ENHANCEMENT OF IMAGE CONTRAST USING COMPUTATIONAL INTELLIGENCE ALGORITHMS

Thesis submitted by

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Statement of Originality

I, Saorabh Kumar Mondal, registered on the 25th of April, 2018 do hereby declare that this thesis entitled "Enhancement of image contrast using computational intelligence algorithms" contains a literature survey and original research work done by the undersigned candidate as part of Doctoral studies.

All information in this thesis has been obtained and presented in accordance with existing academic rules and ethical conduct. I declare that, as required by these rules and conduct, I have fully cited and referred all materials and results that are not original to this work.

I also declare that I have checked this thesis as per the "Policy on Anti Plagiarism, Jadavpur University, 2019", and the level of similarity as checked by iThenticate software is 7%.

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CERTIFICATE FROM THE SUPERVISOR

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This is to certify that the thesis entitled “Enhancement of image contrast using computational intelligence algorithms” submitted by Mr. Saorabh Kumar Mondal, who got his name registered on 25th of April, 2018 for the award of Ph.D. (Engg.) degree of Jadavpur University, is absolutely based upon his own work under the supervision of Dr. Arpitam Chatterjee and neither his thesis nor any part of the thesis has been submitted for any degree/diploma or any other academic award anywhere before.

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Dedicated to

my daughter

ADRITA

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Abstract

Image quality is governed by many visual characteristics of the image for example, brightness, contrast, color distribution, presence of noise, etc. Alteration in those characteristics can cause noticeable perceptual changes of image appearance to human viewer. In several cases degraded images are resulted due to diverse reasons like low illumination, noise in capturing device, wrong color interpretation, etc. Addressing each of such degradation is wide research area. Image contrast enhancement is a frequent image enhancement requirement in diverse applications.

There are many conventional techniques to approach different low contrast in image including filter development, kernel processing, and image transformations in different domains. Those classical approaches can result contrast enhancement however, often their applications found to be limited due to high processing time, computationally expensive and not adaptable in nature or in other medium such as satellite, underwater etc. Many of the times the classical technique involve lots of parameters and tuning of the parameters itself become difficult. These techniques are also suffer from problems like over enhancement, whitening of the image, non preservation of image brightness, false contouring, etc. Another important limitation of conventional techniques has been observed that many such techniques improve the image contrast without maintaining other image characteristics which also gives an artificial appearance to the enhanced images.

Recently computational intelligence (CI) has become a popular tool in image enhancement domain to address limitations resulted by the conventional techniques. The CI algorithms

due to their adoptability, flexibility and optimality can result contrast enhanced images which are improved both in terms of visual and objective assessment. In a general note CI algorithms mimic the natural behavior in biological agents to search optimal solution of the problem. For example, artificial bee colony (ABC) mimics the food searching algorithm of honey bees while grey wolf optimizer (GWO) algorithm is motivated by hunting behavior of grey wolf. The development of CI algorithms is continuing which leaves a considerable room to apply those algorithms in image contrast enhancement tasks.

This work is aimed to explore the possibilities of employing CI algorithms to address image contrast enhancement task while maintaining the other image characteristics like brightness, color, sharpness, etc. Two objective functions based on contrast interpretation and imaging model have been developed to enhance the image contrast and retain the other image characteristics. The fitness function is formulated using different image quality assessment (IQA) metrics. Three advanced CI algorithms i.e. bacteria colony optimization (BCO), grey wolf optimizer (GWO) and bat algorithm (BA) have been consider for this purpose due to their several advantages over other CI algorithms. Both gray scale and color images have been taken from standard databases to vouch the potential of presented techniques. The resulted images have been compared with the results of conventional techniques and other CI algorithms for the image contrast enhancement task under consideration both visually and objectively.

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List of abbreviations

2DHE	Two-dimensional histogram equalization
ABC	Artificial bee colony
ACO	Ant colony optimization
AGC	Adaptive gamma correction
AGCWD	Adaptive gamma correction weighted distribution
AGCWHD	Adaptive gamma correction with weighted histogram distribution
AHE	Adaptive histogram equalization
AMBE	Absolute mean brightness error
AMSR	Adaptive multi scale Retinex
BA	Bat algorithm
BBHE	Brightness preserving bi-histogram equalization
BCO	Bacteria colony optimization
BHENM	Bi-histogram equalization with neighborhood metric
BPDFHE	Brightness preserving dynamic fuzzy histogram equalization
BPDHE	Brightness preserving dynamic histogram equalization
CDF	Cumulative distribution function
CE	Contrast enhancement
CEF	Contrast enhancement factor
CI	Computational intelligence
CLAHE	Contrast limited adaptive histogram equalization
CLAHE-DGC	Contrast-limited adaptive histogram equalization with dual gamma correction
CMYK	Cyan, magnets, yellow and key
CPDF	Cumulative pdf
CSA	Cuckoo search algorithm
CSO	Cat swarm optimization
CSS	Charged system search
DCE	Difference channel estimation
DCP	Dark channel prior
DCT	Discrete cosine transform
DCTCH	DCT coefficient histogram

DCTCS	DCT coefficient scaling
DCT-SVD	DCT pyramid and singular value decomposition
DE	Differential evolution
DHE	Dynamic histogram equalization
DSIHE	Dualistic sub-image histogram equalization
DWT	Discrete wavelet transform
EP	Evolutionary programming
ES	Evolution strategy
FA	Firefly algorithm
FDAHE-GC	Fuzzy dissimilarity adaptive histogram equalization with gamma correction
FFT	Fast Fourier transform
FPA	Flower pollination algorithm
FR	Full reference
FT	Fourier transform
GA	Genetic algorithm
GHE	Global histogram equalization
GLSA	Gravitational local search
GP	Genetic programming
GSA	Gravitational search algorithm
GWO	Grey wolf optimizer
HBA	Honey bee algorithm
HE	Histogram equalization
HSV	Hue, saturation, value
KHA	Krill herd algorithm
LOA	Lion optimization algorithm
MMBEBHE	Minimum mean brightness error bi-histogram equalization
MMLSEMHE	Minimum middle level squared error multi histogram equalization
MPHEBP	Multi peak histogram equalization with brightness preserving
MSR	Multi scale Retinex
MVG	Multivariate Gaussian
MWCVMHE	Minimum within-class variance multi-histogram equalization
NIQE	Natural image quality evaluator

NR	No reference
PCQI	Patch-based contrast quality index
PDF	Probability density function
PSO	Particle swarm optimization
RESECEDCT	Residual spatial entropy based contrast enhancement using DCT
RGB	Red, green, blue
RLBHE	Range limited bi-histogram equalization
RMMGT	Recursive median and mean partitioned one-to-one gray level mapping transformations
RMSHE	Recursive mean-separate histogram equalization
RSIHE	Recursive sub-image histogram equalization
RSWHE	Recursively separated and weighted histogram equalization
SCHE	Spatial entropy-based contrast enhancement
SECE	Spatially controlled histogram equalization
SECEDCT	Spatial entropy-based contrast enhancement in DCT
SFLA	Shuffled frog-leaping algorithm
SI	Swarm intelligence
SSR	Single scale Retinex
VBBPDHE	Variance-based brightness preserved dynamic histogram equalization
WAMSHE	Weighted average multi segment histogram equalization

CHAPTER 1

Introduction and scope of the thesis

1.1. Introduction

Image enhancement is an important process for betterment of image quality in the field of image processing system, such as medical image processing, space image processing, and remote sensing, etc [1]. These operations are applied on digital images to improve the human perception of information. Contrast enhancement is one of the most vital parts of image enhancement systems. A contrast enhancement technique can obtain better-quality image for image-processing application [2].

Fig. 1.1: *Low contrast 'Flower' image from 'TID' database*

Image contrast is an important characteristic of image that largely contributes towards perceived image quality as can be seen in Fig. 1.1. In general, image contrast is the ratio between darkest and lightest part of the image. Contrast sensitivity has two major interpretations namely absolute and perceived contrast sensitivity. The former one is the minimum difference in luminance required for distinguishing between two intensities. The human eyes are not very sensitive to this and as a result very small difference may not be visible. Perceived contrast sensitivity is more important as this is to which human eyes are sensitive. For instance, a bright object is more visible in a dark background than a bright one since the contrast between bright object and bright background is not enough for human eyes to distinguish. This phenomenon is mathematically modeled using contrast sensitivity function. There are interpretations called global and local contrast as well. The global contrast is an overall ratio between luminance of dark and light region of entire image while local contrast is the distinguishing ability of different image regions with reference to the luminance of its local surrounding pixels [3]. Contrast enhancement techniques focus on perceived and local contrast. Due to many reasons, such as insufficient illumination, noise during image acquisition, information loss during image transmission and limitation in sensing capability of the optical sensors, low contrast images are resulted. Low contrast not only results in visual unpleasantness but also limits performance of different image analysis tasks like edge extraction, feature extraction and object recognition. Image contrast enhancement therefore is a key research area. The goal of image contrast enhancement is to reconstruct the low contrast input image with new intensity levels that keep informational symmetry with the original image. In the digital era histogram has evolved as a potential alternative to the gradation curves and differential operators of analog era. Histogram has several advantages as it provides intensity distribution across the available intensity levels as a numeric array. Fig. 1.2 shows a gray scale image and its histogram pattern [4].

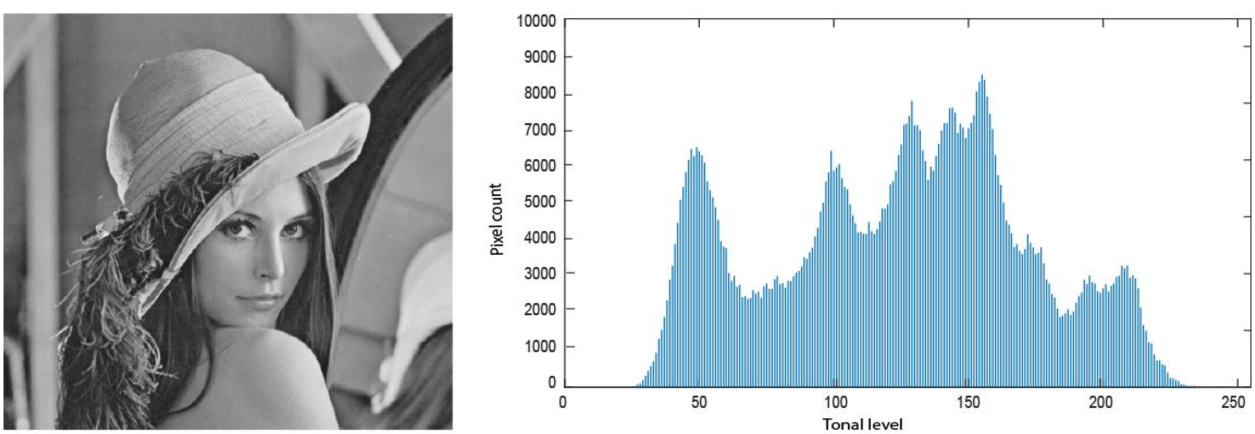

Fig. 1.2: *Gray scale image and its histogram pattern*

Different statistical information of the images can thus be derived from histograms that are widely used for many image processing and transformation operations like image compression, segmentation, etc. It provides better control over different visual regions in the images, i.e. shadow, mid-tone and highlight, since it is a numerical array that provides clear brightness distribution across the local regions of the images. For instance, a narrow histogram conveys the low contrast, since the pixel values can vary only within few intensities and rest of the intensity levels remain unutilized. Histogram can provide better insight of the image information particularly using the probability density function (PDF) which can also convey the gradient curve information when taken in the cumulative manner as cumulative pdf (CPDF). Being powerful and simple, histogram has become the obvious choice for many real-time applications of image reproduction and representation systems. Histogram equalization (HE) widens up the histogram of the input image across the available intensity levels, since the histogram of low contrast images is found with narrow distribution. The two broad categories of approaches towards contrast improvement are spatial intensity based and frequency-based approaches. Global histogram equalization (GHE) [5] is one of the classical techniques under former class that maps the existing intensity levels to new levels that are more apart from each other resulting in better contrast. In GHE, this is achieved probabilistically based on the CPDF of the image.

Let, X =X(i, j) is an input image with L discrete gray levels {0,1,2,3,4,5, ……..……L-1}. where X(i, j) is the intensity of the image at the 2D position (i, j). The histogram of X is as follows:

$$H(X_k) = N_k \tag{1.1}$$

where, X_k is the K^{th} gray level of the image X and N_k is the number of pixels having K^{th} gray level. The probability density function (PDF) of the image is given as:

$$P(X_k)= N_k /N \tag{1.2}$$

where N_k is the number of pixels whose gray level is x_k and N is the total number of pixels.

$$K=0,1,2,3,4,5,\ldots\ldots L-1. \tag{1.3}$$

Cumulative distribution function (CDF) can be calculated using the probability density function (PDF) as shown in Eq. 1.4.

$$C(X_k)= \sum_{j=0}^{k} p(X_j) \tag{1.4}$$

It is hereby calculated that,

$$C(X_{L-1}) = 1 \tag{1.5}$$

HE is a scheme that maps the input image into the entire dynamic range by using the cumulative density function as a transform function. Transform function *f(x)* based on the cumulative density function is presented as Eq. 1.6.

$$f(x) = X_0 +(X_{L-1} – X_0)C(X) \tag{1.6}$$

1.2. Background establishment through existing literature survey

The results of GHE frequently suffer from false contouring and artificial appearance. Many modified algorithms based on histogram equalization were presented towards improvement over the conventional algorithms. Brief descriptions of those techniques are as follows:

i) In 1997, Kim presented the first mean based separation technique called brightness preserving bi-histogram equalization (BBHE) [6] to preserve the mean brightness of the input image, while enhancing the image contrast. Here, the total histogram was divided into two sub histogram based on the mean value of image pixels.

ii) In 1998, Wongsritong et al. presented multi peak histogram equalization with brightness preserving (MPHEBP) [7]. In this technique, local maxima used to divide the input histogram to improve the brightness preservation of the original image.

iii) In 1999, Wang et al. presented another separation based technique called dualistic sub-image histogram equalization (DSIHE) [8], where separation of the input histogram can be done using median instead of mean value of image pixels. Both BBHE and DSIHE provided better results in comparison of GHE to preserve the brightness of input images but not so suitable for those images where higher degree of preservation required. In this case these techniques suffer from annoying artifacts.

iv) In 2003, Chen and Ramli presented an extensive technique of BBHE and the separation occurs based on threshold level minimum mean brightness error bi-histogram equalization (MMBEBHE) [9] for higher degree of preservation. The main target of this technique was to obtain maximum level of brightness preservation almost without annoying artifacts due to extreme equalization. MMBEBHE showed that it preserved better brightness with respect to other previously mentioned techniques as well as it can maintain a more natural enhancement but it failed to control the over enhancement of the image during the time of very much higher brightness preservation.

v) In 2003, Chen and Ramli presented recursive mean-separate histogram equalization (RMSHE) [10], where the input histogram divided into two sub histograms based on its mean value before equalizing them independently. This process was done repetitively to maintain the output image’s mean brightness with the input image’s mean brightness. In case of BBHE, the histogram separated only one time. Mathematically it proved that, more number of recursive mean separations increase the preservation of input image’s mean brightness to the output image.

vi) In 2007, Sim et al. presented another similar type of technique named recursive sub-image histogram equalization (RSIHE) [11] to achieve higher brightness preservation. This technique separated the input histogram based on median value of gray level. Both RMSHE and RSIHE performed very well for low contrast image to enhance the image contrast and to preserve the mean brightness of the input image but these techniques lead to suffer over enhancement in case of input bright images.

vii) Wadud et al. introduced dynamic histogram equalization (DHE) [12] in 2007 to maintain the gray levels stretching by using local minima to maintain the optimum enhancement and to avoid the dominance of higher histogram components over lower histogram components. One drawback of this technique was to give priority of intensity saturation rather than preserving the mean brightness of an input image.

viii) Ibrahim and Kong presented another technique in 2007 called brightness preserving dynamic histogram equalization (BPDHE) [13] to overcome such problem that occur in DHE. This technique separated the input histogram based on local maximum value and it was the updated technique of DHE and MPHEBP. In comparison with DHE, BPDHE had better contrast enhancement capability and in comparison with MPHEBP, BPDHE had better brightness preserving capability.

ix) In 2007, Menotti et al. presented minimum within-class variance multi-histogram equalization (MWCVMHE) [14] and minimum middle level squared error multi histogram equalization (MMLSEMHE) [15] techniques to enhance the image contrast with natural appearance. MWCVMHE separated the input histogram into multiple sub-histograms based on minimizing within-class variance. Each sub histograms separately equalized and finally combined all the equalized histograms to obtain final modified histogram. In case of

MMLSEMHE, the separating points selected based on Otsu threshold selection technique and finally equalized all the sub histograms individually. Among all sub histograms, MMLSEMHE estimated the optimal number of sub-histograms to minimize certain discrepancy functions [15]. That's why MMLSEMHE was more computationally complex in comparison with MWCVMHE.

x) Kim and Chung presented another type of contrast enhancement technique in 2008 which was similar to RMSHE and RSIHE called recursively separated and weighted histogram equalization (RSWHE) [16] for contrast enhancement purpose maintaining the input image brightness. This technique also separated the input histogram into many sub-histograms recursively based on the mean or median of the image. All the sub-image histograms will modify by a weighting process based on the power law function. In case of RMSHE and RSIHE, histogram weighting functions were not applicable. RSWHE technique was classified into two types, RSWHE-M and RSWHE-D. In case of RSWHE-M, segmentation was done based on mean value whereas for RSWHE-D, it was median-based segmentation. Experimentally it observed that, RSWHE-M technique was better than the RSWHE-D technique for contrast enhancement and brightness preserving.

xi) In 2008, Wadud et al. presented another technique called spatially controlled histogram equalization (SCHE) [17], which separated the image histogram into a number of sub-histograms repetitively until all the modified sub histograms did not have any dominating portion. Then, the gray level mapped to each sub histogram by allocating a dynamic gray level range. Based on input image dynamic range and cumulative distribution function (CDF), the output sub histograms dynamic range distributed.

xii) In modification to BPDHE technique, Sheet et al., in 2010 introduced brightness preserving dynamic fuzzy histogram equalization (BPDFHE) [18] which included fuzzy statistics and it computed fuzzy histogram. This fuzzy histogram separated into multiple sub histograms based on local maxima. Each sub histogram was built by taking the valley portion between two consecutive local maxima. During the time of equalization, these peak histograms were not remapped. So, better preservation achieved when enhancing the image contrast.

xiii) Khan et al. introduced weighted average multi segment histogram equalization (WAMSHE) [19] in 2012, where the input histogram segmented based on optimal thresholds. The main advantage of this technique was that not only it could preserve mean brightness and enhanced the image contrast properly but helped to minimize the input image noise.

xiv) Sengee et al. introduced bi-histogram equalization with neighborhood metric (BHENM) [20] in 2010. This technique separated the original histogram into two sub histograms based on mean value. The main important feature of this technique was that, it divided the large histogram bins into sub-bins to remove the present artifacts using neighborhood metrics. The distinction neighborhood metric sorted the image pixels which had equal intensity and made different sub bins to enhance local contrast of an image.

xv) In 2012, Zuo et al presented range limited bi-histogram equalization (RLBHE) [21], which separated the input histogram into two different sub-histograms based on threshold value to reduce the intra-class variance. This technique had the capability to extract the original objects from the background. So, it used in real time image processing and it could enhance the image contrast by preserving the mean input brightness.

xvi) Adaptive histogram equalization (AHE) [22] and its further development named contrast limited adaptive histogram equalization (CLAHE) [22] also showed significant improvement of contrast while addressing the limitations of conventional algorithms. The basic form of the technique was invented independently by Ketcham in 1976, Hummel in 1977, and Pizer in 1981.

Here the adaptive techniques basically performed several histograms and used them to redistribute the image lightness values. Hence these techniques also suitable for local contrast enhancement as well as enhancing the edges of all the region of that image. One of the major limitations of these algorithms was noise amplification.

S. M. Pizer et al. first introduced the modified AHE which was Contrast Limited AHE (CLAHE). In case of AHE, with the amplification of image contrast, there will be chances of noise amplification, which does not happening due to limit of image contrast amplification. In CLAHE, the transformation function slop used to amplification of image contrast.

xvii) In the year 2013, Huang et al. introduced adaptive gamma correction (AGC) [23] and its modified version called adaptive gamma correction weighted distribution (AGCWD) [23] which optimized the gamma parameter based on the weighted distribution function with the help of probability distribution function (pdf) and cumulative distribution function (cdf). This was done to modify each local image pixel value based on cumulative distribution function.

xviii) Many of the lately developed techniques in this paradigm were contrast enhancement using feature preservation bi-histogram equalization (CEFPBHE) [25], variance-based brightness preserved dynamic histogram equalization (VBBPDHE) [26] for image contrast enhancement and recursive median and mean partitioned one-to-one gray level mapping transformations (RMMGT) [27] for image enhancement provided superior results as these algorithms relied on the detailed analysis of plateaus and picked of the image histogram.

xix) The previous techniques mentioned in (xviii) operated in 1D histogram. Reports also conveyed the application of 2D histogram for contrast enhancement. Two-dimensional histogram equalization (2DHE) [28] and residual spatial entropy based contrast enhancement using DCT (RESECEDCT) [29] were two major algorithms in this context but the later one was not solely in spatial domain operations as it involved discrete cosine transform (DCT) coefficient manipulation. A detailed survey of many spatial domains techniques can be found in [30] which also portrayed that the scope of improvement is still open, especially, in terms of higher degree of naturalness and image feature retention in enhanced images which commonly lack due to either over- or under-enhancements. At the same time, many of these algorithms provided compromised results in case the contrast distortion was in higher extent.

xx) Another recent model called Retinex model that removed bias of source lighting from the image, adopted for contrast enhancement as well. It included single scale Retinex (SSR) [31], multi scale Retinex (MSR) [32], and adaptive MSR (AMSR) models [33].

xxi) Some of other recent developments in this field were contrast-limited adaptive histogram equalization with dual gamma correction (CLAHE-DGC) [34], adaptive gamma correction with weighted histogram distribution (AGCWHD) [35] and fuzzy dissimilarity adaptive histogram equalization with gamma correction (FDAHE-GC) [36]. CLAHE-DGC enhanced the contrast by boosting its luminance value in addition of CLAHE technique. AGCWHD was also a modified version of AGC, where a new adaptive gamma correction technique implemented to enhance the contrast, while a weighted histogram distribution employed for natural color and detail preservation. In case of FDAHE-GC, an intensity mapping function developed from fuzzy dissimilarity histogram (FDH) for the purpose of image contrast enhancement and the gamma correction applied to enhance the dark regions.

Frequency domain algorithms has shown better performance over spatial domain approaches in many cases, since transform domains provide better control over local image characteristics which in turn provides improved feature retention. In general, Fourier Transforms (FT), discrete cosine transforms (DCT) and discrete wavelet transform (DWT) were mostly practiced transforms in image processing operations, since they provided deeper insight to the image information and lossless reversibility. Among those transforms DCT was often preferred due to its lower computational complexity and absence of imaginary coordinate like FT. DCT was considerably employed in contrast enhancement.

xxii) DCT coefficient scaling (DCTCS) [37], DCT coefficient histogram (DCTCH) [38], DCT pyramid and singular value decomposition (DCT-SVD) [39] were some of the noted works in this frequency domain. DCTCS included improvement of high frequency regions of input image spectrum that contained low amount of energy by scaling up the transformed image coefficients, while DCTCH performed histogram shifting process. DCT-SVD equalized the low sub band of the image using GHE. The naturalness preservation limitation of conventional HE addressed using a logarithmic law based modification scheme in the DCT domain. The image detail retention and contrast enhancement attained using adaptive geometric filter towards smoothing of histogram peaks followed by DCT coefficient adjustments. Spatial entropy-based contrast enhancement in DCT (SECEDCT) [40] was presented by T. Celik in 2014, was one of the recent image enhancement techniques, which was the modification of SECE technique in DCT domain. SECE algorithm performed the distribution of spatial location of pixel gray-levels to compute the spatial entropy for global contrast enhancement. SECEDCT performed both the global and local contrast enhancement by using DCT coefficients scaling process along with SECE technique.

The applications of different soft computing techniques had well been reported for image enhancement. Biological behavior inspired optimization techniques have shown significant potential in solving engineering problems with better results than traditional complex mathematical approaches. The algorithms in this domain were particularly advantageous for their adaptability and flexibility which in turn result in better search dynamics to find global optima by avoiding the local optima. Based on the characteristics, these algorithm can be classified into evolutionary, physics-based, and swarm intelligence (SI) algorithms.

xxiii) Genetic algorithm (GA) [41] was introduced by John Holland in 1975, is one of the pioneering evolutionary algorithms, which is still popular. Crossover and mutation were two most important steps in GA that mimic the natural reproduction behavior. Genetic programming (GP) [42], differential evolution (DE) [43], evolution strategy (ES) [44], and evolutionary programming (EP) [45] were some of the most commonly practiced evolutionary algorithms. In genetic programming (GP), chromosomes presentation is different from GA. GP used variable shapes and size tree-based chromosomes whereas GA used chromosome of fixed length string based. Differential evolution (DE) was introduced by Storn and Price in 1995 to minimize the continuous nonlinear and non-differentiable functions. Like other evolutionary algorithms, DE was not inspired biologically and no natural paradigm presents there. Evolution strategy (ES) was actually created early in 1960 and then in 1970 and later on it was presented by Ingo Rechenberg, Hans-Paul Schwefel and their co-workers. The search operators of ES were mutation and selection and basically it handled natural problems. Like other evolutionary algorithms, here also loop was used to apply the operators. In the year 1960, Lawrence J. Fogel first introduced evolutionary programming (EP) basically to generate artificial intelligence by the use of simulated evolution as learning process. In comparison of evolution strategies (ES), EP was little bit harder.

xxiv) Another group of algorithms in this context was physics based optimizations and example included charged system search (CSS) [46], gravitational local search (GLSA) [47], gravitational search algorithm (GSA) [48], etc. In general, these algorithms involved number of search agents to find the best solution in the problem space using the various parameters of physics like electromagnetic force, weight, mass, gravitational force, etc. Fuzzy set theory and fuzzy optimization are two frequently practiced algorithms that can result great optimization for complex problems especially where the problem involves many linguistic variables. These algorithms utilized for CE as well. Fuzzy algorithms particularly fuzzy segmentation of image histogram for CE reported in [49].

1.3. Swarm intelligence techniques

One of the subset of soft computing techniques were swarm intelligence techniques. In these techniques, the algorithms are designed based on the behaviors of natural swarms. Based on the collective intelligent behavior of insect or animal groups such as swarms of bees, colonies of ants, flocks of birds, schools of fish etc. swarm intelligence created [50].

In case of performing optimization task, swarm intelligence has a very popular and influential tool. These algorithms are spread in almost all fields due to its high flexibility, to solve complex problems. Swarm intelligence has also found better with respect to classical techniques for its high efficiency in many engineering problems. In swarm intelligence techniques, an individual fixed-size population was used for search across generations. In each generation, those individuals were evaluated to alter the next generation search strategy.

In SI techniques, for solving problems, two important characteristics are there a) self -organization strategies and b) independent work of each individual. In case of self-organizing strategy individually local stimulation performed and collectively it could perform global task. For independent work of individual, basically centralized supervision had been avoided. The collective behavior of insect or animal groups in nature makes it possible to simulate these above characteristics.

Based on simulating behavior of various animals, so many swarm algorithms introduced in last few years including particle swarm optimization (PSO) [51], ant colony optimization (ACO) [52], firefly algorithm (FA) [53], bat algorithm (BA) [54], krill herd algorithm (KHA) [55], cuckoo search algorithm (CSA) [56], honey bee algorithm (HBA) [57], flower pollination algorithm (FPA) [58], lion optimization algorithm (LOA) [59], cat swarm optimization (CSO) [60], artificial bee colony (ABC) [61] algorithm, bacteria colony optimization (BCO) [62], grey wolf optimizer (GWO) [63], etc. It is very important to choose proper algorithm to solve a problem.

Particle swarm optimization (PSO) was first introduced by Eberhart and Kennedy [51]. This technique is a population-based optimization algorithm. It uses a number of agents (particles) that comprise a swarm moving around in the search area looking for the best solution. Each particle keeps track of its positions in the solution space which are related with the best solution (fitness) that has achieved so far by that particle. This value is called personal best (pbest) and another best value that is tracked by the PSO obtained so far by any particle in the neighborhoods is called global best (gbest). Each particle moves with a certain velocity and reaches final location using p_{best} and g_{best} [51].

In the year 1992, Marco Dorigo first presented another swarm intelligence based optimization technique called ant colony optimization (ACO) [52]. Based on the behavior of biological ant, this algorithm was designed [52]. With the help of this technique various computational problems can be simplified by finding good paths through graphs. The aim of this technique was to search an optimal solution by the natural behavior of real ant searching an optimal path in a graph between source of food and their colony [52].

Firefly algorithm (FA) was first introduced in 2007 by Yang [53]. This algorithm was designed based on the behavior of fireflies and their flashing patterns. Any firefly can be attracted by another firefly though they are unisex. This attractiveness was proportional to the flashing brightness of firefly and it decreased when the distance between two fireflies increases. That's why, the less brightness firefly tried to move towards more brightness firefly and if no such brighter firefly found, they moved randomly. Based on this concept this algorithm was designed [53].

Bat algorithm (BA) was developed mimicking the food searching behavior of bat also shown promising potential in diverse applications [54]. BA was inspired by the use of echo by the bats to find the location of the prey. When the bat reached closer to the prey, the emitted sound loudness became decrease and the pulse emission rate increased. The major advantages of BA over other popular metaheuristics were it simplicity, require less parameter tuning and its robustness [54].

Krill herd algorithm (KHA) was introduced by Gandomi and Alavi for solving global optimization function [55]. This algorithm was totally depending on the individual krill's herding behavior. The objective function for the krill movement was formulated by obtaining the minimum distances of each individual krill from food and from highest density of the herd [55]. Based on three main factors, the time-dependent position of the krill individuals was formulated. (a) Movement encouraged by the other individual's presence (b) Foraging activity and (iii) Random diffusion [55].

Cuckoo search algorithm (CSA) was introduced by Xin-She Yang and Suash Deb in 2009 [56]. The concept of laying egg of cuckoo in the nests of host birds of different species was the main theme of this algorithm [56]. Some host birds could not recognize it and taken care of eggs thinking of its own egg. But some host birds identified the eggs and either thrown away from the nest or change the nest. Based on this concept, this algorithm was made.

Honey bee algorithm (HBA) was based on the foraging strategy of honey bees for getting best solution of any swarm based problem [57]. Every food source (flower) is the solution of each candidate solution. *n* number of agents (bees) is used to make a population for search the solution space. To evaluate the fitness, individual solution was trickled by each agent i.e. honey bee [57].

Flower pollination algorithm (FPA) was introduced by Xin-She Yang in 2012 [58]. This algorithm was inspired by the flow pollination process of flowering plants. In FPA, the following four rules were used [58]:

(a) In global pollination, cross and biotic -pollination process had been considered.

(b) Pollinators can develop the reproduction probability of flowers which was similar of involvement of two flowers.

(c) Self-pollination and abiotic pollination were used for local pollination.

(d) Switch probability $p \in [0,1]$ was controlling the switching of global and local pollination or interacting in between these.

Lion optimization algorithm (LOA) or lion's algorithm was first introduced by B. R. Rajakumar in 2012 [59]. In LOA, a set of randomly generated solutions was formed as an initial population. These solutions were called Lions. Among initial population, some of the lions were selected as nomad lions and the remaining populations were randomly partitioned into subsets. [59]. According to the iteration, best solution was obtained for each lion by the best visited position solution. In this way, the optimization process was updated progressively.

Cat swarm optimization (CSO) was presented by Chu et al. in 2006 [60]. It was introduced based on the natural behaviors of cats. According to the behaviors of cats CSO could be categorized into two sub-modes, i) tracing mode and ii) seeking mode [60]. In seeking mode, cats were used to maintain its position without any movement and decided for next suitable movement. In case of tracing mode, with a fixed velocity, cats moved to its next position. This velocity indicated the pattern of chasing the target by the cats [60].

Artificial bee colony (ABC) algorithm was presented by Karaboga and Basturk [61]. It was designed by the natural behavior of real honey bees in food foraging. In ABC algorithm, three types of bees are there: employed bees for searching food source, onlooker bees that are waiting on the dance area to choose a food source and scouts, who carries out a random search for new food source [61]. It was observed that ABC algorithm was very much effective for searching new solutions but not so effective for generation desired final solution [61].

Bacteria colony optimization (BCO) is a popular CI algorithm [62] that was introduced by Passino in 2002. It performed optimization using behavioral pattern on motile bacteria such as Escherichia coli (E. coli), Salmonella and Myxococcus Xanthus (M. Xanthus). In case of BCO the chemotaxis behavior of bacteria for surviving in the environment (such as nutrients) and their movement towards or away from a specific location was employed [62].

In the year 2014, S. Mirjalili et al. introduced another type of algorithm called grey wolf optimizer (GWO), which was based on the leadership hierarchy and the mechanism of hunting procedure of grey wolves. The top of this hierarchy were called alphas (α). Beta (β) and Delta (δ) were the next two positions accordingly. The first three best solutions obtained so far were considered according to the performances of Alpha, Beta and Delta and accordingly the final fitness position achieved.

1.4. Problem description

Literature survey reveals that despite many techniques, the room of improving image feature preservation, while enhancing image contrast is still open. The main target of this work is to enhance the image contrast, while maintaining the other features such as brightness, sharpness, color etc. Most of the contrast enhancement techniques fail to retain the image characteristics, while enhancing the image contrast. As a result, the output enhanced image will become unnatural and visually unpleasant. Apart from that the objective evolutions of enhanced image also show poor performance against quality metrics. Literature survey also reveals that the potential of swarm intelligence in solving complex problems. However, the success of applying swarm intelligence crucially depends on aptness of objective function. Thus, the problem statement is two folds; finding the potential of swarm intelligence techniques to retain image feature and enhance the image contrast. So, this work is focused on designing some objective functions based on shape and magnitude parameters in frequency domain and also to develop mathematical formulations of objective function in such a way that can address the image feature retention requirements.

1.5. Scope of work and research objectives

Image contrast is an important characteristic that drives the visual appearance as well as the feature detection tasks for many computer vision applications. Due to several natural and hardware limitations of the image capturing devices, low image contrast is resulted. Therefore, image contrast enhancement is a prominent research field. Broadly, the different algorithms for contrast enhancement can be divided into two categories; spatial domain and frequency domain operations. The former one is performed on the intensity values using different statistical parameters of the images. Different established techniques under this category succeed to improve the image contrast but most of the techniques provide some undesired results including alteration of mean brightness, over enhancement, false contouring, erroneous color representations, etc. Image brightness is defined as the measure of acquired image intensity or the intensity of those images, which are converted from analog to digital. It is also known as luminous brightness. In case of over-enhancement, the images are suffered from edges loss, important texture change and mostly the images are look unnatural. When the grey level resolution of a digital image become degraded, then false contouring occur. The main reason of false contouring is insufficient number of gray levels present in a digital image. For, erroneous color representation, false color is the main issue. A false-color image is that type of color image, which is totally different from original color image. Human cannot normally see the different wavelengths of color in this type of image but for true color image, it is clearly visible. In this thesis, some techniques have been represented to overcome such limitations and to provide better contrast image maintaining other image futures to improve the overall quality of an image. The objectives of the thesis work can be summarized as follows:

A) A thorough literature survey to find the commonly used contrast enhancement techniques.

B) To find the limitations of such commonly used techniques.

C) To represent the recent advance techniques, where such limitations are minimized.

D) To establish the frequency domain algorithms, that has shown better performance over spatial domain approaches in many cases.

E) To establish the CI algorithms for enhancing image contrast maintaining other image features.

F) To establish the mathematical model and imaging model for computing the objective functions.

G) To represent some with reference and no reference image quality metrics to ensure the overall improvement of input image quality.

1.6. Research questions

The following research questions can be framed by considering the scope and objectives of the thesis work mentioned above.

- **RQ 1:** Can computational intelligence techniques be a potential approach towards contrast enhancement?
- **RQ 2:** Can objective function developed in frequency domain results better improvement than spatial domain?
- **RQ 3:** Which type of objective function can result higher potential, a frequency spectra based or developed based on imaging characteristics?
- **RQ 4:** How extensible the computational approach based models can be across different applications of contrast enhancement?

1.7. Thesis structure

In this thesis, image contrast is one of the most important parameter for every image to identify the image futures as well as for visual satisfaction purpose. As per the literature review, it was observed that so many contrast enhancement techniques introduced to improve the image contrast. But, most of the techniques failed to maintain other image features while enhancing image contrast. So, the overall image quality suffers. Therefore, some alternative techniques based on computational intelligence algorithm have been presented here. Three major algorithms namely bacteria colony optimization (BCO), grey wolf optimizer (GWO), and bat algorithm (BA) have been implemented under this thesis work. Two objective functions have been formulated, which have been optimized by those CI algorithms. In view of the above-mentioned objectives, the entire work has been divided into six chapters. A brief chapter-wise organization of the thesis is presented below.

Chapter 1, ***"Introduction and Scope of the thesis"*** elucidates the importance of contrast enhancement of an image in the field of image processing and outlines the objectives of this thesis work. A brief literature survey has been highlighted. The chapter finally concludes with scope of the thesis and some clearly framed research questions to answer at the end of the thesis work.

Chapter 2, ***"Objective functions formulation and data analysis techniques"*** presents formulation of two different objective functions based on frequency domain analysis and imaging characteristics. This chapter also presents the detail about different evaluation techniques that have been used in this thesis and the images that have been consistently used throughout the thesis.

Chapter 3, ***"Image contrast enhancement using bacteria colony optimization (BCO)"*** presents a new contrast enhancement technique using bacteria colony optimization (BCO). The brief description of algorithm and parameter setting for presented work has been emphasized in this chapter. Both of the formulated objective functions have been subjected to BCO and results have been analyzed in comparative manner to draw the conclusion in terms of potential of BCO for contrast enhancement.

Chapter 4, ***"Image contrast enhancement using grey wolf optimizer (GWO)"*** presents a contrast enhancement technique using gray wolf optimizer (GWO), which optimizes the formulated objective functions. This chapter includes a brief description of GWO algorithm and the parameter settings involved in the presented work. The visual and objective comparisons between the output of GWO and established techniques have been included to show the potential of the GWO based contrast enhancement.

Chapter 5, ***"Image contrast enhancement using bat algorithm (BA)"*** presents another image contrast enhancement technique using bat algorithm (BA). This chapter includes the brief description of BA and the required parameter settings. Like the previous chapters, in this case also both the objective functions have been subjected to BA and the results obtained with different objective functions have been presented in comparative manner against subjective and objective evaluation metrics.

Chapter 6, ***"Concluding remarks***" finally represents the overall comparison between the proposed techniques and an overall summary of the work carried under this thesis. It also highlights the major findings and observations noted in the course of this thesis. The answers to all the previously framed research questions have well been presented in this chapter. The chapter also draws the possible future directions of the presented work.

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CHAPTER 2

Objective functions formulation and data analysis techniques

2.1. Introduction

Objective function is one of the most important parameters in any computational intelligence technique. It is optimized following the dynamics of CI algorithm to obtain optimized solutions. The goal of optimization governs the decision of minimizing and maximizing the value of objective function. However, commonly it is shaped as minimization, since minimizing to 'zero' is more convenient to interpret. Also, minimizing provides better opportunity to interpret objective function as error function. Frequently the maximizing cases are thus reciprocated to convert it into minimizing problem. It may be a test function, where some input variables are presented after calculation; it returns a cost of input.

In case of image contrast enhancement technique, the main objective is to enhance the image contrast. Most of the conventional techniques can perform well in this regard but often they cannot preserve the other image characteristics such as brightness, sharpness, etc., satisfactorily. In this research work, the main focus will be formulating the objective functions based on the parameters which are directly related to image features including contrast and apply these objective functions to the optimization based on algorithms to get optimal outputs. Optimizations can be classified into two types based the variable value. They are constrained optimizations and unconstrained optimizations [1]. Constrained optimizations are those where the values of the choice variables can be a certain values within a higher range. So, there is a limitation of providing the values of any variable presents for constrained optimizations. This type of optimizations is applicable when the problem or any function which have to solve is specific. The choice of constrained optimization technique depends on the specific type of problem and the function to be solved. Lagrange multiplier is the example of such optimization. Constrained optimizations are also two types: hard constraint and soft constraint [2]. In case of hard constraints, the variables have to fulfill the conditions which have given. On the other hand, for soft constraints, it has some variable values which have to maintain during optimization. Unconstrained optimizations are those where no such type of constrain present and any value can be taken as requirement. Some of the examples of this optimization are Newton method, steepest descent method, line search, etc. So, using proper optimization based on objective function and fitness function, the desired solution can be reached.

There is a fundamental difference in between objective function and fitness function. The objective functions are optimized by the optimization techniques whereas the fitness function is that function which is used to guide the optimization [3]. The fitness function is defined as a function based on which the solution is made for a problem. Basically, it represents how fit or how good a solution according to the problem. It is also known as evaluation function. It also provides the closeness of given solution to the optimum solution of a problem. So, based on the value comes from fitness function, it is possible to determine the best solution so far which can satisfy all the desired criteria.

In case of image processing technology using optimization techniques, fitness functions are formulated mostly by different image quality assessment (IQA) metrics [4]. IQA metrics are defined as those parameters which are used to find out the efficiency of image processing techniques to accomplish desired results. Sometimes, it is observed that the enhanced image is visually satisfactory but there is a lack of retaining different important image characteristics. So, proper information cannot be fetched from that image for further processing purpose. IQA metrics provide the objective evolutions to decide the internal quality of the images [4].

This chapter introduces about two different proposals of objective functions which have been used throughout this thesis work in different CI algorithms. The elaborate description will show the motivation of developing such new objective function in order to preserve image characteristics while enhancing the image contrast. The chapter also elucidates the different IQA metrics that have been used throughout this thesis with the interpretations of obtained results.

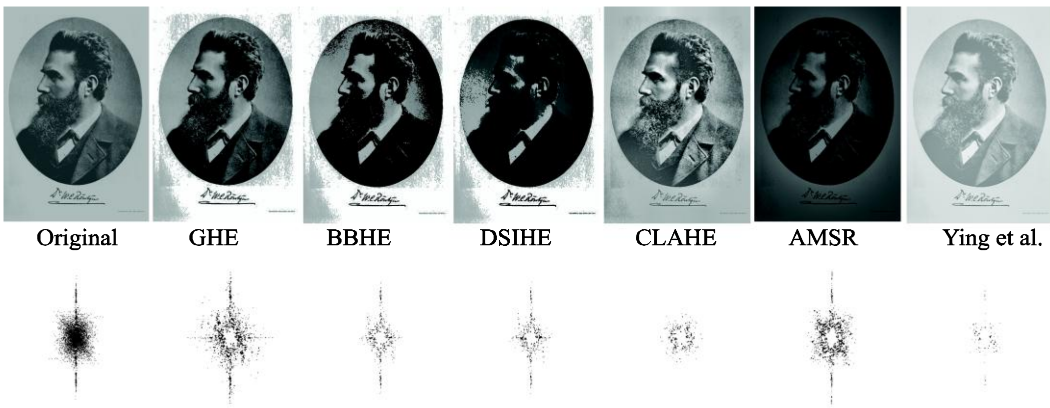
2.2. Objective functions formulation

In this thesis, two conceptually different objective functions have been formulated. The focus has been remained with image characteristics rather use of standard error metrics. In case of objective function 1 (ϕ), an analysis on contrast interpretation has been developed. In case of objective function 2 (φ), a new color channel based estimation of radiance and transmittance [5] has been used.

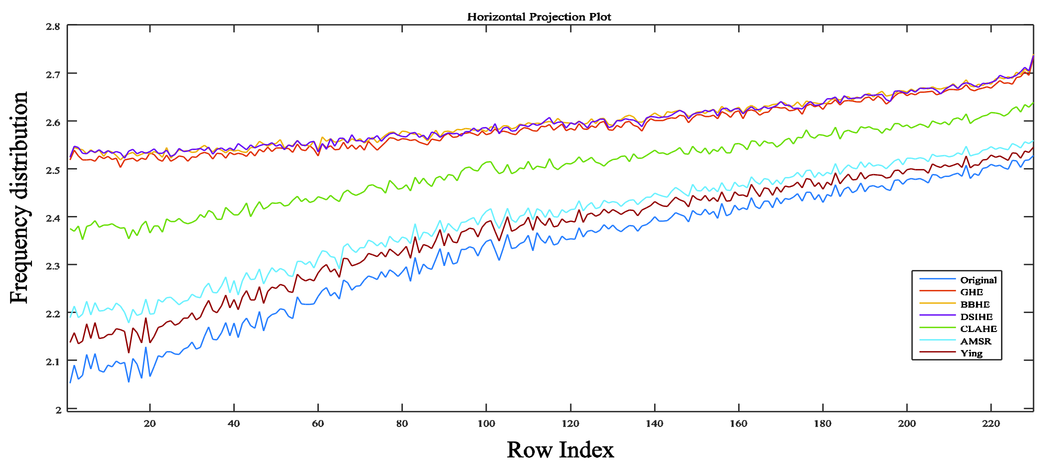
2.2.1. Objective function 1 (ϕ)

This objective function is formulated in frequency domain using Fourier transform (FT). The FT provides better control and insight over local image characteristics than spatial domain.

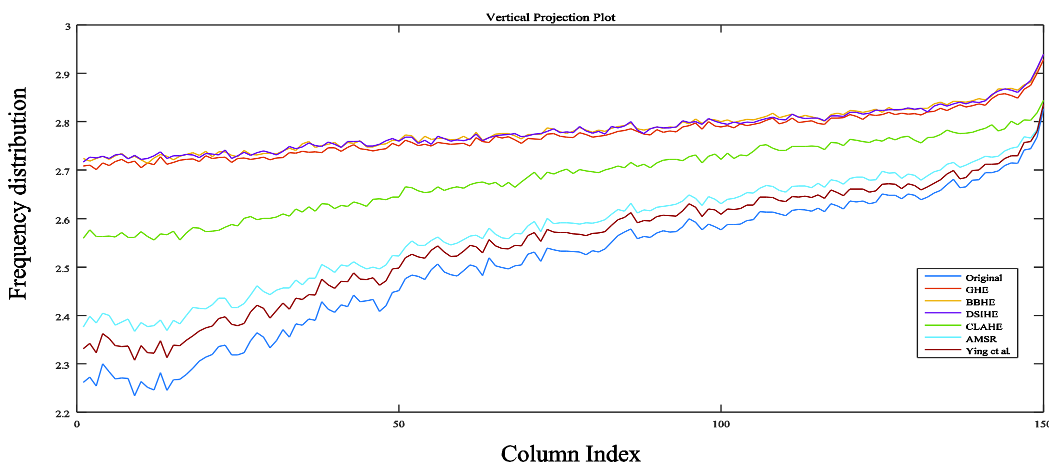
A Fourier domain analysis on the results of some of the conventional techniques towards development of a new interpretation of contrast enhancement in frequency domain and state-of-the-art techniques have been presented namely, GHE, BBHE, DSIHE, CLAHE, AMSR and Ying et al.. These techniques represent different classes of algorithms as mentioned in previous section. The study can be described with the help of Figs. 2.1 and 2.2 where the results of said algorithms, corresponding to difference FFT spectra (original spectrum subtracted from the enhanced image spectrum) and projection plots (horizontal and vertical) of the FFT spectra. It may be noted that the Fourier spectra have been processed to obtain a clear view of resulted changes. The processing here involves binarization of log-transformed fast Fourier transform (FFT) spectrum followed by dilation and erosion morphological operations.



(a) Results of different HE techniques and corresponding FFT spectra



(b) Horizontal projection plots for different techniques



(c) Vertical projection plots for different techniques

Fig. 2.1: *Fourier spectrum analysis of gray scale test image*

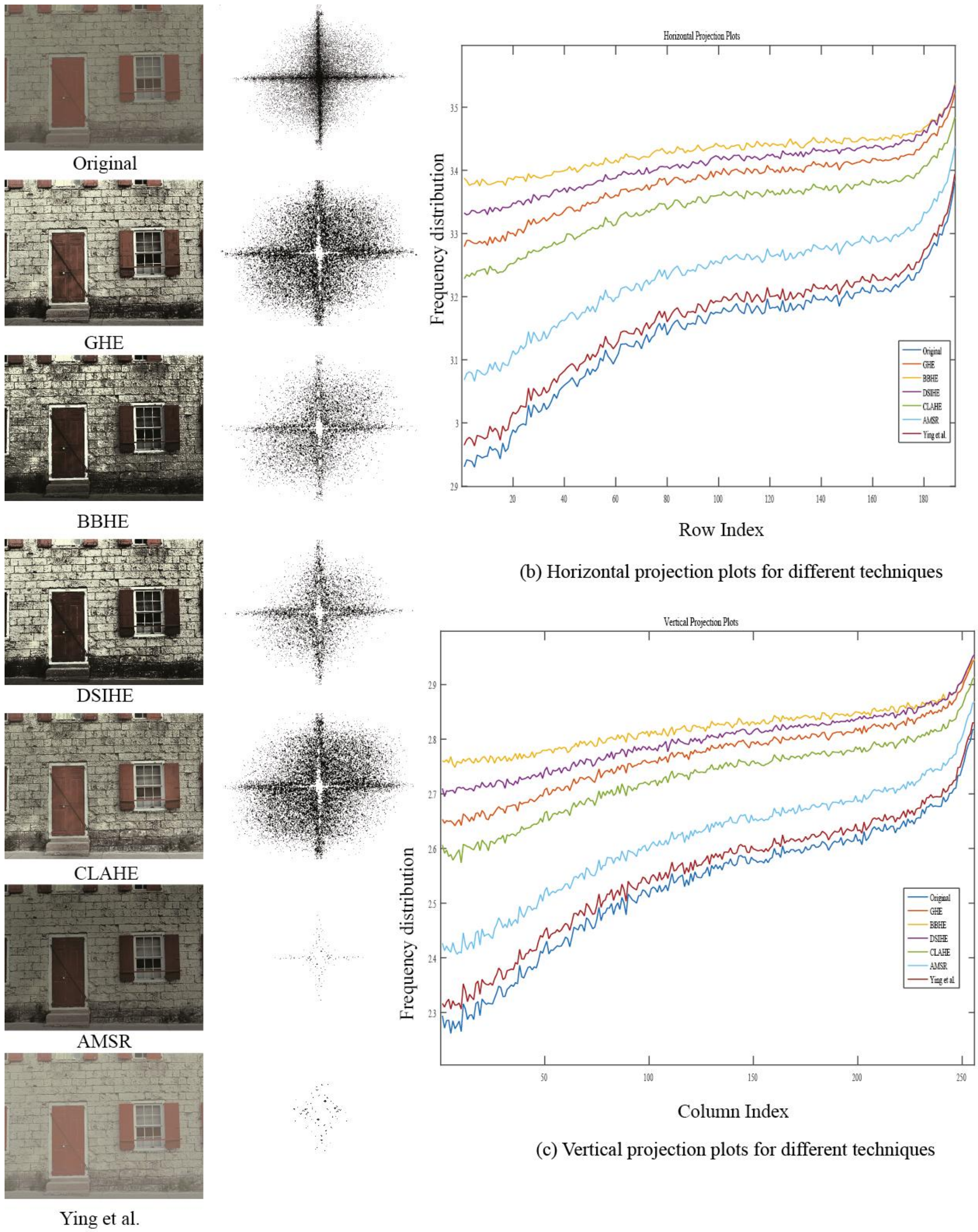


Fig. 2.2: *Fourier spectrum analysis of color test image*

Fig. 2.1 shows that most of the conventional techniques fail to retain the background of the test image while the advanced algorithms namely, CLAHE, AMSR and Ying et al. can successfully retain that. The difference FFT spectra along with the projection plots can be a possible tool to analyze this phenomenon. In frequency domain, the contrast enhancement is expected to introduce more frequency components and an expansion of the Fourier spectrum is desired for better results. But, the expansion in Fourier spectrum should not be random. The contrast enhanced image is expected to generate the Fourier spectrum which will be an expanded or stretched version of the original image spectrum keeping parity to the shape of original image spectrum. Any HE algorithm that results in expansion of spectrum without keeping similarity to the shape of original spectrum will also show improvement in contrast but may not preserve the important characteristics of the original image. As it can be seen in Fig. 2.1, all classical HE result in contrast enhancement as reflected in their difference-spectrum by the resulted expansion but at the same time expanded results are not well conforming to the shape of the original spectrum which results in loss of information as can be seen while comparing the background gray region of original and resulted images. Hence, the algorithms can enhance image contrast undoubtedly but there is noticeable lack in preserving the image characteristics. Non preservation of image characteristics can result in different artifacts like false contour, wrong color representation, artificial appearance, etc.

The projection plots can be a possible assessor of the shape conformance. The projection plots show that GHE, BBHE and DSIHE plots escalate through ‘y’ axis keeping low adherence to the nature of plot for original image. The plots for CLAHE shows comparatively better adherence while AMSR and Ying et al. techniques are showing visibly improved adherence. These adherence results better retention of original image features which can be seen by the retention of background grayness in their results. Nevertheless, the scope of improvement is still open.

The same explanation may be drawn with color images as shown in Fig. 2.2 where Ying et al. does not show any visible expansion over the original image FFT spectra but it shows high degree of conformity to the shape of original image spectra as shown in projection plots of Fig. 2.2. The classical techniques GHE, BBHE and DSIHE are more prone towards expansion of spectra while less conformity to shape. CLAHE makes a balance between the expansion and shape conformity but a bit higher inclination towards spectra expansion while AMSR shows smaller expansion and better conformation to the shape. Visually, such unbalance results in over- and under- enhancement respectively.

From the presented images and the Fourier domain analysis it can be observed that the classical techniques are more towards the magnitude expansion than shape adherence while the advanced techniques attempt to reach the balance between those two parameters. The under- and over- enhancements can also be correlated to the magnitude expansion and shape adherence. The aim of this work is to reach an optimum balance using CI algorithms to avoid such problems. This leads to develop the optimization objective function as a frequency domain parameter that will consider expansion and adherence to the shape of the original input spectrum. To use these parameters as objective function, the representative mathematical expression has been formulated as Eq. 2.1.

$$\phi = w_1 M . w_2 S \tag{2.1}$$

where ϕ is the objective function and the weight parameters w_1 and w_2 are tunable. The tuning of w_1 and w_2 is end-user requirement dependent. In cases where retention of original image feature is of more importance such as in case of computer vision application, the w_2 can be assigned with a higher value. In cases where the visual appearance is more important and loss of features may be compromised for example reproduction operations like printing, the w_1 can be assigned with a higher value. However, their sum must be equal to unity. Here, a considering more general requirement both visual appearance and feature retention have been given equal importance i.e. $w_1 = w_2 = 0.5$. It can be also noted that (.) represented dot operation not multiplication since M and S are vectors.

In Eq. 2.1, *M* is the magnitude function that can be calculated as the difference between processed FFT spectrum of original and enhanced image. It is important to note here that the expectation is towards expansion not in contraction of the FFT spectrum. In case of contraction, the difference spectra become negative where the difference calculated from the binary difference image may be magnitude wise higher but in negative side. This is not the desired case, hence even if the value is higher this need to have a measure of retreatment so that they are not favored over the case where a smaller positive value gets lower merit. To facilitate such cases, the logarithmic value has been taken. Logarithmic transform can help in two ways: the range of the magnitude is reduced which give ease of interpretation and also the contraction cases result in an imaginary value. In such cases, the real value is divided by the imaginary value to get the final *M* value. The calculation of *M* value may be expressed as Eq. 2.2.

$$M = \begin{bmatrix} \log_{10}((D)) \\ if\ imag(M) \neq 0 \\ M = real(M)/imag(M) \end{bmatrix}^{-1} \tag{2.2}$$

where. $D = HE\_FFT - I\_FFT$, HE_FFT and I_FFT indicates the binary FFT spectra of histogram equalized image and original image respectively. The words *real* and *imag* in Eq. 2.2 correspond to real and imaginary respectively.

The shape parameter *S* can be calculated from the projection plots as using the pair-wise Euclidian distance between the observations in Eq. 2.3. Lower the distance between observations interprets better adherence. The combination of pair-wise distance in horizontal and vertical projections is considered in this work.

$$S = pdist(I\_hor, HE\_hor).pdist(I\_ver, HE\_ver) \tag{2.3}$$

where, *I_hor* and *HE_hor* indicate the horizontal projections of original image and histogram equalized image, respectively. Similarly, *ver* represents the vertical projections. '*pdist*' represents pair wise distance.

2.2.2. Objective function 2 (φ)

2.2.2.1. Imaging model

The images captured by the camera are formed capturing the reflected light from the object. The direct transmission of light from the object or scene to be captured is often mixed with different natural distortions due to forward and backward scattering of the natural or external light sources by atmospheric particles. The transmission media as well affect the transmittance and radiance [5] which in turn also causes low contrast images. This motivates to explore imaging paradigm in order to formulate objective function

Figure 2.3 shows the basic light transmission model for air and water as transmission media. It shows that the composition of light spectrum that reaches to the camera substantially vary depending on the wavelength. For instance, in air red light travels highest distance while under water blue light travels more. The transmittance is again affected by the distance of the object of interest. Conventionally the imaging model is represented as Eq. 2.4, where $I_{(i,j)}$ is the distorted image and $t_{(i,j)}$ is the transmittance which approaches 1 as the scattering effects get minimized and calculated using Eq. 2.5. *A* is the global background light which depicts the atmospheric color coefficient. $J_{(i,j)}$ is the distortion free image that need to be solved in Eq. 2.4.

$$I_{(i,j)} = J_{(i,j)} t_{(i,j)} + A\left(1 - t_{(i,j)}\right) \tag{2.4}$$

$$t_{(i,j)} = e^{\beta d_{(i,j)}} \tag{2.5}$$

where, β is the atmospheric scattering coefficient and *d* is the distance map or scene depth. Dark channel prior (DCP) [6] is one of the most notable approaches that has been used towards solving $J_{(i,j)}$ where the dark channel is estimated in a patch based manner. The minimum value in each patch $\Omega_{x,y}$ centered at pixel *(x, y)* for each of the *r, g, b* color channels are calculated to estimate the dark channel using Eq. 2.6.

$$I_x^{dark} = \min_{c \in r,g,b}\left(\min_{y \in \Omega_{x,y}}\left(I^c(y)\right)\right) \tag{2.6}$$

DCP is a popularly used concept in many haze removal algorithms but it is limited by its computational complexity involved in the calculation of transmission refinement employing different approaches [6]. Presented model adopts the concept of DCP to assess $J_{(i,j)}$ but with different interpretation called difference channel estimation (DCE) using the inherent color channel characteristics of color spaces.

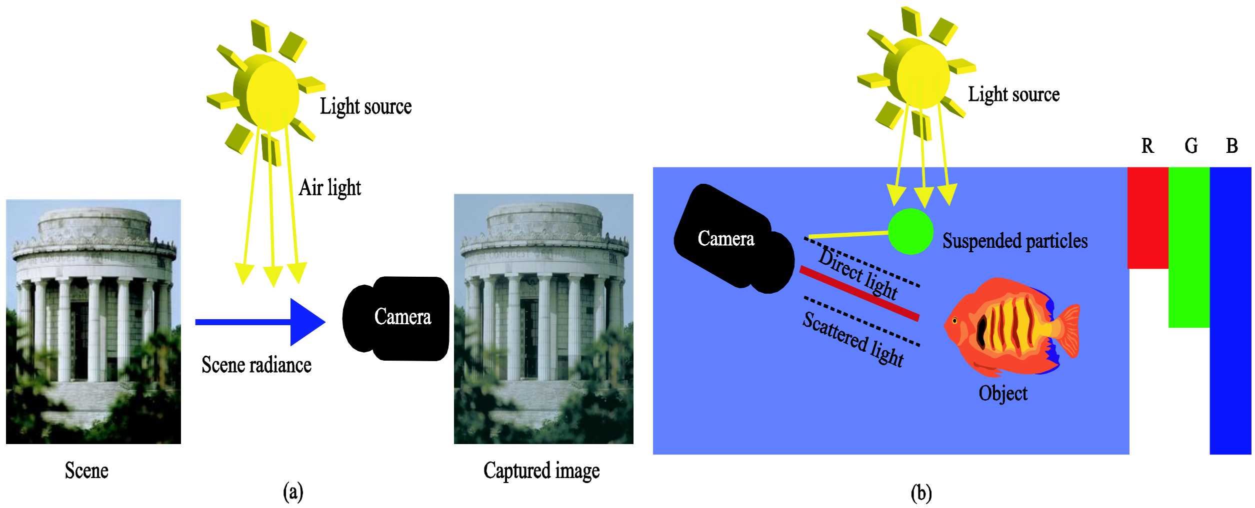


Fig. 2.3: *Imaging model (a) in atmosphere and (b) underwater*

2.2.2.2. Color spaces: a brief overview

Color space is defined as the organization of specific colors. It is the combination of various colors profile which is supported by different physical devices. It also supports the color representation which may be analog or digital. It is a useful tool which will indicate the capability of colors of a device or any digital file. It is indicating the specific combination of a color model. There is a conceptual difference between color space and color model. A color model is a mathematical model which defines the colors which is represented by the combinations of initial letters of all the colors present there.

Four most common color spaces are red, green and blue (RGB) [7], hue, saturation and value (HSV) [8], cyan, magnets, yellow and key (CMYK) [9] and Luma components, blue difference and red difference (YCbCr) [10]. RGB is the color space which is used for sensing, representation and display of various images in any electronic system. In this color space, red, green and blue lights are combined together in different ways to make variety of colors. RGB comes from the initial of three primary colors. These three colors are additive in nature. It is also used in photography purpose. RGB color space is system dependent being used and also device dependent. Different devices provide different outputs for a particular RGB value. So, without color management, RGB color space cannot provide same color for all the devices [7].

HSV (hue, saturation and value) is an alternative representation of RGB color space. It was designed by computer graphics researcher in 1970 [8]. The main focus to design this color space is to align more closely according to the way of human vision. Each hue color is placed in a radial slice and around a central axis of neutral colors. The ranges of these neutral colors are black to white according to bottom to top. It represents the color portion and is measured in degrees from 0 to 360. Different colors falls in different degrees under this portion. Such as red color falls in between 0 to 60 degree, yellow color falls in between 61 to 120 degree, green color is in between 121 to 180 degree, cyan color is in between 181 to 240 degree, blue color is in between 241 to 300 degree and magenta color falls in between 301 to 360 degree [8]. Saturation indicates the percentage of gray in a particular color. The value towards zero represents grayer and towards 100 represents primary color. In case of digital value, the range is from 0 to 1 [8]. Value indicates the amount of brightness or intensity of the color in percentage. Here the value towards zero represents total black and towards 100 represents the full color. HSV color space is basically used for selection of colors during paint or ink [8].

In case of CMYK color space, four different colors such as bright blue, bright red-pink, yellow and black pigments are combined together to get various colors [9]. It is basically used for printing purpose. It is a subtractive color space i.e. opposite characteristics of additive space like RGB. It reduces the reflected lights or brightness from the white color background during printing [9].

In case of YCbCr color space, this space is the combination of two chroma signals and a brightness signal [10]. Here luma indicates the brightness, Cb indicates difference between blue and luma and Cr indicates difference between red and luma [10]. This color space is basically used in video and digital photography systems.

Color space conversion is the transformation of color representation from one pattern to another. In image processing, this conversion is very important to analyse the input color and based on this analysis proper solution can be performed. During the time of conversion, it should be noted that, the translated image should be as similar as possible to the original. The captured images which have to process to improve the quality of the images are basically RGB images. So, sometimes it is necessary to convert those RGB color space to another color space for processing purpose. The conversion of YCbCr and HSV color spaces from RGB color space are performed using conventional formula as given in Eq. 2.7 and 2.8, respectively.

$$[Y(i,j), C_b(i,j), C_r(i,j)] = T_{RGB}^{TCbCr}[R(i,j), G(i,j), B(i,j)] \tag{2.7}$$

$$[H(i,j), S(i,j), V(i,j)] = T_{RGB}^{HSV}[R(i,j), G(i,j), B(i,j)] \tag{2.8}$$

Cr and Cb channels provide the chrominance distribution of red and blue spectrum, respectively.

2.2.2.3. Transmittance estimation using color space dynamics

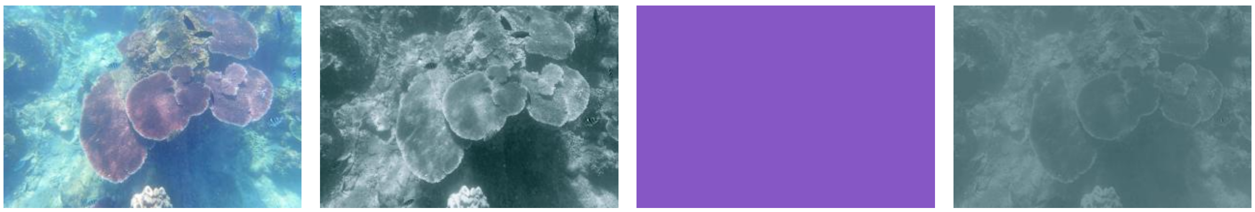
YCbCr and HSV are two color spaces while former one is device dependent and later one is device independent that are often used across different image processing and computer vision tasks. Looking into the color imaging models of Fig. 2.3, it can be assessed that the difference between Cr and Cb can be indicative to the light receiving characteristics. For instance in air, blue light travels less distance hence, the foggy images will have higher energy content in Cr than in Cb while in case of underwater image the energy content of Cb will be higher. To measure the energy different between Cr and Cb, both the channel information were converted to frequency domain using discrete cosine transform (DCT). The selection of DCT is because of its simplicity and absence of imaginary component as in case of Fourier transform. Finally the luminance representation in Y channel of YCbCr can be a possible interpretation of the distance map as closer the object can appear brighter than the far objects assuming uniform illumination. This also can be included in the distance calculation as shown in Eq. 2.9.

$$D = \overline{Y} - abs\left(\overline{Cb} - \overline{Cr}\right) \tag{2.9}$$

where, *D* is the difference channel transform in DCT domain which has to be converted back to spatial domain (*d*) by inverse transform to get the DCE in spatial domain. $\overline{Y}, \overline{Cb}$ and $\overline{Cr}$ are the DCT of *Y*, *Cb* and *Cr* channel, respectively. The difference channel in spatial domain (*d*) has then been used to estimate the background light *Bg*. In this work, the YCbCr values of background light were estimated using centroid of 10% highest values of the *d*. The centroid calculation was performed using k-means clustering algorithm [11]. The transmittance is then estimated using this difference channel transform on the background light weighted input image in YCbCr domain as shown in Eq. 2.10. The resulted *d*, corresponding background light and *T* for two test images are given in Fig. 2.4.

$$\begin{gathered} T = 1 - \eta\, d(M) \\ where, M \underset{c \in YCbCr}{M} = (I / Bg) \end{gathered} \tag{2.10}$$

(a)



(b)

Fig. 2.4: *(From left to right) the input images (left most) and corresponding DCE, background light estimation and transmittance for (a) atmospheric and (b) underwater image*

The estimated transmittance can then be used to assess the distortion free image using the estimated *Bg*, *T* and a constant t_0 as given in Eq. 2.11. In reported literature of haze removal, a single value of t_0 is used however in our case t_0 is a 3×1 vector with different values for Y, Cb and Cr channels which is user defined and application specific.

$$\underset{c \in YCbCr}{J} = \left(\underset{c \in YCbCr}{Bg} - \left(\underset{c \in YCbCr}{I} - \left(Bg - \underset{c \in YCbCr}{\max} (T, t_0) \right) \right) \right) \tag{2.11}$$

The goal of 2nd objective function is to generate a well distributed histogram. The histogram of the transmittance channel as shown Fig. 2.5(b) shows its narrowness and biased nature to either side of the histogram. To achieve the uniform distribution while retaining the characteristics of input image, two different aspects have been included in the objective function (φ) for minimization using CI algorithms. To preserve the original image characteristics in the improved image, the difference in *I2* norm between the input and enhanced image has been used. So the first parameter φ_1 of the objective function has been formulated as Eq. 2.12.

$$\varphi_1 = \left[\sum_{i=1}^{n} (dh_i - eh_i)^2 \right]^{1/2} \tag{2.12}$$

Where, *dh* and *eh* represents the histogram information of DCT of V-channel. *norm* indicates the *I2* norm of the vector represented as $|x| = \sqrt{x_1^2 + x_2^2 + ... + x_n^2}$ where $x_1, x_2, ..., x_n$ are the individual elements of the vectors *dh* and *eh*.

The second parameter of the objective function has been developed based on the skewness and kurtosis of the *dh* and *eh*. As it can be seen in Fig. 2.5 the plot of original V channel histogram is negatively or positively skewed. The target was to reduce the skewness towards zero and maintaining the kurtosis near the ideal value of 3 [12]. Therefore the second parameter φ_2 of φ has been formulated as expressed as Eq. 2.13.

$$\varphi_2 = skewness(eh) + (3 - kurtosis(eh)) \tag{2.13}$$

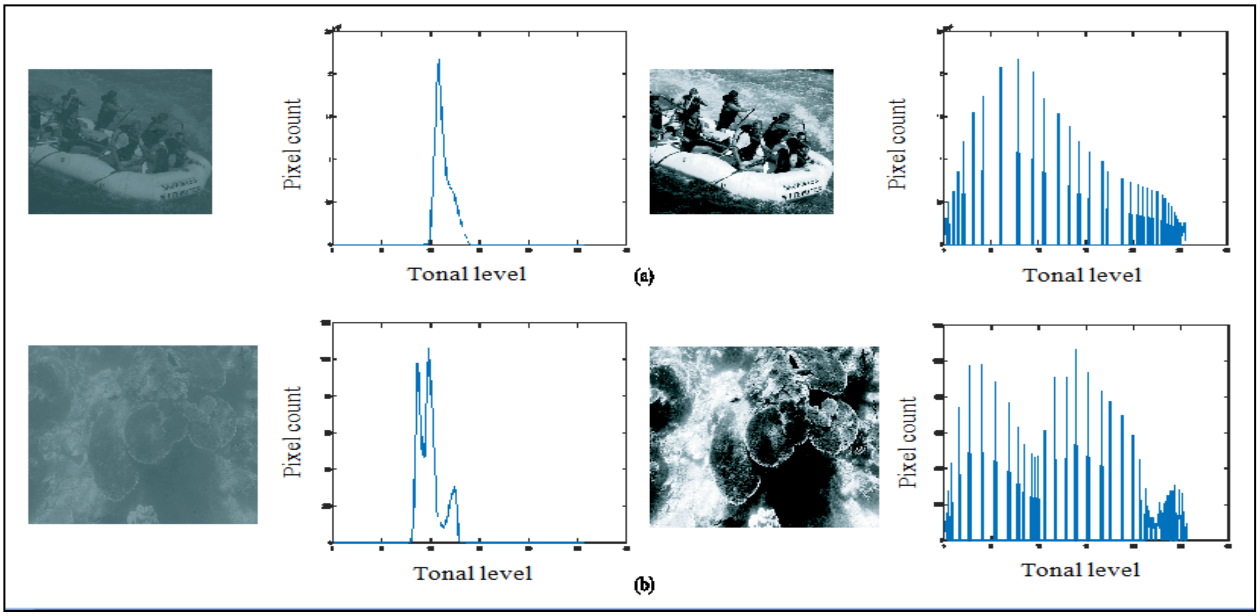


Fig. 2.5: *(Left to right) the original transmittance estimation, corresponding histogram, enhanced transmittance and corresponding histogram for (a) atmospheric and (b) underwater images*

Combining the above two parameters, the objective function has been formulated as Eq. 2.14. Depending on the applications or modeling requirements w_1 and w_2 can be modulated maintaining their sum to unity i.e. $w_1 + w_2 = 1$.

$$\varphi = w_1\varphi_1 + w_2\varphi_2 \tag{2.14}$$

2.3. Fitness function formulation

In this work, the fitness function has been formulated using three different image quality metrics, which are well related to image contrast. These are the brightness distribution, the retention of image information and the contrast information. These parameters can be derived from popular metrics i.e. absolute mean brightness error (AMBE) [13] as expressed in Eq. 2.15, local entropy [14] as expressed in Eq. 2.16 and contrast enhancement factor (CEF) [15] as expressed in Eq. 2.17.

$$AMBE(X,Y) = |E(X) - E(Y)| \tag{2.15}$$

where, *X* and *Y* denote the input image and output image respectively. *E(.)* denotes the expected value of statistical mean. Low value of AMBE indicates the better brightness preservation of the image.

$$Ent[\Omega] = LE(x,y) = -\sum_{\ell}^{L-1} P\ell \log P\ell \tag{2.16}$$

where, Ω is a small neighborhood with size m*n placed at pixel (x, y). *Ent* denotes the entropy, LE is the local entropy, $P\ell$ is indicating the probability of gray level ℓ, which is the difference between two adjacent pixels of the image. High value of entropy indicates the richness of the image quality.

$$C(y) = \sum_{i=1}^{N} C(B_i) \tag{2.17}$$

where, *C(y)* represents the contrast value of the output image y and is calculated by considering the local contrast of non-overlapping image blocks. B_i is the i^{th} image block, $C(B_i)$ is the i^{th} contrast value of image block and N denotes the total number of image blocks. High value of *C(y)* indicates better contrast of image.

The fitness of the solution can therefore be assessed using the function *Θ(.)* combining these three parameters as calculated by Eq. 2.18.

$$\theta(y) = \frac{H(y).C(y)}{|e(x) - e(y)|} \tag{2.18}$$

where, *Θ(y)* denotes the quality of output image y that has been obtained by optimizing the various parameters of input image x.

The Θ has been formulated in such a way that a higher value will indicate better result. Thus, the fittest solution carries the maximum value.

2.4. Image quality assessment metrics

The objective evaluations against the image quality assessment (IQA) metrics are very important assessment to judge the quality of an image. In many of cases where visual outputs are satisfactory but due to poor performance against IQA metrics, proper information cannot be fetched from those images. Among many IQA metrics 4 full reference (FR) [16] and 1 no reference (NR) [17] metrics have been considered in this work. The FR metrics include the ground truth images for evaluation and in this thesis entropy [14], patch-based contrast quality index (PCQI) [18], contrast enhancement factor (CEF) [15], and colorfulness (C) [19] metrics have been used. The NR metric does not include the ground truth for evaluation but it measures overall naturalness in enhanced images and a higher degree of naturalness is desired to avoid over- and under-enhancement causing artificial appearance in the enhanced images. Natural image quality evaluator (NIQE) [17] is considered here as NR metric for this purpose. Local entropy is a popular metric which indicates better information containment by higher values. PCQI is a very important measure particularly for contrast. This metric not only provides value but also provides a binary image (PCQI<1) which shows the amount of contrast distortions present in the processed image. A higher mean-PCQI value indicates better result as well. NIQE is a no-reference metric that vouch the naturalness of processed image and lower values of NIQE indicates better naturalness. CEF indicates the contrast level of output images and higher value of CEF indicates better enhance of image contrast. Colorfulness is also very important image quality metric where the level of color retention can be computed. Higher value of C indicates better color balance and visualization.

The main target to choose these image quality assurance (IQA) metrics is to verify the potentiality of the output images from different aspect including color, fidelity, naturalness, etc.

The mathematical basis of these metrics can be briefed as follows.

Image local entropy is a measurement, which indicates the prosperity of an image. Quality of an image will be proportional to the entropy value. The entropy indicates the content of information and is significant to preserve the data. Local entropy is calculated by Eq. 2.16.

PCQI is a popular metric in contrast enhancement evaluation. Instead of global enhancement it performs local patch based evaluation. It is based on signal decomposition philosophy and is mathematically represented by variations in signal strength and signal structure as presented in Eq. 2.19 [18]. The outcome of PCQI can be interpreted in two ways; the PCQI map which is a graphical representation of contrast enhancement and a mean PCQI value which indicates betterment by higher values. The white and bright patches show improvement while the dark and black patches show degradation. For easier understanding, PCQI map is often binarized setting patches with PCQI<1 to 0 and rest to 1. There may be areas in output image which appear with high contrast and brightness but if that comes as a black patch in the binarized PCQI then it is resulting under- or over-enhancement. Therefore, binarized PCQI map with lesser black patches indicate better enhancement. Similarly, calculating the mean value of patches as shown in Eq. 2.20 [18], the mean-PCQI value is obtained which also have higher values for better enhancement.

$$PCQI(x,y) = q_i(x,y), q_c(x,y), q_s(x,y) \tag{2.19}$$

where, x and y are co-located patches in the input reference image x and enhanced image y respectively. $q_i(x,y)$ is the difference estimation in terms of mean intensity, $q_c(x,y)$ is the parameter corresponds to contrast change and for a better contrast image results $q_c(x,y)>1$, which can be reflected in another IQA metrics CEF.

Finally, $q_s(x, y)$ corresponds to the structural distortion. If there are total *M* patches, then mean PCQI is calculated as

$$PCQI(X,Y) = \frac{1}{M}\sum_{j=1}^{N} PCQI(x_i, y_j) \tag{2.20}$$

The mean PCQI value analysis is further illustrated by the PCQI map as shown in Fig. 2.6. The map is a binary image and black patches show the areas of contrast distortions.

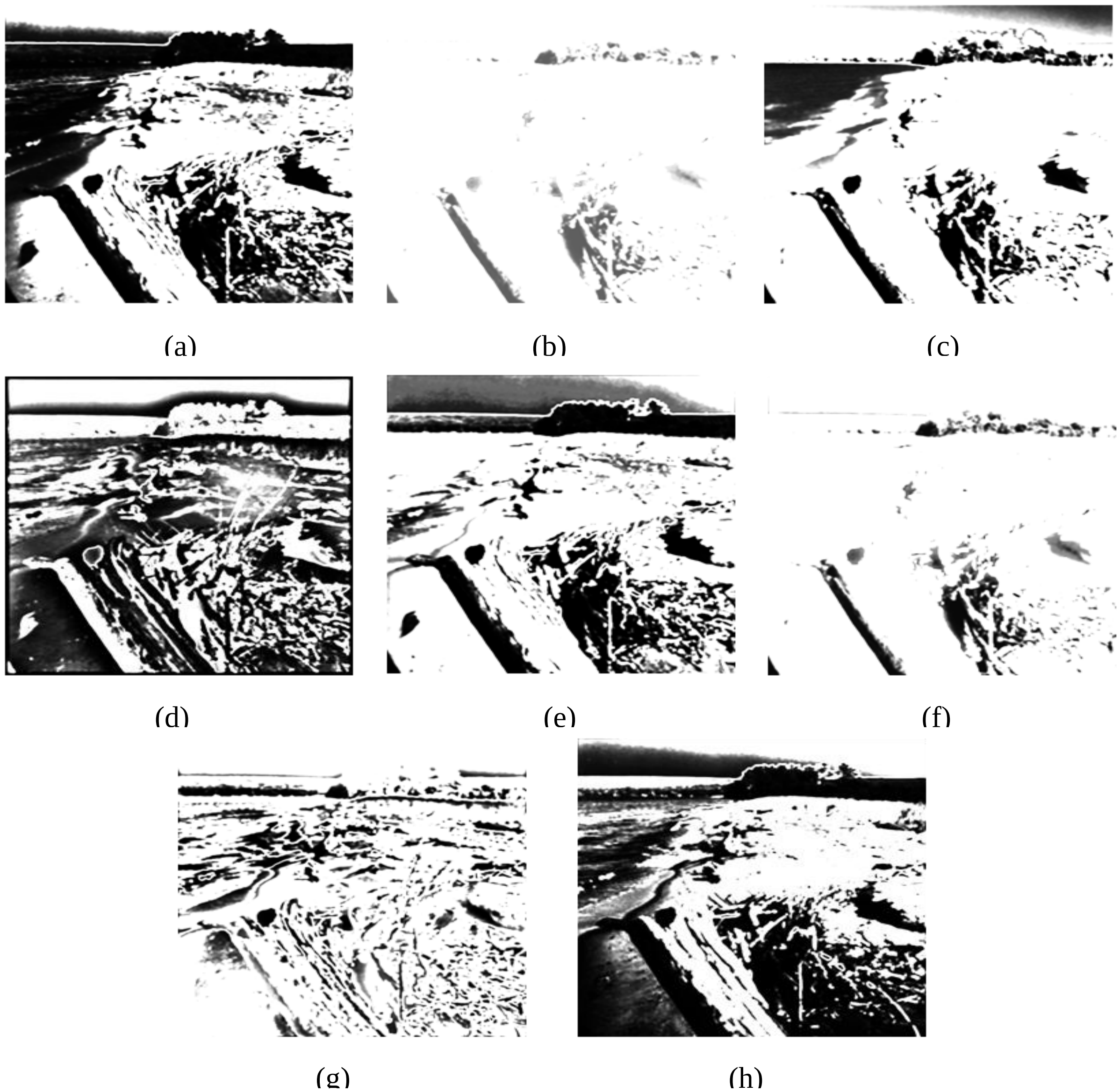


Fig. 2.6: *PCQI map (black pixels indicates less PCQI); a) GHE b) DFHE c) MSR d) SECEDCT e) GA f) ABC G) CLAHE-DGC and h) FDAHE-GC*

NIQE is a feature based metric where a multivariate Gaussian (MVG) fit for the natural scene statistics (NSS) characteristics are pulled out from the experimental image and the quality is assessed as distance between this MVG and a defined MVG of the quality image features extracted from a numbers of natural images. A lower distance as indicated by lower metric value indicates better result. It is expressed as Eq. 2.21 [17].

$$D(v_1, v_2, \sum_1 \sum_2) = \sqrt{(v_1 - v_2)^T (\frac{\sum_1 + \sum_2}{2})^{-1} ((v_1 - v_2)} \tag{2.21}$$

where, v and $\sum$ are mean and covariance matrix, respectively. Index 1 indicates the natural MVG model and index 2 indicates distorted MVG model.

CEF is very important image quality metric for those image processing applications, where the contrast enhancement is required to get the quality output. It is the ratio of overall image pixels intensity distribution with respect to mean intensity value and is expressed as Eq. 2.22 [15].

$$CEF = \frac{\frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N} y(i,j)[y(i,j) - \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N} y(i,j)^2]}{\frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N} y(i,j)} \tag{2.22}$$

where, $y(i, j)$ is the output image pixel value, M and N denotes the row and column dimensions of that image. Higher CEF indicate better contrast balancing and uniformity of the output image.

Colorfulness metric is vital for quality assessment of input color images and it can be calculated as Eq. 2.23 [19].

$$C = \sigma_{rgb} + 0.3 * \mu_{rgb} \tag{2.23}$$

where, σ_{rgb} is the standard deviation and μ_{rgb} is the mean of the pixel intensities and are calculated as Eq. 2.24 and Eq. 2.25 [19], respectively

$$\sigma_{rgyb} = \sqrt{\sigma_{rg}^2 + \sigma_{yb}^2} \tag{2.24}$$

$$\mu_{rgyb} = \sqrt{\mu_{rg}^2 + \mu_{yb}^2} \tag{2.25}$$

where, *rg* represents the difference between red channel and green channel and *yb* represents half of the sum of red channel and green channel minus the blue channel.

2.5. Brief overview of comparing techniques

Researchers have presented different techniques in the field of image processing in different times to improve the image quality. Among these, 8 techniques have been considered for comparison purpose in this thesis work. These techniques cover different paradigms of algorithms in both spatial and frequency domains. These techniques are briefly discussed in Table 2.1.

Table 2.1: *Brief overview of comparing techniques*

Techniques	Presented by	Year	Function
GHE	-	-	It remaps the existing intensity levels to new levels over the entire range of gray levels that are more apart from each other resulting in better contrast and maximize the entropy.
DFHE	Sheet et al.	2010	This fuzzy histogram is separated into multiple sub histograms based on local maxima. Each sub histogram is built by taking the valley portion between two consecutive local maxima. During the time of equalization, these peak histograms are not remapped. So, better preservation has been achieved when enhance the image contrast.
MSR	A. Petro et al.	2014	This algorithm is based on human perception and is capable to retain the original color of an image. It is also used for lightness rendition and dynamic range compression (DRC).
SECEDCT	T. Celik	2014	SECE algorithm performs the distribution of spatial location of pixel gray-levels to compute the spatial entropy for global contrast enhancement. SECEDCT performs both the global and local contrast enhancement by using DCT coefficients scaling process along with SECE technique.
GA	John Holland	1975	This algorithm is one of the pioneering evolutionary algorithms, which is still popular. Crossover and mutation

			are two most important steps in GA that mimic the natural reproduction behavior. In GA, a set of parameters called Genes are used to form a Chromosome, which is basically a solution.
ABC	Karaboga and Basturk	2005	It is designed by the natural behavior of real honey bees in food foraging. In ABC algorithm, three types of bees are there: employed bees for searching food source, onlooker bees that are waiting on the dance area to choose a food source and scouts, who carries out a random search for new food source.
CLAHE-DGC	Y. Chang et. al	2018	In case of CLAHE, the adaptive method basically performs several histograms and uses them to redistribute the image lightness values. Hence, this technique is also suitable for local contrasts enhancement as well as enhancing the edges of all the region of that image. CLAHE-DGC enhances the contrast by boosting its luminance value in addition of CLAHE technique.
FDAHE-GC	M. Veluchamy & B. Subramani	2020	In this technique, an intensity mapping function is developed from fuzzy dissimilarity histogram (FDH) for the purpose of image contrast enhancement and the gamma correction is applied to enhance the dark regions.

2.6. Input test images

The techniques presented in this thesis have been evaluated with 1000 test images taken from standard databases, namely, SIPI [20], TID [21] and CSIQ [22]. These images include gray scale as well as color images with different degree of low contrast and different illumination distortions. Not only that, the low contrast image with different medium has also been considered as test images to assess the potentiality of the proposed techniques in a more general way. However, among these 1000, 5 test images as shown in Fig. 2.7 have been used to illustrate the results in each proposed techniques throughout this thesis. These five images include monochrome or grayscales images and color images captured both in nature and underwater.

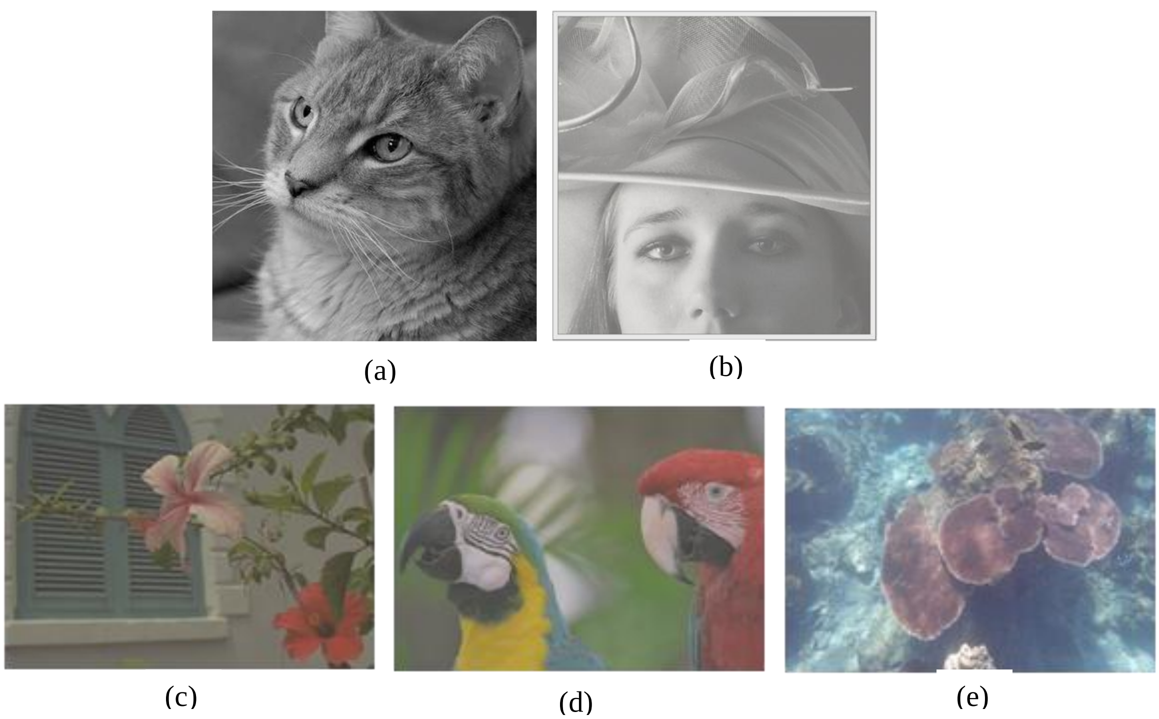


Fig. 2.7: *Input test images (top row gray scale images) a) Cat b) Lady (bottom row color images) c) Flower d) Bird e) Underwater*

2.7. Conclusions

This chapter presented detailed explanation of objective functions and their mathematical formulations. The objective functions have been developed in frequency domain and the fitness function is in spatial domain. So, this can be considered as a trade-off between the frequency domain and spatial domain analysis. The IQA metrics as used in this thesis have as well as been elaborated mathematically. Overall this chapter introduces the important aspects of this thesis work which have been followed in each of the proposed techniques in following chapters. The test images used here for evolution purpose represent various aspect of an image, such as local contrast, background color, underwater image etc. vouch the potential of the proposed techniques discussed for enhancing image contrast in the field of image processing.

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CHAPTER 3

Image contrast enhancement using bacteria colony optimization (BCO)

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3.1. Introduction

BCO is a popular CI algorithm was introduced by Ben Niu et al. in 2012 that performed optimization using behavioral pattern on motile bacteria such as Escherichia coli (E. coli), Salmonella and M.xanthus. In case of BCO, the chemotaxis behavior of bacteria for surviving in the environment (such as nutrients) and their movement towards or away from a specific location was employed. BCO was superior to the other popular algorithms due to its advantage of not largely been affected by the size and non-linearity of the problem. This algorithm also had advantages such as less computational time requirement and can handle more number of objective functions when compared to the other evolutionary algorithms [1].

Up to this time, various optimization algorithms based on swarm intelligence have been introduced, where the simulation process is based on biotic population and the evolution process in nature. Some of the very common such algorithms are artificial bee colony (ABC) algorithm, ant colony optimization (ACO) algorithm, shuffled frog-leaping algorithm (SFLA), particle swarm optimization (PSO) algorithm etc. These algorithms are introduced to mimic the swarm intelligence behavior of biological in nature. They have the characteristics of self-organization, robustness, flexibility, reliable to find a solution from different problems [2]. But these algorithms also have some limitations. For example, in case of particle swarm optimization (PSO), the speed of convergence and searching accuracy are not up to the mark [2]. In case of shuffled frog-leaping algorithm (SFLA), the convergence velocity is slow and easy to falling into the local optimum [2]. The premature characteristics have been noticed for ant colony (ACO) and artificial bee colony (ABC) optimization [2]. The main reason for these limitations is not to maintain the proper balance in between exploration and exploitation. If the exploration value becomes very small, then the convergence will be premature and possibility to bounded into a local optimum. But, if the exploitation becomes very low, then the convergence speed becomes slow [2]. In case of BCO, the optimal solution has been achieved by controlling of four process such as chemotaxis, swarming, reproduction, and elimination and dispersal. So using BCO there will be less possibility of premature and high possibility to works on global optimum. The other advantages of BCO are parallel distributed processing, insensitivity to initial value, global optimization, etc [1]. Due to these advantages, researchers have drawn the attention towards using this algorithm in various domains. Such as “Bacteria colony optimization algorithm based SVM for malignant melanoma detection” presented by S Ilkin in the year 2021, where an effective technique was developed by using SVM algorithm to detect melanoma [3]. In the same year, J Revathi et al. presented “Hybrid data clustering approaches using bacteria colony optimization and k-means” where a new hybrid data clustering technique was presented for solving data clustering problem [4]. In the year 2022, T. Lijing et al. presented “Multi-objective Bacteria Colony Optimization Based on Multi-subsystem for Environmental Economic Dispatching” where a multi-subsystem was developed which will overcome the limitation of BCO when it was used for multi-objective optimization purpose [5].

This chapter presents the study of exploring the potential of BCO for contrast enhancement through optimizing the objective functions formulated in the previous chapter. The major contribution of this chapter includes application of BCO for contrast enhancement. This chapter is structured as follows: In section 3.1, an introduction of this chapter has been established. The detail of bacteria colony optimization (BCO) algorithm with pseudo codes have been presented in section 3.2. In section 3.3, the application of BCO for image contrast enhancement has been discussed. The corresponding results and comparison with other techniques are illustrated in section 3.4. Finally, the conclusions of this chapter are discussed in section 3.5.

3.2. Bacteria colony optimization (BCO)

In BCO the bacterial behavior is mimicked. Like many other agent based search algorithms, BCO also follows the dynamics of bacterial foraging to find an optimum solution for complex problem. Bacteria generally gather to the high nutrient areas by propelling themselves through rotation of the flagella maintaining an activity called ‘‘Chemotaxis’’. The flagellum rotates counter clockwise direction for forward movement. This organism is called “swims” or “runs”. The flagella rotate clockwise direction, causes the bacterium to “tumble” randomly itself in a new direction and swim again. These “swim” and “tumble” activities help the bacterium for searching nutrients in random directions. Swimming and tumbling occurs more frequently for approaching a nutrient gradient by bacterium and to move away from some food for searching more foods. Bacterial Chemotaxis is a complex combination of swimming and tumbling for placing the bacteria to a higher concentration of nutrients. Schematically BCO can be represented as shown in Fig. 3.1. The different mechanisms of BCO have been described in the following sections.

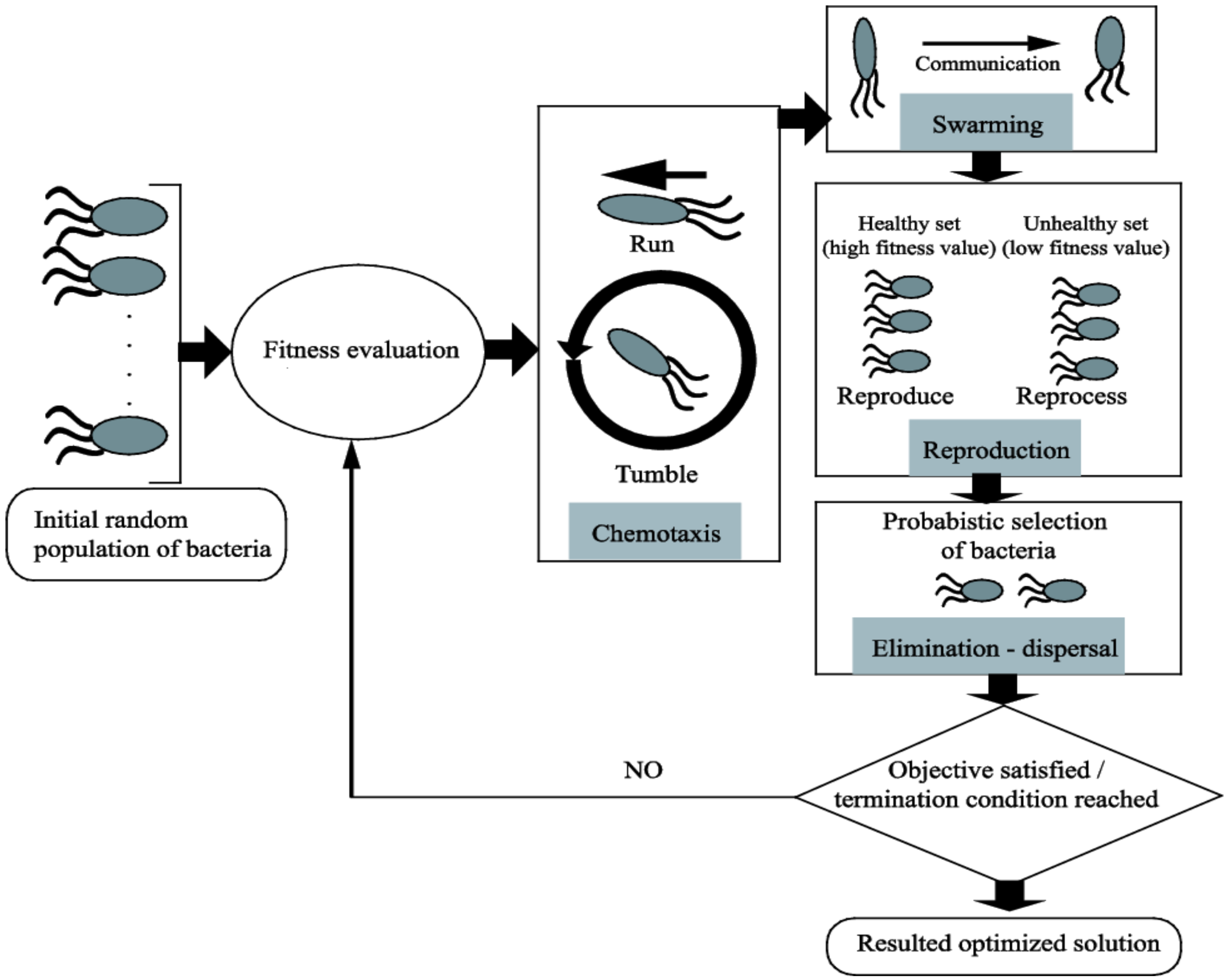


Fig. 3.1: *Schematic representation of BCO algorithm*

3.2.1. Chemotaxis

Chemotaxis mechanism works on the principle of "tumble" and "run" process. The movement of the i^{th} bacterium for every step of chemotactic process is expressed as Eq. 3.1 [1] considering $\theta^i(j,k,l)$ denotes the position of i^{th} bacterium at j^{th} chemotactic, k^{th} reproductive, and l^{th} elimination-dispersal step. *R(i)* represents the step-size of the chemotactic for this bacterium at the time of every run or tumble (run-length unit).

$$\theta^i(j+1,k,l)=\theta^i(j,k,l)+R(i)\frac{\Delta(i)}{\sqrt{\Delta^T(i)\Delta(i)}} \tag{3.1}$$

where *Δ(i)* is the j^{th} chemotactic step direction vector. At the time of '*run*' movement, *Δ(i)* is maintained the same with the last chemotactic step; otherwise, *Δ(i)* is a random vector whose elements are in the range of [-1,1]. This "run" or "tumble" can be utilized as the optimization process.

3.2.2. Swarming

Swarming mechanism as expressed in Eq. 3.2 [1] represents the communication process in between cell-to-cell as each bacterium is capable of actuating, sensing, and decision-making mechanism. During the time of bacterium movement, it releases attractant to provide indication of other bacteria to swarm that direction. In the meantime, every bacterium releases repellent to inform other bacteria to maintain a safe distance from it.

$$\begin{aligned} J_{cc}(\theta, P(j,k,l)) &= \sum_{i=1}^{S} J_{cc}^{i}\left(\theta, \theta^{i}(j,k,l)\right) \\ &= \sum_{i=1}^{S}\left[-d_{attract}\exp\left(-w_{attract}\sum_{m=1}^{P}\left(\theta_m-\theta_m^i\right)^i\right)\right]+\sum_{i=1}^{S}\left[h_{repellant}\exp\left(-w_{repellant}\sum_{m=1}^{P}\left(\theta_m-\theta_m^i\right)^2\right)\right] \end{aligned} \tag{3.2}$$

Where, *Jcc (θ, P (j, k, l))* is the fitness function value with the addition of the actual fitness function for minimizing a time varying fitness function. The total bacteria number is denoted by *S*. The number of parameters presents in each bacterium, to be optimized is denoted by *P*. $w_{attract}$, $w_{repelent}$, $d_{attract}$ and $h_{repelent}$.

3.2.3. Reproduction

The reproduction mechanism maintains the good individual bacterium and eliminates bad ones based on the health condition of every bacterium. This is calculated by the sum of the step fitness during its life, i.e. $\sum_{j=1}^{N_c} J(i, j, k, l)$, where N_c denotes the maximum number of step in a chemotaxis process [1]. The fitness values of all bacteria are sorted in the order of good health status. In the reproduction step, only the first half of total bacteria stay and second half bacteria with poor health status divides into two identical ones, which are placed then in the same location to maintain the number of bacteria constant.

3.2.4. Elimination and dispersal

According to the change of environmental condition, bacteria are greatly affected. In BCO model, when a certain number of reproduction processes happens, the dispersion processes occur. According to a fixed probability P_{ed}, some bacteria are to be selected for elimination and shift to another location within the environment. Simultaneously, the new ones are generated.

3.3. Application of BCO for contrast enhancement

To apply the BCO for color images, first the image was converted to HSV color space from its native RGB color space. The V channel was separated and subjected to the BCO algorithm. The BCO was initiated with predefined number of solutions which were generated randomly in the search space. Since the V channel values can vary from 0- 255 in an 8-bit system, the dimension of the space here is 256. The optimization has been performed towards maximization of the fitness function by optimizing the objective functions discussed in chapter 2. Like all the meta-heuristics algorithms, BCO also is iterative in nature and the solution is found using an objective function.

The pseudo code of the proposed technique is given in Table 3.1.

Table 3.1: *Pseudo code of BCO based contrast enhancement*

/* Assignment */

Load the low contrast image as input.

Compute input image histogram.

Initialize BCO parameters

d: Dimension of the search space

B: Number of bacteria

S_c: Chemotaxis steps

S_s: Swim steps

S_{re}: Reproduction steps

S_{ed}: Elimination and Dispersal steps

P_{ed}: Probability of elimination

R_L: The run-length units during each run or tumble

Initialize random solutions based on input image histogram.

/* Update */

Compute the fitness value of these solutions using Eq. [2.18].

Compute a new solution with improved fitness using the process of *Chemotaxis* loop.

Store the fitness value for finding better value by *run* process of BCO operation.

Generate a number of random solutions based on the number of eliminating solutions by fitness value according to the process of *reproduction* loop and *elimination-dispersal* loop.

Compute the fitness of these randomly generated solutions.

Check the fitness value, whether it is better with respect to the previously selected solutions.

Store the fitness value and select the most-fit solutions.

Find the objective function value resulted with the most-fit solution after iteration using Eq. [2.1, 2.14].

Terminate the loop while meeting the termination condition

/* Enhancement */

Reconstruct the V channel with the best solution found using BCO

Replace the original image V channel with the optimized V channel

Convert the image back to RGB color space for visual presentation

The experimental setup for the tunable parameters was arrived using training: validation: testing method. To decide the parameter values, a set of 100 images from different dataset were maintained. Images with all possible variations from the database were included in this dataset ranging from grayscale to color, different degree of low contrast and different illumination distortions. This dataset was partitioned into train, validation and test set with 60:20:20 proportions. The tunable parameters were varied within the ranges of values as commonly practiced in BCO. The combination that gave best fitness was considered for validation set. The final values arrived with the validation set are presented in Table 3.2 and were used for testing set as well as results presented in this chapter.

Table 3.2: *BCO parameters setting*

d: Dimension of the search space	256
B: Number of bacteria	10
Sc: Chemotaxis steps	50
Sre: Reproductive steps	8
Sed: Elimination and Dispersal steps	5
Ped: Probability of elimination	0.20
RL: The run-length units during each run or tumble	0.1

3.4. Results and discussions

The proposed BCO was tested with different images from standard databases, namely, SIPI, TID, and CSIQ discussed in chapter 2. The algorithms have been implemented using R2015a version of Matlab® software in Windows PC with an Intel Core i5 2.67 GHz CPU and 8 GB of RAM. All the images presented here have been reproduced at 300 dpi resolution.

The results of proposed BCO have been presented with two examples in Fig. 3.2 and 3.3 for grayscale and color images, respectively. In both the cases, results from both the optimization functions and the corresponding histograms are included for understanding the contrast enhancement. In Fig. 3.2, it can be seen that proposed BCO can retain the original image characteristics. The background grayness, since many of the conventional as well later developments of HE techniques could not retain (as shown in Fig. 2.1), has been well retained by proposed BCO. There is no visible false contouring and artificial patches in the proposed BCO results. Also, the balance between the dark and highlight regions is visually pleasant. The results also do not show occurrences of over- or under-exposure, since the results are not inclined to either white or black regions of intensity range. The corresponding histograms also convey the balanced enhancement. Another important observation is retaining the peak information of original histogram.

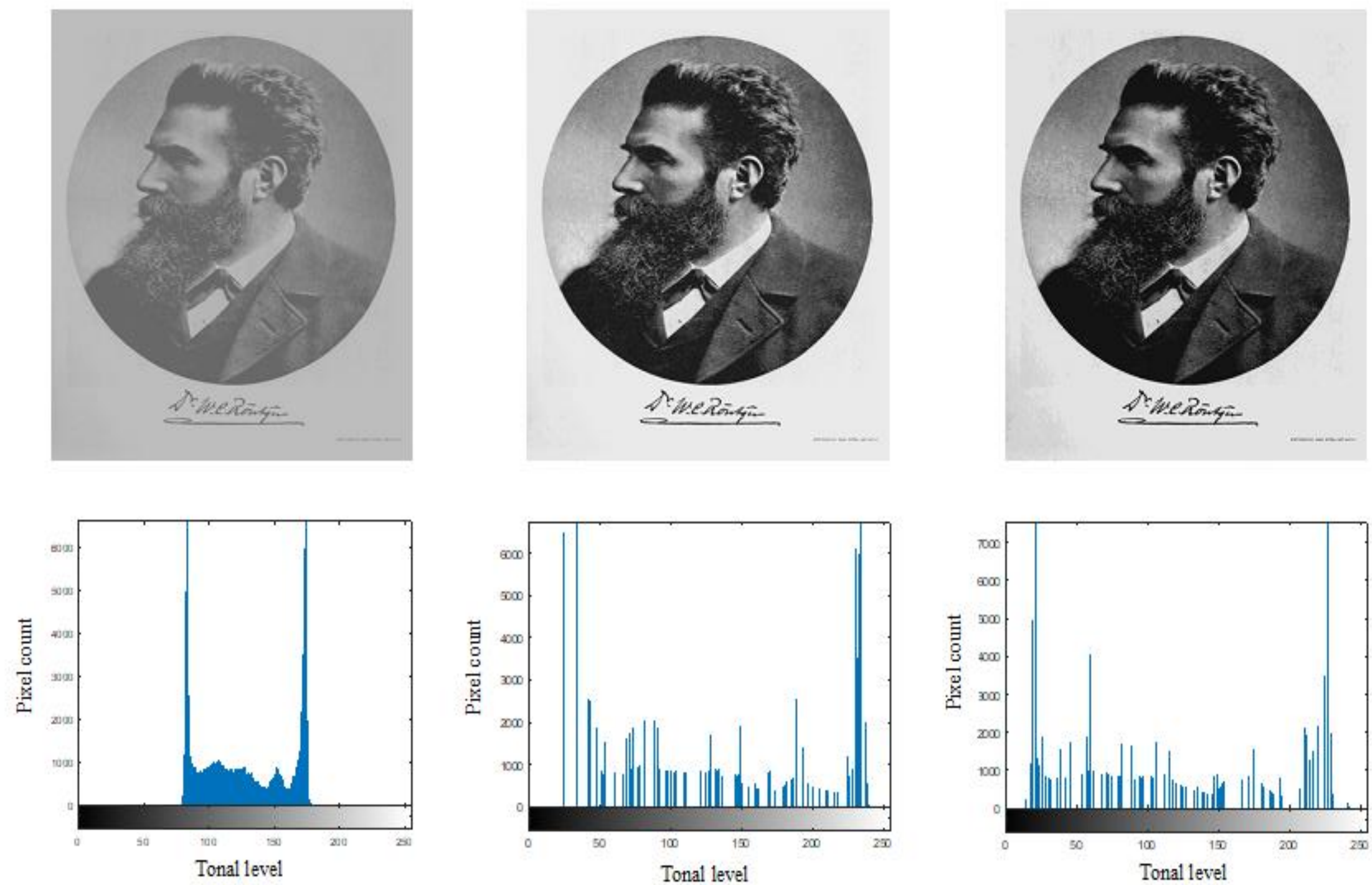


Fig. 3.2: *Result of proposed BCO technique for gray test image. (Top row from left to right) original, proposed BCO (ϕ) and proposed BCO (φ), (bottom row left to right) corresponding histogram of original image, proposed BCO (ϕ) and proposed BCO (φ)*

Fig. 3.3 shows the results with one of the color test images. In this case the corresponding V channels have also been included. It can be clearly seen that the contrast in the V channel has been significantly improved. That in turn results in improved visual appearance of enhanced image. The histograms of V channel convey that the BCO can result in stretching the original narrow histogram across the available intensity levels while maintaining the characteristics of original image histogram.

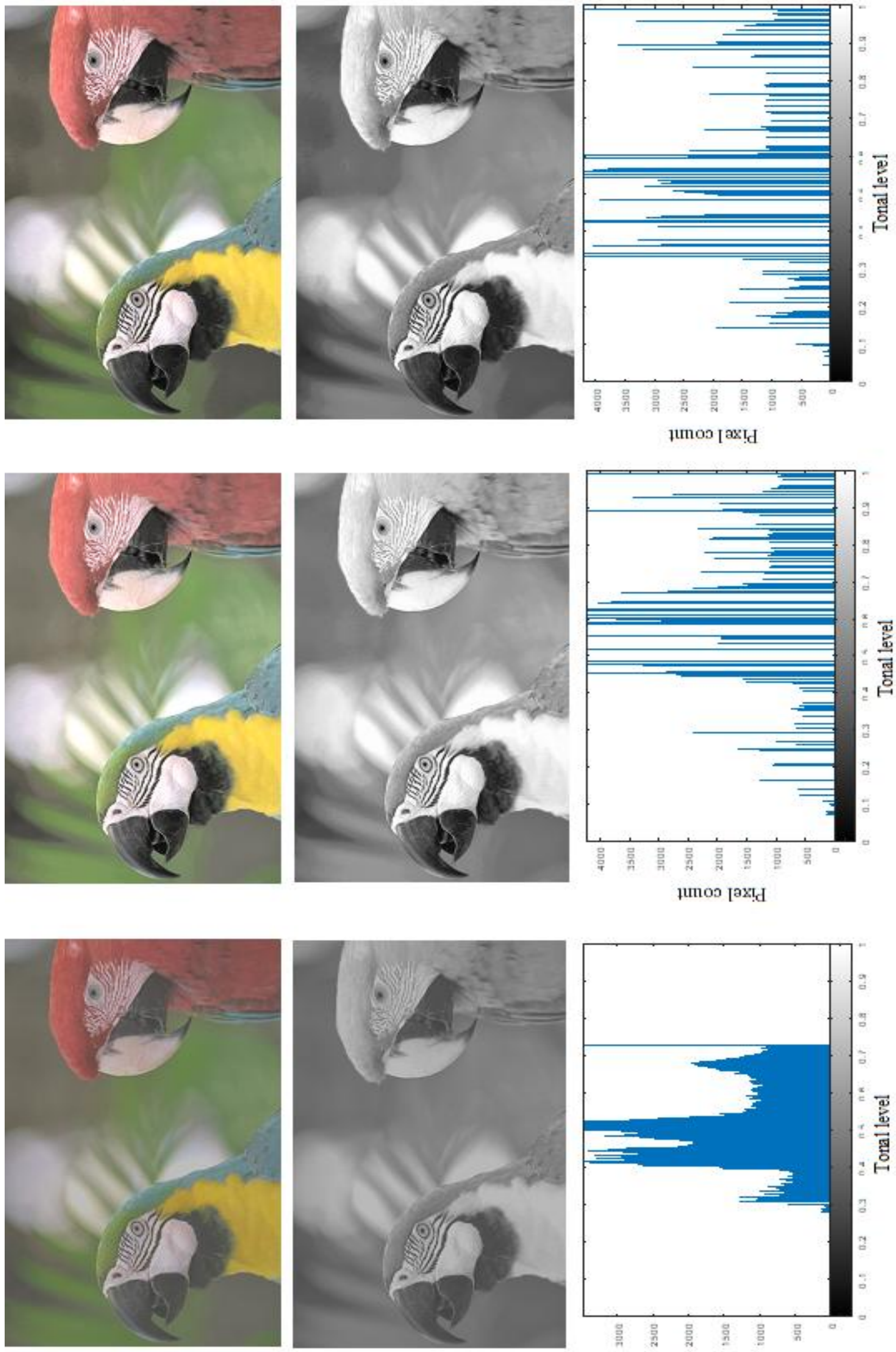
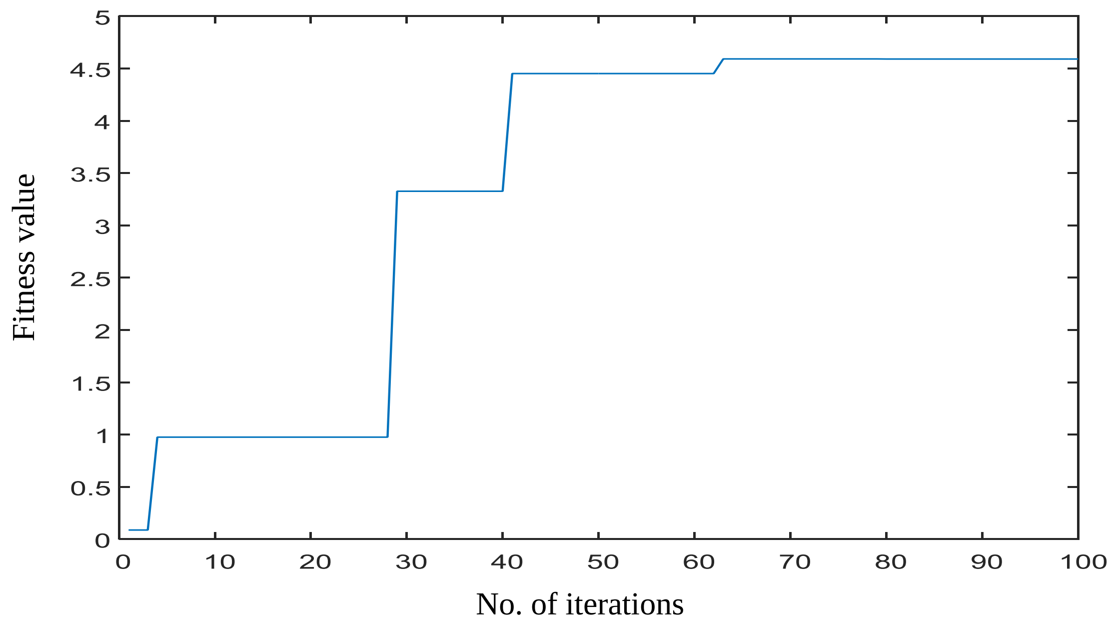


Fig. 3.3: *Result of proposed BCO technique for color test image. (Top row from left to right) original, proposed BCO (ϕ) and proposed BCO (φ), (middle row left to right) corresponding V channel of original image, proposed BCO (ϕ) and proposed BCO (φ), (bottom row left to right) corresponding V channel histogram of original image, proposed BCO (ϕ) and proposed BCO (φ)*

In Fig. 3.4, the nature of convergence for both the objective functions has been presented. It is observed that, the BCO algorithm optimizes smoothly coming to a stable state at the value around 4.5 to 4.6 depending on the fitness value.



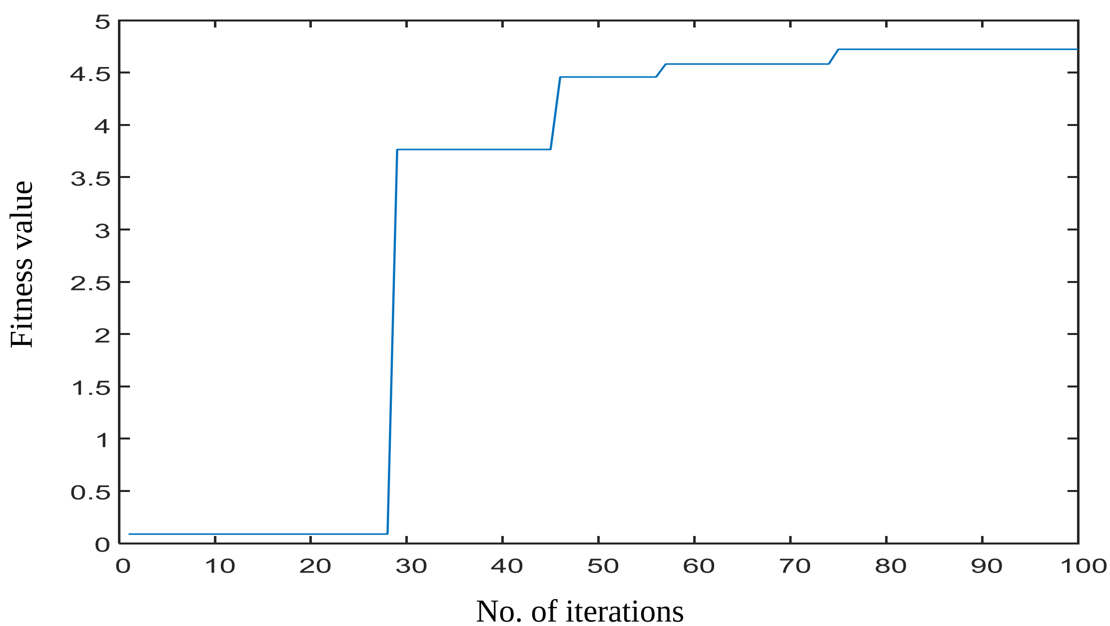


Fig. 3.4: *Convergence curves of proposed technique. Proposed BCO using ϕ (Upper) and proposed BCO using φ (Lower)*

In Fig. 3.5, a detailed retention analysis has been presented. It can be seen that in the enhanced images by proposed technique, the original image details are well retained. Also the enlarged areas of the enhanced proposed BCO images shown in 3.5 (e) and 3.5 (f) portray that the proposed technique can avoid any visual artifacts due to over- or under-enhancement. The technique can also provide good lightness distribution while retaining the white color.

Fig. 3.5: *Local improvement analysis with 'Bird' image; a) original low contrast image, b) enhanced proposed BCO image using ϕ, c) enhanced proposed BCO image using φ, d) the region to focus of (a), e) the region to focus of (b) and f) the corresponding region shown in (c).*

Fig. 3.6 – 3.10 shows the examples of resulted enhanced images including proposed BCO technique with two different objective functions. Among different techniques, 8 have been considered for comparison purpose. These techniques are briefly discussed in previous chapter. These techniques cover different paradigms of algorithms in both spatial and frequency domains. The results are presented in comparative manner where the outputs of some of the established techniques have been included for visual comparison. To decide the potentiality of proposed technique, a set of 1000 images from different dataset was maintained.

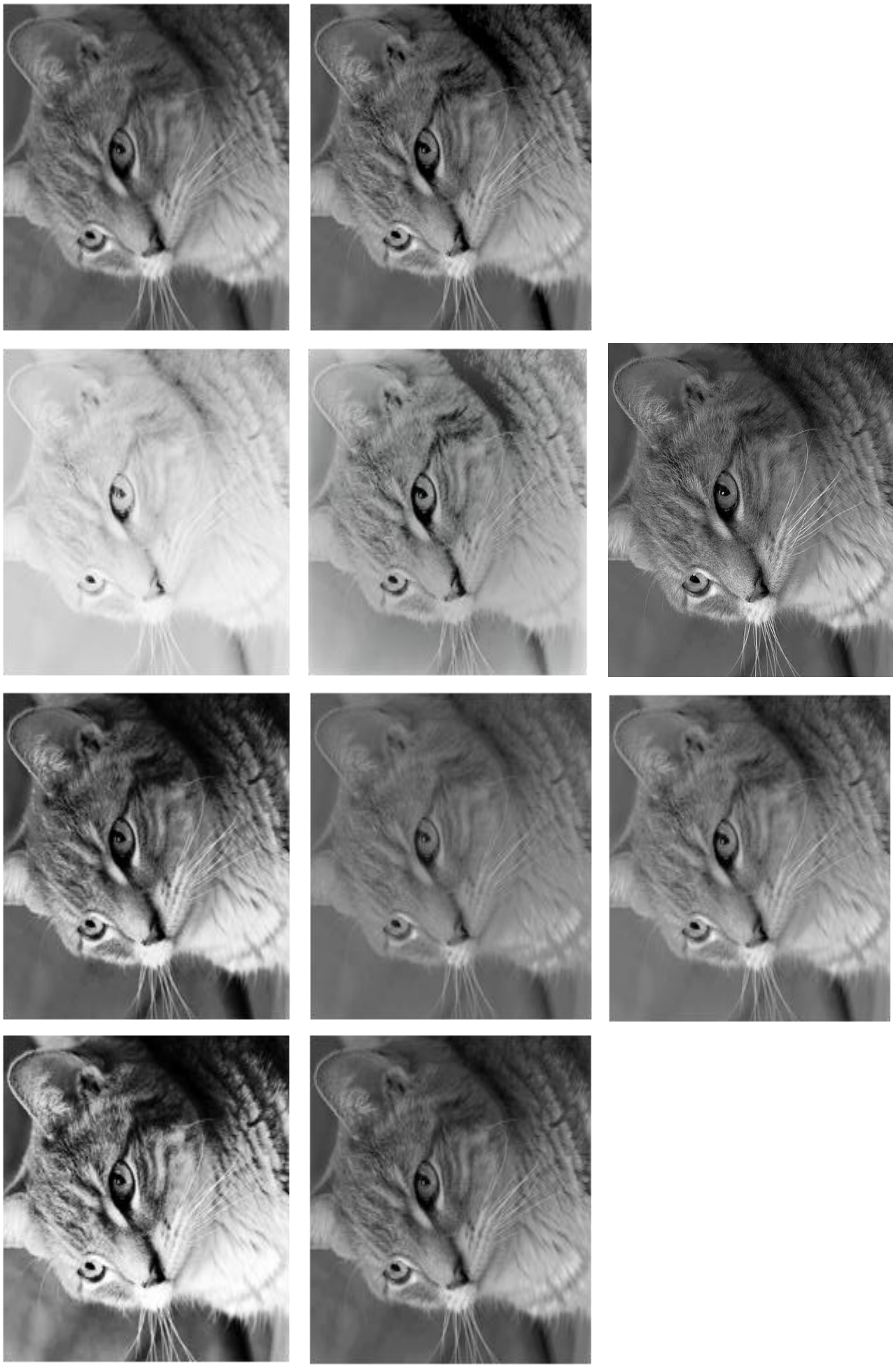


Fig. 3.6: *Result of different techniques for gray test image ‘Cat’. (Top row from left to right) GHE, DFHE, MSR, SECEDCT, (middle row left to right) GA, ABC, CLAHE-DGC, FDAHE-GC, (bottom row left to right) proposed BCO (using ϕ) and proposed BCO (using φ)*

Fig. 3.7: *Result of different techniques for gray test image 'Lady'. (Top row from left to right) GHE, DFHE, MSR, SECEDCT, (middle row left to right) GA, ABC, CLAHE-DGC, FDAHE-GC, (bottom row left to right) proposed BCO (using ϕ) and proposed BCO (using φ)*

Fig. 3.6 and 3.7 show the performance of different algorithms on a grayscale image. In Fig. 3.6, the local contrast in the enhanced image is one of the major visible factors. The enhancement capability of FDAHE-DGC and proposed BCO are visibly better than the other techniques under consideration. Among the statistical HE techniques SECEDCT can enhance the local information efficiently but suffering from under-whiteness problem. Similarly, MSR and ABC results are showing over-whiteness and less sharpness respectively. GHE and DFHE both are suffering from over enhancement problem. Among the computational intelligence driven techniques, GA has comparatively better result with respect to ABC. In both the cases, among the recent algorithms FDAHE-GC provides better balance and more vividness. CLAHE-DGC does not show their capability in terms of retention of image characteristics while improving the contrast. The proposed BCO can show its potential for both the types of objective functions towards visibility of local information as well as global enhancement of the input image contrast.

In case of Fig. 3.7, the enhancement capability of proposed BCO is visibly better than the other techniques under consideration. The result of DFHE and CLAHE-DGC is having higher sharpness while GHE and SECEDCT provide higher smoothness and whiteness. The performance of MSR relatively better comparing with HE based techniques. The CI techniques based algorithms GA and ABC results exhibit comparatively balanced enhancement. FDAHE-GC performs comparatively better with respect to other techniques.

Fig. 3.8 – 3.10 are the examples of results with different algorithms on color test images. In Fig. 3.8, most of the conventional techniques show limitation to retain the color information of input image which is visible in case of leaves that are appearing almost black in the output of most of the conventional techniques. DFHE result is showing the biasness of the level distribution towards dark intensities which caused under-enhancement, while GHE and MSR show tendency

of increasing overall whiteness which causes over-enhancement. SECEDCT and CLAHE-DGC have low contrast and sharpness problem. In terms of optimization techniques, GA and ABC both perform well but the output of GA is better than the ABC output here. The results of FDAHE-GC and the proposed BCO are more appealing but with respect to brightness, sharpness and the most important contrast, the proposed technique with objective function ϕ shows better visual balance to maintain whiteness and darkness.

Fig. 3.8: *Result of different techniques for color test image 'Flower'. (Top row from left to right) GHE, DFHE, MSR, SECEDCT, (middle row left to right) GA, ABC, CLAHE-DGC, FDAHE-GC, (bottom row left to right) proposed BCO (using ϕ) and proposed BCO (using φ)*

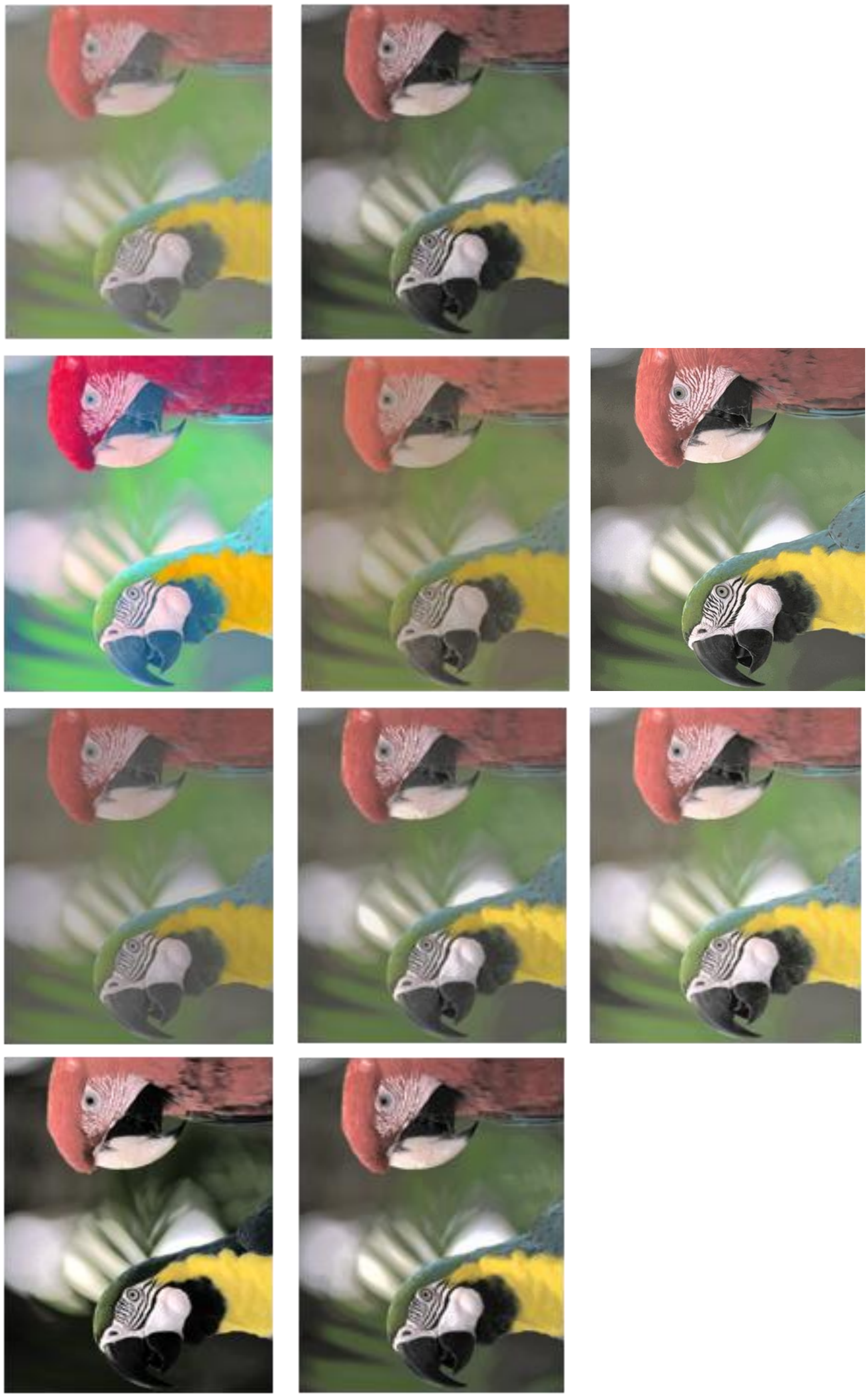


Fig. 3.9: *Result of different techniques for color test image 'Bird'. (Top row from left to right) GHE, DFHE, MSR, SECEDCT, (middle row left to right) GA, ABC, CLAHE-DGC, FDAHE-GC, (bottom row left to right) proposed BCO (using ϕ) and proposed BCO (using φ)*

Image in Fig. 3.9 is also important to observe the color retention as well as balanced sharpness potential of the techniques. Like previous image, DFHE suffers from low contrast effect. SECEDCT and CLAHE-DGC provide low sharpness problem as it is not clear at the eye portion of the image. GHE provides better result in comparison with the above techniques, but it cannot retain the proper color information. ABC and FDAHE-GC provide almost same output of low color retention effect. MSR cannot retain the original color as can be seen in the throat area of first bird and body area of second bird. GA and the proposed BCO technique work well in terms of appearance, brightness distribution and color retention but the proposed technique provides more color retention and enhances the contrast but little bit suffering from over brightness in case of the image using objective function ϕ.

The proposed BCO technique is also showing its potentiality in Fig. 3.10 for the case of underwater image. This type of image enhancement is very much crucial as in most of the case the image is suffering from low contrast due to the presence of water. In this regard, most of the techniques give poor enhancement to enhance the image quality and suffer from black patches (GHE, GA, ABC and CLAHE-DGC), over color effect and it fails to produce a natural effect (MSR), degradation of sharpness (DFHE and SECEDCT) etc. FDAHE-GC performs almost well in maintaining the color and enhancing the contrast but suffering from little bit low sharpness. Among all techniques mentioned here, the proposed technique provide much better in terms contrast enhancement, preserving the brightness, balanced sharpness as well as image information but in comparison with both the presented images, the proposed BCO using objective function φ is better from the proposed BCO using objective functions ϕ, since it is designed based on color imaging characteristics.

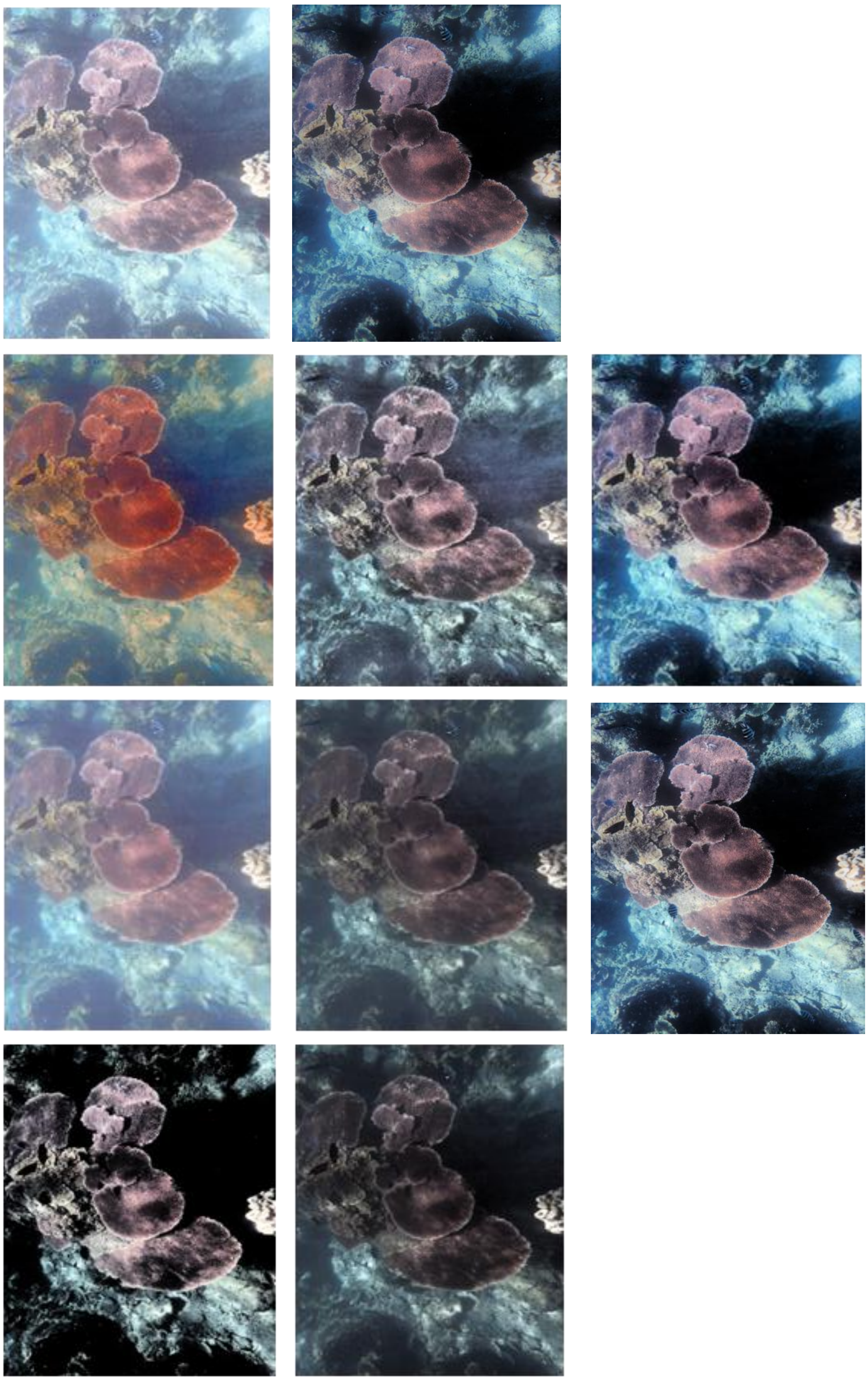


Fig. 3.10: *Result of different techniques for color test image 'Underwater'. (Top row from left to right) GHE, DFHE, MSR, SECEDCT, (middle row left to right) GA, ABC, CLAHE-DGC, FDAHE-GC, (bottom row left to right) proposed BCO (using ϕ) and proposed BCO (using φ)*

Fig. 3.11 shows input and proposed output images of ‘garden’ at two different levels of contrast. The proposed BCO technique using both the objective function is capable producing enhance output images from different levels of low contrast image maintaining the various image features like brightness preservation, proper contrast, sharp edge, white balancing and appropriate visual quality.

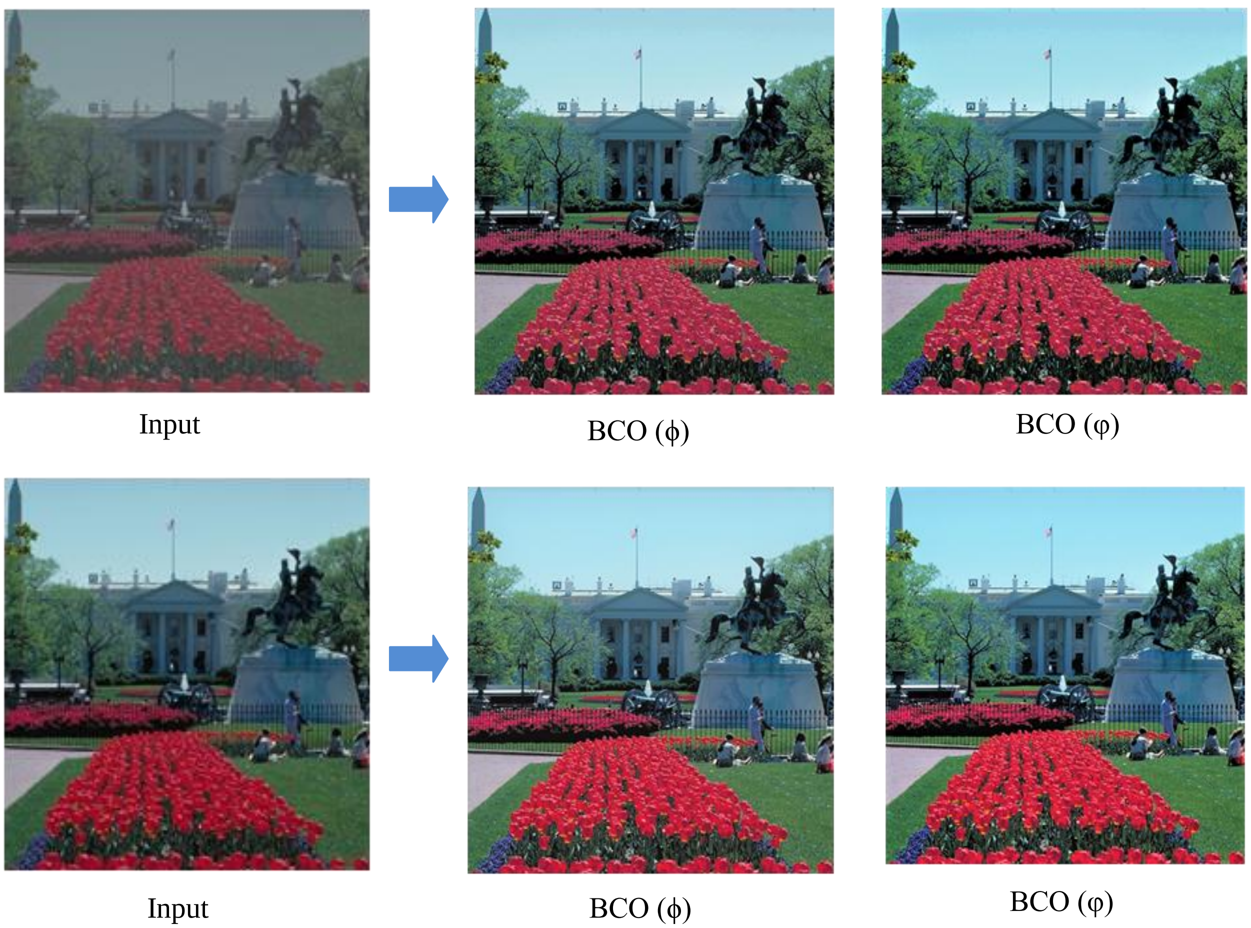


Fig. 3.11: *Visual comparison of ‘Garden’ image at different levels of contrast using proposed BCO.*

The visual analyses have further been extended to the objective evaluations against the image quality assessment (IQA) metrics discussed in chapter 2. Table 3.3-3.7 represents the objective evaluations; in all the tables the top 2 performers have been highlighted using bold font.

Table 3.3 represents the entropy value for different test images from different datasets mention above using various techniques. As it can be seen in Table 3.3, MSR, FDAHE-GC and the proposed BCO technique outperform other techniques by comparatively higher entropy values. GHE also have shown better performance in some images. CLAHE-DGC performs consistent results for all the images but not like FDAHE-GC and the proposed BCO technique. GA, ABC perform almost same. Nevertheless, all the techniques perform almost equivalent but DFHE and SECEDCT has shown poor performances in comparison with the others in some cases. The performance of the proposed BCO technique using φ is relatively better rather than the proposed BCO technique using objective function ϕ. For every image mention in Table 3.3, the proposed BCO technique using objective function φ scored first position. Overall the proposed technique performs better among all the images in comparison with the other techniques mention here.

Table 3.3: *Evaluation of entropy resulted by the different techniques*

	Techniques ➡									
Images ⬇	**GHE**	**DFHE**	**MSR**	**SECE DCT**	**GA**	**ABC**	**CLAHE-DGC**	**FDAHE -GC**	**Proposed BCO (ϕ)**	**Proposed BCO (φ)**
Cat	7.1345	7.0159	6.3204	6.8692	6.5336	6.2144	7.0682	7.2058	**7.2504**	**7.3877**
Lady	6.5890	6.1922	**7.3499**	6.8460	6.1261	6.1114	7.0719	6.9718	7.3354	**7.3844**
Flower	7.6865	6.4900	7.2417	6.6180	6.9113	6.7738	7.0138	6.9768	**7.7242**	**7.7518**
Bird	7.5503	6.7082	7.6087	6.9596	7.2738	7.0269	7.0303	7.1694	**7.6518**	**7.8995**
Underwater	6.2090	7.1498	7.2838	7.3264	6.9878	6.8317	7.4056	**7.8647**	7.6518	**7.9162**

In terms of mean-PCQI values shown in Table 3.4, the proposed BCO technique provides remarkable performances almost for all the images. FDAHE-GC performs better but not to the extent of the proposed BCO technique. The performance of GA and ABC are almost equivalent.

MSR shows little bit poor performance comparing with other techniques. Rest of the techniques has mixed performance for this metric. Like Entropy, here also the proposed BCO technique using objective function φ is relatively better rather than the proposed BCO technique using objective function ϕ but both of them has provided a consistent performance and in all cases both are secured position within top 2 performers.

Table 3.4: *Evaluation of mean PCQI values resulted by different techniques*

Images ⬇ / Techniques ➡	GHE	DFHE	MSR	SECE DCT	GA	ABC	CLAHE-DGC	FDAHE -GC	Proposed BCO (ϕ)	Proposed BCO (φ)
Cat	1.0979	1.0912	0.7622	1.0062	0.9828	0.9341	0.8408	1.1095	**1.1123**	**1.1880**
Lady	1.1559	0.9023	1.0633	1.0119	1.0295	1.0013	0.9669	0.9968	**1.1882**	**1.1944**
Flower	1.1468	1.0073	0.7708	0.9199	1.0809	1.0960	1.1059	1.0950	**1.1793**	**1.1885**
Bird	0.9917	0.9943	0.7539	0.8699	1.0675	1.0558	0.9448	1.0452	**1.0669**	**1.1667**
Underwater	0.8888	0.8816	0.8883	1.0125	0.7730	0.7753	1.0922	1.0437	**1.1184**	**1.1562**

Table 3.5 shows that in terms of NIQE, the proposed BCO technique also perform better result especially by using objective function φ. GHE, MSR and FDAHE-GC perform well in this case and have secured the top 2 position for either of the images. It is also seen that, there is a mixed performance among DFHE, SECEDCT, GA, ABC and CLAHE-DGC in this case, which is not well. The possible reason is under enhancement in DFHE and CLAHE-DGC which causes a loss of naturalness.

Table 3.5: *Evaluation of NIQE values resulted by different techniques*

Images ⬇ / Techniques ➡	GHE	DFHE	MSR	SECE DCT	GA	ABC	CLAHE-DGC	FDAHE-GC	Proposed BCO (ϕ)	Proposed BCO (φ)
Cat	**3.4495**	3.6061	3.8314	3.6658	3.6559	3.8080	4.2559	4.6752	3.5049	**3.3720**
Lady	3.5499	3.8838	4.2417	3.8015	3.7347	3.6969	3.6186	3.7658	**3.4356**	**3.2373**
Flower	3.7289	3.8961	**3.4838**	3.9483	3.6121	3.7798	3.5913	3.5767	3.4906	**3.4819**
Bird	3.9023	5.1887	4.8491	5.2255	4.3068	4.4577	4.4314	4.3022	**3.7866**	**3.5979**
Underwater	2.7113	2.4217	2.2360	2.2432	2.7074	2.6914	2.3745	**2.1293**	2.1687	**2.0837**

Table 3.6: *Evaluation of CEF resulted by the different techniques*

Images ⬇ / Techniques ➡	GHE	DFHE	MSR	SECE DCT	GA	ABC	CLAHE-DGC	FDAHE-GC	Proposed BCO (ϕ)	Proposed BCO (φ)
Cat	1.0020	0.9585	0.7646	1.0722	**1.1035**	1.0131	0.9714	1.0585	**1.1223**	1.0477
Lady	0.9839	0.7223	0.9786	0.8692	0.8598	0.9545	0.7750	0.9333	**1.0209**	**0.9976**
Flower	1.1162	1.1545	0.9869	0.9342	1.4334	1.2919	1.3038	1.4963	**1.6048**	**1.5356**
Bird	1.0658	0.8307	0.8654	0.6696	0.8623	0.7976	0.9040	0.9992	**1.5797**	**1.3048**
Underwater	**1.6003**	0.6957	0.9916	0.7316	1.1391	1.1606	0.9415	1.0931	1.4253	**1.9251**

In terms of CEF as shown in Table 3.6, the proposed BCO technique has shown its potential in all the images. GHE, being a classical and simple technique, has performed equivalently well in this case. DFHE, MSR, SECEDCT, ABC and CLAHE-DGC have similar degree of enhancement. GA and FDAHE-GC perform almost equivalent performance to GHE. The proposed BCO technique using objective function ϕ performs much better with respect to previous metrics except underwater image, where the proposed BCO using objective function φ performs better in comparison with the other techniques as well as the proposed BCO technique using objective function ϕ.

In Table 3.7, only color images have been considered as the metric is applicable to color images only. Here, MSR performs much better with respect to other techniques including proposed BCO technique. The proposed BCO technique and FDAHE-GC also perform very well along with the MSR. GA and ABC perform moderate result in this case. GHE, DFHE, SECEDCT and CLAHE-DGC are equivalent performance and not up to the mark for this purpose due to their over and under whiteness. The output of proposed BCO using objective function φ is better with respect to output using objective function ϕ and secured the top two positions for all the color images.

Table 3.7: *Evaluation of colorfulness resulted by different techniques*

	Techniques →									
Images ↓	**GHE**	**DFHE**	**MSR**	**SECE DCT**	**GA**	**ABC**	**CLAHE-DGC**	**FDAHE -GC**	**Proposed BCO (ϕ)**	**Proposed BCO (φ)**
Flower	3.478	2.315	**5.496**	2.912	2.337	2.348	3.250	2.214	3.561	**3.787**
Bird	4.675	3.781	**8.285**	4.724	4.297	4.246	4.558	3.543	4.987	**5.385**
Underwater	6.024	3.729	**22.683**	14.878	1.111	1.358	10.475	19.074	17.842	**20.154**

Finally the mean values for different metrics for 1000 images under consideration have been consolidated in Table 3.8. It clearly shows the potential of the proposed technique against all the metrics under consideration except colorfulness. In case of colorfulness, MSR perform well in comparison with the proposed BCO. Apart from this, the proposed BCO technique using either objective function secured its position in top two places. This also vouches the generosity of the proposed technique in all aspects.

Table 3.8: *Evaluation of mean values on all the 1000 test images by different techniques*

Metrics ⬇ / Techniques ➡	GHE	DFHE	MSR	SECE DCT	GA	ABC	CLAHE-DGC	FDAHE-GC	Proposed BCO (ϕ)	Proposed BCO (φ)
Entropy	7.468	6.621	7.399	6.970	6.865	6.656	7.073	7.279	**7.598**	**7.722**
PCQI	0.955	0.904	0.762	1.001	1.072	1.037	1.130	1.172	**1.221**	**1.375**
NIQE	9.727	9.797	4.757	3.847	3.773	3.870	3.800	3.450	**3.394**	**3.277**
CEF	1.152	0.903	0.839	0.930	1.006	0.946	1.145	1.182	**1.265**	**1.205**
Colorfulness	10.638	3.094	**16.827**	11.047	3.369	3.469	9.179	10.884	14.825	**15.327**

3.5. Conclusions

The work has presented application of BCO towards contrast enhancement to obtain enhanced images, while preserving the important characteristics of the original image. Two objective functions have been optimized based on the shape and magnitude of frequency spectra and the DCE based imaging model. Both the results have been established here for better analyzing purpose. The results have been presented visually and objective assessments have been drawn in comparison to the established HE techniques as well as CI based algorithms. The comparative analysis shows the competitive potential of proposed BCO against the established techniques while overcoming different limitations of conventional HE approaches. From the above analysis, it is also seen that the diversity of imaging model based objective function over FFT spectrum based objective function, though the former one performs better in case of underwater image also. But as per as proper contrast are concerned, the later one found to be better which are reflecting in CEF. The work can further be extended to the tuning the fitness function for more robustness, BCO parameter optimization, a predictive model of the optimization framework where the input image can be enhanced based on a set of defined equalized histograms obtained by BCO, model based HE applications, inclusion of more optically derived measure of contrast for objective function formulation etc. The proposed technique has been explored considering image appearance in general which provides another important direction towards inclusion of prepress and press parameters in the objective function to obtain improved output quality of different prepress and printing systems. Finally, this chapter has proposed an important step towards applications of BCO algorithm for image characteristics preserving contrast enhancement.

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CHAPTER 4

Image contrast enhancement using grey wolf optimizer (GWO)

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4.1. Introduction

Grey wolf optimizer (GWO) is a new swarm intelligence algorithm introduced by Seyedali Mirjalili et al. in 2014. This algorithm is mainly mimics the hunting mechanism of grey wolves for their livelihood. This algorithm is superior to the other popular algorithms due to its simple operation, high convergence speed, and better search precision [1].

Most of the popular metaheuristics algorithms such as PSO, ABC, ACO, etc. are efficient to provide improved output by searching the optimal solution based on the objective function but they are suffering from problems like slow convergence speed, premature characteristics, falling into the local optima, etc [2]. So there will be a lack of overall improvement observed in many cases. Even the previous proposed BCO technique has one problem which is slow convergence speed due to its various processes to reach optimal output [3]. In case of GWO, the best solution has been assessed by using three solutions computed from three different category of wolf according to the hierarchy, whereas the best solution is computed from a single solution based on fitness value. So using GWO there will be less possibility of premature and high possibility to achieve global optimum [2]. The experimental results show the potentiality of GWO in terms of optimization accuracy and convergence velocity. Using this algorithm, so many works have been done in various fields of engineering and science such as “Grey Wolf Optimization Algorithm for Node Localization Problem in Wireless Sensor Networks” by R. Rajakumar et al. in the year of 2017 [4], where the exact location of unknown nodes using anchor nodes in wireless sensor network have been found by GWO algorithm. In 2019, Jie-Sheng Wang introduced “An Improved Grey Wolf Optimizer Based on Differential Evolution and Elimination Mechanism” [2] where the proper adjustment of exploration and exploitation has been focused. Mehdi Ghalambaz et al. presented “Building energy optimization using Grey Wolf Optimizer (GWO)” in 2021 [5] where the energy consumption has been optimized based on weather condition using GWO, etc.

The major contribution of this chapter includes application of GWO for contrast enhancement of a low contrast image. This chapter is arranged as follows: In section 4.1, an introduction of this chapter has been established. The details of grey wolf optimizer (GWO) algorithm with pseudo codes have been presented in section 4.2. In section 4.3, the application of GWO for image contrast enhancement has been discussed. The corresponding results and comparison with other techniques are illustrated in section 4.4. Finally, the conclusions of this chapter are discussed in section 4.5.

4.2. Grey wolf optimizer (GWO)

GWO is comparatively new and efficient optimization technique based on the characteristics of grey wolves. Grey wolves are considered as at the top of the food chain and preferred to stay in a group. They maintain a very strict social dominant hierarchy. In GWO, three different types of search agents are selected according to the fitness value. The optimal output can be reached by continuously updating the position of the search agents according to the location of target position. GWO is found to be competitive to other algorithms in swarm intelligence due to fewer control parameters, faster convergence and non-requirement of derivative information in initial search.

According to GWO techniques, grey wolves are maintained a social hierarchy as shown in Fig. 4.1 to fulfil any operations successfully. The leaders of this hierarchy are called alphas (α). Alphas are the decision maker i.e. most of the activities throughout the day performed by the group is decide by alpha. The decision of alpha has been followed by the other members in the group. For this reason, the alpha wolf is also called the dominant wolf. Due to their managing capability, the alpha wolves are at the top position of their group. The second position in the hierarchy of grey wolves is beta (β). The beta helps the alphas for managing the group and their various activities. The beta wolf follows the alpha, but gives the instruction to the other lower position wolves as well. The beta gives the suggestion to alpha and spread the alpha's command across the group. The third position in the group is called delta (δ). Delta wolves have to follow the instruction of alpha and beta, but they can give the instruction to the lowest position of grey wolves in the group. The basic composition of this category includes scouts, sentinels, elders, hunters and caretakers. Scouts are liable for giving the warning to the group in case of any problematic situation from outside. Sentinels are responsible for protection and the safety of the group. The experienced wolves are known as elder. They can be alpha or beta. Hunters help the alphas and betas during the time of hunting and help to supply the food among the group. Finally, the caretakers take care of the weak and ill wolves in the group. The lowest position grey wolves are called omega (ω). They are the last ranking wolves that are allowed to eat. Sometimes it is observed that the total group are facing problem in case of losing the omega. Apart from this social hierarchy, grey wolves also perform the group hunting for their livelihood. The main three steps of grey wolf hunting are a) tracking, chasing, and approaching the prey, b) pursuing, encircling, and harassing the prey until it stops moving and finally c) attacking towards the prey.

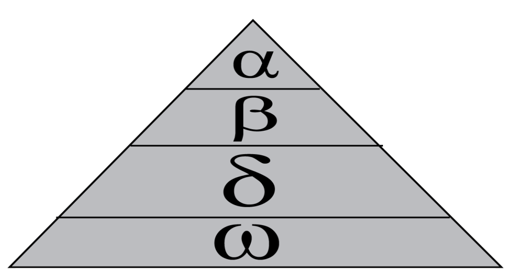

Fig. 4.1: *Structure of grey wolf hierarchy (Top to down dominance approach) [1]*

Encircling the prey is mathematically represented by the Eq. 4.1 – 4.2 [1] where $\overrightarrow{X}$ is the position vector and $\overrightarrow{X_p}$ is the position of prey at current iteration t. $\overrightarrow{D}$ is the distance vector by which a search agent updates its position according to alpha, beta, and delta.

$$\overrightarrow{D} = \left| \overrightarrow{C} . \overrightarrow{X_p}(t) - \overrightarrow{X}(t) \right| \tag{4.1}$$

$$\overrightarrow{X}(t+1) = \overrightarrow{X_p}(t) - \overrightarrow{A}.\overrightarrow{D} \tag{4.2}$$

where, *A* and *C* are co-efficient vectors that are calculated using Eq. 4.3 and 4.4, respectively.

$$\vec{A} = 2.\vec{a}.\vec{r_1} - \vec{a} \tag{4.3}$$

$$\vec{C} = 2.\vec{r_2} \tag{4.4}$$

Where components of a are linearly decreased from 2 to 0 throughout the iterations. r_1 and r_2 are random vectors in [0, 1].

The hunting procedure is generally directed by the alpha. Occasionally the beta and delta also participate for hunting. To express the hunting procedure mathematically, the alpha, beta and delta wolves are considered. These three wolves have better knowledge about the location of the prey. The dynamics of alpha, beta and delta are described as Eq. 4.5, 4.6 and 4.7 respectively [1]. The first three best solutions obtained so far are considered and other agents update their position depending on the position of the target solution using Eq. 4.5 – 4.11 [1].

$$\overrightarrow{D_{\alpha}} = \left|\overrightarrow{C_1}.\overrightarrow{X_{\alpha}}(t) - \overrightarrow{X}\right| \tag{4.5}$$

$$\overrightarrow{D_{\beta}} = \left|\overrightarrow{C_2}.\overrightarrow{X_{\beta}}(t) - \overrightarrow{X}\right| \tag{4.6}$$

$$\overrightarrow{D_{\delta}} = \left|\overrightarrow{C_3}.\overrightarrow{X_{\delta}}(t) - \overrightarrow{X}\right| \tag{4.7}$$

$$\overrightarrow{X}_1 = \overrightarrow{X_{\alpha}} - \overrightarrow{A_1}.\overrightarrow{D_{\alpha}} \tag{4.8}$$

$$\overrightarrow{X}_2 = \overrightarrow{X_{\beta}} - \overrightarrow{A_2}.\overrightarrow{D_{\beta}} \tag{4.9}$$

$$\overrightarrow{X}_3 = \overrightarrow{X_{\delta}} - \overrightarrow{A_3}.\overrightarrow{D_{\delta}} \tag{4.10}$$

$$\overrightarrow{X}(t+1) = \frac{\overrightarrow{X_1} + \overrightarrow{X_{2..}} + \overrightarrow{X_3}}{3} \tag{4.11}$$

Fig. 4.2 shows the position updating procedure of a search agent based on alpha, beta and delta in a 2D search space. It is noticed from the figure that the final position will be any random position inside the circle maintained by alpha, beta, and delta in the search space. The rest of the wolves update their positions randomly circling the prey. According to the figure, the blue color indicates the position of alpha, pink color is beta and green color is delta. The yellow color indicates the estimated prey position based on which all alpha, beta and delta position will be updated.

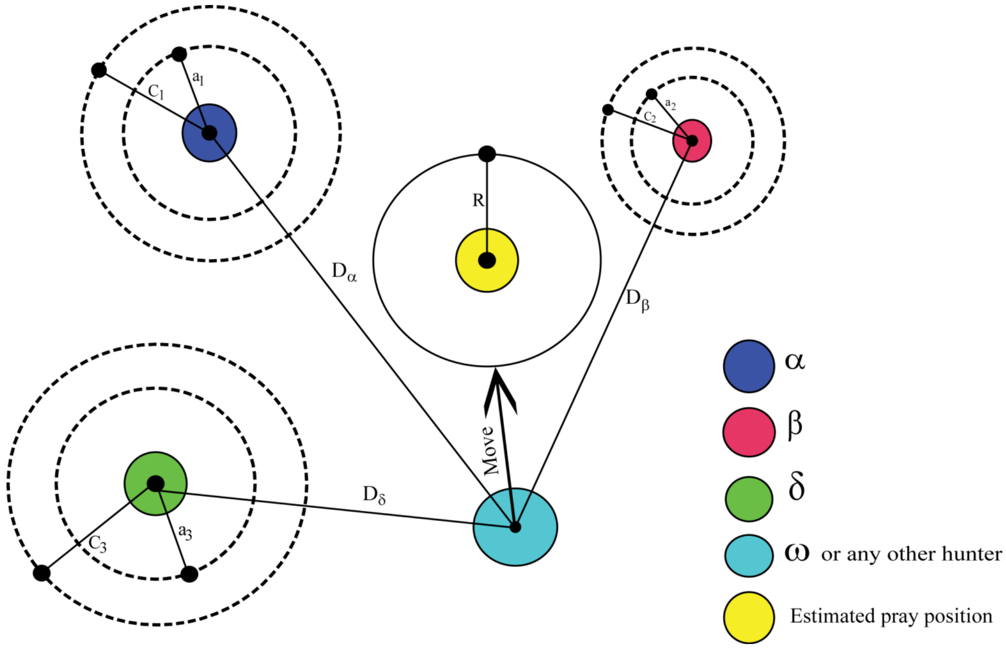

Fig. 4.2: *Position updating procedure by grey wolves in GWO [1].*

The pseudo code of the algorithms can be presented as Table 4.1.

Table 4.1: *Pseudo code of GWO*

Initialize the population of grey wolves $\overrightarrow{X}_i(t)$ where $i=1, 2, 3, \ldots, n$ and $\overrightarrow{X}_i(t)$ represents the position vector of i^{th} wolf at t^{th} iteration.

Initialize the component vector a at 2 and gradually decrease to 0 during entire optimization cycle.

Initialize co-efficient vector A as $\vec{A} = 2.\vec{a}.\vec{r}_1 - \vec{a}$ where $\overrightarrow{r_1} = random \quad (0,1)$.

Initialize co-efficient vector C as $\vec{C} = 2.\vec{r}_2$ where $\overrightarrow{r_2} = random \quad (0,1)$.

Evaluate the fitness values for each solution i of search agent using the fitness function.

Find X_α, X_β and X_δ solutions that are the best, 2nd and 3rd best solutions respectively.

Set iteration counter $= 0$.

While (C< Max number of iteration)

for each search agent

Update the position of current search agent by

$$\overrightarrow{X}(t+1) = \frac{\overrightarrow{X_1} + \overrightarrow{X_{2..}} + \overrightarrow{X_3}}{3}$$

end for

Update *α, A* and *C*

Calculate the fitness of all search agents.

Update the position of X_α, X_β and X_δ

C = C + 1

end while

4.3. Application of GWO for contrast enhancement

For gray scale image, the initial random solutions are initialized based on input image histogram. In case of color image, RGB color space to HSV color space conversion has been performed first and then initializes the initial random solutions based on the histogram of V channel of the HSV color space. The pseudo code of the proposed technique has been presented in Table 4.2.

Table 4.2: *Pseudo code of GWO based contrast enhancement*

/* Assignment */

Load the low contrast image as input.

Compute input image histogram.

Initialize GWO parameters

a: Component vector

A: Co-efficient vector

C: Co-efficient vector

Initialize random solutions based on input image histogram.

/* Update */

Compute the fitness value for each solution using Eq. [2.18].

Find the best, 2^{nd} and 3^{rd} best solutions according to fitness value.

Update the position of current search agent using Eq. [4.11].

Store the fitness values for finding better value by iterative process of GWO operation.

Update the value of a, A and C.

Update the position of X_α, X_β and X_δ

Calculate the fitness of all search agents.

Check the fitness value, whether it is better with respect to the previously selected solutions.

Find the objective function value with the most-fit solution after iteration using Eq. [2.1, 2.14].

Terminate the loop while meeting the termination condition

/* Enhancement */

Reconstruct the V channel with the best solution found using GWO

Replace the original image V channel with the optimized V channel

Convert the image back to RGB color space for visual presentation

The parameters of GWO a, A and C tuned according to the value within the ranges of values as commonly practiced in GWO and are presented in Table 4.3

Table 4.3: *GWO parameters setting*

a: Component vector	2 and gradually decrease to 0
A: Co-efficient vector	Random value in between 0 and 1
C: Co-efficient vector	Random value in between 0 and 1

4.4. Results and Discussions

The proposed GWO was verified by taking different gray scale and color images from standard databases discussed in previous chapter. These algorithms have also been implemented using R2015a version of Matlab® software in Windows PC with an Intel Core i5 2.67 GHz CPU and 8 GB of RAM. and all the images presented here have been reproduced at 300 dpi resolutions.

The results of proposed GWO for gray scale and color images have been presented in Fig. 4.3 and 4.4. In both the cases the output results by using both the optimization functions retain the original image characteristics. No visible false contouring and artificial patches present in the output results. In Fig. 4.4, the corresponding V channels have also been included. This is reflecting the visual appearance of enhanced image. The corresponding histogram of presented V channel vouches the potential of proposed technique.

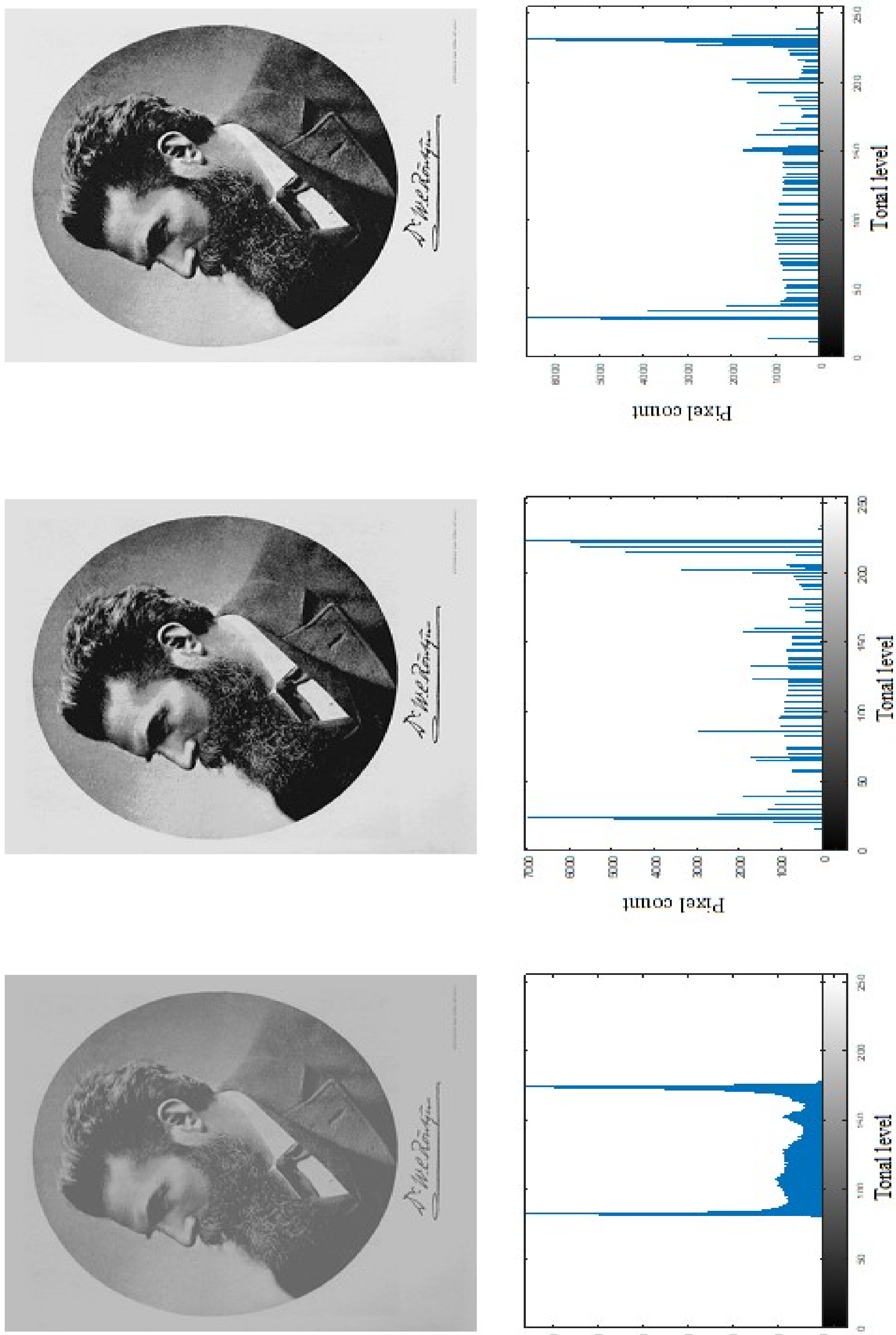

Fig. 4.3: *Result of proposed GWO technique for gray test image. (Top row from left to right) original, proposed GWO (ϕ), and proposed GWO (φ), (bottom row left to right) corresponding histogram of original image, proposed GWO (ϕ), and proposed GWO (φ)*

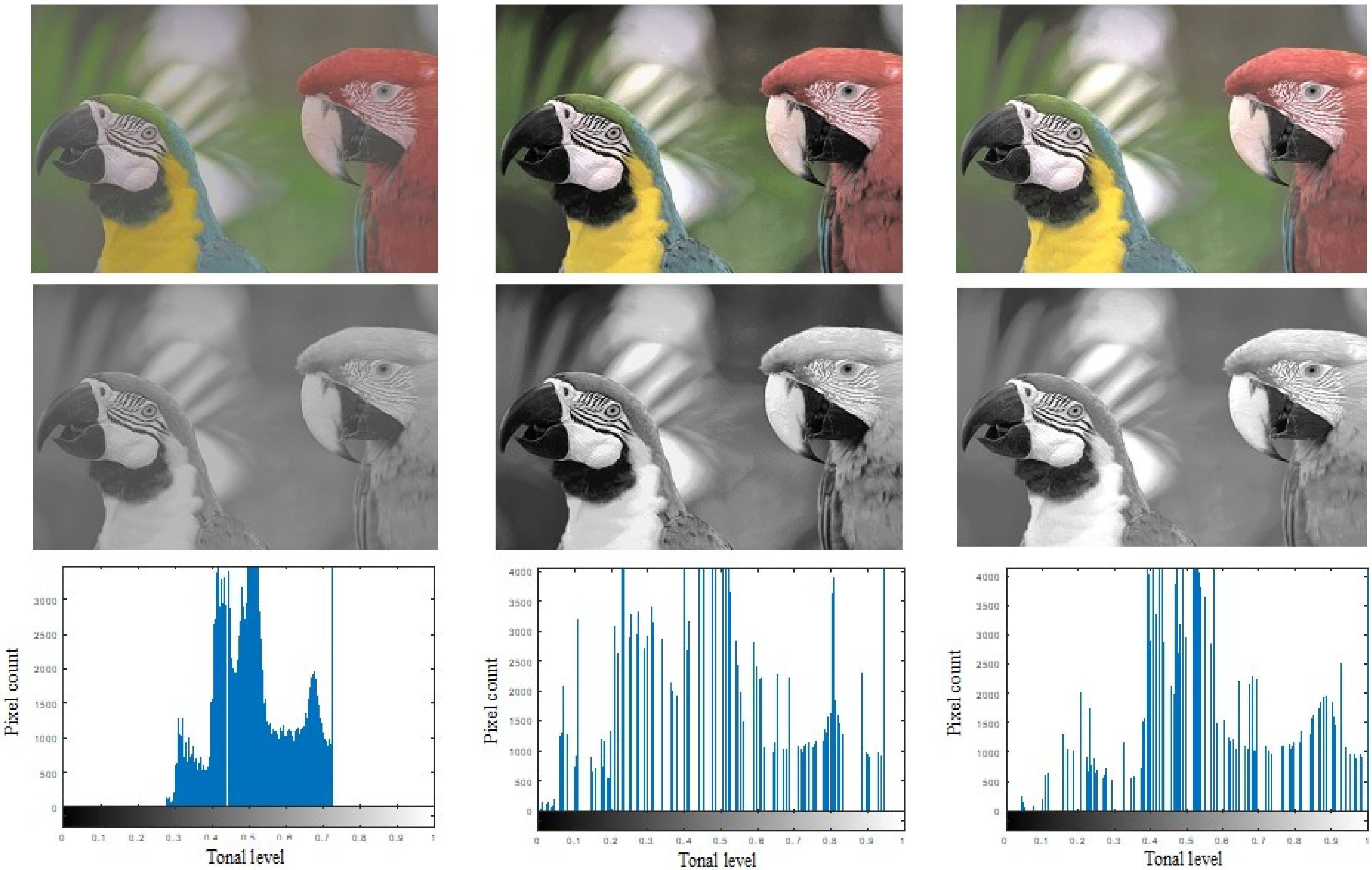

Fig. 4.4: *Result of proposed GWO technique for color test image. (Top row from left to right) original, proposed GWO (ϕ), and proposed GWO (φ), (middle row left to right) corresponding V channel of original image, proposed GWO (ϕ), and proposed GWO (φ), (bottom row left to right) corresponding V channel histogram of original image, proposed GWO (ϕ) and proposed GWO (φ)*

The convergence curves for both the objective functions have been presented in Fig. 4.5. From this curves, the operational speed of GWO algorithm to perform these operations are noticed and maintain the steadiness to provide satisfactory output.

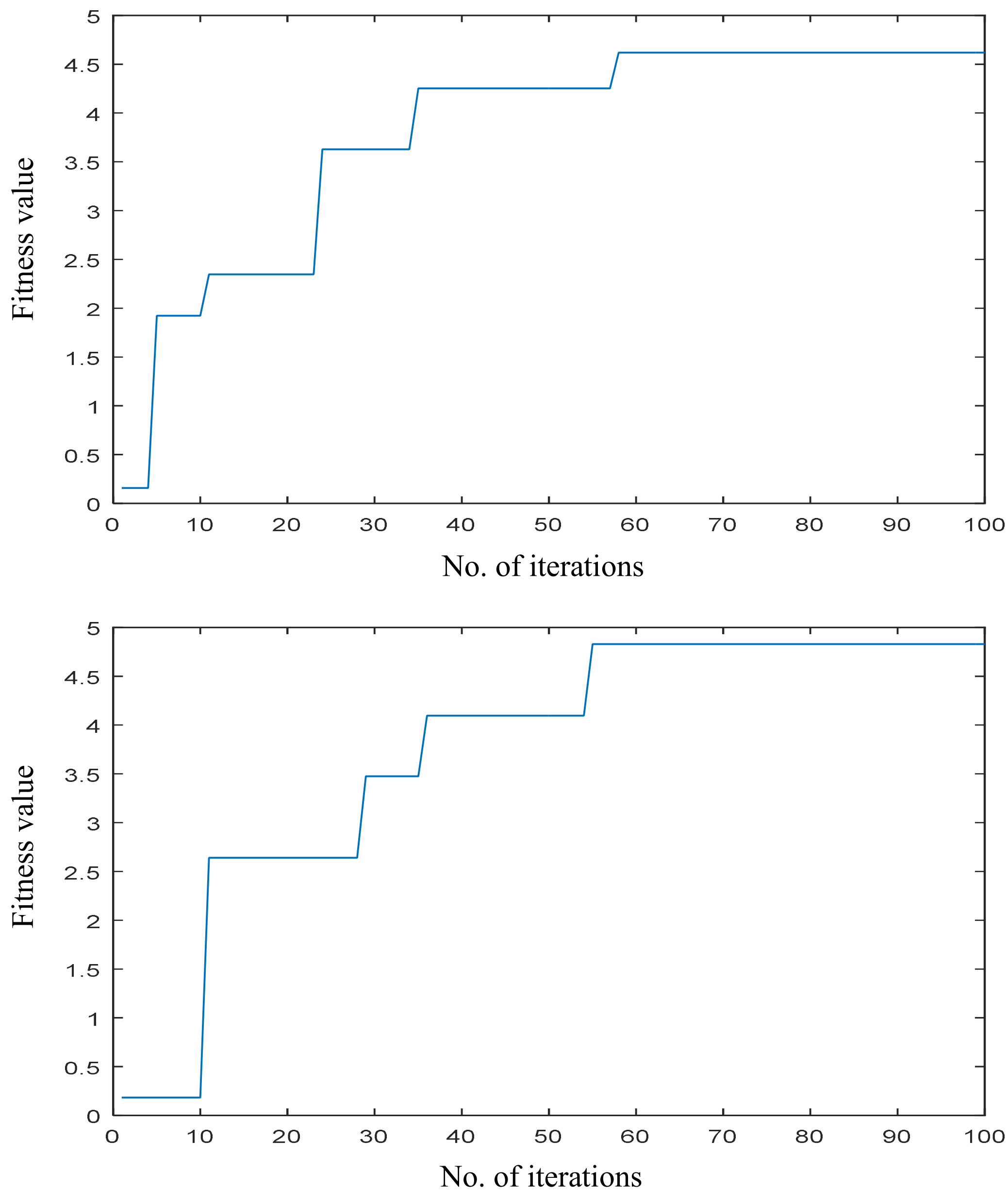

Fig. 4.5: *Convergence curves of proposed technique. Proposed GWO using ϕ (Upper) and proposed GWO using φ (Lower)*

In Fig. 4.6, a detailed retention analysis has been presented like previous chapter and here also it is observed that the original image details are well retained in the enhanced images by proposed technique. The enlarged areas of the enhanced proposed GWO images shown in Fig. 4.6 (e) and Fig. 4.6 (f) reveal the potential of proposed technique to avoid any visual artifacts due to over- or under-enhancement.

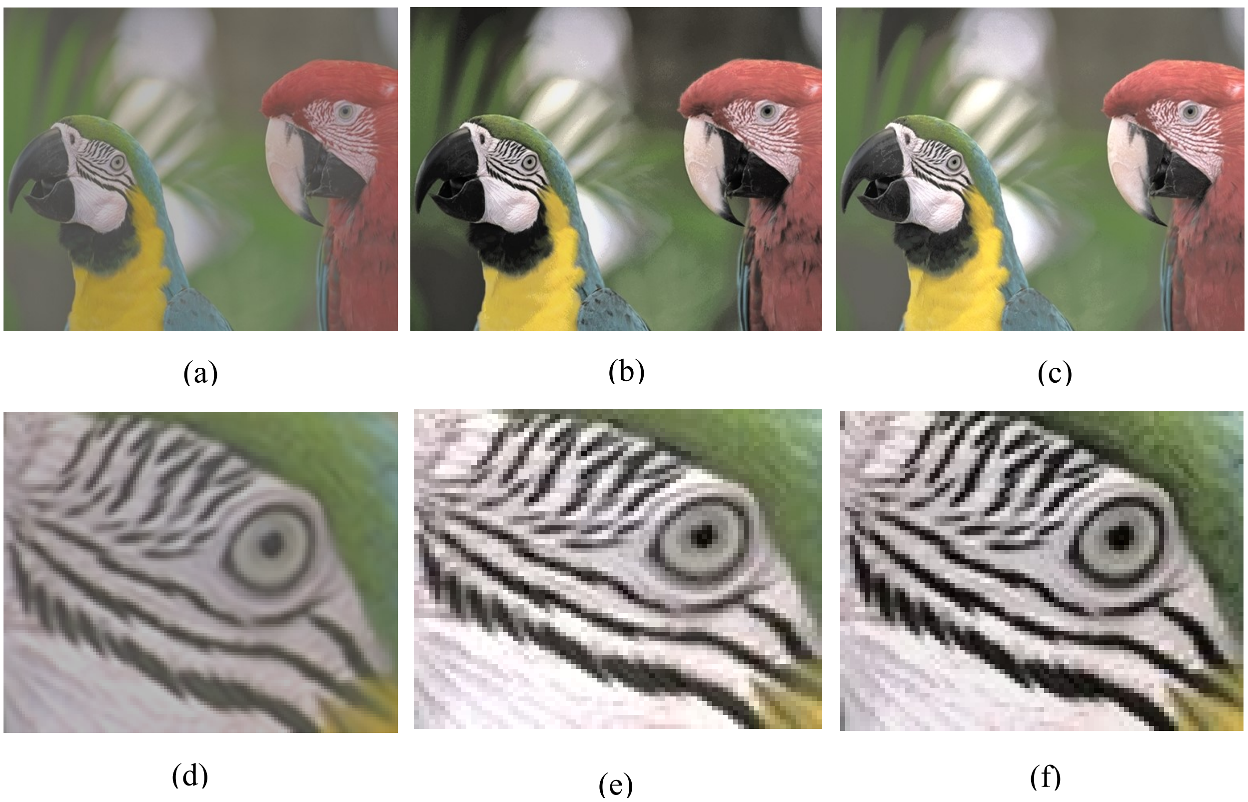

Fig. 4.6: *Local improvement analysis with 'Bird' image; a) original low contrast image, b) enhanced proposed GWO image using ϕ, c) enhanced proposed GWO image using φ, d) the region to focus of (a), e) the region to focus of (b) and f) the corresponding region shown in (c).*

A comparative assessment with the established techniques has been presented in Fig. 4.7-4.11. Like previous chapter (Chapter 3), 8 different techniques have been considered in this chapter for comparative study purpose. These are GHE, DFHE, MSR, SECEDCT, GA, ABC, CLAHE-DGC and FDAHE-GC.

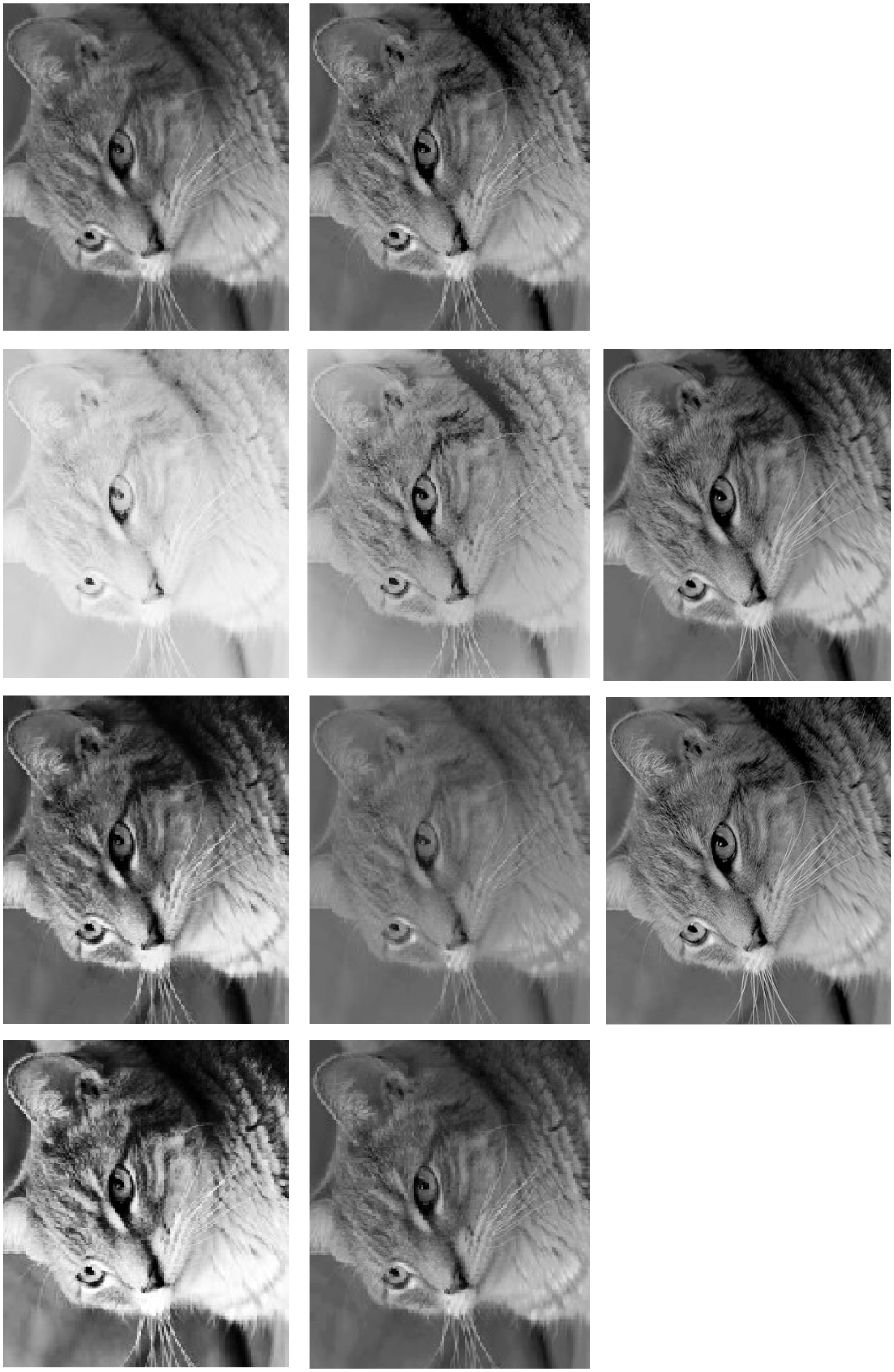

Fig. 4.7: *Result of different techniques for gray test image 'Cat'. (Top row from left to right) GHE, DFHE, MSR, SECEDCT, (middle row left to right) GA, ABC, CLAHE-DGC, FDAHE-GC, (bottom row left to right) proposed GWO (using ϕ) and proposed GWO (using φ)*

Fig. 4.8: *Result of different techniques for gray test image 'Lady'. (Top row from left to right) GHE, DFHE, MSR, SECEDCT, (middle row left to right) GA, ABC, CLAHE-DGC, FDAHE-GC, (bottom row left to right) proposed GWO (using ϕ) and proposed GWO (using φ)*

Figs. 4.7 and 4.8 show the performance of different algorithms on grayscale images. Results show that in both cases the proposed GWO techniques can efficiently improve the contrast of the low-contrast input image, while adhering to the original image characteristics. In case of Fig. 4.7, the enhancement capability of proposed GWO technique is visibly better than the other techniques under consideration. The result of other techniques for this image has already been discussed in chapter 3. In Fig. 4.8, the proposed GWO techniques also show its potential towards visibility of local information as well as global enhancement of the input image contrast like previously proposed technique (BCO). Regarding the comparison among proposed techniques using different objective functions, both the proposed GWO outputs for Fig. 4.7 are almost same visually but in case of Fig. 4.8, the proposed GWO using objective function φ provides output image with little bit over whiteness problem but the proposed GWO using objective function ϕ provides better contrast output.

Fig. 4.9: *Result of different techniques for color test image 'Flower'. (Top row from left to right) GHE, DFHE, MSR, SECEDCT, (middle row left to right) GA, ABC, CLAHE-DGC, FDAHE-GC, (bottom row left to right) proposed GWO (using ϕ) and proposed GWO (using φ)*

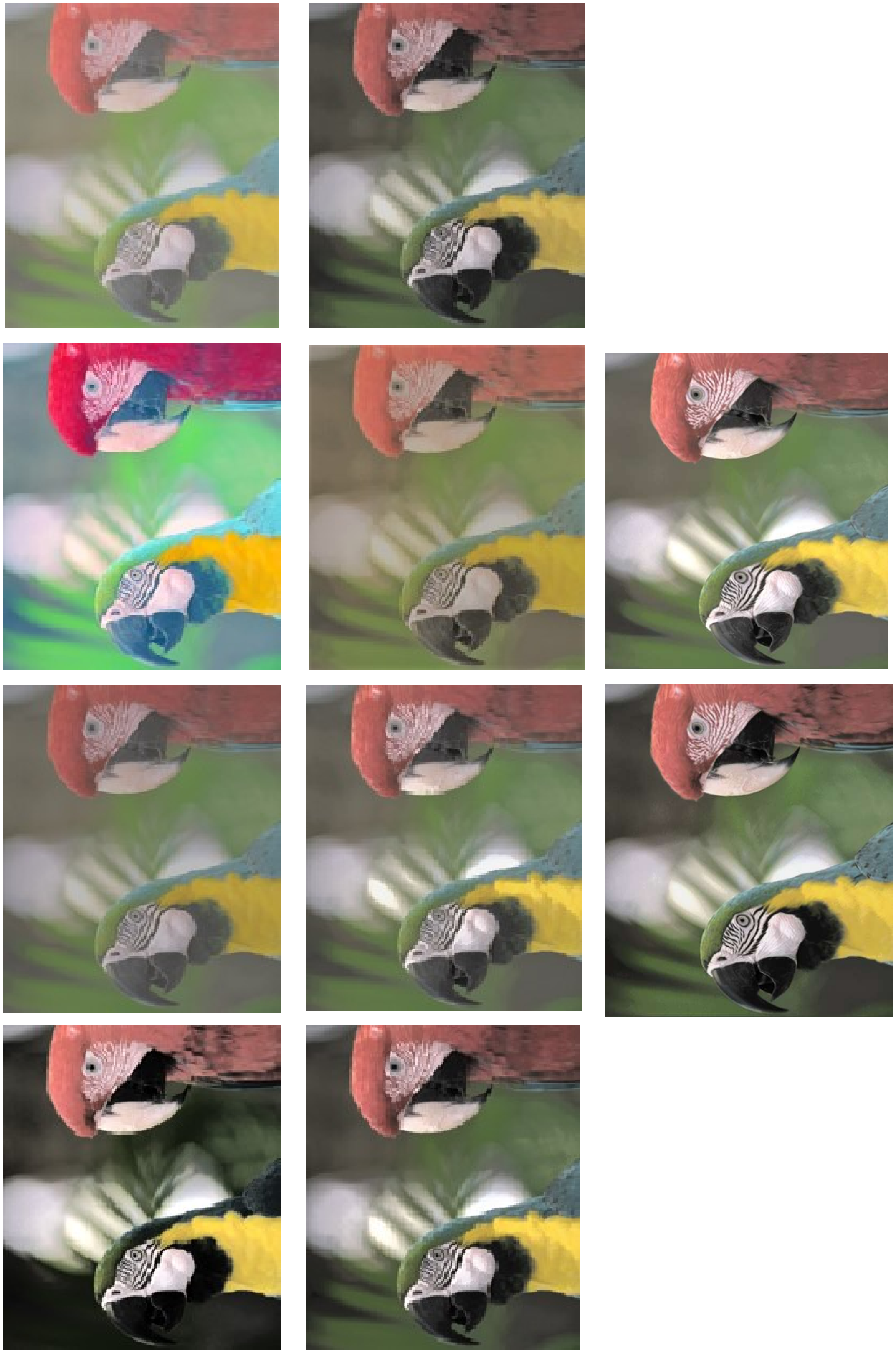

Fig. 4.10: *Result of different techniques for color test image 'Bird'. (Top row from left to right) GHE, DFHE, MSR, SECEDCT, (middle row left to right) GA, ABC, CLAHE-DGC, FDAHE-GC, (bottom row left to right) proposed GWO (using ϕ) and proposed GWO (using φ)*

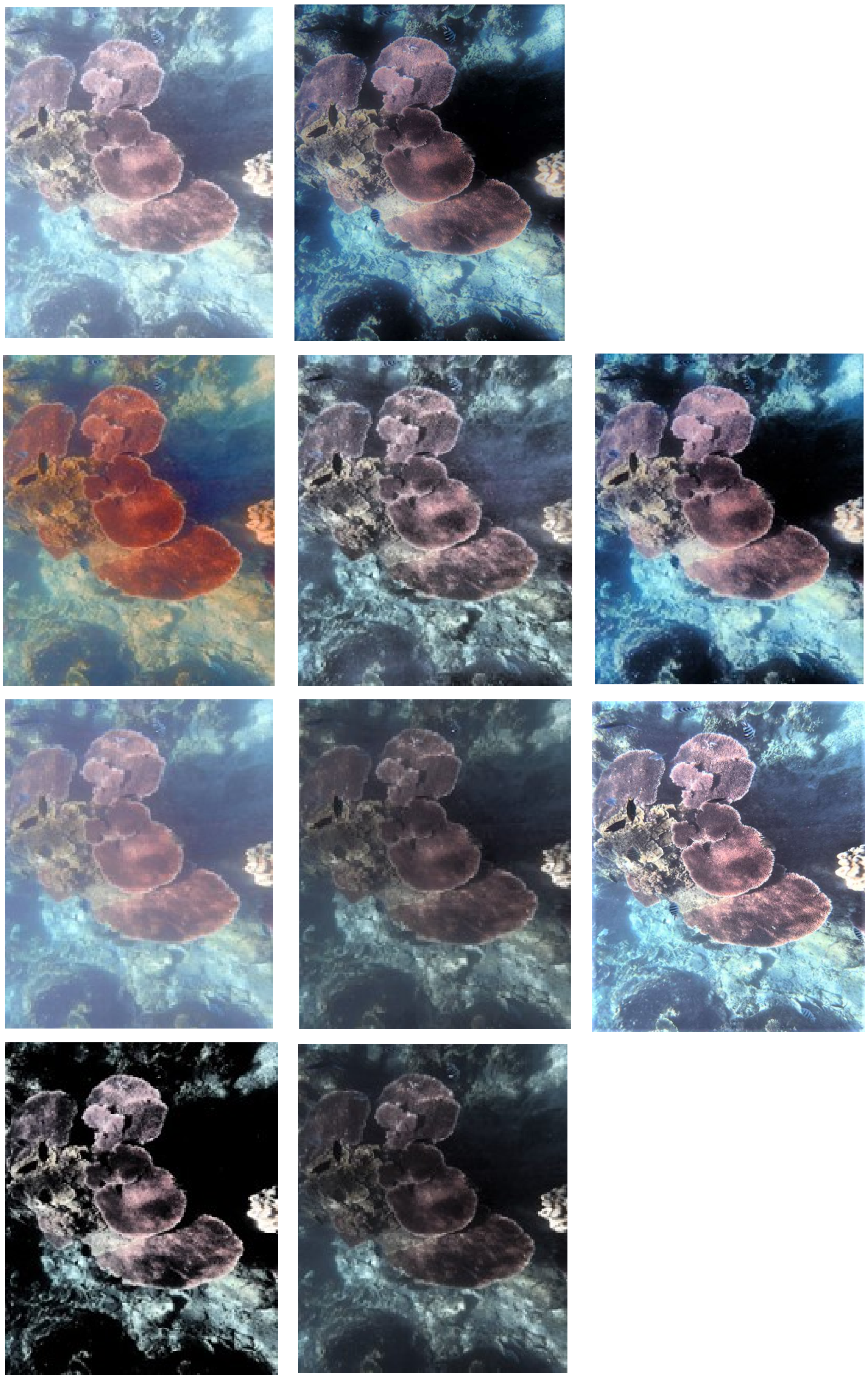

Fig. 4.11: *Result of different techniques for color test image 'Underwater'. (Top row from left to right) GHE, DFHE, MSR, SECEDCT, (middle row left to right) GA, ABC, CLAHE-DGC, FDAHE-GC, (bottom row left to right) proposed GWO (using ϕ) and proposed GWO (using φ)*

Figures 4.9 – 4.11 are the examples of results with different algorithms on color test images from different image databases. The visual appearances of proposed GWO technique's result clearly show the attainment in contrast improvement while retaining the original image characteristics in case of color images as well. The performance of other techniques mentioned here has already been discussed in chapter 3. In case of Fig. 4.9, the proposed GWO technique retain the color information of input image which is visible in case of leaves especially the proposed GWO technique using objective function ϕ. For most of the other techniques, those are appearing almost black in the output. In the case of Fig. 4.10, both the proposed GWO techniques works well in terms of appearance, brightness distribution as well as provides more color retention and enhances the contrast. In Fig. 4.11, the color retention of the proposed GWO technique using objective function φ is much better in comparison of the proposed GWO technique using objective function ϕ. The later one is little bit suffering from low sharpness problem in comparison with the other conventional techniques; both the proposed GWO images perform better in terms of visual aspect.

Two different levels of contrast images of 'garden' and their enhanced output using the proposed technique are shown in Fig. 4.12. Like BCO, here also it is observed that the capability of the proposed GWO technique using both the objective functions to produce the enhanced output images from different levels of low contrast images for visual aspect.

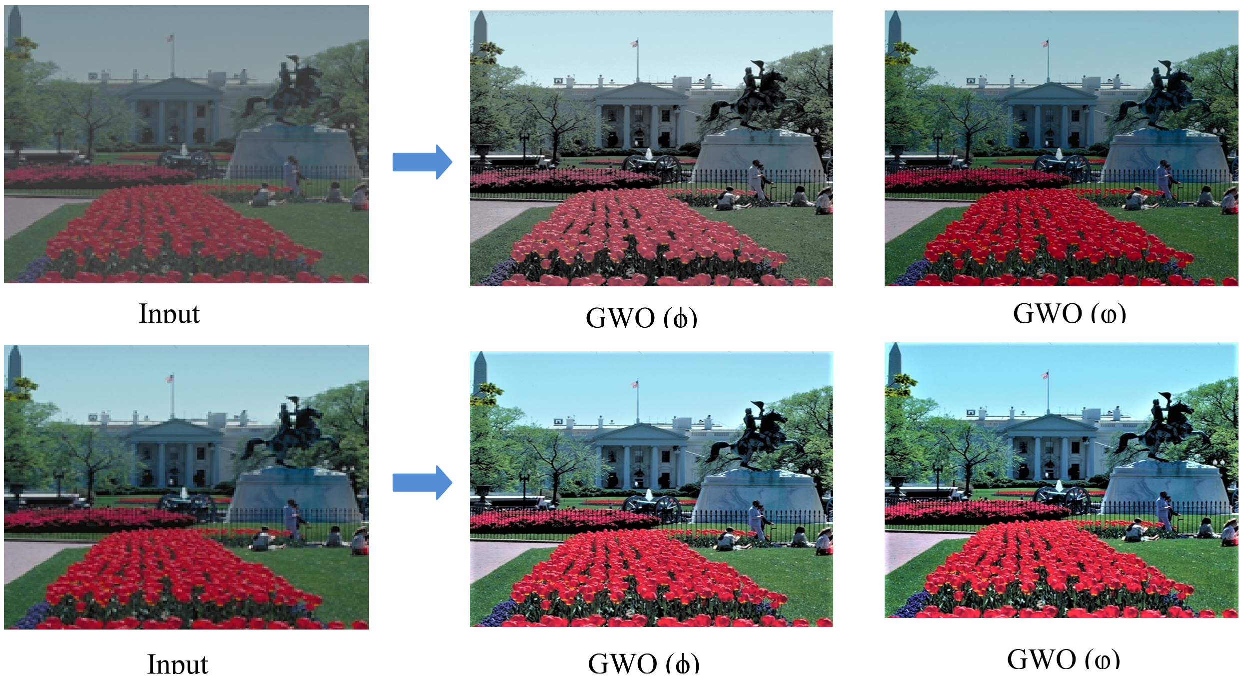

Fig. 4.12: *Visual comparison of 'Garden' image at different levels of contrast using proposed GWO.*

The subjective evaluations were also performed against five popular image quality assessment metrics as like previous chapter. Table 4.4-4.8 represent the various metric values used here for different test images from different datasets mentioned above using various techniques.

Table 4.4: *Evaluation of entropy resulted by the different techniques*

Images ⬇ / Techniques ➡	GHE	DFHE	MSR	SECE DCT	GA	ABC	CLAHE-DGC	FDAHE -GC	Proposed GWO (ϕ)	Proposed GWO (φ)
Cat	7.1345	7.0159	6.3204	6.8692	6.5336	6.2144	7.0682	7.2058	**7.2798**	**7.3877**
Lady	6.5890	6.1922	7.3499	6.8460	6.1261	6.1114	7.0719	6.9718	**7.3651**	**7.3965**
Flower	**7.6865**	6.4900	7.2417	6.6180	6.9113	6.7738	7.0138	6.9768	7.3316	**7.7248**
Bird	7.5503	6.7082	**7.6087**	6.9596	7.2738	7.0269	7.0303	7.1694	7.5753	**7.6825**
Underwater	6.2090	7.1498	7.2838	7.3264	6.9878	6.8317	7.4056	7.8647	**7.8755**	**7.9345**

In terms of entropy shown in Table 4.4 and mean-PCQI values in Table 4.5, the proposed technique provides remarkable performances almost for all the images. FDAHE-GC and GA also perform very well for these metrics. The proposed technique has provided a consistent performance and almost in all the cases secured the position within top 2 performers. The performance of proposed GWO using objective function φ is better than the proposed GWO using objective function ϕ due to its transmittance estimation.

Table 4.5: *Evaluation of mean PCQI values resulted by different techniques*

Images ⬇ / Techniques ➡	GHE	DFHE	MSR	SECE DCT	GA	ABC	CLAHE-DGC	FDAHE -GC	Proposed GWO (ϕ)	Proposed GWO (φ)
Cat	1.0979	1.0912	0.7622	1.0062	0.9828	0.9341	0.8408	**1.1095**	1.0966	**1.3618**
Lady	1.1559	0.9023	1.0633	1.0119	1.0295	1.0013	0.9669	0.9968	**1.1656**	**1.3620**
Flower	1.1468	1.0073	0.7708	0.9199	1.0809	1.0960	1.1059	1.0950	**1.2383**	**1.3274**
Bird	0.9917	0.9943	0.7539	0.8699	**1.0675**	1.0558	0.9448	1.0452	1.0574	**1.1220**
Underwater	0.8888	0.8816	0.8883	1.0125	0.7730	0.7753	1.0922	1.0437	**1.1089**	**1.1337**

In Fig. 4.6, the proposed technique for both the cases outperforms other techniques and in all images, it maintains top two positions. In this case, the performance of proposed GWO using objective function φ is better than the proposed GWO using ϕ due to color imaging characteristics. In terms of CEF as shown in Table 4.7, the proposed technique has performed well like previous metrics in all the images. GHE, being a classical and simple technique, has performed well also. FDAHE-GC on the other hand provides almost equivalent performance to GHE. Here, the performance of proposed GWO using objective function ϕ is better than other.

Table 4.6: *Evaluation of NIQE values resulted by different techniques*

Images ⬇ / Techniques ➡	GHE	DFHE	MSR	SECE DCT	GA	ABC	CLAHE-DGC	FDAHE-GC	Proposed GWO (ϕ)	Proposed GWO (φ)
Cat	3.4495	3.6061	3.8314	3.6658	3.6559	3.8080	4.2559	4.6752	**3.3269**	**3.2702**
Lady	3.5499	3.8838	4.2417	3.8015	3.7347	3.6969	3.6186	3.7658	**3.4330**	**3.3889**
Flower	3.7289	3.8961	3.4838	3.9483	3.6121	3.7798	3.5913	3.5767	**3.4128**	**3.3612**
Bird	3.9023	5.1887	4.8491	5.2255	4.3068	4.4577	4.4314	4.3022	**3.7642**	**3.6781**
Underwater	2.7113	2.4217	2.2360	2.2432	2.7074	2.6914	2.3745	2.1293	**2.1023**	**2.0259**

Table 4.7: *Evaluation of CEF resulted by the different techniques*

Images ⬇ / Techniques ➡	GHE	DFHE	MSR	SECE DCT	GA	ABC	CLAHE-DGC	FDAHE-GC	Proposed GWO (ϕ)	Proposed GWO (φ)
Cat	1.0020	0.9585	0.7646	1.0722	1.1035	1.0131	0.9714	1.0585	**1.1452**	**1.1283**
Lady	0.9839	0.7223	0.9786	0.8692	0.8598	0.9545	0.7750	0.9333	**1.0737**	**0.9975**
Flower	1.1162	1.1545	0.9869	0.9342	1.4334	1.2919	1.3038	1.4963	**1.6380**	**1.5429**
Bird	1.0658	0.8307	0.8654	0.6696	0.8623	0.7976	0.9040	0.9992	**1.1099**	**1.1354**
Underwater	1.6003	0.6957	0.9916	0.7316	1.1391	1.1606	0.9415	1.0931	**1.7628**	**1.8146**

In Table 4.8, MSR performs much better with respect to other techniques including proposed technique. The proposed technique performs better than others but not as well as MSR in this case. CLAHE-DGC also performs well for this metric. Finally, the mean values for different metrics for 1000 images under consideration have been consolidated in Table 4.9 and here also the proposed technique shows it potentiality in comparison with the other techniques mentioned here.

Table 4.8: *Evaluation of colorfulness resulted by different techniques*

Images ⬇ / Techniques ➡	GHE	DFHE	MSR	SECE DCT	GA	ABC	CLAHE-DGC	FDAHE-GC	Proposed GWO (ϕ)	Proposed GWO (φ)
Flower	3.478	2.315	**5.496**	2.912	2.337	2.348	3.250	2.214	4.471	**4.753**
Bird	4.675	3.781	**8.285**	4.724	4.297	4.246	4.558	3.543	5.383	**5.892**
Underwater	6.024	3.729	**22.683**	14.878	1.111	1.358	10.475	19.074	17.842	**18.354**

Table 4.9: *Evaluation of mean values on all the 1000 test images by different techniques*

Metrics ⬇ / Techniques ➡	GHE	DFHE	MSR	SECE DCT	GA	ABC	CLAHE-DGC	FDAHE-GC	Proposed GWO (ϕ)	Proposed GWO (φ)
Entropy	7.468	6.621	7.399	6.970	6.865	6.656	7.073	7.279	**7.536**	**7.829**
PCQI	0.955	0.904	0.762	1.001	1.072	1.037	1.130	1.172	**1.273**	**1.528**
NIQE	9.727	9.797	4.757	3.847	3.773	3.870	3.800	3.450	**3.412**	**3.207**
CEF	1.152	0.903	0.839	0.930	1.006	0.946	1.145	1.182	**1.295**	**1.194**
Colorfulness	10.638	3.094	**16.827**	11.047	3.369	3.469	9.179	10.884	12.382	**14.652**

4.5. Conclusions

This chapter has presented the application of grey wolf optimizer algorithm for contrast enhancement. The technique and algorithm and its application to grayscale and color images has been discussed. The results of applying the proposed technique are portrayed using standard test images. The visual representations show visible improvement over standard techniques which result over- or under-enhancement. The evaluations were extended to objective evaluations against popular metrics and found to provide better results. The enhancement holds true for both grayscale and color images with variety of images with different degree of contrast distortions. One of the major limitations of the proposed technique may be the processing time due to iterative nature of GWO. The possible future directions of the work may include, development of more robust objective function, inclusion of application dependent parameters in objective function e.g. model based contrast enhancement, application to color images incorporating interaction between color channels, exploring other multi-objective algorithms of biological behavior inspired optimization techniques, etc. Overall the proposed technique showed inspiring potential of GWO in image contrast enhancement.

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CHAPTER 5

Image contrast enhancement using bat algorithm (BA)

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5.1. Introduction

Bat algorithm (BA) is one of the renowned metaheuristics algorithm introduced by Xin-She Yang in the year 2010. It was developed mimicking the food searching behavior of microbats. BA is inspired by the use of echolocation of the microbats to find the location of the prey. It has shown promising potential in diverse applications [1]. It has many advantages over other popular metaheuristics algorithms like PSO, ABC, ACO, etc. These are requirement of less parameter tuning (only α and β), high convergence speed due to its automatically zooming capability into a region, used as local and global optimizer due to balanced contribution in between exploration and exploitation, etc [1]. This algorithm has also superior to BCO and GWO in some cases such as it has better local searching ability than BCO and GWO. The convergence speed of bat algorithm is also better than BCO and GWO. There are lots of applications presented by various researchers in various fields due to its advantages. “Bat algorithm for the fuel arrangement optimization of reactor core” by S. Kashi et al. in 2014 [2] where a fitness function was developed based on multiplication factor and power peaking factor to optimize loading pattern of nuclear reactor core, “Adopting the bat-inspired algorithm for interaction testing” by Y. A. Alsariera et al in 2015 [3], where a case study had been done to clarify and benchmark the t-way strategy using bat algorithm, “Multi-objective optimization using bat algorithm for shell and tube heat exchangers” by T. K. Tharakeswar in 2017 [4], where two objective functions have been considered and optimized it by using bat algorithm to get the pareto optimal solution, where one objective can be improved by sacrificing other objective.

The contribution of this work is subjected to optimization of the objective functions discussed in chapter 2 using BA to obtain the contrast improved images. The visual and objective evaluations vouch the competitive potential of the proposed technique. This chapter is structured as follows:

The introduction of this chapter has been established in section 5.1. In section 5.2, bat algorithm and its pseudo codes have been presented. The application of BA for image contrast enhancement has been discussed in section 5.3. Section 5.4 illustrated the results of both the visual and objective comparison against other techniques. Finally, the conclusions of this chapter are discussed in section 5.5.

5.2. Bat Algorithm (BA)

Bat algorithm (BA) is driven using the echolocation characteristics of bats that they use to search for food. Each bat updates their position and velocity at every iteration based on their best position and velocity information. The position and velocity equations are expressed in Eq. 5.1 and 5.2. As the bat approaches closer to the prey, the loudness of the emitted sound decreases while the pulse emission rate increases. The loudness value and the pulse emission rate are different for every bat initially. These different values are initialized randomly. Typically the value of loudness is considered as 1 initially and the value of pulse rate is considering 0. The modified pulse rate and the loudness is defined in Eq. 5.3 and 5.4, respectively. Like other metaheuristics, it also initiates optimization with random solutions generated in the problem space. This generation can be guided towards faster convergence. The BA algorithm can be presented as pseudo code presented in Table 5.1.

$$v_i^t = v_i^{t-1} + \left(x_i^{t-1} - x_{best}\right) f_i \tag{5.1}$$

where, $f_i = f_{\min} + \left(f_{\max} - f_{\min}\right)\beta$; $\beta \in [0,1]$

f_{max} and f_{min} denoted the maximum and minimum pulse frequency.

$$x_i^t = x_i^{t-1} + v_i^t \tag{5.2}$$

$$r_i^{t+1} = r_i^t \left(1 - \exp(-\gamma t)\right) \tag{5.3}$$

where, $\gamma > 0$ is a constant value.

$$A_i^{t+1} = \alpha A_i^t \tag{5.4}$$

where $\alpha > 0$ is a constant value

Table 5.1: *Pseudo code of BA*

Initial population of bat X ($x_1, x_2, \ldots\ldots, x_n$) and associated initial velocity of each bat $(v_1, v_2, \ldots\ldots, v_n)$

Generation

Fitness calculation of each bat using the objective function and find the best solution (x_{best})

Initializing initial pulse frequencies (f_i), pulse rate (r_i), loudness (A_i) and a set of random numbers ($rn \in [-1,1]$) with normal distribution

while (number of iteration (i) <maximum number of iteration or stopping criteria met)

> Update velocity of bat using $v_i^t = v_i^{t-1} + \left(x_i^{t-1} - x_{best}\right) f_i$
>
> where, $f_i = f_{\min} + (f_{\max} - f_{\min})\beta$; $\beta \in [0,1]$
>
> Update location of bat using $x_i^t = x_i^{t-1} + v_i^t$
>
> **if**($r_i \langle rand(0,1)$)
>
> Generate a local solution around the existing solution using
>
> $x_i^t(new) = x_i^t(old) + \varepsilon \overline{A_t}$ where, $\varepsilon \in rand[-1,1]$ and $\overline{A_t}$ is the mean of all A at iteration t
>
> **end if**
>
> Generate a new solution by random flying
>
> **if**($rn_i \langle A_i$ and $fit(x_i^t) \langle fit(x_{best}^t)$)
>
> Accept new solution
>
> Increase pulse rate of the bat using $r_i^{t+1} = r_i^t(1 - \exp(-\gamma t))$ where, $\gamma > 0$ is a constant value controls the movement of bat
>
> Decrease loudness using
>
> $A_i^{t+1} = \alpha A_i^t$ where $\alpha > 0$ is a constant value controls the movement of bat
>
> **end if**
>
> Find the new best location of the bat $\left(x_{best}^{t+1}\right)$

end while

5.3. Application of BA for contrast enhancement

The gray images are analyzed by its histogram and based on the histogram pattern initial random solutions have been generated. In case color images, a color space conversion from RGB to HSV has been performed first. The V (value) channel was separated and optimized by bat algorithm based on the objective functions. The modified V channel then combines with unaltered H (hue) and S (saturation) channels to obtain modified HSV result. Finally, the HSV color space again converts to RGB color space for enhanced output. The pseudo code of the proposed technique has been presented in Table 5.2.

Table 5.2: *Pseudo code of BA based contrast enhancement*

/* Assignment */

Load the low contrast image as input.

Compute input image histogram.

Initializing initial pulse frequencies (f_i), pulse rate (r_i), loudness (A_i) and a set of random numbers ($rn \in [-1,1]$) with normal distribution

Initialize random solutions based on input image histogram.

/* Update */

Fitness calculation of each bat using the fitness function using Eq. [2.18].

Find the best solution (x_{best})

Update the velocity of bat using Eq. [5.1]

Update the position of bat using Eq. [5.2]

Generate a new solution by random flying

Accept new solution if $fit_{Xnew} > fit_{xbest}$

Increase the pulse rate using Eq. [5.3]

Decrease the loudness using Eq. [5.4]

Compute the new best location of the bat $\left(x_{best}^{t+1}\right)$

Check the fitness value, whether it is better with respect to the previously selected solutions.

Find the objective functions value with the most-fit solution after iteration using Eq. [2.1, 2.14].

Terminate the loop while meeting the termination condition

/* Enhancement */

Reconstruct the V channel with the best solution found using BA

Replace the original image V channel with the optimized V channel

Convert the image back to RGB color space for visual presentation

---

In this work, the initial population of 10 bats found to be optimal. The length of the solution was 256, since the DCT domain histogram was the initial position of individual bat. The initialization of individual bat position was random but generated within the range of frequencies present in the image under consideration. The values of $f_{\max}$ and $f_{\min}$ were set as 0 and 1, respectively. The values for both the constants α and β were set as 0.92. The maximum number of iterations was set as 500. Similarly, the loudness parameter A was initiated randomly with $A_{\min}$ and $A_{\max}$ values as 0 and 1, respectively, where resulting $A_{\min}$ interprets the bat has reached the prey and not emitting any sound.

5.4. Results and discussions

Like previous two chapters, the proposed BA was also tested with different images from standard databases and implemented using R2015a version of Matlab® software in Windows PC with an Intel Core i5 2.67 GHz CPU and 8 GB of RAM.

Figs. 5.1 and 5.2 represent the proposed BA outputs using both the objective functions for gray scale and color image, respectively with their corresponding histogram. In case of color image, additionally the V channel of corresponding color images has been included. From both the figures, the potentiality of the proposed technique to improve the image contrast has been reflected. The corresponding histogram for both gray scale and color images output also indicate the enhancement capability of the proposed technique.

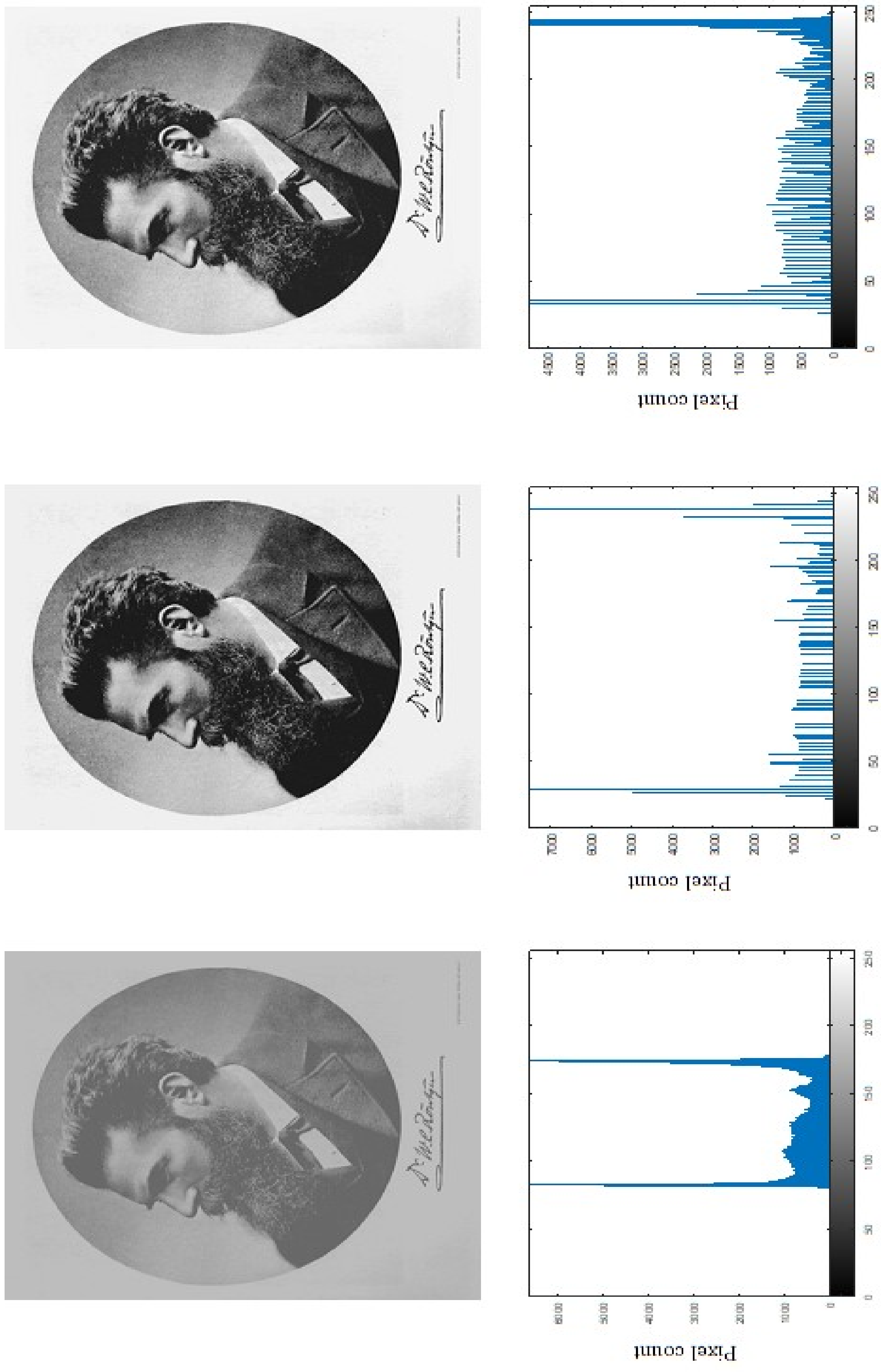

***Fig. 5.1:** Result of proposed BA technique for gray test image. (Top row from left to right) original, proposed BA (ϕ) and proposed BA (φ), (bottom row left to right) corresponding histogram of original image, proposed BA (ϕ) and proposed BA (φ)*

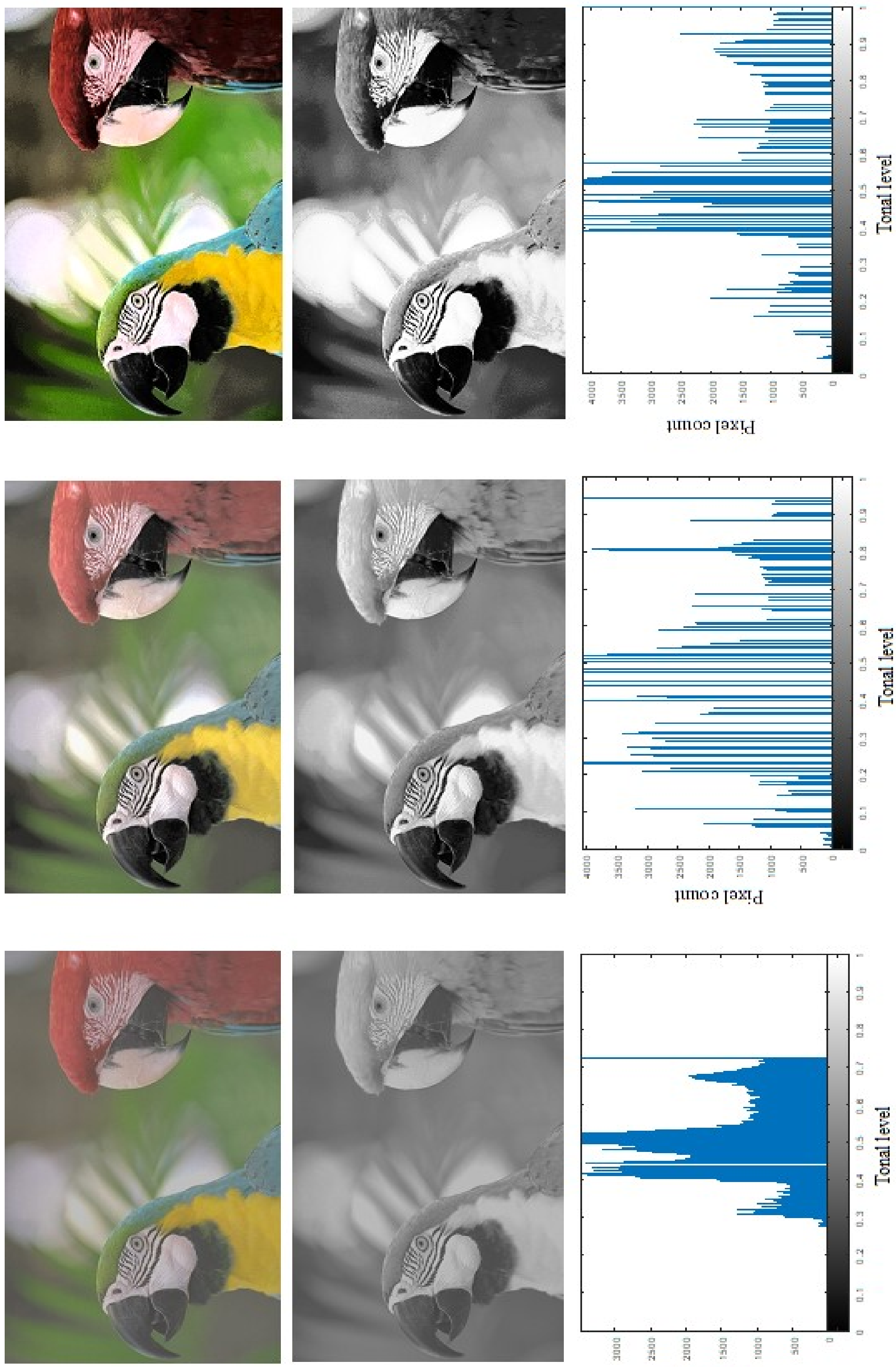

Fig. 5.2: *Result of proposed BA technique for color test image. (Top row from left to right) original, proposed BA (ϕ) and proposed BA (φ), (middle row left to right) corresponding V channel of original image, proposed BA (ϕ) and proposed BA (φ), (bottom row left to right) corresponding histogram of original image, proposed BA (ϕ) and proposed BA (φ)*

In Fig. 5.3, the convergence curves of the proposed technique for both the objective functions have been presented. From this curves, the operational speed of BA algorithm to perform these operations are noticeable and maintain the steadiness to provide satisfactory output.

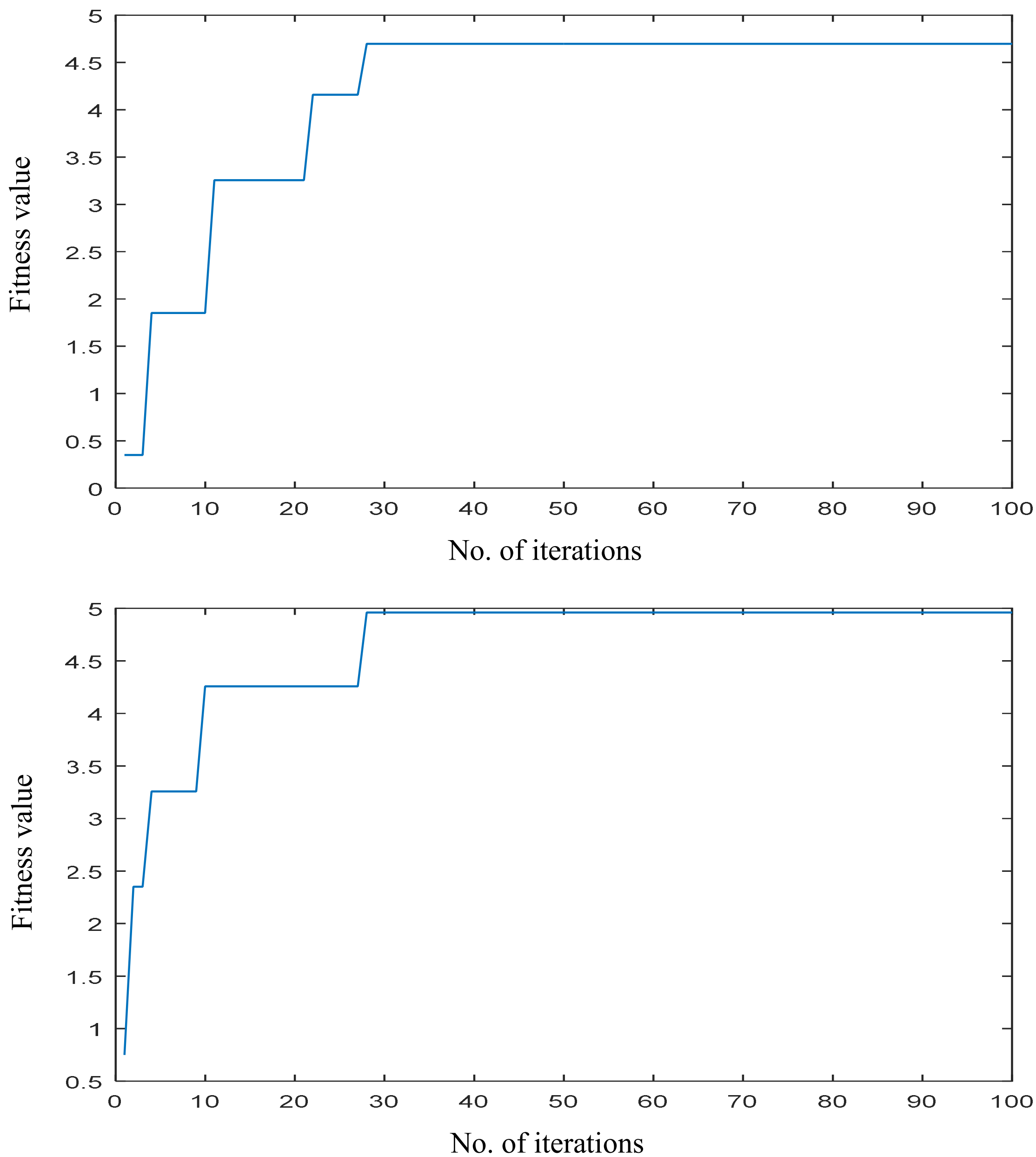

Fig. 5.3: Convergence curves of proposed technique. Proposed BA using ϕ (Upper) and proposed BA using φ (Lower)

In Fig. 5.4, a detailed retention analysis has been presented like previous chapter and here also it is observed that the original image details are well retained in the enhanced images by proposed technique. The enlarged areas of the enhanced proposed BA images shown in 5.4 (e) and 5.4 (f) reveal the potential of proposed technique to avoid any visual artifacts due to over- or under-enhancement.

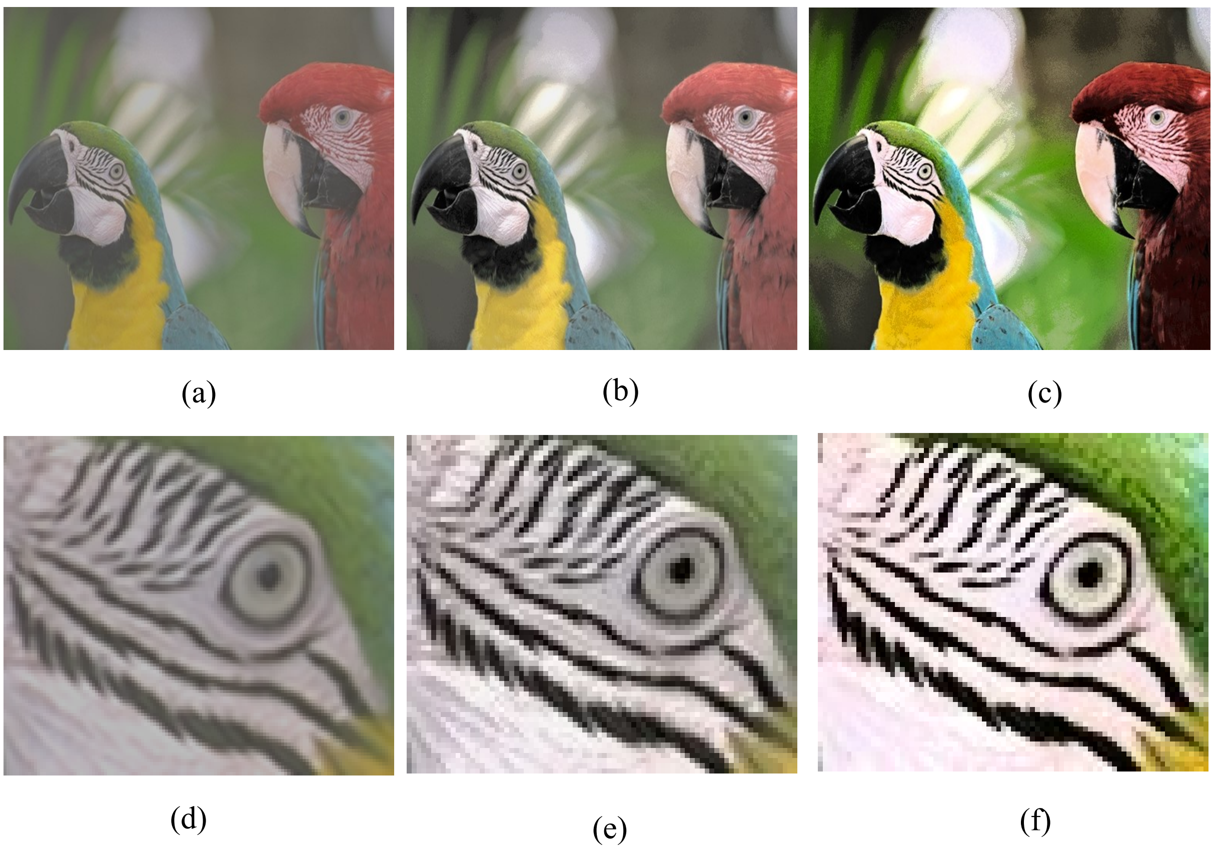

Fig. 5.4: *Local improvement analysis with 'Bird' image; a) original low contrast image, b) enhanced proposed BA image using ϕ, c) enhanced proposed BA image using φ, d) the region to focus of (a), e) the region to focus of (b) and f) the corresponding region shown in (c).*

Figures 5.5 -5.9 show the output of proposed technique along with 8 other established techniques of different test images for comparison purpose. Both gray scale images and color images are used here for better analysis purpose. These are GHE, DFHE, MSR, SECEDCT, GA, ABC, CLAHE-DGC, and FDAHE-GC. All the images have been reproduced at 300 dpi resolution. To decide the potentiality of proposed technique, a set of 1000 images from different dataset namely SIPI, TID and CSIQ were maintained. Various types of degraded images have been considered from each dataset including different degree of low contrast and different illumination distortions.

Figs. 5.5 and 5.6 show the performance of different algorithms on grayscale images. Results show that in both the cases, the proposed technique using objective function ϕ provides better output in comparison with the other techniques including the proposed technique using objective function φ. The proposed technique using φ shows little bit over whiteness and the other techniques have already been discussed in chapter 3.

Fig. 5.5: *Result of different techniques for gray test image 'Cat'. (Top row from left to right) GHE, DFHE, MSR, SECEDCT, (middle row left to right) GA, ABC, CLAHE-DGC, FDAHE-GC, (bottom row left to right) proposed BA (using ϕ) and proposed BA (using φ)*

Fig. 5.6: *Result of different techniques for gray test image 'Lady'. (Top row from left to right) GHE, DFHE, MSR, SECEDCT, (middle row left to right) GA, ABC, CLAHE-DGC, FDAHE-GC, (bottom row left to right) proposed BA (using ϕ) and proposed BA (using φ)*

Figures 5.7 – 5.9 are the examples of results with different algorithms on color test images from different image databases. The performance of the proposed BA technique in case of color images clearly shows the attainment in contrast improvement while retaining the original image characteristics. The performance of other techniques mentioned here has already been discussed in chapter 3. In the case of Figs. 5.7 and 5.8, the proposed BA technique using objective function ϕ retains the color information of input image, which is visible in case of leaves, but the proposed BA technique using objective function φ seems little bit over color effect. In Fig. 5.9, the color retention of the proposed BA technique using φ is much better in comparison of the proposed BA technique using objective function ϕ. The clearness is also visible in case of the proposed technique using objective function φ which is most important though this image is an underwater image and due to presence of water medium proper visible output cannot be possible all the time. The proposed BA technique using objective function ϕ is little bit suffering from low sharpness problem as like as the previously proposed technique (GWO) using same objective function. Still in comparison with the other conventional techniques; both the proposed BA images perform better in terms of visual aspect.

Fig. 5.7: *Result of different techniques for color test image 'Flower'. (Top row from left to right) GHE, DFHE, MSR, SECEDCT, (middle row left to right) GA, ABC, CLAHE-DGC, FDAHE-GC, (bottom row left to right) proposed BA (using ϕ) and proposed BA (using φ)*

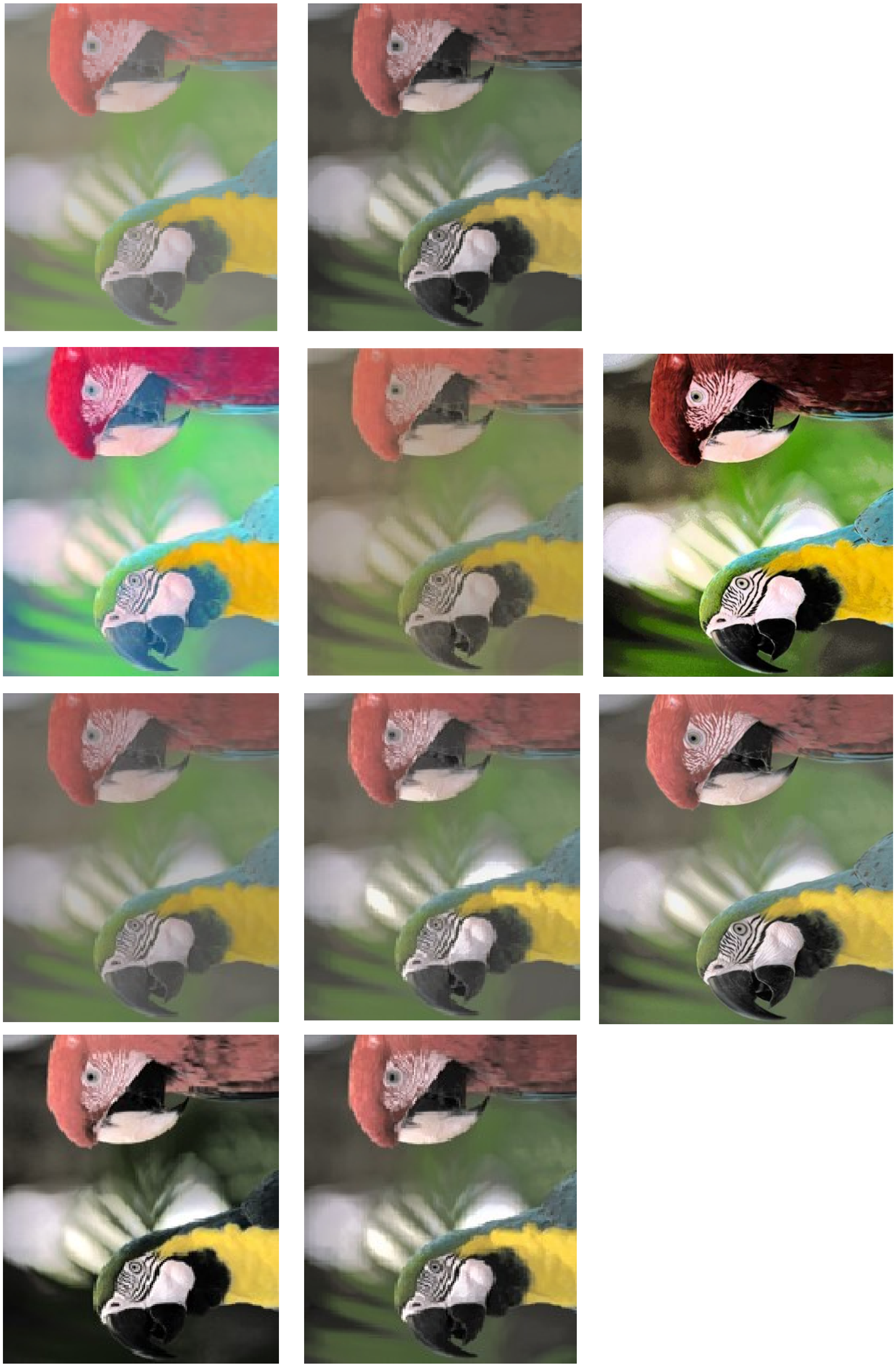

Fig. 5.8: *Result of different techniques for color test image 'Bird'. (Top row from left to right) GHE, DFHE, MSR, SECEDCT, (middle row left to right) GA, ABC, CLAHE-DGC, FDAHE-GC, (bottom row left to right) proposed BA (using ϕ) and proposed BA (using φ)*

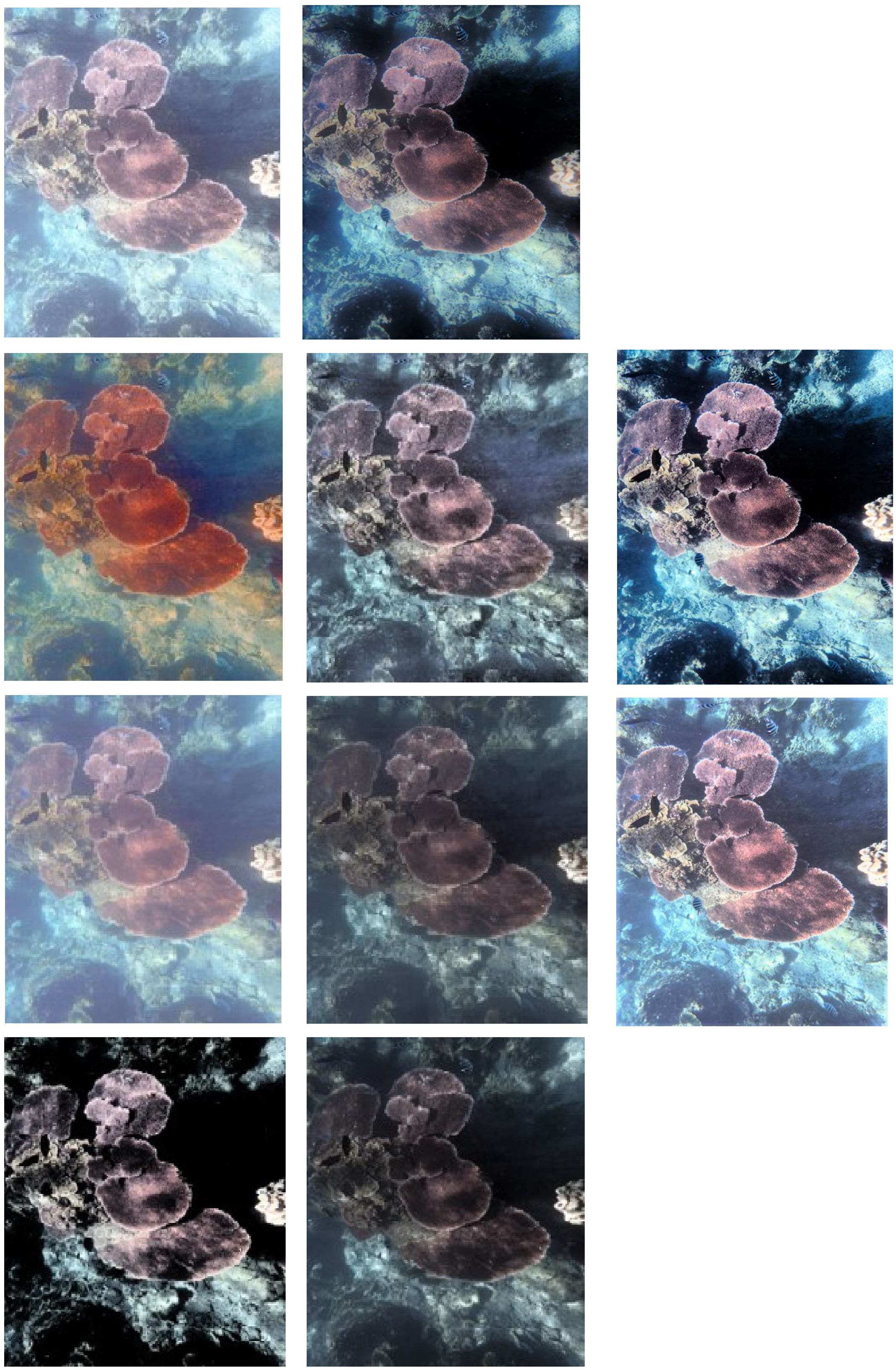

Fig. 5.9: *Result of different techniques for color test image 'Underwater'. (Top row from left to right) GHE, DFHE, MSR, SECEDCT, (middle row left to right) GA, ABC, CLAHE-DGC, FDAHE-GC, (bottom row left to right) proposed BA (using ϕ) and proposed BA (using φ)*

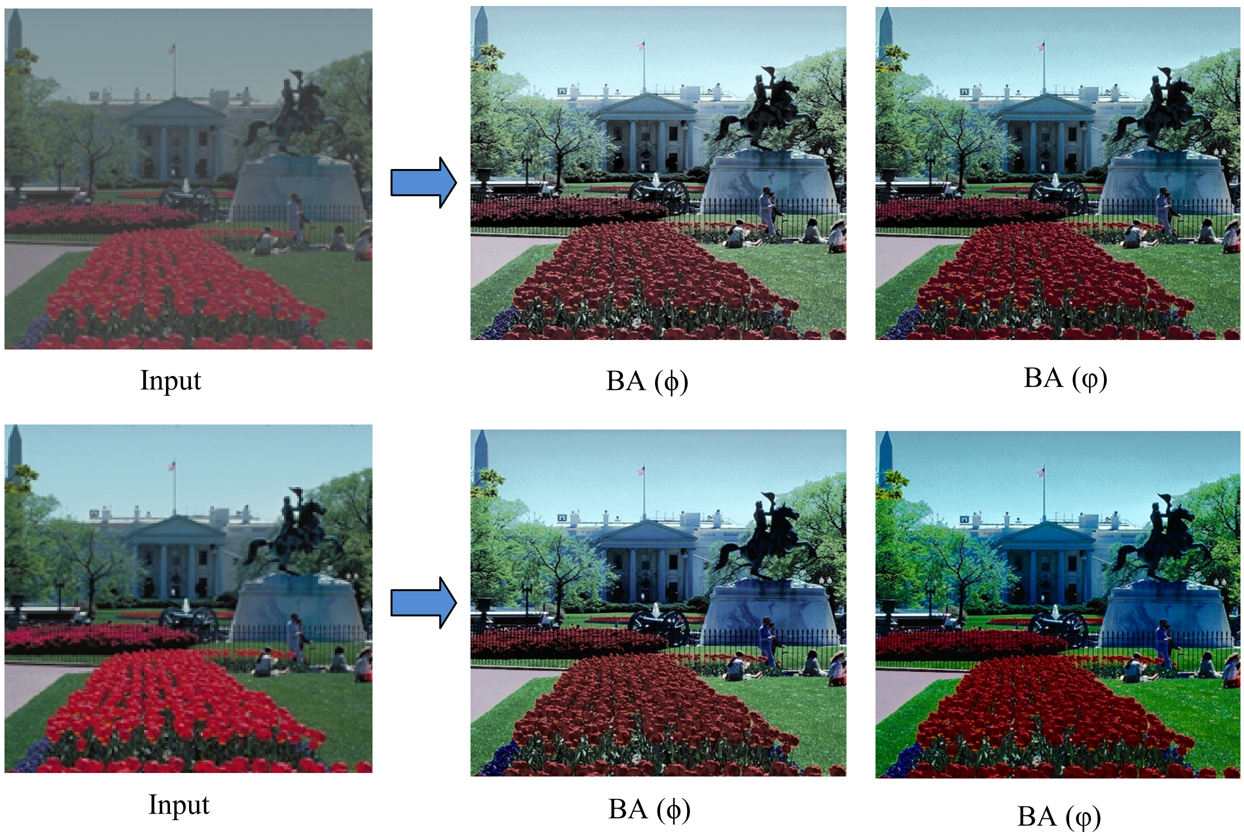

Fig. 5.10: *Visual comparison of 'Garden' image at different levels of contrast using proposed BA.*

Fig. 5.10 shows input and proposed output images of 'garden', at two different levels of contrast. Here also the proposed BA technique using both the objective functions is capable to produce the enhanced output images from different levels of low contrast.

Subjective evaluations were also performed against different popular image quality assessment metrics; Five IQA metrics have been considered for objective evaluation purpose. These are image entropy, patch-based quality index (PCQI), natural image quality evaluator (NIQE), contrast enhancement factor (CEF) and colorfulness. These metric sets have already been discussed in chapter 2. Table 5.2-5.6 represents the objective evaluations using various techniques. In each table, top two best values have been highlighted for better understanding.

Table 5.3: *Evaluation of entropy resulted by the different techniques*

Images ↓ \ Techniques →	GHE	DFHE	MSR	SECE DCT	GA	ABC	CLAHE-DGC	FDAHE-GC	Proposed BA (ϕ)	Proposed BA (φ)
Cat	7.1345	7.0159	6.3204	6.8692	6.5336	6.2144	7.0682	**7.2058**	7.1856	**7.2341**
Lady	6.5890	6.1922	**7.3499**	6.8460	6.1261	6.1114	7.0719	6.9718	**7.3829**	7.3173
Flower	7.6865	6.4900	7.2417	6.6180	6.9113	6.7738	7.0138	6.9768	**7.6994**	**7.7218**
Bird	7.5503	6.7082	7.6087	6.9596	7.2738	7.0269	7.0303	7.1694	**7.7521**	**7.8351**
Underwater	6.2090	7.1498	7.2838	7.3264	6.9878	6.8317	7.4056	7.8647	**7.8802**	**7.9454**

In Table 5.3, proposed BA technique provides better performance and secures its position in first two best values almost for every image. FDAHE-GC and MSR also perform well here in comparison with the other techniques. Comparison between proposed BA techniques using both objective functions, the proposed technique using objective function φ is better than the proposed technique using objective function ϕ. In Table 5.4, the proposed BA technique performs much better for this metric and in all images, it holds the top position. In this table, it is observed that, both the proposed BA techniques perform better in an overall aspect.

In case of NIQE in Table 5.5, proposed BA technique performs consistently well for all images and in this case also the proposed BA technique using objective function φ performs better in comparison with the proposed BA technique using objective function ϕ as like the previous two proposed techniques. In terms of CEF as shown in Table 5.6, the proposed technique has performed consistently well. The performance of GHE is also good being classical and simple technique. Here, the performance of the proposed BA technique using objective function ϕ is better than the proposed BA technique using objective function φ.

Table 5.4: *Evaluation of mean PCQI values resulted by different techniques*

Images ⬇ / Techniques ➡	GHE	DFHE	MSR	SECE DCT	GA	ABC	CLAHE-DGC	FDAHE -GC	Proposed BA (ϕ)	Proposed BA (φ)
Cat	1.0979	1.0912	0.7622	1.0062	0.9828	0.9341	0.8408	1.1095	**1.1736**	**1.1162**
Lady	1.1559	0.9023	1.0633	1.0119	1.0295	1.0013	0.9669	0.9968	**1.2153**	**1.1745**
Flower	1.1468	1.0073	0.7708	0.9199	1.0809	1.0960	1.1059	1.0950	**1.1752**	**1.2642**
Bird	0.9917	0.9943	0.7539	0.8699	1.0675	1.0558	0.9448	1.0452	**1.0798**	**1.1108**
Underwater	0.8888	0.8816	0.8883	1.0125	0.7730	0.7753	1.0922	1.0437	**1.1351**	**1.1957**

Table 5.5: *Evaluation of NIQE values resulted by different techniques*

Images ⬇ / Techniques ➡	GHE	DFHE	MSR	SECE DCT	GA	ABC	CLAHE-DGC	FDAHE -GC	Proposed BA (ϕ)	Proposed BA (φ)
Cat	3.4495	3.6061	3.8314	3.6658	3.6559	3.8080	4.2559	4.6752	**3.3549**	**3.2141**
Lady	3.5499	3.8838	4.2417	3.8015	3.7347	3.6969	3.6186	3.7658	**3.4024**	**3.3294**
Flower	3.7289	3.8961	3.4838	3.9483	3.6121	3.7798	3.5913	3.5767	**3.3250**	**3.1827**
Bird	3.9023	5.1887	4.8491	5.2255	4.3068	4.4577	4.4314	4.3022	**3.7665**	**3.6857**
Underwater	2.7113	2.4217	2.2360	2.2432	2.7074	2.6914	2.3745	2.1293	**2.0652**	**2.0229**

In Table 5.7, the proposed BA technique performs much better than other techniques except MSR. Like previously proposed techniques, here also MSR performs excellent and secured the top position for all images.

Finally the mean values for different metrics of different techniques for 1000 images under consideration have been consolidated in Table 5.8. Like previous two proposed techniques, here also the proposed technique shows its potential for all the metrics in comparison with the other techniques mentioned here.

Table 5.6: *Evaluation of CEF resulted by the different techniques*

Images ⬇ / Techniques ➡	GHE	DFHE	MSR	SECE DCT	GA	ABC	CLAHE-DGC	FDAHE -GC	Proposed BA (ϕ)	Proposed BA (φ)
Cat	1.0020	0.9585	0.7646	1.0722	1.1035	1.0131	0.9714	1.0585	**1.2253**	**1.1328**
Lady	0.9839	0.7223	0.9786	0.8692	0.8598	0.9545	0.7750	0.9333	**1.0956**	**1.0227**
Flower	1.1162	1.1545	0.9869	0.9342	1.4334	1.2919	1.3038	1.4963	**1.8140**	**1.6229**
Bird	1.0658	0.8307	0.8654	0.6696	0.8623	0.7976	0.9040	0.9992	**1.1143**	**1.0828**
Underwater	1.6003	0.6957	0.9916	0.7316	1.1391	1.1606	0.9415	1.0931	**1.7652**	**1.9125**

Table 5.7: *Evaluation of colorfulness resulted by different techniques*

Images ⬇ / Techniques ➡	GHE	DFHE	MSR	SECE DCT	GA	ABC	CLAHE-DGC	FDAHE -GC	Proposed BA (ϕ)	Proposed BA (φ)
Flower	3.478	2.315	**5.496**	2.912	2.337	2.348	3.250	2.214	3.781	**4.292**
Bird	4.675	3.781	**8.285**	4.724	4.297	4.246	4.558	3.543	5.629	**6.352**
Underwater	6.024	3.729	**22.683**	14.878	1.111	1.358	10.475	19.074	19.128	**20.212**

Table 5.8: *Evaluation of mean values on all the 1000 test images by different techniques*

Metrics ↓ / Techniques →	GHE	DFHE	MSR	SECE DCT	GA	ABC	CLAHE-DGC	FDAHE-GC	Proposed BA (ϕ)	Proposed BA (φ)
Entropy	7.468	6.621	7.399	6.970	6.865	6.656	7.073	7.279	**7.574**	**7.816**
PCQI	0.955	0.904	0.762	1.001	1.072	1.037	1.130	1.172	**1.349**	**1.485**
NIQE	9.727	9.797	4.757	3.847	3.773	3.870	3.800	3.450	**3.334**	**3.178**
CEF	1.152	0.903	0.839	0.930	1.006	0.946	1.145	1.182	**1.326**	**1.227**
Colorfulness	10.638	3.094	**16.827**	11.047	3.369	3.469	9.179	10.884	13.752	**15.729**

5.5. Conclusions

The Bat Algorithm has been found efficient optimization process for stretching the histogram while maintaining the features of original low contrast input image. The fast convergence of this algorithm makes acceptable processing time. This work is also found effective where the color retention is a major factor along with the contrast enhancement, especially in case of using the objective function φ. Due to its better performance with fast convergence, the work can be further extended to application in contras enhancement of medical images where the imaging model will be different from the imaging model presented here. The possibilities of improvement can be explored with other bio-inspired optimization algorithms, a more robust fitness or objective function will be developed for the generosity of the operation, and inclusion of multiple objective paradigms. Considering the possible future scopes, the competitive results of the proposed technique vouch its potential as a possible addition to the existing standard contrast enhancement technique.

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CHAPTER 6
Concluding remarks

6.1. Introduction

Contrast is an important characteristic of image that largely contributes towards the perceived image quality. In general, image contrast is the ratio between darkest and lightest part of the image. Contrast sensitivity has two major interpretations namely absolute and perceived contrast sensitivity. The former one is the minimum difference in luminance required for distinguishing between two intensities. The human eyes are not very sensitive to this and as a result very small difference may not be visible. The second one is more important as this is to which human eyes are sensitive. For instance, a bright object is more visible in a dark background than a bright one, since the contrast between bright object and bright background is not enough for human eyes to distinguish. Due to many reasons, such as insufficient illumination, noise during image acquisition, information loss during image transmission and limitation in sensing capability of the optical sensors, low contrast images are resulted. Low contrast not only results in visual unpleasantness but also limits performance of different image analysis tasks like edge extraction, feature extraction and object recognition. The goal of image contrast enhancement is to reconstruct the low contrast input image with new intensity levels that keep informational symmetry with the original image. Many conventional histogram equalization based techniques and CI based algorithms were already presented in the last few years to enhance image contrast and they were successfully done but in most of the cases, it was observed that, those techniques were unable to maintain the image characteristics, which were not visible by human eye due to absolute contrast sensitivity discussed earlier. These types of images were unable to provide various image features precisely for the further analysis of these images. For these reasons, there is a need for such technique, which can enhance the image contrast without over whiteness problem and maintain the other initial image characteristics.

Enhancement of image contrast by maintaining other image parameters and using computational intelligence is the main focus of this research. Different proposed techniques have been discussed in previous chapters. These techniques include both spatial domain and frequency domain operations. In this chapter, the comparison among proposed techniques will be discussed to understand better application of those proposed techniques.

Three different optimization techniques have been applied to optimize the objective functions and to provide better enhanced output. Table 6.1 represents the basic characteristics of these algorithms.

Table 6.1: *Characteristics of BCO, GWO and BA*

Bacterial Colony Optimization (BCO)	**Grey Wolf Optimizer (GWO)**	**Bat Algorithm (BA)**
a) This algorithm is not largely affected by the size and non-linearity of the problem. b) This algorithm has converged to the optimal solution for many problems, where other failed to converge. c) This algorithm can handle multi objective functions and can avoid local optimum.	a) Reduced number of search parameters available in GWO b) For initial search no derivational information is required. c) It is simple, easy to use, flexible and scalable. d) It has the special capability of strike the right balance between the exploration and exploitation during the search which leads to favorable convergence. e) Convergence is faster due to continuous search space reduction.	a) The structure and concept are very simple and able to exploitation. b) High convergence speed due to its automatically zooming capability into a region c) During iteration, the parameters have been updated by applying parameter control. d) It can be used as local optimizer and global optimizer. e) It can efficiently handle multi-modal problems.

From the above table, it is clear that, all the three algorithms are very much efficient to optimize any solution with less computational time and can be used as local optimizer as well as global optimizer according to requirement. Still there will be some differences observed in these work to get the output image in terms of visual perception as well as objective analysis. Hence, it is necessary to realize the condition of usefulness of these algorithms for this type of work.

In this thesis work, a large portion is devoted to find out the right contrast enhancement techniques with which the other image features are maintained properly. Three different proposed techniques have been applied based on the above mentioned target. The study presented in this thesis, is mainly focused on the following aspects while applying the various contrast enhancement techniques:

- To enhance the image contrast to a certain level where other image characteristics can be preserved. Over contrast enhancement sometimes affects the input brightness, color etc.
- Frequency domain based objective function has been formulated depending on the shape and magnitude of FFT spectra for optimization purpose for better control of image characteristics.
- Both gray scale images and color images have been used here to show the potentiality of the proposed techniques in a more general way. In the case of color images, HSV color spaces and YCbCr color spaces have been used because both of these are devices dependent color space hence, cannot interpret color and luminance separately. Also in case of RGB, processing individually to the three channels of RGB can cause erroneous results because post HE mixing between the color channels can result in a totally different perceived color at output image.

- DCE has been used to maintain colorfulness of an image though a global gamma based scaling can cause unnaturalness in enhanced image which may results in over-enhancement.

- Quantitative data analysis by using full references (FR) as well as no reference (NR) to show the potentiality of the proposed techniques.

6.2. Analysis of proposed techniques

This section presents the comparative assessment of all the proposed techniques using BCO (discussed in chapter 3), GWO (discussed in chapter 4) and BA (discussed in chapter 5). For comparison purpose, both the gray images and the color images have been chosen. All the techniques were realized using R2015a version of Matlab® software in Windows PC with an Intel Core i5 2.67 GHz CPU and 8 GB of RAM and all the resulted images have been reproduced at 300 dpi resolutions. All the input images presented here are taken from standard databases, namely, SIPI, TID and CSIQ. The results are presented in comparative manner where the outputs of all the proposed techniques have been included both visual comparison as well as objective comparison.

Figure 6.1 shows the examples of the enhanced images of different proposed techniques using objective function ϕ. From this figure, it is observed that, the proposed BA technique performs better almost in all the images in comparison to other two proposed techniques. The performance of proposed BCO is little bit low in case of contrast enhancement for gray images but for color images, it shows its potential and visually better in comparison with the proposed GWO technique except underwater image. The performance of the proposed GWO technique is visually better in comparison with the proposed BCO technique in case of gray images and underwater image.

In case of Fig. 6.2, the performance of the proposed GWO technique is much better in compare with the other two proposed techniques for objective function φ. For gray images, the proposed BA technique shows over whiteness problem and for color images, over color effect is there. The images of the proposed BCO technique is visually better in comparison with the proposed BA technique but there is further improvement of proper contrast observed here. In case of underwater image, the proposed BA technique performs better in terms of contrast, color, sharpness, etc in comparison with other two proposed techniques.

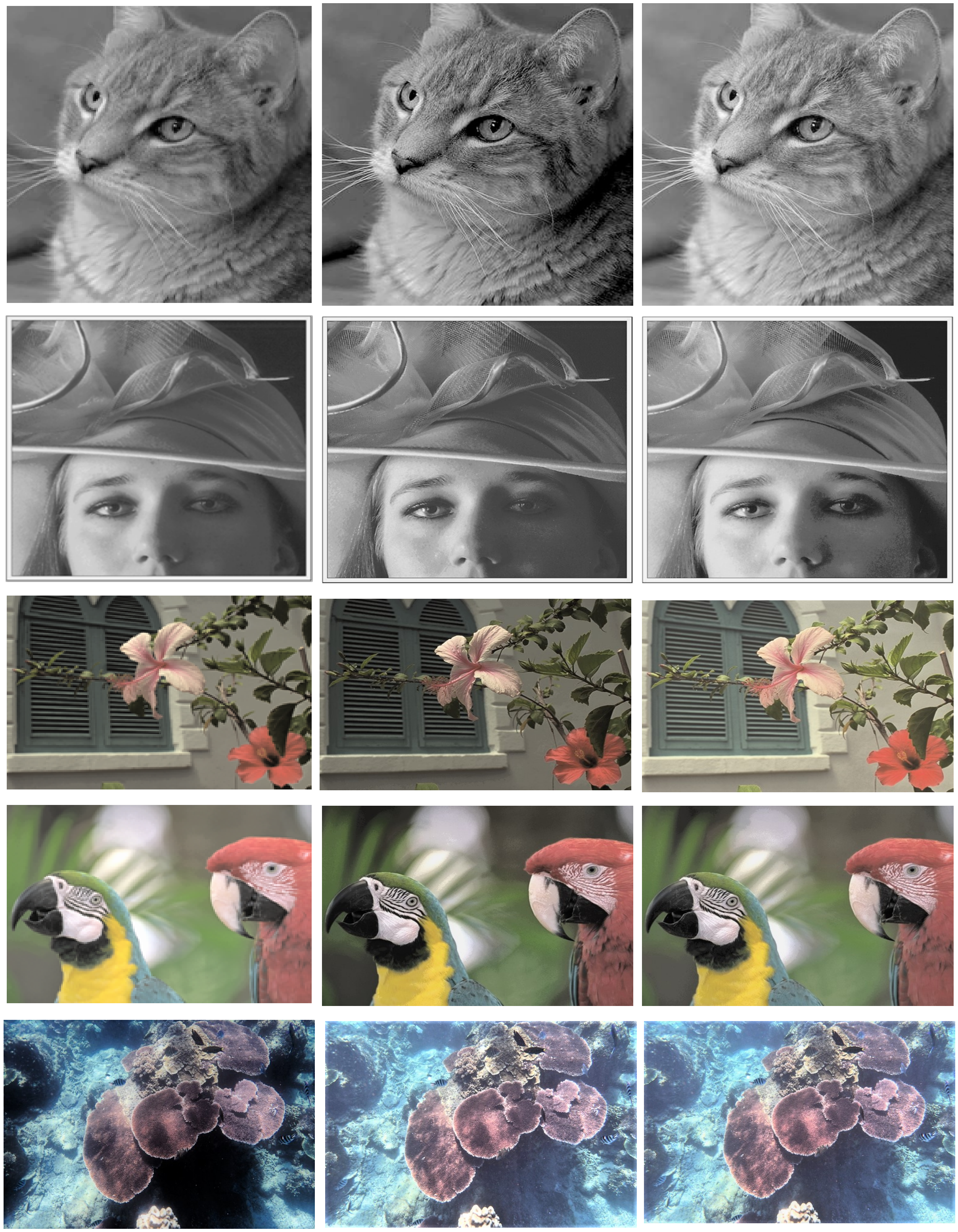

Fig. 6.1: *Result of different proposed techniques using objective function* ϕ *(Left to right: BCO, GWO and BA)*

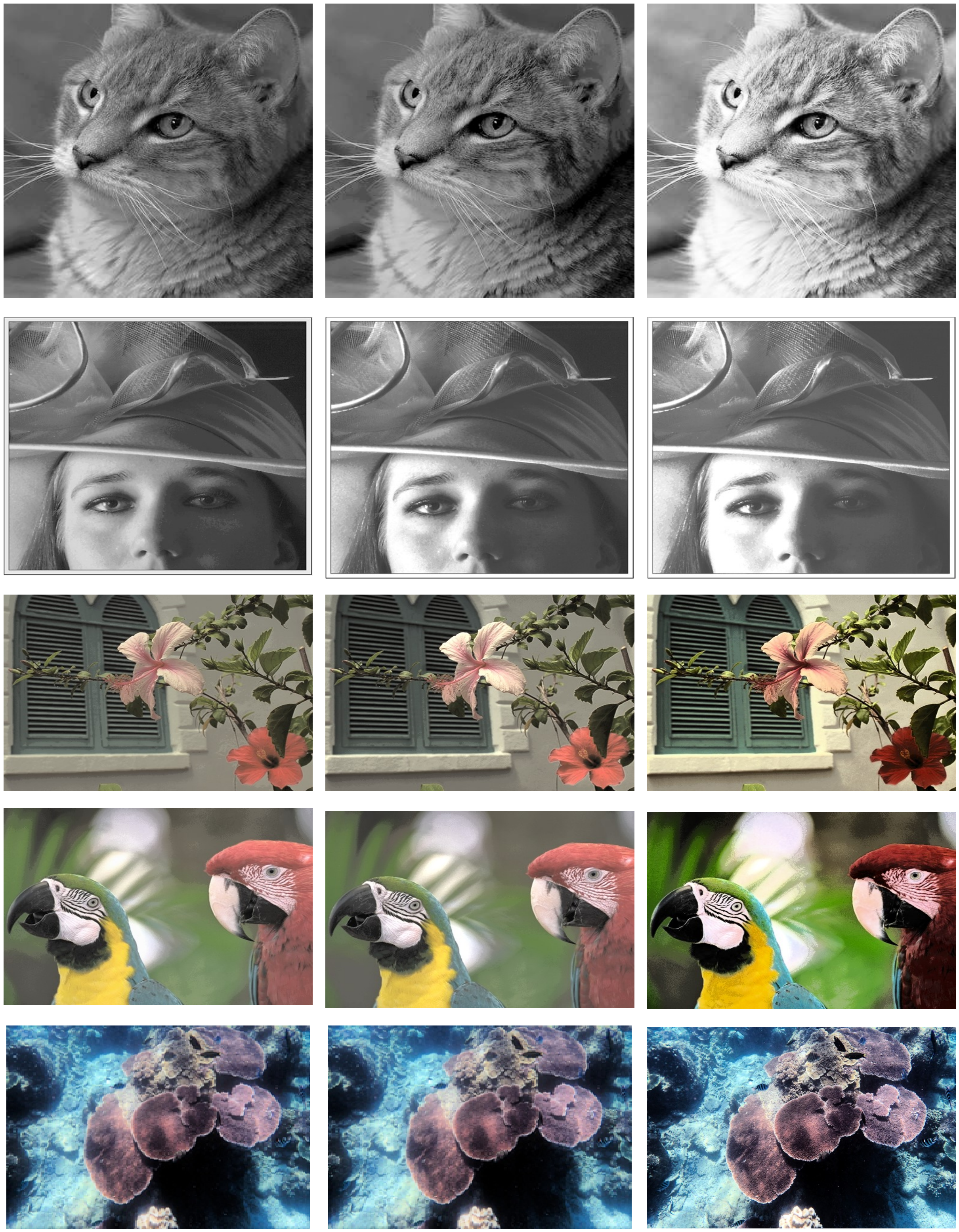

Fig. 6.2: *Result of different proposed techniques using objective function φ (Left to right: BCO, GWO and BA)*

The visual comparisons have further been extended to the objective comparisons against the image quality assessment (IQA) metrics. Like previous chapters, here also 4 full references (FR) and 1 no reference (NR) metrics have been considered for comparison purpose. Table 6.2 represents the various metric values used here for different proposed techniques using both the objective functions.

Table 6.2: *Objective evaluations between proposed techniques*

Objective Function ➡	**Objective Function (ϕ)**			**Objective Function (φ)**		
Techniques ➡	**BCO**	**GWO**	**BA**	**BCO**	**GWO**	**BA**
Metrics ⬇						
Entropy	7.598	7.536	7.574	7.722	**7.829**	7.816
PCQI	1.221	1.273	1.349	1.375	**1.528**	1.485
NIQE	3.394	3.412	3.334	3.277	3.207	**3.178**
CEF	1.265	1.295	**1.326**	1.205	1.194	1.227
Colorfulness	14.825	12.382	13.752	15.327	18.652	**20.729**

In Table 6.2, the best value for each metric has been highlighted for either of the objective functions. From this table, it is observed that, the performance of the proposed BA technique is better with respect to other two proposed techniques in terms of NIQE, CEF and Colorfulness. For entropy and PCQI, the proposed GWO technique provides better results. The performance of the proposed BCO technique comparatively low using objective function φ in comparison with the other two proposed techniques, but it shows its competitiveness especially in case of entropy and colorfulness, it outperforms other two proposed techniques by using the objective function ϕ.

All the proposed techniques have less computational time still in comparison with GWO and BA, BCO takes little bit high due to the optimal solution has been achieved by controlling of four processes such as chemotaxis, swarming, reproduction and elimination and dispersal process. The average computational times in seconds of the three proposed algorithms for providing output for a single color image are shown in Table 6.3.

Table 6.3: *Computational time of proposed techniques*

Proposed technique **using BCO**	**Proposed** technique **using GWO**	**Proposed** technique **using BA**
0.973	0.735	0.551

6.3. Major findings

The major finding from this thesis work can be consolidated as follows:

- The transmittance estimation can be a possible presentation of contrast. As the transmittance also in the range of (0, 1) it can be used to replace the V channel of the HSV image in case of color images. In this case transmittance needs to be optimized for contrast enhancement.

- The competitive performance by proposed BCO, GWO and Bat algorithms vouch the fact that computational intelligence techniques can be possible potential approach to obtain image characteristics preserving contrast enhancement.

- Including image characteristics driven parameters in objective functions can result balanced enhancement avoiding under and over-enhancement.

- Inclusion of image characteristics driven objective functions can also bring improved generalization in the technique which may be used across images of diverse media and applications.

- The objective evaluations reflect the fact that enhancement using proposed techniques can retain the naturalness of the images avoiding problems like false contouring and patches.

6.4. Addressing the research questions

- Computational intelligence (CI) algorithms have shown its potential over conventional techniques to achieve contrast enhancement, where the mathematical formulations are used as an evaluation function, conventionally called fitness function. In these algorithms, the optimal output can be reached by continuously updating the position of the randomly chosen search agents according to the location of target position. The algorithms in this domain are particularly advantageous for their adaptability and flexibility which in turn result in better search dynamics to find global optima avoiding the local optima. This addresses the RQ 1.

- Frequency domain approaches have shown better performance over spatial domain approaches in many cases, since transform domains provide better control over local image characteristics which in turn provides improved feature retention. The objective functions developed in frequency domain in-stead of spatial domain as the features are well observed in transformed domain rather the native intensity domain. Especially, the choice of DCT also provides advantages over other transform domains (DFT or DWT). For example, no imaginary coordinate, exactly reversible to intensity domain and easy understanding of frequency spectra. Therefore, a DCT based objective function may be a balanced compromise between different aspects while obtaining the enhanced images. This addresses RQ 2.

- Both types of objective function have shown their potentiality to improve the overall quality of input images. The selection among these two is end-user requirement dependent. In the cases where retention of original image feature is of more importance such as in the case of computer vision application, the imaging characteristics based objective function (φ) will provide better result over frequency spectra based objective function (ϕ). In other cases where the visual appearance is more important and loss of features may be compromised for example reproduction operations like printing, the frequency spectra based objective function (ϕ) would be the right choice to get proper output. However, in this work, both types of objective functions have been considered and the results have been analyzed for better understanding. This addresses RQ 3

- Result shows that the proposed techniques can perform well for underwater images as well particularly, if the imaging characteristics based objective function (φ) is used. Hence, the RQ 4 has also been addressed, however many other type of images, such as MRI and satellite images need to be further explored to vouch the claim in a more general way.

6.5. Major observations

- The experimental results demonstrated that the feature of the presented algorithms may be useful in providing a rapid and effective optimization based contrast enhancement system for low contrast images.

- The proposed techniques are capable to produce the enhanced output images from different levels of low contrast image maintaining the various image features like brightness preservation, proper contrast, sharp edge, white balancing and appropriate visual quality. The output enhanced contrast depends on input contrast level of an image i.e. it is input contrast level dependent as well as image dependent.

- All the proposed techniques also have less computational complexity due to its fewer parameters and the computational time vouches this potentiality.

- In comparison among the proposed techniques, the BA technique working better than other techniques especially in terms of contrast enhancement, naturalness and retention of original color.

- The objective function φ giving better results than the objective function ϕ almost for all the IQA metrics due to its imaging characteristics, which is formulated base on the concept of transmittance and radiance characteristics of object light. This will indicate better preservation of image characteristics.

6.6. Future work

The presented works can be extended to many directions. Some of them are listed below.

- The proposed techniques can further be extended to the optimization of algorithm's parameters, a predictive model of the optimization framework where the input image can be enhanced based on a set of defined equalized histograms obtained by proposed algorithms, inclusion of more optically derived measure of contrast for objective function formulation.

- Including deep neural network based algorithms for generation of contrast enhanced images.

- Exploring the proposed techniques for different applications like MRI, satellite images to bring more generalization potential.

- Development of more robust objective function, inclusion of application dependent parameters in objective function e.g. model based contrast enhancement, application to color images incorporating interaction between color channels.

- The works can be exploring other multi-objective algorithms of biological behavior inspired optimization techniques, etc.

6.7. Conclusions

The current thesis work is a promising step towards the image contrast enhancement of the degraded low contrast images. Continuous research towards the enhancement of image contrast for the quality control of an image is not only very important for the improvement of scientific knowledge but has an intense impact on the development of the related field of image processing. Concluding this chapter, it is expected that the techniques adopted in this research to be useful for similar types of applications and is expected to open the room for a new paradigm in the quality control and restoration of the poor quality images.

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