Improving Differently-Illuminant Images with Fuzzy Membership Based Saturation Weighting

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Abstract— *Illumination estimation is basic to white balancing digital color images and to color constancy. The key to automatic white balancing of digital images is to estimate precisely the color of the overall scene illumination. Many methods for estimating the illumination's color has proposed. Though not the most exact, one of the simplest and quite extensively used methods are the gray world algorithm, white patch, max-RGB, Gray edge using first order derivative and gray edge using second order derivative, saturation weighting. The first-three methods have neglected the multiple light sources illuminate. In this work, we investigate how illuminate estimation techniques can be improved using fuzzy membership. The main aim of this paper is to evaluate performance of Fuzzy Enhancement based saturation weighting technique for different light sources (single, multiple, indoor scene and outdoor scene) under different conditions. The experiment has clearly shown the effectiveness of the proposed technique over the available methods.*

Keywords— Fuzzy Enhancement, White Balancing Illuminant, Saturation Weighting and Color Constancy.

I. INTRODUCTION

Many images, however, reveal a mixture of illuminates with dissimilar chromaticity. Consider, such as, indoor scenes which are affected by both indoor light sources and outdoor light coming through the windows. So the indoor scene shows great affectability than that of the outdoor scene and hence the illuminate of the light sources gets buried. Extending obtainable color constancy techniques to effectively compute multi-illuminant estimates are a challenging problem.

In this paper, a new method is presented that enables color constancy under different illuminated light sources, i.e. for single as well as for multi illuminate. As color constancy is broadly categorized into two categories: low-level statistic based group and learning based group. The traditional methods like Gray World, White Patch and max-RGB all are falling into this category, but learning based group requires some prior knowledge.

So the proposed methodology is considered according to the following criterion: 1) it should be able to compact with scenes containing single and multiple light sources; 2) it should work on a single image; 3) no human interruption is required; 4) no prior knowledge of the light sources is required.

In this paper, we originate and experimentally compare two different strategies for illuminate estimation. Given an undetected image, it is first classified as indoor or outdoor, and then processed with the algorithm suited for that class.

• Class-Independent (CI): the same algorithm is applied without taking into consideration the image class. The best one has chosen by the vigorous statistical analysis.

• Class-Dependent Algorithms (CDA): for each class a different algorithm is useful. The parameters of each algorithm are optimized for the equivalent class. The best algorithm for indoor and the best algorithm for outdoor are selected by the statistical test. Given an unobserved image, it is initially classified, and then processed with the algorithm chosen for the predicted class.

II. COLOR CONSTANCY ALGORITHMS

Various color constancy techniques are as follows:

1. Gray world
2. White patch
3. Gray edge 1^{st} order derivative
4. Gray edge 2^{nd} order derivative
5. Modified Gray World

2.1 Gray World

Gray-World (GW) is well-known color constancy method by the assumption which assumes that the regular reflectance of surfaces in the world is achromatic. This assumption is held magnificently: in an authentic world image, in most cases it is true but presently exist lots of different color variations. The variations colors are random and independent; the regular would converge to the mean value, gray, by given an enough amount of samples. Color balancing algorithms uses this assumption by forcing its images to have a common average gray value due to its R, G and B components. In case, a graphic is taken by an electronic digital camera using a particular lighting environment, the effect from the special lighting cast is easy to remove by enforcing the gray world assumption within the image. As a result of approximation, along from the image is really a lot far better an original scene [18].

2.2 White Patch

White Patch (WP) method attempts to find the objects which have been truly white, from the scene; by assuming the white pixels are also the brightest (I=R+G+B). White Patch approach is conventional the Color Constancy adaptation, trying to find the lightest patch for a white reference comparable to how the human visual system does. In White Patch, highest value within the image is white. White Patch algorithm is best suited for forest category [18].

2.3 Gray Edge 1st order derivative

In gray Edge 1st order derivative 4-neighbouring pixels are considered. The primary derivative-based edge detection operator detects image edges by computing the graphic gradient values like Robert operator, Sobel operator, Prewitt operator [18].

2.4 Gray Edge 2nd order derivative

The 8-neighbouring pixels are considered, unlike 4-connected pixels. In 8-connected, more information for image correction is available. Gray Edge using 1st order derivative doesn't proof to become efficient because each pixel considers its 4-neighbouring pixels. So, in this process not all the information is accessible for color correction [18].

2.5 Saturation Weighting

Saturation Weighting is based on the strong tendency of the performance changes according to the saturation values. Differently weighted pixels based on their saturation values will improve the performance of the color constancy [10].

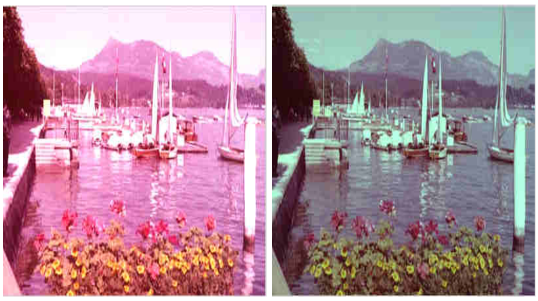


Fig.1: a) Input Image b) Result of Saturation Weighting

2.6 Modified Gray World

In this method, first, saturation weighting function is incorporated into the gray world method, which is called as gray world with saturation weighting (GWSW) given by:

$$w^s(f(x))f_i(x)dx = ke_i \quad (1)$$

Where s denotes the saturation strength factor and (·) is the saturation weighting function,

$$w\ (f(x))= (1-S(f(x))) \quad (2)$$

The smoothing operation reduces the control of noise in an image and it was proven to be helpful for improving the color constancy. By incorporating minowski norm (*p)* and smoothing operation (σ) into GWSW, the better performance has achieved than the general gray world method.

III. FUZZY MEMBERSHIP BASED IMAGE ENHANCEMENT

Previously, no work has done over fuzzy membership. This paper work has done work on fuzzy membership based color image enhancement using edge preserving filtering. Fuzzy membership has used to prevent over enhancement problem. Although, it provides enhancement to only those objects which demands it. Also, it enhanced the object according to membership value. Basically, it decides whether to enhance the object or not [19].

As fuzzy membership exploits two classes because we utilize dual membership functions in this paper work. Improved results have extracted for color constancy from optimal method based on fuzzy membership with edge preservation filtering. An estimation of the proposed technique is also drawn with existing techniques, the comparisons have evidently shown that the fuzzy based color constancy outperforms over the obtainable techniques [19].

IV. PROPOSED METHODOLOGY TO IMPROVE SATURATION WEIGHTING

Saturation Weighting is based on the strong tendency of the performance changes according to the saturation values. Differently weighted pixels based on their saturation values improved the performance of the color constancy [1]. The present paper work proposed to complete various stages which have to be preceded following and first methodology will discuss datasets used for dissertation work, as described below:

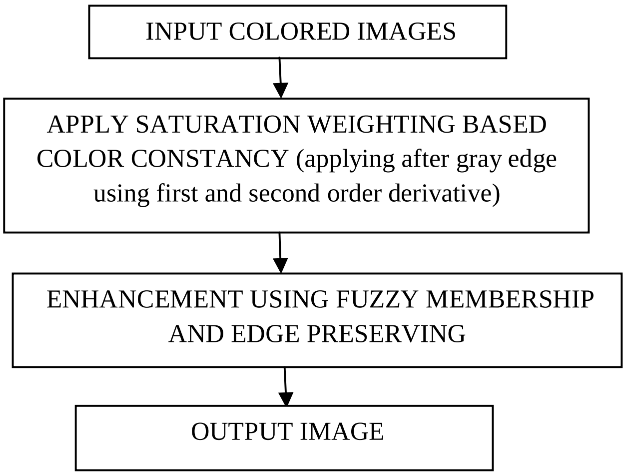


Fig.2: Proposed Methodology

4.1 Dataset:

The color constancy image dataset is a collection of 25 photographs of single and multiple illuminations under different conditions. In this dataset, the total number of 25 images, this has taken at different positions under different illuminate. Few examples have shown in the figure 3. Some of these are given below.

Fig.3: Sample pictures (adapted from dataset) [53]

In total, the images are divided into 25-30 clips, taken at different locations under different illumination. Some examples are shown in the Figure 1. Given images are taken from different data sets.

V. FLOW CHART

Flow chart of proposed methodology describes various phases step by step, which clarify the proper working of current methodology [19].

Below are the steps for the proposed algorithm:

Phase 1: Select the input image of size M* N and changed into the digital image, then locate the dimension of an image using the equation:

$$[M, N, \sim]=\mathrm{SIZE}\ (I) \quad (3)$$

Where M represents row, N represents column, ~Represents any channel i.e. red, green or blue and I represents the image.

Applying Fuzzy membership rules

In Fuzzy membership for gray image enhancement and smoothing two virtues considered. First approach is IF…. THEN ELSE rules for image enhancement, this is to enhance the pixels some directive fuzzy rules same as human-like analysis are given and these rules are generated from the neighbourhood pixel of the image. The second method relays to a rule-based smoothing. Here, on the basis of neighbourhood compatibility dissimilar filter classes are developed. Further, for color images Enhancement three 2-D histograms (RG, GB, BR) technique are used and for color image enhancement using LHS color model, equalization method is used. In the fuzzy approach, some pixel property, like gray tone or color intensity, is modeled into a fuzzy set using a membership function (triangular membership function). In this, an image can be considered as an array of fuzzy singletons having a membership value that denotes the degree of some image property in the range. Rules are described as below:

1) The fuzzy rule for class C1 is represented as follows:

If the difference between x and M is LARGE then the intensity of stretching should be SMALL. The above rule indicates that the pixel values closer to M will be extended higher, whereas values farther from M will be extended lesser. Pixel values in between will be extended proportionately [49].

The following mathematical representation is used: where x Є C1.

Once the membership value for x is obtained, the contrast enhanced case for class C1 is computed as follows:

$$\mu_{D1}(X) = 1 - ((M - X)/M \quad (4)$$

$$Xe = X + \mu_{D1}(X)\,K \quad (5)$$

μ_{D1} (X) decides what quantity of stretching parameter K has to be added to x to get the enhanced value xe. The fuzzy membership value μ_{D2} (X) for class C2 is based on the concept of how far the intensity value x is from the extreme value E.

2) The fuzzy rule for class C2 is represented as follows:

If the difference between x and E is LARGE then the intensity of stretching should be LARGE. The above rule indicates that the pixel values closer to E will be extensive lesser whereas values beyond E will be extended higher [49].

The following mathematical demonstration is used: where x Є C2.

μ_{D2} (X) = E − X /E – M (6)

Once the membership value for x is obtained, the contrast enhanced xe for class C2 can be computed as follows: μ_{D2} (X) decides what quantity of stretching parameter K and the intensity value x has to be utilized to get the improved value xe.

The substitution of the old x values of the V component with the enhanced xe values will cause the V component to be stretched resultant contrast and brightness enhanced component Ve. This improved achromatic information Ve can be shared with the pre-served chromatic information (Hue and Saturation components) to obtain enhanced image HSVe which is finally converted to enhanced RGBe image.

Fuzzy membership function

Membership function used is triangular membership function. A triangular membership function is based on three limits {a, b, c} as follows:

Triangle (x; a, b, c) = {0, x≤ a
x−a/ b−a, a≤ x≤ b
c−x/ c−b, b≤ x≤ c
0, c≤ x

Table.1: List of Various Parameters Used in Fuzzy Enhancement Implementation

Nature	Description
K	Control parameter
M	Control parameter
C_1	Class one having range[0-M-1]
C_2	Class two having range[M-255]
μD_1	First membership value
μD_2	second membership value
X	intensity value
X_e	Enhanced intensity value
V	value
V_e	Enhanced value

Phase 2: Then fuzzy membership have been added to the saturation weighting technique in order to improve the results.

Phase 3: But if in some cases, the edges of the image have been loose and then in that case we have applied the edge preserving filter as a post processing. Median filtering has been used as an edge preserving filter. It preserves edges while removing noise. We have made use of the 2-D median filter where 2-D represents an array. It is useful in preserving edges in an image. It includes further steps:

Step 1: The initial step in the proposed method is to change the given RGB image of size P × Q into HSV along with computing the histogram h(x) where x Є V. h(x) specifies the number of pixels in the figure by means of intensity value x. Proposed method uses two strengthening parameters M and K, which handles the amount at which the intensity value x has to be increased.

Step 2: Now, extract the V component from HSV.

Step 3: The value of K can be computed empirically according to what level the stretching is required. From the experimental analysis, we fixed the value 128 for K, which gives better results for the low contrast and low bright color images. Once the membership value of x is calculated, the contrast enhanced value x_e for class C2 can be computed.

Step 4: The factor M separates the histogram h(x) into two categories or classes. The first class C1 contains pixel values in the range [0, M − 1] and the second class C2 in the range [M, 255].

Step 5: The stretching of V component is approved out supported on two fuzzy membership values µD1and µD2, calculated for C1and C2 class of pixels correspondingly. Parameter M has the main role in the working out of fuzzy membership values; µD1 and µD2. Enhancement parameter K makes a decision the stretching intensity to calculate the enhanced intensity values x_e for the two classes C1 and C2. Parameter K comes to a decision the stretching point to which the intensity values x should be stretched based on the membership values μ_{d1} and μ_{d2}.

Step 6: The replacement of the previous x values of the V factor with the enhanced x_e Values will cause the V component to be extended resulting in contrast and brightness enhanced component V_e.

Step 7: This enhanced achromatic information V_e Can be joint with the preserved chromatic in sequence (Hue and Saturation components) to obtain enhanced image HSV_e which is finally converted to enhanced RGB_e Image.

Algorithm for fuzzy image enhancement

```
for counter = 1:length(low)
    for index =
low(counter):high(counter)
transformationMap(index) =
round((low(counter)-1) +
(range(counter)*(sum(fHistogram(low
(counter):index)))/(sum(fHistogram(
low(counter):high(counter))))));
    end
end

fuzzy_factor_image =
stretchlim(ip_image, fuzzy_factor);
final_image = imadjust(ip_image,
fuzzy_factor_image, []);
```

Edge Preserving Filter

Median filtering has used as an edge preserving filter. It preserves edges while removing noise. We have made use of the two-dimensional median filter where two-dimensional represents an array. It is useful in preserving edges in an image.

Fig.3: a) Input Image b) Modified Gray World with Edge preserving filtering

Modified Gray World (Saturation Weighting incorporated with gray world) which reduces the impact of the light but it also reduces the sharpness of the image and may result in some noise so to remove this problem; we uses an integrated effort of the modified Gray World color constancy with an edge preserving filtering. It not only removes noise but also preserves edges. An edge preserving filter is utilized to reduce the noises. The edge-preserving filter provides extensively noise reduction.

VI. RESULT AND DISCUSSION

Performance Evaluation

Quantitative performance measures are very important in comparing different image enhancement algorithms. Some well-known image performance parameters for digital images have selected to prove that the performance of the proposed algorithm is quite better than the available methods.

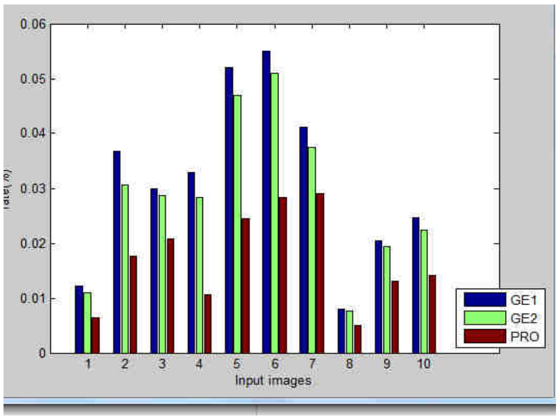
Performance is evaluated on the basis of various parameters like MSE and RMSE. The values of the parameters are taken in the tabular form consisting of four columns, including image number, gray edge using first order derivative, gray edge using second order derivative and optimal method results.

Mean Square Error

Table 2 shows the quantized study of the mean square error. As the mean square error needs to be reduced therefore the algorithm is showing the better results than the available techniques as mean square error is less in every case. The method is experienced on various images and in each case shows the better results than the existing method.

Table.2: MSE Evaluation

Images	Gray Edge 1	Gray Edge 2	Proposed Results
1.	0.0122	0.0110	0.0064
2.	0.0368	0.0307	0.0177
3.	0.0299	0.0287	0.0208
4.	0.0329	0.0283	0.0106
5.	0.0521	0.0469	0.0245
6	0.0550	0.0509	0.0283
7	0.0412	0.0374	0.0291
8	0.0080	0.0076	0.0050
9	0.0204	0.0194	0.0131
10.	0.0247	0.0224	0.0141



Graph 1: MSE Evaluation

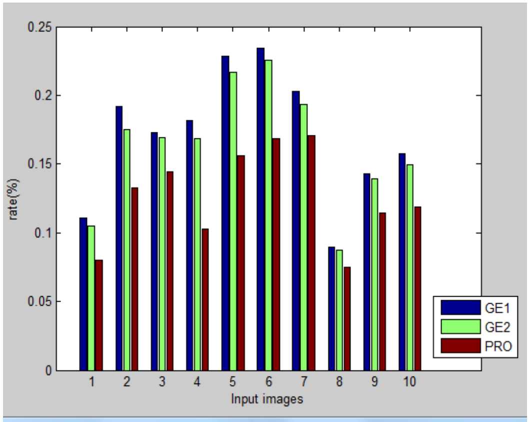
Root Mean Square Error

Table 3 is showing the relative analysis of the root mean square error. Table3 has evidently shown that is root mean square error is less in our case therefore the algorithm has shown better results over the available algorithm.

Table.3: RMSE Evaluation

Images	Gray Edge 1	Gray Edge 2	Proposed Results
1.	0.1105	0.1050	0.0803
2.	0.1919	0.1753	0.1330
3.	0.1729	0.1695	0.1441
4.	0.1814	0.1683	0.1028
5.	0.2281	0.2164	0.1564
6.	0.2346	0.2255	0.1683
7.	0.2030	0.1935	0.1707
8.	0.0892	0.0874	0.0749
9.	0.1429	0.1391	0.1146
10.	0.1573	0.1497	0.1186

Graph 2 shows the quantized analysis of the Root mean squared Error of different images. It is very clear from the graph that there is decrease in RMSE value of images with the use of proposed method over existing method.



Graph 2: RMSE Evaluation

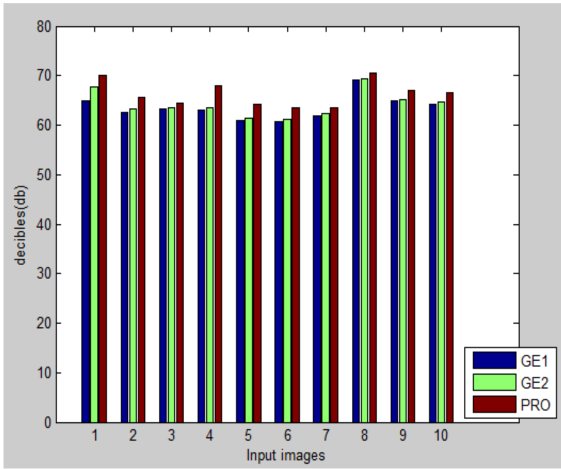
Peak Signal to Noise Ratio

Table 4 shows the comparative analysis of the Peak Signal to Noise Ratio (PSNR). As PSNR need to be maximized; so the main goal is to increase the PSNR. Table 4 has clearly shown that the PSNR is maximum in all the values; therefore algorithm is providing better results than the available techniques. The method is tested on various images and in each case shows better results than the existing method.

Table.4: PSNR Evaluation

Images	Gray Edge 1	Gray Edge 2	Proposed Results
1.	64.8019	67.7085	70.0371
2.	62.4702	63.2560	65.6552
3.	63.3729	63.5477	64.4637
4.	62.9601	63.6105	67.8928
5.	60.9665	61.4237	64.2464
6.	60.7252	61.0669	63.6075
7.	61.9805	62.3981	63.4861
8.	69.1239	69.3033	70.6386
9.	65.0285	65.2618	66.9445
10.	64.1981	64.6286	66.6473

Graph 3 shows the quantized study of the peak signal to noise ratio of different images. It is clear from the plot that there is raise in the PSNR value of images with the use of method over existing methods. This increase represents an enhancement in the objective quality of the image.



Graph 3: PSNR

VII. CONCLUSION

To conclude, the methodology in this paper has shown to extend the existing methods under that scenario where the uniform light-source assumption is too restrictive. In this paper, a new methodology that can be used to apply color constancy for the images that are recorded in the presence of different light sources has been proposed. Several traditional techniques such as Grey-world technique, Max RGB and learning-based technique were utilized to check the color constancy of digital images suffering from a light source. Every one of these techniques has an evident drawback that the source of light throughout the scene is spectrally same.

This assumption is usually violated as there can be multiple source of light illuminating the scene. More focuses on changing the saturation weighting based color constancy using fuzzy membership based color image enhancement and edge preserving filtering.

The issue appears to be justifiable and has great effect vision application since as fuzzy membership based saturation weighting that has decrease the impact of the light but it additionally decreases the sharpness of the image and also has result in certain noise so to eliminate this issue, an integral effort of the edge based color constancy combined with histogram stretching and edge preserving filtering.So the proposed methodology is considered according to the following criterion: 1) it should be able to compact with scenes containing single and multiple light sources; 2) it should work on a single image; 3) no human interruption is required; 4) no prior knowledge of the light sources is required. This scenario proves helpful for indoor as well as outdoor illuminants.

This paper work has not considered any soft computing technique for color constancy to check the optimistic value of a light source for differently-illuminant images. Also the effect of the noise is also ignored, therefore in near future, some well-known image filters will use which depicts the light source for differently-illuminant images under different scenario.

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