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# Computational color constancy using chromagenic filters in color filter arrays

Raju Shrestha and Jon Yngve Hardeberg

The Norwegian Color Research Laboratory, Gjøvik University College, Norway

## ABSTRACT

We have proposed, in this paper, a new color constancy technique, an extension to the chromagenic color constancy. Chromagenic based illuminant estimation methods take two shots of a scene, one without and one with a specially chosen color filter in front of the camera lens. Here, we introduce chromagenic filters into the color filter array itself by placing them on top of R, G or B filters and replacing one of the two green filters in the Bayer's pattern with them. This allows obtaining two images of the same scene via demosaicking: a normal RGB image, and a chromagenic image, equivalent of RGB image with a chromagenic filter. The illuminant can then be estimated using chromagenic based illumination estimation algorithms. The method, we named as CFA based chromagenic color constancy (or 4C in short), therefore, does not require two shots and no registration issues involved unlike as in the other chromagenic based color constancy algorithms, making it more practical and useful computational color constancy method in many applications.

Experiments show that the proposed color filter array based chromagenic color constancy method produces comparable results with the chromagenic color constancy without interpolation.

**Keywords:** Computational color constancy, illuminant estimation, color filter array, CFA, chromagenic

## 1. INTRODUCTION

Color constancy is the ability to account for the color of the light source which allows seeing the color of an object more or less the same under different lighting conditions. Human vision is said to be color constant as it has a natural tendency to correct for the effects of the color of the light source.<sup>1-3</sup> This is why, for example, we see white snow white no matter which time of the day or under which illuminant we observe it. Computational color constancy tries to emulate the color constancy 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 human vision's color constancy capability.

Computational color constancy models, in general, comprise of two steps: illuminant estimation and color correction. The illuminant estimation is the primary task in a computational color constancy algorithm. Often the color of the light source is assumed to be spatially uniform across the scene. Based on this assumption, a computational color constancy algorithm estimates the illuminant under which an image has been captured. The effects of the color of the illuminant are then corrected to obtain the desired color constant image. Since the later part is relatively easy, most color constancy algorithms are characterized by the estimation of the illuminant. Many methods have been proposed for the estimation of the illuminant. Some example methods are gray-world,<sup>4</sup> max-RGB,<sup>5</sup> gamut based algorithm,<sup>6</sup> neural networks based,<sup>7</sup> color-by-correlation,<sup>8</sup> Bayesian based<sup>9</sup> and chromagenic color constancy.<sup>10,11</sup> Our main interest here is on the chromagenic based color constancy algorithms: the chromagenic algorithm first proposed by Finlayson et al.,<sup>10</sup> and the bright-chromagenic algorithm proposed by Fredembach and Finlayson.<sup>11</sup> The chromagenic algorithm estimates an illuminant from the two images of a scene, one normal RGB image, and the other taken with a special filter which they named as chromagenic filter, placed in front of the camera lens. The bright-chromagenic algorithm claimed to improve the results further. This algorithm uses only certain brightest pixels only, instead of considering all the pixels on the two images as in the chromagenic algorithm. We discuss both of these chromagenic algorithms in more details in Section 2.

We propose here a new chromagenic based color constancy algorithm which extends the chromagenic color constancy algorithms further by avoiding their shortcomings, and at the same time produces comparable results. Both the chromagenic and the bright-chromagenic algorithms take two pictures from a scene: a normal one and a filtered one. These methods, therefore, have inherent weaknesses: a need for perfectly registered images, occasional large errors in the illuminant estimation and a need for two shots. Even though Fredembach and Finlayson<sup>11</sup> claimed to remedy the large error problem and relax the registration constraint to some extent, the two shot requirement still severely limit its applicability to static scenes only. In order to avoid both registration as well as two shot constraints, we introduce chromagenic filters into the color filter array (CFA) itself. Instead of using two green filters in a Bayer pattern,<sup>12</sup> we introduce a chromagenic filter on top of *R*, *G* or *B* filters in one of the two green filters. This allows obtaining two images of the same scene via demosaicking, a normal RGB image, and a chromagenic image, equivalent to the RGB image with a chromagenic filter. The illuminant can then be estimated based on the algorithm proposed in<sup>10</sup> or.<sup>11</sup> A custom designed chromagenic filter or an appropriate filter selected from a given set of can be used. We call the proposed new color constancy method as **CFA based chromagenic color constancy (4C)**.

We perform experiments with the proposed 4C method using the same Simon Fraser testing protocol followed by Fredembach and Finlayson,<sup>11</sup> and the method has been validated on real images using a set of hyperspectral images. The results show that the proposed method produces comparable results to the ones obtained without interpolation, both with the chromagenic and the bright-chromagenic algorithms.

In section 2 we discuss the chromagenic and the bright-chromagenic color constancy algorithms. We then present the proposed 4C method in section 3. Section 4 presents experiments and results. Discussion on the results will be made in section 5, and finally conclude the paper in section 6.

## 2. CHROMAGENIC AND BRIGHT-CHROMAGENIC COLOR CONSTANCY

The chromagenic color constancy algorithm was proposed by Finlayson et al.<sup>10</sup> The algorithm is based on the first approximation that the image formed by placing a colored filter in front of the camera is the same as changing the illumination impinging on the scene. In other words, the responses of the camera with and without the filter can be considered as the responses of a single surface under two different illuminants. They named a specially chosen filter chromagenic, if that makes the relationship between filtered and unfiltered RGBs depend more strongly on the illumination. Fredembach and Finlayson<sup>11</sup> proposed bright-chromagenic algorithm, claimed to be an improvement to the original chromagenic algorithm. We will discuss illuminant estimation with both the chromagenic and the bright-chromagenic algorithms in the following subsections.

### 2.1 Chromagenic Illuminant Estimation

The two images: an unfiltered and a filtered version of a scene, captured with the chromagenic system, can be considered as the two images of the same scene taken 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.<sup>13,14</sup> Therefore, if  $C$  and  $C^F$  denote the normal (unfiltered) and the filtered camera responses of a scene, then these responses can be related by the following equation:

$$C^F = MC, \quad (1)$$

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

$$M = C^F C^+, \quad (2)$$

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  $l_i(\lambda)$ ,  $i = 1, \dots, m$  are the spectral power distributions (SPD) of the possible known illuminants, and  $r_j(\lambda)$ ,  $i = 1, \dots, n$  is the reflectances of the  $n$  representative real world surfaces. For each illuminant  $i$ , 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  $j^{\text{th}}$  column contains the camera responses of the  $j^{\text{th}}$  surface under the  $i^{\text{th}}$  illuminant. The transformation matrix  $M_i$  for the  $i^{\text{th}}$  illuminant is obtained using Equation 2.

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

$$est = \underset{i}{\operatorname{argmin}}(e_i), i = 1, \dots, m \quad (3)$$

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

$$e_i = \|M_i C - C^F\|, i = 1, \dots, m. \quad (4)$$

## 2.2 Bright-Chromagenic Algorithm

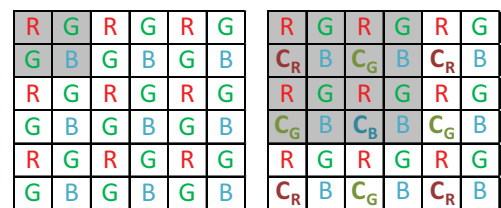
Fredembach and Finlayson<sup>11</sup> proposed the bright-chromagenic algorithm with the aim to improve the two major limitations of the chromagenic algorithm: possible large estimation errors and the need for perfectly registered images. They did extensive analysis on the influences of the illuminants 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 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  $R^2 + G^2 + B^2$  value.

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.

## 3. CFA BASED CHROMAGENIC COLOR CONSTANCY

Even though the bright-chromagenic algorithm tries to address the two inherent weaknesses of the chromagenic algorithm: a need for perfectly registered images, and occasional large errors in the illuminant estimation, it is still severely limited in its use to static scenes only because of the need of the 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. bright pixels may not map well in the filtered and unfiltered images, if we use a filter that varies even a little drastically across the spectrum. We propose here a CFA based chromagenic color constancy (4C) that will solve both the registration as well as the two shot constraints. For this, we introduce the chromagenic filters into the color filter array itself.

The chromagenic filters are placed on top of  $R$ ,  $G$  and  $B$  filters and the resulting filters denoted as  $C_R$ ,  $C_G$  or  $C_B$  respectively are placed for one of the green filters in a Bayer pattern.<sup>12</sup> To compensate for the reduction of a green filter, we use two  $C_G$  filters for one  $C_R$  and one  $C_B$  filters resulting the chromagenic filter pattern of  $C_R C_G C_G C_B$ . This pattern also follows the two important CFA design requirements: the spectral consistency and the spatial uniformity.<sup>15</sup> Figure 1(a) illustrates a Bayer CFA pattern in RGGB and Figure 1(b) illustrates the corresponding CFA pattern after the introduction of the chromagenic filters. Gray blocks in these figures shows the basic block which would be repeated uniformly in the whole image.



(a) Bayer CFA

(b) Chromagenic CFA

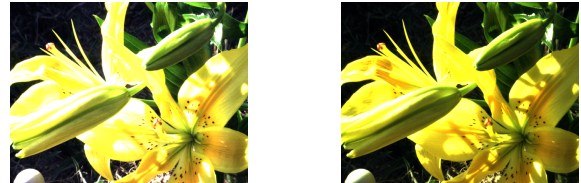
**Figure 1:** Illustration of CFAs with and without the chromagenic filters

The 4C approach allows obtaining two images of the same scene through demosaicking: a normal RGB image, and a chromagenic image, equivalent of RGB image with a chromagenic filter. An unfiltered image is obtained from pixels with  $R$ ,  $G$  and  $B$  filters, using a demosaicking algorithm. Similarly a filtered image is obtained from pixels with  $C_R$ ,  $C_G$  and one  $C_B$  filters. A larger kernel might be required for the demosaicking of a filtered image, as can be seen with bigger gray block in Figure 1(b) and it might reduce some spatial resolution. However, it has been found to be good enough for

our purpose. Many different demosaicking algorithms have been proposed.<sup>16–20</sup> An appropriate algorithm could be used. Figure 2 shows a sample pair of unfiltered and filtered images obtained with a spectral image from Foster et al.,<sup>21</sup> by a Sony DXC-930 camera (Figure 3) and a Kodak Wratten 81B (KW81B) filter (Figure 4) under D65 illuminant, using a bilinear demosaicking algorithm. The process of bilinear interpolation has been well described by Baone and Qi.<sup>22</sup> Having two images: an unfiltered and a filtered, the illuminant can then be estimated using the chromagenic or the bright-chromagenic algorithm discussed in the Section 2. We call the proposed new color constancy method as **CFA based chromagenic color constancy (4C)**.

A chromagenic filter can either be custom designed or selected from a set of filters available. Section 3.2 discusses on the filter selection methods. With the 4C, one might also design sensors for the chromagenic illuminant estimation, but this require consideration of aspects of image quality such as color rendering and image noise and it is not within the scope of this paper.

In order to validate the performance of the proposed 4C system, we have carried out several experiments which are presented in Section 4. We now present the system model of the proposed system in the next sub-section.



(a) Unfiltered

(b) Filtered

**Figure 2:** A sample pair of unfiltered and filtered images produced by the CFA based chromagenic algorithm

### 3.1 System Model

Let  $I(\lambda)$  be the spectral power distribution of the light incident on a surface whose spectral reflectance is  $r(\lambda)$ .  $\lambda$  is the wavelength of the electromagnetic radiation, and here we will be interested in the visible range of the spectrum (from  $\lambda_{\min} = 380\text{nm}$  to  $\lambda_{\max} = 780\text{nm}$ ). Let  $t(\lambda)$  be the spectral transmittance of the chromagenic filter. If  $s_k(\lambda)$  denotes the sensitivities of the camera,  $k = \{R, G, B\}$ , then the unfiltered and the filtered responses of the camera,  $c_k$  and  $c_k^F$  respectively are given by:

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

and

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

A normal image  $I$  is obtained from the unfiltered pixels using a demosaicking algorithm as discussed above. Similarly, a filtered image  $I^F$  is obtained from the filtered pixels also using the same demosaicking algorithm. Let  $C = [c_R, c_G, c_B]^T$  and  $C^F = [c_R^F, c_G^F, c_B^F]^T$  denote the RGB camera responses in vector form of the unfiltered and the filtered images respectively. Here  $x^T$  means the transpose of  $x$ . With these responses which are related by the Equation 1, an illuminant can be estimated with the chromagenic or bright-chromagenic algorithms discussed above in the Section 2.

### 3.2 Selection of the Chromagenic Filter

Choice of the filter and the camera sensors greatly influence the performance of a chromagenic based algorithm. 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.<sup>11</sup> Given a camera, the camera sensitivities are fixed and only controllable parameter will be the filter. The selection of the filter is therefore vital in 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.<sup>10</sup>

One approach of the filter selection would be to select an optimal filter from a given set of filters through exhaustive search. Fredembach and Finlayson<sup>11</sup> selected the Kodak Wratten 81B filter from a set of 53 Kodak Wratten filters.<sup>23</sup> If there is a considerably large number of filters, computational complexity with the exhaustive search could be improved by introducing a secondary criterion which excludes all infeasible filters from costly computations. One such criterion is 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.<sup>24,25</sup>

Alternative approach to the filter selection would be to design a custom filter for a given camera, specifically for the chromagenic processing. Finlayson et al.<sup>26</sup> reported, through simulation, that such a filter produces better results.

#### 4. EXPERIMENTS

Experiments have been carried out with two different sets of data: synthetic and real reflectances, and the estimation results are computed with the chromagenic and 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.

##### 4.1 Experimental Setup

The same setup and the framework as followed in the bright-chromagenic algorithm by Fredembach and Finlayson<sup>11</sup> have been used in the experiments. The Sony DXC-930 camera and the Kodak Wratten 81B filter have been used for the image capture. Figure 3 shows the spectral sensitivities of the camera, and Figure 4 shows the spectral transmittance of the filter.

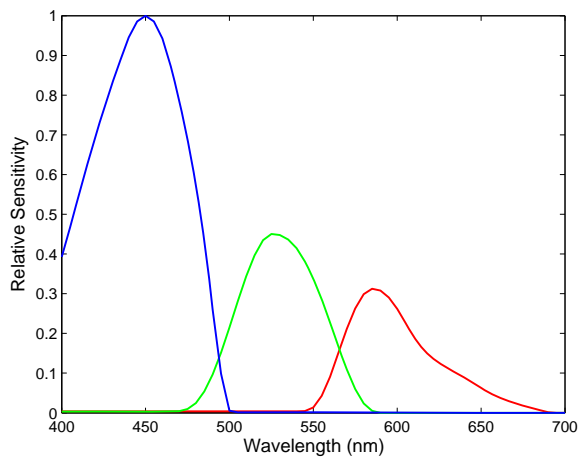


Figure 3: Spectral sensitivities of the Sony DXC-930 camera

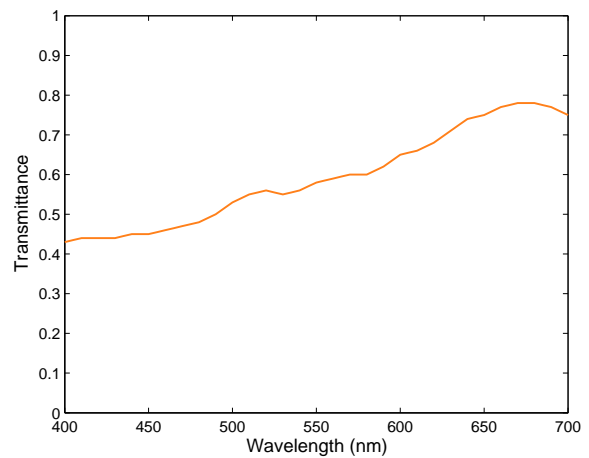


Figure 4: Spectral transmittance of the Kodak Wratten 81B filter

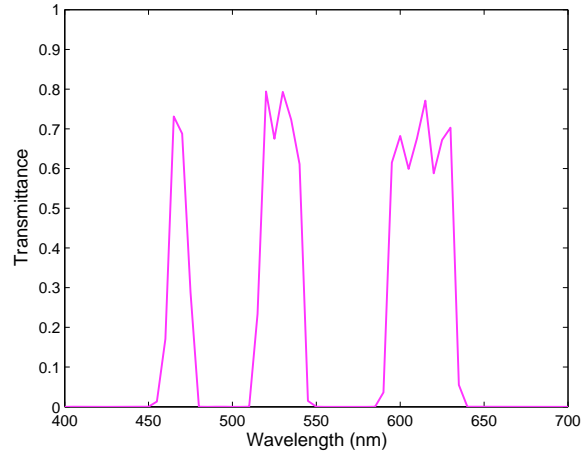
The 1995 Munsell surface reflectances (denoted as  $R$ ) and the illuminants: the 87 measured training illuminants ( $L_{87}$ ) and the 287 test illuminants ( $L_{287}$ ), data from Barnard et al.<sup>27</sup> have been used. The transformation matrices  $M_i$  are computed (using Equation 2) by imaging the whole surface reflectances,  $R$  under the training illuminants  $L_{87}$ , and they will be used to estimate the test illuminants. The test illuminants are estimated with the proposed CFA based chromagenic system using the chromagenic and the bright-chromagenic algorithms. The illuminants are also estimated with the gray world and the max-RGB methods.

The illuminant estimation algorithms are evaluated using error measures. Two most commonly used measures are: the chromaticity error and the angular error. The chromaticity error is the Euclidean distance between the 2-D chromaticity vectors, and the angular error is the angular distance between the 3-D representation of the two vectors.<sup>28</sup> Angular error is intensity independent. Since there is a high degree of correlation between the two measures, one would be sufficient to evaluate the performance, and we have chosen the angular error, the most widely used in the literature.<sup>27-29</sup> If  $C_{l_{act}}$  and  $C_{l_{est}}$  denote the normalized camera responses of a white reflectance under the actual and the estimated illuminants respectively, then the angular error  $e_{ang}$  is calculated as:

$$e_{ang} = \arccos \left( \frac{C_{l_{act}}^T C_{l_{est}}}{\|C_{l_{act}}\| \|C_{l_{est}}\|} \right). \quad (7)$$

The illuminant estimation algorithms are evaluated using the same framework as proposed by Hordley and Finlayson.<sup>28</sup> As recommended by them, the medium angular error has been chosen over the mean root mean square (RMS) error.

We have performed experiments using a different filter also, selected from a set of 265 filters from Omega Optical Inc.<sup>30</sup> through exhaustive search. The filter that gives minimum illuminant estimation error with the filtered and the 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 Section 3.2 to skip the infeasible filters. It has picked the XF3116 as an 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 XF3116 filter.



**Figure 5:** Transmittance of the Omega XF3116 filter

The images generated from the spectral data (reflectance) of an image (synthetic or real) are used in the experiments. All the experiments are carried out with the proposed CFA based chromagenic using bilinear interpolation as well as with the ideal system where we obtain unfiltered and filtered version of the images generated from the spectral data without interpolation to compare the influence of interpolation on the performance of illuminant estimation.

## 4.2 Experiment I: Using Synthetic Reflectances

This experiment has been performed on synthetic images in the same way as did by Fredembach and Finlayson<sup>11</sup> according to the testing protocol proposed by Barnard et al.<sup>27</sup> 1000 unfiltered and the corresponding filtered images containing  $n$  different reflectances are generated for  $n = \{1, 2, 4, 8, 16, 32\}$  randomly picked from  $R$ , by illuminating them with a light, randomly selected from  $L_{287}$ . Figure 6 shows sample pairs of unfiltered and filtered images for  $n = 32$ . The images comprise of  $10 \times 10$  pixel patches corresponding to the randomly picked surface reflectances.

The illuminant of each image is estimated using the proposed CFA based chromagenic using both the chromagenic and the bright-chromagenic algorithms, and also with the gray world and the max-RGB methods. A central pixel from each patch from the demosaicked images are used in the estimation of illuminants. For statistically robust results, the procedure is repeated for each value of  $n$  twenty times, and the average values are taken. In the bright-chromagenic version, the four brightest pixels are used for the images from  $n > 4$  reflectances, while all the pixels are considered for the images from  $n \leq 4$  reflectances.

The experiment has been carried out with both the KW81B and the Omega XF3116 filters. Table 1 shows the median angular errors obtained with the four different illuminant estimation methods, with two different filters, all on the images generated with six different number of reflectances. In this table, Chromag and BChromag denote the chromagenic and the bright-chromagenic algorithms respectively. Since we are using the bi-linear demosaicking, the central pixels of the patches with and without the interpolation would be the same, thus producing the same results.



**Figure 6:** Sample pairs of filtered and unfiltered synthetic images with 32 reflectances under random illuminants from  $L_{287}$

**Table 1:** Median angular errors for the 1000 images generated with 6 different numbers of reflectances

# Refl.	Gray	Max	KW 81B		Omega XF3116	
	World	RGB	BChrom	Chrom	BChrom	Chrom
1	12.30	12.30	6.81	6.81	5.57	5.57
2	9.73	10.65	5.84	5.84	4.39	4.39
4	7.53	7.61	4.94	4.94	3.49	3.49
8	5.41	5.43	3.94	3.88	2.97	2.80
16	4.74	3.75	3.24	2.82	2.77	2.32
32	4.61	2.83	3.44	2.80	2.33	2.06
Avg.	<b>7.39</b>	<b>7.09</b>	<b>4.70</b>	<b>4.52</b>	<b>3.59</b>	<b>3.44</b>

### 4.3 Experiment II: Using Real Reflectances

In this experiment, we use the real images generated from the hyperspectral images of the eight natural scenes from Nascimento et al.<sup>31</sup> The RGB images generated from these hyperspectral images using the Sony DXC-930 camera under the D65 illuminant are shown in Figure 7. Here we obtain the unfiltered and the filtered versions of each image with every test illuminant in  $L_{287}$ . Again, the bilinear interpolation has been used for the demosaicking. The test illuminant is estimated in each case with both the algorithms. Top 3% of the brightest non-saturated pixels are used with the bright-chromagenic. The median angular errors produced by both the chromagenic and the bright-chromagenic algorithms along with the gray world and the max-RGB methods in the case of CFA based chromagenic and the chromagenic without interpolation are given in Table 2.



**Figure 7:** The RGB images obtained from hyperspectral images of the 8 natural scenes from Nascimento et al.<sup>31</sup>

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

Scene #	Chromagenic without interpolation						CFA based chromagenic					
	Gray		Max		Omega XF3116		Gray		Max		Omega XF3116	
	World	RGB	BChrom	Chrom	BChrom	Chrom	World	RGB	BChrom	Chrom	BChrom	Chrom
1	14.40	9.75	4.90	3.92	3.11	3.73	14.36	9.94	7.81	4.62	2.68	3.81
2	19.48	26.83	20.10	8.15	20.11	5.35	19.43	24.39	14.18	9.77	20.11	5.75
3	19.92	6.34	15.06	7.22	18.45	5.23	19.89	7.47	15.52	8.00	18.45	5.35
4	9.87	6.73	7.53	7.58	5.85	6.99	9.84	8.98	12.54	7.66	3.78	7.14
5	11.69	20.77	15.62	3.39	15.18	2.45	11.79	2.70	7.67	3.55	2.56	2.44
6	5.24	9.49	7.19	7.06	5.26	3.92	5.26	9.81	10.57	7.95	11.20	3.94
7	0.01	2.74	5.79	3.74	5.79	5.91	0.01	2.63	9.38	5.79	5.56	5.89
8	5.41	6.50	4.04	3.08	4.10	2.39	5.44	6.71	9.51	6.88	4.04	2.44
<b>Avg.</b>	<b>10.75</b>	<b>11.15</b>	<b>10.03</b>	<b>5.52</b>	<b>9.73</b>	<b>4.50</b>	<b>10.75</b>	<b>9.08</b>	<b>10.90</b>	<b>6.78</b>	<b>8.55</b>	<b>4.60</b>

## 5. DISCUSSION ON THE RESULTS

With the first experiment on the synthetic images, as mentioned above, we don't see the difference in the results from the proposed 4C method and the ideal case of without interpolation. However, we can see the behavior of the four different estimation methods including the two chromagenic methods. We can also see the performance difference with the two different filters used: the KW81B and the Omega XF3116. The results show that the chromagenic based algorithms outperforms (lower median angular errors) both the gray world and the max-RGB methods on the average. Fredembach and Finlayson<sup>11</sup> have also shown that the chromagenic methods performs significantly better than the other well known methods like the gray world, the max-RGB, the color-by-correlation, the gamut based and the neural networks based. However, the results from this experiment do not show any significant difference in the performance of the chromagenic and the bright-chromagenic algorithms.

Results from the second experiment with the real images also show the chromagenic based algorithms performing better than the gray world and the max-RGB methods. The chromagenic algorithm performs surprisingly better than the bright-chromagenic algorithm, with both the filters. However the advantage with the bright-chromagenic algorithm would be the significantly lower computational cost, as we use only a small percentage of the pixel (typically 1-3%) compared to all the pixels used in the chromagenic algorithm. Here we have to note that the bright-chromagenic algorithm has been proposed with the major aim of minimizing the effect (to some extent) of the registration problem. With our proposed 4C approach, there is no issue of registration at all. Furthermore, we can also see that the chromagenic algorithm shows less wild variation in the estimation errors, whereas the other three methods including the bright-chromagenic algorithm show wider variation in the estimation errors with the eight test images.

Results from both the experiments show that the optimal filter selected from a set of 265 filters, the Omega XF3116 performs better than the KW81B. This shows that simply selecting a filter from a set of available filters could give a reasonably good estimation results from both the chromagenic and the bright-chromagenic algorithms. We have used the 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.<sup>30</sup> The performance can be improved further by selecting an optimal filter from a reasonably larger set of filters, possibly from more suppliers.



Furthermore, the proposed 4C method produces comparable results to the ones without interpolation, with both the chromagenic and the bright-chromagenic algorithms, and with both the filters. It is expected to get some higher estimation errors due to the interpolation, however we found that it is not so significantly large. It has to be noted here again that the approach eliminates registration issue by providing one shot solution, and thus making it more practical and useful.

## 6. CONCLUSION

We have proposed here a one shot solution to the chromagenic color constancy by introducing chromagenic filters into the color filter arrays of the sensor. This solves the biggest problem of registration and the two shots requirement in the state-of-the-art chromagenic based color constancy algorithms, and at the same time produces equally good results. The proposed system makes the chromagenic color constancy applicable to the images/videos of the scenes in motion. Therefore, the system will be more useful in wider applications. There could be an issue of loss of some information due to the reduction in the number of green filters in the Bayer's pattern. Analyzing this could be an interesting future work.

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# Computational color constancy using chromagenic filters in color filter arrays

Raju Shrestha and Jon Yngve Hardeberg

The Norwegian Color Research Laboratory, Gjøvik University College, Norway

## ABSTRACT

We have proposed, in this paper, a new color constancy technique, an extension to the chromagenic color constancy. Chromagenic based illuminant estimation methods take two shots of a scene, one without and one with a specially chosen color filter in front of the camera lens. Here, we introduce chromagenic filters into the color filter array itself by placing them on top of R, G or B filters and replacing one of the two green filters in the Bayer's pattern with them. This allows obtaining two images of the same scene via demosaicking: a normal RGB image, and a chromagenic image, equivalent of RGB image with a chromagenic filter. The illuminant can then be estimated using chromagenic based illumination estimation algorithms. The method, we named as CFA based chromagenic color constancy (or 4C in short), therefore, does not require two shots and no registration issues involved unlike as in the other chromagenic based color constancy algorithms, making it more practical and useful computational color constancy method in many applications.

Experiments show that the proposed color filter array based chromagenic color constancy method produces comparable results with the chromagenic color constancy without interpolation.

**Keywords:** Computational color constancy, illuminant estimation, color filter array, CFA, chromagenic

## 1. INTRODUCTION

Color constancy is the ability to account for the color of the light source which allows seeing the color of an object more or less the same under different lighting conditions. Human vision is said to be color constant as it has a natural tendency to correct for the effects of the color of the light source.<sup>1-3</sup> This is why, for example, we see white snow white no matter which time of the day or under which illuminant we observe it. Computational color constancy tries to emulate the color constancy 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 human vision's color constancy capability.

Computational color constancy models, in general, comprise of two steps: illuminant estimation and color correction. The illuminant estimation is the primary task in a computational color constancy algorithm. Often the color of the light source is assumed to be spatially uniform across the scene. Based on this assumption, a computational color constancy algorithm estimates the illuminant under which an image has been captured. The effects of the color of the illuminant are then corrected to obtain the desired color constant image. Since the later part is relatively easy, most color constancy algorithms are characterized by the estimation of the illuminant. Many methods have been proposed for the estimation of the illuminant. Some example methods are gray-world,<sup>4</sup> max-RGB,<sup>5</sup> gamut based algorithm,<sup>6</sup> neural networks based,<sup>7</sup> color-by-correlation,<sup>8</sup> Bayesian based<sup>9</sup> and chromagenic color constancy.<sup>10,11</sup> Our main interest here is on the chromagenic based color constancy algorithms: the chromagenic algorithm first proposed by Finlayson et al.,<sup>10</sup> and the bright-chromagenic algorithm proposed by Fredembach and Finlayson.<sup>11</sup> The chromagenic algorithm estimates an illuminant from the two images of a scene, one normal RGB image, and the other taken with a special filter which they named as chromagenic filter, placed in front of the camera lens. The bright-chromagenic algorithm claimed to improve the results further. This algorithm uses only certain brightest pixels only, instead of considering all the pixels on the two images as in the chromagenic algorithm. We discuss both of these chromagenic algorithms in more details in Section 2.

We propose here a new chromagenic based color constancy algorithm which extends the chromagenic color constancy algorithms further by avoiding their shortcomings, and at the same time produces comparable results. Both the chromagenic and the bright-chromagenic algorithms take two pictures from a scene: a normal one and a filtered one. These methods, therefore, have inherent weaknesses: a need for perfectly registered images, occasional large errors in the illuminant estimation and a need for two shots. Even though Fredembach and Finlayson<sup>11</sup> claimed to remedy the large error problem and relax the registration constraint to some extent, the two shot requirement still severely limit its applicability to static scenes only. In order to avoid both registration as well as two shot constraints, we introduce chromagenic filters into the color filter array (CFA) itself. Instead of using two green filters in a Bayer pattern,<sup>12</sup> we introduce a chromagenic filter on top of *R*, *G* or *B* filters in one of the two green filters. This allows obtaining two images of the same scene via demosaicking, a normal RGB image, and a chromagenic image, equivalent to the RGB image with a chromagenic filter. The illuminant can then be estimated based on the algorithm proposed in<sup>10</sup> or.<sup>11</sup> A custom designed chromagenic filter or an appropriate filter selected from a given set of can be used. We call the proposed new color constancy method as **CFA based chromagenic color constancy (4C)**.

We perform experiments with the proposed 4C method using the same Simon Fraser testing protocol followed by Fredembach and Finlayson,<sup>11</sup> and the method has been validated on real images using a set of hyperspectral images. The results show that the proposed method produces comparable results to the ones obtained without interpolation, both with the chromagenic and the bright-chromagenic algorithms.

In section 2 we discuss the chromagenic and the bright-chromagenic color constancy algorithms. We then present the proposed 4C method in section 3. Section 4 presents experiments and results. Discussion on the results will be made in section 5, and finally conclude the paper in section 6.

## 2. CHROMAGENIC AND BRIGHT-CHROMAGENIC COLOR CONSTANCY

The chromagenic color constancy algorithm was proposed by Finlayson et al.<sup>10</sup> The algorithm is based on the first approximation that the image formed by placing a colored filter in front of the camera is the same as changing the illumination impinging on the scene. In other words, the responses of the camera with and without the filter can be considered as the responses of a single surface under two different illuminants. They named a specially chosen filter chromagenic, if that makes the relationship between filtered and unfiltered RGBs depend more strongly on the illumination. Fredembach and Finlayson<sup>11</sup> proposed bright-chromagenic algorithm, claimed to be an improvement to the original chromagenic algorithm. We will discuss illuminant estimation with both the chromagenic and the bright-chromagenic algorithms in the following subsections.

### 2.1 Chromagenic Illuminant Estimation

The two images: an unfiltered and a filtered version of a scene, captured with the chromagenic system, can be considered as the two images of the same scene taken 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.<sup>13,14</sup> Therefore, if  $C$  and  $C^F$  denote the normal (unfiltered) and the filtered camera responses of a scene, then these responses can be related by the following equation:

$$C^F = MC, \quad (1)$$

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

$$M = C^F C^+, \quad (2)$$

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  $l_i(\lambda)$ ,  $i = 1, \dots, m$  are the spectral power distributions (SPD) of the possible known illuminants, and  $r_j(\lambda)$ ,  $i = 1, \dots, n$  is the reflectances of the  $n$  representative real world surfaces. For each illuminant  $i$ , 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  $j^{\text{th}}$  column contains the camera responses of the  $j^{\text{th}}$  surface under the  $i^{\text{th}}$  illuminant. The transformation matrix  $M_i$  for the  $i^{\text{th}}$  illuminant is obtained using Equation 2.

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

$$est = \underset{i}{\operatorname{argmin}}(e_i), i = 1, \dots, m \quad (3)$$

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

$$e_i = \|M_i C - C^F\|, i = 1, \dots, m. \quad (4)$$

## 2.2 Bright-Chromagenic Algorithm

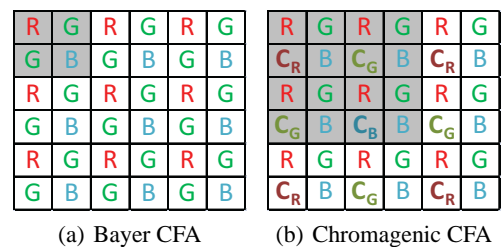
Fredembach and Finlayson<sup>11</sup> proposed the bright-chromagenic algorithm with the aim to improve the two major limitations of the chromagenic algorithm: possible large estimation errors and the need for perfectly registered images. They did extensive analysis on the influences of the illuminants 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 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  $R^2 + G^2 + B^2$  value.

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.

## 3. CFA BASED CHROMAGENIC COLOR CONSTANCY

Even though the bright-chromagenic algorithm tries to address the two inherent weaknesses of the chromagenic algorithm: a need for perfectly registered images, and occasional large errors in the illuminant estimation, it is still severely limited in its use to static scenes only because of the need of the 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. bright pixels may not map well in the filtered and unfiltered images, if we use a filter that varies even a little drastically across the spectrum. We propose here a CFA based chromagenic color constancy (4C) that will solve both the registration as well as the two shot constraints. For this, we introduce the chromagenic filters into the color filter array itself.

The chromagenic filters are placed on top of  $R$ ,  $G$  and  $B$  filters and the resulting filters denoted as  $C_R$ ,  $C_G$  or  $C_B$  respectively are placed for one of the green filters in a Bayer pattern.<sup>12</sup> To compensate for the reduction of a green filter, we use two  $C_G$  filters for one  $C_R$  and one  $C_B$  filters resulting the chromagenic filter pattern of  $C_R C_G C_G C_B$ . This pattern also follows the two important CFA design requirements: the spectral consistency and the spatial uniformity.<sup>15</sup> Figure 1(a) illustrates a Bayer CFA pattern in RGGB and Figure 1(b) illustrates the corresponding CFA pattern after the introduction of the chromagenic filters. Gray blocks in these figures shows the basic block which would be repeated uniformly in the whole image.



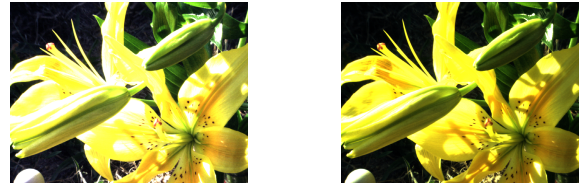
**Figure 1:** Illustration of CFAs with and without the chromagenic filters

The 4C approach allows obtaining two images of the same scene through demosaicking: a normal RGB image, and a chromagenic image, equivalent of RGB image with a chromagenic filter. An unfiltered image is obtained from pixels with  $R$ ,  $G$  and  $B$  filters, using a demosaicking algorithm. Similarly a filtered image is obtained from pixels with  $C_R$ ,  $C_G$  and one  $C_B$  filters. A larger kernel might be required for the demosaicking of a filtered image, as can be seen with bigger gray block in Figure 1(b) and it might reduce some spatial resolution. However, it has been found to be good enough for

our purpose. Many different demosaicking algorithms have been proposed.<sup>16–20</sup> An appropriate algorithm could be used. Figure 2 shows a sample pair of unfiltered and filtered images obtained with a spectral image from Foster et al.,<sup>21</sup> by a Sony DXC-930 camera (Figure 3) and a Kodak Wratten 81B (KW81B) filter (Figure 4) under D65 illuminant, using a bilinear demosaicking algorithm. The process of bilinear interpolation has been well described by Baone and Qi.<sup>22</sup> Having two images: an unfiltered and a filtered, the illuminant can then be estimated using the chromagenic or the bright-chromagenic algorithm discussed in the Section 2. We call the proposed new color constancy method as **CFA based chromagenic color constancy (4C)**.

A chromagenic filter can either be custom designed or selected from a set of filters available. Section 3.2 discusses on the filter selection methods. With the 4C, one might also design sensors for the chromagenic illuminant estimation, but this require consideration of aspects of image quality such as color rendering and image noise and it is not within the scope of this paper.

In order to validate the performance of the proposed 4C system, we have carried out several experiments which are presented in Section 4. We now present the system model of the proposed system in the next sub-section.



(a) Unfiltered

(b) Filtered

**Figure 2:** A sample pair of unfiltered and filtered images produced by the CFA based chromagenic algorithm

### 3.1 System Model

Let  $I(\lambda)$  be the spectral power distribution of the light incident on a surface whose spectral reflectance is  $r(\lambda)$ .  $\lambda$  is the wavelength of the electromagnetic radiation, and here we will be interested in the visible range of the spectrum (from  $\lambda_{\min} = 380\text{nm}$  to  $\lambda_{\max} = 780\text{nm}$ ). Let  $t(\lambda)$  be the spectral transmittance of the chromagenic filter. If  $s_k(\lambda)$  denotes the sensitivities of the camera,  $k = \{R, G, B\}$ , then the unfiltered and the filtered responses of the camera,  $c_k$  and  $c_k^F$  respectively are given by:

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

and

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

A normal image  $I$  is obtained from the unfiltered pixels using a demosaicking algorithm as discussed above. Similarly, a filtered image  $I^F$  is obtained from the filtered pixels also using the same demosaicking algorithm. Let  $C = [c_R, c_G, c_B]^T$  and  $C^F = [c_R^F, c_G^F, c_B^F]^T$  denote the RGB camera responses in vector form of the unfiltered and the filtered images respectively. Here  $x^T$  means the transpose of  $x$ . With these responses which are related by the Equation 1, an illuminant can be estimated with the chromagenic or bright-chromagenic algorithms discussed above in the Section 2.

### 3.2 Selection of the Chromagenic Filter

Choice of the filter and the camera sensors greatly influence the performance of a chromagenic based algorithm. 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.<sup>11</sup> Given a camera, the camera sensitivities are fixed and only controllable parameter will be the filter. The selection of the filter is therefore vital in 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.<sup>10</sup>

One approach of the filter selection would be to select an optimal filter from a given set of filters through exhaustive search. Fredembach and Finlayson<sup>11</sup> selected the Kodak Wratten 81B filter from a set of 53 Kodak Wratten filters.<sup>23</sup> If there is a considerably large number of filters, computational complexity with the exhaustive search could be improved by introducing a secondary criterion which excludes all infeasible filters from costly computations. One such criterion is 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.<sup>24,25</sup>

Alternative approach to the filter selection would be to design a custom filter for a given camera, specifically for the chromagenic processing. Finlayson et al.<sup>26</sup> reported, through simulation, that such a filter produces better results.

#### 4. EXPERIMENTS

Experiments have been carried out with two different sets of data: synthetic and real reflectances, and the estimation results are computed with the chromagenic and 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.

##### 4.1 Experimental Setup

The same setup and the framework as followed in the bright-chromagenic algorithm by Fredembach and Finlayson<sup>11</sup> have been used in the experiments. The Sony DXC-930 camera and the Kodak Wratten 81B filter have been used for the image capture. Figure 3 shows the spectral sensitivities of the camera, and Figure 4 shows the spectral transmittance of the filter.

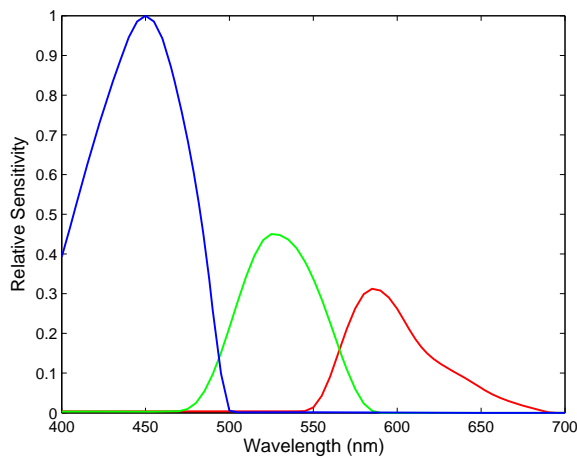


Figure 3: Spectral sensitivities of the Sony DXC-930 camera

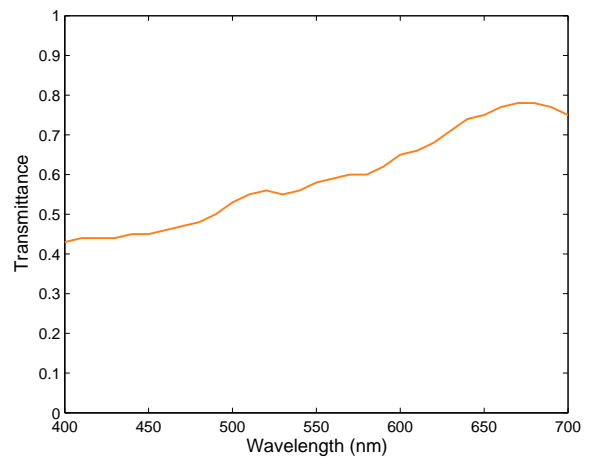


Figure 4: Spectral transmittance of the Kodak Wratten 81B filter

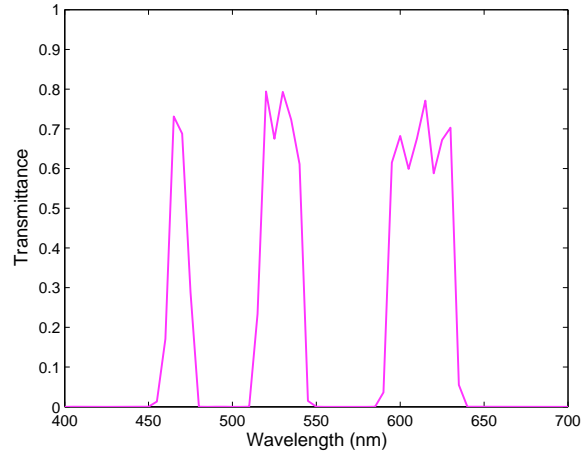
The 1995 Munsell surface reflectances (denoted as  $R$ ) and the illuminants: the 87 measured training illuminants ( $L_{87}$ ) and the 287 test illuminants ( $L_{287}$ ), data from Barnard et al.<sup>27</sup> have been used. The transformation matrices  $M_i$  are computed (using Equation 2) by imaging the whole surface reflectances,  $R$  under the training illuminants  $L_{87}$ , and they will be used to estimate the test illuminants. The test illuminants are estimated with the proposed CFA based chromagenic system using the chromagenic and the bright-chromagenic algorithms. The illuminants are also estimated with the gray world and the max-RGB methods.

The illuminant estimation algorithms are evaluated using error measures. Two most commonly used measures are: the chromaticity error and the angular error. The chromaticity error is the Euclidean distance between the 2-D chromaticity vectors, and the angular error is the angular distance between the 3-D representation of the two vectors.<sup>28</sup> Angular error is intensity independent. Since there is a high degree of correlation between the two measures, one would be sufficient to evaluate the performance, and we have chosen the angular error, the most widely used in the literature.<sup>27-29</sup> If  $C_{l_{act}}$  and  $C_{l_{est}}$  denote the normalized camera responses of a white reflectance under the actual and the estimated illuminants respectively, then the angular error  $e_{ang}$  is calculated as:

$$e_{ang} = \arccos \left( \frac{C_{l_{act}}^T C_{l_{est}}}{\|C_{l_{act}}\| \|C_{l_{est}}\|} \right). \quad (7)$$

The illuminant estimation algorithms are evaluated using the same framework as proposed by Hordley and Finlayson.<sup>28</sup> As recommended by them, the medium angular error has been chosen over the mean root mean square (RMS) error.

We have performed experiments using a different filter also, selected from a set of 265 filters from Omega Optical Inc.<sup>30</sup> through exhaustive search. The filter that gives minimum illuminant estimation error with the filtered and the 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 Section 3.2 to skip the infeasible filters. It has picked the XF3116 as an 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 XF3116 filter.



**Figure 5:** Transmittance of the Omega XF3116 filter

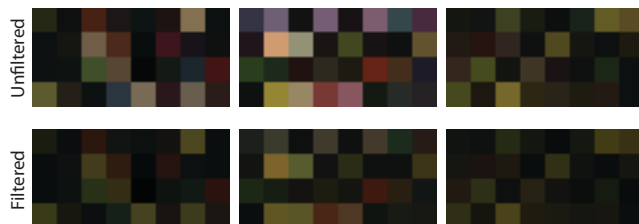
The images generated from the spectral data (reflectance) of an image (synthetic or real) are used in the experiments. All the experiments are carried out with the proposed CFA based chromagenic using bilinear interpolation as well as with the ideal system where we obtain unfiltered and filtered version of the images generated from the spectral data without interpolation to compare the influence of interpolation on the performance of illuminant estimation.

## 4.2 Experiment I: Using Synthetic Reflectances

This experiment has been performed on synthetic images in the same way as did by Fredembach and Finlayson<sup>11</sup> according to the testing protocol proposed by Barnard et al.<sup>27</sup> 1000 unfiltered and the corresponding filtered images containing  $n$  different reflectances are generated for  $n = \{1, 2, 4, 8, 16, 32\}$  randomly picked from  $R$ , by illuminating them with a light, randomly selected from  $L_{287}$ . Figure 6 shows sample pairs of unfiltered and filtered images for  $n = 32$ . The images comprise of  $10 \times 10$  pixel patches corresponding to the randomly picked surface reflectances.

The illuminant of each image is estimated using the proposed CFA based chromagenic using both the chromagenic and the bright-chromagenic algorithms, and also with the gray world and the max-RGB methods. A central pixel from each patch from the demosaicked images are used in the estimation of illuminants. For statistically robust results, the procedure is repeated for each value of  $n$  twenty times, and the average values are taken. In the bright-chromagenic version, the four brightest pixels are used for the images from  $n > 4$  reflectances, while all the pixels are considered for the images from  $n \leq 4$  reflectances.

The experiment has been carried out with both the KW81B and the Omega XF3116 filters. Table 1 shows the median angular errors obtained with the four different illuminant estimation methods, with two different filters, all on the images generated with six different number of reflectances. In this table, Chromag and BChromag denote the chromagenic and the bright-chromagenic algorithms respectively. Since we are using the bi-linear demosaicking, the central pixels of the patches with and without the interpolation would be the same, thus producing the same results.



**Figure 6:** Sample pairs of filtered and unfiltered synthetic images with 32 reflectances under random illuminants from  $L_{287}$

**Table 1:** Median angular errors for the 1000 images generated with 6 different numbers of reflectances

# Refl.	Gray	Max	KW 81B		Omega XF3116	
	World	RGB	BChrom	Chrom	BChrom	Chrom
1	12.30	12.30	6.81	6.81	5.57	5.57
2	9.73	10.65	5.84	5.84	4.39	4.39
4	7.53	7.61	4.94	4.94	3.49	3.49
8	5.41	5.43	3.94	3.88	2.97	2.80
16	4.74	3.75	3.24	2.82	2.77	2.32
32	4.61	2.83	3.44	2.80	2.33	2.06
Avg.	<b>7.39</b>	<b>7.09</b>	<b>4.70</b>	<b>4.52</b>	<b>3.59</b>	<b>3.44</b>



### 4.3 Experiment II: Using Real Reflectances

In this experiment, we use the real images generated from the hyperspectral images of the eight natural scenes from Nascimento et al.<sup>31</sup> The RGB images generated from these hyperspectral images using the Sony DXC-930 camera under the D65 illuminant are shown in Figure 7. Here we obtain the unfiltered and the filtered versions of each image with every test illuminant in  $L_{287}$ . Again, the bilinear interpolation has been used for the demosaicking. The test illuminant is estimated in each case with both the algorithms. Top 3% of the brightest non-saturated pixels are used with the bright-chromagenic. The median angular errors produced by both the chromagenic and the bright-chromagenic algorithms along with the gray world and the max-RGB methods in the case of CFA based chromagenic and the chromagenic without interpolation are given in Table 2.



**Figure 7:** The RGB images obtained from hyperspectral images of the 8 natural scenes from Nascimento et al.<sup>31</sup>

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

Scene #	Chromagenic without interpolation						CFA based chromagenic					
	Gray		Max		Omega XF3116		Gray		Max		Omega XF3116	
	World	RGB	BChrom	Chrom	BChrom	Chrom	World	RGB	BChrom	Chrom	BChrom	Chrom
1	14.40	9.75	4.90	3.92	3.11	3.73	14.36	9.94	7.81	4.62	2.68	3.81
2	19.48	26.83	20.10	8.15	20.11	5.35	19.43	24.39	14.18	9.77	20.11	5.75
3	19.92	6.34	15.06	7.22	18.45	5.23	19.89	7.47	15.52	8.00	18.45	5.35
4	9.87	6.73	7.53	7.58	5.85	6.99	9.84	8.98	12.54	7.66	3.78	7.14
5	11.69	20.77	15.62	3.39	15.18	2.45	11.79	2.70	7.67	3.55	2.56	2.44
6	5.24	9.49	7.19	7.06	5.26	3.92	5.26	9.81	10.57	7.95	11.20	3.94
7	0.01	2.74	5.79	3.74	5.79	5.91	0.01	2.63	9.38	5.79	5.56	5.89
8	5.41	6.50	4.04	3.08	4.10	2.39	5.44	6.71	9.51	6.88	4.04	2.44
<b>Avg.</b>	<b>10.75</b>	<b>11.15</b>	<b>10.03</b>	<b>5.52</b>	<b>9.73</b>	<b>4.50</b>	<b>10.75</b>	<b>9.08</b>	<b>10.90</b>	<b>6.78</b>	<b>8.55</b>	<b>4.60</b>

## 5. DISCUSSION ON THE RESULTS

With the first experiment on the synthetic images, as mentioned above, we don't see the difference in the results from the proposed 4C method and the ideal case of without interpolation. However, we can see the behavior of the four different estimation methods including the two chromagenic methods. We can also see the performance difference with the two different filters used: the KW81B and the Omega XF3116. The results show that the chromagenic based algorithms outperforms (lower median angular errors) both the gray world and the max-RGB methods on the average. Fredembach and Finlayson<sup>11</sup> have also shown that the chromagenic methods performs significantly better than the other well known methods like the gray world, the max-RGB, the color-by-correlation, the gamut based and the neural networks based. However, the results from this experiment do not show any significant difference in the performance of the chromagenic and the bright-chromagenic algorithms.

Results from the second experiment with the real images also show the chromagenic based algorithms performing better than the gray world and the max-RGB methods. The chromagenic algorithm performs surprisingly better than the bright-chromagenic algorithm, with both the filters. However the advantage with the bright-chromagenic algorithm would be the significantly lower computational cost, as we use only a small percentage of the pixel (typically 1-3%) compared to all the pixels used in the chromagenic algorithm. Here we have to note that the bright-chromagenic algorithm has been proposed with the major aim of minimizing the effect (to some extent) of the registration problem. With our proposed 4C approach, there is no issue of registration at all. Furthermore, we can also see that the chromagenic algorithm shows less wild variation in the estimation errors, whereas the other three methods including the bright-chromagenic algorithm show wider variation in the estimation errors with the eight test images.

Results from both the experiments show that the optimal filter selected from a set of 265 filters, the Omega XF3116 performs better than the KW81B. This shows that simply selecting a filter from a set of available filters could give a reasonably good estimation results from both the chromagenic and the bright-chromagenic algorithms. We have used the 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.<sup>30</sup> The performance can be improved further by selecting an optimal filter from a reasonably larger set of filters, possibly from more suppliers.

Furthermore, the proposed 4C method produces comparable results to the ones without interpolation, with both the chromagenic and the bright-chromagenic algorithms, and with both the filters. It is expected to get some higher estimation errors due to the interpolation, however we found that it is not so significantly large. It has to be noted here again that the approach eliminates registration issue by providing one shot solution, and thus making it more practical and useful.

## 6. CONCLUSION

We have proposed here a one shot solution to the chromagenic color constancy by introducing chromagenic filters into the color filter arrays of the sensor. This solves the biggest problem of registration and the two shots requirement in the state-of-the-art chromagenic based color constancy algorithms, and at the same time produces equally good results. The proposed system makes the chromagenic color constancy applicable to the images/videos of the scenes in motion. Therefore, the system will be more useful in wider applications. There could be an issue of loss of some information due to the reduction in the number of green filters in the Bayer's pattern. Analyzing this could be an interesting future work.

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