Nat Comput (2016) 15:307–318
DOI 10.1007/s11047-015-9496-3

Development of firefly algorithm via chaotic sequence and population diversity to enhance the image contrast

Krishna Gopal Dhal[1] · Md. Iqbal Quraishi[2] · Sanjoy Das[1]

Published online: 28 March 2015

Abstract Nature-inspired algorithms have been applied in the optimization field including digital image processing like image enhancement or segmentation. Firefly algorithm (FA) is one of the most powerful of them. In this paper two different implementation of FA has been taken into consideration. One of them is FA via lévy flight where step length of lévy flight has been taken from chaotic sequence. Chaotic sequence shows ergodicity property which helps in better searching. But in the second implementation chaotic sequence replaces lévy flight to enhance the capability of FA. Population of individuals has been created in every generation using the information of population diversity. As an affect FA does not converges prematurely. These two modified FA algorithms have been applied to optimize parameters of parameterized contrast stretching function. Entropy, contrast and energy of the image have been used as objective criterion for measuring goodness of image enhancement. Fitness criterion has been maximized in order to get enhanced image with better contrast. From the experimental results it has been shown that FA with chaotic sequence and population diversity information outperforms the Particle swarm optimization and FA via lévy flight.

✉ Krishna Gopal Dhal
krishnacse42@gmail.com

Md. Iqbal Quraishi
iqbalqu@gmail.com

Sanjoy Das
dassanjoy0810@hotmail.com

[1] Department of Engineering and Technological Studies, University of Kalyani, Kalyani, Nadia, West Bengal, India

[2] Department of Information Technology, Kalyani Government Engineering College, Kalyani, Nadia, West Bengal, India

Keywords Contrast enhancement · Firefly algorithm · Lévy flight · Chaotic sequence · Co-occurrence matrix

1 Introduction

The goal of Image enhancement is to process an image using some transformation function such that the resultant image is more suitable than the original one for some specific applications (Gonzalez and Woods 2002). Enhancement is taken as a pre-processing step in image processing field because many images, such as remote sensing images, medical images and also various real-life images suffer from poor contrast or the image is darker. Image enhancement can be applied for various image processing applications like contrast enhancement, noise reduction, edge enhancement and edge restoration.

In this paper, contrast enhancement of gray level dark images taken into consideration. Not only gray level, color images can be enhanced. Color images can be enhanced by separating the image into the chromaticity and intensity components (Gorai and Ghosh 2009, 2011). Histogram transformation is considered as one of the fundamental processes for contrast enhancement of gray level images (Garg et al. 2011). Histogram equalization (HE) is a mechanism that has no control over the rate of enhancement. The enhanced image always follows the uniform distribution. But the controlled enhancement is done by putting constraints on the probability density function with the bin underflow and bin overflow (Yang et al. 2003). Although based on histogram information different techniques are proposed in literature but enhancement of dark and low contrast images in a controlled fashion is still a big problem. For this reason there is steady rise of soft computing oriented approaches. Recently natures inspired population based metaheuristics have been devised to solve optimization problems (Yang 2010). So, they can also apply in image processing field where some problems like image enhancement, segmentation etc. has been considered as an optimization problems (Pal et al. 1994; Hashemi et al. 2010; Yun-Fei et al. 2012; Ma et al. 2011). Differential Evolution (DE) and Genetic Algorithm (GA) are stochastic and robust metaheuristics in the field of evolutionary computation and also used in image processing field to solve optimization problems (Yun-Fei et al. 2012; Ma et al. 2011; Coelho et al. 2009). Mutation factor and crossover rate have been modified by chaotic sequence of traditional DE algorithm and experimental result shows that modified DE is far better than traditional DE in image enhancement field with fast convergence rate and maintain also a good diversity property (Coelho et al. 2009). Swarm optimization algorithms like PSO based on social behavior of organisms such as bird flocking and fish schooling are have been widely applied in image enhancement field where some parameters are optimized (Gorai and Ghosh 2009, 2011; Braik et al. 2007; Shanmugavadivu et al. 2014). PSO outperforms the GA in image enhancement field (Gorai and Ghosh 2009, 2011). PSO not only used for grey scale image enhancement but also used as a color image enhancement (Gorai and Ghosh 2011). Newly developed another metaheuristic named ant colony optimization (ACO) is also applied in image enhancement technique and it gives better results than PSO and GA (Gupta and Gupta 2012). In this paper image enhancement has been taken as a non-linear optimization problem. In this context, this paper introduces two version of FA to solve this optimization problem. One is FA via lévy flight and another is FA via chaotic sequence. FA is a powerful swarm based optimization technique; it simulates the flashing behavior of fireflies (Yang 2010a, b; Fister et al. 2013). FA via lévy flight outperforms the traditional PSO and genetic algorithm (GA) in some optimization field and lévy flight has been used as random walk to control the diversification (Yang 2010). In the proposed second version of the FA, chaotic sequence has been used to replace lévy flight. Because, Food Collection behavior of bees and birds, cooperative behaviour of ants are also shows chaotic behaviour (Sheikholeslami and Kaveh 2013). Actually, chaotic sequence has been used in metaheuristic algorithms for the two purposes. One is to generate random numbers and another reason is to enhance the searching quality using chaotic search (Sheikholeslami and Kaveh 2013). In evolutionary computation and swarm based computation chaotic sequence is used to enhance the capability of those algorithms (Coelho and Mariani 2008; Leandro and Viviana 2009; Caponetto et al. 2003). With chaotic sequence population diversity is also taken into account in this paper. Population diversity plays an important role in swarm based optimization algorithms. So that the algorithm does not converges prematurely (Fister et al. 2013). In every generation new population of individuals is developed depending upon the population diversity information. There is no analytical proof that which random number generator is best for the specific metaheuristic algorithm. It is problem and domain specific (Sheikholeslami and Kaveh 2013). Because of this in the second version of FA use chaotic sequence as random number generator. In this paper, low contrast images are enhanced using an algorithm that based on the principal of contrast stretching technique described in Sect. 2. FA with lévy flight and FA with chaotic sequence described in Sect. 3. Experimental Results proved that modified FA with chaotic sequence and population diversity information is far better than FA with lévy flight in image enhancement field.

2 Image enhancement as optimization problem

2.1 Image enhancement algorithm

Image enhancement tools better the contrast, features and thereby smoothen the progress of further image processing applications such as segmentation. As a result it improves the ability of human or machine recognition system to understand the useful information in the images (Coelho et al. 2009). The contrast stretching technique (Gonzalez and Woods 2002; Braik et al. 2007) used here to modify the contrast is given below:

$$g(i,j) = [\{f(i,j) - c \times m(i,j)\}/(\max - m(i,j))] \times (M \times k)/(\sigma(i,j) + b) \tag{1}$$

where, $g(i,j)$ and $f(i,j)$ is the gray level intensity of pixels in the output and input images and *max* is the maximum gray scale value. $m(i,j)$ and $\sigma(i,j)$ are the mean and standard deviations of the image, computed using $[3 \times 3]$ window. M is the global mean value of the image. In Eq. (1) *c, k, b* are the associated three parameters to obtain a large variation in resultant image. Range of three parameters are same as (Gorai and Ghosh 2009). $c \in [0, 1]$, $b \in [0, 0.5]$, $k \in [0.5, 1.5]$. Initially k and c have been taken as 1 and b as 0. Parameter c always has been takes as a fractional value so that a fraction of the mean always subtracted from the pixel's grey level intensity value.

2.2 Objective function

The necessity of Objective function of optimization algorithms that used for image enhancement is to select a criterion that is associated to a fitness function which will say all about the image feature. To develop the objective function contrast, entropy and energy of the image has been taken into account. Depending upon the gray level co-occurrence matrix contrast, energy has been calculated. Local variations of gray levels are measured by contrast parameter. Large neighboring gray level differences are associated with high contrast. Energy is the measure of image homogeneity; it reflects pixel-pair repetitions (Haralick 1979). The feature entropy is a measure of non-uniformity in the image or region of interest. Depending upon these three parameters the proposed objective function has been described as:

$$F(I_e) = log\{[\exp(I_{con}) \times \exp(H_e)]/I_{en}\} \quad (2)$$

where, $F(I_e)$ is the fitness function. I_e is the enhanced image, H_e is the entropy of the enhanced image, I_{con} and I_{en} are the contrast and energy of the co-occurrence matrix. *exp* is the exponential operator.

3 Different firefly algorithms for image enhancement

3.1 Lévy flight

Lévy Flight has been used to generate random walk which plays a great role in metaheuristic algorithms. A random walk is a mathematical method of representing a series of consecutive random steps. It has wide applications in the fields of computer science, physics, statistics, economics and engineering (Yang 2010a, b). It can be expressed by the formula

$$S_N = \sum_{i=1}^{N} X_i$$

where, X_i is a random step size drawn from a random distribution and S_N is the sum of each of these consecutive random steps. Lévy Flight is a random walk whose step length is determined from the lévy distribution. It is capable of exploring large amount of search space. Lévy Flight is also found in nature as certain species of birds and insects exhibit this type of motion while gathering food (Yang 2010c). Even physical phenomena such as diffusion of gas molecules have been seen to follow Lévy Flight behavior under the right conditions. Lévy Flight can be produced using different algorithms which include Rejection algorithm, McCulloch's algorithm, Mantegna's algorithm etc. In this study Mantegna's algorithm has been used. It produces random numbers according to a symmetric Lévy stable distribution as described below—

$$\sigma = \left[\Gamma(1+\alpha)\sin(\pi\alpha/2)\Big/\Gamma\Big((1+\alpha)/2\alpha 2^{(\alpha-1)/2}\Big)\right]^{1/\alpha} \quad (3)$$

where, Γ is the gamma function (Yang and Deb 2010; Yang 2010c), $0 < \alpha \leq 2$ (Yang 2010c), in this study it is taken as 1.5 which is same as (Yang and Deb 2010). σ is the standard deviation.

As per Mantegna's algorithm the step length v can be calculated as,

$$v = {}^{x}\Big/{|y|^{1/\alpha}} \quad (4)$$

here, x and y are taken from normal distribution and $\sigma_x = \sigma, \sigma_y = 1$ (Yang 2010c). Where σ is the standard deviation.

The resulting distribution has the same behavior of Lévy distribution for large values of the random variables (Yang and Deb 2010; Leccardi 2005).

Lévy Flight is used for the diversification as well as intensification in stochastic optimization algorithm (Yang 2010b, c; Yang and Deb 2010). For the case of diversification the step length has been taken larger than in the case of intensification. The repetition of the same position in its space by lévy Flight is less than the Brownian motion (Yang 2010b, c).

3.2 Chaotic sequence

It has been proved that the cooperative behavior of ants and food collection behavior of bees and birds also shows chaotic behavior (Sheikholeslami and Kaveh 2013). The complex behavior of non-linear deterministic system is defined by chaos (Boccaletti et al. 2000; Leandro and Viviana 2009). Chaos has non-repetition property and for this it searches best solution faster than any searching strategy that depends upon the probability distribution (Leandro and Viviana 2009). It also has ergodicity property.

Recently, chaos combined with metaheuristic algorihms and produce good result (Coelho and Mariani 2008; Leandro and Viviana 2009; Caponetto et al. 2003). Particle swarm Optimization (PSO) used it for enhance the diversification property (Leandro and Viviana 2009). Evolutionary optimization algorithms can enhance its capability of searching global best solution using chaotic sequences (Caponetto et al. 2003).

There are several chaotic generators like logistic map, tent map, gauss map, sinusoidal iterator, lozi map, chua's oscillator etc. (Caponetto et al. 2003). Among those simple logistic equation that based on logistic map is used in this paper to generate mutation factor. The equation of logistic map is given below:

$$L_{m+1} = aL_m(1 - L_m) \quad (5)$$

a is a control parameter and $0 < a \leq 4$, L_m is the chaotic value at mth iteration. The behavior of the system is mostly depends on the variation of a. Value of a is 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 (Coelho et al. 2009). The range of L_m is transformed to [0, 1] in this study.

3.3 Theory of firefly algorithm

One of the most efficient and rigid metaheuristic algorithm for solving computational problems is the Firefly Algorithm (Yang 2010a, b; Fister et al. 2013).

Firefly algorithm using Lévy flight was originally presented by Xin She Yang under inspiration of flashing behavior of fireflies (Yang 2010).

3.4 Behaviour of fireflies

The model of flashes is often extraordinary for a specific species. The bursting of bright light is created by a method of bioluminescence, and the actual functions of such gestural systems are still in discussion. However, two fundamental functions of such flashes are to attract breeding partners (communication), and to evoke potential prey. The regular pattern of flash, the rate of flashing and the amount of duration form sector of the signal system that attracts both sexes together. Females reacts to a male's creative sequence of flashing in the identical species, while in some categories such as photuris, female fireflies can replicate the mating flashing pattern of other division so as to tempt and eat the male fireflies who may mistake the flashes as a promising appropriate partner (Yang 2010).

So, three flawless guideline of glowing behaviour of fireflies are:

1. All fireflies are unisex so that one firefly will be allured to other fireflies regardless of their sex;
2. Attractiveness proportional to their brightness, thus for any two glowing fireflies, the less bright one will be attracted towards the dazzling one. The attractiveness is proportional to the brightness and they both decrease as their interval amplifies. If there is no lustre one than a particular firefly, it will move haphazardly;
3. The brightness of a firefly is determined by the landscape of the fitness function. In case of maximization problem, the brightness of firefly proportionally related to the value of the fitness function (Yang 2010; Fister et al. 2013).

In the firefly algorithm, there are two main issues: the difference of luminous intensity and production of the attractiveness (Yang 2010; Fister et al. 2013). For a given medium with a fixed light absorption coefficientγ, the light intensity I varies with the distance$r$. For this

$$I = I_0 \times \exp(-\gamma r)$$

where, I is the original light intensity.

As a firefly's attractiveness is proportionally related to the light intensity.

We can now define the attractiveness β of a firefly by

$$\beta(r) = \beta_0 \times \exp(-\gamma r^2)$$

β_0 is the attractiveness at $r = 0$.

3.5 Firefly algorithm with chaotic lévy flight

Begin
Take an objective function *fit*
Create initial population of enhanced images
Light intensity or fitness value I_i of firefly or enhanced image X_i is determined by $fit(X_i)$
Define light absorption coefficient
While (t <= maximum generation)
  For $i = 1$ to n all n enhanced images
    For $j = 1$ to n all n enhanced images
     If ($I_j > I_i$)
Move firefly X_i towards X_j via lévy flight using chaotic step length
     End if
Attractiveness varies with distance
Evaluate new solution and update light intensity or fitness value
    End for j
End for i
Rank the enhanced images and select current best
End while
Post process results
End

In this algorithm, firefly X_i move towards X_j via lévy flight using the equation given below:

$$X_i = X_i + \beta_0 e^{-\gamma r_{ij}^2}(X_j - X_i) + L_m sign\left[rand - \frac{1}{2}\right] \otimes Levy \tag{6}$$

α, γ are the randomization parameter, *sign* function gives the direction, *rand* is a random number within [0, 1], $\otimes$ is the entry-wise multiplication. Choosing of step length of lévy flight is very crucial. In the above algorithm chaotic sequence within the range [0, 0.5] has been used as step length because it has ergodicity property. Lin and Lee (2012) proposed to use chaotic sequence as the step length of lévy flight (Walton et al. 2013).

Distance r_{ij} measured between X_i and X_j using the equation given below:

$$r_{ij} = \sqrt{\sum_{k=1}^{d} \left(X_{i,k} - X_{j,k}\right)^2} \tag{7}$$

where, d is the dimension of the problem.

In this paper$d = 3, \beta_0 = 0.5, \gamma = 0.5$ for the traditional firefly algorithm.

When $\beta_0 = 0$ then firefly do a random walk. There is no share of information or communication between solutions or fireflies. In the traditional firefly algorithm implementation, lévy flight has been used to do this random walk and the reasons are described in Sect. 3.1.

There are several disadvantages of this algorithm. These are listed below:

(a) Several parameters have to maintain in this algorithm $(\beta_0, \alpha, \gamma)$. Appropriate value choosing of these parameters is a crucial matter. In the first algorithm β_0, γ are constant.

(b) This standard FA does not keep information about the population diversity and for this reason the algorithm can be prematurely converge.

(c) Lévy flight is used as random walk in this FA. But lévy flight generates the random numbers from lévy distribution. Thus there is a chance to repeat same value and hence, does not ergodic. But chaotic sequence has non-repetition property (Leandro and Viviana 2009).

3.6 Proposed firefly algorithm with chaotic sequence

In the proposed approach, β_0 has been taken from chaotic sequence within the range [0, 0.5], α, γ are assigned with the value of inverse of golden ratio $\left(1+\sqrt{5}\right)/2$ which has been taken as $\emptyset$. Golden ratio has been taken because it performs better than random fraction (Jamil and Zepernick 2013). Now, we have to measure population diversity so that the algorithm does not converge prematurely. Depend upon the population diversity we have to select individuals to make the population.

3.7 Creation of population

In the traditional FA each parent population has been replaced by the offspring population in each generation. So, each parent is alive for one generation (Fister et al. 2013). Best solution is not kept in memory (Fister et al. 2013). For those reasons this new population making method has been taken into account.

Selection of individuals to make the population is plays an important role in any metaheuristic algorithm. If the population diversity is reach to saturation very quickly then the algorithm converges prematurely (Fister et al. 2013). So, if the population diversity is measured and depends upon this factor the individuals are selected to make the set of population then algorithm does not converge too early or do not trapped in local minima and also gives a balance between exploration and exploitation. This technique also depends upon the fitness value of each solution. The whole idea is depend on the fitness diversity metric (FDM). This FDM is used to measure the population diversity (Fister et al. 2013). On the other hand, this metric helps to balancing between the diversification and intensification in metaheuristic algorithms (Fister et al. 2013). It is defined as follows:

$$\varphi = 1 - mod\left[\left(fit_{avg} - fit_{min}\right)/\left(fit_{max} - fit_{min}\right)\right] \tag{8}$$

where, fit_{avg}, fit_{min}, fit_{max} are the average, minimum and maximum fitness value within the population.

So, from the equation we can deduce that $\varphi \in [0, 1]$.

When the value of φ is close to zero the population diversity is low and when close to one population diversity is high. So population diversity has been measured. The steps to select individuals to make population are:

Step 1: At first 2 N numbers of individuals are created. Where, N is the number of individuals that have been taken for evaluation in algorithm.

Step 2: First N individuals are taken as parent set (P_{parent}) and next N individuals are taken as offspring set ($P_{offspring}$).

Step 3: Sort the 2 N numbers of individuals according to their fitness value. Make two set, P_{high} and P_{low}. Where, P_{high} contains N individuals with higher fitness value and P_{low} contains N individuals with lower fitness value.

Step 4: Select N numbers of individuals from P_{high} and P_{low} by the following rule:

A random number r is generated in the interval [0, 1].

$$\begin{aligned} &if\ r < (0.5 - \varphi) \quad then\ take\ individual\ from\ P_{low} \\ &\qquad\qquad otherwise \quad take\ individual\ from\ P_{high} \end{aligned}$$

By using the above rule make the set P_{eval} with N individual to evaluate in search process.

Step 5: In the next generation the evaluated N individuals from the P_{eval} are replaced the set $P_{offspring}$.

In the every iteration this new population model has been created to maintain population diversity.

3.8 The algorithm is given below

Begin
Take an objective function fit
Create new population model as per Section 3.2.4.1
Light intensity or fitness value I_i of firefly or enhanced image X_i is determined by $fit(X_i)$
Define light absorption coefficient
While (t <= maximum generation)
  For $i = 1$ to n all n enhanced images
    For $j = 1$ to n all n enhanced images
      If $(I_j > I_i)$
Move firefly X_i towards X_j via chaotic sequence
End if
Attractiveness varies with distance
Evaluate new solution and update light intensity or fitness value
      End for j
End for i
Rank the enhanced images and select the current best
End while
Post process results
End

In this algorithm, firefly X_i move towards X_j via lévy flight using the equation given below:

$$X_i = X_i + L_m e^{-\emptyset r_{ij}^2}\left(X_j - X_i\right) + \emptyset sign\left[rand - \frac{1}{2}\right] \otimes L_m \quad (9)$$

In this algorithm, chaotic sequence has been used to generate random number as random walk which replaces the lévy flight. Lévy flight is used in metaheuristic because of a great reason that certain species of birds and insects exhibit this type of motion while gathering food and it has better variance than Gaussian distribution that helps to explore large area (Yang 2010c). Recent studies show that the cooperative behavior of ants and food collection behavior of bees and birds also shows chaotic behavior (Sheikholeslami and Kaveh 2013). Chaotic sequence has non repetition property because it does not generate from probabilistic distribution unlike lévy flight. There is no analytical result that which random number generator is best that enhance the capability of metaheuristic algorithms (Sheikholeslami and Kaveh 2013). As it is experimental, in the second version of modified FA algorithm chaotic sequence has been used as a random number generator (Tables 1, 2).

4 Experimental results

4.1 Enhancement factor (EF)

Enhancement factor (*EF*) is calculated using variance and mean of the image (Jha and Chouhan 2014) as given below—

$$EF = \frac{\left(\sigma_e^2/\mu_e\right)}{\left(\sigma_o^2/\mu_0\right)} \quad (10)$$

where, σ_e^2 and σ_o^2 are the variances of the enhanced and original images, and μ_e and μ_0 are the means of the enhanced and original images.

Table 1 Comparison of contrast, energy, entropy and fitness value

	Contrast	Energy	Entropy	Fitness value
Camera man				
Original image (Fig. 1a)	1.7427	0.1859	7.0691	9.3071
Output of chaotic FA (Fig. 1b)	3.0597	0.1283	7.7508	10.9225
Output of chaotic lévy FA (Fig. 1c)	2.7359	0.17546	7.3987	10.1455
Output of PSO algorithm (Fig. 1d)	1.7693	0.16339	7.2484	9.6307
Output of GA (Fig. 1e)	1.3366	0.1594	7.2741	9.4000
Output of HE (Fig. 1f)	1.4568	0.1132	7.6697	10.2245
Lady				
Original image (Fig. 2a)	1.1467	0.25030	7.0464	8.5684
Output of chaotic FA (Fig. 2b)	1.6407	0.09293	7.6624	10.5335
Output of FA chaotic lévy (Fig. 2c)	1.4268	0.11605	7.6219	10.1311
Output of PSO algorithm (Fig. 2d)	1.4112	0.1260	7.4474	9.8633
Output of GA (Fig. 2e)	1.3412	0.2013	7.2130	9.1095
Output of HE (Fig. 2f)	1.3043	0.1252	7.7817	10.1252
Lena				
Original image (Fig. 3a)	1.2135	0.1102	7.4148	9.8138
Output of chaotic FA (Fig. 3b)	2.0925	0.0708	7.8103	11.1952
Output of chaotic lévy FA (Fig. 3c)	2.3114	0.0871	7.6454	11.0708
Output of PSO algorithm (Fig. 3d)	1.815746	0.088945	7.889623	10.9059
Output of GA (Fig. 3e)	1.4213	0.0981	7.4213	10.0946
Output of HE (Fig. 3f)	1.5370	0.2839	7.8886	10.9355

Table 2 Enhancement factor of the images

	Output of chaotic FA	Output of FA chaotic lévy	Output of PSO algorithm	GA based approach	HE based
Lena	7.12	6.53	6.48	1.49	5.13
Lady	6.91	6.06	5.31	1.58	3.23
Camera man	5.88	4.83	3.81	2.84	4.21

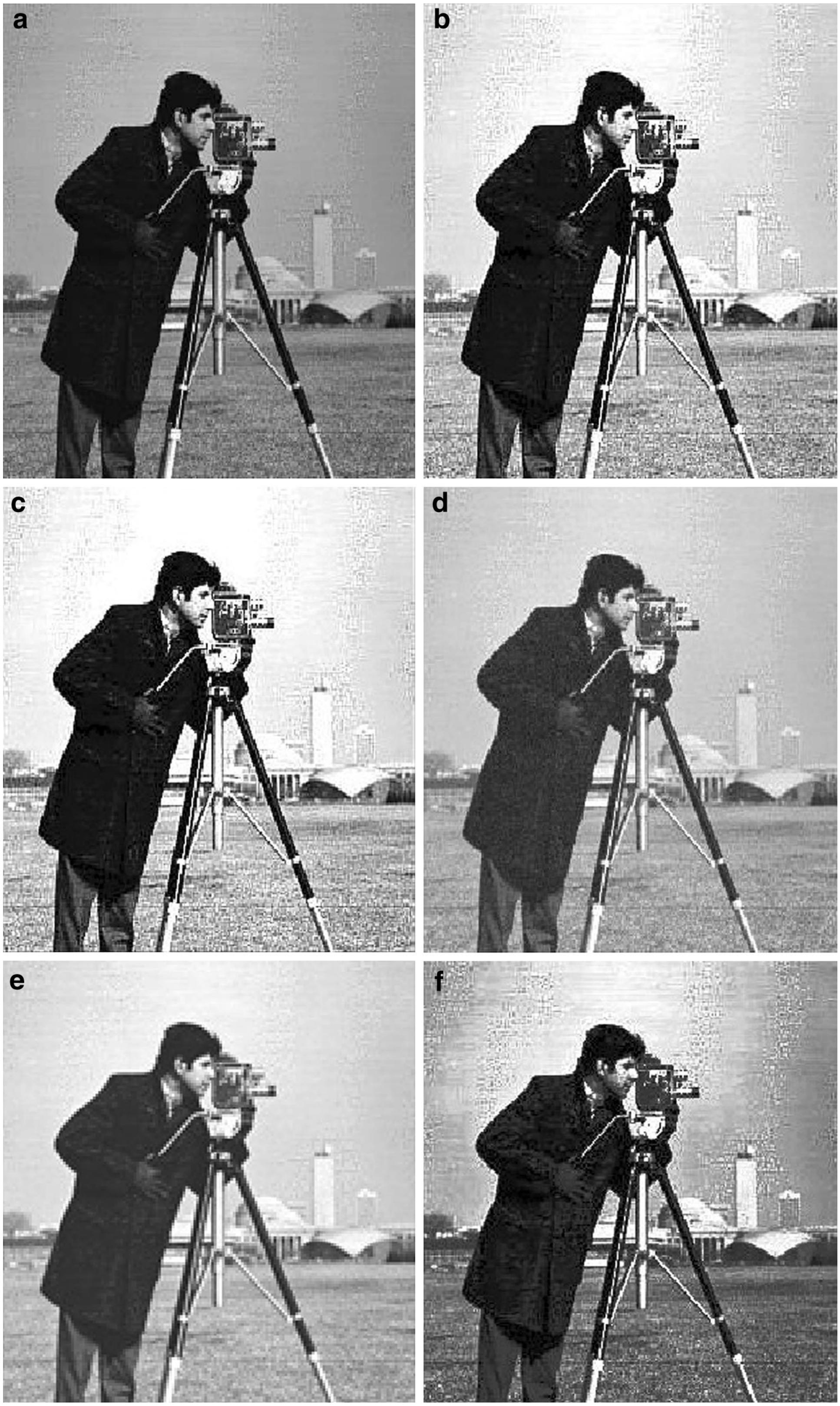

Fig. 1 **a** Original camera man image, **b** output of FA with chaotic sequence, **c** output of FA with chaotic lévy flight, **d** output of PSO, **e** output of GA, **f** output of HE

Fig. 2 **a** Original lady image, **b** output of FA with chaotic sequence, **c** output of FA with chaotic lévy flight, **d** output of PSO, **e** output of GA, **f** output of HE

Fig. 3 **a** Original lena image, **b** output of FA with chaotic sequence, **c** output of FA with chaotic lévy flight, **d** output of PSO, **e** output of GA, **f** output of HE

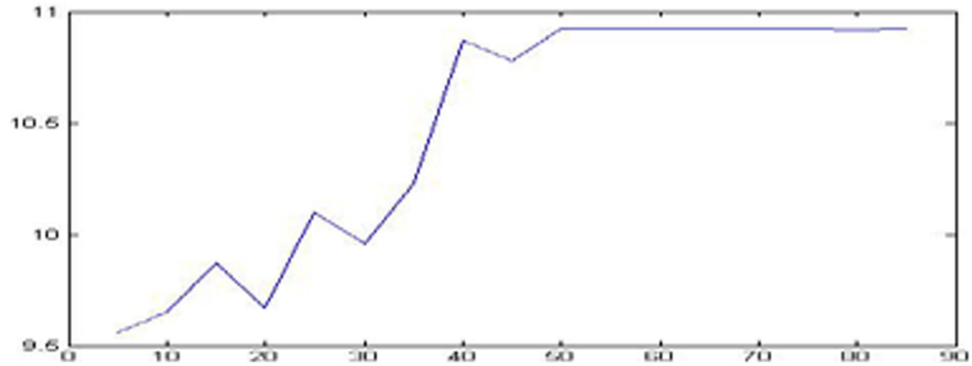

Fig. 4 Maximum generation (X axis) versus fitness value (Y axis) for FA via chaotic sequence for camera man image

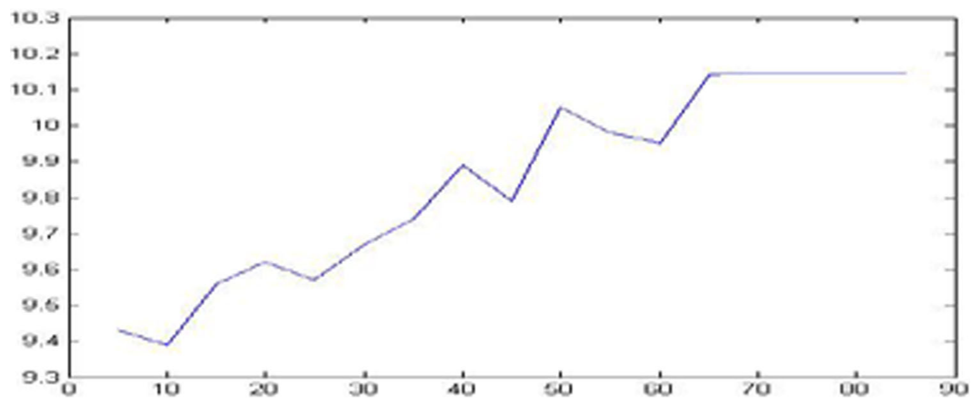

Fig. 5 Maximum generation (X axis) versus fitness value (Y axis) for FA via chaotic lévy for camera man image

4.2 Comparison of the number of maximum generation in graphical form

Three algorithms have been applied over 100 images with initial population number being varied from 10 to 50 and maximum generations up to 100. In this study, numbers of initial populations less than 5 or greater than 40 gives not so good result and it has been put optimally to 25. From the experiment, the maximum generations have been optimally put 50 for FA via chaotic sequence, 70 for FA via chaotic lévy and 95 for PSO. The graphical interpretation has been given below (Figs. 4, 5, 6).

4.3 Parameters setting

In this study ranges of three parameters are same as (Gorai and Ghosh 2009)(Tables 3, 4).

β_0,γ and α controls the diversification power of FA. β_0 and γ influences the movement of a firefly with respect to another firefly. α is the step size of lévy flight which plays a crucial role to amplify the power of convergence rate. It also helps FA so that it does not get trapped in local minima. The experiment has been done over 100 images and best average value of β_0 and γ is found to be near to 0.5 for each image with respect to objective function. Basically the values of both parameters take a scattered value but for the simplicity, average of scatter values has been taken into consideration which is near to 0.5. Lin and Lee (2012) proposed to use chaotic sequence as the step length of lévy flight (Walton et al. 2013). In chaotic lévy FA, chaotic sequence within the range of [0, 0.5] has been taken as step length. The range of chaotic sequence has been chosen optimally from the experiment. But in the case of chaotic FA the value of parameters are different. In Chaotic FA chaotic sequence has been used to generate β_0 within the range of [0, 0.5] which is an experimental feature. For chaotic FA step length α has been set to inverse the value of golden ratio because Golden ratio performs better than random fraction (Jamil and Zepernick 2013). It is also found that average value of α and γ for each image is near to 0.4 with respect to the objective function in chaotic FA.

5 Conclusion

This paper compares the two different FA in the image enhancement domain. The FA with chaotic sequence outperforms the FA with lévy flight. There is no analytical result in literature that chaotic sequence is better than lévy flight to generate random numbers. Those are problem specific. But in this study chaotic sequence enhance the capability of FA better than lévy flight. It also notable that population diversity and golden ratio is also increase the efficiency of FA. FA via chaotic sequence not only gives

Fig. 6 Maximum generation (X axis) versus fitness value (Y axis) for PSO for camera man image

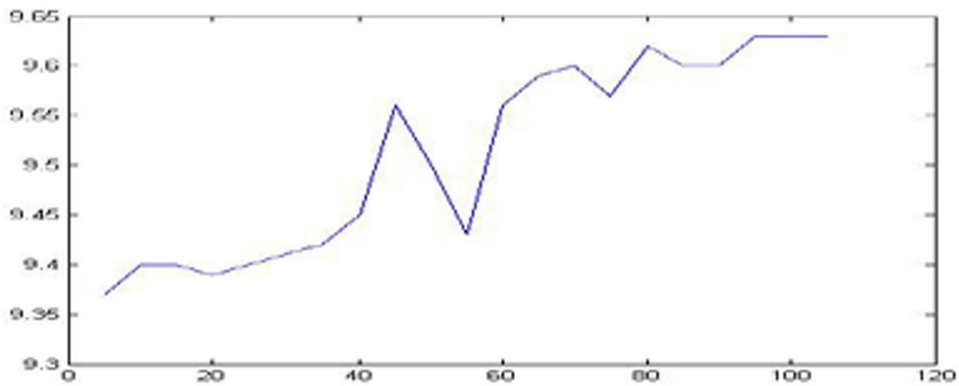

Table 3 Range of parameters of parameterized contrast stretching function

Parameters	Range
c	[0, 1]
b	[0, 0.5]
k	[0.5, 1.5]

Table 4 Parameters of chaotic lévy FA and chaotic FA

Parameters	Chaotic lévy FA	Chaotic FA
β_0	0.5	$L_m \in [0, 0.5]$
γ	0.5	$\frac{2}{(\sqrt{5}+1)}$
α	$L_m \in [0, 0.5]$	$\frac{2}{(\sqrt{5}+1)}$
Maximum generation	70	50
Population number	25	25

better objective value, also takes less number of generations. In further research these efficient algorithms can be applied in image segmentation domain, de-noising domain where these problems have been taken as optimization problem. These algorithms also extended as multi-objective optimization algorithm.

Acknowledgments This research work is funded by DST-PURSE.

References

Boccaletti S, Grebogi C, Lai YC, Mancini H, Maza D (2000) The control of chaos: theory and applications. Phys Rep 329:103–197

Braik M, Sheta A, Ayesh A (2007) Image enhancement using particle swarm optimization. In: Proceedings of the world congress on engineering

Caponetto R, Fortuna L, Fazzino S, Xibilia MG (2003) Chaotic sequences to improve the performance of evolutionary algorithms. IEEE Transact Evol Comput 7:289–304

Coelho LDS, Mariani VC (2008) Use of chaotic sequences in a biologically inspired algorithm for engineering design optimization. Expert Syst Appl 34:1905–1913

Coelho LDS, Sauer JG, Rudek M (2009) Differential evolution optimization combined with chaotic sequences for image contrast enhancement. Chaos Solitons Fractals 42:522–529

Fister I, Yang XS, Brest J, Fister IJ (2013) Memetic self-adaptive firefly algorithm. Swarm Intell Bio-Insp Comput. doi:10.1016/B978/-0-12-405163-8.00004-1

Garg R, Mittal B, Garg S (2011) Histogram equalization techniques for image enhancement. Int J Electron Commun Technol 2:107–111

Gonzalez RC, Woods RE (2002) Digital image processing, 2nd edn. Prentice Hall, New York

Gorai A, Ghosh A (2009) Gray-level image enhancement by particle swarm optimization. In: Proceedings of world congress on nature & biologically inspired computing

Gorai A, Ghosh A (2011) Hue preserving color image enhancement by particle swarm optimization. In: IEEE Conference on recent advances in intelligent computational system (RAICS), pp 563–568

Gupta K, Gupta A (2012) Image enhancement using ant colony optimization. IOSR J VLSI Signal Process 1:38–45

Haralick RM (1979) Statistical and structural approaches to texture. Proc IEEE 67:786–804

Hashemi S, Kiani S, Noroozi N, Moghaddam ME (2010) An image contrast enhancement method based on genetic algorithm. Pattern Recognit Lett 31:1816–1824

Jamil M, Zepernick HJ (2013) Lévy flights and global optimization. Bio-insp Comput. doi:10.1016/B978-0-12-405163-8.00003-X

Jha RK, Chouhan R (2014) Noise-induced contrast enhancement using stochastic resonance on singular values. SIViP 8:339–347. doi:10.1007/s11760-012-0296-2

Leandro CSD, Viviana CM (2009) A novel particle swarm optimization approach using Henon map and implicit filtering local search for economic load dispatch. Chaos Solitons Fractals 39:510–518

Leccardi M (2005) Comparison of three algorithms for Lévy noise generation. ENOC'05. In: Fifth EUROMECH nonlinear dynamics conference, mini symposium on fractional derivatives and their applications

Ma M, Liang J, Guo M, Fan Y, Yin Y (2011) SAR image segmentation based on artificial bee colony algorithm. Appl Softw Comput 11:5205–5214

Pal SK, Bhandari D, Kundu MK (1994) Genetic algorithms for optimal image enhancement. Pattern Recognit Lett 15:261–271

Shanmugavadivu P, Balasubramanian K, Muruganandam A (2014) Particle swarm optimized bi-histogram equalization for contrast enhancement and brightness preservation of images. Vis Comput. doi:10.1007/s00371-013-0863-8

Sheikholeslami R, Kaveh A (2013) A survey of chaos embedded meta-heuristic algorithms. Int J Optim Civil Eng 3:617–633

Walton S, Hassan O, Morgan K, Brown (2013) A review on the development and applications of the cuckoo search algorithm. Swarm Intell Bio-Insp Comput. doi:10.1016/B978-0-12-405163-8.00011-9

Yang XS (2010a) Firefly algorithm, lévy flights and global optimization. Res Dev Intell Syst. doi:10.1007/978-1-84882-983-1_15
Yang XS (2010b) Engineering optimization: an introduction with metaheuristic applications. Wiley, London
Yang XS (2010c) Nature-inspired metaheuristic algorithms, 2nd edn. Luniver Press, UK
Yang XS, Deb S (2010) Engineering optimisation by cuckoo search. Int J Math Model Numer Optim 1:330–343
Yang S, Oh JH, Park Y (2003) Contrast enhancement using histogram equalization with bin underflow and bin overflow. In: Proceedings of International Conference on Image Processing (ICIP-2003)
Yun-Fei C, Yong-Hao X, Wei-Yu Y, Yong-Chang Y (2012) Multilevel threshold image segmentation based on psnr using artificial bee colony algorithm. Res J Appl Sci Eng Technol 4:104–107