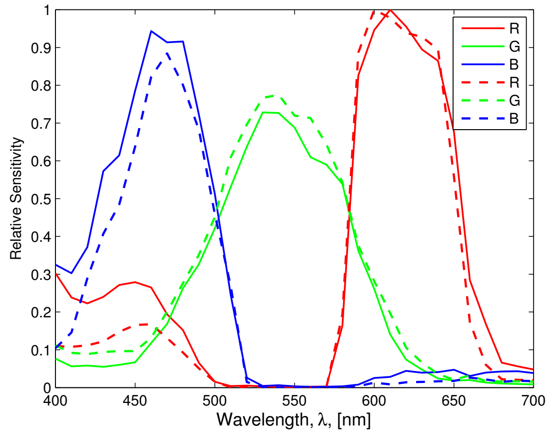


Figure 3. *Spectral sensitivities of the Fujifilm 3D camera (Left - solid, Right - dotted)*

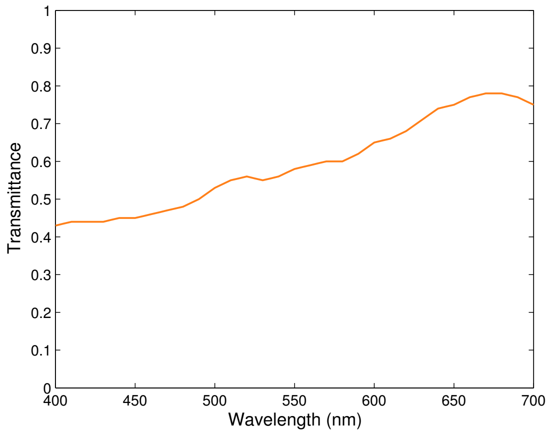


Figure 4. *Transmittance of the Kodak Wratten 81B filter*

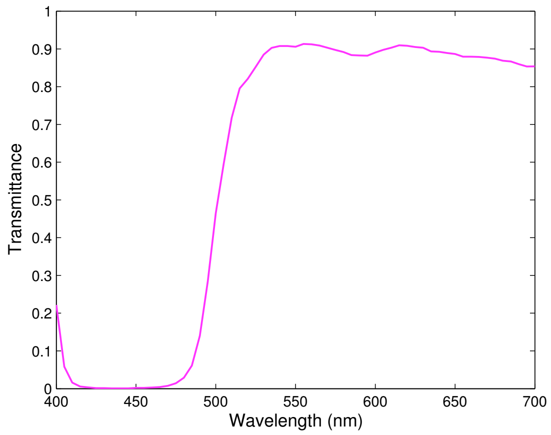


Figure 5. *Transmittance of the Omega XF2008 filter*

The 1995 Munsell surface reflectances (denoted as R) and the illuminants: the 87 measured training illuminants (L_{87}) and the 287 test illuminants (L_{287}), data from Barnard et al. [23] have been used. The transformation matrices M_i are computed by imaging the whole surface reflectances, R under the training illuminants L_{87}, and these metrices are used to estimate the test illuminants. The test illuminants are estimated with the proposed stereo based chromagenic system using the bright-chromagenic, the chromagenic algorithms. The illuminants will also be estimated with the gray-world and the max-RGB methods.

The illuminant estimation algorithms are evaluated using the same framework as proposed by Hordley and Finlayson [24]. They recommended using the median angular error over the mean root mean square (RMS) error. Angular error is intensity independent and it has been widely used in the literature [23–25]. Let $C_{l_{\mathrm{est}}}$ and $C_{l_{\mathrm{act}}}$ be the camera responses of a white reflectance under the estimated and the actual illuminant respectively, then the angular error e_{ang} is calculated as:

$$e_{\mathrm{ang}} = \cos^{-1}\left(\frac{C_{l_{\mathrm{act}}}^T C_{l_{\mathrm{est}}}}{\|C_{l_{\mathrm{act}}}\|\|C_{l_{\mathrm{est}}}\|}\right) \tag{7}$$

We have also performed experiments using a different filter also, selected from a set of 265 filters from Omega Optical Inc. [26] through exhaustive search. The filter that gives minimum illuminant estimation error with the filtered and unfiltered images generated from the surface reflectances R, under the test illuminants L_{287} using the transformation matrices M_i obtained with R and the training illuminants L_{87}, has been chosen. To improve the computational cost of the exhaustive search, we used the secondary criteria as discussed above in the Filter Selection sub-section to skip the infeasible filters. It has picked the XF2008 as the optimal filter and we have used this to analyze the estimation results compared to the ones obtained with the Kodak Wratten 81B filter. Figure 5 shows the transmittance of the Omega XF2008 filter. The images generated from spectral data (reflectance) of the images (synthetic and real) are used in the experiments.

Experiment I: Using Synthetic Reflectances

This experiment has been performed on synthetic images in the same way as by Fredembach and Finlayson [11], and according to the testing protocol proposed by Barnard et al. [23]. 1000 unfiltered and corresponding filtered images containing n different reflectances are generated for $n = \{1,2,4,8,16,32\}$ randomly picked from R, are generated by illuminating them with a light randomly selected from L_{287}. Figure 6 shows three sample pairs of unfiltered and filtered images.

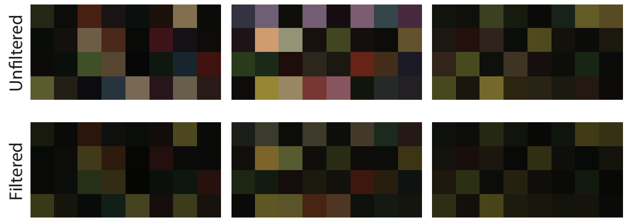


Figure 6. *Sample pairs of synthetic images with 32 reflectances under random illuminants from L_{287}*

The illuminant of each image is then estimated using the chromagenic and the bright-chromagenic algorithms, and also with the gray-world and the max-RGB methods. For statistically robust results, the procedure is repeated for each value of n twenty times, and the average values are taken. For images where $n \le 4$, all the pixels are considered while for $n > 4$, the four brightest pixels are used in the bright-chromagenic algorithm.

The experiment has been carried out with both the Kodak Wratten 81B and the Omega XF2008 filters. Table 1 shows the average median angular errors obtained with the four different illuminant estimation methods on 1000 images generated with 6 different numbers of reflectances. The results show that the average angular errors (for all five reflectance cases) produced by the chromagenic and the bright-chromagenic methods are comparable, while the results are significantly better than those produced by the gray-world and the max-RGB methods.

Table 1. Average angular errors for the 1000 images generated with 6 different numbers of reflectances

# Refl.	Gray World	Max RGB	KW 81B		Omega XF2008	
			B. Chrom	Chrom	B. Chrom	Chrom
1	9.74	9.66	6.00	5.76	5.94	5.88
2	7.28	8.32	5.21	5.26	4.96	5.26
4	5.40	6.10	4.34	4.49	4.26	4.25
8	4.13	4.21	3.95	3.71	3.68	3.48
16	3.41	2.78	3.48	3.04	3.44	2.70
32	3.12	1.93	3.43	2.62	3.20	2.31
Average	**5.51**	**5.50**	**4.40**	**4.15**	**4.25**	**3.98**

Experiment II: Using Real Reflectances

In this experiment, we use the real images generated from hyperspectral images of 8 natural scenes from Nascimento et al. [27]. The RGB images generated from the hyperspectral images using the Fujifilm3D camera and one of the illuminant from L_{87} are shown in Figure 7. These hyperspectral images are available online in $820 \times 820 \times 33$ over 400-700nm bands in 10nm steps. However, the real image contents are less than 820×820, but padded with zeros. Those padded empty data are removed and only real image contents are used. From these hyperspectral images, we obtain the unfiltered and filtered versions of each image for each test illuminant L_{287}. The test illuminant is estimated in each case with both the chromagenic and the bright-chromagenic algorithms. The top 3% of the brightest non-saturated pixels are used with the bright-chromagenic approach.

The median angular errors produced by both the chromagenic and the bright-chromagenic methods along with the gray-world and the max-RGB methods are given in Table 2. Like in Experiment I, both chromagenic methods produce comparable average angular errors, but the results are significantly better than those produced by the gray-world and the max-RGB methods.

Figure 7. *The RGB images generated from hyperspectral images of 8 natural scenes from Nascimento et al. [27]*

Table 2. Median angular errors for the 8 images generated from hyperspectral data of the scenes

Scene #	Gray World	Max RGB	KW 81B		Omega XF2008	
			B. Chrom	Chrom	B. Chrom	Chrom
1	7.88	6.62	4.67	4.53	4.37	3.93
2	9.86	21.85	7.79	8.76	6.59	6.85
3	9.45	3.20	5.59	7.69	4.89	6.49
4	5.50	4.75	7.60	8.49	6.47	7.32
5	7.32	11.04	3.40	2.47	3.66	1.87
6	2.83	6.94	4.48	5.28	5.76	7.13
7	0.99	2.12	3.91	3.42	4.91	3.91
8	2.87	3.10	2.83	3.43	2.55	3.98
Average	**5.84**	**7.45**	**5.03**	**5.51**	**4.90**	**5.19**

Discussion

Results from both the experiments with the synthetic and the real images show that both the chromagenic and the bright-chromagenic color constancy algorithms perform better than the gray-world and the max-RGB algorithms with both the KW81B and the Omega XF2008 filters. Fredembach and Finlayson [11] have shown that the chromagenic based algorithms outperforms other color constancy algorithms like neural network, LP gamut mapping and color by correlation.

Among the bright-chromagenic and the chromagenic algorithms, the first experiment on the synthetic images shows that on the average, the chromagenic algorithm is slightly better than the bright-chromagenic algorithm, while the second experiment on the real images shows the other way around. The small average angular error differences infer that the performance of both the chromagenic and the bright-chromagenic algorithms are more or less the same. However, since we use only small percentage of the pixels (typically 1-3%) in the bright-chromagenic compared to all the pixels in the chromagenic, the bright-chromagenic is preferable over the chromagenic as the computational cost with the first one would be significantly low.

Furthermore, the experimental results show that the optimal filter, the Omega XF2008, selected from the set of 265 filters, performs slightly better than the KW81B, the one used with the Sony-DXC 930 camera by Fredembach and Finlayson [11] in their bright-chromagenic algorithm. This implies that the optimal filter depends on the camera sensor, and simply selecting a filter from a set of available filters could give a reasonably good estimation results from the chromagenic and the bright-chromagenic algorithms. We have used filters from only one supplier as a one point solution, the Omega Optical Inc. has been chosen as it has a larger set of filters, and the data are available online [26]. The performance can be improved by selecting an optimal filter from a reasonably larger set of filters, possibly from more suppliers.

Conclusion

Chromagenic based color constancy algorithms are able to estimate illuminants quite well compared to some of the common estimation algorithms like the gray-world, the max-RGB, gamut based, neural networks and color by correlation. Our proposed stereo based chromagenic system provides a one shot solution which otherwise needs two shots of an image, thus extending the chromagenic based color constancy to scenes in motion. Furthermore, it can be constructed out of off-the-shelf commercial digital stereo camera and a color filter. Having more and more digital stereo cameras available in the market, it is a feasible and practical solution for color constancy and therefore could have wider applications, for example in color imaging and computer vision.

The use of the stereo camera also allows capturing spectral and 3D images. Simultaneous spectral and/or 3D imaging and the illuminant estimation would be an interesting future work.

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