A Novel Approach to Color Constancy using Vector Filtered Edge Weighting

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CERTIFICATE

I hereby certify that the work which is being presented in the thesis entitled, "*A Novel Approach to Color Constancy Using Vector Filtered Edge Weighting*", in partial fulfillment of the requirements for the award of degree of Master of Engineering in *Software Engineering* submitted in Computer Science and Engineering Department of Thapar University, Patiala, is an authentic record of my own work carried out under the supervision of *Mr. Amitava Das and Dr. Parteek Bhatia* and refers other researcher's work which are duly listed in the reference section.

The matter presented in the thesis has not been submitted for award of any other degree of this or any other University.

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ABSTRACT

Computer vision systems like human computer interaction, color object identification, image retrieval and image classification use the color features of the real world scene for computation. But the objects in real world appear to have variation in colors due to different colored illuminants, which place a serious challenge for computer vision systems to detect and characterize the objects. To solve this problem color constancy methods are incorporated in computer vision systems. Color constancy algorithms are used to estimate the color of illuminant and color correction is used to eliminate the illuminant effect.

In this work, various state-of-art algorithms have been studied with their pros and cons. These algorithms are compared using the angular distance between estimate illuminant and natural white illuminant. Effect of the various parameters on these algorithms has been studied to increase accuracy.

All the color constancy algorithms are based on assumptions about the real world scenes. To obtain the optimal solution for the problem of color constancy is impossible. Because real world scene change on run time, information present in image also change, so assumption working for one kind of scene may fail in other kind of scene. Therefore we cannot get complete optimal solution for this problem. In this research work an effort has been made to improve the results to decrease the angular error.

In this thesis, we proposed a new algorithm using vector filtered edge weighting, which is tested on sample images from a publicly available image data set. The experiments show that the proposed color constancy algorithm obtains better results than the current state-of-the-art color constancy methods. The proposed algorithm combines the weighted gray edge and the gray edge method to give 68.45% improvement in existing results.

Keywords: Color constancy, Illuminant estimation, specular edges, Vector Median Filter.

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CHAPTER 1: INTRODUCTION

The Human visual system is an incredible apparatus. Human eye provide us 3D view of the real world. Real world objects reflect light, reflected light is perceived by human eye then object is get recognized. Information processing initiates inside the human eye, but large part of processing is performed inside the human brain. Currently research work is going on to simulate human brain, some amount of work has been done but big challenges are yet to be solved.

Computer Vision is an ability of computers to perceive real world scenes. Human and computer interaction became easy with the help of computer vision. Colors plays very important role in many computer vision applications. Many tasks become easier if computer is able to perceive accurate colors of the objects. If correct colors of the object are recognized then it will be easy in color based object recognition. Let's take an example if one book is of green color and table is of red color, then we can recognize easily that these are two different objects. In this way, color features play very crucial role in identifying and differentiating two objects.

1.1 Digital Image processing (DIP)

A digital image is representation of a real world scene in 2-D format in finite set of digital values, called pixels and picture elements [14]. Pixel values are usually represented as grey values of colors. DIP focuses on two key areas:

1. Pictorial information is improved for human interpretation,
2. Image data processed for transmission, storage and depiction for autonomous machine perception.

To accomplish above mentioned key areas following image processing operations are performed on digital images:

- Image acquisition
- Image enhancement
- Image restoration

- Segmentation
- Object recognition
- Texture analysis etc.

1.1.1 Color Image processing

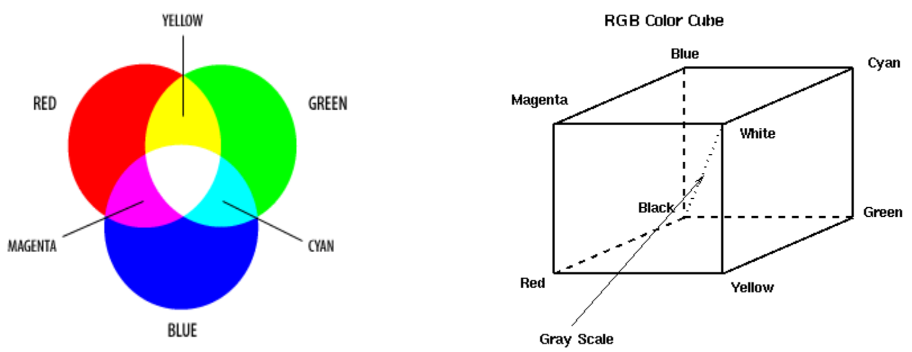
Color simplifies the object identification and extraction process. Colored image is a digital image that consists of color information in each pixel [1]. Camera uses color models to represent real world scenes, which stores large range of colors.

In uint8 image format, color of pixel is in the range of 0-255, lower value represents low intensity (black) and higher value represents higher intensity (white). In uint16 image format, color of pixel is in the range of 0-65535. In binary image format, there are two intensities in image 0, 1. Intensity 0 represent black color and intensity 1 represent white color.

Color models discussed as follow are the mostly used color models:

1.1.1.1 **RGB color model**

The RGB image is stored in the Red, Green and Blue channel. If the RGB image is 24-bit, each channel is of 8 bits [1]. In the following figure 1.1(a) RGB color space model in which primary colors are shown and combination of primary colors make secondary colors. In figure 1.1(b) RGB color cube is shown. As we can see in RGB color cube, the diagonal intensity values are in the range of 0-255, this line also known as grey scale in which only grey value can be represented.

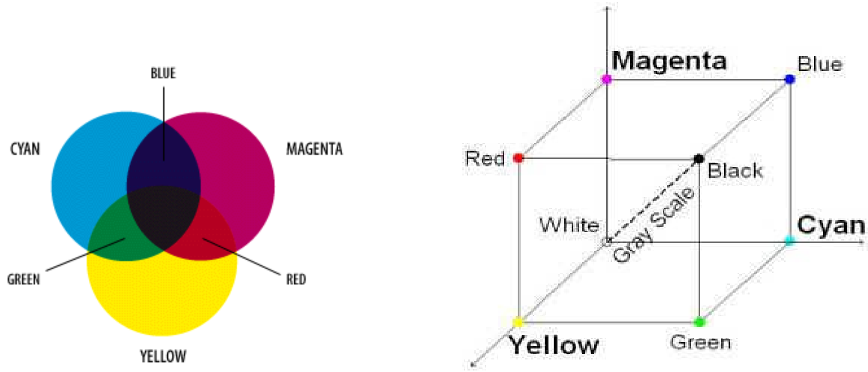


a [2], **b** [3]

Figure 1.1 (a) RGB color space model, (b) RGB color cube

1.1.1.2 **CMY color model**

The CMY image consists of cyan, magenta and yellow channels. These are secondary colors of light [1]. In the following figure 1.2 (a) depicts the secondary colors and combination of secondary colors gives primary colors. In figure 1.2(b) CMYK color cube is shown.

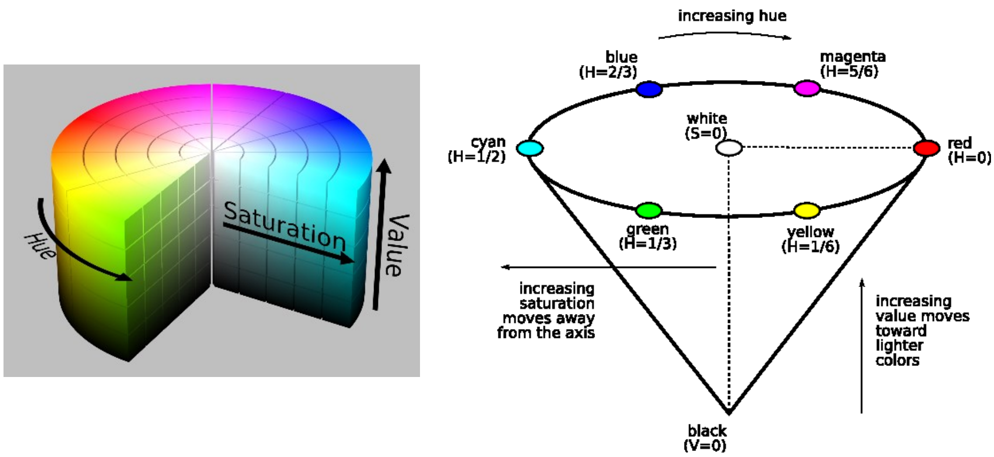


a [4], b [5]

Figure 1.2 (a) CMY color space model (b) CMY color cube

1.1.1.3 **HSV color model**

The HSV image consists of three channels: Hue, Saturation, and Value [1]. This model is used by people to choose specific color. Painters use this color model to pick up particular intensity. Figure 1.3(a) shows HSV color cylinder and figure 1.3(b) represent HSV color cone in which vertical line represents saturation, diameter represents saturation and perimeter represents hue values.



a [7], b [8]

Figure 1.3 (a) HSV color cylinder, (b) HSV color cone

1.1.2 Problems in Color image processing

A real world image consists of several colors and while acquiring an image, noise is added eventually. Noise is random variation in image colors and brightness information. The illuminations affect an image that type of noise is known as illuminant noise. Single and multiple illuminants can also affect the image. Illumination effect on scene changes the original colors of the object. Then computer perceives wrong colors of object when captured under different illumination effect. When single illuminant affect the image that is called uniform effect and when multiple illuminant effect on an image is called non-uniform effect. Color constancy is ability to remove the illuminant effect from the image and gives the standard colored image.

1.2 Color Constancy

Color constancy is the ability to identify colors of the objects independent from the external illuminant effect [1]. Human beings have innate ability to perceive original colors free from the illumination effect; Human visual system is color constant.

Figure 1.4 Various illumination effects on Scene, Natural Scene

Digital cameras and Computers are not color constant. Illuminant color effect the object appearance. Figure. 1.4 showing the various illuminant effect on the scene [6]. Color constancy is very essential preprocessing phase for colored images captured from real world for real time color- robust systems. In color robust systems which use color features to classify objects, if not using color constancy the computation for the classification of objects may go wrong.

Color constancy is prerequisite step for many computer vision systems. Color constancy helps to computer vision system to retain original colors of the objects. So that image classification, object recognition, image retrieval and object tracking can be done accurately.

1.3 Thesis Outline

Chapter 2 will offer a brief synopsis of the related literature in the field of color constancy. All the statics color constancy methods will be discussed in detail.

Chapter 3 will explain the reason why we address the problem of Constancy with the help of problem formulations and assumed hypothesis.

Chapter 4 will explain the methodological approach and design of experiment used for the proposed solution of color constancy.

Chapter 5 will present the results of proposed algorithm on SFU dataset and follow up with a discussion about the achieved results.

Chapter 6 presents the concluded recap of whole thesis followed by future scope.

CHAPTER 2: LITERATURE SURVEY

2.1 Color Constancy in Human Vision

Colors are very essential sign for color image processing and computer vision like interaction between human and computer, color feature extraction, and color models [13, 19]. Colors exist in image are determined by the surface of the object, intrinsic property of the object and colors of light source (illuminant). For robust color-based systems, the effect of the light source should be eliminated; this act of elimination of light source is called color constancy. Human vision has innate ability to perceive the original colors of the objects, independent from various light sources [20]. The method of perceiving the original colors by human eye is not fully understood. Initially the work for color constancy resulted in retinex theory by Land and McCann [21], later on various computational models were derived which were based on retinex theory [22-25]. Kraft and Brainard [26] explained that illuminant computation algorithms cannot fully simulate the human color constancy mechanism, there is still discrepancy between human eye and computational color models.

2.2 Image Formation

The Image $f = (f_R, f_G, f_B)^T$ formation for lambertian surface depends on three factors [12]:

- Color of light source $I(\lambda)$,
- Camera sensitivity function $\rho(\lambda) = \left(\rho_R(\lambda), \rho_G(\lambda), \rho_B(\lambda)\right)^T$,
- Surface reflectance $S(\lambda) = (x, \lambda)$;

Where λ the wave-length of light and x is spatial co-ordinate image is represented in 2.1 as follow:

$$\boldsymbol{f} = \int_{\omega} \boldsymbol{I}(\boldsymbol{\lambda})\boldsymbol{S}(\boldsymbol{\lambda})\,\boldsymbol{\rho}(\boldsymbol{\lambda})\boldsymbol{d\lambda} \qquad 2.1$$

Here we assumed that color of light source is uniform. The aim of color constancy is to observe the color of light source $e(\lambda)$, or its effect on color channels RGB. Observed color of light source $e(\lambda)$ depends on light source $I(\lambda)$ and camera sensitivity function $\rho(\lambda)$ represented in 2.2 as follow:

$$\boldsymbol{e} = (\boldsymbol{e_R}, \boldsymbol{e_G}, \boldsymbol{e_B})^{T} = \int_{\omega} \boldsymbol{I}(\boldsymbol{\lambda})\boldsymbol{\rho}(\boldsymbol{\lambda})\boldsymbol{d\lambda} \qquad 2.2$$

e is estimated color of light source, I is color is original light source. Without knowledge of $I(\lambda)$ *and* $\rho(\lambda)$, estimation of illuminant *e* is difficult. So there are various computations of illuminant based on various assumptions. White patch assumption, grey world assumption, gamut algorithm assumption etc. Based on these assumption color of light source is estimated.

2.3 Image Correction

The focus of this report is to estimate color of light source. However in many cases color of illuminant is less important than appearance of input image in canonical light source. Transformation of input image into canonical colors is linear transformation. This transformation is well thought as an instantiation of chromatic adaptation [13]. Linear transformation is done with the help of diagonal model [14]. This can be formulated in 2.3 as follow:

$$\boldsymbol{f_t} = \boldsymbol{D_{u,t}}\boldsymbol{f_u} \qquad 2.3$$

Where f_u is image taken under unknown light source, f_t is transformed image and $D_{u,t}$ is diagonal matrix, that maps color of unknown light source into corresponding canonical illuminant. It widely accepted color correction model [15-16]. When color of light source is estimate then its transpose is multiplied with original image then we get color corrected image. In this report perfect white light i.e.$\left(\frac{1}{\sqrt{3}}, \frac{1}{\sqrt{3}} \frac{1}{\sqrt{3}}\right)^{T}$, is assumed as canonical illuminant [17, 18].

2.4 State-of-art algorithms

Color constancy algorithms can be classified into three types:

- Pixel based color constancy
- Edge based color constancy
- Gamut based color constancy
- Learning based color constancy

In pixel based color constancy, the color of pixels is used to compute the color of illuminant. These algorithms can be applied on any image without need of training. In other words for various kind of images, the parameter setting will be remain static, same parameters value applied to all the images. In the edge based color constancy higher statistical value of the image are used to compute the color of illuminant. In third and fourth type of algorithms a model need to be trained for illuminant estimation. These methods determine the suitability of the parameters for the real world systems on run time.

2.4.1 Pixel based color constancy

Pixel based methods are based on assumption about the real world scenes. Pixel based algorithms are type of static algorithm because parameter setting remain constant irrespective to change in scenario. In the following sections well known pixel based algorithms are discussed.

2.4.1.1 **White Patch**

Well known White Patch method, based on assumption: *the maximum response in the RGB-channels is caused by perfect reflectance* [27]. Perfect reflectance surface will reflect the full range of color that it captures. The maximum color response given by the color channels is known as color of illuminant. In practice assumption of the white patch is changed by considering each color channel separately called max-RGB algorithm. Estimate the color of illuminant *e* from image (f_c) by taking maximum of each color channel separately depicted in 2.4 as follow:

$$\boldsymbol{max f_c(x) = k e_c} \qquad 2.4$$

Where f is the input image, c={R, G, B}*, k* is the multiplicative constant, chosen such that the illuminant color, e=$(e_R, e_G, e_B)^T$, has unit length.

2.4.1.2 **Grey World**

Another best and mostly used algorithm is Grey World algorithm, based on assumption: *the average reflectance in a scene under a neutral light source is achromatic* [28]. It states that any deviation from the acromaticity is caused by the illuminant color. This directly shows that color of light source *e* can be estimated by computing average color from the image(f_c) formulated in 2.5 as follow:

$$\int f_c(x)dx = ke_c \qquad 2.5$$

Where f is the input image, c={R, G, B}, e is illuminant color. Grey world algorithm can be used with the incorporation of segmentation in the input image. Using the grey world algorithm by segmenting the regions gives the improved results [30]. Because grey world algorithm is highly sensitive to the large uniform colors this often leads to failure of grey world algorithm. Segmentation preprocessing is useful in reducing the effect of large uniform colors, on each segment grey world algorithm can be applied separately.

2.4.1.3 **Local Averaging**

More related algorithms use smoothing step, to reduce the effect of noisy pixels in the image. In this way the accuracy of illuminant estimation can be increased. Gijsenij [29] proposed Color constancy by local averaging, use the Gaussian filter to smooth the image, so that effect of noisy pixels can be reduced.

2.4.1.4 **Minkowski norm framework**

Minkowski norm determines the relative weight of multiple measurements of image Finlayson and Trezzi [31], given the special instantiation of the white patch and grey world algorithm, in the more general minkowski-framework in 2.6 as follows:

$$l_c(p) = \left(\int f_c^p(x)\, dx\right)^{\frac{1}{p}} = ke_c \qquad 2.6$$

Where f is the input image, c={R, G, B}, e is illuminant color, p is known as the minkowski norm. For p=1, the equation act like grey world assumption. For p=Infinity, it act like white patch algorithm. p determines the relative weight of multiple measurements of image. p can be tuned for various data sets. Value of p can be decided for different datasets.

2.4.1.5 **Shades of grey**

Finlayson and Trezzi [31], given algorithm shades of grey based on assumption i.e. *the pth minkowski norm of scene is achromatic*. As given below:

$$\left(\int |f(x)|^p dx\right)^{\frac{1}{p}} = ke \qquad 2.7$$

The assumption of Shades of grey algorithm is based on the distribution of the pixel values that present in image.

2.4.2 Edge based color constancy

In edge based color constancy, the edges information is accessed to compute the color of illuminant, because edge information gives the valuable cue about the color of illuminant. In the following section various edge based color constancy algorithms will be discussed.

2.4.2.1 1st and 2nd Order Grey Edge

Weijer et. al. [32], proposed the incorporation of image derivative or higher order image statistics called Grey Edge method. Based on assumption i.e. *the pth minkowski norm of image derivative in a scene is achromatic.* This method based on 1st order and 2nd order of image derivative. Grey edge framework is given in 2.8 as follow:

$$\boldsymbol{e}^{n,p,\sigma} = \left(\int \left| \frac{\partial^n \boldsymbol{f}_{c,\sigma}(\boldsymbol{x})}{\partial \boldsymbol{x}^n} \right|^p \boldsymbol{dx} \right)^{\frac{1}{p}} = \boldsymbol{k}\boldsymbol{e}_c \qquad 2.8$$

where f is the input image, c={R, G, B} and the three important parameters are: n that determines the order of derivative of image, p (minkowski norm) that determines the relative weight of multiple measurements of image and σ determines the order of smoothening operation performed on image.

2.4.2.2 Max-edge

Weijer et. al [32] given Max-edge assumption i.e. *the maximum reflectance difference in scene is achromatic.* This method represented in 2.9 as follow:

$$\left(\int |\boldsymbol{f}_x^\sigma(\boldsymbol{x})|^\infty \boldsymbol{dx} \right)^{\frac{1}{\infty}} = \boldsymbol{ke} \qquad 2.9$$

1st order derivative structure of image is computed and then maximum response is considered as color of illuminant.

2.4.2.3 Weighted Grey Edge method

An extension of grey edge method is given by Gijsenij et al. [18], different kinds of edges exit in real world. All of them contains different amount of information. They extended grey edge method that assign different weight to different edges according to information of the edges called weighted grey edge method. Then weighted grey edge framework is given by 2.10 as follow:

$$\left(\int \left|w(f)^{k} f_{c,x}(x)\right|^{p} dx\right)^{\frac{1}{p}} = ke_{c} \qquad 2.10$$

Where w(f) is the weighing function, weight assigned to edges, k is constant used to enforce the weight of the edges.

Bianco et al. [38] performed adaptive color constancy on face images using grey edge assumptions algorithm.

Performance of edge based algorithms depends on input image. If image contains medium or high edge information the edge based algorithms gives accurate results. Accuracy also depends on the signal to noise ratio of the image if signal to noise ratio is high then edges based methods will give best results. On the other hand when edges information and signal to noise ratio is low then pixel based methods gives best results [17].

2.4.2.4 **Grid based sampling in Grey Edge**

In color constancy algorithms it is assumed that scene in illuminant by single source of illuminant. But it is not the case in real world scenarios, because real world scenes are illuminated by multiple sources. Singh et al. [32] improved the edge based color constancy using grid based sampling. In grid based sampling, every grid is considered separately and color of illuminant is computed by all grids. In this method author has used bilateral filter for more promising results from the algorithms.

2.4.3 Gamut based color constancy

Forsyth [33] introduced gamut based color constancy algorithm. Gamut mapping is based on assumption that *only a limited number of colors can be recognized in a particular illuminant*. The limited set of colors that can be recognized under a given illuminant is known as canonical gamut. This algorithm consists of three main steps:

1. Gamut of input image is computed by considering that colors present in input image are gamut of input image.

2. Determine set of all feasible mappings that can be used to transform input gamut to canonical gamut.
3. Estimator is used to determine the best mapping to transform input image gamut to canonical gamut.

Various extension of the gamut mapping algorithm proposed to improve the estimation of canonical gamut. One heuristic approach used to increase the canonical gamut size by 5%. Finlayson [34] extend the gamut by 5%, whereas Barnard [35] enlarges the size of canonical gamut by considering different surface that are captured under different light sources, in which diagonal mapping is used to map input gamut to into canonical gamut.

Finlayson [36] a diagonal offset model was proposed to avoid null solution found in the diagonal models. With the simple linear transformation, the translation of input colors is used in diagonal offset model to eliminate null solution.

Gijsenij et al. [37] proposed an extension to the gamut mapping. In this derivative structure of image was used to avoid null solutions.

2.4.4 Learning based color constancy

Learning based color constancy used artificial intelligence to estimate the illuminant. These methods are trained using the appropriate dataset set during training phase. The initial approaches in learning based method were based on neural networks, in which histogram of input image is input to neural networks [39]. This method gives the color of illuminant as output. None of the color constancy algorithm is universal. No method gives promising results for different type of datasets.

Bianco et al. [40] used the intrinsic low level properties of image to improve the illuminant estimation technique. These properties helped to choose best algorithm for given set of algorithm to accurately estimate the illuminant. The best algorithm selection made using decision forest tree.

Dongliang Cheng et al. [41] estimated the illuminant for achieving color constancy and explained the working of spatial domain methods and role of the color distribution. In this study, bright and dark pixels were chosen using a projection distance in the color distribution and then PCA was applied to estimate the illumination direction.

Negrete et al. [42] presents a fuzzy rule based system to select the appropriate algorithm to enhance the dark images. In this work system mainly uses three algorithms: white patch, grey edge and grey world for computation. Fuzzy rule based system given 77 % accuracy in selection of appropriate algorithm.

2.5 Comparison of State-of-art algorithms

	White Patch	**Grey World**	**1st Order Grey edge**
Assumptions	The maximum response in the RGB-channels is caused by perfect reflectance.	The average reflectance in a scene under a neutral light source is achromatic.	The *pth* minkowski norm of image derivative in a scene is achromatic.
Key operation	Max of the individual RGB color channels.	Average of the individual RGB color channels.	1st order derivative of the image.
Type of scene	The White-Patch algorithm will perform best when the pixel values in the image have generally high intensity.	The Grey-World algorithm will be affected by the presence of large parts of (roughly) non uniform colors.	1st order edge based algorithm will work best where Edge information is clear.
Minkowski norm	∞	1	5
Derivative order	0	0	1
Smoothening value	0	0	2

Table 1 Comparison of white patch, Grey world, 1st order grey edge methods.

In table 1 and table 2 comparison of state-of-art algorithm is done. Along with their parameter values.

	2^{nd} order grey edge	Max Edge	Shades of grey	Weighted edge
Assumptions	The *pth* minkowski norm of image 2^{nd} order image derivative in a scene is achromatic.	The maximum reflectance difference in scene is achromatic.	The pth minkowski norm of scene is achromatic.	Different types of edges have distinctive influence on the performance of illuminant estimation.
Key operation	2^{nd} order derivative of the image.	Max reflectance of the 1^{st} order image derivative.	pth minkowski norm of the image.	Assign weights to edges according to their influence.
Type of scene	2^{nd} order edge based algorithm will work best where Edge information is clear.	Max edge based algorithm will work best where Edge information is clear.	Shades of grey will perform best when average color is grey or maximum is white.	Weighted grey edge method work for highlighted edge information.
Minkowski norm	5	∞	5	2
Derivative order	2	1	0	2
Smoothening value	2	4	0	4

Table 2 Comparison 2^{nd} order grey edge, max edge, shades of grey and weighted grey edge methods.

2.6 Application of Computer Vision Systems

There are several applications in computer vision which are using color features of the image for computation, i.e. Color based object recognition, Image retrieval, Image classification and Object tracking [9-11].

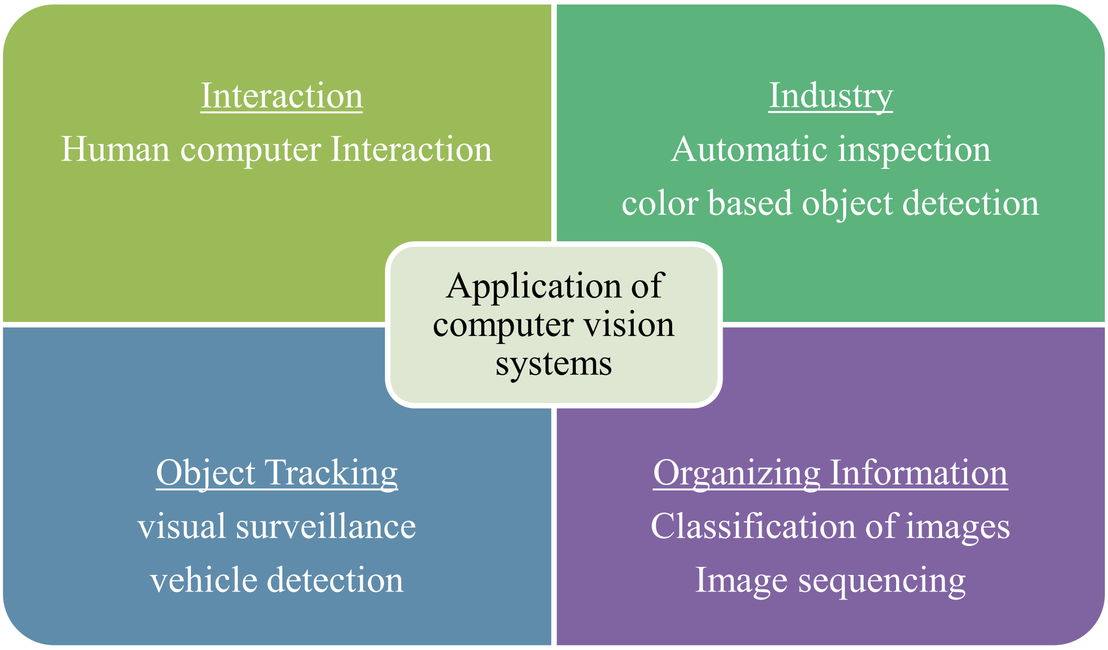


Figure 2.1 Applications of Computer Vision System

2.7 Summary

In this chapter we discussed the taxonomy state of art algorithms in which pixel based algorithms, edge based algorithms, gamut mapping and learning based algorithms were explained with their different variations.

CHAPTER 3: PROBLEM FORMULATION AND HYPOTHESIS

In this chapter, we will discuss hurdles to solve the problem of color constancy and we will formulate hypotheses to solve the problem.

3.1 Problem Formulation

Colors play very important role in real life to identify and classify objects. Human eyes are inherently able to easily perceive right intensities of colors from the real world scene called color constancy. To incorporate this ability in computer vision systems we use color constancy algorithms. There are wide range of applications in which computer vision system use color features to identify the objects.

Color constancy is very challenging problem for computer vision systems. This problem may be solved by analyzing and estimating the various effects on real world scenes i.e. illuminant effect and noise effect. Noise effect can be eliminated so that color information can be preserved. Illuminant estimation problem can be solved by making various kinds of assumptions about the scenes as discussed in chapter 2.

In this work a novel algorithm has been proposed which effectively removes noise from the image as well as preserves the color fidelity and correctly estimates the illuminant so that higher accuracy can be achieved.

3.2 Gap Analysis

For the problem of color constancy, there is no such algorithm has been proposed which can give completely accurate results. Color constancy is under constrained problem which cannot be solved without making assumptions. All the solutions that are present so far are based on assumptions about the scenes. So it is fairly conclusive that this problem will remain under constrained. In research work the focus is to improve the accuracy of the illuminant estimation, so that the original colors can be recovered.

3.3 Hypothesis

The objective is to accurately estimate the color of illuminant. The hypothesis for the thesis is as follows:

Hypothesis 1: Spectral edges or highlights are used to estimate the illuminant color.

H01: Spectral edges or highlights information will accurately estimate the illuminant color.

HA1: Spectral edges or highlights information will not accurately estimate the illuminant color.

Hypothesis 2: Vector median filter is used to improve the illuminant estimation.

H02: Vector median filter will significantly improve the accuracy of the illuminant estimation.

HA2: Vector median filter will not significantly improve the accuracy of the illuminant estimation.

Summary

In this chapter formulation of problem and hypotheses for the proposed method are stated. In next chapter methodology and design of experiment will be explained.

CHAPTER 4: METHODOLOGY AND DESIGN OF EXPERIMENTS

In this chapter we will discuss the complete Methodology, Design of experiment, complexity analysis and programming environment of the novel proposed algorithm.

4.1 Methodology

In section, step by step methodology of proposed algorithm has been explained. To conclude the hypotheses stated in chapter 3, the following fig 4.1 show the complete methodology:

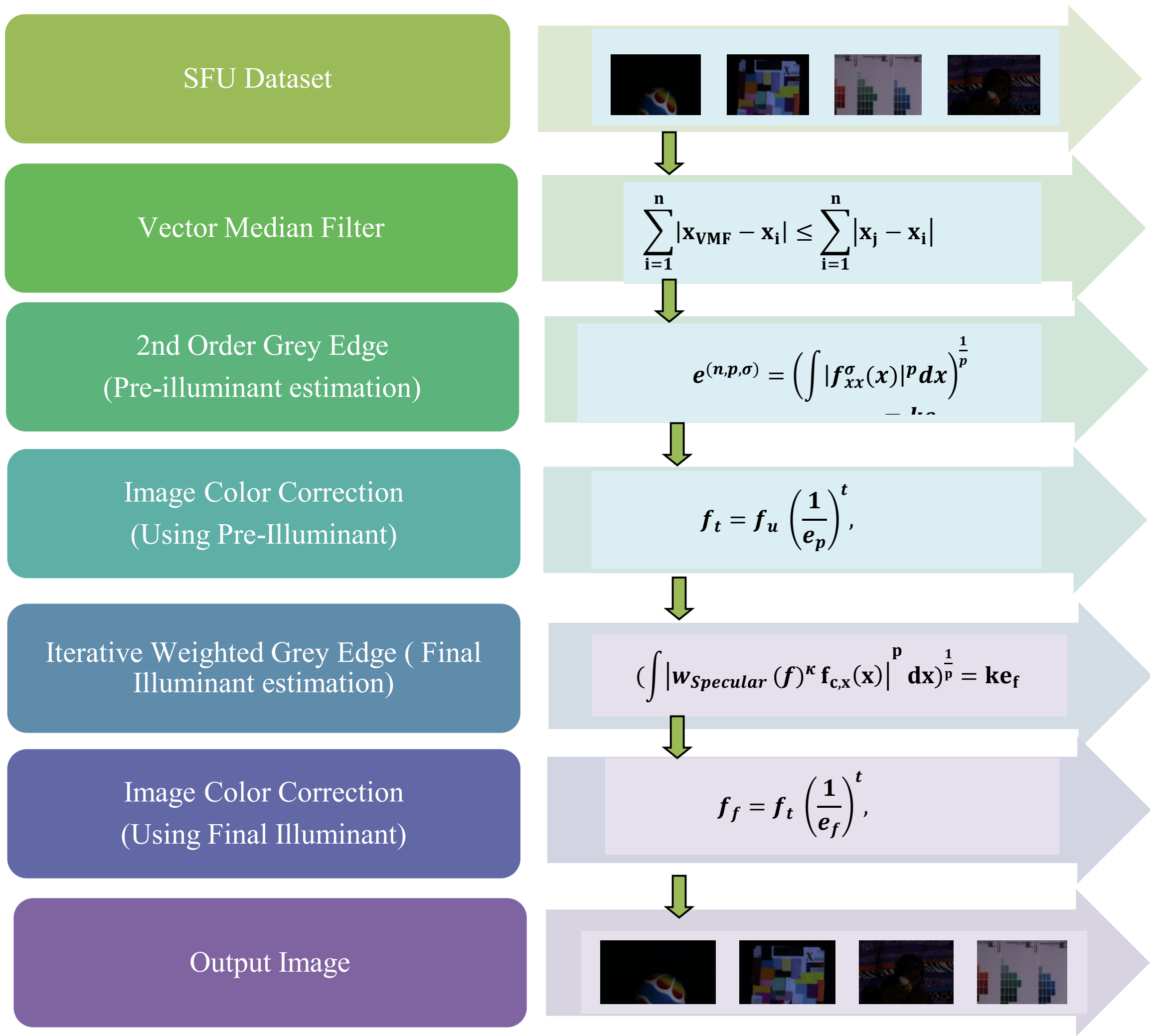


Figure 4.1 Block Diagram of Complete Methodology

4.1.1 SFU Dataset:

The proposed algorithm has been tested on SFU dataset [43]. This dataset is indoor controlled dataset which contains the images with minimal secularity and non-negligible di-electric secularities. Minimal secularity images contains no highlights and non di-electric secularities images contains some highlights since these are indoor images the illuminant is completely artificial. Some examples images are shown in Fig 4.2.

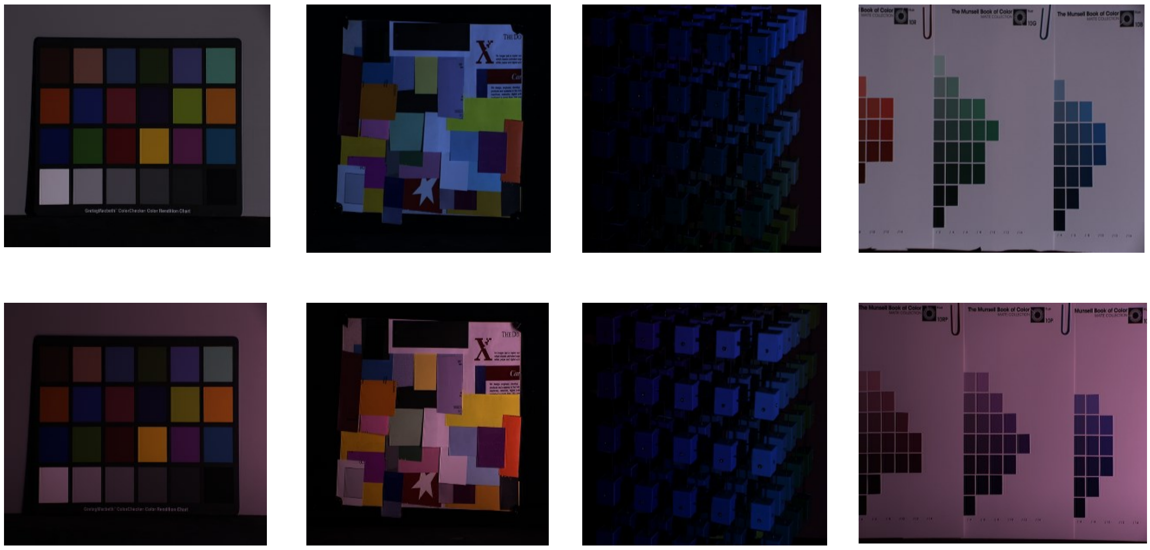


Figure 4.2 SFU dataset example images in different illuminants.

4.1.2 Vector Median Filter:

A vector median filter is generally used to discard the impulses and preserves the edges and details in the image. Vector median filter is used for color images. Vector median filter consider RGB color channels in combination. This 3-D vector filter has the following form as shown in 4.1 and 4.2:

$$x_{VMF} \in (x_i, i = 1, 2, \ldots, n) \qquad 4.1$$

$$\text{With } \sum_{i=1}^{n} |x_{VMF} - x_i| \le \sum_{i=1}^{n} |x_j - x_i| \qquad 4.2$$

Vector Median filter (VMF) basically orders the input pixel vectors according to their relative magnitude differences inside the processing window using the Minkowski metric as a distance measure. L1 (Manhattan distance) and the L2 (Euclidean distance) norms are most widely used distance measures.

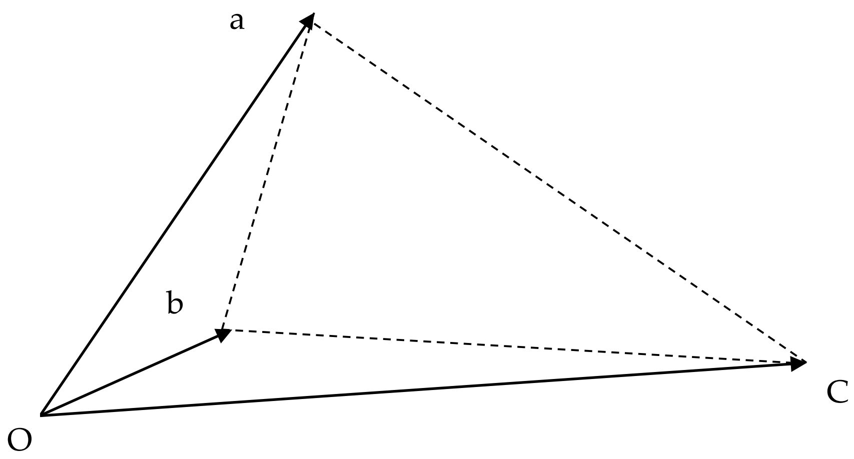


Figure 4.3Three vectors a, b, c

The Vector median filter depends on the choice of the minkowski norm ,in Figure 4.3 if we choose minkowski norm L2 and median point *a*, because the Euclidean distance between *a* to *c* is smaller than b to c. For the minkowski norm L1 distance between a to c is larger than b to c because the vertical distance from a to b is larger than the horizontal distance [44].

In the proposed algorithm, vector median filter is used to preserve the edges in the input image by taking the vector median of a region around each pixel, and as this region gets filtered in each iteration, the pixel color vector that is at minimum deviation from the nearby color vectors are selected. The advantage of using this operation lies in the fact that there are no chromatic shifts near the edges which causes loss of color fidelity. This vector based operation enhances the edges information that will affect the illuminant values estimated from the sample image.

4.1.3 2nd Order grey edge method (Pre-illuminant estimation):

2nd order Grey edge method is based on the 2nd order Grey Edge assumption, this states that *pth minkowski norm of the 2nd order derivative reflectance of the image is achromatic* [31]. This framework is depicted as follow :

$$e^{(n,p,\sigma)} = \left(\int |f_{xx}^{\sigma}(x)|^{p} dx\right)^{\frac{1}{p}} = ke_p \qquad 4.3$$

Where n is the order of derivative, p is minkowski norm, σ is the smoothing factor, f(x) is the input image preprocessed by vector median filter, e_p is the pre-illuminant which will be used to color correct image. In 2nd order grey edge method order of derivative is 2 which precisely give the edge information. Edges give the important cue for estimating the color of illuminant, by taking the derivative of the image edges information is extracted from the image. Illuminant is estimated by taking the average of the extracted edge information.

In the proposed algorithm, 2nd order Grey Edge method is used to estimate pre-illuminant. Pre-illuminant is used to color correct image before estimating the final illuminant. This step shift color towards the original colors, which leads to significantly improvement in final results.

4.1.4 Image Color Correction (using pre-illuminant e_p):

The main objective of color constancy algorithm is to shift color of the image to unknown light source to known light source, called linear transformation. This transformation of colors toward the original color is an instantiation of chromatic adaptation [14]. In the proposed algorithm image processed by vector median filter is color corrected using pre-illuminant estimate by 2nd order Grey Edge method. Linear transformation is done with the help of estimated illuminant formulated in 2.4 as follow [5]:

$$\boldsymbol{f_t} = \boldsymbol{f_u}\left(\frac{\boldsymbol{1}}{\boldsymbol{e_p}}\right)^{\boldsymbol{t}} \qquad 4.4$$

Where f_u is image taken under unknown light source, f_t is transformed image and e_p is the estimated pre-illuminant, that maps color of unknown light source into corresponding canonical illuminant. It widely accepted color correction model [14-16]. This Color corrected image will become input image for weighted grey edge method. Perfect white light source $\left(\frac{1}{\sqrt{3}},\frac{1}{\sqrt{3}},\frac{1}{\sqrt{3}}\right)^T$ is assumed as Canonical light source or known light source which is used to compare the estimated illuminant [17, 18].

4.1.5 Iterative Weighted Grey Edge (Final Illuminant estimation $\boldsymbol{e_f}$):

Edge based color constancy use the image derivative to find the illuminant. But there exist different types of edges like:

1) Material edges,

2) Shadow edges,

3) Highlighted (Specular) edges.

Material edges are caused by two different objects and surfaces. Shadow edges are shadow of the object which is caused by obstruction of light source by the objects. Specular edges are present because of highlights. All of them contains different amount of information. The proposed algorithm emphasize on specular edges or highlights because highlights or specular edges give the most valuable cue for illuminant estimation [45-47]. In the proposed algorithm specular edges type is used to estimate final illuminant. The framework weighted grey edge algorithm using the specular edge information is given by 4.5 as follow:

$$\left(\int \left| w_{\mathrm{Specular}}\,(f_t)^{\kappa}\, f_{t,x}(x) \right|^{p} dx \right)^{\frac{1}{p}} = k e_f \qquad 4.5$$

Where $w_{Specular}\,(f_t)^k$ is the weighing function for specular edges, κ is constant used to enforce the weight of the edges (more the value of k more will be emphasize on higher weight) c is the R, G, B color channels and e_f is final illuminant.

4.1.5.1 **Weighing scheme for specular edges:**

To design the weighting scheme for edges the quasi invariants are used, which results in an incorporation of weighing scheme in grey edge method [48]. Specular edges provide valuable information that’s why these are used to estimate the final illuminant. Quasi invariants are calculated using the image derivative as shown in 4.6:

$$\boldsymbol{f}_x = (\boldsymbol{f}_{R,x}, \boldsymbol{f}_{G,x}, \boldsymbol{f}_{B,x})^{\ \boldsymbol{T}} \qquad 4.6$$

These are three photometric variants. Elimination of these three photometric variants from the image, quasi invariants are computed. Derivative of image is decomposed into three directions by quasi invariants [18]. The projection of image derivative in specular direction is known as specular variants, is defined as 4.7:

$$\boldsymbol{O}_x = (\,\boldsymbol{f}_x.\hat{\boldsymbol{c}}^i)\hat{\boldsymbol{c}}^i \qquad 4.7$$

Where O_x is the specular variants, $\hat{c}^i$is the color of light source is assumed to be white$\left(\frac{1}{\sqrt{3}}, \frac{1}{\sqrt{3}}, \frac{1}{\sqrt{3}}\right)^T$ and dot denotes the vector inner product. Elimination of specular variants from the input image results in specular quasi- invariants is shown below in 4.8:

$$\boldsymbol{O}_x^t = \boldsymbol{f}_x - \boldsymbol{O}_x \qquad 4.8,$$

The edge is specular or not is computed using the ratio of energy in specular direction and total amount of image derivative energy. This ratio results in following 4.9 specular weighing scheme:

$$w_{specular}(\boldsymbol{f}_x) = \frac{|\boldsymbol{O}_x|}{||\boldsymbol{f}_x||} \qquad 4.9,$$

where $w_{specular}$ is the specular weight of image (f_x) , $|O_x|$ is the absolute value of O_x and $||f_x|| = \sqrt{f_{R,x}^2 + f_{G,x}^2 + f_{B,x}^2}$.

4.1.6 Image Color Correction (Using Final Illuminant):

Using the iterative weighted grey edge method final illuminant (e_f) is computed as shown in 4.10. Now transformation of f_t image is done using the following equation

$$\boldsymbol{f}_f = \boldsymbol{f}_t \left(\frac{\boldsymbol{1}}{\boldsymbol{e}_f}\right)^t \qquad 4.10,$$

where f_f is the final output image.

4.1.7 Output Image:

Image correction using the final illuminant gives the final output image f_f , which is used by computer vision systems in many application like human computer interaction, color image classification and color object detection by computing the color features and color models.

The performance measure is done using the angular error, which is discussed in next sections. Angular error is angular distance between natural illuminant and estimated illuminant from the proposed algorithm

Above discussed complete methodology is used in proposed algorithm to give significant improvement in results as compare to state of art algorithms. . This method comprises the enhancement of edges in image thereby the distribution of the color derivatives from such images exhibits the largest variation in the light source direction. This will assist the grey edge method by using second order derivatives to approximate this direction. For improvement in this approximated illuminant, the corrected image using this prior estimated illuminant is used for updating weights iteratively till an increase in the accuracy of the illuminant is achieved.

The proposed algorithm used vector filter and edge weighting information to compute the color of illuminant. So we named proposed algorithm vector filtered edge weighing color constancy.

4.2 Design of Experiment

4.2.1 Dataset Selection

The proposed vector filtered edge weighing algorithm basically access the edges information present in image to estimate the color of illuminant. As we discussed the importance of specular edges in estimating the color of illuminant, we carefully selected the SFU laboratory dataset to perform the experiment [43]. SFU dataset is used by many researchers [17, 18, 32] to validate their results that's why we will use SFU laboratory dataset, so that we can validate and compare our results with state of art algorithms. Figure 4.2 shows some example images, various objects captured under different light sources to access the effect of light source on the performance of algorithm.

4.2.2 Performance measure (Angular Error)

The performance evaluation of the proposed vector filtered edge weighing algorithm and its comparison with the state-of-the-art color constancy methods was carried out using angular error measurements on a set of 50 images of SFU dataset [43]. The color constancy algorithms were implemented using image processing toolbox available in Matlab [49]. The correct color of the light source e_l (ground truth) is known *a priori* for all images in the dataset. The dot product of the estimated color of the illuminant e_e and the ground truth e_l , $(\hat{e_l} . \hat{e_e})$ is used to determine the angular error [17,18,32] using the formula in 4.11 as follow:

$$\boldsymbol{angular\ error} = \boldsymbol{cos^{-1}}(\hat{\boldsymbol{e_l}}.\hat{\boldsymbol{e_e}}) \qquad 4.11$$

Perfect white light i.e. $e_l = \frac{1}{\sqrt{3}}(1,1,1)^T$ illuminant is used as color of light source (ground truth) [3, 8].

4.2.3 Influencing Parameters

This experiment was performed to achieve the higher accuracy in illuminant estimation. The performance of proposed algorithm is influenced by the following parameters:

1. Order of derivative structure of image (n),
2. Smoothening parameter sigma (σ) ,
3. Minkowski norm (p) used to emphasize the measurements,
4. Value of kappa (κ) used to enforce the weight of edge type used in iterative weighted grey edge method.

Derivative structure of the image gives the edges information of the image. Higher order derivative structure gives accurate estimation of the color of illuminant. Smoothening parameter sigma helps to eliminate noise effect from the image that affects the color of illuminant. Minkowski norm is used to emphasize the measurements of derivative structure of the image. Value of kappa is used to enforce the weight of highlight edges present in image.

The experiment is performed on proposed algorithm to decide the optimal values of above discussed parameter for the SFU dataset. The experiment is performed iteratively so that optimal values of influencing parameters can be decided. The design of experiment for influencing parameters is shown in following figure:

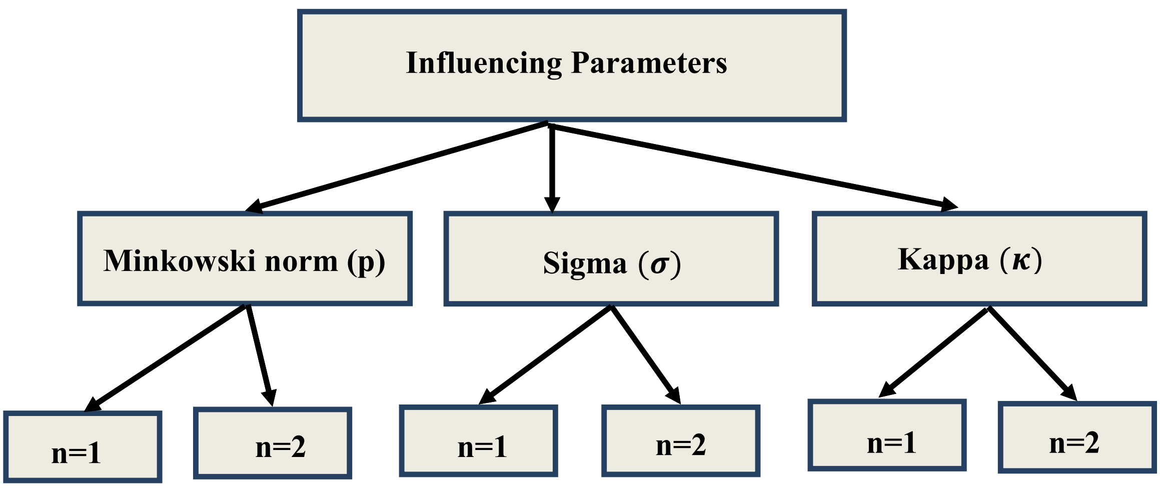


Figure 4.4 Influencing Parameters

In the above figure 4.4, various parameters that influence the performance of proposed algorithm are shown. Experiment was performed by taking all the combinations of influencing parameters. Derivative structure of the image highly impacts the performance of proposed algorithm. In the following graphs we will see the effect of higher order derivative structure with all the influencing parameters.

4.2.3.1 **Variation in Minkowski norm with order=1**

In the proposed vector filtered edge weighing, the optimal values minkowski norm with order=1was decided by comparing the variation in minkowski norm with constant derivative order=1. From figure 4.5 we can easily make out that angular error with respect to minkowski norm variation with derivative structure of image order=1.

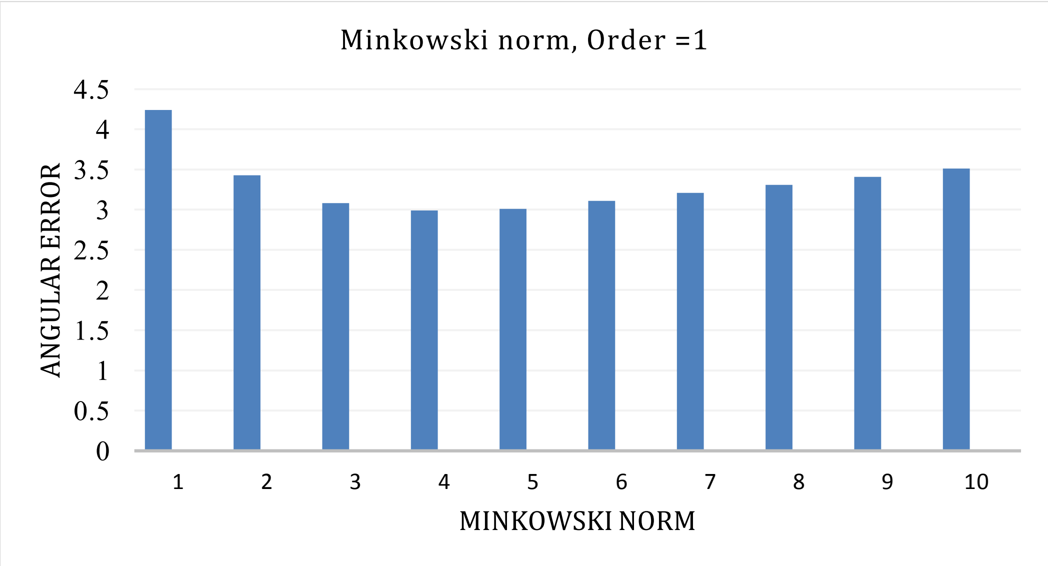


Figure 4.5 Effect of variation in Minkowski norm and Order =1

From the figure 4.5, the fall in angular error in left middle portion of the graph. At minkowski norm = 4 the angular error = 2.99 when derivative structure=1.

4.2.3.2 **Variation in Minkowski norm with order=2**

Higher order derivative structure of image give significantly fall in angular error, because 2nd order of derivative precisely access the edge information and gives the accurate illuminant estimation.

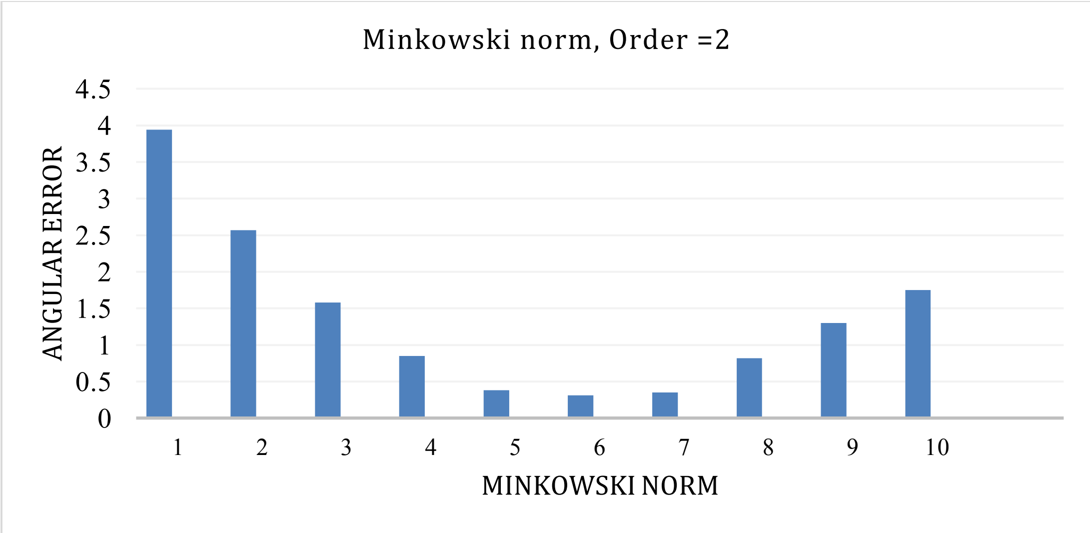


Figure 4.6 Effect of variation in Minkowski norm and Order =2

The figure 4.6 depicts decrement in angular error in the middle portion of the graph. From the figure 4.6 the minkowski norm=6, Order=2 gives minimum angular error = 0.31, which is most accurate estimation of color of illuminant.

4.2.3.3 **Variation in Sigma Value with order=1:**

Sigma is smoothening parameter in the proposed algorithm that removes the extra noise effect from the image and helps to accurately estimate the color of illuminant.

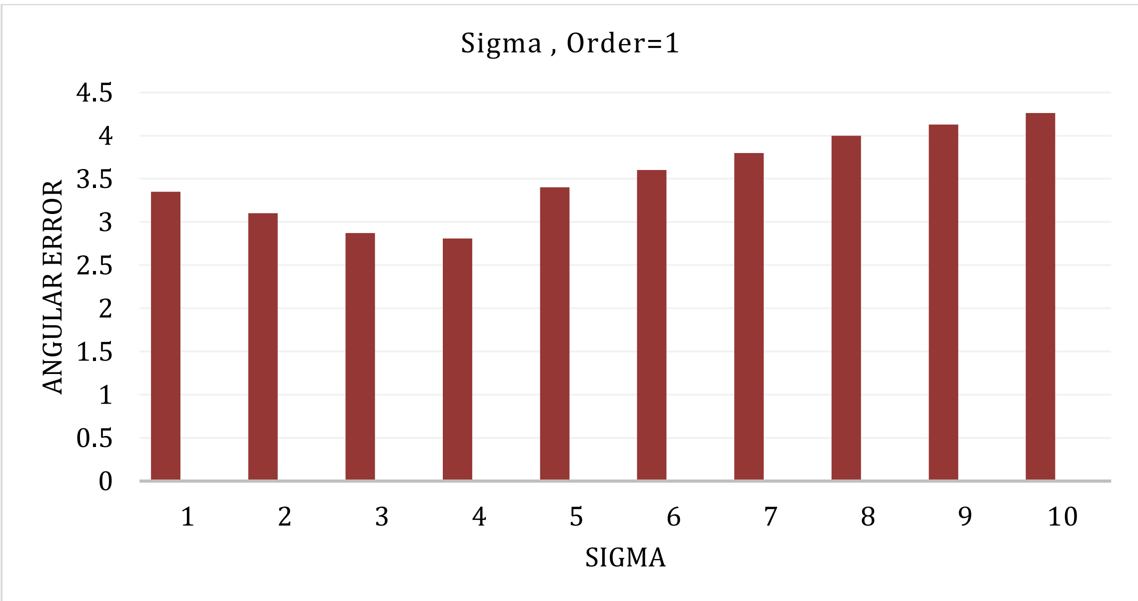


Figure 4.7 Effect of variation in Sigma and Order =1

From the fig 4.7 sigma=4 and order =1 gives the minimum angular error=2.8. As we can see in figure 4.7, optimal sigma=4, if we increase the sigma value it start to eliminate edge information which results in increase in angular error consistently.

4.2.3.4 **Variation in Sigma Value with order=2**

2nd order derivative structure of image outperform over 1st order derivative structure. Figure 4.8 depicts that order=2 of image significantly fall the angular error value. A higher order derivative structure of image minutely takes the edge information and gives the minimum angular error.

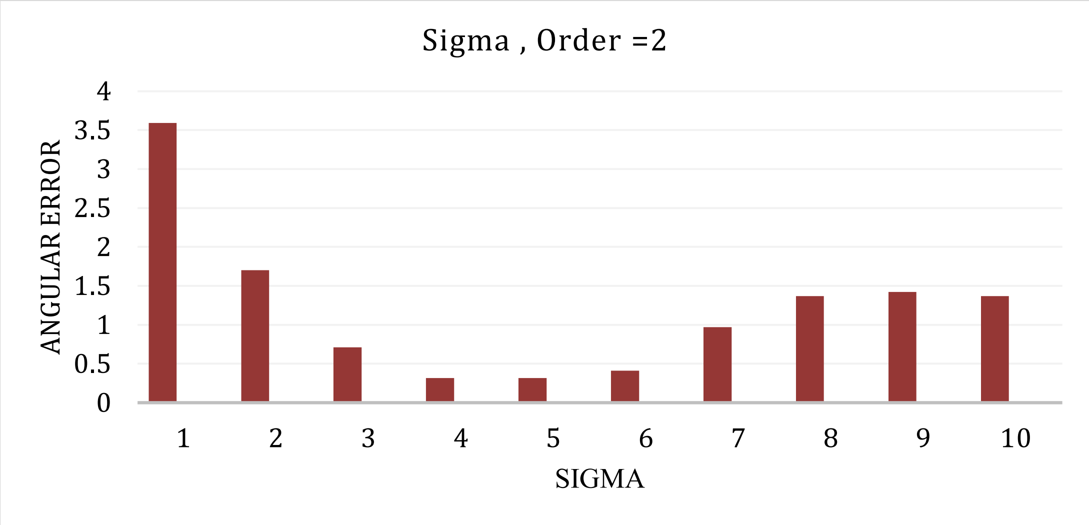


Figure 4.8 Effect of variation in Sigma and Order =2

The fig 4.8 depicts the sharp fall in angular error as we increase the sigma value. After sigma=4, angular error start increasing slowly. For order =2 of image the sigma =4 is the optimal value which results in angular error = 0.31.

4.2.3.5 **Variation in Kappa Value with order=1**

In the proposed algorithm value kappa is used to enforce the weight of specular edges of the image. Higher value of Kappa put more emphasize on higher weight of edge information. As discussed in iterative weighted grey edge method higher value of kappa more emphasize on higher weighted edges of the image.

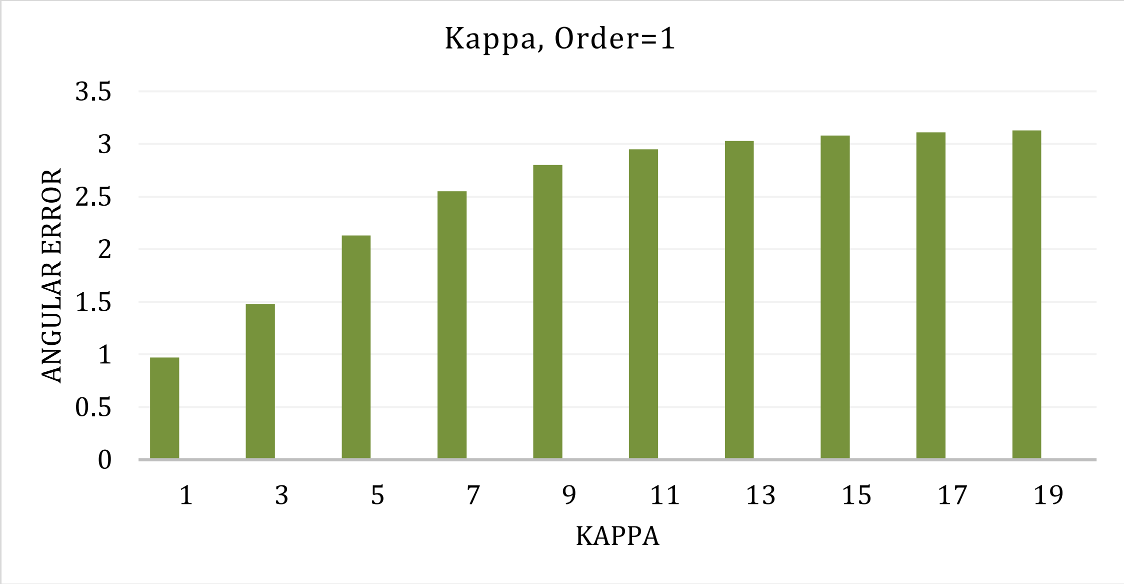


Figure 4.9 Effect of variation in Kappa value and Order =1

Figure 4.9 depicts the low value of kappa for 1st order derivative structure of image will give less angular error. For the 1st order derivative structure of image kappa=1 gives the minimum value of angular error= 0.97, this is the highest accuracy achieved using kappa parameter.

4.2.3.6 **Variation in Kappa Value with order=2**

With the parameter kappa, we can make the same inference that higher order derivative of image significantly improve the accuracy of illuminant estimation. Higher the kappa value higher emphasize on weight of specular edges. In the following figure 4.10 we can see the sharp fall in angular error as we increase the kappa value. At kappa =17 there is minimum angular error=0.31. After kappa=17 the angular error starts increasing slowly. Hence optimal value of kappa for 2nd order image is 17.

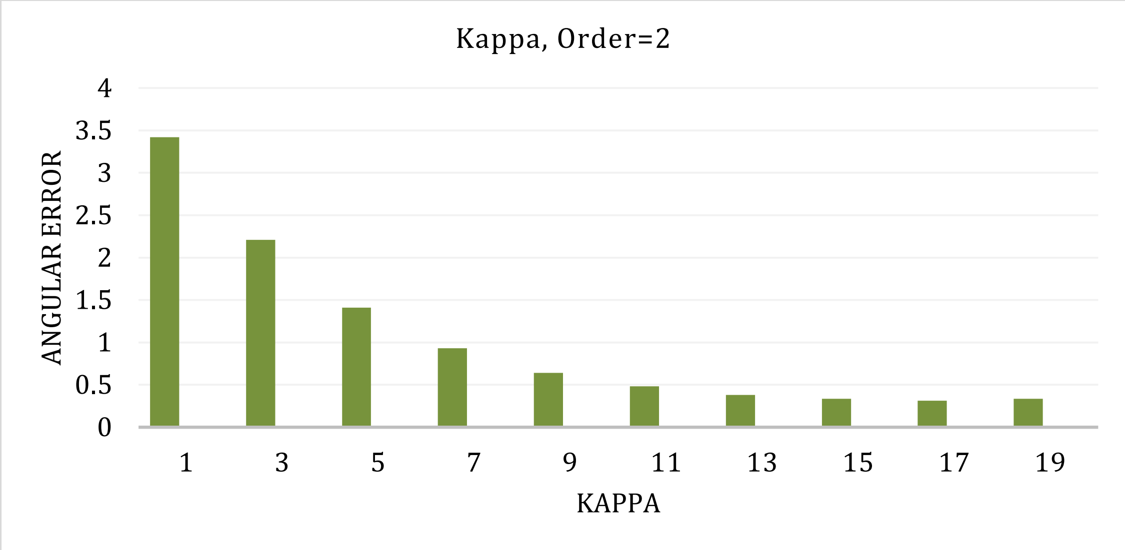


Figure 4.10 Effect of variation in Kappa value and Order =2

In the design of experiment we discussed effect of influencing parameters, and then we decided the optimal values for the proposed algorithm for SFU laboratory dataset. In chapter 5 we will apply proposed algorithm on SFU dataset using optimal values.

4.3 Complexity analysis

Image is stored in the format of 2-D matrix, as we know color images consists of three color channels so there are three 2-D matrices are stored in memory. Time and space complexity of the proposed algorithm for computing the color of illuminant according to given input image is O(n*m*C) and O(n*m*C) where n is number of rows in 2-D color channel, m is number of columns in 2-D color channel and C is number of color channels, which will be 3 for RGB color image. Hence time and space complexity of proposed algorithm is O(n*m*C) and O(n*m*C) respectively. Image is stored in the uint8 format; more precisely we can say that units for space complexity will be uint8 and time complexity depends on speed of processor.

4.4 Summary

In this chapter we discussed methodology followed for proposed vector filtered edge weighing algorithm. In design of experiment we decided optimal parameters for the algorithms. At the end we calculated time O(n*m*C) and space complexity O(n*m*C) of the algorithm.

CHAPTER 5: RESULTS AND DISCUSSION

5.1 Implementation Environment Specification

Static algorithms for color constancy are implemented using software MATLAB 8.1 release name R2013a. MATLAB (**MAT**rix **LAB**oratory) is Fourth generation programming language and multi-paradigm numerical computing environment, Developed by Mathworks. MATLAB allows matrix manipulations, implementation of algorithms, plotting of functions and data, creation of user interfaces, and interfacing with programs written in other languages, including C, C++, Fortran, Java and Python.

Matlab is installed under environment of 32-bit Microsoft Window 7 professionals. Computer hardware configuration: 2GB RAM, Intel® core™ i5 processor @ 3.20GHz.

5.2 Optimal parameters for proposed algorithm

The effect of the parameters that influence the performance of the proposed algorithm as we discussed in chapter 4 is concluded in this section. Parameters are the minkowski norm p that determines the relative weights from the set of iterations, k is used to impose weights, n is the order of the derivative and the scale of the local measurements is denoted by σ. All these parameters were analyzed and the best color constancy results were obtained using p=6, σ=4, n=2 for grey edge part and p=2, σ=4, n=2, k=17 for weighted gray-edge method using corrected grey-edge image as an input image. Results of this experiment indicate that the second order derivative (n=2), scale of σ=4, kappa =17 gives the best estimation of the illuminant.

5.3 Snapshots

Figure 5.1 shows the graphical user interface for static algorithms. In left top we can see menu for selecting the operations we want to perform. First operation need to perform is to go into File->input image tab to insert image.

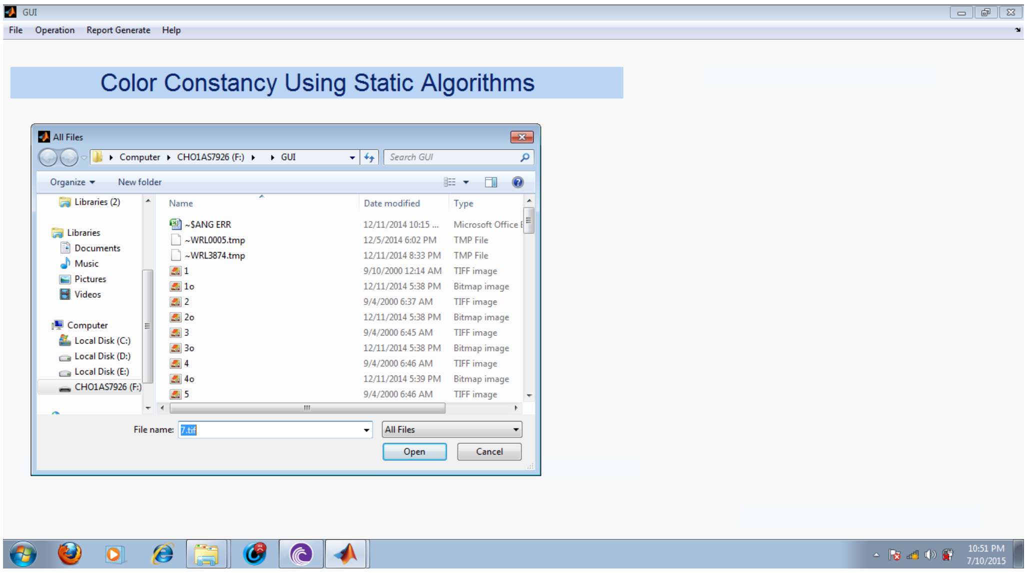


Figure 5.1 Input image

Figure 5.2 depicts that in operation tab there are state-of-art algorithms. We can choose particular algorithm to get the angular error from that method.

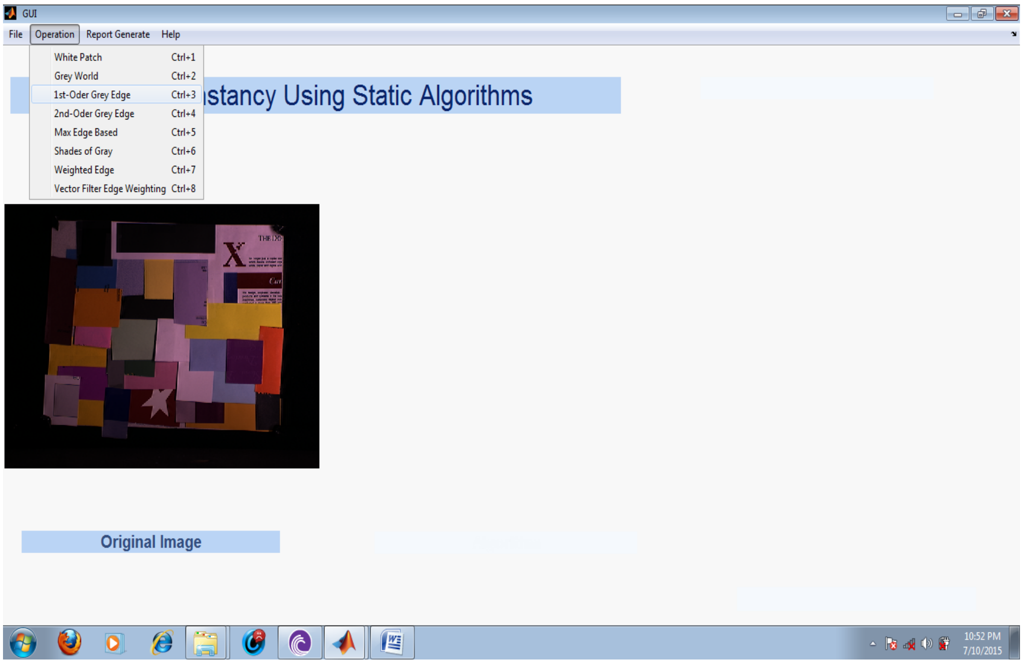


Figure 5.2 Select Algorithm from operation Tab

In figure 5.3 we can see that we selected 1st order grey edge operation from the list and we get angular error =9.56°.

Figure 5.3 Selecting 1st order grey edge

Figure 5.4 shows that selecting the operation 2nd order grey edge gives the improved results as compare to 1st order grey edge method as shown in figure 5.3. As we discussed in previous section that higher order derivative gives improved results as compare to lower order.

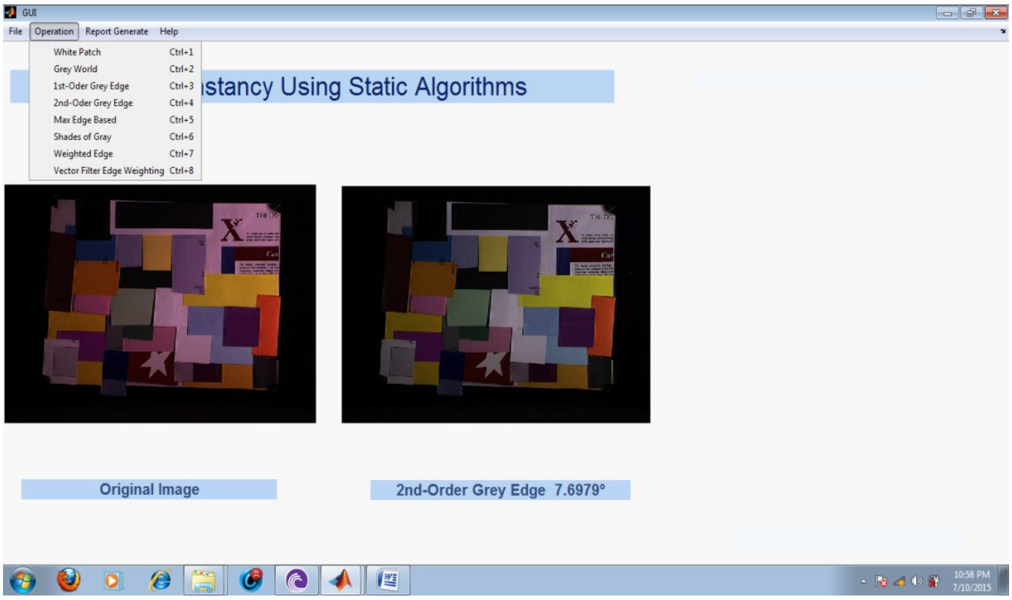


Figure 5.4 Selecting 2nd order grey edge

In figure 5.5 shows the results of white patch algorithm, which is lesser the both 1st order and 2nd order grey edge.

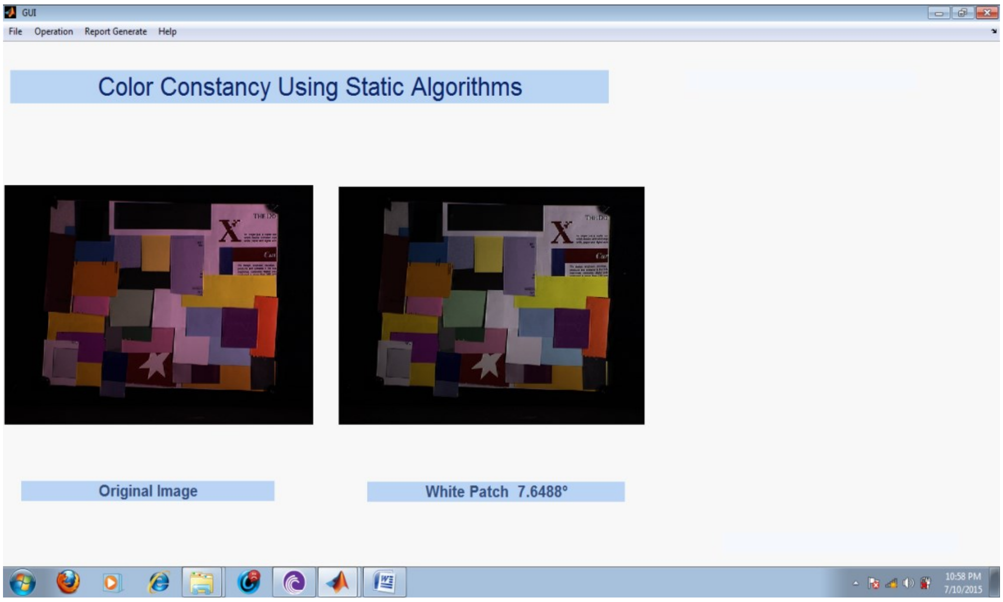


Figure 5.5 selecting white patch algorithm

In the figure 5.6 we can see the performance of proposed vector filtered edge weighting, which significant fall in angular error as compare to other algorithms. Vector filtered edge weighing angular error is 0.31, this shows that illuminant estimated is accurate.

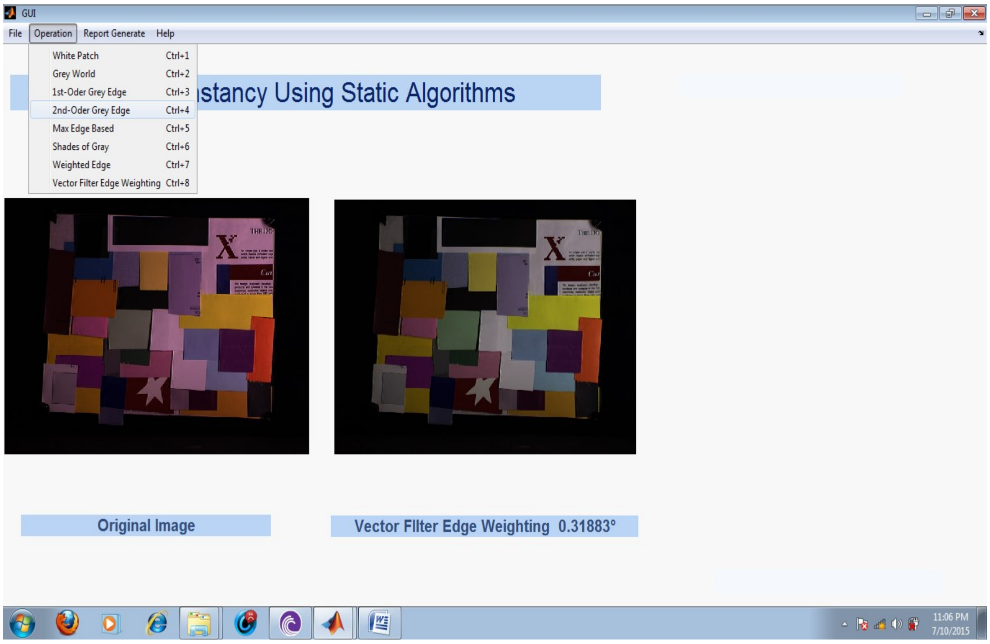


Figure 5.6 Selecting proposed Vector filtered edge weighing

Figure 5.7 depicts that in report generate tab we can choose table of all the angular errors and Bar graph of all the errors in order to compare results.

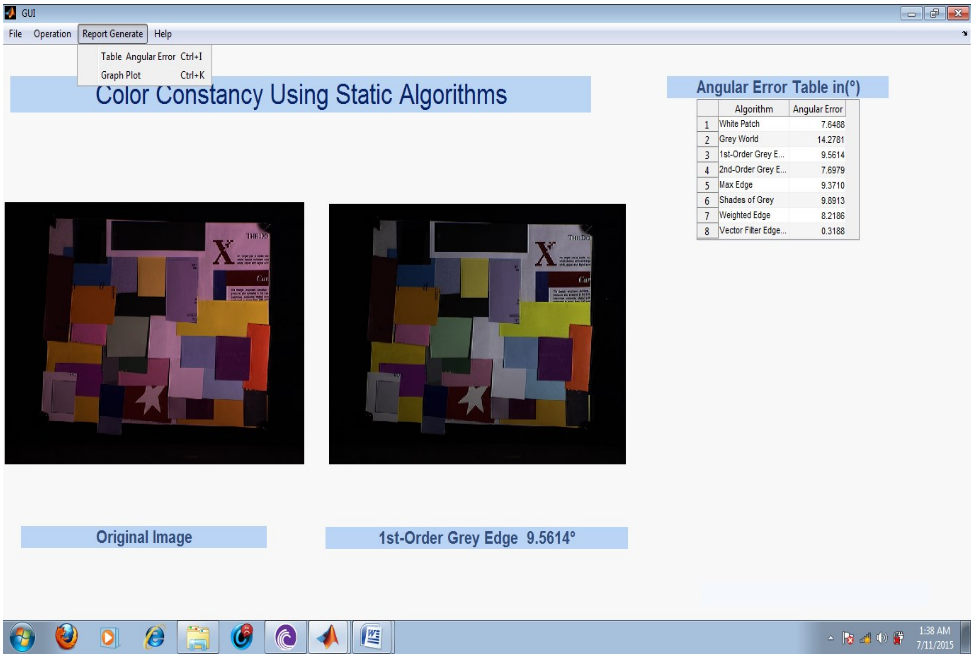


Figure 5.7 Angular Error Table

In figure 5.8 we can compare the results using bar graph. Bar graph can be plotted using Report Generate->Bar Graph. Using the bar graph we can easily compare the results and visualize results.

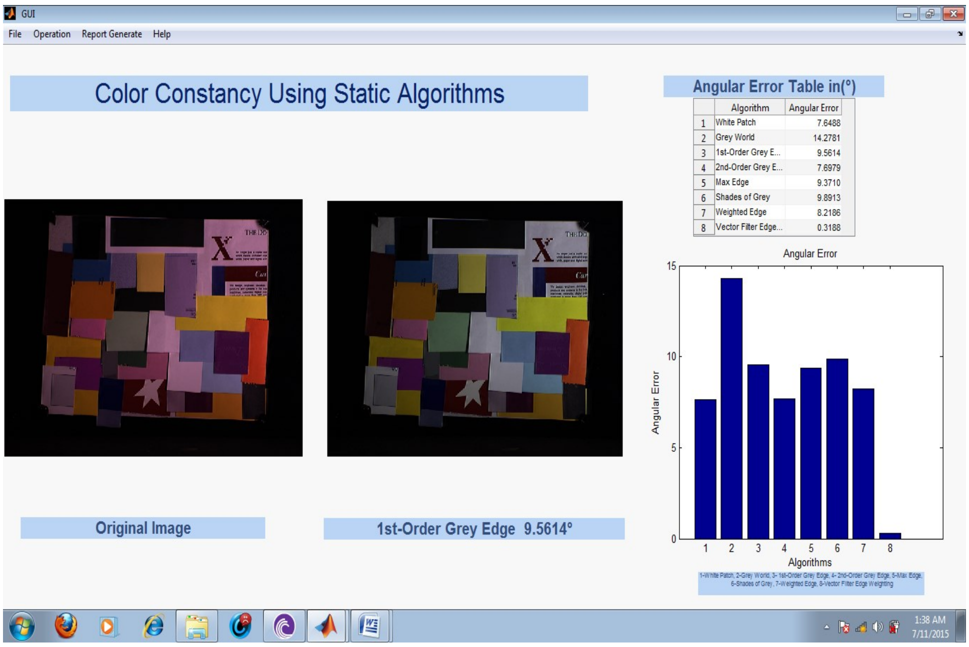


Figure 5.8 Plotting Bar Graph

In figure 5.9 we can see that we can export the results in the form of output .BMP format image. We have to choose File->Export image->save.

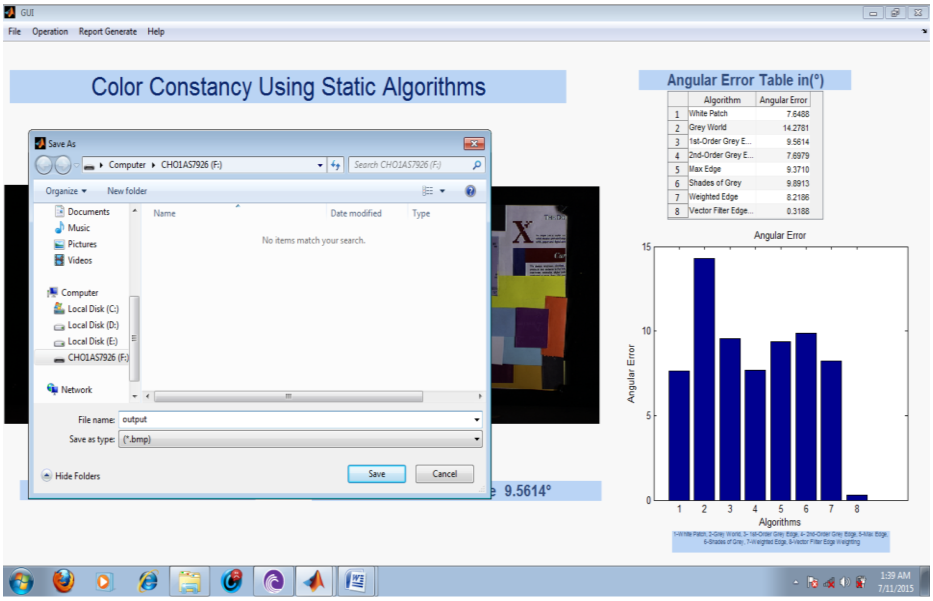


Figure 5.9 exporting the output image

Figure 5.10 shows that we can export results in the form of excel sheets. We need to go into File->Export data->save. We can export data for future use.

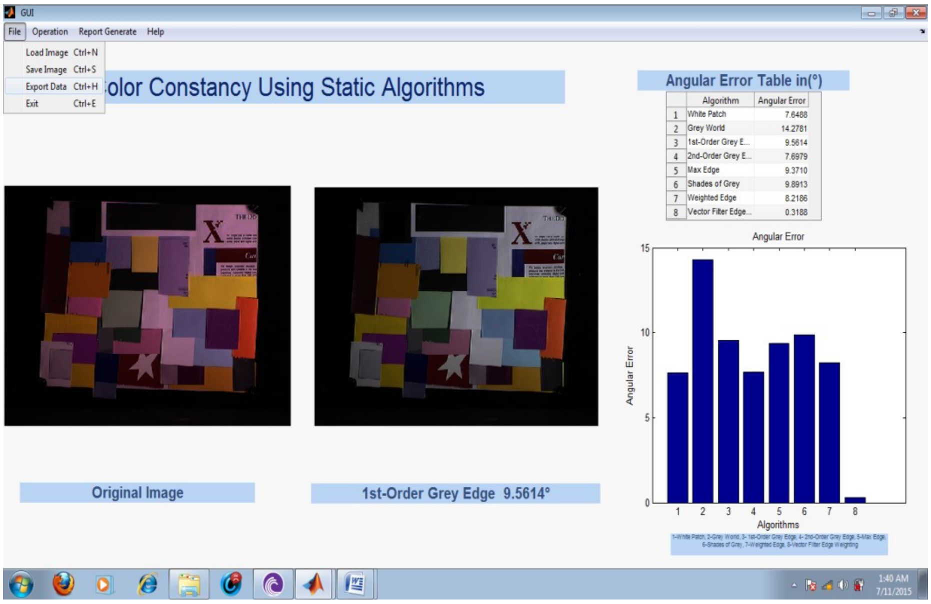


Figure 5.10 exporting data in the excel format

In figure 5.10 we can see the exit option we close the application.

5.4 Experimental Results

Algorithms are compared using the angular error results computed on the set of 50 images. In this section we will discuss the results obtained using the GUI application designed for thesis work.

Figure 5.11 shows angular error of algorithms in the form of the scattered plot. In this plot white patch, grey world, 1st order grey edge, weighted grey edge and vector filter edge weighting. Dark red line depicting the performance of proposed vector filtered edge weighting. Orange line of grey world algorithm is giving worst performance on the set of 50 images.

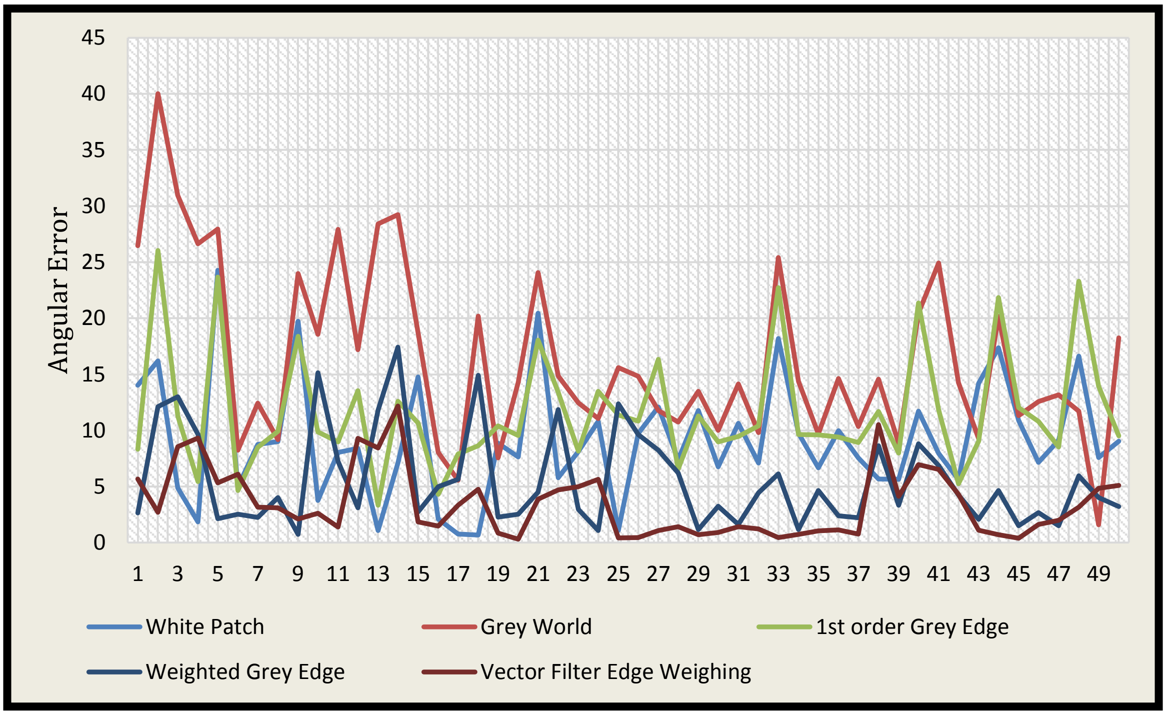


Figure 5.11 Comparison of state of art algorithm with vector filter edge weighting

Figure.5.12 showing that grey world is worst in terms of median angular error of 50 images of SFU dataset. Bar of proposed VFEW algorithm is lowest.

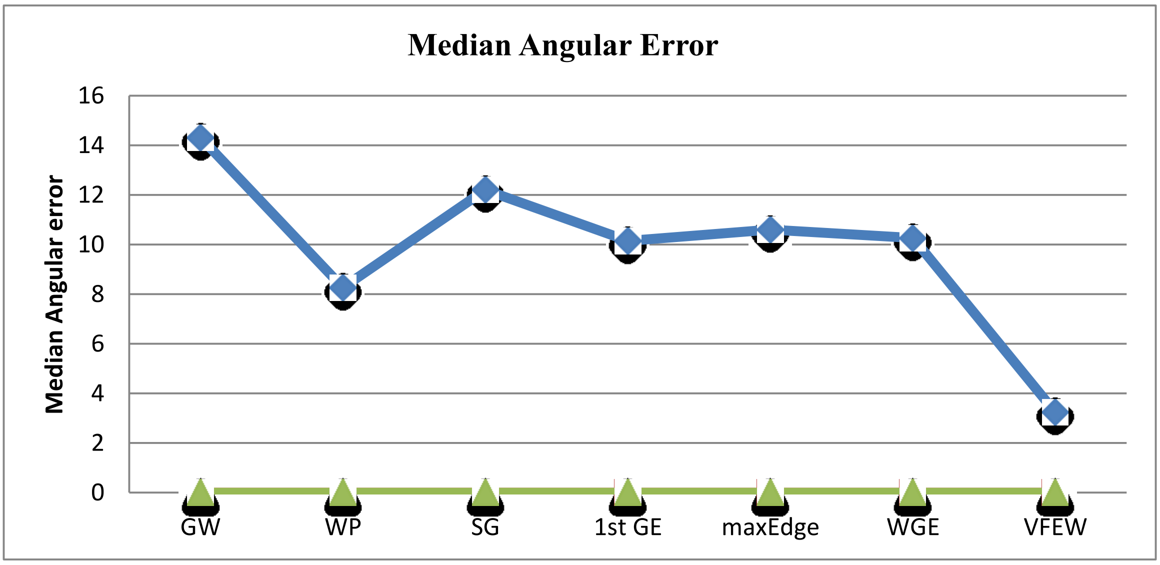


Figure 5.12 Line plot of median angular error

Figure.5.13 showing that max edge is worst in terms of mean angular error of 50 images of SFU dataset. Mean angular error of VFEW of proposed algorithm is lowest.

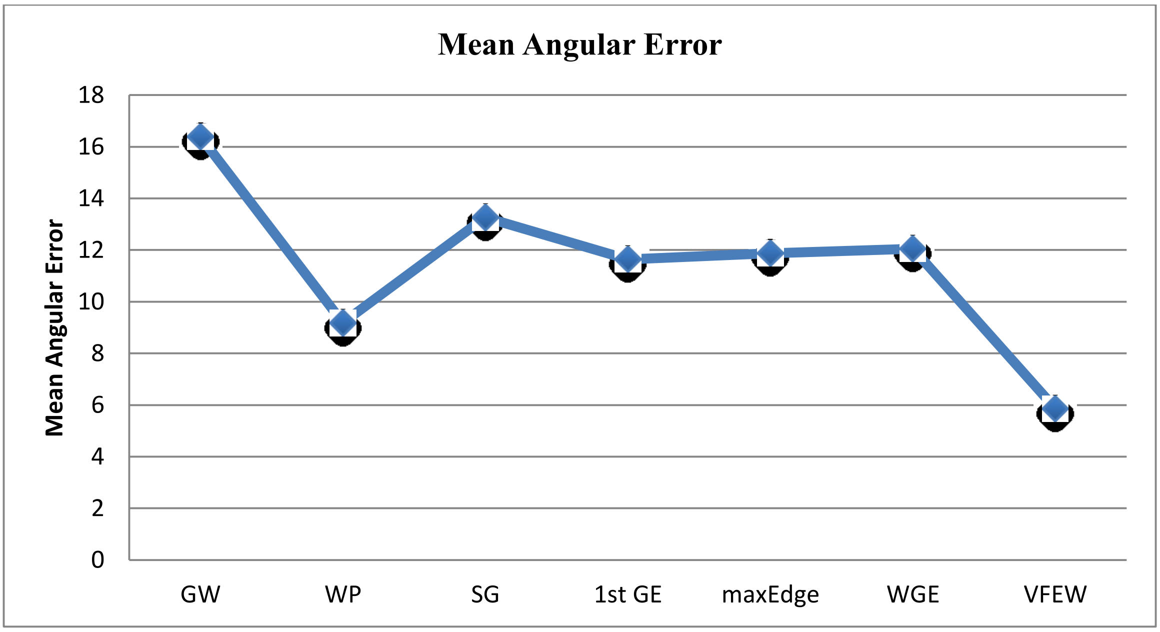


Figure 5.13 Line plot of Mean angular error

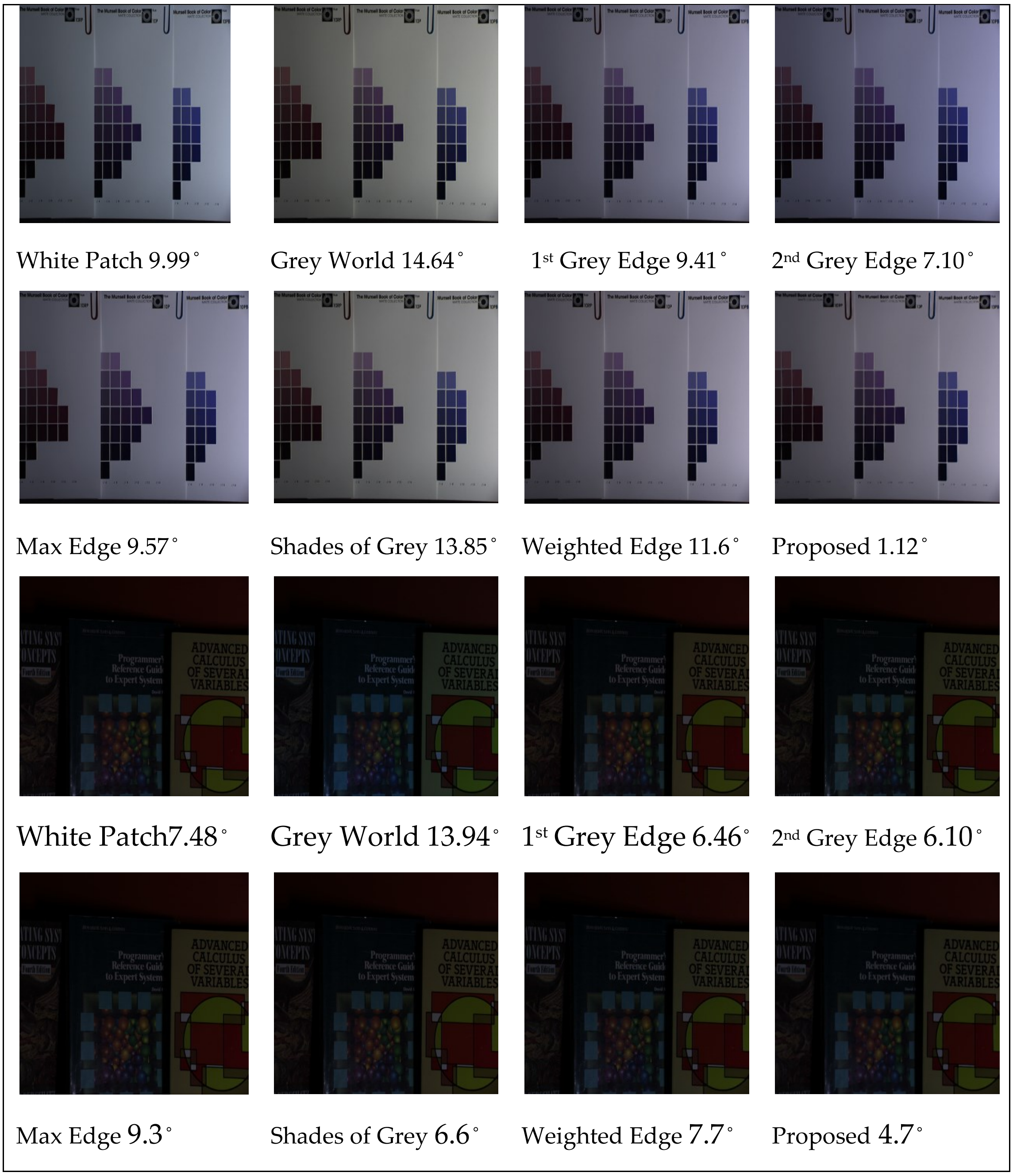


Figure 5.14 Output image of various algorithms

CHAPTER 6: CONCLUSION AND FUTURE SCOPE

6.1 Conclusion

In this thesis, we investigated one of the computer vision system problem that deals with color features of real world scene. Color constancy is an ability to identify right intensity of colors from the real world scene invariant from illuminant color. With the incorporation of color constancy ability in computer visions systems, the real time applications will give desired results. Color constancy methods can be a suitable solution for solving the chromatic problems caused due to varying illumination.

We propose a new algorithm using vector filtered edge weighting, which is tested on sample images from a publicly available image data set. The efficacy of color constancy methods are evaluated by calculating the angular error between the estimated and the known standard light source. The proposed method uses gray edge algorithm and weighted gray edge algorithm in pipeline with the combination of vector based filter, to improve the results of color constancy as compare to the state-of-the-art methods.

For the problem of color constancy, there is no such algorithm been proposed, which can give accurate results. In research work related to color constancy, the focus is to improve the accuracy of the illuminant estimation, so that the original colors can be recovered.

Time and space complexity of the proposed algorithm for computing the color of illuminant according to given input image is O(n*m*C) and O(n*m*C) where n is number of rows in 2-D color channel, m is number of columns in 2-D color channel and C is number of color channels, which will be 3 for RGB color image. The method is derived from the weighted gray-edge method that reports the color constancy based on specular edges that result in accurate illuminant estimates. The proposed vector filter edge weighing algorithm combines the weighted gray edge and the gray edge method to give 68.45% improvement in existing results.

6.2 Future Scope

In the future work, artificial intelligence can be incorporated in the project so that system can automatically choose the best algorithm according to image features. Therefore it is required to analyze the image features for which particular algorithm gives accurate estimation of illuminant.

Features that can used to analyze the algorithms may be Color features, histogram features, and noise effect present in image. For artificial intelligence neural network, k-mean or support vector machine can be used to access the accuracy of the system.

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