Edge-based and Efficient Chromaticity Spatio-Spectral Models for Color Constancy

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***Abstract*— Fast and accurate estimation of the transformation imposed by the illuminant to the colors of an image taken under that illuminant is of crucial importance in real-time computational color constancy applications. To this end, we present an edge based and an efficient chromaticity spatio-spectral model which are modified versions of the spatio-spectral method introduced by Chakrabarti et al [1]. As compared with the conventional color constancy methods, the spatio-spectral model improves the accuracy of estimation at the cost of increasing the execution time and storage dramatically. This increase makes the spatio-spectral model impractical and inappropriate for real-time applications. Our proposed methods aim at reducing the computational burden and required storage for the spatio-spectral modeling while retaining its accuracy of estimation. Evaluation of the performance of the proposed methods on a synthetic color image database and also the "Color Checker" database [2] are presented.**

Keywords-color constancy; spatio-spectral model;

I. INTRODUCTION

A great feature of our visual system is that we can perceive the color of an object rather the same way under different color lights; in other words, human visual system is color constant. The bulk of the research has been conducted to investigate color constancy in human beings to figure out how our visual system is color constant, and how to incorporate the mechanism of human color constancy into machine vision. Color constancy is a branch of the computer vision field which deals with effects of the color of an illuminant on the appearance of the objects seen under that illuminant. Color constancy is of vital importance in many machine vision applications such as: object recognition, object tracking, surveillance, image retrieval, and image enhancement; among them, the first three are examples of the real-time applications of the color constancy. Moreover, photography and film industry are two other real-time application of color constancy where the rendered images and videos should be consistent with the human color perception. The aim of color constancy is to compensate for the skews brought about by the color of the illuminant on the color of the objects in the images.

A. *Literature Review*

A group of color constancy methods tries to recover the whole spectrum of the illuminant or the spectral reflectance function of surfaces in the image. The pioneering work of Maloney and Wandel [3] falls within this category. They proposed a low-dimensional linear model for recovering surface spectral reflectance assuming that every ambient light can be reconstructed well enough by a few fixed known basis lights and every surface reflectance function can be reconstructed well enough by a few fixed known basis reflectance functions. However, this method makes a very restrictive assumption and also is computationally complex.

Estimating the color of the illuminant in terms of the camera response is another approach to recover the original colors of the image which is also the focus of the present research. In this way, the number of unknowns in the color constancy problem ~~reduces~~ [4]. Several methods have been proposed to estimate the color of the illuminant; each of them has made some assumptions to solve the color constancy problem. We can mention a group of low-level color constancy approaches which are simple and fast, among them the gray-world, max-RGB and shade of gray are well-known. The gray-world method assumes that the average reflectance of a scene is achromatic [5]. It is a naïve assumption which may not hold for every image. Max-RGB is another approach which assumes that the color of the illuminant in an image can be obtained by taking the maximum response of the different color channels [6]. The shade of gray method takes the L^n Minkowski norm of the image as the color of the illuminant [7]. All of these methods are conceptually simple and fast, however, many other algorithms are proposed to achieve better performance. The 3D Gamut mapping method developed by Forsyth [8] assumes that there is a limited set of colors that can be viewed under a canonical illuminant and then, finds all diagonal matrices which transform every single point of the image gamut into the canonical gamut space. The intersection of the transformations gives us all the feasible mappings which map the image gamut to the canonical gamut. Among these feasible solutions, Forsyth suggested the intuitive way of choosing the solution with the maximum variance. The 3D gamut mapping works well with the images met the predefined assumptions; however, the assumptions do not hold for the real images where we face with specular surfaces and non-uniform illumination. This method is also computationally intensive. Color in perspective, which is also known as 2D gamut mapping, proposed by Finlayson [9]; and is the extension of 3D gamut mapping. 2D gamut mapping tries to ~~encounter~~ ~~with~~ specular surfaces and non-uniform illuminations. Considering the fact that these unwanted effects just can change the color length and not its orientation provides Finlayson an incentive to get rid of the intensity information in the color space. To this end, colors are projected to the two dimensional chromaticity spaces. Due to eliminating one dimension, this algorithm takes advantage of less computational complexity, but it still requires ~~great~~ computations and it cannot deal with real images ~~as~~ well. The color by correlation method proposed by Finlayson et al. [4] introduces a great contribution to the field of color constancy. As with the color in perspective, this algorithm also works in the chromaticity space. Two main strengths of the method are: first, the method is able to unify the large group of prevailing methods in the color constancy (prior to the time of publishing the article); and second, the proposed method is practical for real images besides synthetic images. The main weaknesses of this algorithm are that it requires the training data and the camera sensors sensitivity curves.

The edge-based color constancy method (i.e. gray-edge) proposed by Weijer et al. [10] falls within another group of color constancy methods trying to take into account the high-level visual information in the estimation process. The gray-edge method is one of the pioneering works which incorporated image derivatives into the color constancy method. They hypothesized that "the average of the reflectance differences in a scene is achromatic." Another method which lies within this category is the spatio-spectral model proposed by Chakrabarty et al. [1]. The spatio-spectral modeling is an attempt towards incorporating the spatial dependencies among pixels by filtering out the images rather than treating them individually. The spatio-spectral model shows higher estimation accuracy compared with well-known simple methods like gray-world and gray-edge methods. However, in terms of the execution time and the amount of required storage which are important factors in the real-time applications, spatio-spectral model shows unsatisfactory results.

To address these problems, the edge-based and efficient chromaticity spatio-spectral models are presented. The proposed methods in this work reduce the redundant information in an image before start modeling in two different ways. The edge-based method takes into account the edges and their neighborhood for spatio-spectral modeling and the efficient chromaticity approach considers the pixels bringing new chromaticity information. The remainder of this paper organized as follows. In the section 2, our proposed methods are introduced after a brief overview on the spatio-spectral modeling. Section 3 shows and discusses the results of the experiments have been conducted over synthesized and real image databases. Section four concludes the paper.

II. METHOD

Before introducing our method, we should briefly describe spatio-spectral model which is the basis for our contributions in this paper. Then later in this section we will present the edge-based and efficient chromaticity spatio-spectral model.

A. *Spatio-Spectral Modeling Overview*

In the following subsection, we summarize ~~this~~ model and keep the notations the same as they proposed in the original paper.

At first, a spatial decorrelating transform, which is a set of spatial subband filters, is applied to the input image. Among different alternatives of spatial filters, second-derivative Gaussian filters at different scales are chosen ~~because of their popularity in the image filtering application.~~ Using K different subband filters $\{f_k\}_{k=1}^{K}$, each colored image $x(n)$ is decomposed to K images $\{x_k(n)\}_{k=1}^{K}$. Secondly, the spatio-spectral model assumes that the joint probability distribution of each subband component $x_k(n)$ corresponding to the canonical color image is modeled as the radial exponential distribution

$$p(x_k) = \frac{1}{\pi\sqrt{\det(\Sigma_k)}}\exp(-2\sqrt{x_k{}^T\Sigma_k{}^{-1}x_k}) \tag{1}$$

where Σ_k is the 3 by 3 covariance matrix. These subband components are deemed independent from each other.

We should emphasize that this model is just valid for the canonical image and not for an arbitrary image. The parameters of this model i.e. the covariance matrices corresponding to subbands have to be obtained in the training phase. It is worth mentioning that the required storage for the filtered image is K times greater than that of the image.

1) *Training Phase*

In the training phase, given a set of T canonical images $\{x_t\}_{t=1}^{T}$ the covariance matrices Σ_k corresponding to subband models are obtained using the maximum log-likelihood method as follows.

$$\begin{aligned}\Sigma_k &= \arg\max \sum_t \log p(x_{k,t} \mid \Sigma)\\ &= \arg\max\,(-\frac{T}{2}\log\det(\Sigma) - \sum_t 2\sqrt{x_{k,t}^T\Sigma^{-1}x_{k,t}})\end{aligned} \tag{2}$$

However, this problem does not have a closed form solution. Chakrabarti et al. proposed an iterative method to solve this optimization problem: Σ_k is initialized as an identity matrix and then updated using the current estimate Σ_k^* at each iteration, as follows.

$$\Sigma_k = \frac{4}{T}\sum_t \frac{x_{k,t}x_{k,t}^T}{\sqrt{x_{k,t}^T \Sigma_k^{*-1} x_{k,t}}} \tag{3}$$

2) Estimation Phase

It has been shown that the transformation imposed by the illuminant on the perceived color of surfaces in the image can be modeled by a linear mapping with a sufficient accuracy in many cases [1]. This hypothesis suggests that an image taken under an arbitrary illuminant can be transformed to the corresponding canonical image using a 3 by 3 linear mapping of the following form

$$x(n) = M^{-1} y(n) \tag{4}$$

where *x(n)* and *y(n)* are canonical image and given image under an arbitrary lighting respectively. Assuming that three color channels are independent from each other we can consider *M* as a diagonal matrix. Therefore, our objective is to estimate three diagonal entries of the matrix *M* based on the obtained probability distribution function of the decomposed canonical images. Given the matrix *M*, we can calculate the likelihood $p(y_k \mid M)$

$$p(y_k \mid M) = \frac{\exp(-2\sqrt{y_k^T (M\Sigma_k M)^{-1} y_k})}{\pi\sqrt{\det(M\Sigma_k M)}} \tag{5}$$

The *M* can be obtained using the maximum likelihood method; however, this problem also does not have a closed-form solution and has to be solved using iterative methods.

$$\hat{M}_{ML} = \arg\max_M \sum\nolimits_{k,n} \log p(y_k(n) \mid M) \tag{6}$$

To this end, *M* is initialized as an identity matrix and then it is updated based on the current estimate M^*. If we define $m = [m_1 \quad m_2 \quad m_3]$ and $w = [w_1 \quad w_2 \quad w_3]$ as the diagonal elements of *M* and M^{-1}, it has been shown that m_i can be obtained as

$$m_i = \frac{1}{2}\left(\sum_{j\neq i}\frac{A_{ji}^*}{m_j} + \sqrt{(\sum_{j\neq i}\frac{A_{ji}^*}{m_j})^2 + 4A_{ii}^*}\right) \tag{7}$$

A^* is a 3 by 3 symmetric matrix given by

$$A^* = \frac{4}{N}\sum_k\left(\sum_n \frac{y_k(n)y_k^T(n)}{y_k^T(n)\left(M^*\Sigma_k M^*\right)^{-1} y_k^T(n)}\right)\circ \Sigma_k^{-1} \tag{8}$$

where $N = \sum_{k,n} 1$, and "$\circ$" represents the entry-wise product of two matrices. For further details on the method, we refer you to the original article. Up to this point, we described the maximum likelihood solution of the color constancy problem which implicitly assumes that illuminants are equally likely. Another contribution of Chakrabarti et al. is to incorporate the illuminant prior to increase the accuracy of the estimation. They deem the illuminant prior distribution as follows

$$p(M) = \left(\frac{2}{\pi}\right)^{1.5}\frac{\det(Q)^{-0.5}}{m_1^2 m_2^2 m_3^2}\exp\left(-\frac{1}{2}w^T Q^{-1} w\right) \tag{9}$$

where *Q* is a 3 by 3 positive definite matrix. Using the illuminant prior, the illuminant estimate can be obtained by

$$\begin{aligned}\hat{M}_{ML} = \arg\max_M &\left[\sum\nolimits_{k,n} \log p(y_k(n) \mid M)\right] \\ &+\alpha \log p(M)\end{aligned} \tag{10}$$

where the coefficient α determines the relative weight of the prior information; in other words, it determines ~~that~~ how much we trust the prior information. Updating the iterative solution based on the new objective function, the illuminant estimate can be calculated the same way except replacing A^* with A_p^*. A_p^* is given by

$$A_p^* = \frac{NA^* + \alpha Q}{N + 2\alpha} \tag{11}$$

The parameters α and *Q* should be learned during the training phase and for obtaining them we use the same procedure as they have used in their codes. In the next section, we will come up with two solutions to reduce the required storage and speeding up the execution of the algorithm.

B. Edge-based spatio-spectral method

In the first attempt to speed up the spatio-spectral model and reducing the required storage, we introduce the edge-based spatio-spectral modeling which is based on the fact that most of information in an image concentrated around edges. In other words, uniform regions in an image do not bring the spatio-spectral model with new information, and simply we can neglect them in the process of filtering. Therefore, the spatio-spectral modeling can be confined to the regions around edges. After finding edges, they should be dilated to incorporate the neighboring pixels in the modeling. A question may arise is that "How many pixels around edges should be considered?" The size of dilation can be determined adaptively based on the scale of the second order Gaussian filter. We assume that 6σ pixels around edges contain the required information. The edge-based spatio-spectral model can be summarized as follows:

1- Edges of a given image is obtained using "canny" or "sobel" filter
2- The edges are dilated based on the scale of second order Gaussian filter to incorporate the neighboring pixels of edges
3- The spatio-spectral modeling is confined to the mask obtained from the previous step

To visualize the first and second steps, Figure 1. shows a case in point trying to build masks for each scale of the second-derivative Gaussian filter over which the spatio-spectral modeling will be done.

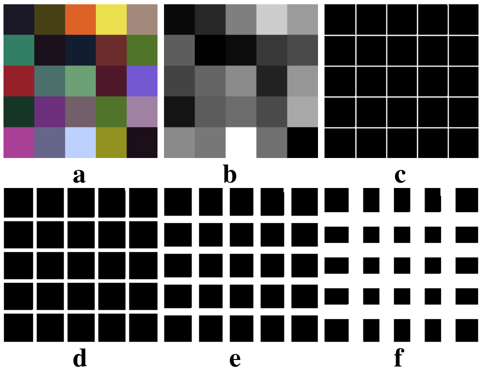

Figure 1. Visualizing step 1 and step 2 of the edge-based spatio-spectral modeling, a) input color image b) corresponding gray-scale image c) edges of the gray-scale image d, e, and f) dilated edges for σ=1,2, and 4 respectively.

In the next section, we introduce another way of reducing redundant information in an image based on finding chromaticities of the image.

C. *Efficient Chromaticity spatio-spectral modeling*

As we mentioned before, the spatio-spectral model deals with all the pixels in an image within which exist great amount of redundant information. In every natural image, we frequently see that an image is covered with the big regions of uniform colors (such as blue sky) which are several pixels with redundant information. Dealing with vast number of uniform patches in an image brings about huge amount of computations in the estimation phase and consequently, the algorithm loses its value in the real-time applications, and also it may decrease the accuracy of estimation. In the remainder of this section, we propose another solution to resolve the mentioned problems. To remove the redundancies between image patches, we propose a simple algorithm which constitute the overall chromaticity region for each image and evaluate the pixels in terms of their information based on the new chromaticites they add to the overall chromaticity region. To transform the camera RGB vector $(p_1\ p_2\ p_3)^T$ at every pixel to the chromaticity values, we use the following equations proposed by Finlayson et al. [4].

$$c_1 = (\frac{p_1}{p_2})^{\frac{1}{3}},\ c_2 = (\frac{p_3}{p_2})^{\frac{1}{3}} \tag{12}$$

It is assumed that all the possible colors in images can be confined to the chromaticity space, C, defined by $[c_1^{\min}, c_1^{\max}]\times[c_2^{\min}, c_2^{\max}]$ which is uniformly partitioned into $N\times N$ chromaticity regions (see Fig. 2).

$$c_1 = (\frac{p_1}{p_2})^{\frac{1}{3}},\ c_2 = (\frac{p_3}{p_2})^{\frac{1}{3}} \tag{13}$$

$$C = \{c = (x,y) \mid c_1^{\min} \le x \le c_1^{\max}, c_2^{\min} \le y \le c_2^{\max}$$
$$= \{c \mid c \in [c_1^{\min}, c_1^{\max}]\times[c_2^{\min}, c_2^{\max}]\} \tag{14}$$

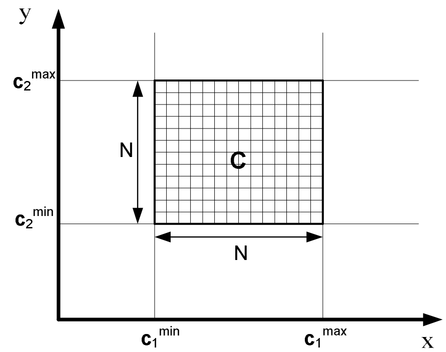

Figure 2. Discretized chromaticity space

So, N^2 different colors can be identified in images. ~~The~~ bigger N makes it possible to describe the overall chromaticity space finer. The value of N depends on the application. To constitute the overall chromaticity region for each image, our algorithm takes the pixels one by one from the first in the upper left corner to the last in the lower right corner of the image, and then the corresponding chromaticity values to that pixel is computed. Before any pixel comes, the overall chromaticity region is empty; and as the pixels come in gradually this region grows based on the chromaticities of the pixels. If the chromaticity of a new pixel already exists in the overall chromaticity region, then we can treat that pixel as a redundant pixel and get rid of it. Pseudo-code for removing redundant information among patches is given as follows.

1- Compute the chromaticity of jth pixel.

2- If the pixel does not introduce any new chromaticity to the overall chromaticity region then, get rid of that patch, $j \rightarrow j+1$, and go to 1.

3- Update the overall chromaticity region based on the new chromaticity of the jth pixel. Save the pixel as an effective pixel for using in the spatio-spectral modeling.

4- Dilate the effective pixels based on the scale factor of the second-order Gaussian filter to incorporate their neighboring pixels in the spatio-spectral modeling.

Analogous to the the edge-based method, the size of dilation is dynamic and should be set as a constant multiplication of the filter scale factor where this constant can be determined based on the size of the image. Similar to the edge-based reduction method, let us visualize the procedure described above for the same image used in the

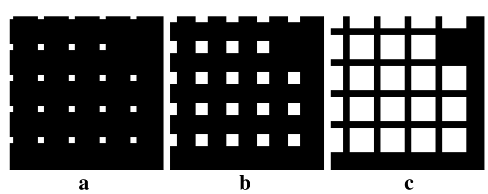

Figure 3. Computing masks for incorporating effective pixels and their neighborhood in the spatio-spectral modeling, a, b, and c) dilated effective pixels in the image by a factor of 10 for σ=1,2, and 4 respectively.

Fig. 1. As you may notice, one of the patches (in the second row and last column) in the image is ~~removes~~ because it is of the same color (and chromaticity) as another one at the intersection of the fourth row and the forth column.

III. EXPERIMENTS AND RESULTS

This section discusses experiments have been done to evaluate the performance of the proposed edge-based and efficient chromaticity spatio-spectral modeling. The experiments are done over both synthesized and real images. At first, we show the results of the algorithm against synthesized images, and then we will move to the "Color Checker" database containing real images collected by Gehler et al. [2]. The original spatio-spectral model is implemented by Chakrabarti et al. [1] and their codes are available. We have used these codes and ~~modify~~ them based on the proposed ideas. In the implementation of the original spatio-spectral method, the scales of the second derivative Gaussian filter are set as $\sigma=\{1, 2, \text{and } 4\}$. The performance of their algorithm is reported in three cases: first, the maximum likelihood method without any prior information is used; second, the ML estimate is obtained with general prior information over all images; and third, the ML estimate obtained when two distinct priors are assumed for indoor and outdoor images. In the same way, we will report our results for these three cases when the indoor and outdoor images are categorized (e.g. the "Color Checker" database) and neglect the third case for our experiments over the synthesized database. The angle between the estimated color and the actual color of the illuminant, referred to as angular error, is used as a measure of performance. The execution time of the spatio-spectral method and our proposed methods can be split into the pre-computation time and estimation time. The former process filters out the image to obtain the subband images and the latter uses the result of pre-computation process and estimates the illuminant color. The addition of the two execution times indicates the overall execution time of the algorithm. It is worth mentioning that the training time is not demonstrated here because in most applications, the training process is done off-line. We conduct our experiments over 4 scenarios defined as follows.

Scenario1: The performance of the original spatio-spectral method is examined.

Scenario 2: The edge-based spatio-spectral model is put under test. The edge dilation size is set equal to 6σ. Edges are computed using the *Sobel filter*. The threshold of detection is adjusted equal to a constant multiplication of the median of the gray-scale image. This constant is chosen as 0.2 for all images.

Scenario 3: The experiments are conducted over efficient chromaticity spatio-spectral method. In this case, the chromaticity space is confined to the $[0.1,2.5]\times[0.2,2.5]$ region and discretized using a 500×500 grid. The dilation size is selected equal to 15σ for all images.

A. *Synthetic Image Database*

In this section, a synthesized image database is constructed in a similar way proposed in [4] with slight modifications to assess the proposed method. A set of 1296 Munsell chips [11] is used as the surface reflectance database, and a set of 87 lights including variety of indoor and outdoor illuminants collected by ~~Branard~~ et al. [12] comprises our illuminant database. The images are synthesized by choosing a set of surfaces from the surface reflectance database randomly and selecting an illuminant from the illuminant database. For each image with a given number of surfaces, a set of surface reflectance functions and also a single illuminant are drawn randomly to render a 256×256 image. The spectral sensitivity curves of the Sony DXC-930 three chip CCD camera measured by Barnard et al. [12] is used for the rendering purpose. The selected surfaces are distributed randomly in a checkerboard pattern. Additionally, knowing the color of the illuminant for each rendered image, a ground-truth for the color of the illuminant is created. All the experiments have been conducted over a set of synthesized images with {4, 9, 16, 25, 36, 49, 64} surfaces. Some sample images of this database are shown in the Figure 4.

The experiments over synthesized database are run using the Intel Core™ i7 - 720QM processor (1.60GHz) with Intel Turbo Boost Technology up to (2.80GHz) and 6GB of system memory. We invoke the two well-known color constancy methods: gray-world and grayedge, which are implemented by Weijer et al. [10], to compare their performance with that of the spatio-spectral and the algorithms proposed in this paper. The codes of these reference methods are available on: http://lear.inrialpes.fr /people/vandeweijer/research. In the codes, the Minkowski norm, sigma of Gaussian filter, and the differential order for the gray edge method are set to 5, 2, and 1 respectively. The accuracy and execution time of each algorithm together with that of scenarios are tabulated in Table 1.

The results indicate that the conventional color constancy methods are fast and in this regard they are suitable for real-time applications; however, in terms of accuracy, they do not provide accurate estimations. Bear in mind that both the

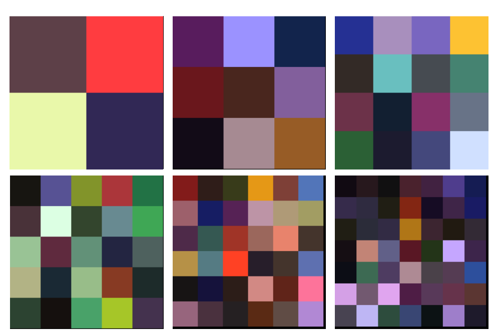

Figure 4. Sample cases of the synthesized image database with 4, 9, 16, 25, 36 and 49 patches

Table 2. Angular Errors for different methods on the synthesized database

	All Images			Execution Time (s)
	Mean	Median	Worst 25%	
Gray World	5.6°	4.5°	11.5°	0.013
Gray Edge	6.4°	4.9°	13.9°	0.069
Scenario 1 (ML)	3.6°	2.7°	8.2°	0.682
Scenario 1 (GP)	3.5°	2.7°	7.8°	0.689
Scenario 2 (ML)	4.6°	3.1°	10.7°	0.343
Scenario 2 (GP)	4.0°	3.0°	8.7°	0.351
Scenario 3 (ML)	4.2°	2.9°	9.7°	0.345
Scenario 3 (GP)	**3.8°**	**2.9°**	**8.0°**	**0.358**

accuracy and time are important in practice. At the other side, the spatio-spectral method is more accurate; however, the execution time is much more than simple color constancy methods. In contrast to ~~the both mentioned groups~~, our proposed methods give rise to an ~~acceptable~~ accuracy which is very close to that of original spatio-spectral method, and doubles the speed of the first scenario. We should add that the accuracy of our methods get closer and closer to that of the spatio-spectral as the number of surfaces in a synthesized image increases (see Figs. 5 and 6). Since in the real images the number of surface patches is more than just 10 or 20 surfaces, we can expect that all these three methods exhibit similar accuracies over real images. This hypothesis will be investigated in the next section.

B. Real Images

The “Color Checker” database is used to evaluate the proposed methods in this paper and compare the results with the mentioned conventional color constancy methods and also the spatio-spectral approach. This database consists of 568 images separated into the indoor (246 images) and outdoor (322 images) categories. The color of true illuminant is given for every image in the database which is used as a ground-truth for the training and also calculating the estimation error of the algorithms. Each image in this database includes the picture of a Macbeth color checker which is excluded for the training and the test. The “Color Checker” dataset is available in several versions; we used the one prepared by Shi and Funt [14]. In this version, images are not gamma corrected; and auto-white balance is not applied to the images. The experiments have been done using the Intel(R) Xeon(R)-E5645, 2.40GHz CPU with 48GB system memory. Table 2 shows the results of different methods.

The results demonstrate that the proposed methods are efficient in terms of keeping the precision of spatio-spectral method and speeding up this algorithm. Scenarios 2 and 3 increase the accuracy of estimation; one explanation is that

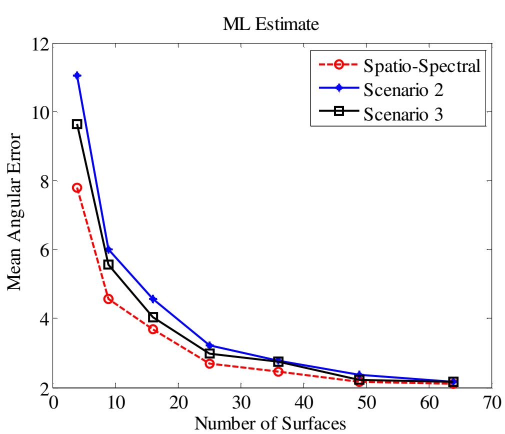

Figure 5. Mean angular error of the ML estimate as a function of the number of surfaces is shown for the spatio-spectral method and our proposed methods.

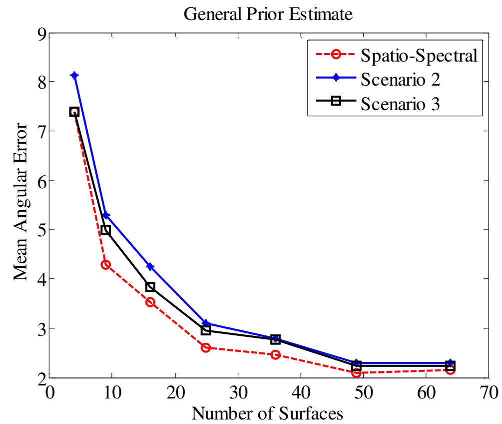

Figure 6. Mean angular error of the GP estimate as a function of the number of surfaces is shown for the spatio-spectral method and our proposed methods.

Table 1. Angular Errors for different methods on the “Color Checker” database

	All Images			Execution Time (s)
	Mean	Median	Worst 25%	
Gray World	6.1°	6.5°	8.0°	0.673
Gray Edge	3.9°	2.8°	8.5°	2.525
Scenario 1 (ML)	3.7°	3.0°	7.6°	23.034
Scenario 1 (GP)	3.6°	3.0°	7.4°	23.038
Scenario 1 (CWP)	3.1°	2.3°	6.5°	23.039
Scenario 2 (ML)	3.5°	2.7°	7.3°	12.835
Scenario 2 (GP)	3.4°	2.7°	7.1°	12.840
Scenario 2 (CWP)	3.0°	2.2°	6.3°	12.840
Scenario 3 (ML)	3.7°	2.9°	7.8°	8.930
Scenario 3 (GP)	3.6°	2.9°	7.6°	8.935
Scenario 3 (CWP)	**3.0°**	**2.2°**	**6.4°**	**8.935**

removing the redundancies existing in an image leads to a better modeling, because redundant information can play a similar role as the noise signal for the model which degrades the modeling precision. The execution time of the spatio-spectral model is ~~dramatically~~ high and this ~~quantity~~ is ~~improved~~ approximately by ~~the~~ factor of 2 and 3 in the edge-based and efficient chromaticity spatio-spectral methods; however, it requires still more improvement to be considered as a choice for real-time applications. In this regard, we apply downsizing to the images for further speeding up the algorithm and investigate its effects on the precision of estimation. Bear in mind that the size of the images in the “Color Checker” database varies between 6 to 10 MB. The huge file size overfeeds the spatio-spectral model, ~~rises~~ the required storage, and slows down the algorithm. In the Tables 3 and 4, the results of scenarios 2 and 3 are shown when the images are downsized by a factor of 0.5 and 0.25 before being fed to the algorithms.

Take a brief look at the results of Table 3 indicates that downsizing the images not only speeds up the algorithm significantly but also improves the accuracy of estimation in some cases. The reason is that downsizing the huge size files can reduce the redundant information such as false positive edges which do not bring out any new information for the spatio-spectral model.

For the sake of convenience, the average angular error and the execution time of the scenarios over different experiments are plotted in the Figure 7. This figure illustrate that: first, using the proposed methods in this paper we can double or triple the speed of the spatio-spectral model; second, the edge-based method and the efficient chromaticity spatio-spectral method keeps the accuracy of the spatio-spectral method relatively constant and in some cases, improves the precision; third, downsizing of the huge size image files will not reduce the performance of the proposed methods and even make them totally appropriate for real-time applications.

Table 3. Angular Errors of scenarios 2 and 3 on the “Color Checker”

	All Images			Execution Time (s)
	Mean	Median	Worst 25%	
Downsized database by the factor of 0.5				
Scenario 2 (ML)	3.5°	2.7°	7.5°	3.900
Scenario 2 (GP)	3.4°	2.7°	7.3°	3.905
Scenario 2 (CWP)	2.9°	2.2°	6.3°	3.905
Scenario 3 (ML)	3.7°	2.9°	7.8°	2.874
Scenario 3 (GP)	3.6°	2.8°	7.6°	2.879
Scenario 3 (CWP)	**2.9°**	**2.1°**	**6.4°**	**2.879**
Downsized database by the factor of 0.25				
Scenario 2 (ML)	3.6°	2.7°	7.7°	1.124
Scenario 2 (GP)	3.5°	2.6°	7.4°	1.129
Scenario 2 (CWP)	2.9°	2.1°	6.4°	1.129
Scenario 3 (ML)	3.6°	2.7°	7.8°	1.059
Scenario 3 (GP)	3.5°	2.7°	7.5°	1.063
Scenario 3 (CWP)	**2.9°**	**2.1°**	**6.4°**	**1.064**

IV. CONCLUSION

In this paper, we contributed the *edge-based* and *efficient chromaticity* spatio-spectral modeling to improve the spatio-spectral method presented in [1] to fit the requirements of the real-time applications. The proposed methods in this work try to get rid of redundant information in an image before start modeling in two different ways. The edge-based method takes into account the edges and their neighborhood for spatio-spectral modeling and the efficient chromaticity approach considers the pixels bringing new chromaticity information. The evaluation of the proposed methods on the synthesized and real images shows promising results. As we expected, both approaches are effective in speeding up the spatio-spectral method while keeping the high accuracy of estimation. Comparing with the conventional computational color constancy methods, main strengths of the modified spatio-spectral color constancy are: first, take into account dependencies among neighboring pixels; second, improves the accuracy of estimation; however, the major weakness of this algorithm is that it requires the training phase. So we cannot expect this method to provide a good estimation for images with a new illuminant which is too different from those illuminants used in the training phase.

Finally, we should point out some challenges that can be

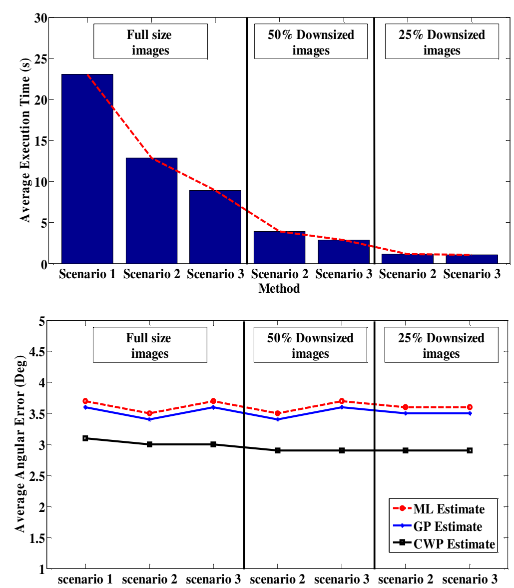

Figure 7. The results of Tables 2-4.are ~~summed up~~. The upper and lower plot shows the variation of the execution time and the mean angular error over different scenarios respectively.

the subject of ~~our~~ future work. First, the category-wise prior assumes that the indoor and outdoor labels are provided every image; however, it is not always the case in the practice. Second, we should find a mechanized way to determine that to which degree the image can be downsized without losing the accuracy.

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