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# IMPROVED COLOR CONSTANCY ALGORITHMS USING FUZZY TECHNIQUE

**Parastoo Fathi [a*], Mohsen Ebrahimi Moghadam [a]**

[a] *Electrical and Computer Engineering Department, Shahid Beheshti University, IRAN.*

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**ABSTRACT**

Color constancy is the ability to recognize the color of objects independent of the light source luminance. Color processing and especially color constancy performs an important role in computer vision and image processing applications such as image retrieval, image classification, color object recognition, and object tracking. Color constancy is usually understood as the task of finding descriptors which are invariant to illumination changes in surfaces of a scene while correcting colors in an image is considered as a different phase. This paper proposes a new combinational method based on fuzzy method and clustering to estimate the chromaticity of the light source as the major step of color constancy. In this algorithm, after fuzzification different features of the image by using a clustering algorithm estimates the light source illuminant. To verify the proposed method, four well-known algorithms were selected based on the best algorithm by the proposed approach. In selecting these methods, it was tried to choose the ones which had better performance in comparison to other methods. It is shown in this article that the proposed approach performs better than other proposed methods for color constancy most of the time.



## 1. INTRODUCTION

One of the most important capabilities of the human visual system is to determine the color of the object, independent of light source illumination. This capability is so-called “color constancy” and it’s memorable, because, human eyes’ receptors measure only the light reflected from objects and this reflected light changes by color image variation, is applying the color constancy on them. This capability has particular importance in the various areas of machine vision as well as in the field of digital imaging.

Computational color constancy uses computational models for color constancy. In this process, the color of the light source of the images estimated first and then by the use of obtained estimates, input images are rectified in such a way which represent that same input image as it seems was taken

*Corresponding author (Parastoo Fathi) E-mail: fathi.parastu@yahoo.com, 

under the white light. Over the past few decades, a variety of computational methods have been used to estimate the color of the light source. A brief description of these methods will be expressed in the next section.

This work explains the proposed approach and its structure and shows experimental results. This study also makes a comparison with other color constancy algorithms.

## 2. RELATED WORKS

Numerous methods and algorithms have been proposed in order to solve the issues related to the color constancy, that the set of these methods could be discussed and reviewed in two general categories. The first category includes consistent algorithms based on mathematical calculations and uses the properties of the low level of the image in order to estimate the color of the light source and they are usually considered as old algorithms. The second category includes learning-based methods and combined algorithms that are either the outcomes of combining other methods or selecting the best method of color constancy among the several existing methods for the existing image and they are usually newer algorithms.

### 2.1 THE OLD ALGORITHM

These methods are generally older than the other methods for color constancy and in order to estimate the color of the light source, mathematical calculations, and properties of the low level of the image are typically used for color constancy algorithms, and so-called ‘white patch algorithm’ was introduced. The primary assumption of white patch method is that if a white spot exists on the scene; this spot reflects the maximum possible light in each of the red, green and blue bands which is actually the same color of the light source [7]. Likewise, one of the simplest methods of color constancy is the MAX RGB method. This algorithm works based on the white patch algorithm with the difference which in that maximum value of each channel instead of using the white spot within the image, considered as the color of the light source parameter in that channel. ‘Gray world’ method is one of the well-known methods and is consistently based on this assumption that the average reflectance of all three channels of RGB space color is equal. In other words, the average reflectance of objects in the image is colorless (gray) [1]. Shades of gray method, is a large family of color constancy methods which white patch and gray world methods are parts of this family. For this reason, between these algorithms similar positive and negative features can be seen [9]. In the reference [10] a method called gray-edge has been introduced for color constancy algorithms. Which in that, to acquire the color of the light source, the information obtained through various derivatives of the image is used. The basic idea used in this method is also consistent based on the gray-edge assumption.

### 2.2 NEWER ALGORITHMS

This class of color constancy algorithms uses a training phase to acquire an estimate of the color of the light source. In this methods for the training phase, generally, use a set of images that the color of their light sources is specified. In the training phase of this methods, features extracted from images of the training set, and algorithm learn the relationship between these features and light of the training images source. After training, to estimate the color of new images light, algorithm generalizes the relationship between image features and source light. Neural network-based algorithms are one of these algorithms in references [4] for network training, used all color histogram in RGB space as images feature. Thus, a very large number of neurons form in the input layer of the network that highly complicated the training of such networks. In [5], another neural algorithm exists. This algorithm considered a discrete network for each one of the red, blue and green channels. And as the input of every three networks, using the four estimations corresponding to the color of the light source vector, that acquired by the use of four algorithms: gray world, gray edge, white patch and shades of gray. Gamut mapping-based algorithms are one of well-known combinational algorithms. The primary assumption used in this method is consistent on light gamut [7]. One of these methods is GAMUT-Constrained illuminant estimation method. In this method, the assumption is that the colors existent in the real world are bounded and also considered a number of light vectors as the probable lights. Therefore, by observing very much levels, obtained the light area for each one of these lights. In [7] an algorithm is presented for gamut mapping called ‘generalized Gamut mapping’. That is it uses the derivation of the image instead of direct use of existent pixels in the image. This algorithm has greater accuracy compared to the other gamut mapping algorithms, because, in this method using the derivation of the image in addition to pixel values of the image.

In the combinational method based on fuzzy measure and fuzzy integral that presented in reference [8], used fuzzy concepts for combining outputs of several color constancy methods. In this method, an estimate of color of the light source achieved with assigning appropriate fuzzy measures to the desired methods and any multiple combinations of them and then applying fuzzy integral on them. Another group of color constancy algorithms which are known as ‘committee-based color constancy’; combined three achieved outputs of three algorithms: white patch, gray world, and neural networks, for estimating the color of the light source. Different methods have been used for combining outputs of these three algorithms which simplest of them is averaging from algorithms outputs. In [10] has used a weighted average instead of averaging with equal weights, and by using a set of training images, has achieved optimal weights of each algorithm. Also in [10] for combining the outputs of algorithms, used a neural network with 6 neurons in the input layer, 6 neurons in the hidden layer and 2 neurons in the output layer. The algorithm from [26], entitling color constancy with indoor and outdoor classification, divides the images into two categories: indoor images (Pictures taken indoors) and outdoor images (Pictures taken outdoors), and trains the decision tree. Then by use of the trained tree, the input image is determined to be indoor or outdoor. Also the best algorithm for each of the categories (indoor and outdoor image categories) and also the best algorithm for the entire set of training images, characterized in the training phase [11]. Color constancy algorithm selection and combination (CAS) is one of the best color constancy methods. The main purpose of this algorithm is to discover the best algorithm between the five predetermined algorithms. In the training phase of this method, some features extracted from any set of training images, afterward, classify the images by using a decision tree [12].

Color constancy algorithm with using of the Natural Image Statistics (NIS) and Scene Semantics is also one of the most famous color constancy methods. In the training phase of this method, first, between the several predetermined color constancy methods, the best color constancy method is determined for each one of the training set images. In the next stage, features vector of that image extracted and by using this information, and a Mixture of Gaussian (MOG) will be trained. Theoretically by using this method we can combine an unlimited number of color constancy algorithms together. But practically, whatever number of methods increases more, the complexity of the classify method will increase the same amount, this lead to an increase in classification error. Totally, can be expressed in this way that with increasing the number of color constancy algorithms, the performance of these methods decreases [13]. In [14] this method used for combining 17 color constancy methods and a relatively good result is achieved.

## 3. DIAGONAL MODEL

The focus of this paper is on estimating the color of the light source. However, in many cases, the color of the light source is of less importance than the appearance of the input image under a reference light (called canonical light source). Therefore, the aim of most of the color constancy methods is to transform all colors of the input image, taken under an unknown light source, to colors as they appear under this canonical light source. This transformation can be considered to be an instantiation of chromatic adaption. Chromatic adaptation is often modeled using a linear transformation, which in turn can be simplified to a diagonal transformation when certain conditions are met. So the diagonal model that is used is given by:

$$f^c = D^{u,c} f^u \tag{1}$$

Where $f^u$ is the image taken under an unknown light source, $f^t$ is the same image transformed, so it appears if it was taken under the canonical illuminant, and $D^{u,c}$ is a diagonal matrix which maps colors that are taken under an unknown light source u to their corresponding colors under the canonical illuminant c:

$$\begin{pmatrix} R^c \\ G^c \\ B^c \end{pmatrix} = \begin{pmatrix} \alpha & 0 & 0 \\ 0 & \beta & 0 \\ 0 & 0 & \gamma \end{pmatrix} \begin{pmatrix} R^u \\ G^u \\ B^u \end{pmatrix} \tag{2}$$

Even though this model is merely an approximation of illuminant change and might not accurately be able to model photometric changes due to disturbing effects like highlights and interreflections, it is widely accepted as color correction model and it underpins many color constancy algorithms. The diagonal mapping is used throughout this paper to create output image after correction by a color constancy algorithm, where a perfect white light, is used as a canonical illuminant.

## 4. THE PROPOSED ALGORITHM

In this paper propose an approach based on a fuzzy system that improves the performance of present color constancy algorithms. An approach used in this paper to select the best color constancy algorithm is using the fuzzy clustering-based algorithms. First based on a set of input image features, a fuzzy histogram of images extracted; and then this histogram, given to a clustering algorithm as an input to obtain the best algorithm for the desired image. participating algorithms in the proposed method are the gray world, white patch, first order gray edge, and second order gray edge, along with the fifth algorithm as (DN) or 'Do Nothing' (for each image, gives the same estimate to light's color).

## 4.1 FUZZY TEXTURE SEGMENTATION

In the first stage, a one- level wavelet is performed that by using a normalized image, provides the possibility to obtain text and shape information from the image. In the second stage by using the intensity information, color model transport from RGB space to YIQ space. In the third stage, the structural features values module is extracted.

To achieve texture information of the image used three features which demonstrate energy in wavelet high-frequency bands. These elements are the square root of second-order components of wavelet coefficients in high-frequency bands. In achieving these features, will be used Haar transform on Y (Shine caused by color) component of YIQ color space. Decision making about the size of the image blocks depends on the image dimensions and will be described in the next section. For example, suppose that the block size is 4 × 4. After applying one- level wavelet, each block will be decomposed into four frequency bands. Each block also includes 2×2 coefficients. Available coefficients in HL band has been named as: $C_{K,L}$,$C_{K,L+1}$ , $C_{K+1,L}$ and $C_{K+1,L+1}$. One of these features calculates as Equation (3), [62].

$$f = \left(\frac{1}{4}\sum_{i=0}^{1}\sum_{j=0}^{1} C^2_{k+i,l+j}\right)^{\frac{1}{2}} \qquad (3)$$

Other two features also calculate similar to this. With the exception that one of them is in LH and another is in HH frequency band. Using them is due to the reflection of these features from image texture specifications. Using the components of the wavelet coefficients in different frequency bands helps in better detection the texture. These texture features also, establish a good compromise between computational complexity and effectiveness [15].

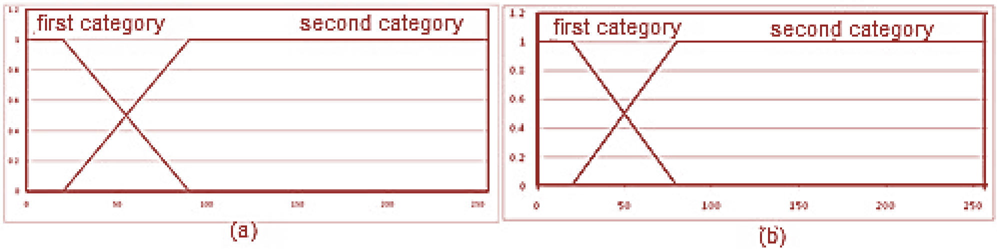


**Figure 1**: (a) membership function fLH and fHL , (b) membership function fHH.

In the second stage, $F_{LH}$ , $F_{HL}$, $F_{HH}$ components are normalized and used in the related fuzzy system as input to generate a histogram with eight bit as output. Next stage is a description of membership functions which determines membership measure of different features contents into the various classes. Figure (1-a) shows the membership function for $f_{LH}$, $f_{HL}$ and also Figure (1-b) shows the membership function used for $f_{HH}$. In both membership functions used two fuzzy regions. After Fuzzification of the input and output features, the second stage is to modeling rules expression and fuzzy inference. Each one of these rules determines the combinational effects of used features on system performance from the desired perspective. Used rules in this fuzzy system include eight fuzzy rules existent in [16].

## 4.2 FUZZY CLASSIFICATION OF EDGES

In this system, the gray level difference of Xi calculates as

$$x_i = Gray_{Dif(Q,i)} = Gray(i) - Gray(Q) \text{and } i \in \{1,2,\dots,8\} \quad (4).$$

where Gray(Q) is the grey level of the central pixel Q, and Gray(i) is the grey level of the neighbor pixel i.

$$POS(x) = \begin{cases} 0 & x \leq a \\ \frac{x-a}{c-a} & a < x < c \\ 1 & x \geq c \end{cases} \quad (5)$$

$$NEG(x) = \begin{cases} 1 & x \leq -c \\ \frac{x+a}{a-c} & -c < x < -a \\ 0 & x \geq -a \end{cases} \quad (6)$$

Here POS is bright membership function and NEG is dark membership function. Two parameters a and c are determined automatically. In [17], a variable amount will be equal to zero. Because the negative gray level difference cannot be effective on bright membership function as well as positive gray level difference cannot be effective on dark membership function. To determine the value of c also acts according to references [17, 18]. These references the value of c will be determined by maximum fuzzy entropy. Based on the information contained in reference [18] the larger the entropy, also has more information of the system .also will use of 16 fuzzy rules contained in [23] as this system fuzzy rules.

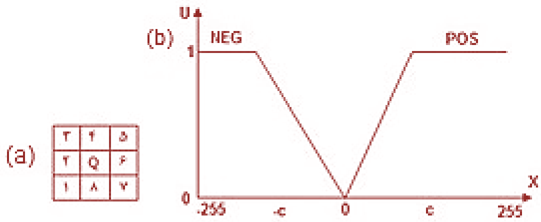


**Figure 2**: (a) window $3 \times 3$ (b) Grey level difference membership functions.

Output fuzzy vector of this system has 16 members, and each one of these members is representative of one of 16 rules. In fact, for each of the rules R1-R16 there is an output variable which gathers homonymous RI's. This fuzzy vector after normalizing will be placed the sixteen bin of the ultimate histogram.

## 4.3 FUZZY COLOR SEGMENTATION

In [19] proposed a fuzzy histogram which received three HSV color channel as the fuzzy system inputs and gives 10 bins to the system as output . each of the bins is representative of one of following colors: (0)black, (1)gray, (2)white, (3)red, (4)orange, (5)yellow, (6)green, (7) cyan, (8) blue, (9) rouged. These colors have been named based on previously obtained results in [20].

According to Figure (3-a), H channel divide into eight fuzzy areas, and they determine as follows : (0) red to orange, (1) orange, (2) yellow, (3) green, (4) cyan, (5) blue, (6) rouged, (7) blue to red.

According to Figure (3-b), S channel also divides into two fuzzy areas. This channel determines the shade of colors related to white. The first area will have a mean in combination with fuzzy areas of V channel. In this way that if a color is bright enough, will place in one the categories which histogram H specified, otherwise, classified into a shade of white or gray colors.

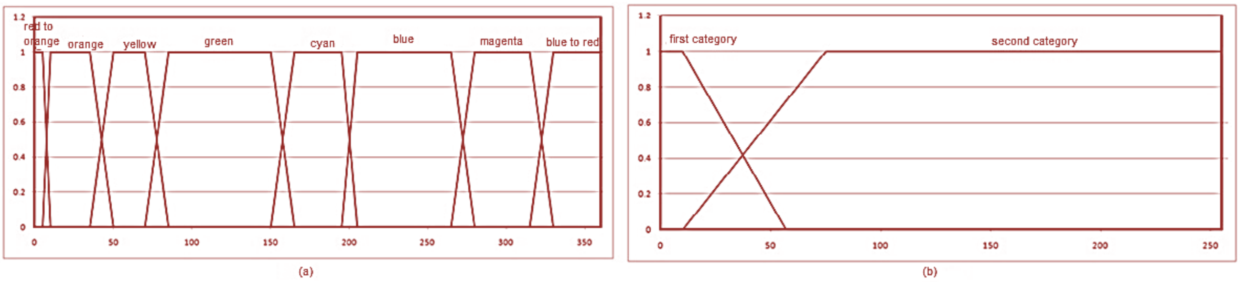


**Figure 3**: (a) membership function H (b) membership function S.

V channel is the third input of fuzzy histogram of color, which according to Figure (4-a) divide into three fuzzy areas. The first area that operates independently of the values of the other two features, is for when that input is black. The second fuzzy area generates gray color in combination with values of the S channel. Set of fuzzy rules contained in reference [16] will be used as fuzzy rules of this system. This is done in a number of decision rules, only based on one or two of the input channels.

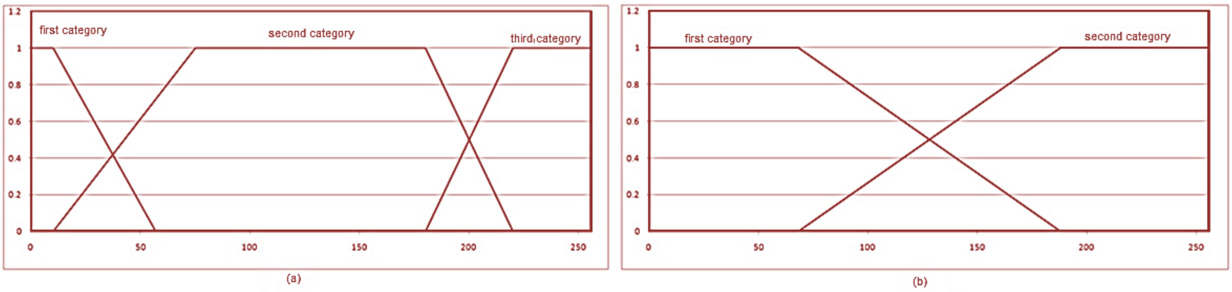


**Figure 4**: (a) membership function V (b) membership function S and V.

In fact, in this system, each input block of the image is mapped to one of these 10 output bins. And to calculate the outcome variable, Multi Participate algorithm is used.

In the next stage, the output of this fuzzy system enters the second fuzzy system as input. The function of this system is separating each color into three areas. output bins of this system, are defined by a predetermined color : (0) black ,(1) gray,(2) white, (3) dark red, (4) red, (5) light red, (6) dark orange,(7) orange,(8) light orange,(9) dark yellow,(10) yellow,(11) light yellow,(12) dark green, (13) green, (14) light green, (15) dark cyan, (16) cyan, (17) light cyan, (18) dark blue, (19) blue, (20) light blue,(21) dark rouged,(22) rouged,(23) light rouged .

Generally, the second fuzzy system operates as follows: According to figure (4-b) S and V channel classified into two fuzzy areas. In fact, this system has a function that categorizes input blocks into one (or more) of three color areas. These colors defined as follows: dark color, normal color, and light color. Four fuzzy rules contained in [16] are used as fuzzy rules of this system . And to calculate the outcome variable value, algorithm MP will be used. And finally, for HSV color space a 24part fuzzy vector of the image will be obtained.

### 4.4 OUTPUT COMBINATION OF FOUR FUZZY SYSTEMS TO OBTAIN COLOR OF LIGHT SOURCE

The final feature vector configuration is as follows: each of the established eight regions during the fuzzification of image texture, classified into 24 other areas by a fuzzy system of color.

Combination outcome of fuzzy systems of color and texture have $8 \times 24 = 192$ bins, which along with sixteen output bins of edge fuzzy system, as an ultimate vector, generate a vector with 208 parts or a histogram with 208 bins.

### 4.4.1 HISTOGRAM CONFIGURATION

In order to form color and texture histogram, the image at first is divided into 1600 blocks. The number of blocks is obtained based on the balance between image details and computational demands. Each block repeatedly passes all fuzzy systems (three fuzzy systems of color and texture). The whole process of generating the 208member final histogram describes as follows: each block transferred to YIQ color space and Haar wavelet applied on it. Therefore values of $F_{LH}$, $F_{HL}$, and $F_{HH}$ are calculated, and through fuzzy system related to texture, each block categorized to one of the eight output bins. For example, suppose that the categorizer mappings the desired block to the second bin (low energy horizontal activity). Then the same block transferred to HSV color space and mean values of S, H, and V of that block are calculated. These input values, form the second fuzzy system which fuzzy histogram has 10 bins. Again suppose that the categorizer mappings this block to the fourth bin (red color). Then, the other fuzzy system of color, by use of mean values of S and V calculates the color value and forms the histogram which has 24 bins. Again suppose that the categorizer mappings this block to the third bin (dark red color). These operations repeated for all blocks and formed zero bin histogram normalized, finally, a histogram with 192 bins is formed. To form the ultimate histogram, we also need the 16 bins of the fuzzy histogram of edges.

To form the histogram of 16 bins, the gray level difference must calculate for each Q pixel $\mathrm{Gray}_{\mathrm{Dif}(Q,i)} = \mathrm{Gray}(i) - \mathrm{Gray}(Q)$and $i \in \{1,2, \ldots ,8\}$ (i is an index of eight neighbor pixel). Then the gray level values $\mathrm{Gray}_{\mathrm{Dif}(Q,i)}$ fuzzificate based on NEG POS fuzzy functions and calculate $R_J(Q), J = 1,2, \ldots 16$ values for it . And eventually $R_J(Q), J = 1,2, \ldots 16$ values of homonymous Rjs of all the pixels are added together. This 16part feature vector along with 192part feature vector forms the ultimate vector of features.

In the training section, after extracting the appropriate features, to determine classes 208 part feature vector applied to the input of C-Means (Fuzzy c-mean) clustering algorithm. In this clustering to determine the distance between the clusters, the Euclidean distance is used. And with a repetitive algorithm with the criterion of the minimum sum of distances, a number of clusters for 130 different clusterings the value of 142 is obtained.

After the performing clustering phase, a classifier is made; in which images of training set classified to 142 classes. In each of these classes, there are a number of images from a set of training data. For each class, be a better probability of five algorithms present in the composition will be characterized.

In test time also after extracting 208part feature vector (similar to the training phase), this vector compares to all image profiles of image bases which the label of them is determined. Then according to input vector distance with closer neighbors as well as the membership function of selected neighbors to different semantic groups, the level of the input image belongs to the existent groups is determined. Then, the class of the image is obtained, and the best algorithm for the desired class will be selected through the results of the training phase. In fact, by use of this 208element vector, optimal estimate of color of the light source to the desired image will be achieved.

## 5. EXPERIMENTAL RESULTS

To evaluate proposed algorithm approach, its performance will be measured on image database provided by Cardei and Funt, which usually used in evaluating the color constancy algorithms, for each image in this database there is also the real color of the light of that image. This database includes 11346 images. A gray space at the bottom right corner of the image is located which used for estimate real color of the scene light. During testing, the right side of the images which contain the gray space will be cut.

### 5.1 PERFORMANCE EVALUATION

As Hordley and Finlayson claimed, to evaluate the outcome of color constancy methods, several criteria have been introduced that they are most commonly used is angle error criterion, which indicates the angle between the vector of the light source and estimated vector of light by color constancy methods. This criterion is to be calculated using Equation (7).

$$\varepsilon = \cos^{-1}(\widehat{e_l}.\widehat{e_e}) \qquad (7).$$

In this equation, $\widehat{e_l}$ shows the normalized vector of the real color of the light source and $\widehat{e_e}$ shows the normalized vector of estimated light (the outcome of color constancy method). The symbol '.' also shows the inner product of two vectors. Thus, to the overall evaluation of color constancy methods on a set of experimental images, the median angle error will be used which are the best and most suitable criteria for this work.

### 5.2 PERFORMANCE EVALUATION OF THE COMPOSITION OF FOUR FUZZY SYSTEMS

Now compare the proposed algorithm to select the best algorithm for each image with the other original and single algorithms of color constancy. Results contained in Table 1 indicates that the performance of the proposed algorithm is clearly superior to most of the algorithms (at least based on a database that is considered). It seems that our selection strategies to perform this task has been very effective. But, according to results contained in Table 2, applying the algorithm on the existent database [24], except a limited number of algorithms has acted weaker than other algorithms. Table 3 applying the algorithm on the existent database [26], the results is better than other algorithms.

**Table 1**: Summarizes the results of applying Color constancy algorithms, comparing our algorithm and the work [24].

| METHOD | MEDIAN ERROR |
|---|---|
| Grey-World | 7.0 |
| White-Patch | 5.3 |
| Shade-of-Grey | 5.3 |
| 1st-order Grey-Edge ($p = 1, \sigma = 1$) | 4.7 |
| 2st-order Grey-Edge ($p = 1, \sigma = 1$) | 4.9 |
| Exemplar-Based Color Constancy | 3.4 |
| NIS | 4.2 |
| NIS-Cross validation | 3.7 |
| CAS | 3.21 |
| Proposed Algorithm | 3.13 |

**Table 2**: Results of applying the algorithm from [23].

| METHOD | MEDIAN ERROR |
|---|---|
| White-Patch | 5.7 |
| Grey-World | 6.3 |
| Shade-of-Grey | 4 |
| 1st-order Grey-Edge ($p = 1, \sigma = 1$) | 4.5 |
| 2st-order Grey-Edge ($p = 1, \sigma = 1$) | 4.4 |
| NIS | 3.1 |
| Proposed Algorithm | 3.09 |

**Table 3**: Results of applying the algorithm from [25].

| METHOD | MEDIAN ERROR |
|---|---|
| Shades-of-Grey | 4 |
| Grey-World | 6.3 |
| 1st-order Grey-Edge ($p = 1, \sigma = 1$) | 4.5 |
| 2st-order Grey-Edge ($p = 1, \sigma = 1$) | 3.8 |
| Proposed Algorithm | 3.07 |

## 6. CONCLUSION

In this paper, a new algorithm is presented for the color constancy which acts based on fuzzy clustering methods. The proposed algorithm recognizes the color of the light source. This algorithm is consistently based on the assumption that the combinational algorithms in color constancy obtain better results. It seems that the related algorithm in the database [5, 6] obtained a better result than the other algorithms. The median angular error of the proposed algorithm in this database is 3.13. That can be said the propose method has performed better than most of the algorithms. But the objection for this algorithm is its high computational time. In the future, apply the related algorithm for more color constancy algorithms as well as to improve the accuracy of the algorithm, it is possible to use more features of the images as the input of the algorithm.

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**Parastoo Fathi** is associated with Department of Computer Science, University of Kurdistan, Sanandaj, Iran. She was awarded a Bachelor's degree from Kharzami University. She completed her Master’s degree from Shahid Beheshti University. Her research is in the field of Color and Vision.

**Dr. Mohsen Ebrahimi Moghadam** is an Associate Professor at Department of Computer Science and Engineering of Shahid Beheshti University. He had completed all undergraduate, graduate and postgraduate degrees in Computer Engineering at Sharif University of Technology in Computer-Software Engineering. His researches are Image Processing, Computer Vision, and Operating system.