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Performance evaluation of Enhanced 2nd Order Gray Edge Color Constancy Algorithm Using Bilateral Filter

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Abstract

The color constancy techniques becomes an important pre-processing technique which reduces the effect of the light source on the given image or scene. It is found that light effects lot on a given scene. So effect of the light source may degrades the performance of certain applications a lot like face recognition, object detection, lane detection etc. Color constancy has ability to detection of color independent of light source. It is a characteristic of the distinct color awareness organization which guarantees that the apparent color of objects remains relatively constant under altering illumination conditions. The overall goal of this paper is to propose a new algorithm 2nd order gray edge based color constancy algorithm using bilateral algorithm. The overall attention is to enhance the color constancy algorithm further. The histogram stretching is also used to improve the results. The comparison has shown the significant improvement over the available techniques.

Keywords: Color constancy, Light source, light, Edge based color constancy and Gray world.

Introduction

The human visual system is able to regulate the color of objects from the spectral power distribution entering the eye. This ability to calculate color constant or approximately color constant descriptors is called color constancy. Even though a number of theories exist, it is not known exactly how the human brain computes color constant descriptors. Color constancy is very significant for many different areas, such as consumer photography or automatic color-based object recognition. Many different algorithms have been planned in order to solve the problem of color constancy. Whereas most color constancy algorithms accept that the objects shown in the image can be modelled as diffuse reflectors, some algorithms also take specular reflections into account, color constancy.

Color Constancy can be defined as ability to recognize colors of objects, invariant to illuminant. This ability is usually endorsed to the Human Visual System, while the accurate details remain uncertain. By taking into consideration a camera's response to objects in two different illuminates the fact can be made clear that colour constancy is a non-trivial property of a visual system. Figure 1.1 shows two images of the camera output from a digital camera. In the right-hand image the scene was taken under a daylight simulator while the image on the left-hand was taken under tungsten illumination. There is a apparent change in colour between these two images: the colours in the view light by the bluish daylight illuminant appear bluish than those light by the reddish tungsten illuminant.

Figure 1.1 : The image on the left shows an object viewed under tungsten illumination. On the right the same object is shown under blue sky daylight.

Computational Color Constancy follows different ways to maintain color appearance evenly under different light sources. The problem is approached using two phases. First approach is based on number of assumptions; the light source color can be estimated from an input image.

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The color of objects is primarily affected [10] by the color of the light source. The related object, taken by the same camera but beneath different light, may vary in its measured color appearance. This color deviation may negatively affect the result of image and video processing methods for different applications such as image segmentation, object recognition and video retrieval. The purpose of color constancy is to eliminate the effect of the color of the light source.

Because existing color constancy algorithms are based on precise assumptions, none of them can be considered as widespread. A number of color constancy methods have been proposed which take upper level visual information into account. For example, high-level visual information is used for color constancy. The image is shown as a combination of semantic classes, such as sky, grass, road and buildings Image statistics are used in to get better color constancy. It is shown that images with similar image statistics should be corrected by the identical color constancy algorithms. Also, similar image statistics specify a specific image category (i.e. scenes). For particular instance, the White-Patch color constancy algorithm is appropriate for the forest category while the 1st-order Grey-Edge is appropriate for the street category. Hence, it shows that there is a correlation among image statistics, scene types and color constancy algorithms.

A. Image Correction

The input image can be corrected if the chromaticity of the source light is known. When an input image is converted under an unknown light source, into an output image under a canonical light source, is called adaptation. When certain conditions are met chromatic adaptation can be modelled using a linear transformation, which can be simplified by a diagonal transformation.

Color correction methods are used to compensate for illumination conditions. In human perception such correction is called color constancy- the ability to perceive a relatively constant color for an object even under varying illumination. Most computer methods are pixel-based, correcting an image so that its statistics satisfy assumptions such as the average intensity of the scene under neutral light is achromatic, or that for a given illuminant, there is a limited number of expected colors in a real-world scène. Various schemes have been proposed to use features instead of pixels including higher order derivatives.

Image features are selected based on their probability to best characterize the illuminant color and ignore the specific color of the objects in the scene. For example, higher order derivatives are used based on the assumption that the average of reflectance differences in a scene is achromatic. However, to the best of knowledge, none of the existing methods account for the fact that even at the level of the distinct pixels, the reliability of the color information varies. Introduce the notion of color strength, a measure of color information accuracy.

Methods of Color Constancy

There are three types of methods that are distinguished, from each other with their own advantages and disadvantages.

A. Static Methods

Static methods are applied to images having fixed parameter setting. These can be based either on low-level statistics or on the physics-based dichromatic reflection model. First type of methods includes the Grey-World, the White-Patch and the Grey-Edge methods, integrated in one framework by van de weijer et al.

The grey world algorithm takes an assumption that the average color in a scene is achromatic under a white light source. This means that by the effects of the source light deviation of the average color away from grey is caused. In color space, it can be defined as the bulk of the image colors of an image under a white light source are aligned with the intensity axis and the bulk of the image colors of an image under arbitrary light source are aligned with the color of the light source.

The White-Patch algorithm assumes that the maximum pixel value is white. This assumption alleviate by considering the color channels separately, which results in the max-RGB algorithm.

The Grey-Edge algorithm is defined as the average edge in a scene is grey. Instead of pixels derivatives of image are used. This method clearly models the spatial dependencies between pixels.

Physics-based methods are the second type of static algorithms. Such methods frequently assume the more general dichromatic reflection model rather than the Lambertian reflectance model. The main difference between the two is the addition of a specular component, which is used to model the reflectance in the viewing direction. These methods use information about the physical interaction between the light source and the objects in a scene. The basic assumption of most methods is that all pixels of one surface fall on a plane in RGB color space. Multiple of such surfaces result in multiple planes, so the intersection between the planes can be used to compute the color of the light source.

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B. Gamut Mapping

Gamut mapping is method which is based on the assumption, that for a given illuminant in real-world images, only a limited number of colors are observed. For that reason, deviation in the color of light source leads to unpredicted variation in the colors of an image. The term called canonical gamut is learned from a training set defined as restricted set of colors that occurs under a given illuminant. Trained set contains any number of images. Then input gamut can be constructed for any input image, which can be used as set of colors for the light source to record the input image. Set of mappings can be computed by using the canonical gamut and the input gamut that maps the input gamut totally inside the canonical gamut. Out of the feasible multiple mappings, one of the mappings has to be selected as the estimated illuminant. Finally, output image is constructed by selected mapping is used to construct the output image

C. Learning-based Methods

The learning based algorithms uses a model learned on training the data to estimate the illuminant. Learning techniques feature vector extracted from the input image. None of the color constancy algorithms can be considered as universal with respect to large variety of available methods.

Literature Review

Color constancy is very significant for many different areas, such as photography or automatic color-based object recognition. Many different algorithms have been proposed in literature to solve the problems of color constancy. Different assumptions are considered. Still it needs to be further explored. The brief literature survey is as follows.

Ebner et al. [10] had demonstrated that the color constancy is vital for digital photography and automatic color-based object recognition. There are number of algorithms developed for color constancy but the author had reviewed two well-known color constancy algorithms. They are the gray world assumption and the Retinex algorithm which showed how a color constancy algorithm can be integrated into the JPEG2000 framework with Local space average color. Local space average color is used as an estimate of the illuminant; it can be used to integrate into decoding devices.

Arjan et al. [3] proposed a new methodology that enables color constancy under multiple light sources. The procedure used to design this methodology is that it must work on a single image; it should be supposed to be deal with scenes containing multiple light sources; there is not any requirement of human intervention and no prior knowledge on the spectral distributions of the light sources is required. But it focuses on scenes taken under one or two distinct light sources. Firstly existing methods are extended to be more realistic scenarios where the assumption of uniform light-source is too restrictive. The extension is done by applying color constancy locally to image patches, then estimates are joint into more strong estimations, and a local correction is applied based on a modified diagonal model. The proposed methodology reduces the control of two light sources concurrently present in one scene by quantitative and qualitative experiments on real and spectral images.

Lu et al. [12] has demonstrated that the objective of color constancy is to identify the object under the effect of the color of the light source. The author had proposed a stage model which is 3-D models of a scene can be used to select a proper algorithm for a given image by considering the angular error of the five different color constancy algorithms. An experiment was performed on large scale image dataset which had demonstrated that the proposed color constancy algorithm outperforms state-of-the-art single color constancy algorithms with an improvement of nearly 8%.

Abdeldjalil et al. [1**]** presented the problem of the color correction for images displayed by a projector on a non-white screen and under bright conditions. This was addressed using the model of the perceived image and exploiting the color constancy concept. The first method overcomes the problem of the color constancy that conserves the look of images displayed by a projector. The second method focuses on the surrounding lights and the projection screen. By using this image model and the color constancy requirement between the observed images, it presumes a linear transform that allows compensating the surrounding light by a single matrix multiplication.

Arjan et al. [4] demonstrated the use of different edge types to improve the performance of edge-based color constancy by computing a weighted average of the edges. To estimate the illuminant Edge-based color constancy method uses image derivatives. Using a photometric edge classification scheme the weights are computed. By means of a weight map which is based on shadow edges performs somewhat worse than specular edges, but significantly improved than using material edges as such methods frequently assume that the scene is illuminated by a white light resource the routine detection of such edges can happen to be incorrect when the color of the light source is not white. The motivation after this approach is to entirely use the information that is enclosed in the

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image, and at the same time increase the accuracy of the illuminant estimation and edge detection.

Choudhury et al. [2] proposed a new technique for color constancy which was based on the statistics of images with color cast. The method was based on the observation that under colour illumination an image of a scene has one color channel that had significantly different standard deviation from at least one other color channel. The denoising algorithms were used to solve the problem of noise. Experiments had been performed on two generally used datasets which had shown that the given technique was strong to choice of dataset and had given results that were at least as good as existing color constancy methods.

Brown et al. [9] presented the concept of color strength which was defines as combination of intensity and saturation information. The advantage of using color strength model was that it can be used to estimate the reliability of the color information contained in a pixel. It was tested on two datasets with ground-truth color information and in both datasets the color strength model had strong analytical power for hue error. The author had demonstrated that pixels with the lowest color strength would provide the important information for color correction for four standard color constancy methods.

Hyunchan et al. [5] proposed a novel algorithm for the color constancy based on the low low-level statistics. To improve color constancy the existing low low-level statistics statistics-based methods are extended to a more general framework. These statistics are broadly used because of their low computational complexity, their simplicities and with adequate parameters satisfactory performances. The proposed method improves the color constancy with a simple and effective manner by performing experiments on two widely used datasets. In nearly all cases, their method shows reasonable performances but in some cases a lot of pixels with low saturation values have different color characteristics from the light source, our method shows fewer accurate performances. In the future, it can be improved by combining it with other low-level statistics statistics-based methods, as the combination method and attain the improved performance of the color constancy.

Negrete et al. [6] had presented two recognized color constancy algorithms one is white patch Retinex (WPR) and the other one is Gray world algorithm combined with gamma correction. The performance was evaluated by comparing the Average Power Spectrum Value of the test images and their following results. It was observed that the application of the gamma correction after a color constancy algorithm results in an improved image quality.

Khan et al. [11] presented that under illumination source the illumination correction was independent of ability of humans for solving the visible colors of objects in a given scene. The Gray-Edge CC, Gray-World CC, max-RGB CC, Shades-of-Gray CC and Bayesian CC are five CC approaches studied for the YCbCr skin filter. It was observed that CC algorithms before applying static skin classifiers and filters improves performance.

Simone et al. [13] proposed a new method to estimate the scene illuminant using faces. In the image faces are detected and skin color information is extracted using a rough skin detector. It is based on the assumption that skin colors outline a suitably solid cluster in the color space to represent a suitable trace for illuminant estimation. The method is based on two interpretations that in the color space, skin colors tend to outline a cluster in the color space and secondly that numerous photographic images are contain people or portraits. An experimental result has shown that the proposed method is able to advance illuminant estimation accuracy with respect to the state-of-the-art algorithms using both a manual and a real face detector.

Bianco et al. [14] presented improved illuminant estimation accuracy by an image classifier which was trained to classify the images as indoor and outdoor. Then the best algorithm was selected for each class by performing different experiments. The authors had investigated an indoor/outdoor parameterization strategy which represent a color constancy algorithm, whose parameters were set on the basis of the class predicted by the classifier whereas an indoor/outdoor algorithm selection strategy according to which the best algorithm are set on the basis of the class predicted by the classifier.

Weijer et al. [7] investigated a new approach known as edge-based color constancy. This technique was based on derivative structure of images whereas existing color constancy algorithms were based on zero-order structure of images. It was derived from grey edge hypothesis which states that the average reflectance of surfaces in the world is achromatic..

Agarwal et al. [15] demonstrated that color strength to illumination difference is important for video tracking algorithm. The authors had presented a review of well-known color constancy approaches. They examined whether these approaches can be applied to the video tracking problem. It was grouped into two categories first one is Pre-Calibrated and second one is Data-driven approaches.

Weijer [8] proposed a new approach for color constancy named as Grey- World assumption which states that the average reflectance of surfaces in the world is achromatic. Grey-World hypothesis and the max-RGB method two well-known algorithms were shown to be two instantiations of a Minkowski norm based color constancy method. It was tested on a large data set of images under different illuminates. The results showed that the new technique performs better than the Grey-World assumption and the max-RGB method.

Gaps in Literature Work

The color constancy is a procedure that measures the influence of different light sources on a digital image. The image recorded by a camera depends on three factors: the physical content of the scene, the illumination incident on the scene, and the characteristics of the camera. The goal of the computational color constancy is to account for the effect of the illuminate.

Many traditional methods such as Grey-world method, Max RGB and learning-based method were used to measure the color constancy of digital images affected by light source. All these methods have an obvious disadvantage that the light source across the scene is spectrally uniform. This assumption is often violated as there might be more than one light source illuminating the scene. For instance, indoor scenes could be affected by both indoor and outdoor illumination, each having distinct spectral power distributions.

By conducting the review on existing techniques we have found that the most of existing researchers has neglected at least one of the following:

1. The effect of the multiple lights has been ignored in the most of the existing research.
2. The effect of color artefacts due to color constancy has been also ignored.
3. The effect of the low illumination is also ignored.

Proposed methodology

Step 1: First of all given image will be acquired and converted into a digital image to apply vision processing operations.

Step 2: Now we will apply the edge based 2nd order derivation color constancy algorithm to remove the effect of light and then color normalization will come in action to balance the effect of the poor light.

$$\frac{\int |\boldsymbol{f_x(x)}| \boldsymbol{dx}}{\int \boldsymbol{dx}} = \frac{\mathbf{1}}{\int \boldsymbol{dx}} \iint_{\omega} \boldsymbol{e(\lambda)} |\boldsymbol{s_x(\lambda, x)}| \boldsymbol{c(\lambda) d\lambda dx} \quad \textbf{... (1)}$$

$$= \int_{\omega} \boldsymbol{e(\lambda)} \left(\frac{\int |\boldsymbol{s_x(\lambda, x)}| \boldsymbol{dx}}{\int \boldsymbol{dx}} \right) \boldsymbol{c(\lambda) d\lambda} \quad \textbf{... (2)}$$

$$= \boldsymbol{K} \int_{\omega} \boldsymbol{e(\lambda) c(\lambda) d\lambda} = \boldsymbol{Ke} \quad \textbf{... (3)}$$

Where $|\boldsymbol{f_x(x)}| = (|\boldsymbol{R_x(x)}|, |\boldsymbol{G_x(x)}|, |\boldsymbol{B_x(x)}|)^{\boldsymbol{T}}$

The image values, f = (R, G, B) ^{T,} for a Lambertian surface are dependent on the light source $e(\lambda)$,Where λ , is the wavelength, the surface reflectance s (λ) and the camera sensitivity functions c (λ) = (R (λ),G (λ),B (λ) where ω is the visible spectrum and bold fonts are applied for vectors.

Step 3: Now bilateral filter will be applied on the output of edge based 2nd order derivation color constancy algorithm to reduce the effect of the noise.$I^{filtered}(x) = \frac{1}{W_p} \sum_{x_i \in \Omega} I(x_i) f_r(\|I(x_i) - I(x)\|\, g_s(\|x_i - x\|)$where the normalization term

$$W_p = \sum_{x_i \in \Omega} f_r(\|I(x_i) - I(x)\|) g_s(\|x_i - x\|)$$

Ensures that the filter preserves image energy and

- I^{filtered} is the filtered image;
- I is the original input image to be filtered;
- x are the coordinates of the current pixel to be filtered;
- Ω is the window centered in x;
- f_r is the range kernel for smoothing differences in intensities. This function can be a Gaussian function;
- g_s is the spatial kernel for smoothing differences in coordinates. This function can be a Gaussian function;
-

Step 4: Now histogram stretching will be applied to get the final color constant image The formula for stretching the histogram of the image to increase the contrast is

$$g(x, y) = \frac{f(x, y) - fmin}{fmax - fmin} * 2^{bpp}$$

where f(x, y) denotes the value of each pixel intensity and bpp denotes bits per pixel.

Step 5: End

Performance metrics

The quality of an image is examined by objective assessment as well as subjective assessment. For subjective assessment, the image has to be observed by a human expert. The human visual system is so intricate that it is not yet modeled correctly. As a result, besides objective assessment, the image must be observed by a human expert to judge its quality. There are various metrics used for objective assessment of an image. Some of them are mean squared error (MSE), mean absolute error (MAE) and peak signal to noise ratio (PSNR).

Peak Signal to Noise Ratio (PSNR):

PSNR computes the peak signal-to-noise ratio, in decibels, between two images. This ratio is used as a quality measurement between the original and a reconstructed image. The higher the PSNR, the better is the quality of the reconstructed image. To compute the PSNR, first we have to compute the mean squared error (MSE) using the following equation:

$$MSE = \frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{n}(A_{ij} - B_{ij})^2 \; PSNR$$

$$= 10 * \log_{10}(\frac{peak^2}{MSE})$$

PSNR value should be as high as possible.

Normalized Cross Correlation (NCC):

Normalized cross correlation is used to find out similarities between fused image and registered image is given by the following equation:

$$\mathbf{NCC} = \sum\nolimits_{\mathbf{i=1}}^{\mathbf{m}}\sum\nolimits_{\mathbf{j=1}}^{\mathbf{n}}(\mathbf{A_{ij}} * \mathbf{B_{ij}})$$

Structural Content (SC):

The structural content measure is used to evaluate two images in a number of small image patches the images include in familiar. The patches to be compared are selected using 2D continuous wavelet which acts as a low level corner detector. The large value of structural content SC means that image is poor quality

$$SC = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n}(A_{ij})^2}{\sum_{i=1}^{m}\sum_{j=1}^{n}(B_{ij}{}^2)}$$

Maximum Difference(MD):

Difference between any two pixels such that the larger pixel appears after the smallest pixel. The large value of maximum difference means that image is poor in quality.

$$MD = Max(|A_{ij} - B_{ij}|)$$

Normalized Absolute Error (AE):

The large value of normalized absolute error means that image is poor quality. NAE is defined as follows

$$NAE = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n}(|A_{ij} - B_{ij}|)}{\sum_{i=1}^{m}\sum_{j=1}^{n}(A_{ij})}$$

Mean Squared Error (MSE):

Mean square error is a measure of image quality index. The large value of mean square means that image is a poor quality. Mean square error between the reference image and the fused image is

$$MSE = \frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{n}(A_{ij} - B_{ij})^2$$

Where Ai, j and Bi, j are the image pixel value of reference image.

Median Angular Error (MAE):

Median angular error between the estimated light source e_e and the actual light source e_l is used as an error measure:

$$angular\ error = \cos^{-1}(\widehat{e_l}.\widehat{e_e})$$

Where $(\hat{.})$ indicate a normalized vector.

Average Difference (AD):

The Average maximum difference corresponds to pixel which have a value which is less than the pixel in original image and the Average minimum difference corresponds to pixel which have a value which is more than the pixel in original image. The average difference is defined as a value of the difference between maximum and minimum. It needs to be minimized

$$\mathbf{AD} = \frac{\mathbf{1}}{\mathbf{mn}}\sum_{\mathbf{i=1}}^{\mathbf{m}}\sum_{\mathbf{j=1}}^{\mathbf{n}}[\mathbf{A}(\mathbf{i},\mathbf{j}) - \mathbf{B}(\mathbf{i},\mathbf{j})]$$

Experimental Set-Up

In order to implement the proposed algorithm, design and implementation has been done in MATLAB using image processing toolbox. In order to do cross validation we have implemented the edge based color constancy with bilateral filter. Table 1 is showing the various images which are used in this research work. Images are given along with their formats. All the images has different kind of the light i.e. more or less in some images.

Table 1. Experimental images

S.No	NAME	FORMAT
1	image1	JPEG
2	image2	JPEG
3	image3	JPEG
4	image4	JPEG
5	image5	JPEG
6	image6	JPEG
7	image7	JPEG
8	image8	JPEG
9	image9	JPEG
10	image10	JPEG

Experimental Results

For the purpose of cross validation we have taken 10 different images and passed to the edge based using first order, edge based using second order, and proposed algorithm. Subsequent section contains a result of one of the 10 selected images to show the improvisation of the proposed algorithm over the other techniques.

Figure 1 has shown the input image for experimental purpose. The image has low brightness and the impact of red color on the image is more. The overall objective is to improve the brightness of the image and to remove the effect of the color of the light source.

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Figure 1. Input image

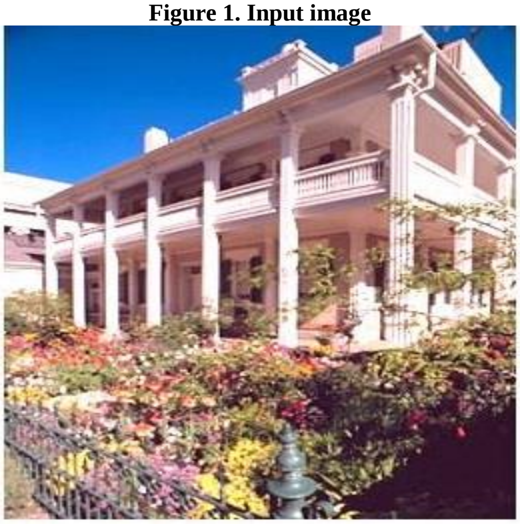

Figure 2. Edge based using first order

Figure 2 has shown the output image taken by the Edge based using first order. The image has contained more brightness and some more effect of the red color. However the problem of this technique is found to be some artifacts which have degrades the quality of the image.

Figure 3. Edge based using second order

Figure 3 has shown the output image taken by the Edge based using second order. The image has more brightness. However the problem of this technique is found to be is the effect of the green channel has not been minimized as expected.

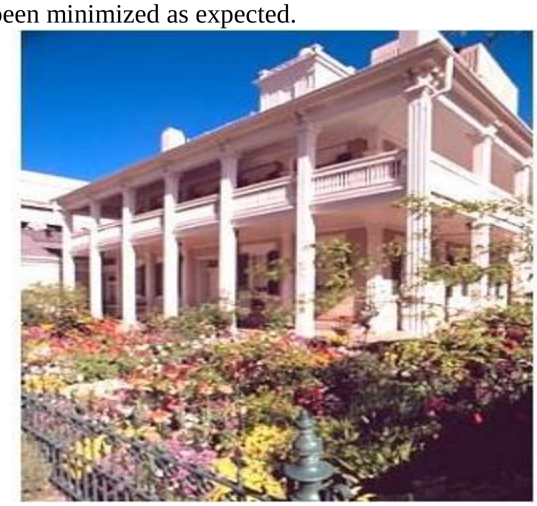

Figure 4. Improved edge based using second order

Figure 4 has shown the output image taken by the integrated technique of the bilateral filter with edge based using second order. The image has contained too much brightness but still has more effect of the red color.

Figure 5.Final proposed image

Figure 5 has shown the output image taken by the integrated technique of the bilateral filter with edge based color constancy. The image has contained the balanced brightness and the impact of the red channel is also reduced. Comparing with other method the proposed has shown quite significant result with respect to all cases. The effect of the individual channel has also been normalized as well as the effect of the brightness is also normalized.

Performance Analysis

This section contains the cross validation between existing and proposed techniques. Some well-known image performance parameters for digital images have been selected to prove that the performance of the proposed algorithm is quite better than the available methods.

Table 2 has shown the quantized analysis of the mean square error. As mean square error need to be reduced therefore the proposed algorithm is showing the better results than the available methods as mean square error is less in every case.

Table 3 is showing 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 as much as possible. Table 3 has clearly shown that the PSNR is maximum in the case of the proposed algorithm therefore proposed algorithm is providing better results than the available methods.

Table 2. Mean Square Error

Image Name	Edge based using first order	Edge based using second order	Proposed
Img1	0.0162	0.0133	0.0084
Img2	0.0064	0.0059	0.0049
Img3	0.0154	0.0144	0.0098
Img4	0.0395	0.0359	0.0338
Img5	0.0444	0.0418	0.0284
Img6	0.0253	0.0227	0.0115
Img7	0.0375	0.0351	0.0102
Img8	0.0311	0.0301	0.0193
Img9	0.0268	0.0228	0.0101
Img10	0.0172	0.0156	0.0104

Table 3. Peak Signal –to- Noise Ratio

Image Name	Edge based using first order	Edge based using second order	Proposed
Img1	66.0482	66.8954	68.9092
Img2	70.0371	70.3957	71.2580
Img3	66.2616	66.5499	68.2200
Img4	62.1619	62.5826	62.8475
Img5	61.6559	61.9228	63.6032
Img6	64.1044	64.5666	67.5211
Img7	62.3854	62.6769	68.0528
Img8	63.2068	63.3470	65.2788
Img9	63.8515	64.5515	68.1005
Img10	65.7698	66.2062	67.9775

Table 4 is showing the comparative analysis of the Average Difference. As Average Difference needs to be minimized; so the main objective is to reduce them Average Difference as much as possible. Table 4 has clearly shown that Average Difference is less in our case therefore the proposed algorithm has shown significant results over the proposed algorithm.

Table 4. Average Difference

Image Name	Edge based using first order	Edge based using second order	Proposed
Img1	0.0162	0.0133	0.0084
Img2	0.0064	0.0059	0.0049
Img3	0.0154	0.0144	0.0098
Img4	0.0395	0.0359	0.0338
Img5	0.0444	0.0418	0.0284
Img6	0.0253	0.0227	0.0115
Img7	0.0375	0.0351	0.0102
Img8	0.0311	0.0301	0.0193

Img9	0.0268	0.0228	0.0101
Img10	0.0172	0.0156	0.0104

Table 5 is showing the comparative analysis of the Mean Absolute Error. Mean Absolute Error contains the average difference between input and output image. Table 5 has clearly demonstrated that the Mean Absolute Error is quite less in the case of the proposed algorithm; therefore proposed algorithm is providing better results.

Table 5. Mean Absolute Error

Image Name	Edge based using first order	Edge based using second order	Proposed
Img1	0.2033	0.1838	0.1300
Img2	0.0704	0.0677	0.0611
Img3	0.1730	0.1676	0.1152
Img4	0.3489	0.3319	0.2950
Img5	0.4782	0.4633	0.3214
Img6	0.3415	0.3232	0.1830
Img7	0.2858	0.2765	0.1221
Img8	0.3199	0.3145	0.2082
Img9	0.2223	0.2056	0.1159
Img10	0.2105	0.2002	0.1412

Table 6 shows the comparative analysis of the Normalized Cross-Correlation (NCC). As NCC needs to be close to 1, therefore proposed algorithm is showing better results than the available methods as NCC is close to 1 in every case.

Table 6. Normalized Cross-Correlation

Image Name	Edge based using first order	Edge based using second order	Proposed
Img1	1.1832	1.1665	1.1159
Img2	1.0617	1.0596	1.0508
Img3	1.1603	1.1557	1.0973
Img4	1.3282	1.3143	1.2528
Img5	1.4737	1.4597	1.3489
Img6	1.3261	1.3101	1.1406
Img7	1.2723	1.2642	1.0662
Img8	1.3088	1.3042	1.2159
Img9	1.2042	1.1898	1.0855
Img10	1.1901	1.1815	0.9352

Table 7. Structural Co-relation

Image Name	Edge based using first order	Edge based using second order	Proposed
Img1	0.7091	0.7303	0.7971
Img2	0.8836	0.8875	0.9026
Img3	0.7394	0.7455	0.8230
Img4	0.5637	0.5762	0.6226
Img5	0.4600	0.4690	0.5428
Img6	0.5666	0.5809	0.7505
Img7	0.6146	0.6228	0.8660
Img8	0.5822	0.5864	0.6695
Img9	0.6845	0.7021	0.8398
Img10	0.7006	0.7113	1.1126

Table 7 is showing the comparative analysis of the Structural Correlation. As SC needs to be close to 1, therefore proposed algorithm is showing better results than the available methods as SC is close to 1 in every case.

Table 8. Median Angular Error

Image Name	Edge based using first order	Edge based using second order	Proposed
Img1	6.3548	5.7642	4.5714
Img2	4.0147	3.8524	3.4883
Img3	6.2005	5.9981	4.9489
Img4	9.9406	9.4707	9.1862
Img5	9.7245	9.4177	8.2011
Img6	7.9486	7.5366	5.3636
Img7	9.6881	9.3684	5.0451
Img8	8.8139	8.6728	6.9433
Img9	8.1835	7.5498	5.0175
Img10	6.5617	6.2402	5.0890

Table 8 is showing the comparative analysis of the Median Angular Error**.** As Median Angular Error needs to be minimized; so the main objective is to reduce the Median Angular Error as much as possible. Median angular error is less in our case therefore the proposed algorithm has shown significant results over the proposed algorithm.

Figure 6 has shown the quantized analysis of the mean square error. As mean square error need to be reduced therefore the proposed algorithm is showing the better results than the available methods as mean square error is less in every case.

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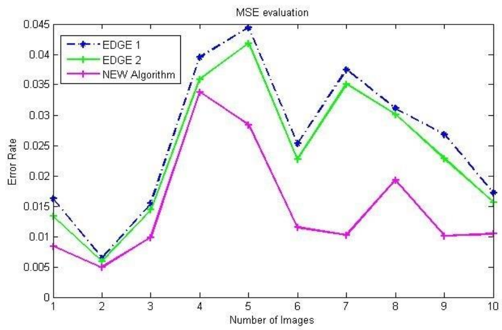

Figure 6.Mean Square Error

Figure 7 is showing 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 as much as possible. Table 3 has clearly shown that the PSNR is maximum in the case of the proposed algorithm therefore proposed algorithm is providing better results than the available methods.

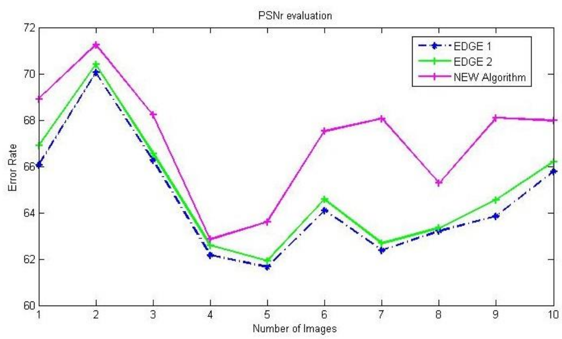

Figure 7.Peak Signal –to- Noise Ratio

Figure 8 is showing the comparative analysis of the Average Difference. As Average Difference needs to be minimized; so the main objective is to reduce them Average Difference as much as possible. Figure 8 has clearly shown that Average Difference is less in our case therefore the proposed algorithm has shown significant results over the proposed algorithm.

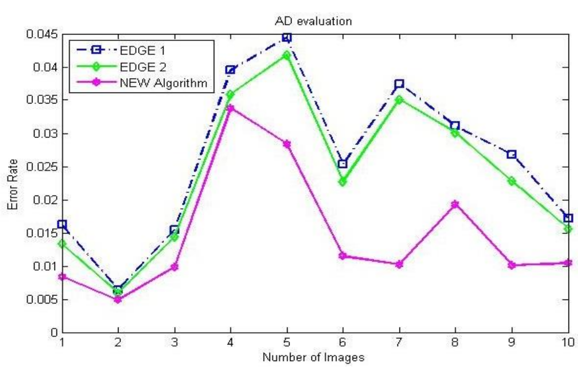

Figure 8. Average Difference

Figure 9 is showing the comparative analysis of the Mean Absolute Error. Mean Absolute Error contains the average difference between input and output image. Figure 9 has clearly demonstrated that the Mean Difference is quite less in the case of the proposed algorithm; therefore proposed algorithm is providing better results.

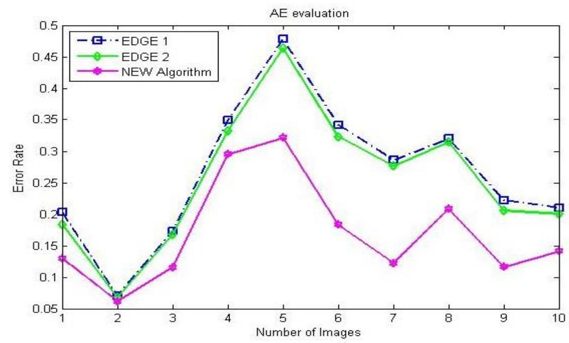

Figure 9. Mean Absolute Error

Figure 10 is showing the comparative analysis of the Normalized Cross-Correlation (NCC). As NCC needs to be close to 1, therefore proposed algorithm is showing better results than the available methods as NCC is close to 1 in every case.

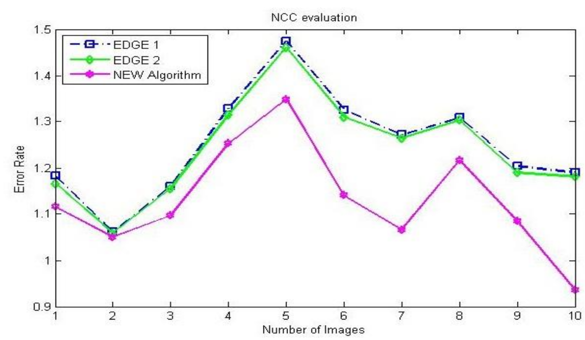

Figure 10. . **Normalized Cross-Correlation**

Figure 11 is showing the comparative analysis of the Structural Correlation. As SC needs to be close to 1, therefore proposed algorithm is showing better results than the available methods as SC is close to 1 in every case.

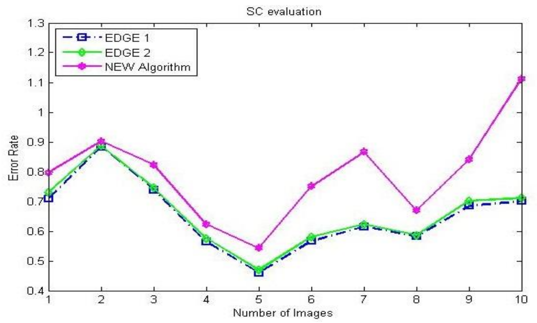

Figure 11. Structural Co-relation

Figure 12 is showing the comparative analysis of the Median angular error. As Median angular error need to be reduced therefore the proposed algorithm is showing the better results than the available methods as Median angular error is less in every case.

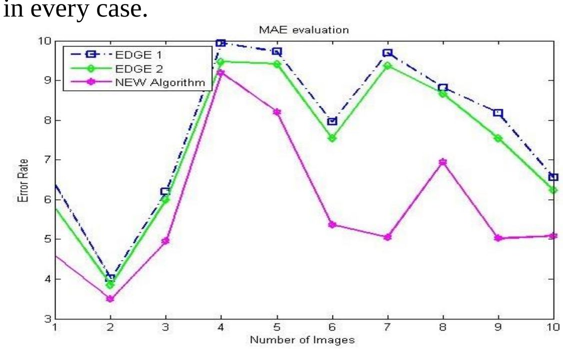

Figure 12 Median angular error

Conclusion & Future Work

This paper has proposed a new color constancy algorithm by integrating the 2nd order gray edge based color constancy algorithm with bilateral algorithm. The 2nd order derivative based edge based color constancy has ability to significantly improve the effect of the color light source. But it may introduce some Gaussian noise and also degrade the effect of the brightness in the image. So bilateral filter is used to remove the Gaussian noise and the histogram stretching is also used to improve the brightness of the image. The comparison of the proposed algorithm with other color constancy algorithms has shown the significant improvement over the available techniques.

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