Modified Edge Based Color Constancy Using Non-Local Means
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Abstract
The color constancy is a procedure that measures the influence of different light sources on a digital image. 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. This paper has proposed a modified edge based color constancy using non local means and the adaptive histogram equalization. The proposed algorithm has ability to reduce the uneven illuminate problem of edge based color constancy and also non-local means has produced sharper results. The proposed algorithm is designed and implemented in the MATLAB using image processing toolbox. The comparison among the modified edge based color constancy and the edge based color constancy has shown that the proposed algorithm is quite effective over the available methods.

INDEX TERMS: Color constancy, Illuminates, light source, Gray world and Non local means.

I. INTRODUCTION
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.

The main objective of this work is to implement modified Edge Based Color Constancy using non local means and to check various test images under multiple light sources. The problem is seem to be justifiable and will have great impact on vision application because as edge based color constancy will reduce the impact of the light but it also reduces the sharpness of the image and also may result in some noise so to remove this problem we will use an modified effort of the edge based color constancy along with the non-local means based noise removal. In order to validate the performance of the proposed algorithm design and implementation is done in MATLAB using image processing toolbox. The comparison among state of art techniques has also been drawn by considering the well-known image processing performance metrics.

Color constancy [4] is the capability to identify colors of objects invariant of the color of the illumination source. It commonly consists of two steps. Firstly, the illumination source color is estimated from the image statistics. Secondly, illuminant invariant descriptors are computed, which is usually completed by adjusting the image for the color of the light source such that the object colors look like the colors of the objects under a known light source. A straightforward color constancy technique, called max-RGB, estimates the light source color from the maximum response of the different color channels.

One more renowned color constancy technique is based on the Grey-World hypothesis, which assumes that the average reflectance in the scene is achromatic. Although
more detailed algorithms exist, methods like Grey-World and max RGB are still generally used because of their low computational costs. They have pursued color constancy by the Grey Edge hypothesis, which assumes the average edge difference in the scene to be achromatic. The technique is based on the surveillance that the division of color derivatives exhibits the biggest variation in the light source path. The average of these derivatives is used to estimate this path.

\[
\left( \int \frac{d^n f^\sigma(x)}{dx^n} \right)^p \| dx \right)^{1/p} = k_e^{n,p,\sigma}
\]

i. The order n of the image structure is the parameter determining if the method is a gray-world or a gray edge algorithm.

ii. The Minkowski norm p which determines the relative weights of the multiple measurements from which the final illuminant color is estimated. A high Minkowski norm emphasizes larger measurements whereas a low Minkowski norm equally distributes weights among the measurements.

iii. The scale of the local measurements as denoted by sigma. For first- or higher order estimation, this local scale is combined with the differentiation operation computed with the Gaussian derivative. For zero-order gray-world methods, this local scale is imposed by a Gaussian smoothing operation.

Color Constancy [7] is a phenomenon that defines the human ability to estimate the actual color of a scene irrespective of the color of illumination of that scene. Since an image is a product of the illumination that falls on the scene and the reflectance properties of the scene, attaining color constancy is an ill posed problem and various techniques have been planned to address it. Our method is based on the observation that an image of a scene, taken under colored illumination, has one color channel that has significantly different standard deviation from at least one other color channel.

The standard deviations of the color channels of an image with no color cast are very alike to each other. We discover the ratio of the maximum and minimum standard deviation of color channels of local patches of an image and usage as a prior to estimate the color of illumination and achieve color constancy.

In order to purify [10] the acquired image as close as possible to what a human observer would have observed if placed in the original scene, the first stage of the color correction pipeline aims to emulate the color constancy feature of the human visual system (HVS), the ability to perceive relatively constant colors when objects are lit by different illuminants. The dedicated module is usually referred to as automatic white balance (AWB), which should be able to determine from the image content the chromaticity of the ambient light and compensate for its effects. The only information available are the camera responses across the image, color constancy in as under determined problem ; and thus further assumptions and/or knowledge are needed to resolve it. Typically, some information about the camera being used is exploited, and/or assumptions about the statistical properties of the expected illuminants and surface reflectance.

Color correction methods [12] are used to compensate for illumination conditions. In human perception such correction is called color constancy the capability to perceive a relatively constant color for an object even under changing illumination. Most computer methods are pixel based, correcting an image so that its statistics fulfill assumptions such as the average intensity of the scene under neutral light is achromatic, or that for a given illuminant, there is an inadequate number of expected colors in a real world scene. Various schemes have been proposed to use features instead of pixels including higher order derivatives or homogeneous color regions.

A. NON LOCAL MEAN

Non-local means is an algorithm in image processing for image denoising. Unlike “local smoothing” filters, non-local means does not update a pixel’s value with an average those of the pixels around it - instead, it updates it using a weighted average of the pixels judged to be most similar to it, judged by its distance in color space. The weight of each pixel depends on the distance between its intensity grey level vector and that of the target pixel. The methods that estimate pixel intensity based on information from the whole image and thereby exploiting the presence of similar patterns and features in an image are referred as non-local.

A non local method called as non-local means which estimates a noise-free pixel intensity as a weighted average of all pixel intensities in the image, and the weights are proportional to the similarity between the local neighborhood of the pixel being processed and local neighborhoods of surrounding pixels. The method is quite spontaneous and powerful that results in comparable psnr and visual quality to other non-local methods.
If compared with other well-known denoising techniques, such as the gaussian smoothing model, the anisotropic diffusion model, the total variation denoising, the neighborhood filters and an elegant variant, the wiener local empirical filter, the translation invariant wavelet thresholding, the non-local means method noise looks more like white noise.

Given an image \( Y \), the filtered value at a point \( p \) using the NLM method is calculated as a weighted average of all the pixels in the image following this formula:

\[
NLM(Y(p)) = \sum_{q \in Y} w(p, q) Y(q)
\]

where \( p \) is the point being filtered and \( q \) represents each one of the pixels in the image. The weights \( w(p, q) \) are based on the similarity between the neighborhoods \( N_p \) and \( N_q \) of pixels \( p \) and \( q \). \( N_j \) is defined as a square neighborhood window centered around pixel \( i \) with a user-defined radius \( R_{sim} \).

The similarity \( w(p, q) \) is then calculated as:

\[
w(p, q) = \frac{1}{Z(p)} e^{-\frac{d(p, q)}{h^2}}
\]

where \( d(p, q) \) is the Euclidean distance between pixels \( p \) and \( q \). The denominator \( Z(p) \) normalizes the weights to ensure that their sum is 1.

### Advantages:

This technique works for the removal of noise and it gives better results compared to previous denoising techniques that lead to the smoothing of images.

### Disadvantages:

This denoising method works only for low noise levels.

**B. ADAPTIVE HISTOGRAM EQUALIZATION**

Ordinary histogram equalization uses similar transformation derived from the image histogram to convert all pixels. This works fine when the division of pixel values is similar all through the image. However, when the image have regions that are considerably lighter or darker than most of the image, the contrast in those areas will not be sufficiently enhanced. Adaptive histogram equalization (AHE) improves on this by transforming each pixel with a conversion function derived from a neighborhood area.

When the image section containing a pixel's neighborhood is fairly uniform, its histogram will be strongly peaked, and the transformation function will plot a narrow range of pixel values to the whole range of the result image. This causes AHE to over amplify small amounts of noise in largely uniform regions of the image. This method is used to get better contrast of the images. It varies from histogram equalization with respect that the adaptive method make the computation of the several histograms, every corresponding to a different segment of the image, and use to reallocate the lightness values of the image. It is therefore suitable for to increase the local contrast of an image and put across more detail.

With histogram equalization [30] the mapping function \( m(i) \) is proportional to the cumulative histogram

\[
m(i) = (\text{display range}) \times (\text{cumulative histogram}(i) / \text{range size})
\]

Since the derivative of cumulative histogram is the histogram, the slope of mapping function at any input intensity i.e. the contrast enhancement, is proportional to the height of the histogram at that intensity:

\[
\frac{d_m}{d_i} = (\frac{\text{display range}}{\text{region size}}) \times \text{histogram}
\]

Therefore, limiting the slope of the mapping function is equivalent to clipping the height of the histogram.

**II. RELATED WORK**

The problem of illuminant estimation [1] for given image of a sight is recorded under an unidentified light; they can recover an estimate of that light. Obtaining such an estimate is a vital part of solving the color constancy problem that is of recovering an illuminant self-governing demonstration of the reflectance in a scene. They start by determining which image colors can take place under each of a set of probable lights.

The color constancy problem; that is how can discover an estimate of the unknown illuminant in a captured scene. They have shown a correlation framework to solve color constancy problem that is of recovering an illuminant self-governing demonstration of the reflectance in a scene. They start by determining which image colors can take place under each of a set of probable lights.

The color constancy problem; that is how can discover an estimate of the unknown illuminant in a captured scene. They have shown a correlation framework to solve color constancy. The straightforwardness, flexibility, and sturdiness of this framework make solving for color constancy easy. A number of other formerly proposed algorithms were also positioned within the correlation framework, and others which, while they cannot be exactly...
formulated within the framework, were shown to be closely interrelated to it.

For a constant visual world, the colors[3] of objects should appear the similar under different lights. This property of color constancy has been assumed to be elementary to vision, and lots of experimental attempts have been made to enumerate it. So, does color constancy exist? Advancement has been made in quantifying the level, to which it might hold, but present measurement techniques remain unfinished, and their restrictions need to be made clearer.

The straightest method, color naming, might be enhanced by training subjects to use a superior vocabulary, but, without additional scales or ratings, it is improbable to attain the precision of similar procedures. Individually, the other two major methods, of asymmetric color matching and achromatic alteration, are not sufficiently specific to detecting changes in surface reflectance, but they might be when taken jointly. Is there a way, therefore, to merge them naturally into a single measure? This represents an interesting problem although the illuminant can only be predictable reliably in scenes with many surfaces, it is not understandable that surface color perception is different in scenes with just a small number of surfaces. Until that problem is determined or other specific measurement methods are devised, then whether color constancy exists, other than in nominal terms, will remain unverified.

A well known color constancy method [4] is based on the Grey World assumption i.e. the average reflectance of surfaces in the world is achromatic. The Grey Edge hypothesis assuming that the average edge difference in a scene is achromatic. Based on this hypothesis, they projected an algorithm for color constancy.

Color constancy[5] is the capability to compute colors of things independent of the color of the light source. A renowned color constancy method is based on the gray world assumption which assumes that the average reflectance of surfaces in the world is achromatic. A new theory for color constancy namely the gray edge hypothesis, which assumes that the standard edge difference in a scene is achromatic. Color constancy algorithms obtain equivalent results as the state of the art color constancy methods with the merit of being computationally more efficient.

In comparison to existing methods, which are based on zero order configuration of the image, their method is based on the higher order configuration of images. Furthermore, the outcomes show that color constancy based on the gray edge hypothesis obtains better outcome than those obtained with the gray world technique for real-world images.

Light, which is reflected from an object, varies with the kind of illuminant used. Nevertheless, the color of an object appears to be something like constant to a human observer. The ability to calculate color constant descriptors from reflected light is called color constancy. In order to solve the problem of color constancy, some assumptions have to be prepared.

Natural scenes regularly have multiple illuminants. A room may be illuminated by artificial light as well as reflected sunlight. Even if there is only a single illuminant, the intensity of the illuminant usually varies across the image. In order to calculate color constant descriptors from the calculated data, one has to estimate the illuminant locally for each image pixel. A simple yet very efficient method is the use of local space average color.

Images with color cast [7] have standard deviation of one color channel significantly different from that of other color channels. This observation is also valid to local patches of images and ratio of the maximum and minimum standard deviation of color channels of local patches is used as a prior to select a pixel color as illumination color.

A new technique use to achieve color constancy that is based on the statistics of images with color cast. The illumination estimation may not always be correct if noise is present as it may cause abnormal modification in the ratio of standard deviations. Preprocessing with denoising algorithms will solve this problem.

A color gradient [8] is presented with good color constancy preservation properties. The method does not need a priori information or variations in color space. It is naturally invariant to intensity magnitude, indicating high robustness against bright spots produced be specular reflections and dark regions of low intensity. It does not imply or need color segmentation, on the contrary can provide good color region split-up with little assumptions. It works on the RGB space, which the most common color processing space.
Computational color constancy purposes to estimate the actual color in an acquired scene disregarding its illuminant. Many illuminant estimation solutions have been suggested in the last few years, although it is known that the problem addressed is actually ill-posed as its solution lacks uniqueness and stability. To handle with this problem, different solutions usually exploit some assumptions about the statistical properties of the estimated illuminants and/or of the object reflectance in the scene.

Until now, most methods have been [11] based on physical constraints or statistical assumptions derived from the scene, whereas very little attention has been paid to the effects that selected illuminants have on the final color image representation. They describe the category hypothesis, which weights the set of possible illuminants according to their capacity to map the corrected image onto specific colors.

These color categories encode natural color statistics, and their relevance across different cultures is specified by the fact that they have received a common color name. From this category hypothesis, they suggest a fast implementation that allows the sampling of a large set of illuminants.

A fast implementation is simply defined by working in log space. Method is a purely bottom up method providing a framework for further combination with complementary visual information. Results have been attained without the need for a training step, as required in many other approaches. The suggested method can be enclosed within the family of statistical methods that estimates the illuminant by voting.

Color information [12] is a significant feature for many vision algorithms including color correction, image retrieval and tracking. The limitations of color measurement accuracy and explore how this information can be used to improve the performance of color correction. The notion of color strength, which is a combination of saturation and intensity information to define when hue information in a scene is reliable.

The principle advantage of the color strength model is that it can be used to estimate the reliability of the color information contained in a pixel. The color strength model can be used to expand the performance of many other algorithms which rely on hue information such as image retrieval by color, object tracking, and person re-identification.

Image enhancement [13] issues are addressed by analyzing the effect of two well-known color constancy algorithms in combination with gamma correction. Those effects are studied applying the algorithms separately and in combination. The performance of the approaches is evaluated comparing the Average Power Spectrum Value of the test images and their corresponding outcomes, as a quality measure. According to the experimental results, it is observed that the application of the gamma correction after a color constancy algorithm results in an improved image quality.

Gamma correction [13] illuminates dark areas in the image, allowing a more clearly distinction of colors. Gamma correction is mainly used in practical applications requiring a dynamic range correction, an effect that also color constancy produces. Image enhancement produced by a single algorithm, the combined application of a color constancy algorithm and afterwards the gamma correction, yields a better result. The use of gamma correction after a color constancy algorithm for dark image enhancement. Such improvement can be useful in a number of computer vision and image processing tasks.

An improved color constancy approach [14] is obtainable by considering the drawback of the well-known max- RGB algorithm: Only the unreliable maximum intensities are taken for illuminant estimation. In addition, to get better the color correction results on images lighten by multiple illuminants, soft clustering is performed to first divide the image pixels into a number of groups; the predictable illuminants of these groups are then joint for each image pixel specifically based on its membership values. The experiments on both the widely-used datasets and numerous web images show the efficiency of their approach.

III. GAPS IN LITERATURE

i. Edge based Color Constancy [13] will reduce the impact of the light thus may results in low brightness.

ii. The use of Non Local Mean [22] has been neglected by many researchers for Color Constancy algorithm

iii. Edge based Color Constancy [28] also may introduce Gaussian/random noise.
1. PROPOSED ALGORITHM

Fig 1. Proposed algorithm

Steps of proposed algorithm:

Step i: First of all digital image will be passed to the proposed algorithm and it should be Colored in nature. Because color constancy algorithms are only for colorful images.

Step ii: Now saturation points will be removed. The motivation is to remove the colors which are not required.

Step iii: Now estimation of colors will be done using grey edge hypothesis. Gray edge hypothesis will be calculated based upon the neighbors (4 or 8).

(a) The order n of the image structure is the parameter determining if the method is a gray-world or a gray edge algorithm.

(b) The Minkowski norm p which determines the relative weights of the multiple measurements from which the final illuminant color is estimated. A high Minkowski norm emphasizes larger measurements whereas a low Minkowski norm equally distributes weights among the measurements.

(c) The scale of the local measurements as denoted by sigma. For first- or higher order estimation, this local scale is combined with the differentiation operation computed with the Gaussian derivative. For zero-order gray-world methods, this local scale is imposed by a Gaussian smoothing operation.

Step iv: After this color normalization will be done using NLM. It will remove of effect of color light source. Given an image Y, the filtered value at a point p using the NLM method is calculated as a weighted average of all the pixels in the image following this formula

\[ NLM(Y(p)) = \sum_{q \in \mathcal{Y}} w(p, q) Y(q) \]  

Where p is the point being filtered and q represents each one of the pixels in the image. The weights w(p, q) are based on the similarity between the neighbourhoods Np and Nq of pixels p and q. Nj is defined as a square neighborhood window centered around pixel i with a user-defined radius Rsim.

The similarity w(p, q) is then calculated as:

\[ w(p, q) = \frac{1}{z(p)} e^{-\frac{d(p, q)}{h^2}} \]  

Step v: Adaptive histogram equalization will be come in action to improve the contrast in images.

With histogram equalization [30] the mapping function \( m(i) \) is proportional to the cumulative histogram

\[ m(i) = (DR) * \left( \frac{cumulative}{H(i)} \right) \text{range size} \]  

DR is display range whereas \( H(i) \) is histogram. Since the derivative of cumulative histogram is the histogram, the slope of mapping function at any input intensity i.e the contrast enhancement, is proportional to the height of the histogram at that intensity:

\[ \frac{dm}{di} = \frac{(DR/\text{regionsize}) * H}{H} \]  

Therefore, limiting the slope of the mapping function is equivalent to clipping the height of the histogram.
Now visualization of the result will be done and quantitative evaluation will be done.

IV. EXPERIMENTAL RESULT

The proposed algorithm is designed and implemented in MATLAB using image processing toolbox. This section contains the various experimental results.

Fig 2.1 input image

Fig 2.1 is showing the original image that is passed to the developed simulation in Matlab using image processing toolbox.

Fig 2.2 output of general grey edge 1.

Fig 2.2 shows the result of general grey edge 1. In this the maximum reflectance difference in a scene is achromatic. The root mean square, peak signal to noise ratio, normalized cross correlation value for this image is 0.2777, 59.2601 and 1.4715 respectively.

Fig 2.3 output of general grey edge 2

Fig 2.3 shows output of general grey edge 2. There is not much difference in output of general grey edge 1 and general grey edge 2 algorithm. In this the pth Minkowski norm of the second order derivative in a scene is achromatic. The root means square, peak signal to noise ratio, normalized cross correlation value for this image is 0.2715, 59.4557 and 1.4629 respectively.

Fig 2.4 Output using NLM edge based using 2nd order

Fig 2.4 shows the output using NLM edge using 2nd order. It basically removes the noise from the image. It is denoising algorithm. This technique work for the removal of noise and it give better result as compare to the previous denoising techniques that leads to the smoothing of image.

Fig 2.5 Output image

Fig 2.5 shows the output image after applying adaptive histogram equalization. This technique over amplify small amounts of noise in largely uniform regions of the image and used to get better contrast of the images. The root means square, peak signal to noise ratio, normalized cross correlation value for this image is 0.1971, 62.2373 and 1.3495 respectively. The value of root mean square decreases, peak signal to noise ratio value increases,
normalized cross correlation value also decreases which means the output is effective.

**Fig 3.1 input image**

Fig 3.1 is showing the original image that is passed to the developed simulation in Matlab using image processing toolbox. Image is red light infected image.

**Fig 3.2 output of General grey edge 1**

Fig 3.2 is showing the output of general grey egde1 with root mean square value 0.1966, peak signal to noise ratio 62.2578, normalized cross correlation 1.6747. General grey edge 1 works on 4 neighbors so it does give more effective result.

**Fig 3.3 output of General grey edge**

Fig 3.3 is showing the output of general grey edge 2 with root mean square value 0.1924, peak signal to noise ratio 62.4238 and normalized cross correlation value 1.6624. It works on 8 neighbors so it produces more effective result than general grey edge 1. As we can see from the values that they are more effective in case of general grey edge2 as compare to general grey edge 1.

**Fig 3.4 Output using NLM edge based using 2\(^{nd}\) order**

Fig 3.4 is showing the output using NLM edge based using 2\(^{nd}\) order. This algorithm is basically used for denoising which makes the image smoother.

**Fig 3.5 Output image**

Fig 3.5 is showing the output image which is obtained after applying adaptive histogram equalization with root mean square value 0.1473, peak signal to noise ratio 64.7650, normalized cross correlation value 1.5079. This balances the contrast of the image and make brighter. As we see from the values the resultant image is more effective than the above images.

## 2. PERFORMANCE ANALYSIS

This section contains the comparison among proposed and some state of art methods. As the proposed work has modified edge based color constancy therefore we have compared the proposed algorithm with the edge based color constancy algorithms.
Table 1.1 input image

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<th>Size</th>
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<tr>
<td>2</td>
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Table 1.1 is showing the sample images for experimental purpose.

Table 1.2 root mean square analysis

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<th>GGE2</th>
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<td>0.2585</td>
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Root mean square error is a difference between predicted values and observed values. It should be close to 1. As we see in the above table the rmse value for proposed algorithm is less as compare to value for general grey edge 1 and general grey edge 2 so the image is effective.

Table 1.3 peak signal to noise ratio analysis

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Peak signal to noise ratio is ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. Higher the psnr value, more effective is the image. It should be close to 100. In the above table the value of psnr is higher in proposed algorithm so the image is more effective.

Table 1.4 normalized cross correlation

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<tr>
<th>Image</th>
<th>GGE1</th>
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<th>Proposed</th>
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Normalized cross correlation is one error measure. It should be close to 1. The value of NCC is less for proposed
algorithm as compare to general grey edge 1 and general grey edge 2 as achieved by doing experiment on different images. So the images produce effective result.

Fig 4. Root mean square analysis

Fig 4. Shows graph of the root mean square analysis. The value root mean square should be close to 1. The value of rmse in proposed algorithm is less than value in general grey edge 1 and general grey edge 2. So the results are effective.

Fig 5. Peak signal to noise ratio analysis

Fig 5. Shows graph of the peak signal to noise ratio analysis. The value of peak signal to noise ratio should be close to 100. The value of peak signal to noise ratio of proposed algorithm is more than the value of general grey edge 1 and general grey edge 2 as shown in fig 5. So the results are effective.

V. CONCLUSION AND FUTURE WORK

This paper has proposed a modified edge based color constancy using non local means and the adaptive histogram equalization. The proposed algorithm has ability to reduce the uneven illuminate problem of edge based color constancy and also non-local means has produced sharper results. The proposed algorithm is designed and implemented in the MATLAB using image processing toolbox. The comparison among the modified edge based color constancy and the edge based color constancy has shown that the proposed algorithm is quite effective over the available methods.

In near future to enhance the results further we will modify the edge based color constancy further by using the fuzzy set theory to correct color in more efficient way.

REFERENCES
