Color Correction Based Color Image Enhancement

Major Project submitted in partial fulfilment of the requirements for the award of degree of

Master of Technology
In
Information Systems

Submitted by:

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(10/IS/2010)

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(2010-2012)

CERTIFICATE

This is to certify that **Ms. Rajni Gumber (10/IS/2010)** has carried out the major project titled **"Color Correction Based Color Image Enhancement"** as a partial requirement for the award of Master of Technology degree in Information Systems by Delhi Technological University.

The major project is a bonafide piece of work carried out and completed under my supervision and guidance during the academic session **2010-2012**. The matter contained in this report has not been submitted elsewhere for the award of any other degree.

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ABSTRACT

Color correction is an important step in image enhancement. It improves the appearance of the images affected by color cast. There are many color correction algorithms available in literature. Gray world assumption takes into account human visual system and form the basis for many color correction algorithms. A new image enhancement approach for color correction which modifies gray world correction algorithm is proposed using fuzzy logic technique. Fuzzy logic deals with the uncertainty of information. Here, fuzzy logic is employed to deal with the uncertainty of color cast in the image. RGB channels are fuzzified individually using Gaussian membership function between two sets the LOW and the HIGH. Six fuzzy rules have been defined to find the cast in the color image. Then according to the cast, correction factor is found using the mean of RGB channels as done in gray world based correction. This correction factor is non-linearized by raising it to power of gamma. Out of many performance metric for color correction algorithms, CIE L*a*b metric performance measure called image distance is used in the proposed approach. Image distance has been used as objective function for the optimisation. Bacterial Foraging optimisation is applied for finding the optimal value of gamma which improves the objective function. Results of the proposed scheme are better as compared to Gray World. Quantitative analysis of the results has been done using CIE L*a*b metric called image distance whose value should be lesser for better result.

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LIST OF SYMBOLS

$\mu_X(x)$: Degree of Membership of x in the fuzzy set X.

$\bar{R}$: Mean of Red Channel of Image.

$\bar{G}$ **:** Mean of Green Channel of Image.

$\bar{B}$: Mean of Blue Channel of Image.

α_r : Scale Factor for Red Channel of Image.

α_b : Scale Factor of Blue Channel of Image.

$\tilde{R}$: Color Corrected Red Channel of Image.

$\tilde{G}$: Color Corrected Green Channel of Image.

$\tilde{B}$: Color Corrected Blue Channel of Image.

β_r : New Scale Factor for Red Channel of Image.

β_g : New Scale Factor for Green Channel of Image.

β_b : New Scale Factor for Blue Channel of Image.

Chapter 1
INTRODUCTION

In image processing and photography, Image enhancement is an important step for getting aesthetic and color pleasant images. Images captured by digital cameras are usually different from the original image in terms of color and intensity of the scene captured. Various factors like color of ambient light, low or high contrast, over-exposure or under-exposure of some of the regions lead to this difference. Thus, enhancement of color images is required.

1.1 Color Correction

Color correction is the concept of altering the color balance of an image to achieve a desired effect. It applies creative adjustments to an image to resolve variations in lighting and viewing conditions and stylize the appearance of the images.

Color correction is generally broken down into two distinct processes: primary and secondary color correction. Primary color correction is the process of setting the overall tone, contrast, and color balance of an image. Secondary color correction is a further step that refines the image in specific geographical regions or in specific color vectors of the image.

The first step in any color correction is to assess the tonal range of the picture being corrected. Many color correction plug-ins or color correction systems built in to nonlinear editors have “automatic” buttons that will attempt to spread out the tonal range for you based on purely technical information. These automatic systems assume that the brightest parts of the picture should be as bright as possible while remaining legal, and the darkest part of the picture is also set automatically to be as low as possible while remaining legal. Legal means that the brightness and color saturation of an image does not exceed minimum or maximum levels. There are two big problems with this. Simply setting the brightest pixel to 100 and the darkest pixel to 0 with all of the intermediate pixels spread evenly between them does not necessarily provide the best spread of the tonal range across the most visually important parts of an image. The other problem is that the image may not need to have either its brightest pixel at 100 or its darkest pixel at 0.

Hence, to proceed with color enhancement, the color of ambient light should be known in prior to remove its undesired effect. The undesirable effect of ambient light is called color cast, this color cast is removed using various color correction techniques like white patch, gray world etc. There are some automated tools are also present in various photographic software tools like adobe photoshop, picassa etc. But the automation doesn't work as desired. The manual correction in these software depend upon one's perception of quality of image, hence results may vary from person to person.

1.2 Related Work

Generally color correction techniques rely on human visual system based method called Gray World assumption and retinex theory. Kwok *et al.*[1] proposed color correction based on a modified implementation of the gray world assumption by employing a gamma correction to avoid color saturation as encountered in the conventional approach. In order to further improve the image visual quality, an intensity preservation criterion is adopted as an additional means to produce the resultant image. But [1] changed the linear behaviour of gray world. M. A. Berbar [2] retained the linear behaviour of gray world and proposed two approaches Modified Gray World (MGW) that uses a reference value calculated using the means of RGB color components. The second approach is MGWWP to use the new MGW approach followed by white patch approach. Rizzi *et al.*[3] however merged both Gray World and retinex theory to get new chromatic correction algorithm, called Automatic Color Equalization (ACE), which is able to perform color constancy even if based on Gray World approach. E.Y. Lam[4] also combined the gray world and white patch algorithm but he preserved the strength of both methods. Iqbal *et al.*[5] proposed Unsupervisied Color Correction Method (UCM) based on colour balancing, contrast correction of RGB colour model and contrast correction of HSI colour model which give better result as compared to Gray World, White Patch. Since the decision of color quality of image is some sort of fuzzy in nature, fuzzy logic is an appropriate choice for color image enhancement. Hence fuzzy sets [6] provide a nice solution to the vague concepts like 'high red component' or high green component etc. Jou *et al.*[7] proposed a tree based fuzzy inference technique which is cost effective and give good correction effects. Another color enhancement technique is proposed by M. Hanmandlu *et al.*[8] in which a new contrast intensification parameter, t is calculated globally for image enhancement by minimizing the fuzzy entropy of the image information. A visible improvement in the image quality for human contrast perception is observed by the reduction in 'index of fuzziness' and 'entropy' of the output image.

Instead of using some fuzzy parameters, fuzzy filters have also been proposed for image enhancement. Conflicting goals of image enhancement: (i) removing impulse noise, (ii) smoothing out non-impulse noise, and (iii) enhancing (or preserving) edges and certain other salient structures. Y.S. Choi *et al.*[9] proposed robust image enhancement using three different filters for each of the above three tasks using the weighted (or fuzzy) least squares (LS) method, and define the criteria for selecting each of the three filters. Another filter based technique is proposed by Farbiz, F. *et al* [10] in which fuzzy-logic-control based filters are applied having the ability to achieve the same three goals. These filters are based on the idea that individual pixels should not be uniformly fired by each of the fuzzy rules.

Fuzzy technique is also merged with evolutionary techniques to get better image enhancement. Hanmandlu *et al.*[11] proposed a novel optimal fuzzy system for color image enhancement using bacterial foraging which optimises Entropy and the visual factors to learn the parameters of membership function used for Fuzzification. O.P.Verma *et al.*[12] proposed an objective function comprising of Shannon entropy function as the information factor and visual appeal indicator is optimized using Artificial Ant Colony System to ascertain the parameters needed for the enhancement of a particular image. Results with this fuzzy approach are better than the bacterial foraging results of [11].

1.3 Project Objective

In this paper, a color correction approach has been devised where we have modified the basic gray world approach using the concept of fuzzy. The Gaussian membership function is used to define two classes viz. the low and the high for all three color components namely red, green and blue. Using these membership values and some fuzzy rules defined we find the cast in the image. On the basis of cast found, a correction factor is calculated in a manner somewhat similar to gray world. Image enhancement is directly proportional to correction factor. In gray world this correction factor is taken linear. But we raised the correction factor to a factor gamma whose optimal value is found using bacterial foraging technique for a better enhanced image. The objective function for bacterial foraging is a CIE Lab performance measure image distance which should be minimised.

1.4 Thesis Layout

The project report has been divided into 7 chapters. Each chapter deals with one component related to this project work. Chapter 1 being introduction to this project work gives us the brief introduction to this project works, there after chapter 2 explains the fuzzy logic and fuzzy rules. Chapter 3 deals with the Gray World Assumption and correction algorithm

Chapter 4 deals with Bacterial Foraging, the Evolutionary algorithm used in the project for optimization. Chapter 5 deals with color correction method explained in the proposed method. This method modifies the gray world correction algorithm and provides very significant results which are quantitatively proved better than gray world results.

Chapter 6 compares the results of Gray World Assumption with the proposed scheme by using the test images. Finally chapter 7 concludes the project work.

Chapter 2

FUZZY LOGIC AND FUZZY RULES

2.1 Advantages of Fuzzy Logic

Fuzzy logic has rapidly become one of the most successful of today's technologies. The reason for which is very simple. Fuzzy logic addresses such applications perfectly as it resembles human decision making with an ability to generate precise solutions from certain or approximate information. It fills an important gap in engineering design methods left vacant by purely mathematical approaches (e.g. linear control design), and purely logic-based approaches (e.g. expert systems) in system design. While other approaches require accurate equations to model real-world behaviours, fuzzy design can accommodate the ambiguities of real-world human language and logic. It provides both an intuitive method for describing systems in human terms and automates the conversion of those system specifications into effective models. The first applications of fuzzy theory were primaly industrial, such as process control for cement kilns. However, as the technology was further embraced, fuzzy logic was used in more useful applications. It is being used in image processing also and there are many reasons to use fuzzy logic in image processing:

- Fuzzy techniques are powerful tools for knowledge representation and processing.
- Fuzzy techniques can manage the vagueness and ambiguity efficiently.
- Fuzzy logic is tolerant of imprecise data. Everything is imprecise if we look closely enough, but more than that, most things are imprecise even on careful inspection. Fuzzy reasoning builds this understanding into the process rather than tacking it onto the end.
- Fuzzy logic can model nonlinear functions of arbitrary complexity. We can create a fuzzy system to match any set of input-output data.
- Fuzzy logic is based on natural language. The basis for fuzzy logic is the basis for human communication. This observation underpins many of the other statements about fuzzy logic.
- Fuzzy logic can be blended with conventional control techniques. Fuzzy systems don't necessarily replace conventional control methods. In many cases fuzzy systems augment them and simplify their implementation.

- Fuzzy logic is conceptually easy to understand. The mathematical concepts behind fuzzy reasoning are very simple.
- Fuzzy logic is flexible. With any given system, it's easy to manage it or layer more functionality on top of it without starting again from scratch.

2.2 Fuzzy Sets

Fuzzy Set Theory [6] was formalised by Professor Lofti Zadeh at the University of California in 1965. Fuzzy sets are a further development of mathematical set theory. It is possible to express most of mathematics in the language of set theory, and researchers today are looking at the consequences of 'fuzzifying' set theory, resulting in, for example, fuzzy logic, fuzzy numbers, fuzzy intervals, fuzzy arithmetic, and fuzzy integrals.

Fuzzy logic is based on fuzzy sets and with fuzzy logic a computer can process words from natural language, such as 'small', 'large', 'approximately equal'.

Classic sets give a two-valued logic in which a system can have propositions that are either 'true' or 'false'. But two-valued logic is only an approximation to human reasoning as Zadeh observed:

Clearly, the "class of all real numbers which are much greater than 1," or "the class of beautiful women," or "the class of tall men," do not constitute classes or sets in the usual mathematical sense of these terms (Zadeh, 1965).

Following Zadeh a membership grade allows finer detail, such that the transition from membership to non-membership is gradual than abrupt as in crisp set. The membership grade for all members defines a fuzzy set (Fig. 2.1).

Universe- members of fuzzy set are taken from the universe of discourse, or universe.

Membership function - In fuzzy logic, it represents the degree of truth as an extension of valuation. For any set X, a membership function on X is any function from X to the real unit interval [0,1]. The membership function which represents a fuzzy set X is usually denoted by μ_X . For an element x of X, the value $\mu_X(x)$ is called the **degree of membership** of x in the fuzzy set X.

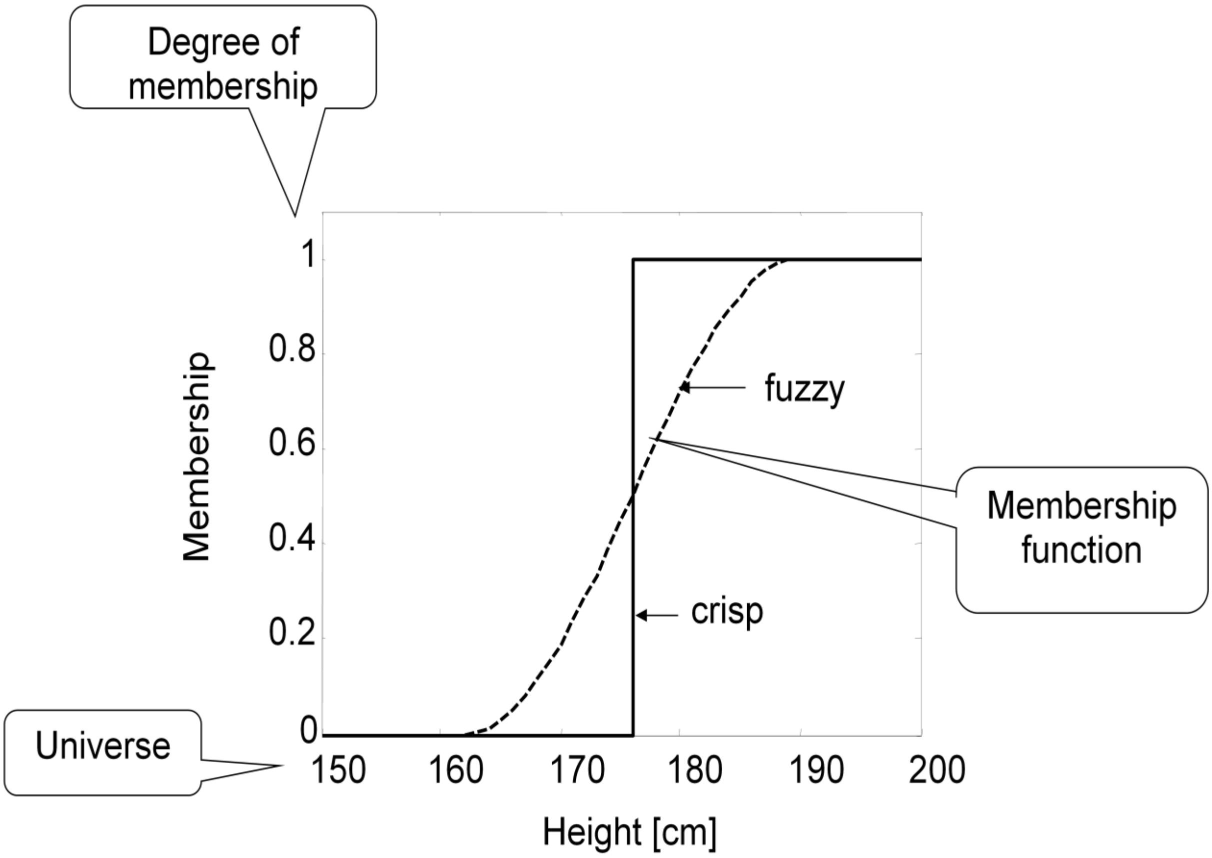


Fig.2.1 Two definitions of the set of a "tall men", a crisp set and a fuzzy set

2.3 Fuzzy Rules

Human beings make decisions based on rules. Although, we may not be aware of it, all the decisions we make are all based on computer like if-then statements. If the weather is fine, then we may decide to go out. If the forecast says the weather will be bad today, but fine tomorrow, then we make a decision not to go today, and postpone it till tomorrow. Rules associate ideas and relate one event to another.

Fuzzy machines, which always tend to mimic the behaviour of man, work the same way. However, the decision and the means of choosing that decision are replaced by fuzzy sets and the rules are replaced by fuzzy rules. Fuzzy rules also operate using a series of if-then statements. For instance, if X then A, if y then b, where A and B are all sets of X and Y.

Some examples of these rules are:

i) If angle is zero and angular velocity is zero then speed is also zero. ii) If angle is zero and angular velocity is low then the speed shall be low.

Chapter 3

GRAY WORLD ASSUMPTION AND CORRECTION TECHNIQUE

While implementing color correction algorithms, certain assumptions are generally made out about the basic nature of the color components of the images like Gray world assumption, White patch assumption and many more.

Gray world assumption was proposed by Buchbaum[13]. It estimates the illuminant using the average color of the pixels. The gray world assumption is probably one of the best-known algorithms for color constancy. Gray world color correction algorithm is basically based on the assumption that if there is sufficient amount of color variation within a given image, then the average value of R, G and B components of the image should be a common gray value. For example in the case an image is taken by a digital camera under a particular lighting environment, the effect of the special lighting cast can be removed by enforcing the gray world assumption on the image. As a result of approximation, the color of the image is much closer to the original scene. Color balancing algorithms can make use of this assumption by forcing images to have a uniform average gray value for R, G, and B color components. For example, if an image was shot with a camera under yellow lighting, the camera output image will have a yellow cast over the entire image. The effect of this yellow cast disturbs the Gray World Assumption of the original image. By enforcing the Assumption on the camera output image, we would be able to remove the yellow cast and re-acquire the colors of our original scene, fairly accurately.

A simple method of Gray World Assumption enforcement would be to find out average values of image's R, G and B components and to use their average to determine an overall gray value of the image. Many algorithms have been proposed with use gray world assumption in one way or another. M. Ebner [15] devised a parallel algorithm for color constancy which runs on a two dimensional grid of processors each of which can exchange information with its four neighbouring processors. Each processor calculates local average color. This information is then used to estimate the reflectance of the object. Reinhard et al. [16] also used the assumption for color correction by choosing an appropriate source image and apply its characteristic to another image. This imposes characteristics of source image in the other. On the other hand, Weijer et al.[17] proposed gray edge hypothesis which is a modification of gray world hypothesis and used this hypothesis for color constancy.

Consider the image I(i,j), where (i,j) represents the corresponding pixel coordinates in RGB format,

$$I_{i,j} = (R_{i,j}, G_{i,j}, B_{i,j})$$

$$R_{i,j}, G_{i,j}, B_{i,j} \in [0,255]$$

$R_{i,j}$, $G_{i,j}$, $B_{i,j}$ represents the magnitude of R, G, B components of the image respectively. The value of i = 1… m and j = 1…n as m and n are the number of pixels in the row and column respectively.

In the conventional gray world color correction approach the mean values of the RGB color channel is calculated for all the pixels of the image I denoted by $\bar{R}$, $\bar{G}$, $\bar{B}$.

$$\bar{R} = \sum_{j=1}^{n}\sum_{i=1}^{m} R_{i,j} \, , \quad \bar{G} = \sum_{j=1}^{n}\sum_{i=1}^{m} G_{i,j} \, , \quad \bar{B} = \sum_{j=1}^{n}\sum_{i=1}^{m} B_{i,j} \qquad (1)$$

Using these average values computed in eqn. 4, two scale factors α_r and α_b are calculated for the R- and B- channels respectively taking green channel as base channel. Because in general observation of various color images, it has been found out that green channel of the image is least affected by the distortion and ambient light of the scene in which image is captured. The scaling factors calculated by the gray world assumption is an approximation of the measurement taken by digital still and video cameras by capturing an evenly lit white sheet of paper or similar.

$$\alpha_r = \frac{\bar{G}}{\bar{R}}, \alpha_b = \frac{\bar{G}}{\bar{B}} \qquad (2)$$

Each color component is then scaled according to the amount of deviation from this gray value. The corrected and enhanced image is obtained by multiplying the R-and B-channels with their associated scaling factors while the G-channel is left unchanged.

$$\tilde{R} = \alpha_r R, \tilde{G} = G\ , \tilde{B} = \alpha_b B \qquad (3)$$

Chapter 4

BACTERIAL FORAGING OPTIMIZATION ALGORITHM

Bacteria Foraging Optimization Algorithm (BFOA), proposed by Passino [17], is a new comer to the family of nature-inspired optimization algorithms. For over the last five decades, optimization algorithms like Genetic Algorithms (GAs), Evolutionary Programming (EP), Evolutionary Strategies (ES), which draw their inspiration from evolution and natural genetics, have been dominating the realm of optimization algorithms. Recently natural swarm inspired algorithms like Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO) [6] have found their way into this domain and proved their effectiveness. Following the same trend of swarm-based algorithms, Passino proposed the BFOA. Application of group foraging strategy of a swarm of E.coli bacteria in multi-optimal function optimization is the key idea of the new algorithm. Bacteria search for nutrients in a manner to maximize energy obtained per unit time. Individual bacterium also communicates with others by sending signals. Foraging theory relies on the fact that animals search for food and obtain nutrients in a way that maximizes their energy intake per unit time spent foraging. In other words, they try to minimise the cost or effort of searching the food.

Hence in bacterial foraging, bacteria try to minimise the cost of finding the food. Bacteria forage for their food in following four stages chemo taxis, swarming, reproduction, and elimination and dispersal.

Let θ be the position of a bacterium and $J(\theta)$ in Eqn. (4) represents the value of the objective function, i.e. a measure of nutrients available at θ.

Let j be the index for the chemo tactic step, k be the index for the reproduction step and l be the index of the elimination-dispersal event and let the position of each member in the population of the S bacteria at the j^{th} chemotactic step, kth reproduction step, and l^{th} elimination-dispersal event be given by

$$P(j,k,l) = \left\{ \theta^{i}(j+1,k,l) \mid i = 1,2,....S \right\} \quad (4)$$

Instead of $J(\theta)$, we consider $J(I, j, k, l)$ to be the cost at the location of the i^{th} bacterium.

4.1 Steps of Bacterial Foraging Algorithm

(a) Chemo taxis: This is a very important stage of BF. It decides the direction in which the bacterium should move. The motile bacteria such as Escherichia coli propel themselves by rotating their flagella. They rotate their flagella counter clockwise to move forward rotate also called as “swimming” (or “runs”). But to move the bacteria in random direction i.e. “tumble” they rotate their flagella clockwise and then swims again. Tumbling just changes the direction of movement of bacteria. The bacteria first of all tumble in random direction to search for food. As the bacteria found the food in a particular direction it then swims toward the food in that direction. An alternation between “swim” and “tumble” enables the bacteria to search for food in random directions. Thus, Depending upon the rotation of the flagella, each bacterium decides whether it should swim (move in a predefined direction) or tumble (move in an altogether different direction).Hence, A chemo tactic step is defined as a tumble followed by a tumble or a tumble followed by a run. To represent a tumble, a unit length of random direction, say $\phi(j)$ is generated; this will be used to define the direction of movement after a tumble. Let

$$\theta^i(j+1,k,l) = \theta^i(j,k,l) + C(i)\phi(j) \quad (5)$$

so that $C(i)$ is the size of the step taken in the random direction specified by the tumble by the *i*th bacterium. If the cost $J(i, j+1, k, l)$ at $\theta^i(j+1, k, l)$ is lower) than at $\theta^i(j, k, l)$, then another step of size $C(i)$ in the same direction will be taken, and again.

The swim is continued as long as it continues to reduce the cost, but only up to a maximum number of steps N_s. The total lifetime of a bacterium is represented by the number of chemo tactic steps taken N_c during its life.

(b) Swarming: An interesting group behavior has been observed for several motile species of bacteria including *E.coli* and *S. typhimurium*, where intricate and stable spatio-temporal patterns (swarms) are formed in semisolid nutrient medium. A group of *E.coli* cells arrange themselves in a travelling ring by moving up the nutrient gradient when placed amidst a semisolid matrix with a single nutrient chemo-effecter. The cells when stimulated by a high level of *succinate*, release an attractant *aspertate*, which helps them to aggregate into groups and thus move as concentric patterns of swarms with high bacterial density. The cell-to-cell signalling in *E. coli* swarm may be represented by the following function. As part of this task, the bacteria following the optimum path of food try to attract other bacteria so that together they more rapidly reach the desired location. The effect of swarming is to introduce an additional cost in J(i, j , k, l). But this step is neglected in the case of modified bacterial foraging used in our proposed approach for the sake of simplicity.

(c) Reproduction: After N_c chemotactic steps, a reproduction step begins its loop. Let N_{re} be the number of reproduction steps. For convenience, we assume that the number of bacteria S is a positive even integer. We choose

$$S_r = S/2 \qquad (6)$$

as the number of population members having sufficient nutrients so that they will reproduce (split up into two) with no mutations. For reproduction, the population is sorted in the ascending order of the accumulated cost (the higher cost indicates that a bacterium has not got as many nutrients during its lifetime of foraging and hence is not ‘‘healthy’’ and thus unlikely to reproduce); then the least healthy bacteria Sr die and each of the other healthiest bacteria Sr split up into two, which are placed at the same location. This method rewards bacteria that have encountered a lot of nutrients and allows us maintain a constant population size. Here the minimum value of all the cost functions in the chemo tactic step is retained for deciding the bacterium’s health to speed up convergence.

(d) Elimination and Dispersal: Gradual or sudden changes in the local environment where a bacterium population lives may occur due to various reasons e.g. a significant local rise of temperature may kill a group of bacteria that are currently in a region with a high concentration of nutrient gradients. Events can take place in such a fashion that all the bacteria in a region are killed or a group is dispersed into a new location. To simulate this phenomenon in BFOA some bacteria are liquidated at random with a very small probability while the new replacements are randomly initialized over the search space.

Let N_{ed} be the number of elimination-dispersal events and for each elimination dispersal event each bacterium in the population is subjected to elimination-dispersal with probability P_{ed}. This helps in reducing stagnation (i.e., being trapped in a premature solution point or local optima).

The selection of the initial parameters of the algorithm such as the number of iterations, number of bacteria etc. plays a key role in arriving at the optimum value in less time. These parameters depend on the application. These parameters depend upon the application.

4.2 BFO Algorithm

The brief outline of BFO algorithm is given below

Step 1. Initialize parameters $n,S,N_c,N_s,N_{re},N_{ed},P_{ed}$, c(i) (i = 1, 2, . . . , S), φ^i
Where, n: dimension of the search space,
S: the number of bacteria in the colony,

N_c : Chemotactic steps,

N_s : Swim steps,

N_{re} : Reproductive steps,

N_{ed} : Elimination and dispersal steps,

P_{ed} : Probability of elimination,

Step 2. Elimination-dispersal loop: l = l + 1.

Step 3. Reproduction loop: k =k +1.

Step 4. Chemotaxis loop: j = j + 1.

Substep 4.1. For i= 1= 1, 2, . . ., S, take a chemotactic step for bacterium i as follows.

Substep 4.2. Compute fitness function, J(i, j, k, l).

Substep 4.3. Let j_{last} = J(i, j, k, l) to save this value since we may find better value via a run.

Substep 4.4. Tumble. Generate a random vector $\Delta(i) \in R^n$, with each element $\Delta m(i)$, m =1, 2, . . . , n, a random number on [−1, 1].

Substep 4.5. Move. Let

$$\phi^i(j+1,k,l) = \phi^i(j,k,l) + C(i)\frac{\Delta(i)}{\sqrt{\Delta^T(i)\Delta(i)}} \quad (7)$$

This results in a step of size $C(i)$ in the direction of the tumble for bacterium i.

Substep 4.6. Compute $J(i, j+1, k, l)$ with $\varphi^i(j+1, k, l)$.

Substep 4.7. Swimming.

Let m = 0 (counter for swim length).

While m < N_s (if has not climbed down too long), the following hold.

• Let m= m + 1.

• If J(i, j + 1, k, l)< j_{last} let j_{last} = J(i, j+ 1, k, l), then another step of size *C*(*i*) in this same direction will be taken as (4.5) and use the new generated.

• φ^i(j +1, k, l) to compute the new J(i, j+ 1, k, l).

• Else let m = N_s.

Substep 4.8. Go to next bacterium (i +1). If i ≠ S, go to Substep 4.2 to process the next bacterium.

Step 5. If j < N_c , go to Step 3. In this case, continue chemotaxis since the life of the bacteria is not over.

Step 6. Reproduction.

Substep 6.1. For the given k and l, and for each i = 1, 2, . . . ,S, let

$$J^i_{health} = \sum_{j=1}^{N_c+1} J(i,j,k,l) \tag{8}$$

be the health of the bacteria. Sort bacteria in order of ascending values (J_{health}).

Substep 6.2. The S_r bacteria with the highest J_{health} values die and the other S_r bacteria with the best values split and the copies that are made are placed at the same location as their parent.

Step 7. If k < N_{re} , go to Step 2. In this case the number of specified reproduction steps is not reached and start the next generation in the chemotactic loop.

Step 8. Elimination-dispersal: for i =1, 2, . . . , S, with probability P_{ed} , eliminate and disperse each bacterium, which results in keeping the number of bacteria in the population constant. To do this, if a bacterium is eliminated, simply disperse one to a random location on the optimization domain. If l < N_{ed} , then go to Step 2; otherwise end.

The flow chart of Bacterial foraging algorithm is shown in the fig 4.1 below.

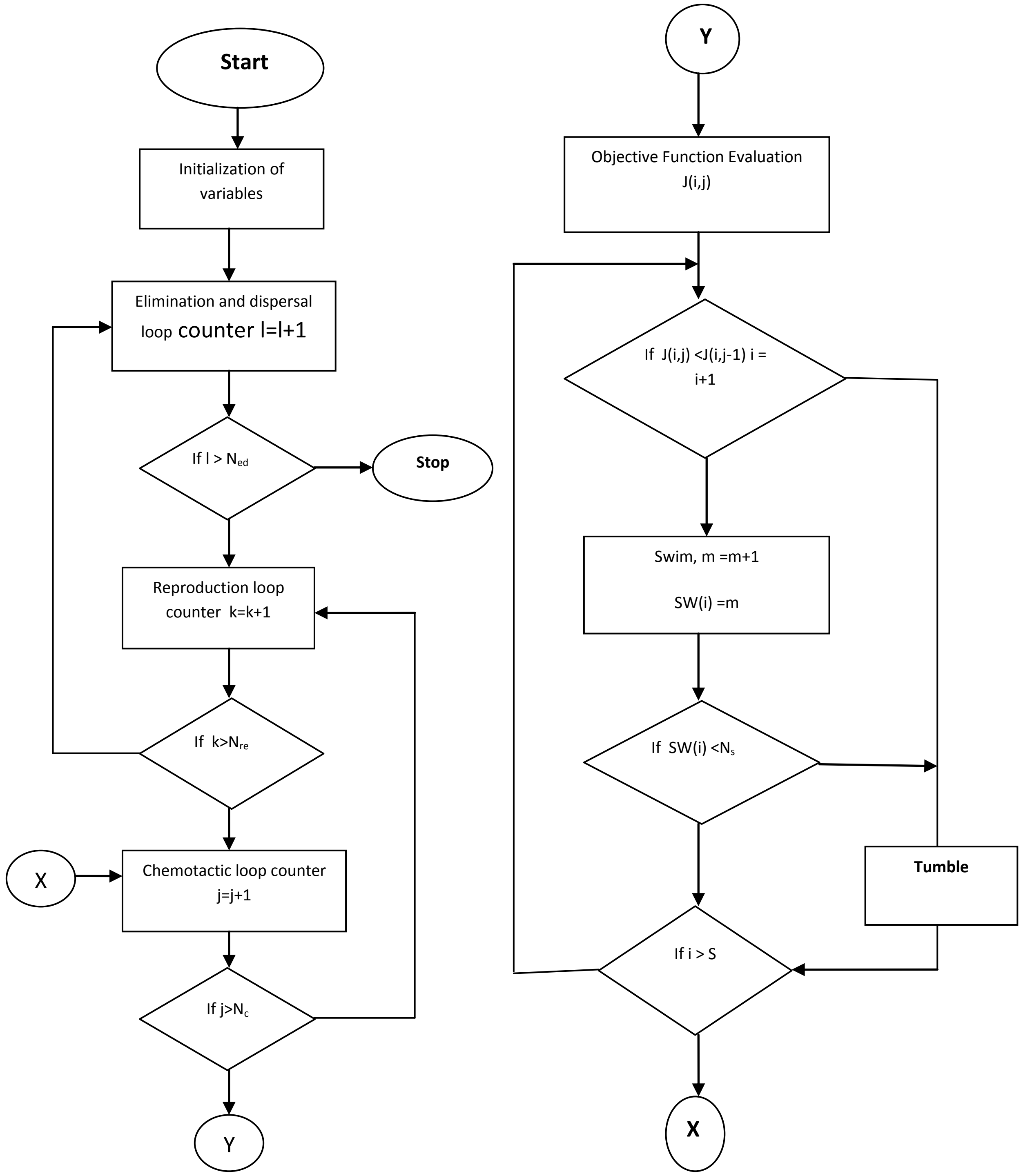


Fig. 4.1: Flowchart of Modified Bacterial Foraging Algorithm

Chapter 5
PROPOSED APPROACH

In the proposed approach, a color correction algorithm based on Gray world assumption is proposed with the aid use fuzzy logic. Gray world algorithm is one of the best known techniques for color correction since it takes into account human visual system. Proposed approach not only modifies the gray world approach but also uses optimization for getting better results as compared to gray world algorithm.

5.1 Modified Gray World Algorithm

In the proposed approach, Gray world correction algorithm is modified by finding the base channel for color correction instead of assuming green channel as base. This base channel is actually equal to the color cast since the channel which is least affected would be the one which has color equivalent to the color cast on the image. Color cast is found using the fuzzy rules defined in the next section. The correction method is also modified which is explained in the further sections.

5.2 Fuzzification And Fuzzy Set

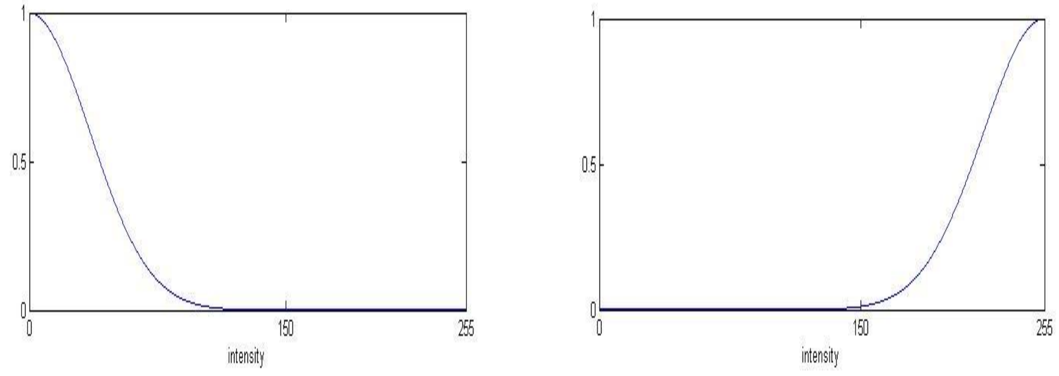
Fuzzy logic deals with the reasoning based on vague concept rather than on exact and precise. In image enhancement, there is vagueness in relation to the color cast i.e. which color has put an adverse effect on the captured image. To resolve this vagueness, fuzzy logic is employed. Individual color channels are fuzzified using Gaussian membership function into two fuzzy sets viz. the low and the high.

Gaussian membership function is a fuzzy membership function that is often used to represent vague, linguistic terms. Gaussian membership is given by:

$$\mu_A(x) = \exp\left(-\frac{(c-x)^2}{2\sigma^2}\right) \quad (9)$$

Here, c and σ are center and width of the fuzzy set A and $x \varepsilon$ A.

For the LOW set value of c_l is 0 and σ_l is 35 and for the HIGH set value of c_h is 255 and σ_h is 35.The membership curve for LOW and HIGH are shown in fig. 5.1



(a) (b)

Fig 5.1: (a) Gaussian membership curve for low (b) Gaussian membership curve for high

Gaussian membership function for LOW is

$$\mu_{LOW}(x) = \exp\left(-\frac{(-x)^2}{2(35)^2}\right) \tag{10}$$

Gaussian membership function for HIGH is

$$\mu_{HIGH}(x) = \exp\left(-\frac{(255-x)^2}{2(35)^2}\right) \tag{11}$$

Here, x denotes the pixel intensity.

5.3 Fuzzy Rules

The fuzzy sets and their membership to the sets provide as information. Now some inference method is needed to obtain knowledge from this information. Rules help in taking the decision.

Representation of knowledge as rules is the most popular form.

if p is A then q is B

(where A and B are linguistic values defined by fuzzy sets on universes of discourse X and Y).

In the proposed approach, Six Fuzzy Rules have been used which decides the color cast in the image. Following are the rules

1. If R(i,j) is HIGH and G(i,j) is LOW and B(i,j) is LOW then cast is Red.
2. If R(i,j) is LOW and G(i,j) is HIGH and B(i,j) is LOW then cast is Green.
3. If R(i,j) is LOW and G(i,j) is LOW and B(i,j) is HIGH then cast is Blue.
4. If R(i,j) is HIGH and G(i,j) is HIGH and B(i,j) is LOW then cast is Red and Green.
5. If R(i,j) is LOW and G(i,j) is HIGH and B(i,j) is HIGH then cast is Green and Red.
6. If R(i,j) is HIGH and G(i,j) is LOW and B(i,j) is HIGH then cast is Red and Blue.

Here R(i,j), G(i,j) and B(i,j) denotes the pixel intensity for red, green and blue channel respectively.

Here the corresponding pixel value belong to a set if its membership for that set is more than the other set. i.e. if membership for HIGH is greater than membership for LOW then pixel belong to HIGH and vice versa. These rules are applied on each pixel of the image and the rule to which maximum number of pixels agree decide the overall cast on the image.

Depending on the six rules, color cast in an image fall in six classes:
Class 1: Red cast
Class 2: Green cast
Class 3: Blue cast
Class 4: Red and Green cast
Class 5: Green and Blue cast
Class 6: Red and Blue cast

Hence for color correction, we find the mean value of red, green and blue channels as defined in eqn (1).

Now depending on the class, a base is defined for the scaling factors for each of the channel. Value of Base for different classes of cast is given below in Table I:

Table I

Value of base for different classes of cast

Class	**Base**
Class 1	$\bar{R}$
Class 2	$\bar{G}$
Class 3	$\bar{B}$
Class 4	$\bar{R}+\bar{G}/2$
Class 5	$\bar{G}+\bar{B}/2$
Class 6	$\bar{R}+\bar{B}/2$

Now the scale factors are defined for each channel denoted β_r, β_g and β_b. These scale factors are given as:

$$\beta_r = \frac{Base}{\bar{R}}, \beta_g = \frac{Base}{\bar{G}}, \beta_b = \frac{Base}{\bar{B}} \qquad (12)$$

Now the gray world correction algorithm is modified by using the following equation:

$$\tilde{R} = \beta_r^{\lambda} R, \ \tilde{G} = \beta_g^{\lambda} G, \ \tilde{B} = \beta_b^{\lambda} B \qquad (13)$$

Here value of λ is found out by optimising the performance measure using Bacterial foraging optimization algorithm.

5.4 Performance Measure

There are many metrics available in literature for performance evaluation of color correction algorithm. But in the proposed approach, CIE L*a*b metric described in [18] has been used for performance evaluation.

Individual pixel distances are defined as follows:

$$\Delta E_{damaged} = \sqrt{\Delta L^2 + \Delta a^2 + \Delta b^2} \qquad (14)$$

Image distances are then defined as follows:

$$\Delta E = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n} \Delta E_{damaged}(i,j)}{\sum_{i=1}^{m}\sum_{j=1}^{n} \Delta E_{reference}(i,j)} \qquad (15)$$

Where

$$\Delta E_{reference} = \sqrt{L^2 + a^2 + b^2} \qquad (16)$$

Here reference image is the original image without any bad illumination effect. These images are distorted by adding color cast to them. Now the distorted images are corrected using proposed approach and the image distance is calculated using eqn (15). This image distance is to be minimised using bacterial foraging optimisation technique.

5.5 Modified Bacterial Foraging Optimisation Algorithm

Here the Bacterial Foraging algorithm is little modified by removing the swarming step in the algorithm. Hence, the cost of finding food is referred to as objective function denoted by J used in modified bacterial foraging optimization. Value of J for proposed scheme is image distance, denoted by ΔE.

$$J = \Delta E \qquad (17)$$

The parameters of modified Bacterial Foraging Optimization are initialized as follows:

p: dimension of search space=1

S: Number of bacteria=10

N_c: Number of chemo tactic steps=12

N_s: swim length=4

N_{re}: Number of reproduction steps=2,

N_{ed}: Number of elimination dispersal events=2

P_{ed}: Probabitlty of elimination dispersal=0.25.

Position of each bacteria: The location of each bacterium, which is a function of several parameters, i.e., $f(p,S,N_c,N_{re},N_{ed})$, is specified by a random number in the range [0–1]. This position indicate the value of λ, parameter used in image enhancement , for which the value of J in eqn. 4 is optimised by the algorithm.

5.6 Algorithm

1. Initialize six variables each corresponding the number of pixels complying with each rule, r1=0; r2=0, r3=0, r4=0, r5=0, r6=0.
2. Input the color image I of size m×n×3 in RGB format.
3. Separate the R,G,B components
4. For each pixel (i,j) in image I
5. Compute $\mu_{low}(R(i,j))$ and $\mu_{high}(R(i,j))$ using Eq. (2) and Eq. (3),
   if $\mu_{low}(R(i,j)) > \mu_{high}(R(i,j))$, r=low , else r=high
6. Compute $\mu_{low}(G(i,j))$ and $\mu_{high}(G(i,j))$ using Eq. (2) and Eq. (3),
   if $\mu_{low}(G(i,j)) > \mu_{high}(G(i,j))$, g=low , else g=high
7. Compute $\mu_{low}(B(i,j))$ and $\mu_{high}(B(i,j))$ using Eq. (2) and Eq. (3),
   if $\mu_{low}(B(i,j)) > \mu_{high}(B(i,j))$, b=low , else b=high
8. Apply fuzzy rule to the values of r, g and b for pixel (i,j) and increment the count of the rule that pixel(i,j) follows.
9. If all the pixels not scanned, go to step 5.
10. Class of color cast is hence denoted as
    $class = \arg\{\max(r1, r2, r3, r4, r5, r6)\}$
11. Calculate mean of R, G, and B component using Eq. (4).
12. Calculate base corresponding to the cast class found in step 10 using the table 1.
13. Compute $\alpha_r, \alpha_g, \alpha_b$ using Eq. (7).
14. Compute the objective function using Eq. (12) and optimize it using Bacterial Foraging optimization and find the optimized values of parameter λ .
15. Find corrected R, G, B components of image using the optimised value of parameter λ as stated in Eq. (8).
16. Finally, combine the corrected R, G, B components to get the enhanced image.

Chapter 6

RESULT AND COMPARISON WITH GRAY WORLD TECHNIQUE

6.1 Comparison With Other Color Correction Techniques

The proposed approach has been implemented on Intel Core i3 at 2.40 GHz using MATLAB version 2009b. Measuring the performance of color correction approaches is not easy task. There are two types of evaluation for image enhancement algorithms. One is subjective evaluation which takes into account human perception of the image. Since Image quality may appear different to different individual so views may vary. Second type is objective. In objective evaluation, some metrics is used to quantify the quality of the image. Objective evaluation is more reliable, consistent and replicable especially when the goal is to compare relative approaches performance. In the literature, many different color distance metrics have been proposed. We have implemented the CIE L*a*b metric described in [18].

Since we want to find 'image distance', this performance metric is applied on CIE Lab format. Hence we need to change RGB image into CIE Lab format. For objective evaluation using Image distance, we need a reference image, test image. We have taken around 50 images which are free from color cast and illumination defect. These are the reference images. These reference images are distorted by adding color cast to them using Adobe Photoshop 5.0. These distorted images are the test images.

Hence, Before using this performance measure, the test image and reference image are converted from their format to CIE Lab format and then the image distance is found using Eq. (10).

Now, the test image is corrected using color correction approach, the image distance is calculated from the reference image. This measure has been used as the objective function for bacterial foraging optimisation.

For subjective evaluation of the approach, results of few test images have been shown in fig 6.1-6.10. The captions are as follows: (a) reference image, (b) test image, (c) the result of Gray World Correction [13],(d) Result of Automatic Color Equalization (ACE) [3] (e) the result of proposed approach.

(a) (b)

(c) (d)

(e)

Fig.6.1: (a) Reference image1, (b) Test image1 (c) Gray World Corrected Image1, (d) ACE Corrected Image1, (e) Proposed Approach Corrected Image1

(a) (b)

(c) (d)

(e)

Fig.6.2: (a) Reference image2, (b) Test image2 (c) Gray World Corrected Image2 (d) ACE Corrected Image2, (e) Proposed Approach Corrected Image2

(a)

(b)

(c)

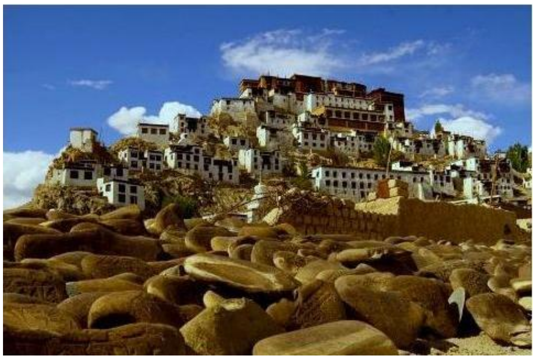
(d)

(e)

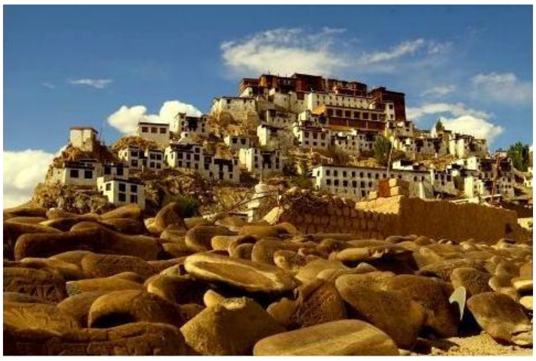
Fig.6.3: (a) Reference image3, (b) Test image3 (c) Gray World Corrected Image3 (d) ACE Corrected Image3, (e) Proposed Approach Corrected Image3

(a) (b)

(c) (d)



(e)

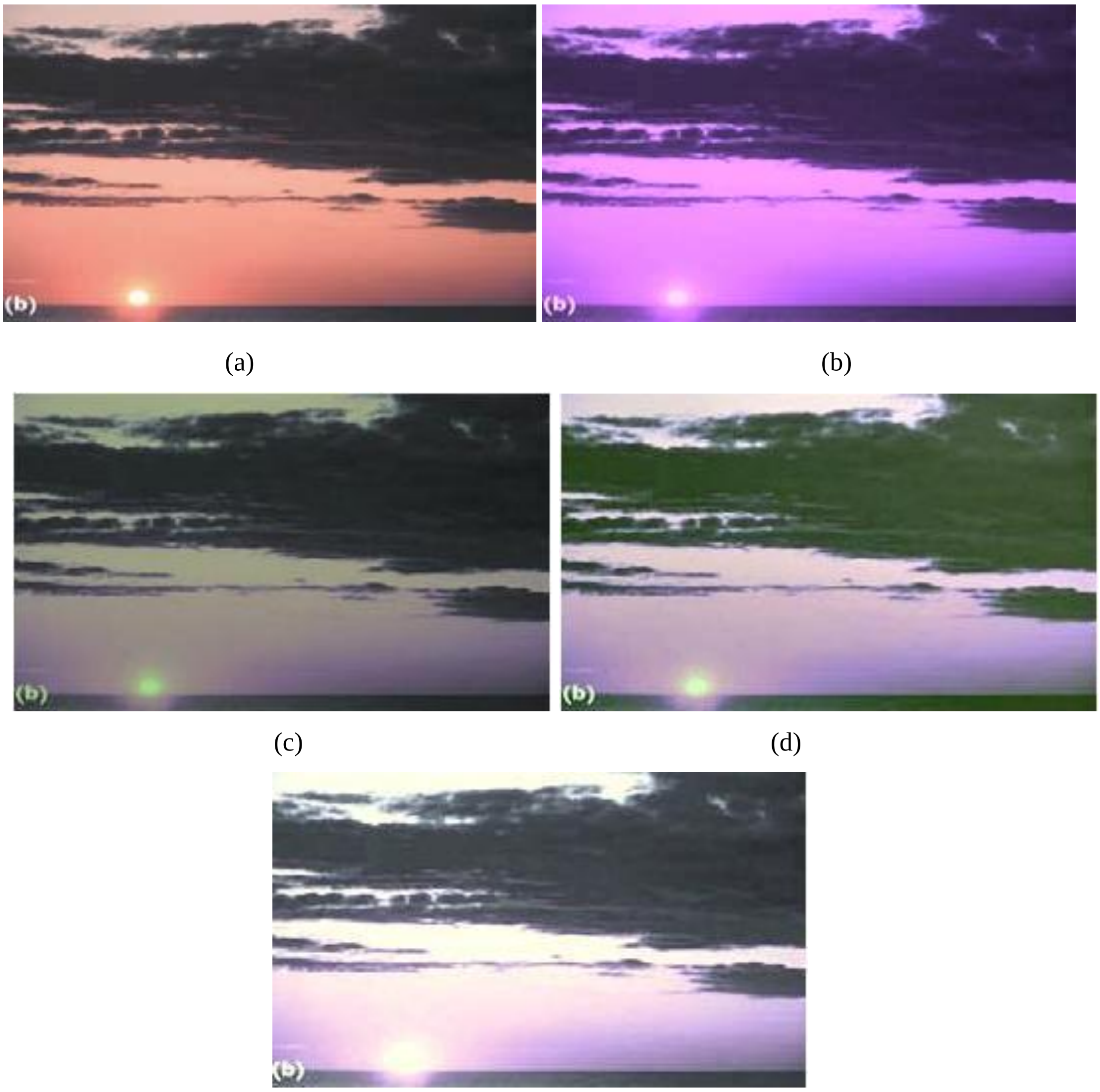
Fig.6.4: (a) Reference image4, (b) Test image4 (c) Gray World Corrected Image4 (d) ACE Corrected Image4, (e) Proposed Approach Corrected Image4


(a) (b)


(c) (d)

(e)

Fig.6.5: (a) Reference image5, (b) Test image5 (c) Gray World Corrected Image5 (d) ACE Corrected Image5, (e) Proposed Approach Corrected Image5



(a) (b)

(c) (d)

(e)

Fig.6.6: (a) Reference image6 (b) Test image6 (c) Gray World Corrected Image6 (d) ACE Corrected Image6, (e) Proposed Approach Corrected Image6

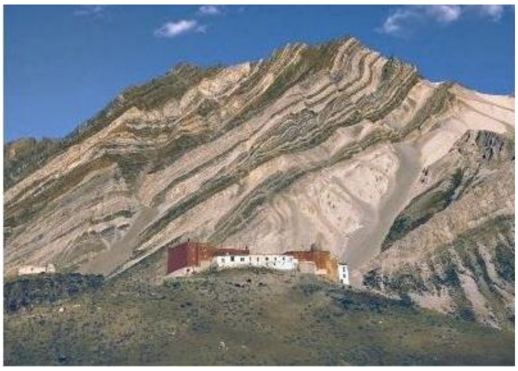

(a) (b)


(c) (d)

(e)

Fig.6.7: (a) Reference image7, (b) Test image7 (c) Gray World Corrected Image7 (d) ACE Corrected Image7, (e) Proposed Approach Corrected Image7

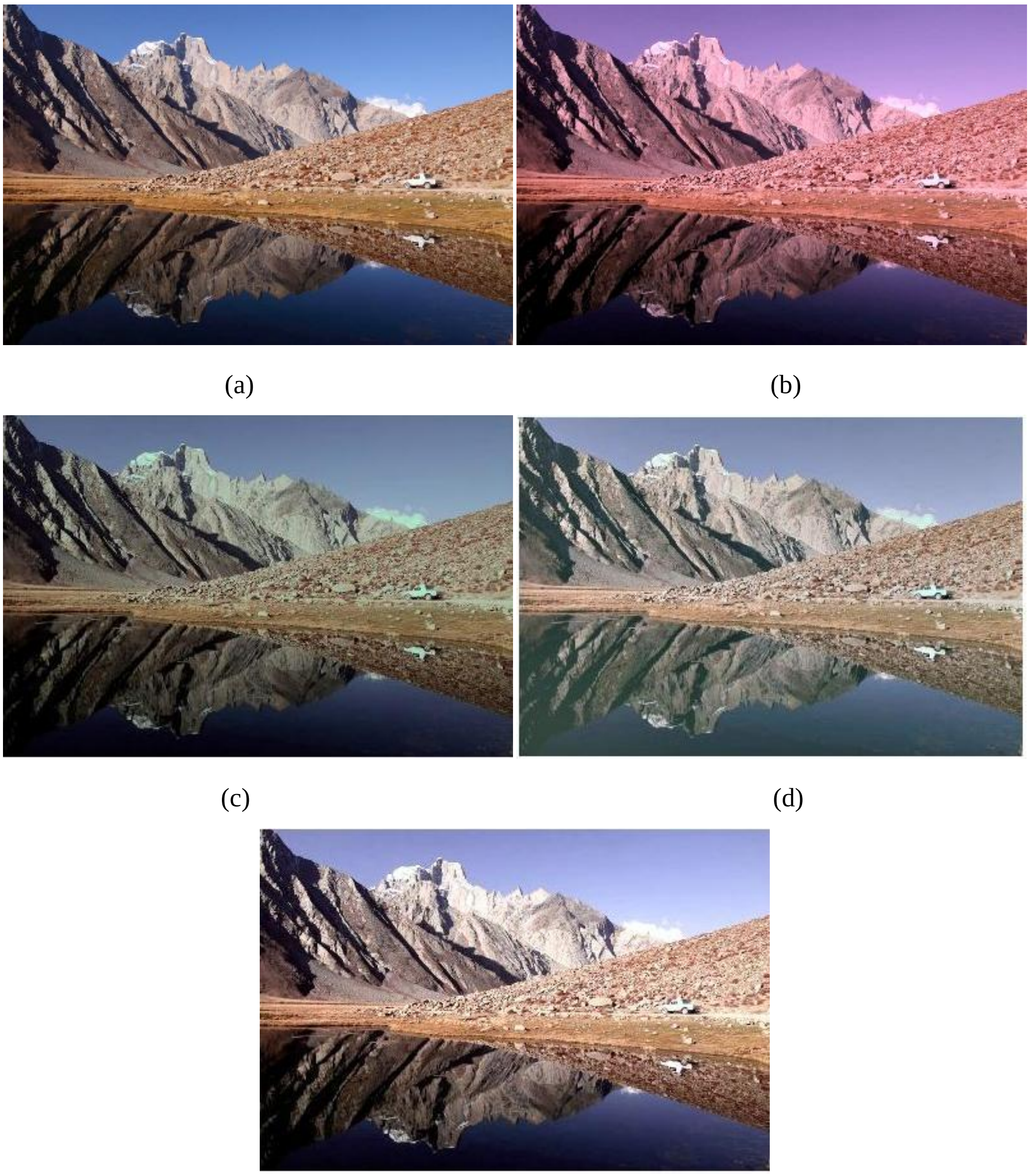
(a) (b)



(c) (d)

(e)

Fig.6.8: (a) Reference image8, (b) Test image8 (c) Gray World Corrected Image8 (d) ACE Corrected Image8, (e) Proposed Approach Corrected Image8



(a) (b)

(c) (d)

(e)

Fig.6.9: (a) Reference image9, (b) Test image9 (c) Gray World Corrected Image9 (d) ACE Corrected Image9, (e) Proposed Approach Corrected Image9


(a) (b)


(c) (d)

(e)

Fig.6.10: (a) Reference image10, (b) Test image10 (c) Gray World Corrected Image10 (d) ACE Corrected Image10, (e) Proposed Approach Corrected Image10

6.2 Quantitative Analysis

For quantitative analysis of the color correction algorithms, CIE Lab metric 'Image Distance' has been used. Value of Image distance should be low for better results. Lower value of image distance implies that the corrected image is closer to the reference image. Since the proposed approach finds the optimal value of image distance by finding λ. Optimal values of λ for few test images are given in Table II below:

Table II

Optimised Value of λ

Image	λ
Image1	0.387
Image2	1.5534
Image3	-0.9825
Image4	0.4124
Image5	1.4846
Image6	0.9076
Image7	0.4201
Image8	0.1304
Image9	0.7084
Image10	0.407

The above table shows that the value of the power λ depends upon the image.
Table III gives the value of image distance for gray world, ACE, Proposed Approach with $\lambda=1$ and proposed approach with optimised value of λ.

From the table values, it can be judged that proposed approach even without the optimised value of λ, perform better than Gray world and ACE for many of the images. Out of 10, only in 4, Gray world has outperformed the proposed approach which has not been optimised which shows that even without optimisation; proposed approach is worth considering for color correction. With optimisation, proposed approach always gives better results than the other techniques. ACE technique; however, perform better than Gray world in 6 out of 10 images. But performance evaluation shows that the proposed method is far better than ACE.

TABLE III

Value of Image Distance for Few Test Images

Image	**Gray World[12]**	**ACE[3]**	**Proposed Approach**	
			λ=1	**Optimal λ**
Image1	0.3922	0.7872	0.5833	0.1292
Image2	0.9851	0.8194	0.8664	0.5225
Image3	0.6205	0.5158	0.6222	0.0119
Image4	0.6464	0.5747	0.4855	0.1877
Image5	0.1	0.1934	0.101	0.0048
Image6	0.8483	0.9141	0.681	0.6543
Image7	0.857	0.8753	0.857	0.6702
Image8	0.9996	0.8353	0.9692	0.0171
Image9	0.837	0.5408	0.3915	0.2023
Image10	0.8868	0.9995	0.8936	0.8542

Chapter 7
CONCLUSIONS

Images captured by digital camera are usually give different view as compared to the original scenario due to the effect of ambient light, temperature conditions, low or high exposure of some regions of the scene etc. Such images need color correction for better image perception.

Color correction is the concept of altering the color balance of an image to achieve a desired effect. Color correction is generally broken down into two distinct processes: primary and secondary color correction. Primary color correction is the process of setting the overall tone, contrast, and color balance of an image. Secondary color correction is a further step that refines the image in specific geographical regions or in specific color vectors of the image. The proposed approach deals with primary color correction. It finds the color cast in image and finally removes the effect of that cast.

Cast of ambient light can be due to the effect of primary components of light i.e. red, green and blue. Gray world based correction algorithm assumes the color cast irrespective of the image. However, the proposed approach finds the actual cast in an effective manner without assuming it.

This uncertainty of color cast is removed using the fuzzy logic in the proposed approach. Since Gray World correction procedure is one of the finest and widely accepted criteria because it is based on Human Visual System., Proposed method adapted the Gray world correction algorithm with slight modification. With this modification, it gives more effective results as compared to conventional Gray World Correction Algorithms

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