Combinational color constancy method using dynamic weights

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Abstract

Illuminant estimation is the primary step to solve the colour constancy problem. Already, various unitary algorithms were proposed to estimate illuminant chromaticity. Since the existing methods are all based on specific spatial and spectral characteristics of images, there is no unique algorithm which can perform well on images with different settings and scenes. Therefore, this paper proposes an illuminant estimation framework which combines the best performing unitary methods using dynamic weight. The proposed method uses edge and colour features to generate the dynamic weight. Experimental results on real-world data set clearly demonstrate the effectiveness of the proposed method.

Introduction

The image captured using digital camera is affected by the surface reflectance, camera sensitivity and illuminant spectral properties. Therefore the same scene captured under the different illumination spectrum results in different image colour.To sove this issue, the computational colour constancy aims to estimate the illuminant chromaticity from the captured image and correct the image [1]. Already researchers have proposed many illuminant estimation methods and it can be classified into two types: 1) statistical-based method and 2) learning-based methods [2]. The first type of methods make use of some assumption based on the statistical properties of the scene illuminant and the second type of illuminant estimation method has a learning phase and use this learning phase information to estimate the illuminant.

The White Patch algorithm [3], Grey World [4], Shades of Grey [5], and Grey Edge [6] are some of the well-known statistic based methods. All these statistic based methods mentioned above are derived from the Retinex theory by Land and MaCann [7]. The learning based methods include algorithm that uses gamut boundaries [8, 9], machine learning algorithms [10, 11, 12, 13, 14, 15] or probabilistic models [16, 17] for illuminant estimation. Since the illuminant estimation is an underconstrained problem, all the above mentioned unitary method is based on either statistical assumptions or a trained model. Therefore, it is hard to choose an algorithm which can perform well on all image scenes. To overcome this, Hordley [18] suggested that illuminant estimation can be improved by the combination of different algorithms. Later, researchers started focusing more on combinational methods and published different strategies to combine unitary methods[19, 20, 21, 22].

In [23], Li et al. had surveyed the existing combinational methods and classified into two categories - guided combination (GC) and direct combination (DC) method. GC method selects the best colour constancy algorithm for a specific image depending on image characteristics and estimates the illuminant using the selected algorithm. Natural image statistic (NIS)[19], image classification (IC)[20], indoor-outdoor classification [24], 3D Scene Geometry [25], High level visual Information (HVI) [21] and Hierarchical Classification Model (HCM) [26] are some of the guided combination methods. According to Li et al. [23], there are some potential difficulties which limits the performance of GC methods. The first is the difficulty in choosing an image feature which can differentiate and correlate the images to the best unitary method (i.e., conventional statistic and learning based method). Second, an increase in the number of unitary methods reduces the classification accuracy. Since the real world images consist of wide range of image settings, it is difficult to formulate a GC method with limited number of unitary methods. Unlike GC methods, DC methods either use the weight learned from a supervised training to combine the algorithm or directly combines the algorithm. Since the weight of DC methods were optimised for a specific set of images, they are incapable of processing a wide range of images. This issue motivated us to propose a framework that combines different statistical method using dynamic weight learned from image features. As the weight used in this method changes with the image characteristics, the proposed framework can address the problems in the combinational method that uses static weight. The concept of this algorithm is inspired by a recent work which uses corrected edge and colour moments of an image for the illuminant estimation [27, 28]. The detail explanation of the proposed method given in the following section. The experiments and comparisons are presented in section III. Finally, Section IV concludes the paper.

Proposed Method

The main premise of this method is that statistical methods have the capability of estimating illuminant of some set of images and It varies with the assumptions used in the method. The work presented in [27] shows its importance. Previously, many researchers proposed different combinational methods which make use of the potential of the statistical method. However, most of them are based on static weight. Since the weights of these methods were optimised for a specific set of images, they are incapable of processing a wide range of images. The proposed method address this issue by introducing a dynamic weight, which changes according to the image characteristics.

To demonstrate the effectiveness of the proposed framework, five well-known statistical methods are chosen. The Grey world, White Patch, Shades of Grey, 1st and 2nd Order Grey Edge method are the selected algorithms. The proposed system combines the illuminant estimated using these selected algorithms using dynamic weight W_{dyn} that derive from the image scene. Figure 1 shows the overall flow of the proposed combinational method. The detailed explanation on the dynamic weight and illuminant estimation are given in following subsections.

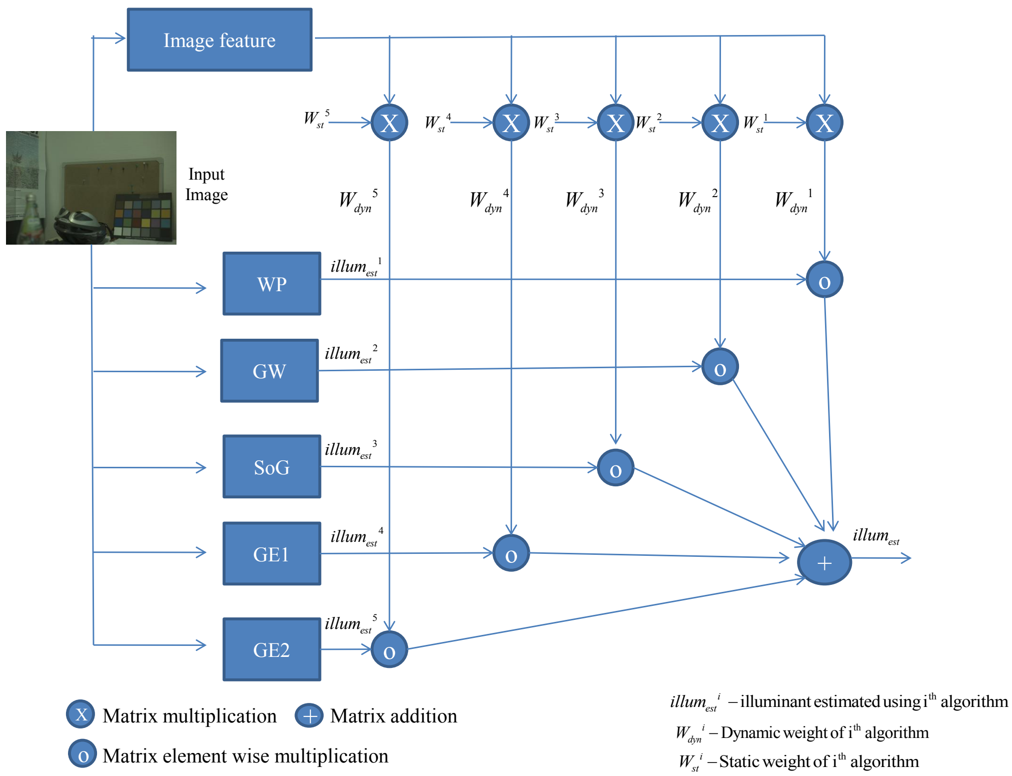

Figure 1: Block diagram of the proposed framework

Weighted illuminant estimation

As shown in Figure 1, the proposed framework estimate illuminant $illum_{est}$ by the weighted sum of the illuminant estimated using the selected statistical algorithm. Here, the weights are dynamic and change according to the image feature. Equation 1 shows the illuminant estimation using this proposed framework. In this equation, $\circ$ represents the element wise multiplication of matrix. ${W_{dyn}}^i$ denotes the dynamic weight of i^{th} method. M represents the number of statistical method used, $illum_{est}$ and ${illum_{est}}^i$ denotes the illuminant estimated using this proposed framework and illuminant estimated using i^{th} method, respectively. ${W_{dyn}}^i$, $illum_{est}$ and ${illum_{est}}^i$ are of size $3x1$.

$$illum_{est} = \sum_{i=1}^{M} {illum_{est}}^i \circ {W_{dyn}}^i \tag{1}$$

The dynamic weight ${W_{dyn}}^i$ used in this framework is designed in such a way that ${W_{dyn}}^i$ changes with the image scene. The dynamic weight for the i^{th} statistical method can be estimated by the multiplication of the image feature E and a static weight ${W_{st}}^i$. The equation 2 shows the details of the ${W_{dyn}}^i$ estimation. The size of E and ${W_{st}}^i$ is depended on the image feature. If the size of E is 1xN, the size of ${W_{st}}^i$ is Nx3. Here, each column of ${W_{st}}^i$ corresponds to the static weight for each colour channel. Therefore the matrix multiplication of E and ${W_{st}}^i$ (i.e. ${W_{dyn}}^i$) has a size of $1x3$. In this framework, the colour and edge moment feature presented in [27] used as the image feature E. In [27], author introduced cross moments and moments with different degrees. In our study, we found that selection of higher degree and cross moments image feature will not improve the performance much. Therefore, in this framework, second order edge moment is selected as the image feature E.

$${W_{dyn}}^i = E * {W_{st}}^i \tag{2}$$

The main purpose of the ${W_{st}}^i$ is to control the effect of the image feature in generating the dynamic weight for each statistical method. In addition, this static weight value is different for each colour channel. Therefore, ${W_{st}}^i$ overall controls the impact of image feature E and it directly influences the performance of the proposed framework. To find the optimum value of ${W_{st}}^i$, this problem can be framed as an optimisation problem to reduce the angular error of the estimated illuminant $illum_{est}$. Angular error e_{ang} is the statistical measure to find the closeness of estimated illuminant $illum_{est}$ with the ground truth $illum_{gd}$. The mathematical representation of e_{ang} is shown in equation 3.

$$e_{ang}(illum_{gd}, illum_{est}) = \cos^{-1}\left(\frac{illum_{gd}.illum_{est}}{\left\|illum_{gd}\right\| \left\|illum_{est}\right\|}\right) \tag{3}$$

Therefore the optimum value of ${W_{st}}^i$ is estimated by the minimization of mean angular error for the given data set. The cost function to find the optimum value of ${W_{st}}^i$ that framed using equation 1 and 2 is shown in the equation 4. To minimise this cost function, Particle swarm optimisation (PSO) is used. The main reason to choose PSO for finding the optimal values of ${W_{st}}^i$ is its ability in solving high dimensional optimisation problems and its random nature that reduces the chance of finding a local minimum. The following subsection discusses more on PSO and estimation of ${W_{st}}^i$.

$$\text{costfunction} = \frac{1}{N}\sum_{j=1}^{N} e_{ang}({illum_{gd}}^j, {illum_{est}}^j) \tag{4}$$

N denotes the total number of images,$illum_{gd}$ represents the ground truth of j^{th} image and $illum_{est}$represents the illuminant estimated using the weighted sum of illuminant estimated using M statistical methods.

PSO and static weight estimation

Particle swarm optimization (PSO) is a swarm intelligence-based evolutionary optimization technique developed by Ebherhat and Kennedy [29, 30]and inspired by the swarm behavior of bird flocking and fish schooling. The simplicity, high convergence speed, and easy implementation of PSO have made it a successful optimization tool for many real-world applications [31, 32, 33, 34]. The PSO algorithm consists of a swarm of particles, where each particle k is represented by a position vector $\mathrm{p}_k = \{p_{k1}, p_{k2}, ..., p_{kD}\}$in D-dimentional space and a velocity vector $\mathrm{v}_k = \{v_{k1}, v_{k2}, ..., v_{kD}\}$. Each particle represents a potential solution and flies through the multidimensional solution space to find the optimum solution. The position and velocity vector of each particle k is first randomly initialized within the range, and then updated with each iteration as follows:

$$\mathrm{v_k}(t+1) = \omega \mathrm{v_k}(t) + c_1 r_1[\mathrm{p}_{best_k} - \mathrm{p}_k] + c_2 r_2[\mathrm{g}_{best} - \mathrm{p}_k] \tag{5}$$

$$\mathrm{p}_k(t+1) = \mathrm{p}_k(t+1) + \mathrm{v_k}(t+1) \tag{6}$$

where p_{best_k} is the best position attained by k^{th} particle, g_{best} is the global best position, t is the iteration number, c_1 and c_2 are the two positive acceleration coefficients that adjust the movement of particles towards local and global best position and r_1 and r_2 are the uniformly distributed random values. The inertial weight ω linearly varies within a range of $[\omega_{min}, \omega_{max}]$ as follow.

$$\omega = \omega_{max} - \left(\frac{(\omega_{max} - \omega_{min})t}{t_{max}}\right) \tag{7}$$

where t is the iteration number and t_{max} is the maximum number of iterations. As shown in equations (5) and (6) particle accelerate towards p_{best_k} and g_{best} location with a random weighed acceleration. Thus, each particle moves around the solution space in a random manner looking for the best solution. The quality of each particle is then evaluated with the help of a cost or objective function.

Thus, for each statistic method ${W_{st}}^i$ is estimated by minimising the cost function given in (4) using PSO. To achieve that, each particle is considered as the M number of static weight ${W_{st}}^i$ of size Nx3 (N is the size of image feature E). The quality of each particle is estimated using the cost function. PSO finds the optimal value of ${W_{st}}^i$ that minimises the cost function. In this algorithm, Initially PSO particle, i.e., ${W_{st}}^i$ is assigned with some random values. Later these values are optimised using velocity equation mentioned in 6. The overall flow of the proposed PSO based ${W_{st}}^i$t estimation is illustrated below.

Step. 1 Start

Step. 2 Initialize the particle i.e., ${W_{st}}^i\big|_{i=1:M}$ with n random position/values.

Step. 3 Generate the dynamic weight using the random generated ${W_{st}}^i\big|_{i=1:M}$ and image feature (Color/Edge Moment) for each image and estimate cost function.

Step. 4 Initialize $\mathrm{p}_{best_k}\big|_{k=1:n}$ with the cost function corresponds to k^{th} particle

Step. 5 Assign the ${W_{st}}^i$ or particle with minimum cost function value to g_{best}

Step. 6 Loop until t reaches the maximum iteration t_{max} (for t = 1 to t_{max})

- **Step. 6.1** Loop until all particle exhaust (k = 1to n)
  - **Step. 6.1.1** Position and velocity of k^{th} particle are updated with the present p_{best_k} and g_{best} (using equation 5 and 6)
  - **Step. 6.1.2** Generate the dynamic weight for each image and estimate cost function.
  - **Step. 6.1.3** If the cost function evaluated using k^{th} particle is less than the cost function evaluated using p_{best_k} then $\mathrm{p}_{best_k} = \mathrm{p}_k$
  - **Step. 6.1.4** Go to step 6.1
- **Step. 6.2** Find the $\mathrm{p}_{best_k}\big|_{i=1:n}$ that can generate image with less cost function value.
- **Step. 6.3** Go to step 6

Step. 7 Output g_{best} the optimum static weight ${W_{st}}^i\big|_{i=1:M}$.

Step. 8 Stop

Experimental results

In this section the proposed method is compared to the state-of-the-art methods on SFU grey ball dataset [40] and colour checker dataset[41][42]. The SFU grey ball dataset consists of 11,346 nonlinear images and the colour checker dataset contains 568 high dynamic images that include both indoor and outdoor scenes. The colour checker board and grey ball in the datasets were masked during the experiments for an unbiased comparison of the proposed method with the existing colour constancy methods. For each data set, we give a performance statistic of the proposed method and other state-of-the-art methods. This paper used angular error (AE) as the statistical measure to evaluate the methods as it is most widely used.

In this experiment, PSO parameters for the estimation of static weight ${W_{st}}^i$ were configured as same as the conventional PSO. The inertia weight upper limit and lower limit of the PSO set at 0.9 and 0.4, respectively, acceleration parameter c1 and c2

Table 1: Performance of various color constancy algorithm on color checker dataset

	Method	Median	Mean	Best 25%	Worst 25%
Statistical-based method	Grey World [4]	6.28	6.36	2.33	10.58
	White Patch [3]	5.68	7.55	1.45	16.12
	Shades of grey [5]	4.01	4.93	1.14	10.20
	1st order grey edge [6]	4.52	5.33	1.86	10.03
	2nd order grey edge [6]	4.44	5.13	2.11	9.26
	Bright and Dark color PCA [35]	2.14	3.52	0.50	8.74
Learning Based Method	Pixel based Gamut [36]	2.33	4.20	0.50	10.72
	Edge based Gamut [36]	5.04	6.52	1.90	13.58
	Intersection based Gamut [36]	2.39	4.20	0.51	10.70
	SVR Regression [37]	-	3.23	-	-
	Bayesian [41]	3.46	4.82	1.26	10.49
	Exemplar based [38]	2.27	2.89	0.82	5.97
	19-Edge Corrected-moment [27]	2.04	2.86	0.70	6.84
	Illuminant estimation using simple features [14]	1.65	2.42	0.38	5.87
Combinational Method	Natural Image Statistics [19]	3.13	4.19	1.00	9.22
	CART-based Combination [39]	2.91	3.9	1.02	8.27
	Multi-objective optimization based color constancy [31]	3	4.3	-	-
	Proposed Method	2.51	3.14	0.84	6.54

Table 2: Performance of various color constancy algorithm on grey ball dataset

	Method	Median	Mean	Best 25%	Worst 25%
Statistical-based method	Grey World [4]	6.97	7.87	2.16	15.25
	White Patch [3]	5.31	6.81	1.18	14.72
	Shades of grey [5]	5.29	6.11	1.76	11.84
	1st order grey edge [6]	4.89	5.74	1.7	11.31
	2nd order grey edge [6]	5.08	5.96	1.72	11.73
Learning based method	Pixel based Gamut [36]	5.82	7.07	1.67	14.75
	Edge based Gamut [36]	5.82	6.82	1.92	13.49
	Intersection based Gamut [36]	5.88	6.90	1.92	13.65
	SVR Regression [37]	-	1.32	-	-
	Exemplar based [38]	3.42	4.38	1.01	9.36
Combinational method	Natural Image Statistics statistics [19]	3.93	5.19	1.21	11.15
	Multi-objective optimization based color constancy [31]	3.3	5.2	-	-
	Proposed Method	4.03	5.00	1.13	10.51

maintained at 2.1. The particle swarm size was set at 1000. The lower and upper limit for the particles was set at 0.001 and 010, respectively. Plus, the maximum magnitude of velocity was set at 0.5. For real validation of the proposed framework, the data set images are divided into three groups and performed leave-one-out cross-validation on all datasets.

Performance Comparison on dataset

Table 1 shows the performance statistics of various methods on Gehler-Shi colour checker dataset. The proposed method surpassed most of the illuminant estimation methods (Table 1) in terms of mean angular error and worst 25% mean angular error. Note that the exemplar based, 19-Edge Corrected moment, illuminant estimation using simple features performed better compared to the proposed approach. However, the proposed method has surpassed all the statistic and combinational method mentioned in Table 1.

Nextly, we have compared the performance of the proposed method on the grey ball dataset. The proposed approach has outperformed all the statistical-based and combinational algorithm in terms of mean angular error as shown in Table 2. More specifically, the proposed approach has improved its mean and median angular error approximately by 12% and 18% respectively, compared to the best statistical-based method, i.e., the grey edge algorithm. Except exemplar based method, the proposed method surpassed all other learning based method. Even though the proposed methods performance is not up to the exemplar based method, it only requires less computation power. The main highlight of the proposed method was the reduction of the mean 'worst 25 %' angular error on colour checker and grey ball dataset images.

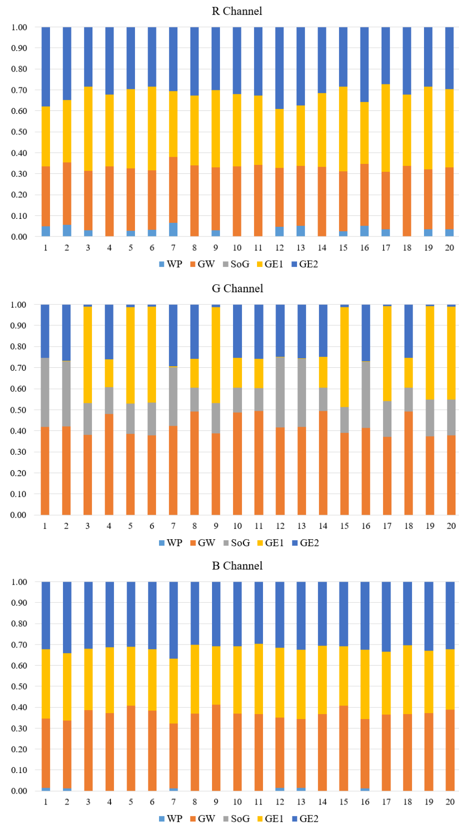

Figure 2: Influence of dynamic weight on different statistical algorithm

Influence of dynamic weight on different statistical algorithm

To analyse the impact of dynamic weight on different statistical algorithm, we have selected 10 colour checker data set images in which the proposed framework works well and 10 images in which the proposed framework fails. Later, we have plotted statistical algorithms dynamic weights for all the selected 20 images as a bar graph. Figure 2 shows this bar graph and in this dynamic weights are plotted separately for each colour channel. Here, Shades of Grey (SoG) has no influence on R and B channel, whereas the Grey World (GW) algorithm has a noticeable influence in all the channels. 1st and 2nd Order Grey Edge algorithm has a great influence in R and B channel, and SoG and GW dominant in G channel.

Conclusion

This paper proposed an illuminant estimation framework that based on a statement that no algorithm is bad or good at estimating illuminant for all set of images. Therefore, proposed method combines the illuminant estimated by various statistic method using dynamic weight. This dynamic weight changes according to the image characteristics. Experiments showed that the proposed approach has competitive performance. In future, we plan to extend our idea to formulate a framework that dynamically selects both algorithm and weight to combine the selected algorithm.

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