Cuckoo Search with Search Strategies and Proper Objective Function for Brightness Preserving Image Enhancement[1]

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Abstract—Image enhancement can be formulated as an optimization problem where one parameterized transformation function is used for enhancement purpose. The proper enhancement significantly depends on two factors- fine tuning of the parameters of the corresponding parameterized transformation function and other one is the selection of a proper objective function. In this study a parameterized variant of histogram equalization (HE) has been used for enhancement purpose and to tune the parameters of that variant a modified cuckoo search (CS) with new global and local search strategies is employed. This paper also concentrates on the selection of a proper objective function to preserve the original brightness of the image. A new objective function has been developed by combining fractal dimension (FD) and quality index based on local variance (QILV). Visual analysis and experimental results prove that modified CS with search strategies outperforms the traditional and some other existing modified CS algorithms. Considering the image's brightness preserving capability, the proposed objective function significantly outperforms other existing objective functions.

Keywords: histogram equalization, brightness preservation, cuckoo search, search strategies, fractal dimension, QILV

DOI: 10.1134/S1054661817040046

1. INTRODUCTION

Image enhancement by preserving the original brightness is the main criterion in consumer electronics field. Image enhancement implies the application of different transformation functions. Usage of different transformation function depends on the objective of enhancement. Some popular spatial gray level image enhancement methods are histogram equalization (HE), power-law transformation, contrast stretching, and so on [1]. Among those methods, HE is very powerful and widely accepted method for its simplicity. But over-enhancement is the main demerit of traditional HE as it flattens the input histogram. Several modifications have been done over HE to overcome that problem. All the modified variants of HE have been developed based on the segmentation and modification of the histogram which are listed below.

Histogram Segmentation Based Methods

These methods divide the image into two or more parts based on some specific thresholds and then equalize each part individually [2–6]. Brightness preserving bi-histogram equalization (BBHE) was one of such variants [2, 3, 5]. In BBHE, histogram of the image was separated around its mean and then the two divided parts were equalized separately [2, 7]. In dualistic sub-image histogram equalization (DSIHE) proposed by Wan [2, 7], the procedure was same as BBHE, but the histogram was separated by median instead of mean [2, 5–7]. Chen and Ramli proposed minimum mean brightness error bi-histogram equalization (MMBEBHE) method [2, 5], in which the histogram was separated using a specified threshold which preserved the minimum mean brightness error between input and output images and then the two parts were equalized independently. This technique was better than BBHE and DSIHE, but it still suffered from deficiency of contrast and brightness [7]. The same authors presented recursive mean separate histogram equalization (RMSHE) method where the input image was separated recursively [2, 6, 7]. RMSHE method was better than BBHE as RMSHE could preserve the brightness efficiently and could give natural enhancement [2]. The disadvantage of RMSHE was its large time complexity for recursion. Dynamic histogram equalization (DHE) method was reported by Abdullah et al. [8], in which the histogram was separated recursively into several parts depending upon local minima of the corresponding histogram to

[1]The article is published in the original.

Received December 15, 2016

remove the presence of any dominating gray level. Zuo et al. [9] proposed range limited bi-histogram equalization (RLBHE) in which the division had been done by Otsu method and the equalization range was optimized by minimizing AMBE. Experimental results proved its supremacy over existing methods.

Histogram Modification Based Methods

All the pure segmentation based HE variants are unable to preserve of original brightness to some great extent. As, those techniques do not change the normalized histogram or the probability density function (PDF) before equalization step. In PDF modification based methods, proper weighting and thresholding techniques are applied to modify the original PDF [10–12]. Gain-controllable clipped histogram equalization (GC-CHE) had been proposed by Kim et al. [13] in which brightness preservation of the image crucially depended on the clipping factor on which the modification of the original histogram significantly depend. Wang and Ward proposed a fast and effective image and video contrast enhancement technique, known as weighted threshold HE (WTHE) [10], in which the PDF of the image was modified by weighting and thresholding prior to HE. The advantages of WTHE were the adaptivity of different images and the control over the enhancement. However, the manual selection of the values of the parameters was the only demerit of WTHE. Some hybrid methods are also proposed which are the combinations of segmentation and PDF modification [7, 11, 12]. Weighted clustering HE (WCHE) method presented by Sengee et al. [11] and recursively separated and weighted HE (RSWHE) proposed by Kim et al. [12]. The RSWHE method was the combination of the RMSHE and weighting technique. Shanmugavadivu et al. proposed a HE variants, optimised bi-histogram equalization (OBHE), which combined WTHE and BBHE [7] and the results proved its supremacy over existing methods. The optimal parameters of OBHE had been found by using particle swarm optimization (PSO). Therefore, it is clear from the literature that proper segmentation of the input histogram and its modification using thresholding and weighting play an important role in brightness preserving enhancement field. The only demerit of the most histogram modification based techniques is the selection of proper thresholding and weighting parameters. To find the optimal parameters nature inspired optimization algorithm can be employed [7] but, the proper enhancement depends on the selection of proper objective function and the optimization efficiency of the employed optimization algorithm. Section 3 clearly states that the efficiency increment of the traditional nature inspired optimization algorithms can be done by using proper modification techniques. Discussion about the proposed HE variant has been done in Section 2. Application of nature inspired optimization algorithms in image enhancement domain has been discussed in Section 3. Proposed modified CS algorithm has been explained in Section 4. In Section 5, experimental results prove the supremacy of proposed modified CS over existing CS variants.

2. PROPOSED HE VARIANT

The proposed methods combine the power of Otsu segmentation technique [14], WTHE, and CS. Otsu method has been used because proper segmentation significantly helps to preserve the original brightness of the image [9, 31]. The idea behind the proposed method isas follows.

1. Histogram of the image has been separated based on the threshold level.

2. Formulate the upper and lower weighing constraints to modify the lower and upper histogram.

3. Optimize the constraints by CS and its variants.

4. Apply HE method over lower and upper histogram independently.

5. Then unite the both to get an enhanced image.

Suppose the original image $f(i,j)$ has total W number of pixels within the dynamic range $[X_0, X_{L-1}]$. If L is the number of discrete gray levels, then the probability density function $PDF(X_k)$ of intensity level X_k of the image is given by:

$$PDF(X_k) = \frac{n_k}{W} \quad \text{for} \quad 0 \le k \le L-1, \tag{1}$$

where, n_k is the total number of pixels with intensity level X_k.

The pseudo-code of the proposed method is as follows.

1. The threshold X_T has been computed by Otsu method.

2. Compute PDFs for lower histogram i.e., PDF_L and upper histogram i.e., PDF_U.

3. Compute the mean of the PDF_L and PDF_U i.e., m_L and m_U, respectively.

4. Applying the following constraints to the PDF_L, computes weighted and thresholded PDF_L (PDF_{LWT}):

$$PDF_{LWT}(X_k) = \theta(PDF(X_k))$$
$$= \begin{cases} P_u & \text{if} \quad PDF(X_k) > P_u \\ \left(\dfrac{(PDF(X_k) - P_l)}{(P_u - P_l)}\right)^{r_l} \times P_u & \text{if} \quad P_l \le PDF(X_k) \le P_u \\ 0 & \text{if} \quad PDF(X_k) < P_l, \end{cases}$$

where, $P_u = v_l \times \max(PDF(X_k))$, in which, $0 < v_l \le 1$ and $P_l = 0.0001$, r_l is the power factor and $0 < r_l \le 1$.

5. Compute the mean of PDF_{LWT} i.e., m_{LWT}.

6. Find the mean error $m_{eL} = (m_{LWT} - m_L)$.

7. Add m_{eL} to PDF_{LWT}.

8. Find the cumulative density function of the PDF_{LWT}

$$CDF_{LWT}(X_k) = \sum_{i=0}^{k} PDF_{LWT}(X_i).$$

9. Equalization step of lower part:

$$f_L^o(X) = X_0 + (X_T - X_0).CDF_{LWT}(X).$$

10. Applying the following constraints to PDF_U.

Compute Weighted and thresholded PDF_U i.e., (PDF_{UWT}):

$$PDF_{UWT}(X_k) = \theta(PDF(X_k))$$

$$\begin{cases} h_u & \text{if} \quad PDF(X_k) > h_u \\ \left(\dfrac{(PDF(X_k) - h_l)}{(h_u - h_l)}\right)^{r_u} \times h_u & \text{if} \quad h_l \le PDF(X_k) \le h_u \\ 0 & \text{if} \quad PDF(X_k) < h_l, \end{cases}$$

where, $h_u = v_u \times \max(PDF(X_k))$ in which, $0 < v_u \le 1$ and $h_l = m_U$, r_u is the power factor and $0 < r_u \le 1$.

11. Compute the mean of PDF_{UWT} i.e., m_{UWT}.

12. Find the mean error $m_{eU} = (m_{UWT} - m_U)$.

13. Add m_{eU} to PDF_{UWT}.

14. Find the cumulative density function of the PDF_{UWT}

$$CDF_{UWT}(X_k) = \sum_{i=0}^{k} PDF_{UWT}(X_i).$$

15. Equalization step of upper part:

$$f_U^o(X) = (X_T + 1) + (X_{L-1} - (X_T + 1))CDF_{UWT}(X).$$

16. Output image: $f^o = f_L^o \cup f_U^o$.

In lower part, $P_l = 0.0001$ which is very low. It means that the contribution of such intensities is negligible for the enhancement process. For upper part, $h_l = m_U$. This step helps to control the mean brightness error between the input and output images. There are four parameters v_l, r_l, v_u, and r_u which control the enhancement process of the image. v_l and v_u do not let the high probable intensity values to dominate over the less probable intensity values. r_l and r_u control the rate of enhancement. When any of them approaches to 1, the proposed method behaves like traditional HE in the relevant part. When their values exceed 1 then over enhancement occurs.

Basically, the proper selection of these four parameters with diverse ranges has been formulated as optimization problem because finding the optimal values of those four parameters for different kind of images is not an easy task. Manual selection of the parameters values does not impart fully automation power to the proposed method. That's why CS and its variants with four objective functions have been employed in this study. The application of nature inspired optimization algorithms with different objective functions has been discussed below.

3. APPLICATION OF NATURE INSPIRED OPTIMIZATION ALGORITHMS IN IMAGE ENHANCEMENT FIELD

Recently nature inspired optimization algorithms are widely employed in image enhancement field to find the optimal parameters of different parameterized transformation functions by minimizing or maximizing the proper objective functions. Evolutionary algorithms such as genetic algorithm (GA) [15, 16] and differential evolution (DE) [17, 18] had been applied successfully in this domain. Pal et al. [15] developed one GA based image enhancement procedure by considering entropy, compactness, index area coverage and their combinations as objective functions. Hashemi et al. also proposed one GA based method but the objective function was developed based on edge information [16]. Coelho et al. [17] proposed one variant of DE algorithm by modifying the crossover (CO) rate and mutation factor (MF) with the help of chaotic sequence which outperformed the traditional DE. Dhal et al. [18] proposed two variants of DE algorithms by incorporating Lévy flight, chaotic sequence and population diversity information and the modified DEs outperform the traditional one. Both authors considered the combination of entropy and edge information as objective function. Particle Swarm Optimization (PSO) outperformed GA in image enhancement field by considering the same objective function as in [19, 20]. PSO based brightness preserving enhancement model with entropy as an objective function had been proposed by Shanmugavadivu et al. [7]. Chaotic sequence, Lévy flight and population making mechanism had been incorporated in Firefly Algorithm (FA) to increase its efficiency in image enhancement field [21]. The modified FA outperformed the FA via Lévy flight algorithm, PSO and GA by maximizing the combination of entropy, energy and contrast as objective function. Bat Algorithm (BA) was employed to enhance the standard as well as fingerprint images [22, 23, 29]. BA outperformed the

Table 1. Objective functions

Name	Quality parameters involved	References
OBJ1	Combination of entropy and edge information	[19]
OBJ2	Combination of entropy, contrast and energy	[21, 25]
OBJ3	Entropy	[7]
OBJ4	Combination of fractal dimension and QILV	....

PSO, Cuckoo search (CS) [23], FA [29] with respect to the same objective function as in [19]. Artificial Bee Colony (ABC) algorithm based edge image enhancement model had been proposed by Benala et al. [24] and ABC outperformed GA in this field. Chaotic sequence based ABC algorithm had also been applied for brightness preserving image enhancement domain [25]. The proposed ABC outperformed the traditional ABC and PSO by considering the same objective function as in [21]. CS algorithms with Lévy flight and chaotic sequence had been employed in image enhancement field [23, 26–28, 31]. One Cauchy mutation and inertia weight based CS had been proposed by Maurya et al. [30] which surmounted CS via Lévy flight and PSO algorithm by considering the same objective function as in [19]. Dhal et al. [31] proposed one modified CS algorithm in brightness preserving image enhancement domain which surpassed the modified CS proposed by Walton et al. [32], CS via Lévy flight [33] and PSO algorithm by considering the maximization of the objective function was same as in [21, 25]. In this study one modified CS algorithm has been developed by incorporating the proposed global and local search strategies which is discussed in Section 4. One novel objective function has been devised for brightness preserving image enhancement which is discussed in the next sub-section.

3.1. Objective Functions

This paper concentrates on the original brightness preservation of the image. Some objective functions already exist in literature. Some popular objective functions are given in the Table 1. This paper also concentrates on finding one proper objective function to preserve the original brightness. In this study one novel objective function has been proposed to accomplish that necessity. The proposed objective function is the combination of Fractal Dimension (FD) [34] and Quality Index based Local Variance (QILV) [35].

3.1.1. Fractal dimension (FD). The fractal is based on the self-similarity and the fractal dimensionis are the quantitative expression of the inherent dimension of the images [34]. The basic method of deriving fractal dimension is box-counting method. Box counting is making the whole dimension by figuring out the points within determined box or grid. Mathematically, FD is computed using the following formula:

$$D = \frac{\log N_{\mathrm{r}}}{\log\left(\frac{1}{r}\right)}, \tag{2}$$

where D is the fractal dimension. Maximum and minimum intensity for each box (2 × 2) are obtained to sum their difference, which gives the N and r as follows:

$$r = \frac{s}{M}, \tag{3}$$

where $M = \min(R, C)$, s denotes scale factor, R and C denote the number of rows and number of columns respectively when the grid size gets doubled, R and C reduces to half of its original value and above procedure is repeated iteratively until $\max(R,C)$ is greater than 2. Linear regression model uses to fit the line from plot $\log N$ vs. $\log(1/r)$ and the slope gives the FD as:

$$\log N_r = D\log\left(\frac{1}{r}\right). \tag{4}$$

3.1.2. Quality index based on local variance (QILV). QILV is used to measure the structural information of the image [35]. A great amount of the structural information of an image is coded in its local variance distribution. Local variances features of an image can help to compare two images properly. The local variance of an image I is defined as $Var(I_{i,j}) = E((I_{i,j} - \overline{I_{i,j}})^2)$, being $\overline{I_{i,j}} = E(I_{i,j})$ the local mean of the image. It may be estimated using a weighted neighbor-hood $\eta_{i,j}$ pixel under analysis with respective weights ω_p as:

$$Var\left(I_{i,j}\right) = \frac{\sum_{p\in\eta i,j} \omega_p (I_{i,j} - \overline{I_{i,j}})^2}{\sum_{p\in\eta i,j} \omega_p}; \qquad \overline{I_{i,j}} = \frac{\sum_{p\in\eta i,j} \omega_p I_p}{\sum_{p\in\eta i,j} \omega_p}. \tag{5}$$

Table 2. Initial population generation in different variants

Variants	∂ Generation	Population size taken	Year	Reference
CS	Uniform distribution	30	2010	[33]
Modified CS (MCS)	Uniform distribution	30	2011	[32]
Modified CS version 2 (MCS2)	Logistic equation	30	2016	[31]
Self-adaptive CS (SACS)	Uniform distribution	30	2014	[38]
Proposed CS	Logistic equation	30	....	....

The estimated local-variance of the image will be used as a quality measure of the structural similarity between two images. The mean of the local variance μ_{V_I} is estimated as:

$$\mu_{V_I} = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N} Var\left(I_{i,j}\right). \quad (6)$$

The (global) standard deviation of the local variance is defined as:

$$\sigma_{V_I} = \left(\frac{1}{MN-1}\sum_{i=1}^{M}\sum_{j=1}^{N}\left(Var\left(I_{i,j}\right)-\mu_{V_I}\right)^2\right)^{\frac{1}{2}}. \quad (7)$$

Finally, the covariance between the variances of two images I and J is defined as:

$$\sigma_{V_I V_J} = \frac{1}{MN-1} \times\sum_{i=1}^{M}\sum_{j=1}^{N}(Var(I_{i,j})-\mu_{V_I})(Var(J_{i,j})-\mu_{V_J}). \quad (8)$$

Quality index based on local variance (QILV) between two images I and J as follows:

$$\mathrm{QILV}(\mathrm{I},\ \mathrm{J}) = \frac{2\mu_{V_I}\mu_{V_J}}{\mu_{V_I}^2+\mu_{V_J}^2}\cdot\frac{2\sigma_{V_I}\sigma_{V_J}}{\sigma_{V_I}^2+\sigma_{V_J}^2}\cdot\frac{\sigma_{V_I V_J}}{\sigma_{V_I}\sigma_{V_J}}, \quad (9)$$

where $0 < \mathrm{QILV} \le 1$.

The first term of QILV equation carries out a comparison between the mean of the local variance distributions of both images. The second one compares the standard deviation of then local variances. The third term is the one to introduce spatial coherence. To avoid some computational problems with small values, some constants may be added to every term in equation.

Fractal dimension (FD) measures the roughness of the image. It was reported that local variance distribution gives the information about the structure of the image [36]. If QILV increases then the structural information of the enhanced image is preserved. Therefore, In order to perform the proper enhancement, the combination of FD and QILV is taken as objective function.

The objective function is defined as:

$$fit\left(v_l,\ r_l,\ v_u,\ r_u\right) = \left\{\exp(\mathrm{FD}) + \exp(\mathrm{QILV})\right\}, \quad (10)$$

where, $fit(.)$ is the objective function. FD and QILV represent the fractal dimension and quality index based on local variance of the corresponding image respectively; exp is the exponential operator. Therefore, from the definition of the objective function it can be easily verified that if the proposed objective function is maximized then the FD and QILV of the corresponding image are maximized i.e., the structural information and original brightness of the images are preserved. So, the optimization problem has been defined as:

$$\{v_{l0}, r_{l0}, v_{u0}, r_{u0}\} = \arg[\max_{v_l, r_l, v_u, r_u}\{fit(v_l, r_l, v_u, r_u)\}]. \quad (11)$$

3.1.3. Normalized fitness value. The normalized fitness value of each solution has been calculated by the following expression.

$$fit_N^t\left(X_i\right) = \frac{fit^t\left(X_i\right)}{fit\left(X_{gbest}\right)};\quad 0 < fit_N^t\left(X_i\right) \le 1, \quad (12)$$

where $fit_N^t\left(X_i\right)$ is the normalized fitness value of the solution X_i at iteration number *t*.

4. CUCKOO SEARCH (CS) AND ITS VARIANTS

CS via Lévy flight is a population based powerful metaheuristic algorithm [33]. To increase its efficiency, some modifications have been done. The different variants have been summarized in Table 2. The methodology to create the initial population of different variants is given below.

4.1. Creation of Initial Population

The initial population is usually created randomly. The equation of standard method is given below:

$$x_i = low + (up - low) \times \partial \quad (13)$$

where x_i is the *i*th individual; up and low are the upper and lower bound of the search space of objective function; ∂ is the random variable that belongs to [0, 1].

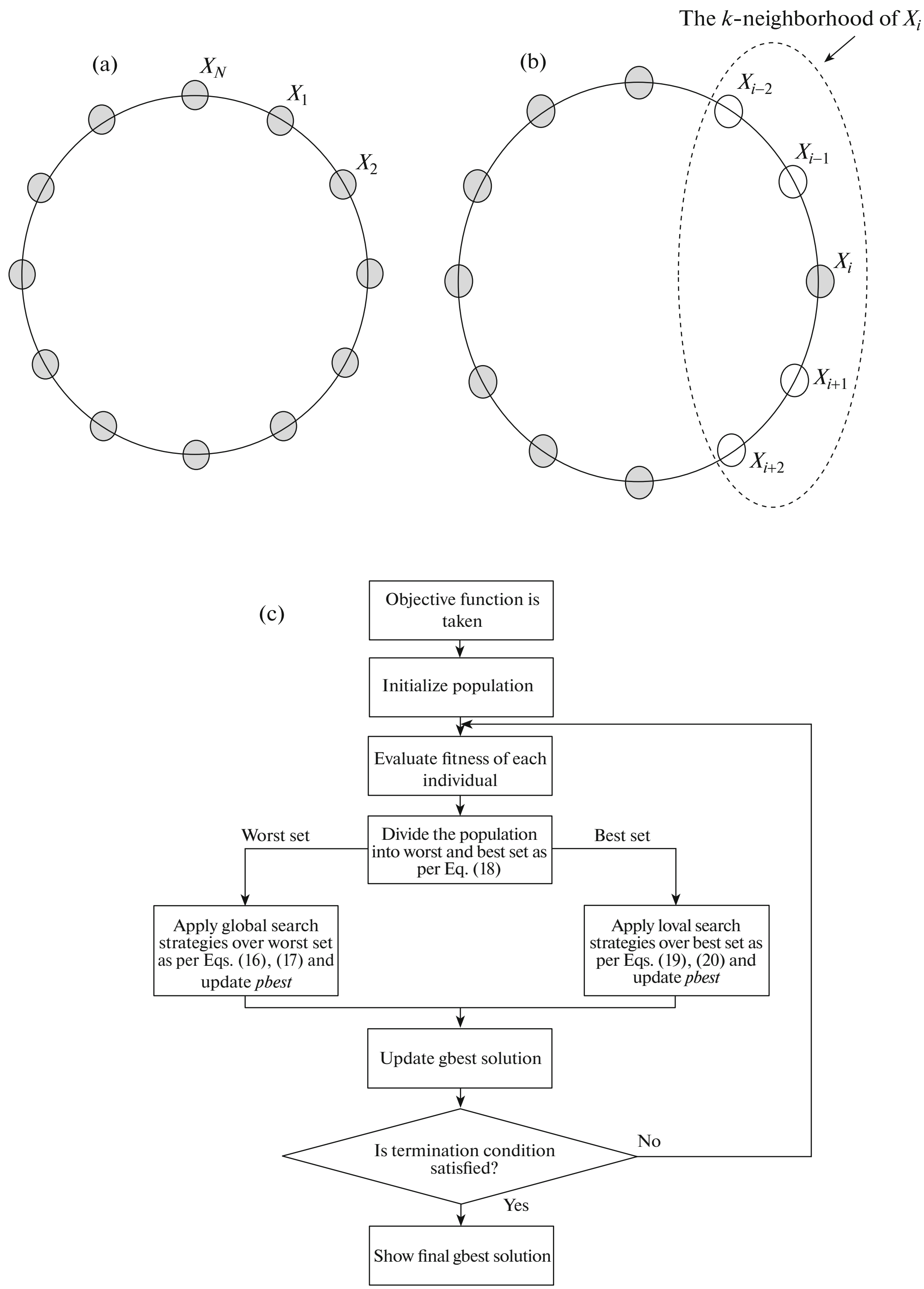

Fig. 1. (a) Circle topology; (b) k-neighborhood of ith individual and $k = 2$; (c) flowchart of the proposed CS algorithm.

If the initial population carries a great variance then it helps to restrict the premature convergence of the algorithm. Average population diversity is good when is generated using logistic equation which is one well known chaotic sequence generator [31]. In literature, has been generated by different techniques which are summarized in Table 2. Figure 9 reveals that logistic equation based initial population carries better solution than uniform distribution based population.

4.2. Cuckoo Search via Lévy Flight Algorithm

(1) Objective function has been taken.

(2) Initialize the population of cuckoos, $X = \{X_i | i = 1,2,3,\dots N\}$, where N is the number of cuckoos and X_i is the ith cuckoo.

(3) Gets a random cuckoo or solution by modifying the parameters using Lévy flight

$$X_i^{t+1} = X_i^t + \alpha \times \text{Lévy } (\lambda),$$

here, $\alpha = 0.8$ has been assumed.

(4) Evaluate its quality or fitness value (fit_i) of X_i.

(5) Choose a nest with another solution among n randomly and say this solution is j.

(6) Compare the two fitness values.

(7) If $fit_i > fit_j$ then replace X_j by X_i.

Otherwise do nothing.

(8) According to fitness fit_i of solution X_i, probability value p_i is calculated as follows:

$$p_i = fit_i / Max_{\forall i}(fit_i).$$

(9) Worst nests with probability value (p_i) is less than one specific threshold $(t_h = 0.6)$ are abandoned and new solutions (X_l) are generated using Lévy flight around the abandoned solutions (X_k).

If $fit_l > fit_k$ then replace X_k by X_l.

Otherwise, do nothing.

(10) Find the global best solution.

(11) Processes 3–10 are repeated until the stopping criterion.

4.3. Demerits of CS via Lévy Flight

The traditional CS algorithm is very simple algorithm in terms of number of parameters. But there are some demerits of traditional CS algorithm. These are given below.

a. There is no communication and sharing of information between solutions.

b. Guidance of global best (*gbest*) and particle best (*pbest*) are not present in traditional CS.

c. Only Lévy flight with a fixed step size has been used for global as well as local search. It does not show ergodicity behavior. Appropriate step size for diversification and intensification techniques plays great role in any metaheuristic algorithm.

To overcome those problems, modifications have been done on CS which are explained below.

4.3.1. Appropriate step size for Lévy flight. The fixed step size problem of Lévy flight has been surmounted by the following solution's fitness based step size. The strategy has been discussed as follows:

$$\text{Step Size } (SS_i^t) = \left| \frac{Fit_{gbest} - Fit_i^t}{\max\left(Fit_{gbest}, Fit_i^t\right)} \right|, \qquad (14)$$

where Fit_{gbest} is the fitness value of global best solution up to generation number t. Fit_i^t is the fitness value of ith individual at generation number t. It is easily understood that $(0 \le SS \le 1)$.

From the Eq. (14) it is clear that *SS* strictly depends on the fastness of convergence of the solution to the global best solution. It is also clear that *SS* performs the main criteria of any metaheuristic algorithm that the step size is be decreased or increased depending upon whether the solution is good or bad very well. Hence *SS* may be called as *Fitness-based Step-size.*

4.3.2. Removal of guidance and communication problems. In this study two global and two local search strategies have been developed to increase the efficiency of the traditional CS algorithm. The methodologies for developing those strategies have been explained below:

a. Topology Structure among Individuals

Topology structures among individual effect the efficiency of the algorithm. Kennedy proposed four topology structures which are circle, wheel, star and random [39]. It has been reported that PSO with small neighborhood perform better for complex problems [40]. But with large neighborhood it can be better for multi-modal problems because large neighborhood increases the chance of escaping from local optima [40]. In this study circle topology has been used as it is successfully already employed for DE [41], PSO [40], and FA [42]. Assume that all N individuals are organized in a circle topology according to their indices. For example, X_N and X_2 are two immediate neighbor of X_1. Figures 1a, 1b represent the circle topology with 12 individuals. Based on circle topology k-neighborhood concept has been proposed by Das et al. which is discussed below.

b. k-Neighborhood Concept

Das et al. [41] proposed k-neighborhood concept to balance between exploration and exploitation. Balance between exploration and exploitation plays a significant role in any swarm based algorithm. Exploration indicates the capability of global search or to explore the every region of the feasible search space. On the other hand exploitation means the ability of local search which accelerates the algorithm to converge into a nearly optimal solution. For each individual X_i, its k-neighborhood consisting of $2k+1$ cuckoos i.e., $X_{i-k},\ldots,X_i,\ldots,X_{i+k}$, where k is an integer $0 \le k \le \frac{N-1}{2}$. Figures 1a, 1b represent the k-neighborhood for X_i where $k = 2$. The concept of k-neighborhood is successfully applied to increase the efficiency of DE, PSO, and FA. Neighborhood based mutation operator has been used by Das et al. [41] to increase the efficiency of traditional DE algorithm. Wang et al. [40] proposed two global and one local search strategies with the help of k-neighborhood concept to increase the efficiency of the PSO algorithm. Same strategy has been employed for FA by Wang et al. [42].

c. Chaotic Sequence

Recently, chaotic sequence has been incorporated with nature inspired algorithms to enhance their capability [21, 25, 31, 43–45]. Chaotic sequences are used in metaheuristics algorithms for three purposes 1. To generate random numbers 2. To generate inertia weight 3. To perform the local search. Chaotic local search is helpful for finding the promising solution [46, 47]. Chaotic inertia weight helpful to maintain the balance between exploitation and exploration [48]. In this study the chaotic sequence based inertia weight and local search have been successfully applied. There are several chaotic generators like logistic map, tent map, gauss map, sinusoidal iterator, lozi map, chua's oscillator, etc. [49]. Among those logistic equation is used in this paper as it carries greater variance and outperforms others [31, 46]. The equation of logistic map is given below:

$$L_{m+1} = aL_m(1 - L_m), \tag{15}$$

a is a control parameter and $0 < a \le 4$, L_m is the chaotic value at mth iteration. The behavior of the system mostly depends on the variation of a. Value of a is set to 4 and L_0 does not belong to {0, 0.25, 0.5, 0.75, 1} otherwise the logistic equation does not show chaotic behavior [17].

In this study k-neighborhood concept and chaotic sequence have been used to build the local search strategies. The search strategies have been explained below.

4.3.3. Global search strategies (GSS). Two global search strategies have been developed based on Cauchy mutation, Lévy mutation and the guidance of global best solution. The strategies are explained below.

a. Global search strategies 1 (GSS1):

$$X_i = w.X_i + (X_{gbest} - X_i).\theta + SS.levy(). \tag{16}$$

This global search strategy has been developed based on the guidance by global best solution (X_{gbest}) and Lévy distribution [33] based mutation. The modification of the solution X_i greatly depends on X_{gbest}. But if X_{gbest} is trapped in a local minimum then the solution X_i will rapidly move to that local minimum and $(X_{gbest} - X_i)$ takes small value. Finally X_i converges to the minima $(X_i = X_{gbest})$. To overcome that problem Lévy mutation has been added to this strategy. Lévy mutation very powerful and plays significant role in traditional CS algorithm [33]. It also helps to modify the solution X_{gbest} as for global best solution the factor $(X_{gbest} - X_i)$ becomes zero. Fitness based step size (SS) has been multiplied to control the mutation. $\theta = \frac{2}{1+\sqrt{5}}$ i.e., the inverse value of the golden ratio. Inverse value of golden ratio has been taken as it performs better than random fraction [50]. w is serving as inertia weight which is generated by the chaotic sequence (logistic equation). w helps to balance between exploration and exploitation [48].

b. Global search strategies 2 (GSS2):

$$X_i = w.X_i + (X_{best} - X_{worst}).\theta + SS.Cauchy\,(). \tag{17}$$

X_{best}, X_{worst} are the randomly selected solutions from *best* and *worst* set respectively. In GSS1, if $X_i = X_{gbest}$ then only Lévy mutation works and no information sharing will occur. To overcome that problem GSS2 has been formulated. GSS2 is formulated by combining both the information sharing and Cauchy distribution based mutation. Here two individuals have been chosen from the two direction of the whole population. At first, the whole population is divided into two set called *best* and *worst* according to their normalized fitness value (see Section 3.1.3) by the following rule:

$$\begin{aligned} &\text{if } \{fit_N^t(X_i) \ge \theta\} \quad \text{then} \quad X_i \in \text{best}, \\ &\qquad\qquad\qquad\qquad\quad \text{else} \quad X_i \in \text{worst}. \end{aligned} \tag{18}$$

Then the two individuals are selected from two different set because this strategy helps to increase the global search efficiency [40, 55]. In GSS2, Cauchy mutation is another vital part. It has been reported that the Cauchy mutation is significantly helpful when the global optimum is adequately far away from the current search point [40, 51]. θ is same as before.

4.3.4. Local search strategies (LSS). Local search strategies are beneficial when large jumps move the solution into a poor position and finding the global optimum is a step by step fine tuning procedure. In this study, two LSS have been developed based on chaotic sequence and k-neighborhood concept.

a. Local search strategies 1 (LSS1)

$$X_i = w.X_i + (X_{pbest} - X_i)\theta + (X_p - X_q)\theta. \quad (19)$$

This local search strategy has been developed based on the previous best position i.e., X_{pbest} of the corresponding solution and the k-neighborhood concept. Guidance by the previous best position of the solution helps to increase the local search ability [40]. Here, X_p and X_q are the k-neighborhood of the X_i solution, $p,q \in [i-k, i+k]$ and $p \neq q \neq i$, $\theta = \frac{2}{\sqrt{5}+1}$. It is reported that this k-neighborhood based searching strategy is significantly useful to perform local search [40–42].

b. Local search strategies 2 (LSS2)

$$X_i = X_i + SS.L_m. \quad (20)$$

Here, L_m is the chaotic sequence generated by logistic equation. In LSS2, the chaotic local search has been done as it helps to converge into global optima [31, 47, 48]. Chaotic sequence based CS outperforms the Lévy flight based CS in image enhancement field [31].

4.4. Proposed Cuckoo Search Algorithm

Based on those four strategies one modified CS has been proposed here. The pseudo-code of that CS variant is given below.

Step 1. Objective function has been taken.

Step 2. Initialize the population of cuckoos $X = \{X_i | i = 1,2,3,\ldots N\}$ where, N is the population size and X_i is the ith cuckoo.

Step 3. Initialize the *pbest* and *gbest* solutions.

Step 4. Evaluate fitness value (fit_i) of each X_i.

Step 5. Divide the population into two set *best* and *worst* according to their fitness values (see Section 4.3.3b).

Step 6. For all solutions belong to the *worst* set are modified by the proposed two global search strategies.

/ Application of Global search strategies */*

a. Let by using two GSS (Eqs. (16) and (17)) two trail solutions X_i^1 and X_i^2 are generated.

b. Calculate fitness values of each trial solution and select the best one and store in X_b.

Then replace X_i by X_b.

c. Update *pbest* value of ith solution by the best of X_i and X_b.

Step 7. For all the solutions belong to the *best* set apply the local search strategies.

/ Application of local search strategies */*

a. Pick one nest randomly say X_j.

b. Apply LSS and generate trial solutions.

/ Application of Local search strategies */*

Suppose, by using two LSSs (Eqs. (19) and (20)) two trail solutions X_j^1 and X_j^2 are generated.

Calculate fitness values of each trial solution and select the best one and store in X_l.

Then replace X_j by X_l.

c. Update *pbest* value of jth solution by the best of X_i and X_l

Step 8. Update the global best (*gbest*) solution by choosing the best *pbest* solution.

Step 9. Repeat steps 4–8 until the stopping criterion. Figure 1c represents the flowchart of the proposed CS algorithm.

4.4.1. Stopping condition of CS and its variants. The Stopping condition has been selected experimentally. The two stopping criteria are.

1. It stops the iteration when the fitness value of the global best solution does not change significantly (difference is less than 10^{-4}) for continuous 10 iterations for a specific image.

2. The maximum limit of iterations number is 250.

4.5. Quality Parameters

4.5.1. Absolute mean-brightness error (AMBE). *AMBE* is basically used to measure the degree of the brightness preservation [31]. Let input image is f and output image is G then the AMBE is calculated as:

$$AMBE = |Mean_f - Mean_G|, \quad (21)$$

where $Mean_f$ and $Mean_G$ are the mean of the input and output image, respectively. If the value of AMBE is low then the brightness preservation is better.

4.5.2. Peak-signal to noise ratio (PSNR). This statistical metric is also used to measure the performance of the image enhancement methods. PSNR is the ratio between the maximum possible power of the signal and the power of the noise [54]. It is actually distortion metric which is crucially depends on mean-squared error (MSE). MSE defined as:

$$MSE(f,G) = \frac{\sum_{i=0}^{N-1}\sum_{j=0}^{M-1}[f(i,j) - G(i,j)]^2}{M \times N}, \quad (22)$$

where f and G are the input and output image respectively; M and N are the number of rows and columns of the image.

The PSNR is calculated as follows:

$$\mathrm{PSNR}(f,G) = 10\log_{10}\left(\frac{(L-1)^2}{MSE(f,G)}\right), \tag{23}$$

L is the number discrete grey level. For 8 bit image it is 256.

If the value of PSNR is increased then contrast of the image is also enhanced and absolute mean brightness error (AMBE) is also reduced to some extent.

5. EXPERIMENTAL RESULTS

For each image each optimization algorithm has been run 10 times and the enhanced image with maximum fitness value has been taken into consideration.

5.1. Results of Traditional CS Algorithm with Different Objective Functions

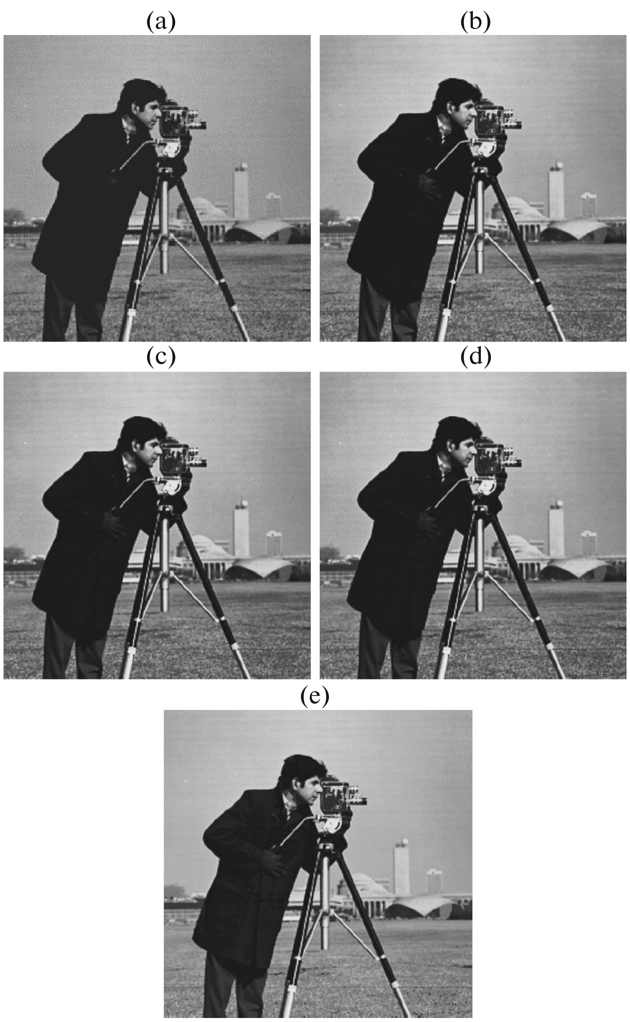

Fig. 2. Cameraman image: (a) original, (b) result of OBJ4, (c) result of OBJ3, (d) result of OBJ2, (e) result of OBJ1.

5.2. Results of MCS1 with Different Objective Functions

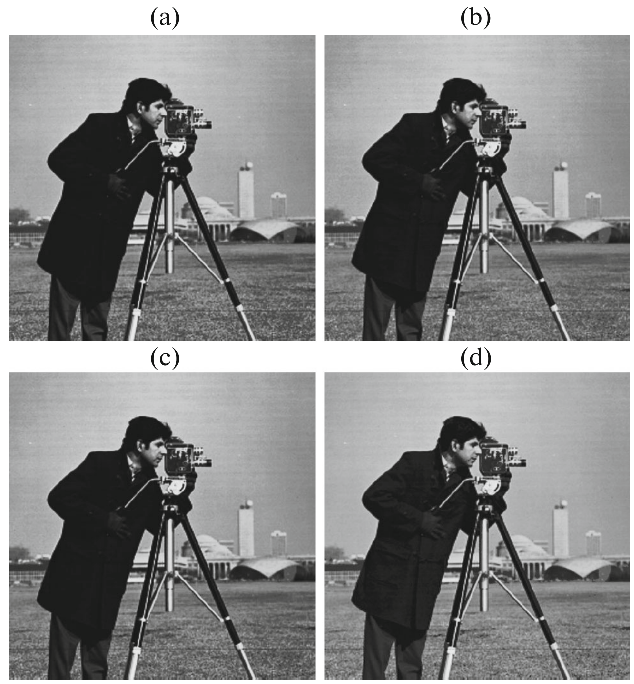

Fig. 3. (a) Result of OBJ4, (b) result of OBJ3, (c) result of OBJ2, (d) result of OBJ1.

5.3. Results of MCS2 with Different Objective Functions

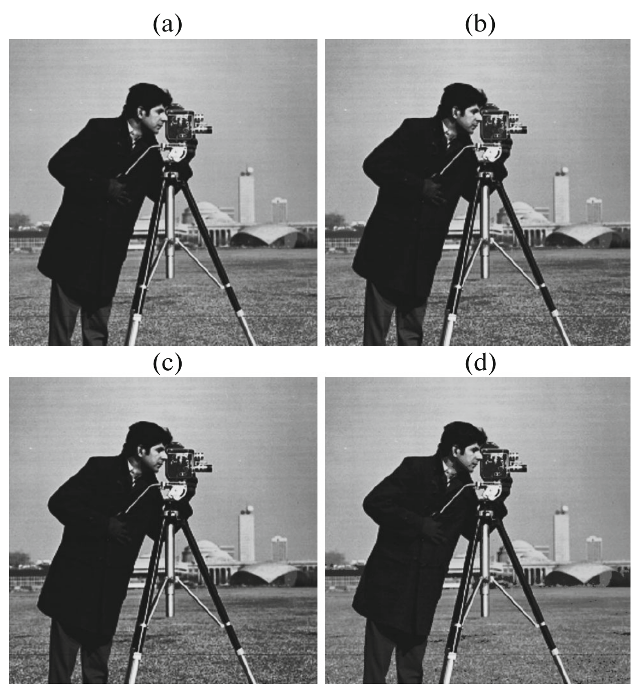

Fig. 4. (a) Result of OBJ4, (b) result of OBJ3, (c) result of OBJ2, (d) result of OBJ1.

5.4. Results of Proposed CS with Different Objective Functions

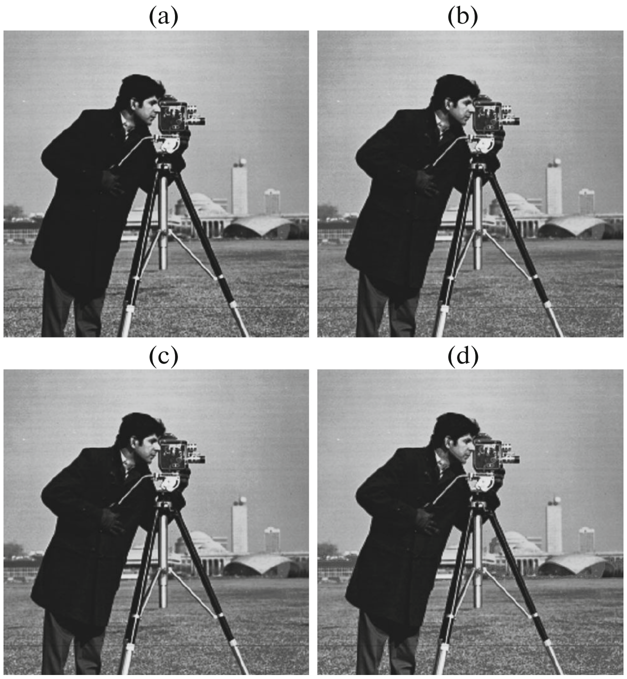

Fig. 5. (a) Result of OBJ4, (b) result of OBJ3, (c) result of OBJ2, (d) result of OBJ1.

5.5. Results of SACS with Different Objective Functions

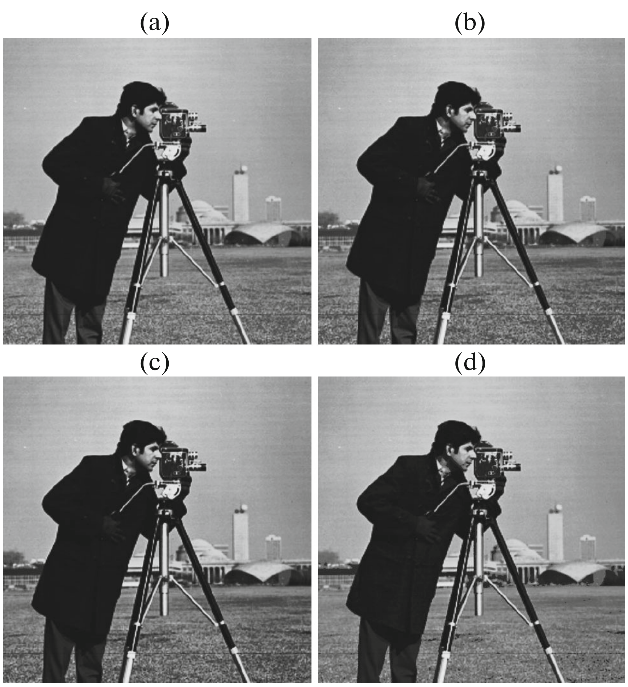

Fig. 6. (a) Result of OBJ4, (b) result of OBJ3, (c) result of OBJ2, (d) result of OBJ1.

Figures 2 to 6 represents the enhanced cameraman images corresponding to each CS variant with each mentioned objective function. From Figs. 2e, 3d–5d, it is clear that OBJ1 produce enhanced images with washed out effect and there is losing of detailed information. Table 3 states that average AMBE value is also greater for OBJ1. Figures 2c, 2d clearly states that OBJ3 and OBJ2 sometimes enhanced the images with some extra smoothness and loose the sharpness of the image i.e., edge information. But from the Figs. 2b and 3a–6a, it is clear that OBJ4 always generates enhanced image with better visual effect and without any washed out effect. Table 3 and graphical analysis (see Section 5.10) also support the brightness preservation capability of OBJ4.

5.6. Analysis of the Brightness Preservation Property of the Objective Functions

The efficiency of the objective functions to preserve the original brightness has been measured by the following procedure.

1. The proposed CS algorithm has been executed 10 times for each image with each objective function individually.

2. AMBE values of the 10 enhanced images corresponding to step 1 has been measured.

3. The AMBE and fitness values of the two enhanced images corresponding to Step 2 are reported for each objective function in Table 4 which are:

a. enhanced image with lowest AMBE and its corresponding fitness value;

b. enhanced image with maximum fitness value and its corresponding AMBE.

Average AMBE of 10 enhanced images is also computed to measure the average brightness preservation ability of each objective function.

From the Table 3, it is clear that proposed objective function i.e., OBJ4 always gives minimum average AMBE values and always the values of the proposed objective function increases when AMBE value reduces. Table 4 represents the ranking of the objective functions by considering their original brightness preservation capability i.e., by computing the average AMBE over 100 images for each objective function with proposed CS algorithm.

5.7. Analysis of the Consistency of the CS and Its Variants

Consistency of the CS and its variants has been measured by maximizing the proposed objective function iteratively. Each variant has been executed 10 times for each image and the maximum fitness value (*Max Obj.*), minimum fitness value (*Min Obj.*), average fitness value (*Avg. Obj.*), and difference between *Max Obj.* and *Min Obj.* i.e., *Diff* for those 10 runs are recorded in Table 5.

Table 3. Values of the AMBE and objective functions

Obj. func.	Img.	Enhanced image with lowest AMBE value		Enhanced image with maximum fitness value		Avg. AMBE
		AMBE	obj.	AMBE	obj.	
OBJ1	Fig. 2a	8.867	1.6583	10.7744	1.6869	9.976
OBJ2	Fig. 2a	2.7784	19.6768	2.8884	19.6874	2.9867
OBJ3	Fig. 2a	5.8902	7.576	6.2944	7.603	6.1087
OBJ4	Fig. 2a	1.0469	8.719	1.0469	8.719	1.086

Table 4. Ranking of the objective functions based on brightness preservation ability

OBJ1		OBJ2		OBJ3		OBJ4	
rank	avg. AMBE	rank	avg. AMBE	rank	avg. AMBE	rank	avg. AMBE
4	9.972	2	2.9853	3	6.1055	1	1.079

Table 5. Consistency of the CS and its variants

Variants	Img.	*Max Obj.*	*Min Obj.*	*Avg. Obj.*	*Diff*
Proposed CS	Fig. 2a	8.719	8.674	8.7085	0.0450
MCS1	Fig. 2a	8.6444	8.356	8.4780	0.2884
MCS2	Fig. 2a	8.6792	8.497	8.5931	0.1822
SACS	Fig. 2a	8.6652	8.4811	8.5810	0.1841
CS	Fig. 2a	8.4777	8.006	8.2466	0.4717

Consistency represents the stability or the robustness of the algorithm. Here, it has been taken as the difference between *Max Obj*. and *Min Obj*. Therefore, the less difference represents better consistency. It can be seen from the Table 5 that the value of *Diff* less for the proposed CS algorithm for Fig. 2a and it is also true that proposed CS maximizes the objective function properly than the traditional and other existing CS variants in image enhancement field. The same methodology has been used for 100 images. Then the average difference (*AD*) over 100 images has been computed by the following equation:

$$\text{Average Difference}(AD) = \frac{1}{p}\sum_{i=1}^{p} Diff\,(X_i), \quad (24)$$

$$Diff\,(X_i) = [MaxObj\,(X_i) - MinObj\,(X_i)]; \quad p = 100,$$

where $MaxObj\,(X_i)$ and $MinObj\,(X_i)$ are the maximum and minimum objective function values over 10 iterations for *i*th image respectively and $Diff\,(X_i)$ is the difference between these two. The values *AD* for each CS variants have been given in Table 6 and their ranking is also done based on *AD*.

5.8. Analysis of the Quality Parameters and Objective Functions

Proposed CS and existing modified variants of CS have been tested over 100 images with stated four objective functions. The average values of AMBE, PSNR, QILV, and corresponding objective function values are recorded in Tables 7 to 10. From Table 7, it can be easily verified that maximization of OBJ1 does not imply that PSNR increases and AMBE decreases. In Table 7, AMBE and PSNR values of MCS2 and SACS are better than proposed algorithm but the objective function values corresponding to those algorithms are less than proposed one. The graphical analysis of brightness preservation ability of each objective function has been explained in Section 5.10. Theoretical analysis of the brightness preservation of the employed objective functions is done in Section 5.6.

Friedman ranking [56] of CS variants has been done in Table no. 11 based on their objective function maximization ability for comparing between multiple algorithms.

Table 6. Ranking and AD values of the CS variants according to consistency

Variants	Proposed CS	MCS1	MCS2	SACS	CS
Rank	1	4	2	3	5
AD	0.0587	0.2971	0.1923	0.1931	0.4792

5.9. Application for Color Images

In this study, proposed grey level image enhancement methodology is also applied in color image enhancement domain. Chien et al. [52, 53] proposed exact Hue-Saturation-Intensity (eHSI) model to enhance the color images. Any gray level contrast enhancement method can be successfully employed for color image by using eHSI model. eHSI model is a hue preserving model which has the capability to resolve the out-of-gamut i.e., the pixel values of output RGB image always lie within their respective intervals. Traditional HE was applied by the author for enhancement purpose [52]. But in this paper proposed HE variant with proposed CS

Table 7. Quality parameters of CS variants with OBJ1

Variants	Average OBJ1	Average AMBE	Average PSNR	Average QILV
Proposed CS	1.6867	9.972	24.627	0.9463
MCS1	1.6232	12.2051	23.1525	0.9394
MCS2	1.6454	8.3577	25.033	0.9487
CS	1.5982	13.4597	22.2937	0.9325
SACS	1.6481	8.6681	25.210	0.9466

Table 8. Quality parameters of CS variants with OBJ2

Variants	Average OBJ2	Average AMBE	Average PSNR	Average QILV
Proposed CS	19.6874	2.9853	25.6805	0.9485
MCS1	19.5581	5.4616	25.2761	0.9463
MCS2	19.625	5.5455	24.1658	0.9407
CS	18.5984	9.5558	22.7459	0.9168
SACS	19.4991	5.850	24.72	0.9398

Table 9. Quality parameters of CS variants with OBJ3

Variants	Average OBJ3	Average AMBE	Average PSNR	Average QILV
Proposed CS	7.603	6.1055	25.7672	0.9488
MCS1	7.5658	6.5308	25.2428	0.9432
MCS2	7.5338	6.0268	24.976	0.9443
CS	7.5145	5.8383	25.5525	0.9384
SACS	7.5698	6.6108	25.012	0.9441

Table 10. Quality parameters of CS variants with OBJ4

Variants	Average OBJ4	Average AMBE	Average PSNR	Average QILV
Proposed CS	8.719	1.079	27.4248	0.9553
MCS1	8.6444	2.9612	25.9187	0.9421
MCS2	8.6792	2.032	26.2869	0.9529
CS	8.4777	4.021	25.725	0.9463
SACS	8.6511	2.8601	25.9082	0.9407

$$\begin{bmatrix} r\\ g\\ b\end{bmatrix} \xrightarrow{RGBtoeHSI} \begin{bmatrix} eH\\ S\\ I\end{bmatrix} \xrightarrow{Ipart} \boxed{I \xrightarrow{method} I'} \rightarrow \begin{bmatrix} eH\\ S\\ I'\end{bmatrix} \xrightarrow{Inverse} \begin{bmatrix} r'\\ g'\\ b'\end{bmatrix}$$

Fig. 7. Block diagram of the color image enhancement scheme.

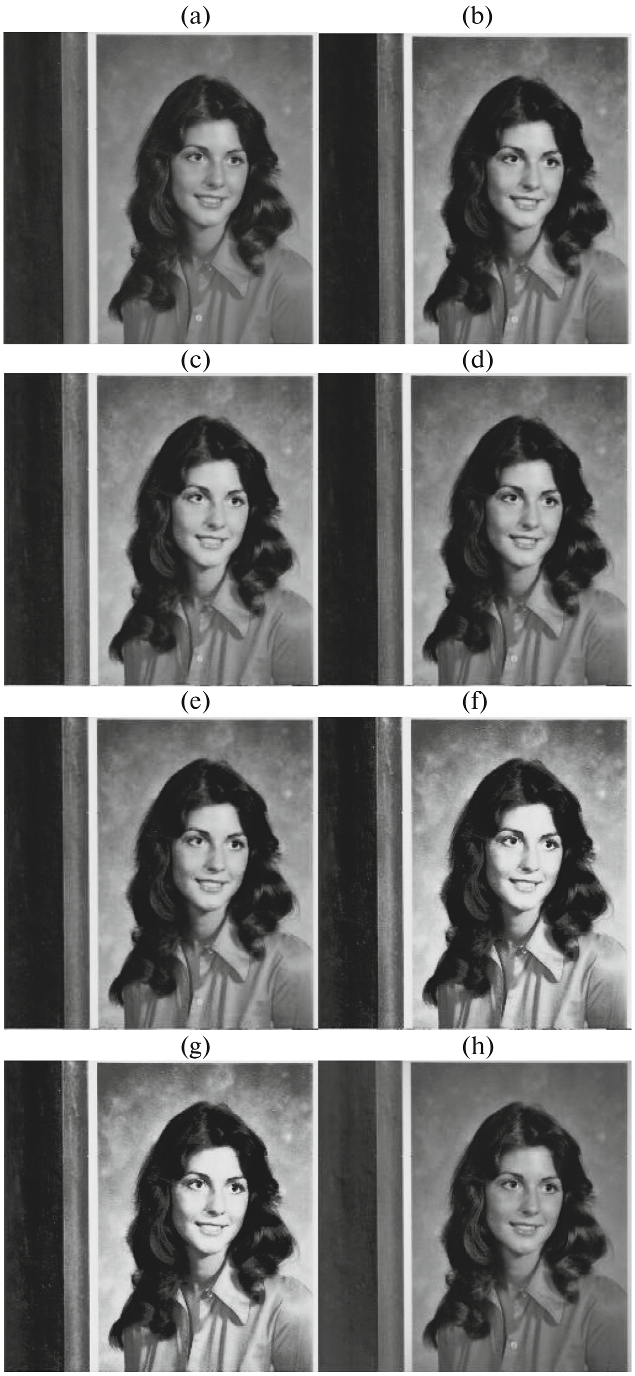

Fig. 8. Woman image: (a) original, (b) result of OBJ4, (c) result of OBJ3, (d) result of OBJ2, (e) result of OBJ1, (f) result of eHSI with HE, (g) result of Naik's model [58], (h) result of automatic color equalization (ACE) method [57].

and every objective function is employed to obtain a natural enhanced image. The flowchart of the enhancement process is as follows:

Visual analysis of the Fig. 8 reveals that proper and natural enhancement of color image occurs when proposed HE variant is applied with proposed CS and proposed objective function. That's why Fig. 8b is the best outcome and other enhanced results have some washed out t and over brightened effect. It can be easily conclude that proposed objective function plays an important role in natural color image enhancement domain. The enhanced results compare with popular automatic color equalization (ACE) [57] method and Naik's color image enhancement model [58]. Results prove that proposed methods outperform these both existing methods.

5.10. Graphical Analysis

Convergence of all CS variants with different objective functions in the case of *Cameraman* image has been given in Fig. 9. It is quite clear that proposed CS always outperforms other variants in terms of convergence speed. Figure 10 represents the changes of AMBE and PSNR with respect to the increasing values of four objective functions. When the values of OBJ4 increases, the values of AMBE always reduce and values of PSNR increase. But in the case of other objective functions these are not maintained. For proposed CS and MCS2, the initial population has been generated by using logistic equation and for others variants, uniform distribution is used. All the starting points of Fig. 9 reveal that logistic equation based population generation technique outperforms the uniform distribution based technique in terms of producing of better individuals. The fitness value of the initial *gbest* solution of the logistic equation based initial population is better than uniform distribution based *gbest*. The starting points of proposed CS and MCS2 always above the traditional CS, MCS, and SACS in Fig. 9.

5.11. Execution Time

The experiment has been done using MATLAB R2012b with x64-based PC using 100 images. The average execution times of different methods are given below.

Therefore, Table 12 reveals that the execution time of the proposed CS algorithm is far better than the existing CS variants.

6. CONCLUSION

In this paper, one modified CS with four global and local search strategies has been proposed in brightness preserving image enhancement domain. This study also concentrates to develop one hybrid parameterized HE variant with the help of histogram

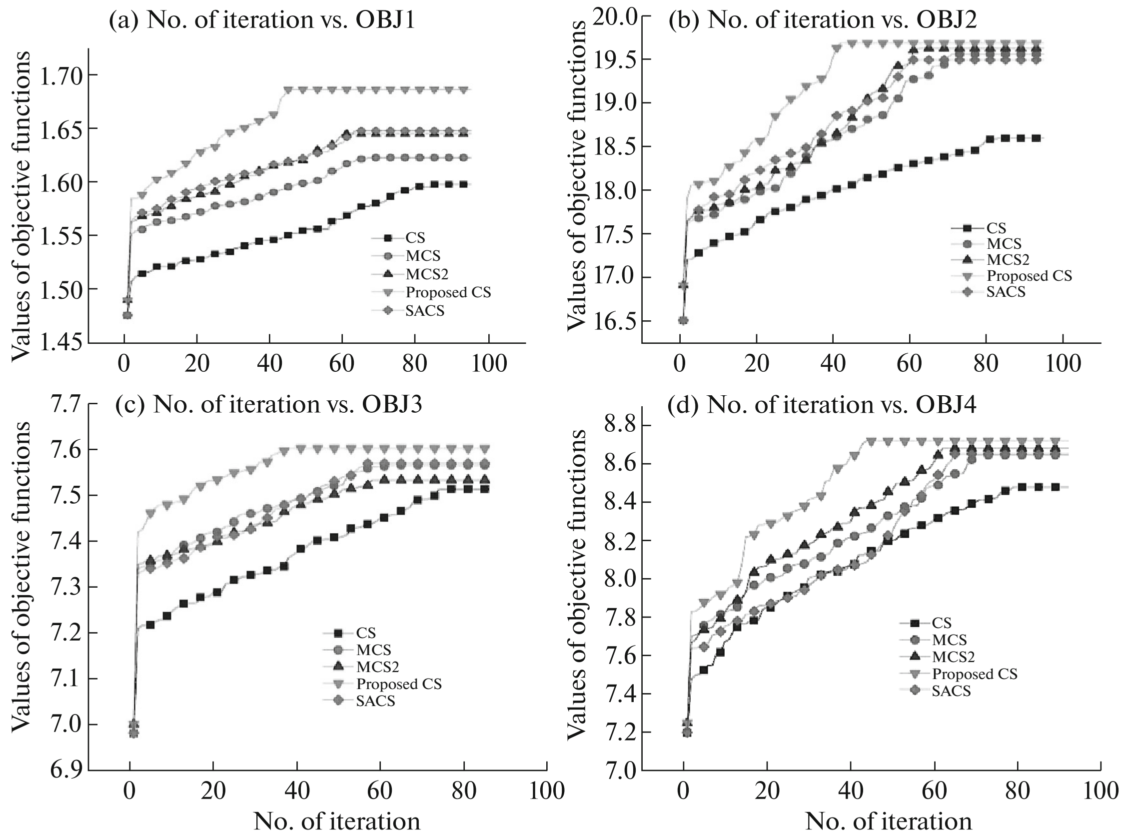

Fig. 9. Convergence curves of the traditional CS, MCS, MCS2, SACS, and proposed CS for different objective functions.

modification and segmentation to preserve the original brightness of the enhanced image. The brightness preservation ability of that proposed HE variant significantly depends on its associated four parameters. Those parameters have been optimized with the help of CS and its variants by maximizing the proposed objective function which is the combination of fractal dimension and QILV. It is proved in this study that the proposed objective function outperforms some existing and popular objective functions in terms to maintain the original brightness of the input image. Original brightness always preserved when the proposed objective is maximized. Two GSSs of the proposed CS have been developed based under the guidance of global best solution, chaotic inertia weight, Lévy and Cauchy distribution based mutation. Two LSSs are constructed based on chaotic local search, particle's previous best position (*pbest*) and *k*-neighbourhood concept in circle topology. GSSs and LSSs significantly help to explore and exploit the search space. Chaotic inertia weight facilitates to maintain the balance between the exploration and exploitation. The proposed CS with those search strategies gives better performance than the traditional CS and three other existing CS variants in terms of convergence speed, robustness and by maximizing the objective functions within less computational time. In future, the strategies can be applied to other metaheuristic algorithms and the proposed enhancement model can be applied in medical image enhancement domain.

Table 11. Friedman ranks

Objective function	Proposed CS	MCS	MCS2	SACS	CS
OBJ1	1	4	3	2	5
OBJ2	1	3	2	4	5
OBJ3	1	3	4	2	5
OBJ4	1	4	2	3	5
Average rank	1	2.8	2.2	2.2	5

Table 12. Average execution time in seconds

Proposed CS	MCS1	MCS2	SACS	CS
45.66	52.34	50.15	53.96	68.87

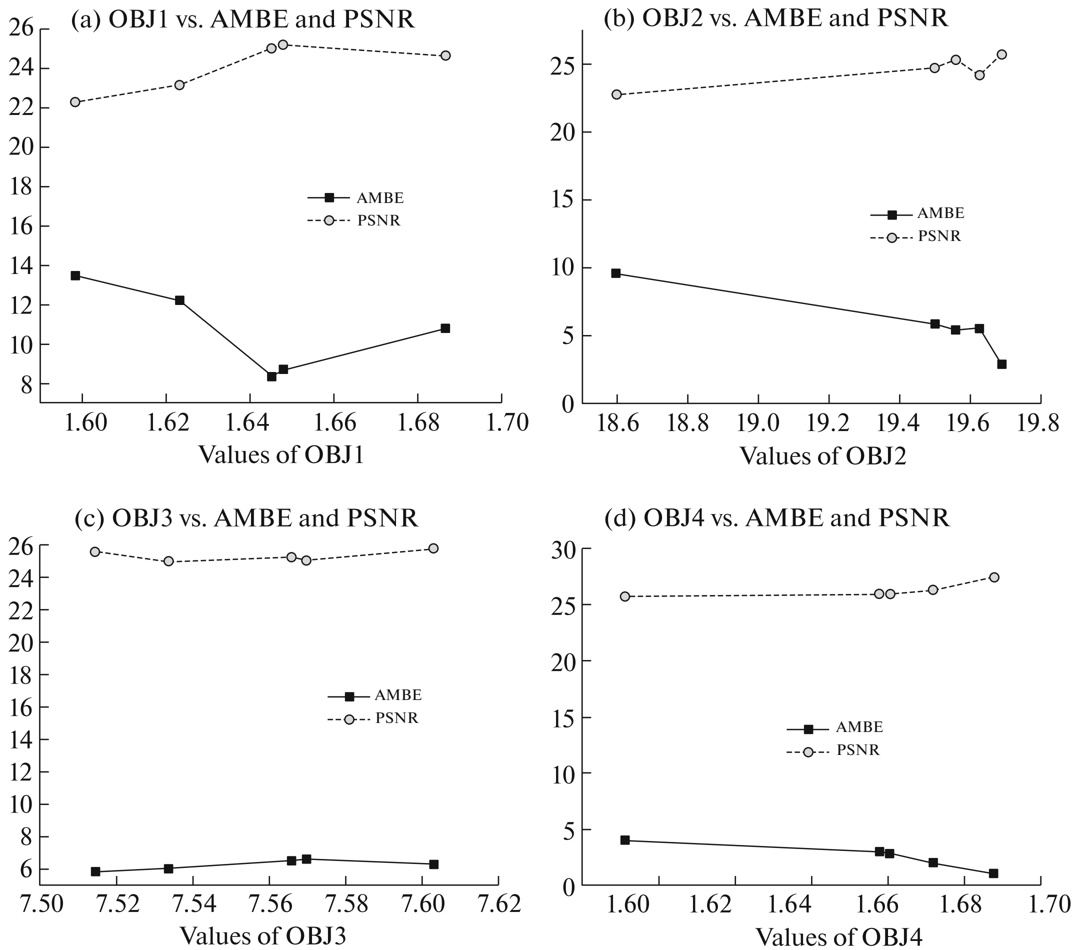

Fig. 10. Changes of AMBE and PSNR with respect to different objective functions.

ACKNOWLEDGMENT

This research work is funded by DST-PURSE.

REFERENCES

1. R. C. Gonzalez and R. E. Woods, *Digital Image Processing,* 2nd ed. (Prentice Hall, New York, 2002).
2. S. D. Chen and A. R. Ramli, "Preserving brightness in histogram equalization based contrast enhancement techniques," Digital Signal Processing **14**, 413–428 (2004).
3. Y. T. Kim, "Contrast enhancement using brightness preserving bi-histogram equalization," IEEE Trans. Consum. Electron. **43** (1), 1–8 (1997).
4. H. D. Cheng and X. J. Shi, "A simple and effective histogram equalization approach to image enhancement," Digital Signal Processing **14**, 158–170 (2004).
5. S. D. Chen and A. R. Ramli, "Minimum mean brightness error bi-histogram equalization in contrast enhancement," IEEE Trans. Consumer Electron. **49**, 1310–1319 (2003).
6. S. D. Chen and A. R. Ramli, "Contrast enhancement using recursive mean separated histogram equalization for scalable brightness preservation," IEEE Trans. Consumer Electron. **49** (4), 1301–1309 (2003).
7. P. Shanmugavadivu, K. Balasubramanian, and A. Muruganandam, "Particle swarm optimized bihistogram equalization for contrast enhancement and brightness preservation of images," Vis. Comput. **30**, 387–399 (2014).
8. M. Abdullah-Al-Wadud, M. H. Kabir, M. A. A. Dewan, and O. Chae, "A dynamic histogram equalization for image contrast enhancement," IEEE Trans. Consumer Electron. **53** (2), 593–600 (2007).
9. C. Zuo, Q. Chen, and X. Sui, "Range limited bi-histogram equalization for image contrast enhancement," Optik **124**, 425–431 (2013).
10. Q. Wang and R. K. Ward, "Fast image/video contrast enhancement based on weighted thresholded histogram equalization," IEEE Trans. Consumer Electron. **53** (2), 757–764 (2007).
11. N. Sengee and H. K. Choi, "Brightness preserving weight clustering histogram equalization," IEEE Trans. Consum. Electron. **54**, 1329–1337 (2008).
12. M. Kim and M. G. Chung, "Recursively separated and weighted histogram equalization for brightness preser-

vation and contrast enhancement," IEEE Trans. Consum. Electron. **54**, 1389–1397 (2008).

13. T. Kim and J. Paik, "Adaptive contrast enhancement using gain-controllable clipped histogram equalization," IEEE Trans. Consumer Electron. **54** (4) (2008).
14. N. Otsu, "A threshold selection method from graylevel histograms," IEEE Trans. Sys., Man., Cyber. **9** (1), 62–66 (1979).
15. S. K. Pal, D. Bhandari, and M. K. Kundu, "Genetic algorithms for optimal image enhancement," Pattern Recogn. Lett. **15**, 261–271 (1994).
16. S. Hashemi, S. Kiani, N. Noroozi, and M. E. Moghaddam, "An image contrast enhancement method based on genetic algorithm," Pattern Recogn. Lett. **31**, 1816–1824 (2010).
17. L. D. S. Coelho, J. G. Sauer, and M. Rudek, "Differential evolution optimization combined with chaotic sequences for image contrast enhancement," Chaos, Solitons Fractals **42**, 522–529 (2009).
18. K. G. Dhal, I. M. Quraishi, and S. Das, "Performance enhancement of differential evolution by incorporating Lévy flight and chaotic sequence for the cases of satellite images," Int. J. Appl. Metaheuristic Comput. **6**, 69–81 (2015).
19. A. Gorai and A. Ghosh, "Gray-level image enhancement by particle swarm optimization," in *Proc. World Congress on Nature and Biologically Inspired Computing* (Coimbatore, 2009).
20. M. Barik, A. Sheta, and A. Ayesh, "Image enhancement using particle swarm optimization," in *Proc. World Congress on Engineering* (London, 2007).
21. K. G. Dhal, I. M. Quraishi, and S. Das, "Development of firefly algorithm via chaotic sequence and population diversity to enhance the image contrast," Natural Comput. **14**, 1–12 (2015).
22. A. Bouaziz, A. Draa, and S. Chikhi, "Bat algorithm for fingerprint image enhancement," in *Proc. 12th Int. Symp. on Programming and Systems (ISPS)* (Algiers, 2015), pp. 1–8.
23. K. G. Dhal, I. M. Quraishi, and S. Das, "Performance analysis of chaotic Lévy bat algorithm and chaotic cuckoo search algorithm for gray level image enhancement," in *Information Systems Design and Intelligent Applications* (Springer, 2015), pp. 233–244.
24. T. R. Benala, S. D. Jampala, S. H. Villa, and B. Konathala, "A novel approach to image edge enhancement using artificial bee colony optimization algorithm for hybridized smoothening filters," in *Proc. World Congress on Nature and Biologically Inspired Computing* (*NaBIC 2009*) (Coimbatore, 2009), pp. 1071–1076.
25. K. G. Dhal and S. Das, "Diversity conserved chaotic artificial bee colony algorithm based on brightness preserved histogram equalization and contrast stretching method," Int. J. Nat. Comput. Res. **5**, 45–73 (2015).
26. S. Agrawal and R. Panda, "An efficient algorithm for gray level image enhancement using cuckoo search," in *Proc. SEMCCO 2012* (Bhubaneswar, 2012), pp. 82–89.
27. A. K. Bhandaria, V. A. Sonia, A. Kumar, and G. K. Singh, "Cuckoo search algorithm based satellite image contrast and brightness enhancement using DWT–SVD," ISA Trans. **53**, 1286–1296 (2014).
28. S. Ghosh, S. Roy, U. Kumar, and A. Mallick, "Gray level image enhancement using cuckoo search algorithm," in *Advances in Intelligent System Computing* (Springer, 2014), pp. 275–286.
29. K. G. Dhal, I. M. Quraishi, and S. Das, "A chaotic Lévy flight approach in bat and firefly algorithm for gray level image enhancement. I," J. Image, Graph. Signal Processing **7**, 69–76 (2015).
30. L. Maurya, P. K. Mahapatra, and G. Saini, "Modified cuckoo search-based image enhancement," in *Proc. 4th Int. Conf. on Frontiers in Intelligent Computing: Theory and Applications* (*FICTA*) (Durgapur, 2015), pp. 625–635.
31. K. G. Dhal, I. M. Quraishi, and S. Das, "An improved cuckoo search based optimal ranged brightness preserved histogram equalization and contrast stretching method," Int. J. Swarm Intellig. Res. **8**, 1–29 (2017).
32. S. Walton, O. Hassan, K. Morgan, and M. R. Brown, "A review of the development and applications of the cuckoo search algorithm," Swarm Intellig. Bio-Inspired Computation (2013). http://dx.doi.org/ doi 10.1016/B978-0-12-405163-8.00011-9.10.1016/B978-0-12-405163-8.00011-9
33. X. S. Yang and S. Deb, "Engineering optimisation by cuckoo search," Int. J. Math. Modelling Num. Optimis. **1**, 330–343 (2010).
34. O. S. Al-Kadi and D. Watson, "Texture analysis of aggressive and non-aggressive lung tumor CE CT images," IEEE Trans. Biomed. Eng. **55**, 1822–1830 (2008).
35. S. Aja-Fernández, R. S. JoséEstépar, C. Alberola-López, and C. F. Westin, "Image quality assessment based on local variance," in *Proc. 28th IEEE EMBS Annu. Int. Conf.* (New York, 2006), pp. 4815–4818.
36. S. Aja-Fernández, R. S. JoséEstépar, and C. Alberola-López, "Full reference image quality assessment based on local statistics," LPI Tech Rep. (Universidad de Valladolid, Jan. 2014), No. TECH-LPI2014-01.
37. J. Derrac, S. García, D. Molina, and F. Herrera, "A practical tutorial on the use of nonparametric statistical tests as a methodology for comparing evolutionary and swarm intelligence algorithms," Swarm Evolut. Computat. **1** (1), 3–18 (2011).
38. X. Li and M. Yin, "Modified cuckoo search algorithm with self-adaptive parameter method," Inf. Sci. (2014). http://dx.doi.org/. doi 10.1016/j.ins.2014.11.042
39. J. Kennedy, "Small worlds and mega-minds: effects of neighborhood topology on particle swarm performance," in *Proc. 1999 Congress on Evolutionary Computation* (Washington, 1999).
40. H. Wang, Z. Wu, and S. Rahnamayan, "Particle swarm optimisation with simple and efficient neighbourhood search strategies," Int. J. Innovat. Comput. Appl. **3**, 97–104 (2011).
41. S. Das, A. Abraham, U. K. Chakraborty, and A. Konar, "Differential evolution using a neighborhood-based mutation operator," IEEE Trans. Evolutionary Computat. **13**, 526–553 (2009).
42. H. Wang, Z. Cui, H. Sun, S. Rahnamayan, and X. S. Yang, "Randomly attracted firefly algorithm with neighborhood search and dynamic parameter adjustment mechanism," in *Soft Computing* (Springer, Berlin,

Heidelberg, 2016), pp. 1–15. doi 10.1007/s00500-016-2116-z

43. C. S. D. Leandro and C. M. Viviana, "A novel particle swarm optimization approach using Henon map and implicit filtering local search for economic load dispatch," Chaos, Solit. Fractals **39**, 510–518 (2009).
44. R. Sheikholeslami and A. Kaveh, "A survey of chaos embedded meta-heuristic algorithms," Int. J. Opt. Civil. Eng. **3** (4), 617–633 (2013).
45. L. D. S. Coelho and V. C. Mariani, "Use of chaotic sequences in a biologically inspired algorithm for engineering design optimization," Expert Syst. Appl. **34**, 1905–1913 (2008).
46. A. R. Jordehi, "A chaotic-based big bang–big crunch algorithm for solving global optimisation problems," Neural Comput. Appl. **25**, 1329–1335 (2014).
47. C. Choi and J. J. Lee, "Chaotic local search algorithm," Artif. Life Robotics **2**, 41–47 (1998).
48. J. C. Bansal, P. K. Singh, M. Saraswat, A. Verma, S. S. Jadon, and A. Abraham, "Inertia weight strategies in particle swarm optimization," in *Proc 3rd World Congress on Nature and Biologically Inspired Computing* (Salamanca, 2011), pp. 640–647.
49. R. Caponetto, L. Fortuna, S. Fazzino, and M. G. Xibilia, "Chaotic sequences to improve the performance of evolutionary algorithms," IEEE Trans. Evolut. Comput. **7**, 289–304 (2003).
50. M. Jamil and H. J. Zepernick, "Lévy flights and global optimization," Bio-Inspired Comput. (2013). http://dx.doi.org/ doi 10.1016/B978-0-12-405163-8.00003-X.10.1016/B978-0-12-405163-8.00003-X
51. X. Yao, Y. Liu, and G. Lin, "Evolutionary programming made faster," IEEE Trans. Evol. Comput. **3**, 82–102 (1999).
52. C. L. Chien and D. C. Tseng, "Color image enhancement with exact HIS color model," Int. J. Innovat. Comput., Inf. Control **7**, 6691–6710 (2011).
53. C. L. Chien and W. H. Tsai, "Image fusion with no gamut problem by improved nonlinear HIS transforms for remote sensing," IEEE Trans. Geosci. Remote Sensing **52**, 651–663 (2014).
54. C. Yim and A. C. Bovik, "Quality assessment of deblocked images," IEEE Trans. Image Processing **20**, 88–98 (2011).
55. R. Wang, Y. Zhou, C. Zhao, and H. Wu, "A hybrid flower pollination algorithm based modified randomized location for multi-threshold medical image segmentation," Bio-Med. Mater. Eng. **26**, 1345–S351 (2015).
56. J. Derrac, S. Garcia, D. Molina, and F. Herrera, "A practical tutorial on the use of nonparametric statistical tests as a methodology for comparing evolutionary and swarm intelligence algorithms," Swarm Evolut. Comput. **1**, 3–18 (2011).
57. C. Gatta, A. Rizzi, and D. Marini, "ACE: an automatic color equalization algorithm," in *Proc. 1st European Conf. on Color in Graphics Image and Vision (CGIV02)* (Poitiers, 2002).
58. S. K. Naik and C. A. Murthy, "Hue preserving color image enhancement without gamut problem," IEEE Trans. Image Processing **12**, 1591–1598 (2003).

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