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Contrast enhancement of Color Images with Preservation of Brightness by using Clipped Optimized Multi-Histogram Equalization

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Abstract: *This study proposes a Clipped Optimized Multi-Histogram Equalization (COMHE) technique for contrast enhancement of color images while preserving their brightness level. In this technique, the input image histogram is partitioned into t+1 sub-histograms using t threshold values. Each sub-histogram is then clipped using a dynamic plateau level. Multi- histogram equalization is then applied to these sub-histograms. The optimization of threshold values used for segmenting the input image histogram is done by using Artificial Bee Colony, a swarm intelligence based optimization algorithm. A new fitness function is presented in this study to appraise the contrast of the enhanced image, which leads the artificial bee colony algorithm in search of optimal thresholds. Comparative analysis of the results produced by the proposed method with the results of some other traditional as well as metaheuristic approaches of contrast enhancement is performed using quantitative measures i.e. AMBE (Absolute Mean Brightness Error), PSNR (Peak Signal to Noise Ratio), SSIM (Structural Similarity Index), and Entropy. Comparisons reveal that the proposed method outperforms in attaining better contrast enhancement of images while maintaining their brightness.*
Keywords: *contrast enhancement; multi-histogram equalization; histogram clipping; artificial bee colony optimization;*

I. Introduction

Contrast enhancement and brightness preservation are basic preprocessing steps applied to experimental images by almost all algorithms in the realm of digital imaging. In general, contrast enhancement techniques are applied to enhance visual interpretation or recognition of information within images. Most contrast enhancement techniques used Histogram modification as the key strategy. Global Histogram Equalization (HE) is a classic and widely used method for enhancing image contrast[1].This method utilizes the image histogram's cumulative density function (CDF) as the intensity remapping function to achieve uniform distribution among pixel intensities. It works well in the fields of medical and radar image processing as well as texture analysis. Due to mean shifting problem of this method, it is not very common in the consumer electronics field. This method shifts the mean brightness of the enhanced image from true mean to the input image's middle intensity level. This can lead to annoying artifacts and excessive brightness variations in the output image, which is undesirable for consumer electronics. To overcome the limitations of GHE, its several useful variants have been proposed. Two broad categories of these techniques are Bi-Histogram Equalization and Multi-Histogram Equalization*[2]*.

II. Related works

2.1. Bi-Histogram Equalization

Brightness preserving Bi-Histogram Equalization (BBHE) [3] technique used the mean brightness as a threshold to divide the histogram of input image into two sub-histograms. It then equalizes these sub-histograms separately. As compared to GHE, this method preserves the mean brightness while reducing abnormal enhancement as well as undesirable artifacts. The equal area Dualistic Sub-Image Histogram Equalization (DSIHE)[4], an extension of BBHE, used median instead of mean to divide the histogram of input image. This method works well in case of images having non-uniform intensity distribution. An another extension of BBHE is MMBEBHE[5]. In this method, image's histogram is split into two sub-histograms using a threshold level that yields minimum Absolute Mean Brightness Error (AMBE) to maximize brightness preservation. Although these methods can improve contrast enhancement, they also produce unpleasant side effects due to varying gray level distribution of the histogram. Range Limited Bi-histogram Equalization (RLBHE)[6] is another bi-histogram equalization based technique. This method works on the assumption that every image has two categories of pixels, the first is background pixels and the second is foreground pixels. This technique used the Otsu's method to automatically find a threshold value based on the histogram's shape to split the input histogram that minimized the intra-class variance between these two classes. Output images produced by this technique achieves more visually pleasing contrast enhancement and maintains the input mean brightness.

2.2. Multi-Histogram Equalization

Multi-Histogram Equalization is based on the division of image histogram into multiple sub-histograms and equalizes each sub-histogram individually by applying classical HE processes. Multi-HE based contrast enhancement methods are supposed to preserve the mean brightness and natural appearance in the enhanced image more accurately as each sub-histogram yields lesser shift in brightness when equalized independently [2].

Pseudocode: General pseudocode of Multi-histogram Equalization

1. Determine the t thresholds based on some criteria.
   $TH = \{th_1, th_2, \ldots, th_t\}$
2. Partition the histogram of input image $X[x^l, x^h]$ into $t+1$ sub-histograms using t thresholds.
   $\{X_1[x^l, th_1],\ X_2[th_1+1, th_2], \ldots, X_{t+1}[th_t+1, x^h]$
3. Determining and mapping of each partition to a new dynamic range (Optional).
4. Compute the total pixels M_i contained in each sub-histogram X_i
5. Equalize each sub-histogram using the following function.
   $$f_i(k) = x_i^l + \left(x_i^h - x_i^l\right).\sum_{j=x_i^l}^{k}\frac{h(j)}{M_i} \quad for\ i = 1 \ldots t+1\ and\ k = x_i^l, \ldots.x_i^h$$
6. Produce the Output Image Y as follows:
   $Y(i,j) = f_i(X_i(i,j))$

Recursive Mean-Separate Histogram Equalization (RMSHE) [7], proposed by Chen & Ramli (2003) and Recursive Sub-image Histogram Equalization (RSIHE) [8], proposed by Sim et al. (2007) are Multi-HE based recursive variants of BBHE and DSIHE, which recursively splits the histogram of input image into multiple sub-histograms by using mean and median intensity values respectively. These methods succeed in achieving the objective of higher brightness preservation as compared to other conventional HE and Bi-HE based methods. But, both RMSHE and RSIHE suffer from a common problem of defining the optimal recursion limit.

Minimum Middle Level Squared Error Multi-HE (MMLSEMHE) and Minimum Within-Class Variance Multi-HE (MWCVMHE) are proposed in [9] by Menotti et al. (2007). In these methods, a cost function is used to automatically optimize the number of sub-images. Results produced by these methods are more natural looking images with more brightness preservation as compared to other HE methods.

DHE (Dynamic Histogram Equalization) [10] is a smart local contrast enhancement method proposed by Wadud et al. (2007). This method used local minima for partitioning the histogram of input image into multiple sub-histograms and each partition is assigned a specific range of gray levels. To eliminate any dominating portion in the sub-histograms, a repartitioning test is applied to each partition. This simple and computationally effective method achieved better overall contrast enhancement without introducing any side effects. Multipeak Histogram Equalization with brightness preserving (MPHEBP) [11] is the method that detects the peak intensity values in the original histogram and split it into multiple sub-histograms based on these values.

RSWHE (Recursively separated and weighted Histogram Equalization) [12] is another MHE based method proposed by Kim & Chung (2008), which recursively segments the input image histogram into multiple sub-histograms. After that, a weighting process is used to modify these sub-histograms before equalizing them independently. Researchers showed that this method produced well contrast enhanced images and brightness is also more accurately preserved as compared to other similar recursive methods such as RMSHE [7] and RSIHE [8].

A merger technique of MPHEBP [11] and DHE [10] is BPDHE (Brightness Preserving Dynamic Histogram Equalization) [13] presented by Ibrahim & Kong (2007). This method pre-processes the input image histogram for smoothening and also for filling the disappeared levels of brightness. Histogram is then partitioned based on local maxima. This procedure is similar to which used in MPHEBP. Like DHE, this method spans the dynamic range assigned to each partition. After assigning a new range, each partition is equalized separately. Normalization of output intensities is performed thereafter to maintain nearly the same average intensity as the input intensity. In another study [14] by Kong & Ibrahim in 2008, authors have tried to explore the different possible applications of BPDHE for contrast enhancement of color images.

BPDFHE (Brightness Preserving Dynamic Fuzzy Histogram Equalization) [15] is a modified version of BPDHE [13] offered by Sheet et al. (2010). To achieve the contrast enhancement in images, this technique has used fuzzy set theory. To better handle the gray value inaccuracies, a fuzzy histogram has been calculated using the triangular fuzzy membership function. Local peak intensities are then used to divide this fuzzy histogram into multiple sub-histograms. Each sub-histogram is then equalized dynamically. Peak values have not been remapped for preserving mean brightness. Researchers claimed that this method produced better contrast enhanced images as compared to BPDHE in most cases of experiments.

2.1.1 Histogram Equalization with Clipping Limits

With the objective of avoiding over enhancement in output images of Histogram Equalization (HE), various researchers used the concept of histogram clipping. This is the concept of modifying input image histogram by the application of a clipping limit also called plateau level. This is the process of reducing those histogram values which are greater than the clipping limit. All histogram values are restricted to this clipping limit **[16]**. In some clipping based HE methods, clipped values are equally redistributed to all the histogram bins. Histogram Equalization is then performed on this clipped Histogram.

Pseudocode: General pseudocode of Clipped/Plateau Histogram Equalization

1. Determine the value(s) of clipping limit or limits (in case of clipped Bi-HE or clipped Multi-HE).
2. Clip the histogram bins by setting values above the clip limit(s) to the clip limit(s) itself. If cl_i is the clip limit for sub-image X_i, with the range of $[x_i^l, x_i^h]$, then the clipped sub-image CX_i is achieved as follows:
$$CX_i(k) = \begin{cases} X_i(k), & if\ X_i(k) \le cl_i \\ cl_i, & elsewhere \end{cases}$$
3. Perform Histogram Equalization based on Cumulative Density Function(s) of Clipped Histogram(s) using the following function.
$$cf_i(k) = x_i^l + (x_i^h - x_i^l).\sum_{j=x_i^l}^{k} \frac{ch(j)}{M_i} \quad for\ i = 1 \dots t+1\ and\ k = x_i^l, \dots .x_i^h$$
where $ch(j)$ is the number of pixels with intensity j in clipped histogram, and M_i is the total pixels contained in the clipped sub-image CX_i.
4. Produce the Output Image Y as follows:
$$Y(i,j) = cf_i(X_i(i,j))$$

A Plateau Histogram Equalization based contrast enhancement technique for infrared images is proposed in **[17]** by Wang at el. (2006). In this technique, the threshold value is self-adaptively achieved by analyzing the image histogram. Researchers proved experimentally that this Self-Adaptive Plateau Histogram Equalization has performed better than histogram equalization in achieving contrast enhancement of infrared images.

Another clipped histogram based method is presented by Kim & Paik (2008) in **[18]**. The authors referred this method as Gain Controllable Clipped Histogram Equalization to achieve adaptive contrast enhancement with controllable gain. This method adaptively decides the clipping threshold with the objective to preserve the mean brightness. The aim of this method is to achieve better contrast enhancement while preserving the original intensity distribution. Experiments prove that this method with a simple computational structure outperforms other HE based methods.

Another similar method was proposed by Kong et al. (2009) for contrast enhancement of microscopic images and named it as modified Self Adaptive Plateau Histogram Equalization **[19]**. This method automatically decides the plateau threshold value based on the median of the histogram bins with non-zero values. Output images prove that this method successfully enhanced the contrast in microscopic images as compared to global Histogram Equalization while restricting the amplification of noise levels.

A hybrid method of Bi-HE and Clipped HE is proposed in **[20]** by Ooi et al. (2009). This method is named Bi-Histogram Equalization with a Plateau Level (BHEPL). Like BBHE, BHEPL also partition the histogram of input image using its mean intensity value and produced two sub-histograms. These two sub-histograms are then clipped independently using two plateau levels which are the average of their sub-histograms. Histogram equalization is then applied on these clipped sub-histograms. Researchers proved that the proposed method successfully enhances contrast while maintaining mean brightness and avoiding unwanted artifacts in output images.

Another clipped HE method, ADPHE [21] proposed by Liang et al. (2012) has used adaptively computed two clipping threshold levels to avoid unwanted enhancement in background noise while preserving detailed information. Researchers proved with experiments that the proposed method can enhance contrast in infrared images while constraining the background noise.

One more Clipped HE based method for contrast enhancement is Median-Mean Based Sub-Image-Clipped Histogram Equalization (MMSICHE) **[22]** proposed by Singh & Kapoor (2014). This method bisects the input image histogram into four sub-histograms using its median and mean values. The median of the histogram intensities is used as the plateau limit for clipping the histogram. Researchers show that this method is robust in achieving contrast enhancement while maintaining the mean brightness and information content. It also avoids over-enhancement.

Jenifer et al. (2016) has developed a hybrid contrast enhancement method for mammogram images by applying fuzzy inference based clipped-CLAHE [23]. To decide the clipping rate, the values of contrast and entropy of input image is taken as input parameters by the triangular membership function based fuzzy inference system. The evaluation of results produced by the proposed method proves that the contrast and entropy of input images has improved without affecting the detailed information.

The improved ADPHE method [24] presented by Li et al. (2018) for contrast enhancement of infrared images has used the normalized coefficient of variation of the histogram (NCVH) for adaptively determined the two plateau threshold levels. This method constantly adjusts the plateau threshold levels until a desired level of NCVH is achieved. The process of computing upper threshold value is more complex. Researchers have proved with experiments that the proposed method is stable in achieving good enhancement in infrared images under different scenarios.

With the objective to use information of each pixel and its neighbouring pixels for improving the contrast of an image, Agarwal et al. (2019) suggested a novel method and has named it Joint Histogram Equalization (JHE) [46]. An average image from original image is derived by substituting each pixel intensity value by the average intensity value of its local neighbourhood pixels window having size $w \times w$. Joint histogram in two dimensional form is generated from the original image's and its average image's pixel values. New pixel intensity values are computed from two dimensional CDF. Researchers proved by experiments that the proposed method produced better results as compare to other state-of-art methods especially for images having narrow dynamic range. Determination of best neighbouring window size for computing average image can be optimized in future work.

2.1.1.1 Artificial Bee Colony Optimization based techniques

Artificial Bee Colony algorithm is a swarm intelligence based metaheuristic motivated by the smart foraging behavior of natural honeybees. It was proposed by Dervis Karaboga in 2005. ABC algorithms imitate the collective search and exploitation of food sources by honeybees to solve optimization problems. Three kinds of honey bees (the employed bees, the onlookers and the scouts) worked collectively in search of food sources. The main components and steps of the ABC algorithm are as follows [25]:

a. Initialization: Create an initial population of employed bees. Each employed bee represents a potential solution or a food source to the optimization problem.
b. Employed Bee Phase: Each employed bee explores a new solution by modifying its current solution using local search mechanisms. These modifications can be random or guided by problem-specific operators. The quality of each solution is evaluated using an objective function.
c. Onlooker Bee Phase: Onlooker bees select better quality solutions among those found by the employed bees on the basis of their fitness values. The probability of selecting a solution is determined by its fitness value relative to the fitness values of other solutions. The onlooker bees then perform local search on the selected solutions to potentially improve them.
d. Scout Bee Phase: If a certain number of iterations pass without finding an improved solution, a scout bee is activated. The scout bee randomly generates a new solution after some food source is rejected due to low quality with the objective explore unexplored regions of the search space.
e. Updating Process: At the end of each iteration, the employed bees, onlooker bees, and scout bee exchange information to update the population. The employed bees share their solutions and fitness values, while the onlooker bees update their probabilities based on the fitness values. This information exchange encourages exploration and exploitation of the search space.
f. Termination: The ABC algorithm continues iterating through the employed bee, onlooker bee, and scout bee phases for a specified number of iterations or until a termination condition is met. Termination conditions can include reaching a satisfactory solution, achieving a certain fitness threshold, or exceeding a predefined number of iterations.

An image enhancement technique based on Artificial Bee Colony (ABC) algorithm is proposed by Draa and Bouaziz (2007) in [26]. In this research, ABC is used as an optimizer to search for the best mapping of gray levels in an image that maximizes the objective function. Comparisons of the results of proposed ABC algorithm with the Genetic algorithm and Cuckoo search algorithm show the superiority of proposed approach for image contrast enhancement.

Another Artificial Bee Colony (ABC) based approach for contrast enhancement of gray as well as color images is proposed by Chen et al. (2018) in [27]. In this study, authors formulated a new faster and efficient parametric transformation function along with a new objective fitness function as image contrast measure for contrast enhancement. Search for optimal parameters required in transformation function is performed using ABC algorithm. Experimental results shows that the proposed approach produced better enhanced images in terms of both visual quality and objective performance measure.

Keerthanaa and Radhakrishnan (2020) proposed an improved contrast enhancement approach by using Artificial Bee Colony Algorithm [28]. In this research, a modified local global transformation function for contrast enhancement was proposed and parameters of that function are optimized using ABC algorithm.

Another adaptive and metaheuristic based method for contrast enhancement of gray scale images is proposed by Fawzi et al. (2021) [29]. This method is named as Adaptive Clip Limit Tile Size Histogram Equalization (ACLTSHE). This method first optimizes the tile size range (TSR) and clip limit range (CLR) for using as parameter to standard CLAHE. Among the selected TSR and CLR, optimal values for tile size and clip limit are searched using Whale Optimization Algorithm (WOA). A new objective function named Data Signal is used to guide the WOA in search of optimal values. Researchers compared the performance of proposed method with some state-of-the-art clip limit histogram equalization techniques using quantitative measures like AMBE, Discrete Entropy and PSNR.

III. The Proposed Method

The proposed technique is based on clipped multi-histogram equalization. With the objective of preserving mean brightness, the input image histogram is segmented into multiple sub-histograms. The Artificial Bee Colony optimization algorithm has been used to perform the selection of thresholds for segmentation. Before equalizing each sub-histogram separately, clipping has been implemented by using mean-based separate plateau limits for each sub-histogram. The proposed method is organized into the following modules:

3.1 Finding Thresholds for Histogram Segmentation using Artificial Bee Colony (ABC) Optimization

During literature study, it has been found that swarm intelligence based algorithms can be successfully exercised in solving a wide variety of problems[30],[31]. These algorithms can be used for searching the best thresholds for splitting an image histogram into multiple sub-histograms. These thresholds can be used in multi-histogram equalization to achieve contrast enhancement and brightness preservation in digital images. In this study, Artificial Bee Colony (ABC) algorithm is used for finding optimal multilevel thresholds. ABC is a metaheuristic algorithm based on swarm intelligence developed by Karaboga in 2005. The motivation behind ABC algorithm is the smart foraging behavior of natural honeybees. This algorithm follows a population-based search procedure in which global sources of food (solutions) are discovered and these food sources are evaluated iteratively by the artificial bees in order to locate the superior sources of food [32]. The operational steps of this algorithm are based on the collective efforts made by honeybees in finding food locations. These food locations are equivalent to possible solutions.

In ABC algorithm, three classes of honeybees i.e., the employed bees, the onlookers, and the scouts work collectively to find optimal food locations which correspond to the optimal solutions. A possible food location is selected by each bee and then its neighborhood is exploited in search of a better source of food (solution). Classification of bees into three categories is based on how they select the possible solution to exploit. The employed bee considers various sources of food around the food sources in her memory and if found a better solution then she updates this in her memory. Information about these newly found sources of food is communicated by the employed bees with the onlooker bees. These newly found food sources are evaluated by onlooker bees to select better quality food sources among these. After rejection of some low-quality food sources, new possible food sources are randomly searched by the scout bees [27]. The brief description of primary phases of ABC algorithm are as:

Initialization: In ABC algorithm, each possible food source position for the bee colony corresponds to a solution vector f_i with n values, $f_{ij}, j = 1 \dots n$. The problem in question is to search an optimal vector f which maximize/minimize the objective fitness function. Population of m solution vectors is initialized, and the fitness of each solution is quantized. Initialization of population is done randomly within the search space using the equation (1).

$$f_{ij} = l_j + rand(0,1) \times (u_j - l_j) \quad (1)$$

where, u_j and l_j represents the upper and lower limits of jth parameter in solution vector f.

Following phases are iteratively performed until the stop condition is fulfilled or the maximum number of iterations is performed.

Employed bee stage: Each employed bee tries to find a better new solution y_i by moving randomly in the vicinity of its current solution x_i. Employed bee would replace the old solution with the new solution if the new solution produced better fitness value than the old solution, otherwise it will keep the old solution. Equation for selecting/generating a new solution is given below:

$$y_{ij} = x_{ij} + rand(-1,1) \times (x_{ij} - x_{kj}) \quad (2)$$

where k is the randomly chosen index.

Onlooker bee stage: When all employed bees have finished searching for better solutions, they share this information to onlookers. Each onlooker bee applies roulette wheel selection method for probable selection of a solution based on its fitness value. The following equation assigns fitness-based probability Pr_i to each solution.

$$Pr_i = \frac{fitness_i}{\sum_{k=1}^{n} fitness_k} \quad (3)$$

In the above equation, $fitness_i$ represents the fitness of solution i and n represents the total number of solutions. After selecting a solution, the onlooker bee tries to search for a better new solution corresponding to the selected solution just like the employed bee by using equation (2). A greedy selection is adopted to choose among the probabilistic and new solutions.

Scout bee stage: If a solution's fitness value does not improve over a few generations (iterations), then that solution is abandoned. Then the abandoned solution is replaced with a new solution. This new solution is developed by applying the initialization process. Here the greedy approach is being followed for updating the solutions. The best solution found during the whole iterative process is recorded with its fitness value.

In this proposed work, we used Artificial Bee Colony (ABC) algorithm for optimizing the threshold levels for segmenting the input image histogram into multiple sub-histograms. In this technique, a set of threshold levels is replaced by a new set in the search of a solution that produces a better contrast enhanced image after applying clipped multi-histogram equalization. When an optimization algorithm is used for image contrast enhancement, there is a need of two functions, transformation function and objective fitness function. A transformation function is required for producing new pixel intensities which are used to replace existing pixel intensities with the objective to produce a contrast enhanced image. An objective fitness function is required for guiding the optimization algorithm by measuring the quality of the contrast enhanced image produced after applying the transformation function[27]. Design of these two important functions highly influenced the enhancement of contrast in the output image.

The transformation function used in our proposed technique is described in equation (16). This transformation function is exercised to each clipped sub-histogram obtained after segmenting the input image histogram using t thresholds levels. Procedure of Clipping the sub-histograms is discussed in next section. As discussed above, we use ABC algorithm inthis proposed technique to optimize the t threshold levels (solution) for segmenting the input image histogram into t+1 sub-histograms. An optimal set of t threshold levels (solution) is that which produce a best contrast enhanced image after implementing the clipped histogram equalization through the equation (8) equation (16). To find the optimal solution, there is the need of a criteria to check the quality of solutions produced by ABC algorithm. The objective fitness function is used for this purpose. It guides the movement of Artificial bees in finding the optimal solution.

We used a fitness function based on the number of edge pixels, their intensity values, Entropy, PSNR and Contrast of the whole image. With the application of these measures, Objective Fitness Function (OFF) is defined in two parts:

$$OFF1 = \left(\log\left(\log\left(E(I_s)\right)\right)\right)\frac{n\left(edges(I_s)\right)}{m.n} . H(I_e). PSNR(I_e) \quad (4)$$

$$OFF2 = 10log_{10}\, C_{contrast}(I_e) \quad (5)$$

$$OFF = 0.75 \times OFF1 + 0.25 \times OFF2 \quad (6)$$

In the above formula, I_e is the enhanced image, $E(I_s)$ is the sum of edge intensities of the Sobel edge image [33] obtained after applying the Sobel filter on the enhanced image I_e,$n\left(edges(I_s)\right)$ is the number of the edges in the Sobel edge image, $H(I_e)$ is the entropy and $PSNR(I_e)$ is the peak signal to noise ratio of the enhanced image. m and n are the dimensions in terms of horizontal and vertical pixels of the image respectively. $C_{contrast}$[21] is used here to evaluate the contrast improvement. Its formula is:

$$C_{contrast} = \frac{1}{MN}\sum_{m=1}^{M}\sum_{n=1}^{N} {I_e}^2\,(m,n) - \left|\frac{1}{MN}\sum_{m=1}^{M}\sum_{n=1}^{N} I_e\,(m,n)\right|^2 \quad (7)$$

where M and N represents the number of pixels on X and Y axis of the image, $I_e(m,n)$ is the intensity value at (m,n)location in the enhanced image I_e. $C_{contrast}$ represents the deviation of intensity levels. Its higher value implies more informative image having good contrast because of larger dynamic range of intensity levels.

The implementation of ABC algorithm is relatively simple and straightforward to solve optimization problems. In various studies, ABC algorithm has been proved its effectiveness at low computational cost. Many researchers in their studies [34],[35],[36] have evaluated and compared the performance of the ABC algorithm with other well-known evolutionary algorithms like GA, PSO, ACO & DE to show the effectiveness of ABC algorithm. The proposed methodology helps in finding the optimal thresholds for segmenting the input histogram into multiple sub-histograms by which more local details can be preserved after applying histogram equalization to these sub-histograms.

3.2 Multi-Plateau Clipping of Sub-Histograms

In Multi-Histogram Equalization (MHE), image histogram is partitioned into several segments called sub-histograms and then histogram equalization is applied individually on these sub-histograms. MHE can achieve both local contrast stretching and local adaptability. Moreover, it reduces the level of compression caused by high frequency histogram segments in global HE [37]. With the objective of limiting the enhancement rate, the proposed method applies clipping to each sub-histogram. Plateau limit used in this method for clipping a sub-histogram is simply the average frequency of the intensity values contained in that sub-histogram. If pl_i is the plateau limit for sub-histogram sh_i then the clipped sub-histogram csh_i is achieved by equation (8).

$$csh_i(k) = \begin{cases} sh_i(k), \ if \ sh_i(k) \ \le \ pl_i \\ \quad pl_i, \ elsewhere \end{cases} \tag{8}$$

In the above equation, $\boldsymbol{sh_i(k)}$ and $\boldsymbol{csh_i(k)}$ are thefrequency values before clipping and after clipping of $\boldsymbol{kth}$ histogram bin in $\boldsymbol{ith}$ sub-histogram.

3.3 Equalizing each Sub-Histogram independently.

The method for equalizing each sub-histogram independently is similar to Global Histogram Equalization (GHE). In Transformation Function $tf(k)$ of GHE for a digital image X , $x(i,j)$ represents intensity value corresponding to the pixel at (i,j) location. Image X has N pixels and its intensity is digitized into L levels that are $\{x_0, x_1, x_2, \dots, x_{L-1}\}$. As a function of intensity k, the histogram h_k is defined as:

$$h(k) = \ n_k, \qquad for \ k = 0,1,2,\dots,L-1 \tag{9}$$

In the above equation, n_k represents the count of total pixels having k intensity level in the image X.The probability density function, $pdf(k)$ is defined as:

$$pdf(k) = \frac{h(k)}{N}, \qquad for \ k = 0,1,2,\dots,L-1 \tag{10}$$

The cumulative density function, cdf(k) is defined as:

$$cdf(k) = \sum_{l=0}^{k} pdf(l), \qquad for \ k = 0,1,2,\dots L-1 \tag{11}$$

The transformation function *f(k)* based on cumulative density function for histogram equalization is defined by the following equation:

$$tf(k) = x_0 + (x_{L-1} - \ x_0).cdf(k) \tag{12}$$

Then, the output image Y, after applying the transformation function to input image X can be expressed as:

$$Y = \{y(i,j)\} = \{tf\big(x(i,j)\big) \big| \ \forall x(i,j) \in X\} \tag{13}$$

where (i,j) represents a pixel's spatial coordinatesin the image.

In Multi-histogram Equalization (MHE), histogram of an image is divided into t+1 segments by determining t thresholds. This can be defined as:

$$TH = \{th_1, th_2, \dots, th_t\} \tag{14}$$

By using these thresholds, input image $X[x^l, x^h]$ is decomposed into $t+1$ sub-images as $\{X_1[x^l, th_1], \ X_2[th_1+1, th_2], \dots, X_{t+1}[th_t+1, x^h]\}$.

After partitioning, the input image can be defined as:

$$X[x^l, x^h] = \bigcup_{i=1}^{t+1} X_i\big[x_i^l, x_i^h\big] \tag{15}$$

where, X_i represents i^{th}sub-image of X. x_i^l, x_i^h represents the lower and uppermost boundaries of i^{th} out of $t+1$ sub-images respectively. It should be noted that lower boundary of first sub-image i.e. $x_1^l$is equal to $x^l$and uppermost boundary of last sub-image i.e. $x_{t+1}^h$is equal to x^h. In literature, application of histogram equalization (HE) after segmented an image into two sub-images (number of thresholds i.e. t = 1) and more than two sub-images (number of thresholds i.e. t> 1) are referred to as Bi-Histogram Equalization and Multi-Histogram Equalization respectively.

For each sub-image X_i, with the range of $\big[x_i^l, x_i^h\big]$, the transformation function $tf_i(k)$ is defined as:

$$tf_i(k) = x_i^l + \big(x_i^h - \ x_i^l\big).\textstyle\sum_{j=x_i^l}^{k} \frac{h(j)}{M_i} \ for \ i = 1 \dots t+1 \ and \ k = x_i^l, \dots . x_i^h \tag{16}$$

where $tf_i(k)$ represents the new intensity level corresponding to the k^{th} intensity level in the original image, $h(j)$is the number of pixels with intensity j, and M_i is the total pixels contained in the sub-image X_i.

In this study, we have implemented Clipped Optimized Multi-Histogram Equalization (COMHE) for contrast enhancement in color images. First, conversion of RGB image into HSV image is performed. Contrast Enhancement is achieved by applying the proposed technique on V Channel of HSV image. The t threshold levels used for partitioning the image histogram are optimized using Artificial Bee Colony (ABC) algorithm. Before applying histogram equalization to t+1 sub-histogram, dynamic plateau limits are used to clip each sub-histogram. The value of t is initialized with the number of peaks founded in the input image histogram. The upper limit of t is restricted to 5, as a greater number of thresholds decreases the level of contrast enhancement. The number of artificial bees used in ABC optimizer is fixed to 30 and the maximum iterations used are 100. Matlab programming language is used to implement the proposed method on a PC with Intel Core^{TM} i5 CPU 2.3 GHz and 4 GB RAM.

IV. Experimental Results

It is very hard to determine or evaluate the quality of the output image produced after applying any contrast enhancement technique. We use both qualitative as well as quantitative measures to compare the results of the proposed technique with some conventional as well as soft computing based contrast enhancement techniques. The following quantitative image quality measures are applied to evaluate the results produced by the proposed approach.

4.1 Absolute Mean Brightness Error (AMBE)

It refers to the absolute difference between the mean intensity values of input and output images.

$$AMBE = |m_i - m_o| \tag{17}$$

where m_i and m_o are the computed mean intensities of the input and output images as defined in the following equation

$$m = \frac{\sum_{k=0}^{L-1} i_k \times n_k}{N} \tag{18}$$

where i_k is the kth intensity value and n_k is the number of pixels at that intensity value. L is the maximum intensity value and N is the total number of pixels in the image. Smaller AMBE values indicate small differences between the input and output average intensities. In other words, a method which produce smaller AMBE value does preserve the mean brightness of the image [37].

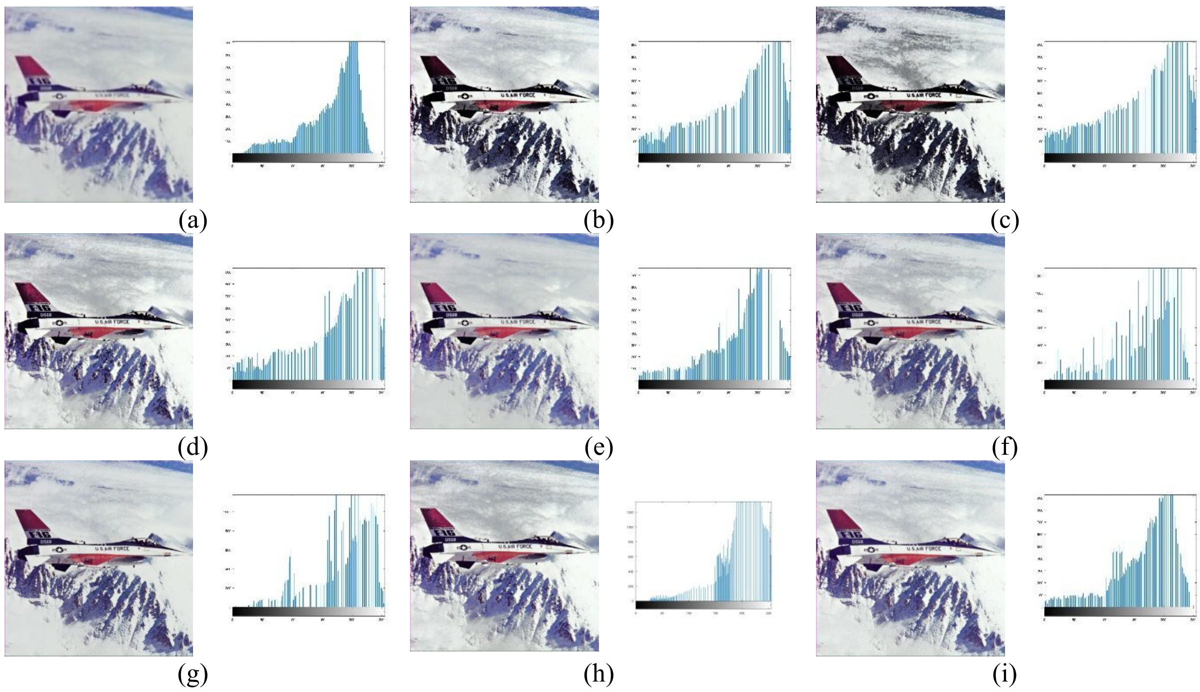

Figure 1. *Images and their histograms (a) Original Image (b) BBHE (c) DSIHE (d) MMBBHE (e) RMSHE (f) GA (g) ABC (h) OMHE (i) Proposed Approach*

4.2 Mean Square Error (MSE)

MSE is the average of squared differences of input and enhanced image intensities. It measures the pixel differences.

$$MSE(X,Y) = \frac{1}{MN}\sum_{m=1}^{M}\sum_{n=1}^{N}(X(m,n) - Y(m,n))^2 \qquad (19)$$

where X and Yrefers to input and enhanced images respectively. M and N represents the count of rows and columns in the images. Thus, a method which produce lower MSE value gives better image enhancement.

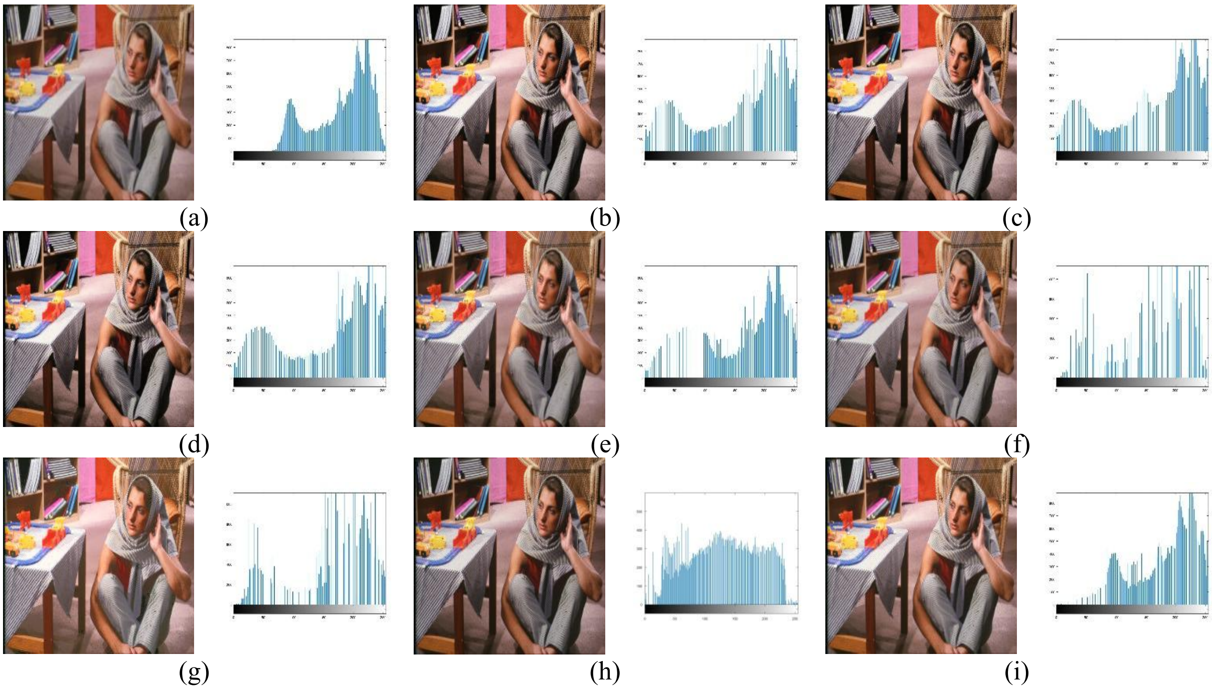

Figure 2. *Images and their histograms (a) Original Image (b) BBHE (c) DSIHE (d) MMBBHE (e) RMSHE (f) GA (g) ABC (h) OMHE (i) Proposed Approach*

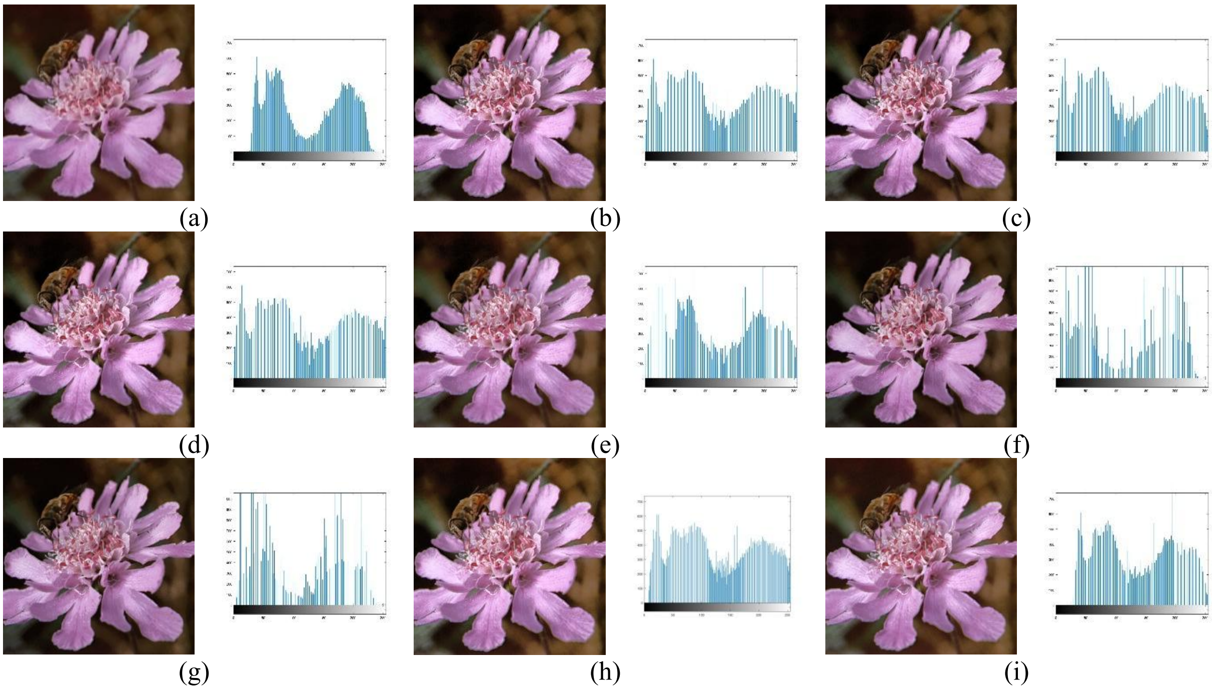

Figure 3. *Images and their histograms (a) Original Image (b) BBHE (c) DSIHE (d) MMBBHE (e) RMSHE (f) GA (g) ABC (h) OMHE (i) Proposed Approach*

4.3 Peak Signal-to-Noise Ratio (PSNR)

An important metric for evaluating the performance of contrast enhancement techniques is PSNR. It is a ratio between the maximum possible signal power and the noise power. It is a distortion metric which heavily relies on Mean-Squared Error (MSE). PSNR is defined as:

$$PSNR(X,Y) = 10log_{10}\frac{(L-1)^2}{MSE(X,Y)} \quad (20)$$

L represents the possible discrete grey levels in the images. The maximum PSNR represents better quality of the enhanced image.

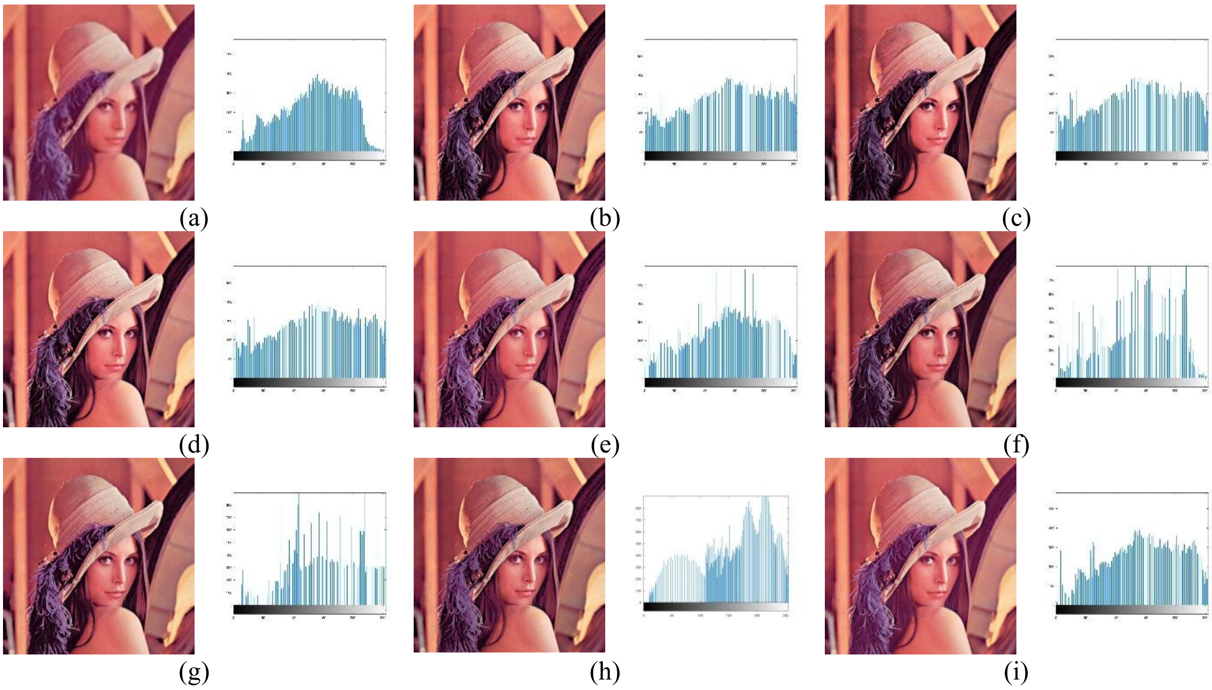

Figure 4. *Images and their histograms (a) Original Image (b) BBHE (c) DSIHE (d) MMBBHE (e) RMSHE (f) GA (g) ABC (h) OMHE (i) Proposed Approach*

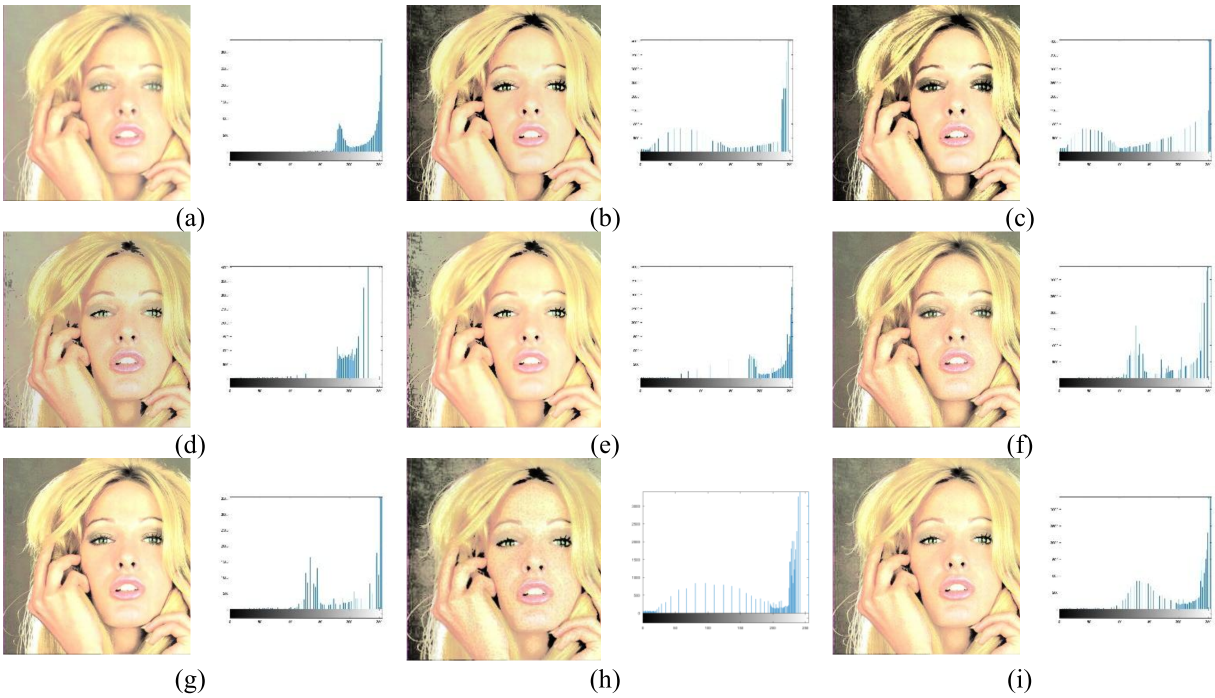

Figure 5. *Images and their histograms (a) Original Image (b) BBHE (c) DSIHE (d) MMBBHE (e) RMSHE (f) GA (g) ABC (h) OMHE (i) Proposed Approach*

4.4 Structural Similarity Index (SSIM)

Two images are compared using Structural Similarity Index to determine their visual similarity. It evaluates the luminance, contrast and correlation factors of the image [38]. Higher value of SSIM indicates the greater similarity between the images. It is computed as

$$SSIM = \frac{(2\mu_X\mu_Y + C_1)(2\sigma_{XY} + C_2)}{(\mu_X^2 + \mu_Y^2 + C_1)(\sigma_X^2 + \sigma_Y^2 + C_2)} \quad (21)$$

Here μ_X, μ_Y, aremean values and σ_X^2, σ_Y^2 are variance values of image X and Y. σ_{XY} is covariance of X and Y.

4.5 Entropy

Entropy is used to measure how rich an Image's information content is. It is defined as:

$$H = -\sum_{i=0}^{N-1} p(i)\, log_2 p(i) \quad (22)$$

where $p(i)$denotes the probability of intensity i and N is the number of intensity levels in the considered image. A higher entropy value means, output image has more detailed information content. If, entropy values computed for the enhanced image and input image are close, then we can say that the enhancement method has the capability to maintain the information content of the image [39].

V. Performance Evaluation

To show the effectiveness and robustness of the proposed method, we selected 17 miscellaneous color images with diverse features from the USC-SIPI Image Database. Results of the proposed method are compared with traditional contrast enhancement techniques – BBHE[3], DSIHE[4], MMBBHE[5], RMSHE[7], and also with some state-of-the-art metaheuristic based enhancement techniques –Genetic Algorithm[41], Artificial Bee Colony Algorithm[26], OMHE[42]. Enhanced images produced by all these methods have quantitatively evaluated by computing AMBE, PSNR, Entropy and SSIM values. In addition to this quantitative analysis, for qualitative analysis in context of human visual perception, the output images and their histogram plots produced by applying proposed and existing contrast enhancement techniques for five sample images are shown in Figures 1 to 5. By visually observing the results, it is clear that the output images produced by the proposed method are comparatively better contrasted and more natural-looking in almost all types of images. This proves that COMHE technique is robust for contrast enhancement of low-contrast color images compared to other conventional techniques as well as some ultra-modern metaheuristic techniques. While preserving the details of the input images, proposed technique also suppresses over enhancement.

Table 1. Computed AMBE values for enhanced images by Proposed technique and other methods for Comparative evaluation.

Test Images	**AMBE**							
	BBHE	DSIHE	MMBEBHE	RMSHE	GA	ABC	OMHE	Proposed technique
airplane	13.0757	5.5142	24.9135	12.3782	13.2468	45.9054	**1.1605**	12.0832
baboon	2.8954	0.5369	1.4165	1.2300	5.4121	43.8353	0.9035	**0.0376**
barbara	4.5526	2.8867	3.6039	4.7525	3.9150	24.1185	2.8391	**2.8225**
boats	19.0493	4.6856	**1.9515**	9.5015	3.1316	31.6465	8.2503	4.2247
cablecar	7.6855	3.6030	1.1365	3.9410	9.3153	20.7453	6.7435	**1.0351**
cornfield	4.4385	1.8941	2.2093	4.6979	7.7676	21.9408	2.0150	**0.1695**
flower	0.9522	**0.2298**	4.8468	2.6467	21.8628	9.4622	7.3219	13.3632
fruits	13.4872	9.0768	9.3280	8.7829	7.8922	45.1092	**5.6534**	7.3774
girl	15.6810	1.9230	7.9632	9.5681	2.8252	64.8608	2.7149	7.4147
goldhill	1.2894	5.8495	11.7685	1.3759	5.7112	20.3549	4.7980	**0.9090**
lenna	2.5439	5.3373	21.4544	2.3059	**1.6901**	34.2987	5.6200	3.8477
monarch	2.3049	0.3030	4.5054	**0.1756**	12.6141	37.0455	9.5766	2.9774
pens	6.3598	3.5238	10.8170	**0.0103**	3.4197	51.3406	4.6092	4.7612
pepper	7.7692	**2.5441**	14.1314	8.8595	9.1063	46.7046	9.4344	6.7298
soccer	12.7020	7.7657	7.4455	4.9610	1.1062	48.7963	4.6687	**0.5862**
tiffany	**3.1744**	10.8713	40.7510	7.9527	24.9408	32.1951	16.5779	20.5648
yacht	2.5685	2.2910	1.5091	7.7259	8.2531	51.5544	**0.6474**	2.3936

Table 2. Computed PSNR values for enhanced images by Proposed TECHNIQUE and other methods for comparative evaluation.

Test Images	PSNR							
	BBHE	DSIHE	MMBEBHE	RMSHE	GA	ABC	OMHE	Proposed technique
airplane	11.0192	10.2968	9.6599	14.0484	17.3204	11.1952	**18.4882**	18.3933
baboon	14.0094	14.0989	14.2420	17.3698	16.3777	11.6535	18.5666	**18.6988**
barbara	12.5909	12.6430	12.7633	16.0609	15.1139	12.6705	17.4747	**17.4791**
boats	12.3815	12.3639	12.4215	15.8527	16.8914	11.5891	14.7254	**17.8687**
cablecar	14.3526	14.4508	14.6435	15.7752	15.8118	15.4183	**18.5465**	18.0600
cornfield	13.6260	13.6341	13.7089	16.3744	16.0333	16.9131	**18.5678**	18.3053
flower	13.2968	13.3432	13.4226	15.5101	13.3591	10.8663	**17.0620**	16.4716
fruits	12.5539	12.6562	12.7833	15.7643	**17.3270**	11.2753	16.3193	16.9135
girl	12.8049	12.5965	12.4737	16.0579	18.0208	8.9698	17.9844	**18.7841**
goldhill	12.5413	12.4375	12.3830	16.1227	15.2025	13.5432	15.9765	**16.1377**
lenna	13.1503	12.8133	12.1901	16.0215	**16.3214**	12.7185	13.8752	15.5100
monarch	12.4340	12.5119	12.5845	16.2570	15.9573	12.8041	16.2646	**18.2259**
pens	12.7792	12.6420	12.5893	16.1304	15.7132	9.3715	16.0122	**16.4797**
pepper	12.7058	12.4053	12.1133	15.9581	18.7109	12.0576	17.7821	**19.0112**
soccer	12.4087	12.5219	12.6395	15.6790	16.2201	10.7759	**17.8595**	17.4253
tiffany	11.4654	10.3735	8.8014	13.3526	15.9088	14.2843	16.0252	**16.6596**
yacht	12.0554	12.1170	12.2197	15.1350	13.9303	10.2942	14.0781	**16.4179**

Table 3. Computed ENTROPY values for enhanced images by Proposed approach and other methods for comparative evaluation.

Test Images	ENTROPY								
	Original Image	BBHE	DSIHE	MMBEBHE	RMSHE	GA	ABC	OMHE	Proposed technique
airplane	5.6286	7.2344	7.1827	7.0495	6.7259	6.4884	6.5857	6.9037	6.7427
baboon	6.6752	7.6896	7.6930	7.6778	7.2991	7.3769	7.4036	7.4088	7.4148
barbara	6.6392	7.8282	7.8111	7.7972	7.4572	7.4632	7.5709	7.4989	7.5127
boats	6.3174	7.6314	7.6500	7.6499	7.3087	7.1757	7.2561	7.5106	7.1820
cablecar	6.4146	7.5360	7.5932	7.6025	7.4877	7.1259	6.9427	7.3834	7.2650
cornfield	6.6585	7.6832	7.6980	7.6731	7.4255	7.4280	6.8526	7.3844	7.4065
flower	6.6273	7.7526	7.7395	7.7555	7.5642	7.2614	7.2474	7.4972	7.4537
fruits	6.4630	7.7091	7.6990	7.7006	7.3440	7.2515	7.2153	7.4315	7.3845
girl	6.4055	7.6591	7.6907	7.7027	7.3382	7.1139	6.9556	7.2142	7.2248
goldhill	6.5719	7.7437	7.7617	7.7659	7.2722	7.4243	7.1720	7.5525	7.5614
lenna	6.6672	7.6750	7.6815	7.6475	7.3884	7.3341	7.3396	7.6338	7.5055
monarch	6.4808	7.7186	7.7231	7.6883	7.3389	7.2830	7.1015	7.4242	7.3275
pens	6.5339	7.6826	7.7265	7.7344	7.2786	7.3844	6.9930	7.5401	7.4671
pepper	6.7092	7.6883	7.6686	7.6280	7.4106	7.2734	7.1602	7.4069	7.3188
soccer	6.5827	7.7062	7.7317	7.7104	7.4482	7.2747	7.3492	7.4012	7.4157
tiffany	5.9023	7.2298	7.3403	7.3633	7.0183	6.6641	6.6770	6.7728	6.7263
yacht	6.5714	7.7668	7.7567	7.7710	7.4309	7.4607	7.1311	7.6264	7.4853

Table 4. Computed SSIM values for enhanced images by Proposed approach and other methods for comparative evaluation.

Test Images	SSIM							
	BBHE	DSIHE	MMBEBHE	RMSHE	GA	ABC	OMHE	Proposed technique
airplane	0.5370	0.4252	0.3599	0.6118	0.8204	0.7941	0.7457	**0.8622**
baboon	0.7310	0.7316	0.7402	0.8277	0.8177	0.7144	0.8711	0.8777
barbara	0.6846	0.6838	0.6877	0.8095	0.7639	0.7283	0.8500	**0.8502**
boats	0.6906	0.6237	0.6062	0.7638	0.7922	0.6748	0.7372	0.8668
cablecar	0.6590	0.6684	0.6839	0.7054	0.8195	0.8116	0.7850	**0.8718**
cornfield	0.7845	0.7847	0.7921	0.8552	0.8482	0.8608	0.8965	0.8907
flower	0.7462	0.7461	0.7633	0.7920	0.6922	0.5963	0.8497	0.8410
fruits	0.7693	0.7633	0.7717	0.8318	**0.8632**	0.7695	0.8409	0.8563
girl	0.6315	0.5596	0.5276	0.7094	0.8170	0.7217	0.8236	**0.8322**
goldhill	0.6547	0.6587	0.6735	0.8283	0.7841	0.7626	0.7953	0.8123
lenna	0.7858	0.7631	0.7176	0.8347	0.8708	0.8344	0.7958	0.8656
monarch	0.7469	0.7547	0.7498	0.8633	0.8532	0.8565	0.8639	**0.9112**
pens	0.6543	0.6461	0.6567	0.8288	0.7916	0.6377	0.7857	0.8296
pepper	0.7705	0.7368	0.7057	0.8665	0.9291	0.8607	0.9058	**0.9321**
soccer	0.6715	0.6608	0.6657	0.7377	0.7878	0.7476	0.8467	0.8406
tiffany	0.6576	0.5762	0.3888	0.6558	0.8830	0.9058	0.7877	**0.9174**
yacht	0.6834	0.6850	0.6906	0.7989	0.7780	0.7900	0.7474	**0.8506**

Tables 1-4 show the comparison of results yielded by quantitative measures applied on the output images produced by different enhancement methods. A comparison of AMBE values in Table 1 shows that the proposed approach outperforms the other enhancement methods by producing minimum values in majority of sample images. It proved that the proposed COMHE method has succeeded in better preserving the mean brightness of input images as compared to other methods. Table 2 shows that the COMHE enhanced images have higher PSNR values as compared to other methods in 10 out of 17 experiments. This means that COMHE approach proves its superiority in achieving better contrast enhancement. Computed Entropy values of enhanced images produced by different methods are shown in Table 3. Analyzing the entropy values, it is apparent that values computed for COMHE enhanced images are very close to the entropy values of their respective input images. It proves that the proposed method is successful in preserving the information content of input images. Upon analysing SSIM values (Table 4) computed for output images produced by different methods, it is apparent that proposed technique and DHE, both have higher values as compared to other methods. But DHE method did not perform good in terms of PSNR and AMBE values. Proposed technique has also gained highest average SSIM value for seventeen tested images. It certified that almost all the output images produced by proposed technique are structurally very similar to input images.

Comparisons of visual and quantitative results certified that proposed technique has performed relatively better in achieving contrast enhancement of images. It also restrict the over enhancement by the use of clipped histogram equalization. Proposed technique outperforms over other techniques in terms of visual quality assessment. It also shows supremacy against other methods in terms of image quality measures. Experiments proved that proposed method remain successful in achieving its main aim of contrast enhancement while preserving the mean brightness.

VI. Conclusion

This study proposed and tested a hybrid technique for contrast enhancement of color images called Clipped Optimized Multi-Histogram Equalization (COMHE). It is clear from experimentations that in the majority of the cases, the proposed technique produced more natural-looking contrast-enhanced images in contrast to other traditional as well as some state-of-the-art metaheuristic methods. It has also preserved the brightness and other details of input images. The proposed method produced maximum PSNR, SSIM and minimum AMBE values in most of the cases. However due to the use of optimization technique in finding the best solutions, computational complexity is higher than other traditional methods. It is purely dependent on the parameters used in ABC optimizer. These parameters are number of arguments in the solution to be optimized, number of artificial bees and number of iterations used in the ABC optimization. So, the limitation of proposed techniques is that these are not suitable for real time systems as the time complexity is comparatively high.

Accordingly, there is a scope of further work on the proposed methods to reduce computational time complexity.

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