Chapter 8 Cuckoo Optimization Algorithm (COA) for Image Processing

Noor A. Jebril and Qasem Abu Al-Haija

Abstract Image optimization is the process of enhancing the image quality and visual appearance in order to provide preferable transfer representation for many future automated images such as medical images, satellite and aerial images which might suffer from poor and bad contrast and noise. There are many state-of-art algorithms in the literature that have been used for image optimization process in which they were inspired from the nature such as the Particle Swarm Optimization (PSO), Differential Evolution (DE) and more recently, the Cuckoo Optimization Algorithm (COA). COA is very efficient optimization technique developed by Yang and Deb through applying a special versions of gauss distribution for solving optimization problems. COA is differentiated from the life-style and the characteristics of Cuckoo sparrow clique. Cuckoo sparrow society initiates with an elementary inhabitance that is classified into two portions: cuckoos and eggs. The cuckoo societies then start to change their environment to better one and start reproducing and putting eggs. Such endeavor of Cuckoos to enhance their life's environment is the Cuckoo Optimization Algorithm. In this chapter, a comprehensive discussion about one of the metaheuristic algorithms called Cuckoo Search Optimization (CSO) has been carried out. Also, the usefulness of CSO for solving image optimization problems is discussed in detail. Moreover, to support the theoretical discussion of CSO algorithm, the performance evaluation of CSO algorithm is provided in the results and comparisons section which compare and benchmark the execution of CSO algorithm with other genetic algorithms and particle swarm optimization. Finally, the analysis of comparison results illustrated the superior capability of Cuckoo search algorithm in optimizing the enhancement functions for digital image processing.

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8.1 Introduction

In the last decades, the image processing and optimization have played the key role in many areas such as computer science, medical and astronomy fields as well as many other fields of engineering and technology. Most of these disciplines need to increase the capabilities of digital cameras and emerging devices—like Google Glass and autonomous driving cars- to Magnetic Resonance Imaging (MRI) and analyzing astronomical data that require many processing stages such as image transformation, correction of distortion effects, noise purge, histogram equalization, Image contrast enhancement, noise elimination, thresholding, edge detection and image segmentation. These processing steps are the key stages in the digital image processing techniques.

The image is vulnerable to be influenced by the noise process resultant from the image transmission which may produce harmful effects on the image during the image processing operations. Thus, to eliminate all these effects, the noise must be passed through removing or diminishing stage keeping all information of the image as possible.

The image information should be kept clean and safe as its considered crucial for helping the image processing specialized in making decisions depending on the information provided from the processed image. Therefore, high-performance image enhancement mechanisms are required for processing and analyzing the data generated from imaging systems. This is needed due to the huge amount of data doubled by high resolution and frame rates and the requirements of interactive and mission-critical applications. Consequently, the active domain of the nominated image features of the in-process-image must be increased as it is deemed an essential operation of the image-enhancement systems. Whenever the image is transformed from its specific sort to another sort after external operations such as photography, image scanning, or transferring, this processing will produce output results with more quality-dependent image over the authentic inputted-image.

There is much relevant information that can be obtained from an image such as the value of intensity from an image or the edge of the image. In similar cases, the transformed image from one form to another is required to get the required features since the image processing generates these result as needed. The enhancement of an image is one strategy under image processing [[1\]](#page-23-0).

The most essential property of any image is that it's usually stored and processed in a discrete (i.e. digital) form. In the digital image, the pixel concept is a physical point in a raster image which is the smallest controllable element of an image that appears on the screen. The pixels are the function of spatial coordinates of an image represented as [\[1](#page-23-0)]:

$$
p = (x, y) \tag{8.1}
$$

where: x and y are the image spatial coordinates and p is the resultant pixel value which might be any of the image-intensity at that point to the gray-scale value.

All the image processing mechanisms are essentially performed as applications of the mathematical function in which they are applied over each pixel with its encirclement pixels [[1\]](#page-23-0) where all mechanisms strive to get information from a certain pixel along with its encirclement pixels and then obtain new value for the targeted pixel.

In the meantime, image enhancement is a mechanism of image processing which strives to generate a more visually-appropriate digital image as the appearance of its visional inspection by individuals or devices.

The prime dilemma of applying conventional image enhancement mechanisms is the need for human intervention to inspect and decide whether the processed image became convenient for the desired mission or not. This is due to the absence of pre-defined or specific criteria to measure the amount of image enhancement. Therefore, it can only be drawn and then the human can inspect and evaluate the processed image to judge if the resultant image is appropriate or not $[1]$ $[1]$. Thus, huge efforts where consumed later to replace human inspection and construing of the processed images by the introduction of metaheuristic algorithms and genetic approaches [[2\]](#page-23-0).

The metaheuristic algorithms and genetic approaches would get better image-enhancement neutralizations and equations in which can be elaborated in the topmost level of effectiveness or as confined by the user to generate the desired outcomes. For instance, Munteanu and Rosa [[3\]](#page-23-0) were the first researchers who have proven the employment of genetic algorithms to beat the human-intervention dilemma and have proven the upgraded capability of the image-enhancement functions in the field of image transformation mechanisms. These consequences have a key role in raising the use of image enhancement-based metaheuristic algorithm operations.

Continuing the enormous successive developments which are later implemented in metaheuristic algorithms, it was discovered that as the algorithm became more capable, then the capacity of the function is increased. The genetic algorithm (GA) was followed by particle swarm optimization (PSO) and then cuckoo search optimization (CSO) has been recently shown up as an efficient solution for the aforementioned issues.

This chapter discusses the strengths of CSO based optimization for image-enhancement functions and formulas and discusses the results of several classical grayscale image enhancement mechanisms by employing several enhancement techniques such as Cuckoo Search (CS), Histogram equalization (HE) and Linear Contrast Stretch (CS) techniques [[4\]](#page-23-0). In comparison with other metaheuristic algorithms, CSO has proved to be more efficient in image enhancement process. The coming text will thoroughly debate the capability of CSO and the comparison if its performance with other stated approaches.

8.2 Image Enhancement Functions

Image enhancement is the most important image processing techniques that convert the image to another enhanced image in which it can be used for perception or explanation of information for human viewers, or to get the best input for other image processing techniques (i.e. in serial image processing system that contains many stages). A Genetic Algorithm (GA) was suggested in [[5\]](#page-23-0) to enhance the digital images by implementing the contrast enhancement of multi-objective function that contains four non-linear mapping functions. It is used to find the optimal mapping of the grey levels of the input image to new grey levels that can give better contrast for the image.

Lately, the quality of the image is measured and used for grey-level and color image enhancement. Particle Swarm Optimization (PSO) has been proposed in [\[6](#page-23-0)] which is primarily used for preserving the mean value of image intensity for improving the contrast levels of digital grayscale images.

Generally, image enhancement approaches have four basic classifications: point operations, spatial operations, transformations, and pseudo-coloring methods. Contrast stretching, window slicing, modeling of the histogram are zero memory operations that assign a given input grayscale image into output grayscale image. The most popular between the classification is the linear contrast stretch and histogram equalization. In spatial operations, each value for all original pixels is replaced with the neighborhood pixel value, this process provides enhancement of the noise in the input image, but it might result with some degree of smoothing the image which can affect the accuracy of image details. The Linear, homomorphic and root filtering employed under transform operations depends on the inverse transformation of the transformed image.

In pseudo coloring methods, the grayscale image is colored by using a suitable color map, and due to non-singularity of the color maps, a lot of trails have been required to choose a suitable mapping. The function which is used to define the amount of the quality for the enhanced image for all the methods is known as the evaluation function or criterion.

8.2.1 \mathbf{B} . \mathbf{B} is the Formulas Formulas \mathbf{B}

In this operation, the image can be enhanced by employing the image transformation function that uses the intensity value of each pixel of a $(P \times Q)$ image. The process of manipulating the gray level distribution for each pixel in the neighborhood of the input image by the implemented image transformation function is called local enhancement technique. The traditional local enhancement transformation function is given in Eq. ([8.2](#page-4-0)) below [[7\]](#page-23-0):

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$$
g(x, y) = \frac{G}{\sigma(x, y)} (f(x, y) - m(x, y))
$$
\n(8.2)

where, $m(x, y)$ is the gray level mean and $\sigma(x, y)$ is the standard deviation which both calculated in a neighborhood centered at (x, y) contain $M \times N$ pixels, G is the global mean of the input image and $f(x, y)$ as well as $g(x, y)$ are the gray level intensities for the input and output images' pixel at location (x, y).

The other method of local enhancement technique is adaptive histogram equalization which is used in medical image processing. Also, one of the simplest and most popular methods to achieve the mission contrast enhancement is the global intensity transformation in which its function is derived from Eq. (8.2) and applied to each pixel at location (x, y) of the given image as in the following equation [[7](#page-23-0)]:

$$
g(x, y) = \frac{k \cdot G}{\sigma(i, j) + b} [f(x, y) - c \times m(x, y)] + m(x, y)^a
$$
 (8.3)

Here:
$$
5 < k < 1.5
$$
, $a \in \psi_1$, $b \in \psi_2$, $c \in \psi_3$ with $\psi_1, \psi_2, \psi_3 \subset R$

where, $b \neq 0$ allows for zero standard deviation in the neighborhood, $c \neq 0$ allows for the only fraction of the mean value $m(x, y)$ to be subtracted from original pixel gray level. The last term might have brightened and smoothened the effects on the image. G is the global mean, m (x, y) is the local mean and $\sigma(x, y)$ is defined as the local standard deviation of the pixel (x, y) of the input image over $n \times n$ window, that can be debriefed as [[7\]](#page-23-0):

$$
m(x, y) = \frac{1}{n \times n} \sum_{x=0}^{n-1} \sum_{y=0}^{n-1} f(x, y), \quad and \ G = \frac{1}{M \times N} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x, y),
$$

$$
\sigma(x, y) = \sqrt{\frac{1}{n \times n}} \sum_{x=0}^{n-1} \sum_{y=0}^{n-1} ((f(x, y) - m(x, y))^2)
$$
(8.4)

The accurate value of a, b, c and k parameters in the Eq. (8.3) , will give a large variation in the processed output image by keeping the original version of it.

8.2.2 $\frac{1}{2}$.

To evaluate the quality of the enhanced image without human intervention, a specific pre-defined function can be used to measure the image performance in terms of the number and intensity of edge pixels and entropy of the whole image.

Image entropy is the amount of information which must be coded by a compression algorithm. Low entropy images, like the black sky, have very little contrast and large runs of pixels with the same DN values. An image that is completely flat contains an entropy of zero. Therefore, this can minimize the size to the lowest, on the contrary of the image that has high entropy such as the image of cratered areas on the moon that cannot be compressed. Image entropy is calculated with the same formula used by Galileo imaging team [[8\]](#page-23-0) as follows:

$$
Entropy = -\sum_{i} P_i \log_2 P_J \tag{8.5}
$$

where P_i is the probability that the difference between two adjacent pixels is equal to I, and Log 2 is the base 2 logarithms.

Image quality metrics is mentioned in [\[7](#page-23-0)] which describes the final quality of the enhanced image. Hence, Peak Signal-to-Noise Ratio (PSNR) is one of the goals in the objective function. Thus, we put the aggregated weight based on objective function as follows:

$$
OF = W_1 \times OF_1 + W_2 \times OF_2 \tag{8.6}
$$

where OF is the objective function, W_1 and W_2 are weight factors such that $W_1 = 0.5$ and $W_2 = 0.5$ (equal weight age).

$$
OF_1 = F(I_e) = \log(\log(E(I_s))) \times \frac{n_{edges(s(I_s))}}{M \times N} \times H(I_e),
$$

\n
$$
OF_2 = PSNRI(I_e)
$$
\n(8.7)

- $F(I_e)$ is the objective function that describe the quality of the output image with transformation function Eq. (8.7).
- $F(I_s)$ is the sum of edge pixel intensities that calculated by using Sobel edge detector.
- $n_{edgels(I_s)}$ is the number of edge pixels.
- $H(I_e)$ is the entropy value.
- M and N are the number of pixels.
- *PSNRI* is peak signal to noise ratio of the enhanced image, where is used the mean squared error [\[9](#page-23-0)]:

$$
MSE = \frac{1}{mn} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} [I(i,j) - K(i,j)]^2
$$
\n(8.8)

The PSNR is defined as:

$$
PSNR = 10 \log_{10} \left(\frac{MAX_I^2}{MSE} \right) = 20 \log_{10} \left(\frac{MAX_I}{\sqrt{MSE}} \right) \tag{8.9}
$$

$$
Therefore, PSNR = 20.log10(MAXI) - 10.log10(MSE)
$$
\n(8.10)

where MAX_I is the most (largest) conceivable value of the image pixel. Similarly, many other Sobel operators can be used for the same purposes such as Canny Operators in which are proposed in [[3\]](#page-23-0).

The automatic threshold detector needs the edge detector where the summation of the intensity of the edges is calculated using the following equation [[7\]](#page-23-0):

$$
E(I(J)) = \sqrt{\partial u(x, y)^2 + \partial v(x, y)^2}
$$
\n(8.11)

where:

$$
\partial u(x, y) = g(x+1, y-1) + 2g(x+1, y) + g(x+1, y+1)
$$

\n
$$
- g(x-1, y-1) - 2g(x-1, y) - g(x-1, y+1)
$$

\n
$$
\partial v(x, y) = g(x-1, y+1) + 2g(x, y+1) + g(x+1, y+1)
$$

\n
$$
- g(x-1, y-1) - 2g(x, y-1) - g(x+1, y-1)
$$

8.2.3 $\frac{3}{2}$

Parameters a, b, c and k are determined by the real positive numbers in comparing of Eqs. (8.2) – (8.3) . The values of the parameters are used as constants as follows:

$$
b = 0, \quad c = 1 \quad k = 1 \quad m(x, y) = 0
$$

In Eq. [\(8.3\)](#page-4-0): $b = 0$ prohibits the *Not A Number* (*NAN*) values, $c = 1$ allows for only a fraction of the mean to be subtracted from the pixel's input gray-level intensity value, while the last term may have brightened and smoothened the effects on the image. Accordingly, Eq. ([8.2](#page-4-0)) broadened the spectrum of the transformation output range by modifying the original equation.

The optimization algorithm drives the solutions of the image enhancement problem by setting the four parameters $(a, b, c \text{ and } k)$ to obtain the maximum possible mix based on the objective standards that mention the contrast in the image. The selected variable is given as in [[10\]](#page-24-0):

$$
a \in [0, 1.5], b \in [0, 0.5], c \in [0, 1] \quad \text{and } k \in [0.5, 1.5]
$$

However, they failed to get a perfect output that provides the domain of b since the difference value of b will have a significant effect on the intensity stretch even if the difference is small. Therefore, the original image might get lost by the intensity normalization value. Thus, to overcome this problem, we need to modify b to [1, G/2] where G is the global mean of the input image $[11]$ $[11]$.

8.3 Related Work

Recently, the image enhancement has been heavily researched by collaborators and contributors as a world-wide critical research topic. There are many recent state-of-art works that focus on this issue. For instance, Weigel et al. 2013 [\[12](#page-24-0)] provided a mechanism to associate Image Inversion Microscopy (IIM) with digital holography by applying additional computations to prove their proposed essence by means of the utilization of Point Spread Function (PSF). The PSF function describes the reply to point object from an imaging system. The system's impulse response is a general expression of PSF in which it focused on optical systems as they also presented an explanation of how to reduce the distance between the first zeros by a factor of about two. Figure [8.1](#page-8-0) shows image formation in a confocal microscope: central longitudinal (XZ) slice that distribution arises from the convolution of the real light sources with the PSF, as used general form, as follows:

$$
Image (Object1 + Object2) = Image (Object1) + Image (Object2)
$$
 (8.12)

In addition, they listed images of 10 gratings to clarify and comprehend the boosted resolutions and to calculate a portion of the optical transfer functions of the coherent, the incoherent and the image-inverted case.

In a related work, Lin (2011) [[13\]](#page-24-0) proposed another scheme for enhancing the image quality by a means of Infrared images (IR) for an extended-domain surveillance system. The Infrared images which were taken at long-domain that encompass reduced contrast and brightness levels. The most important feature of the proposed method is that no need for pre-knowledge about the IR image and no parameters must be preset. Briefly, two main objectives for this research: enhancement for adaptive contrast by using Adaptive Histogram-Based Equalization (AHBE), and enhancement of the strength of elevated spatial-frequency of infrared images to maintain the datum of original inputted- images.

Another noticeable technique has been proposed by Zhao (2011) [\[14](#page-24-0)] who suggested to employing the Gravitational Search Algorithm (GSA) for image enhancement method. Gravitational Search Algorithm (GSA) strives to make the best and most effective use of the normalized incomplete Beta function parameters by employing the greyscale image generalized convention. This function used to enhance the damaged image which gives effectively enhanced results, as follows:

$$
f(i_{xy}, \alpha, \beta) = \frac{\int_0^{i_{xy}} t^{a-1} (1-t)^{\beta-1} dt}{B(\alpha, \beta)}
$$
(8.13)

The fitness function is defined as:

$$
Fintness(f) = \frac{1}{n} \sum_{x=1}^{M} \sum_{y=1}^{N} f^{2}(x, y) - \left(\frac{1}{n} \sum_{x=1}^{M} \sum_{y=1}^{N} f(x, y)\right)^{2}
$$
(8.14)

Fig. 8.1 The point spread function (PSF)

where M and N are the coordinates of the image to be enhanced with $n = M \times N$, and $f(x, y)$ is the enhanced pixel value of the input image. Thus, the higher value of the fitness function, the image will be more enhanced. Figure [8.2](#page-9-0) shows the flowchart of adaptive enhancement for greyscale image based on GSA and it also explains the gravitational search algorithm [\[6](#page-23-0)].

The histogram improvement-based solutions were also valid and practiced in many state-of-the-art works such as the unprecedented formulation of image

histogram operation to ameliorate the contrast process of the mage which was formally proposed by Zeng et al. (2012) [[15\]](#page-24-0). Zeng method encompasses several steps started by dividing the image into several equal-sized regions by using the values of the intensities of gradients, followed by adjusting their values of gray levels and finally, the histogram for the whole image can be obtained by the summation of all weighted values of the divided regions. This method improved the enhancement by testing X-Ray images that support this method. Figure [8.3](#page-10-0) shows the final content of adaptive contrast enhancement algorithm.

Furthermore, recently, Santhanam and Radhika (2010) [\[16](#page-24-0)] have implemented a mechanism in which they employed the noise identification predominant operation in the processing stages of any digital image operation to distinguish the image smoothing filters. The noise detection was performed by using Artificial Neural Network (ANN) to isolate the noise and extracts needed features [\[8](#page-23-0)]. Eventually they concluded that ANNs provided a better solution in identifying the noise which provide the precise filter that can be used for enhancing the given image.

Finally, several enhancement algorithms for enhancing the digital image have been implemented by Garg et al. (2011) [\[17](#page-24-0)] through the manipulation of the greyscale Histogram-Equalization and greyscale Filtering. The most noticeable issue of the set of proposed frameworks is that they preserve the brightness level of the inputted-image on the resultant outputted-image by applying considerable enhancement in the image-contrast levels. Histogram-Equalization (HE) scheme can be effectively used to re-modulate the image gray grades. Figure [8.4](#page-11-0) shows the effect of HE method on the entered (pre-processed) image [\[9](#page-23-0)].

Fig. 8.3 Flowchart of the adaptive contrast enhancement algorithm

8.4 An Introduction to Cuckoo Search Optimization Algorithm

Cuckoo search (CS) [[5\]](#page-23-0) is a meta-heuristic algorithm inspired by the cuckoo bird, these are the "Brood parasites" birds. It is impossible to create its nest and place its eggs in the nests of other birds. Some steward fowls can engage directly with the other cuckoo that comes to own nest. The host bird recognizes the eggs if they belong to its nest or not. If the eggs are not belonging to it, it will throw the eggs away or remove the nest and build another one. According to this phenomenon, suppose that each existing egg is a solution and cuckoo egg is a new and workable solution. Thus, for every nest, there has one egg of cuckoo in which every nest shall contain various eggs that appears as a group of solutions.

Practically, any new egg put by cuckoo acts as an unprecedented settling to the search algorithm and prior the implementation of the next step, a distribution process formula defines the number of remaining eggs. The new number of eggs can be represented as the populace for the next iteration; therefore, increasing the

Fig. 8.4 a The original picture of the tire. b HE's picture of the tire

number of iterations is better to obtain enhanced results. The iterations carry on until satisfying the desired optimization. Shortly, CS algorithms and morphological operations are efficiently used to enhance the image by modifying its contrast and intensity. Figure [8.5](#page-12-0) clarifies the general steps of CS algorithm. Eventually, CS

Fig. 8.5 General CS Algorithm Steps

algorithm became very applicable in many optimization fields and its exemplary for how the upbringing behavior [[7\]](#page-23-0) since it has been successfully implemented to solve the scheduling issues and design optimization problems such as speech recognition, job scheduling, and global optimization.

8.5 Image Enhancement via Cuckoo Search Methodology

Cuckoo search algorithm focuses mainly on the repeated calculation of the Mean Square Error (MSE) and Minimum Fitness Function (MFF) until the optimum requested results are satisfied (reaching the threshold values). Figure [8.6](#page-13-0) explains the exact steps of CS algorithm in which it contains mainly two iteration steps: one for checking the population (less than the max value) and the other iteration step for checking if the condition is met or not [\[18](#page-24-0)].

Fig. 8.6 The flowchart of Cuckoo Search (CS) Method

The fitness function is defined as:

$$
Fitness Function = W1 \times MSE + W2 \times Iteration
$$
 (8.14)

The main idea of the image enhancement techniques is to get rid of noise and its process can be summarized as follow: Consider I is the original inputted image with dimensions $P \times Q$. The first step is the transforming of the original image (I) from its RGB coloring system into gray-scale coloring system, by applying the next formula [[19\]](#page-24-0):

$$
I_{gy} = 0.289 \times r + 0.5870 \times g + 0.1140 \times b \tag{8.15}
$$

where: R, G, B are the levels of image-coloring components and I_{gy} is the transformed grayscale image. Also, the mean value (μ) of the grayscale image can be obtained by applying the following law [[19\]](#page-24-0):

$$
\mu = \frac{\sum_{p=0}^{p-1} \sum_{q=0}^{Q-1} lqp}{P \times Q} \tag{8.16}
$$

At this stage, the image is ready to be applied to Cuckoo Search algorithm via Levy flight to obtain an enhanced image and the process works as follows:

- (1) Every cuckoo place only single egg at a time and into any of the selected nests.
- (2) The top-quality eggs of the superior nest will be renewed to the next descent.
- (3) The number of ready host nest doesn't change and when a host bird recognizes the cuckoo egg with the probability of $p \in (0, 1)$ [\[20](#page-24-0)], the host bird can either remove the egg away or leave them and build a new nest.

In the Lévy flight, the third method is selected to implement the cuckoo search and could be converged as the fraction ' p ' of the 'n' nests. Many researchers proved that the flight behavior of many animals and insects has the typical features of Lévy flights which is a random walk; that the stages are determined according to the step-lengths, which contain a specific probability distribution with the directions being random. This random walk can be seen in animals and insects. The next motion depends on the current position which produces new settlings $x(t + 1)$ for a cuckoo is considered as integrating between Levy flight with controls of the search capability. This can be implemented by the following equation [\[19](#page-24-0)]:

$$
X_i(t+1) = X_i(t) + \alpha \oplus \text{Levy}(\lambda)
$$
\n(8.17)

where: $\alpha > 0$ is the stage size and in most case, α is supposed to equal to one, and the product \oplus is entry-wise multiplication; in other words, it is an Exclusive-OR operation. Levy-flight is a random walk with random stage size and it is considered as step lengths that are distributed according to the following probability distribution equation (PDE) [[20\]](#page-24-0):

$$
levy \sim u = t^{-\lambda} (1 < \lambda \le 3)
$$
\n(8.18)

The produced image can be acquired by utilizing the structuring-element of the genuine image. Thereafter, the adjusted pixels of the entered-image are calculated to build up the numerical value for each pixel into the produced image. The image I is transformed to the binary digital form I_b through the adjustment process of both factors; the intensity and the contrast of the image. Finally, the enhanced image is earned by applying the morphological operation in which it depends on the use of the structuring element 'se' as follows [\[19](#page-24-0)]:

$$
I_b \oplus Se = Se \oplus I_b \tag{8.19}
$$

8.6 Pseudo-code of Cuckoo Search and Algorithm Implementation

The Pseudo-code of Cuckoo Search is shown below [\[18](#page-24-0)]:

By using the connotation of Cuckoo searching and Levy flight, the developed algorithm is giving an efficient image optimization results. The implementation steps of the algorithm are shown in the flowchart of Fig. [8.7](#page-16-0) and explained below in details [\[21](#page-24-0)]:

Stage 1: Reading the colored-image and converts it into its grayscale equivalent image. The function that is used for the conversion process is:

rgb2rray function. grayl = rgb2gray(imread(fn));

Fig. 8.7 A flowchart explaining the steps of the algorithm

Stage 2: Threshold will be created, and its upper and lower bounds are defined as:

> $Lb=0$; $Ub=255$; for $i=1:10$, for $j=1:1$ nest (i, j) = round((Lb+(Ub-Lb). * rand (size (Lb))));

Stage 3: The best solution of threshold among the set of generated populations is chosen and used to segment the grayscale image. The best solution is selected by using the following code:

$$
a=0;
$$
\n
$$
b=0;
$$
\n
$$
c = zeros;(10,1)
$$
\n
$$
d = zeros;(10,1)
$$
\nfor k=1:10\n
$$
a=0; b=0;
$$
\nfor j=1: k\n
$$
[c (k), d (k)] = \text{calbest} (gi, nest (k, j), a, b, j);
$$
\n
$$
a = c (k);
$$
\n
$$
b = d (k); % best solution of each nest
$$

Stage 4: The generation of the threshold by Cuckoo Search via Levy Flight Algorithm is accomplished by using the following piece of code:

```
cl=0;dl=0;for k=1:10for j=1: kcuck = levii (nest (k, j), d1, j);if cuck \sim = z[c2 d2] = calbest (gi, cuck, c1, d1,1);
              c1 = c2;dl = d2;
```
Stage 5: The Levy flights concepts will be used in the generation the optimized threshold values as in the following code:

```
beta=3/2:
sigma=(gamma(1+beta) *sin(pi*beta/2)/(gamma((1+beta)/2)
              *beta*2 ^ ((beta-1)/2))) ^ (1/beta);
                          for j=1: k,
                             s=n;
                 u = randn (size(s)) * sigma;
                     v = \text{randn}(\text{size}(s));step = u./abs (v) ^ (1/beta);
                       best = \text{curther}stepsize = 0.01*step * (s-best);
              s = s + stepsize * randn (size (s));s = round(s);
```
Stage 6: This step is used if you need to segment the image by using all the obtained solutions. The code for segmenting an image and calculating the correlation of segmented image as follows:

```
function [gil] = seg (gi, bestthresh)[o p] = size (gi);for i = 1: 0for j = 1: pif gi (i, j) < bestthresh
                        g1 (i, j) = 0;else gil (i, j) = 255;
                      end; end; end;
message = sprintf ('Best Threshold Value: %d', bestthresh');
                    msgbox (message);
                            end;
```
8.7 MSE and PSNR Value Calculations

After getting the segmented image, the mean squared error (MSE) of the image is created using the grayscale image and the final segmented image to get the PSNR value. The higher value of PSNR the better the result [[21\]](#page-24-0).

The term 'signal' in the PSNR value formula shows that the original image has some 'noise' that will produce an error in the image segmentation process. Thus, if high PSNR value is found, it gives an idea that decent quality segmentation and success. The term "MSE" will be used in the formulas to give the cumulative squared error between the segmented image and the original image. The code for getting the MSE and PSNR values is as shown below:

function [sei] = $psnrl$ (gi, gil) format long g; format compact; fontSize = 20 ; $ii = gi$ [rows columns] = size (ii); $si = gi1$: sei = (double (ii) – double (si)) $\hat{ }$ 2; mse = sum (sum (sei)) / (rows * columns); PSNR = 10 * log10 (256 $^{\circ}$ 2 / mse);

8.8 Results and Discussion

The performance of CS algorithm and morphological operation [\[19](#page-24-0)] which were used in the image enhancement process has been tested with different images and the upcoming figures and values show the execution of the suggested methodology. Here, independent stages are performed sequentially: firstly, we processed the cuckoo search algorithm, then we applied a morphological operation to improve the image and finally, the enhanced image was obtained. In order to adjust the contrast value of the processed image, the CS algorithm was iteratively applied until we obtained the optimal contrast value.

GA	PSO.	ABC	CS
16.8841	18.11698	18.65656	18.61738
17.7551	18.06440	18.07211	18.71658
15.0671	15.56377	15.76718	15.71828
14.208	15.10659	15.41357	16.23400

Table 8.1 Performance analysis of GA, PSO, ABC, and CS

Fig. 8.8 Performance benchmarking of GA, PSO, ABC, and CS for four images

Table 8.1 benchmarks the performance of CS algorithm with other three well-known existing algorithms namely: genetic algorithm (GA), particle swarm optimization algorithm (PSO), and Artificial Bee Colony (ABC) respectively. Also, Fig. 8.8 illustrates the graphical representation of the comparison result between GA, PSO, ABC, and CS in terms PNSR for the images provided in the figure set [8.9](#page-21-0)a–d that provides the input images and their enhanced images. It's clearly seen that GA, PSO, ABC, and CS have recorded PNSR values as 17.627926, 16.0594, 17.113572, and 17.334228 respectively. The performance figures show that the grey images are effectively improved with image enhancement technique by using CS algorithms and morphological operations.

Another noticeable system implementation has been found in $[21]$ $[21]$ where they have used the MATLAB package to utilize the identical combination of algorithms [\[7](#page-23-0)] as shown the figure set [8.10](#page-22-0). It is clearly seen that the resulted image contains a very little amount of noise due to the high PSNR value with significantly less size but the same quality as the original image, because of the algorithm.

Fig. 8.9 Four original images each with its enhanced image

Fig. 8.10 The sample results of several processing stages at MATLAB

8.9 Conclusions

The development of image enhancement techniques was a worldwide research for a long time ago. Such issue formed a pool of research to avoid or mitigate image noise to clarify several image features which positively contribute to many image processing operations such as the image segmentation, image detection, feature extraction, edge detection and others. The milestone discovery of Cuckoo Optimization Algorithm (COA) in the image processing world has maximally improved the image enhancement techniques by minimizing the human intervention in the image operations using an artificial selection of image parameters to optimize the inline image processing algorithm. To sum up, the CO algorithm works by firstly transforming the inputted full-colored image into gray-scale image and followed by computing the image-contrast parameter by applying the fitness function of the CS algorithm. The main purpose of using CS algorithm to elevate the merit and quality of the image to obtain the most effective and desirable amount of contrast factor in addition to the morphological processes which were fulfilled by adjusting the intensity parameters. CS algorithm showed the best results of noise removal from the image and choose the best parameter and contrast value to enhance the image.

References

- 1. Gonzalez, R.C., Woods, R.E.: Digital Image Processing, 3rd edn. Pearson Publications, Upper Saddle River, NJ (2007)
- 2. Singh, N., Kaur, M., Singh, K.V.P.: Parameter optimization in image enhancement using PSO. Am. J. Eng. Res. (AJER) 2(5), 84–90. e-ISSN: 2320-0847, p-ISSN: 2320-0936
- 3. Munteanu, C., Rosa, A.: Towards automatic image enhancement using Genetic Algorithms. In: Proceedings of the 2000 Congress on Evolutionary Computation, vol. 2, pp. 1535–1542. Instituto Superior Tecnico, University Tecnica de Lisboa, Portugal (2000)
- 4. Gupta, A., Tripathi, A., Bhateja, V.: De-speckling of SAR images via an improved anisotropic diffusion algorithm. In: Proceedings of (Springer) International Conference on Frontiers in Intelligent Computing Theory and Applications (FICTA 2012), Bhubaneswar, India. AISC, vol. 199, pp. 747–754 (2012)
- 5. Pal, S.K., Bhandari, D., Kundu, M.K.: Genetic algorithms for optimal image enhancement. Pattern Recogn. Lett. 15(3), 261–271 (1994)
- 6. Kwok, N.M., Ha, Q.P., Liu, D., Fang, G.: Contrast enhancement and intensity preservation for gray-level images using multiobjective particle swarm optimization. IEEE Trans. Autom. Sci. Eng. 6(1), 145–155 (2009)
- 7. Thampi, S.M., Gelbukh, A., Mukhopadhyay, J. (eds.): Advances in signal processing and intelligent recognition systems. Adv. Intell. Syst. Comput. (2014). [https://doi.org/10.1007/](http://dx.doi.org/10.1007/978-3-319-04960-1_25) [978-3-319-04960-1_25](http://dx.doi.org/10.1007/978-3-319-04960-1_25)
- 8. Shannon, C.E.: A mathematical theory of communication. Bell Syst. Tech. J. 27, 379–423 (1948)
- 9. Jaime, M., Beatriz, J., Salvador, S.: Towards no-reference of peak signal to noise ratio. (IJACSA) Int. J. Adv. Comput. Sci. Appl. 4(1) (2013)
- 10. Lei, X., Hu, Q., Kong, X., Xiong, T.: Image enhancement using hybrid intelligent optimization. Opt. & Optoelectron. Technol. 341–344 (2014)
- 11. Gorai, A., Ghosh, A.: Gray-level image enhancement by particle swarm optimization, pp. 72– 77 (2009)
- 12. Weigel, D., Elsmann, T., Babovsky, H., Kiessling, A., Kowarschik, R.: Combination of the resolution enhancing image inversion microscopy with digital holography. Opt. Commun. 291, 110–115 (2013). [https://doi.org/10.1016/j.optcom.2012.10.072](http://dx.doi.org/10.1016/j.optcom.2012.10.072)
- 13. Lin, C.L.: An approach to adaptive infrared image enhancement for long-range surveillance. Infrared Phys. Technol. 54, 84–91 (2011). [https://doi.org/10.1016/j.infrared.2011.01.001](http://dx.doi.org/10.1016/j.infrared.2011.01.001)
- 14. Zhao, W.: Adaptive image enhancement based on gravitational search algorithm. Procedia Eng. 15, 3288–3292 (2011). [https://doi.org/10.1016/j.proeng.2011.08.617](http://dx.doi.org/10.1016/j.proeng.2011.08.617)
- 15. Zeng, M., Li, Y., Menga, Q., Yang, T., Liu, J.: Improving histogram-based image contrast enhancement using gray-level information histogram with application to X-ray images. Optik Int. J. Light Electron Opt. 123, 511–520 (2012). [https://doi.org/10.1016/j.ijleo.2011.05.017](http://dx.doi.org/10.1016/j.ijleo.2011.05.017)
- 16. Santhanam, T., Radhika, S.: A novel approach to classify noises in images using artificial neural network. J. Comput. Sci. 6, 506–510 (2010). [https://doi.org/10.3844/jcssp.2010.506.](http://dx.doi.org/10.3844/jcssp.2010.506.510) [510](http://dx.doi.org/10.3844/jcssp.2010.506.510)
- 17. Garg, R., Mittal, B., Garg, S.: Histogram meequalization techniques for image enhancement. Int. J. Electron. Commun. Technol. 2, 107–111 (2011)
- 18. Pentapalli, V.V.G., Varma, R.K.P: Cuckoo Search Optimization and its Applications: A Review. CSE Department, MVGR College of Engineering, Vizianagaram, India1 Associate. Professor, CSE Department, MVGR College of Engineering, Vizianagaram, India
- 19. Babu, R.K., Sunitha, K.V.N.: Original Research Paper Enhancing Digital Images Through Cuckoo Search Algorithm in Combination with Morphological Operation (2014)
- 20. Yang, X.-S., Deb, S.: Cuckoo search via Lévy flights. In: Proceedings of World Congress on Nature and Biologically Inspired Computing (NaBIC 2009), India, pp. 210–214. IEEE Publications, USA (2009)
- 21. Prashar, P., Jain, N., Mahna, S.: Image optimization using Cuckoo search and levy flight algorithms. Int. J. Comput. Appl. (0975–8887) 178(4) (2017)

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