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A FEATURE SEGMENTATION RELATED TO MULTILEVEL THRESHOLDING PROCEDURE USING MODIFIED CUCKOO SEARCH TECHNIQUE FEATURE SEGMENTATION

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ABSTRACT
Image segmentation is the process of dividing an image into many regions in order to find individual object in an image. Image segmentation is one of the principle steps to be followed in image processing. The traditional bi-thresholding technique used in image segmentation is not efficient in case of multiple regions of interest in image. In order to overcome this problem multilevel thresholding based image segmentation is proposed. Unlike bi-level thresholding, multi-level thresholding technique can encounter more than one gray-level threshold values making it easier to make out the object of interest within the image, but it exhibits increased time complexity. Thus, an evolutionary algorithm based segmentation approach is proposed to overcome this problem. Adaptive image processing is used to enhance or restore data by removing noise without significantly blurring the structures in the image with respect to change in environmental factors. There are several bio-inspired evolutionary algorithms like firefly, Sparrow search, Artificial Bee Colony (ABC) and many more. Although these algorithms are efficient they have few optimization problems. Cuckoo search algorithm is a nature inspired optimization Meta-heuristic algorithm that can be applied in solving optimization problems and computational intelligence. An important advantage of this algorithm is its simplicity. One of the major limitations of CS algorithm is slower convergence rate. In this project, a Modified CS algorithm is proposed to improve the convergence rate even at high number of dimensions. In MCS, a dynamic weighted random walk is also adopted in order to enhance local search efficiency.
Keywords: Image Segmentation, Multi-level thresholding, Modified Cuckoo Search Algorithm, Objective functions.

1. Introduction

Image segmentation is the introductory pre-processing step to examine the image and it finds operations in videotape processing, medical analysis, computer vision, artificial production and so forth [1]. The aim of the image segmentation is reducing and simplifying the presentation of the image for easier analysis. The segmentation process separates the pixels of the image into different groups according to their similitude [2]. Thresholding technique is one of the most simple and effective segmentation system among all existing methods. Its accuracy, simplicity and robustness make it so popular when compared with other available techniques [2].

Threshold segmentation algorithm is a simple and efficient system in image segmentation, which has the advantages of small computation, simple perpetration, and stable performance. It is to divide the image pixel points into several classes grounded on several suitable thresholds setup in the whole image, and to ensure that each set of pixel points divided is consistent from the perspective of gray level. Generally speaking, image segmentation is substantially divided into single-threshold and multi-threshold, and this paper will study image segmentation under multi-threshold based on the maximum entropy value method [5]. . Generally, the query in the way real-world systems completes the search for optimality. So, for finding an optimum result of a particular problem, we need to observe a set of rules. For this purpose, a sketch of an effective Nature-inspired algorithm is made which is original to mimic evaluation of the left organizing system [6].

Nature inspired man to mimic life around him which paved way to the development of numerous meta-heuristic approaches for enforcing optimization algorithms to solve complex problems (Coello, Van Veldhuizen, & Lamont, 2002; Hammouche, Diaf, &Siarry, 2010; Ouadfel&Meshoul, 2014). Several thresholding algorithms preceded this framework using various evolutionary techniques such as Genetic algorithm (Deb, Pratap, Agarwal, &Meyarivan, 2002; Tao, Tian, & Liu, 2003; Gallotta, 2007), Particle Swarm Optimization (PSO) algorithm (Kennedy & Eberhart,1995, 2010; Sathya&Kayalvizhi, 2010; Horng, 2011), Firefly algorithm (Yang, 2009; Horng& Jiang, 2010; Brajevic& Tuba, 2014), Ant Colony Optimization (ACO) algorithm (Dorigo et al., 1999; 2008; 2010; Tao, Jin, & Liu, 2007), Bacterial Foraging Optimization (BFO) algorithm (Passino,2002, Sathya and Kayalvizhi, 2011 Brabazon, ONeill, and McGarraghy, 2015;), Honey Bee Mating Optimization (HBMO) algorithm (Haddad, Afshar, &Mariño, 2006; Horng, 2010), Cuckoo Search (CS) algorithm (Yang & Deb, 2009; Bhandari, Singh, Kumar, & Singh, 2014; Brajevic& Tuba, 2014; Bhandari, Kumar, & Singh, 2015b) and Artificial Bee Colony (ABC) algorithm (Karaboga&Basturk, 2008; Horng, 2011; Hassanzadeh, Vojodi, &Moghadam, 2011; Karaboga, Gorkemli, Ozturk, &Karaboga, 2014).

In this paper, we propose cuckoo search algorithm for solving optimization problems in image segmentation. In the original CS algorithm, there is no mechanism for controlling the step size in the redundancy procedure that can be instructions to arrive at a global minimum or maximum. In the MCS algorithm, the authors attempt to include a step function

The paper is structured as follows: Section 2 briefly explains about the different thresholding ways for image segmentation. Section 3 gives an overview about various nature inspired algorithms used in our study. Section 4 gives the impact and a fine basis of levy flight modeling in Cuckoo Search algorithm. Section 5 explains the proposed algorithm in detail. Experimental results and discussions are given in Section 6 which is validated by a set of figures and tables. Eventually Section 6 presents the concluding reflections of the study.

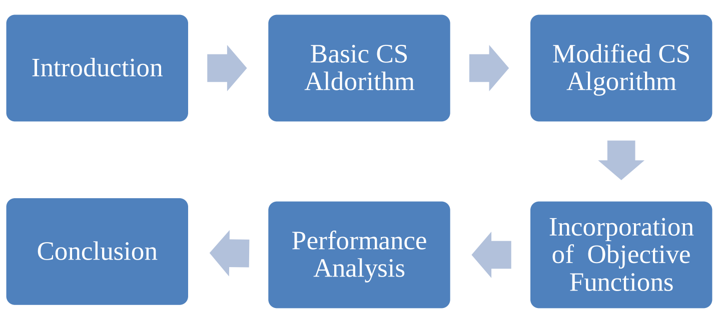

Fig.1 Block diagram of proposed system

2. Thresholding Techniques for segmentation of image

Thresholding is an extensively used and one of the simple method among the all being segmentation ways. Thresholding methods perform based on gray scale histogram of images. Generally, thresholding techniques can be classified into two approaches named as parametric and nonparametric approaches. In the parametric approaches, each group of gray scale range is supposed to accord to a Gaussian distribution. Then, the approaches work to find best parameters of Gaussian distribution to fit the histogram. On the other side, based on some criteria, nonparametric approaches attempt to find the threshold values that separate image into analogous region [2]. Thresholding is the process of creating black and white image out of a gray scale image by setting exactly those pixels to white whose value is above a given threshold, setting other pixels to black. To select a suitable threshold, thresholding methods generally optimize a criterion function; for example, maximizing between-class variance, or minimum classification error. Entropy is a measure of uncertainty in an information source, and has received increasing attention from researchers for the selection of thresholding values. Thresholding techniques are astronomically divided into bi-level thresholding and multilevel thresholding. The same approach for thresholding can be extended to colour images also.

2.1 Bi-level thresholding

For a gray scale image with intensity values ranging from 0 to $N - 1$ where N is the maximum intensity value possible. Bi-level thresholding of that image finds an intensity value which makes the foreground and background object of the image distinguishable. For finding the threshold value it binarizes the image in this way. Several methods are adopted, like calculating the variance of pixel values, entropy values etc.

$$G(x,y) = \begin{cases} 1, & f(x,y) > T \\ 0, & f(x,y) < T \end{cases} \quad \ldots\ldots\ldots(1)$$

2.2 Multilevel Thresholding

Multilevel thresholding is a process that segments a gray level image into several distinct regions. This technique determines further than one threshold for the given image and segments the image into certain brilliance regions, which correspond to one background and several objects. The method works veritably for objects with multi-colored or complex backgrounds. The same can be extended to color images also where we have to process R,G,B channels individually each with N different gray levels.

For multi-level thresholding techniques, number of the threshold value is greater than one and an output image has multiple groups which is generated according to equation (). In equation (1), f(x,y) is input image, m is the number of thresholds and $t_i$is the i^{th} threshold value where i=1... m.

$$M_0 = \{g(x, y) \in f(x, y) | 0 \leq g(x, y) \leq t_1 - 1\}$$

$$M_1 = \{g(x, y) \in f(x, y) | t_1 \leq g(x, y) \leq t_2 - 1\}$$

$$M_i = \{g(x, y) \in f(x, y) | t_i \leq g(x, y) \leq t_{i+1} - 1\} \quad \ldots\ldots\ldots(2)$$

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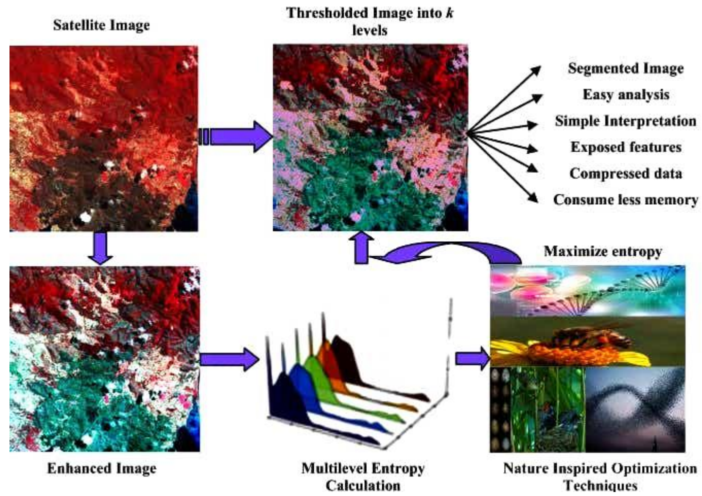

Fig.2 Representation of Multilevel Thresholding

2.3 Otsu's Thresholding

Otsu's method is considerably used in pattern recognition, document binarization, and computer vision. In numerous cases, Otsu's method is used as a introductory technique to segment an image for further processing such as feature analysis and quantification. Otsu's method searches for a threshold that minimizes the intra-class variances of the segmented image and can achieve good results when the histogram of the original image has two distinct peaks, one belongs to the background, and the other belongs to the foreground or the signal. The Otsu's threshold is found by searching across the whole range of the pixel values of the image until the intra-class variances reach their minimum.

Simply, it is defined as Non-parametric segmentation technique and which aims to maximize the between class (inter-class) variance thereby minimizing the within class variance measure between the pixels in each class.

$$\sigma_B^2 = w_b w_f \left(\mu_b - \mu_f\right)^2 \text{...........(3)}$$

Where,

$W_{b,f}$ =No.of pixels height in back ground (foreground)/Total number of pixels

$\mu_{b,f}$= Mean intensity of background (foreground)

2.4 Tsalli's entropy

Tsalli's entropy is used in image processing, involved in the image segmentation made in the frame work of the maximum entropy principle. A conception of Tsalli's entropy measure to a non-extensive system governed by a entropy formula.

$$\sigma_B^2 = w_b w_f \left(\mu_b - \mu_f\right) S_q = \left(\frac{1-\sum_{i=1}^{k} p_i^q}{q-1}\right)$$

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……….(4)

p_i = Pixel and its value are varied from 0 to 1 which designates the likelihood of the designed structure to be in an instant i.

$$S_q\left(f_g^c+b_g^c\right)=S_q\left(f_g^c\right)+S_q\left(b_g^c\right)+\left(1-q\right).S_q\left(f_g^c\right).S_q\left(b_g^c\right) \quad \ldots(5)$$

$$c = \begin{cases} 1, 2, 3 \text{ for color image (RGB)} \\ 1, \text{ for gray scale image} \end{cases} \quad \ldots\ldots\ldots\ldots\ldots\ldots(6)$$

where,

f_g = Foreground of an image.

b_g = Background of an image.

Considering $S_q \geq 0$ in the pseudo-additive formalism, three entropic classifications are defined as follows

- Sub-extensive entropy (q<1)
  $S_q(A+B) < S_q(A) + S_q(B)$
- Extensive entropy(q=1)
  $S_q(A+B) = S_q(A) + S_q(B)$
- Super-extensive entropy(q>1)
  $S_q(A+B) > S_q(A) + S_q(B)$

Sub-extensive entropy: Sub-extensive entropy is also called as not comparable. Having a combined system entropy that is less than the sum of the entropies of the independent systems.

Extensive entropy: In a extensive entropy having a combined system entropy is equal to the sum of the entropies of the independent system.

Super-extensive entropy: In a Super-extensive entropy having a combined system entropy is that exceeds the sum of the entropies of the independent system.

2.5 Kapur's Entropy

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The concept of Kapur's entropy measure for image segmentation arises from the fact that an image is viewed comprising a foreground and a background region which contribute towards the probability distribution of the intensity values in an image (Kapur, Sahoo, & Wong, 1985). The entropies of both the regions are separately calculated and their sum is maximized. An optimum threshold value is then computed which maximizes the sum of the entropy. The same concept can be easily extended to multilevel image thresholding which can be mathematically formulated as

$$H_m = -\sum_{i=t_m}^{N-1} \left(\frac{p_i}{\omega_m}\right) \log_2 \left(\frac{p_i}{\omega_m}\right) \quad \text{....(7)}$$

$$H_o = -\sum_{i=0}^{t_1-1} \left(\frac{p_i}{\omega_o}\right) \log_2 \left(\frac{p_i}{\omega_o}\right) \quad \text{....(8)}$$

$$H_j = -\sum_{i=t_j}^{t_{j+1}-1} \left(\frac{p_i}{\omega_j}\right) \log_2 \left(\frac{p_i}{\omega_j}\right) \quad \text{....(9)}$$

$$\omega_0 = \sum_{i=0}^{t_1-1} p_i;\ \omega_1 = \sum_{i=t_1}^{t_2-1} p_i \quad \text{....(10)}$$

Where,

H_m is the entropy of each pixel in image.

p_i is the probability of pixel intensity value to be i ranges from0 to 255.

N is the total number of distinct intensity levels in the gray scale image.

where H_0, H_1, ... H_m are the entropy values of m + 1 different regions or classes and pi is the probability of the pixel intensity value to be i where i ranges from 0 to 255 and N is the total number of distinct intensity levels in the gray scale image. It can be used for colour image segmentation by processing R, G and B channel separately.

3. Nature Inspired Algorithms

An bio-inspired is an algorithm that uses mechanisms inspired by nature and solves problems through processes that emulate the geste of living organisms.

3.1 PSO Algorithm

An introductory variant of the PSO algorithm works by having a population (called a swarm) of candidate solutions(called particles). These particles are moved around in the search-space according to a few simple formulae. The movements of the swarms are guided by their own best-known position in the search-space as well as the entire swarm's best-known position. When bettered positions are being discovered these will also come to guide the movements of the swarm. The process is repeated and by doing so it is hoped, but not guaranteed, that a satisfactory result will eventually be generated.

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3.2 ABC Algorithm

Inspired by the intelligent foraging geste of a honeybee swarm, the ABC algorithm consists of three essential factors: food source positions, nectar amounts and several honey-bee classes. Each food source position represents a feasible solution for the problem under consideration. The nectar-amount for a food source represents the quality of similar result according to its fitness value. Each bee-class symbolizes one particular operation for generating new seeker food source positions (i.e. candidate solutions). The ABC algorithm starts by generating a randomly distributed initial population (food source locations). After initialization, an objective function evaluates whether similar candidates represent an acceptable solution (nectar-amount) or not. Guided by the values of similar objective function, candidate solutions are evolved through different ABC operations (honey-bee types). When the fitness function (nectar-amount) cannot be further improvised after a maximum number of cycles, its affiliated food source is assumed to be abandoned and replaced by a new randomly chosen food source location and a optimum solution is aqquainted.

3.3 ACO Algorithm

Ant colony optimization (ACO) is a population-grounded metaheuristic that can be used to find approximate solutions to reduce optimization problems. In ACO, a set of software agents called artificial ants search for good results to a given optimization problem. To apply ACO, the optimization problem is converted into the problem of finding the best path on a weighted graph. The artificial ants (henceforth ants) incrementally build solutions by moving on the graph. The solution construction process is stochastic and is biased by a pheromone model, that is, a set of parameters associated with graph factors (either nodes or edges) whose values are modified at runtime by the ants.

3.4 Firefly Algorithm

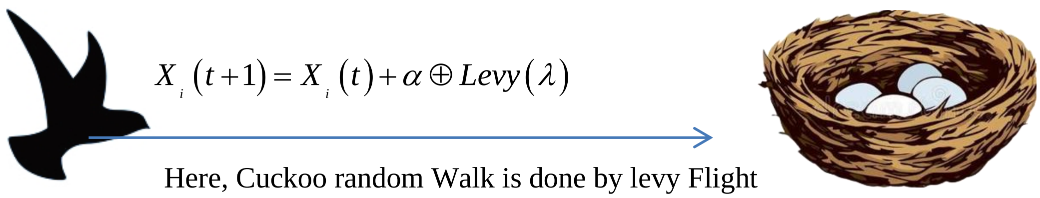
Firefly algorithm is one of the new metaheuristic algorithms for optimization problems. The algorithm is inspired by the flashing geste of fireflies. In the algorithm, randomly generated results will be considered as fireflies, and brilliance is assigned depending on their performance on the objective function. One of the rules used to construct the algorithm is, a firefly will be attracted to a brighter firefly, and if there is no brighter firefly, it will move randomly. This kind of arbitary movement of the brighter firefly by generating random directions in order to determine the best direction in which the brilliance increases .However, it'll remain in its current position, If such a direction isn't generated.

3.5 CS Algorithm

Cuckoo search (CS) algorithm (Yang & Deb, 2009) is a recently introduced meta-heuristic algorithm and is grounded on the obligate brood parasitic geste of cuckoo species found in nature.Some cuckoos have a specialty of imitating colors and patterns of eggs of a many chosen host species. This reduces the probability of eggs being abandoned. However, if host bird discovers foreign eggs, they either abandon the eggs or throw them away. Parasitic cuckoos choose a nest where the host bird just lays its eggs. Eggs of cuckoo hatch earlier than their host eggs and when it hatches, it propels the host eggs out of the nests. Hence cuckoo chicks get a good share of food and occasionally they indeed imitate the voice of host chicks to get more food (Payne, 2005). Substantially, cuckoos search food by a simple arbitary walk, where the arbitary walk is a Markov chain whose coming position is grounded on current position and transition probability of coming position. Using Levy flights instead of simple arbitary walks improve the search capabilities. Levy flight is a random walk in step-lengths following a heavy-tailed probability distribution (Yang & Deb, 2009). Each cuckoo acts as a potential solution to the problem under consideration. The main aim is to induce a new and potentially better solution (cuckoo) to be replaced with a not so good solution. Each nest has one egg but as the problem complexity increases, multiple eggs can be used to represent a set of solutions. There are three basic idealized rules of CS.

1. Each cuckoo lays one egg and dumps it in a random nest.
2. The nest with the highest fitness will carry over to next generations.
3. The number of available host nests is kept fixed and the egg laid by cuckoo is discovered by host bird with a probability p[0,1]. And depending on p, the host bird either throws the egg away or abandons the nest.

Based on the three rules, the cuckoo search has been implemented. To generate a new solution x(t+1) i for ith cuckoo, Levy flight is performed. This step is called global random walk and is given by



$$X_i(t+1) = X_i(t) + \alpha \oplus Levy(\lambda) \quad \text{.........................} (11)$$

Here,

$$Levy(\lambda) = t - \lambda;\ 1 < \lambda \leq 3 \quad \text{.............................} (12)$$

The nonlinear relationship of variance of levy flight as given in below equation which helps in exploring large unknown search spaces more efficiently compared with those models with linear relationship.

$$\sigma^2(t) \sim t^{2-\beta};\ 1 \leq \beta \leq 2 \quad \text{..........................} (13)$$

The iterative process continues till it reaches the global optima. This preferably avoids the problem of being caught in local optima which usually appears in PSO algorithm.

In this equation where;

$X_i(t+1)$ is the New Solution

t is the Current iteration

$X_i(t)$ is the Current location

α is the Step Size

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$\oplus$ is the Entry Wise Multiplication

$Levy(\lambda)$ is the Levy Exponent

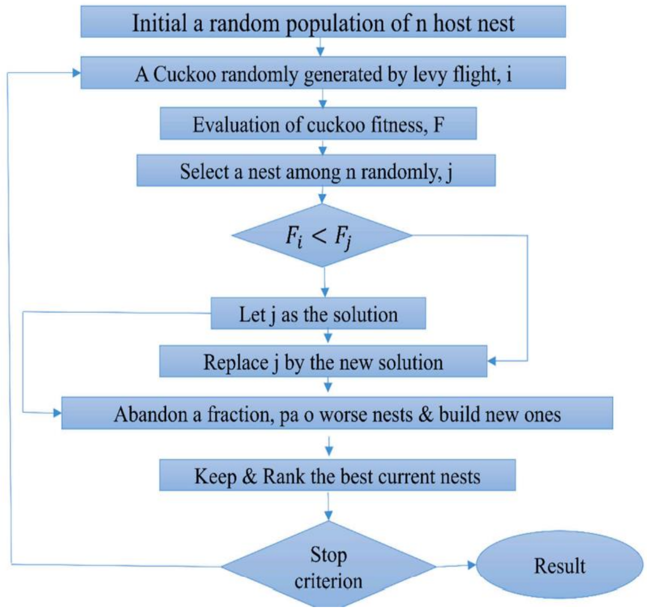

Fig.3Flow chart of CS Algorithm

4. MCS Algorithm

Modified Cuckoo Search(MCS) is an evolutionary optimization algorithm enforced from the standard CS algorithm and was proposed to find a better solution than CS algorithms to overcome the optimization problem.In MCS, it includes a step function, which is commensuate to the fitness of a distinctive nest in the search space.In the proposed MCS algorithm, an exertion is fashioned to build the CS Modified,without exercising the Levy distribution. The flowchart of Modified Cuckoo Search Algorithm is shown in fig

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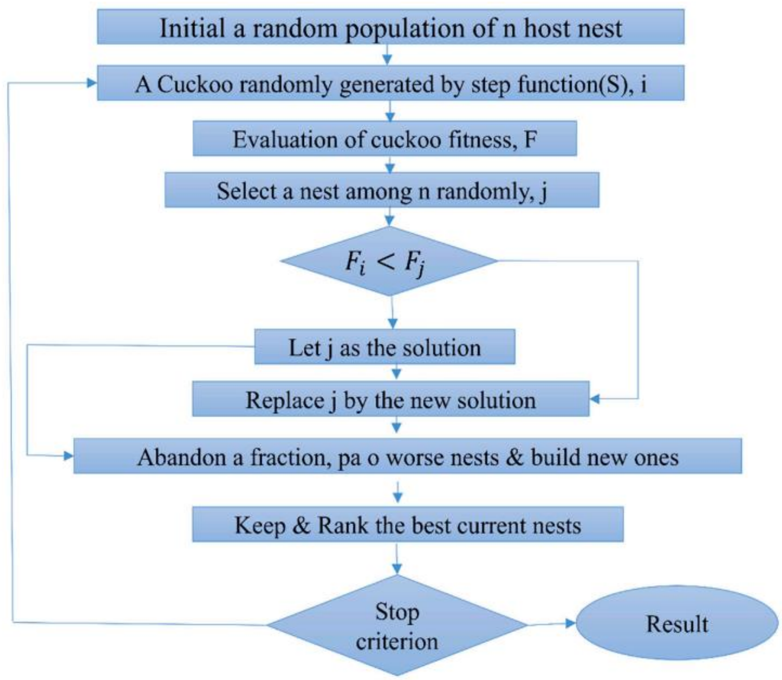

Fig.4 Flow chart of MCS Algorithm

In standard CS algorithm generally uses the Levy distribution for exploring the search space. The Levy step size be attained from either Mantegna or McCulloch's method. The authors Yang and Deb recommended that the levy step size attained from McCulloch's method is more effective than the Mantegna approach. Hence genearlly, the CS algorithm pursues the Levy distribution.

In the original CS algorithm, there is no medium for controlling the step size in the redundancy procedure that can be instructions to arrive at a global minimum or maximum. In the MCS algorithm, the authors attempt to include a step function. It is commensurate to the fitness of a distinctive nest in the search space of the present generation. In another way, in a few articles α pick up as a steady parameter but in MCS, the α parameter was excluded. Hence the step function in the MCS algorithm can be calculated by Eq

$$s_i(t+1) = \left(\frac{1}{t}\right)^{\left|\frac{best(t)-fit(t)}{best(t)-worstf(t)}\right|} \quad \text{..................... (14)}$$

Where,

t =Generation of the cuckoo

$fit_i(t)$ = Value offitness function ofithnestintthgeneration

$bestf(t)$ = Maximum value of fitness function ofthetthgeneration.

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$worstf(t)$ = Minimum value of fitness function of thet^{th}generation

The stepwise procedure for Step Function for Cuckoo Search Optimization is shown below:

1. Initialize “n” number of host nests with arbitrary population.
2. Gain a cuckoo xi at random by **Step function** calculation
3. Select a nest randomly as x_j
4. Compare $Y(x_i)$ and $Y(x_j)$ values if xi is best means then replace j with new solution and stop else
5. Discard the dradeful nest and construct new one using step.
6. Continue the process still the stopping criterion satisfies.

5. Experimental results

In this section, the experimental outcomes of Modified Cuckoo Search Algorithm with three different objective functions namely Otsu’s method, Tsalli’s entropy and Kapur’sentroy function have been deliberated. The experimental outcomes for each gray scale and color image are demonstrated in Fig.8.2. The comparison of best threshold values has been given in it demonstrates that Tsalli’s entropy function chooses the optimum threshold values whereas Otsu’s method reaches the satisfactory optimum threshold values. Moreover, it has been demonstrated in Table.8.1 that computational complexity in terms of CPU running time reduces using Otsu’s method comparing toTsalli’s entropy function and Kapur’s entropy function in MCS algorithm for segmenting color and gray scale images. Whereas, Otsu’s has provided acceptableoutcomes.

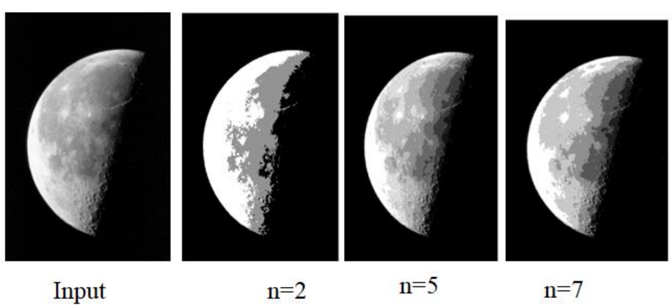

Fig.5. Experimental results of input image using MCS Algorithm using Tsallis entropy as an objective function

Here n represents the thresholding level considered for segementation .We can observe that as the number of thresholding level increases the images gets segments into various regions where each region has a different pixel value. Also, the histogram of segmented images can be used to know the no. of thresholding levels assigned to the image

Input N= 2 N= 5 N = 7

Fig.6. Experimental results of input image using MCS Algorithm using Kapur's entropy as an objective function

Input N=2 N=5 N=7

Fig.7. Experimental results of input image using MCS Algorithm using Otsu's method as an objective function

Table1. Comparision of running time for different thresholding levels using three different objective functions

Thresholding	Kapur's	Tsalli's	Otsu's
N=2	2.425	2.213	2.166
N=5	2.621	2.52	2.445
N=7	2.939	2.725	2.673
N=9	3.574	3.087	3.277

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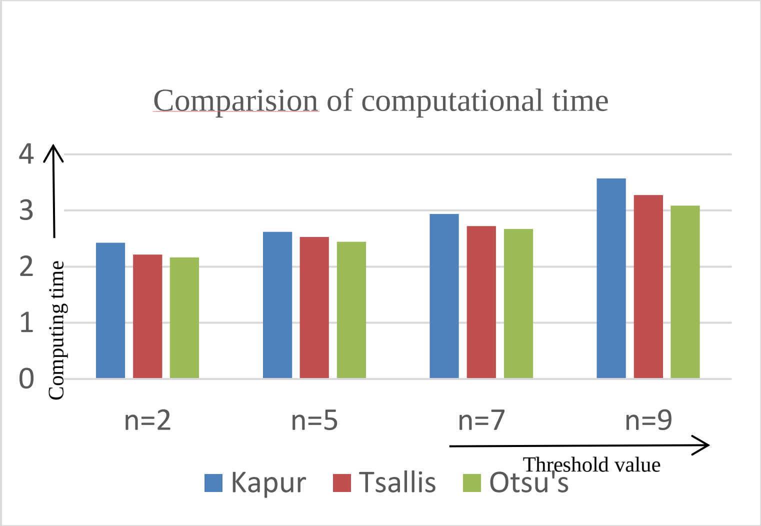

Fig.8.Graphical demonstration of CPU running time for 3 objective functions

Conclusion

Nature-inspired algorithms face some problems like execution time complexity with increasing the amount of the thresholding level for color image segmentation. In several previous studies, it's been reported CS algorithm is simpler and efficient tools for image segmentation and it required fewer parameters within the evolution process. The variant of the cuckoo search algorithm uses levy flight to explore the search space globally to seek out the most effective threshold value. Therefore, levy flight modeling plays a very important role to the convergence speed of the Cuckoo Search algorithm. One among the constraints is to pick out parameters ahead, which can affect the performance of the optimization algorithm. Performance is also associated to the convergence speed, reaching a global minimum, or being at a local minimum. Therefore, a Modified Cuckoo Search (MCS) algorithm has been used to minimize the parameters and adaptively determine the search path in less time to reach the best threshold value without thinking about the concepts of levy flight and the additional benefit of MCS is that it is aa parameter-free algorithm. In this current project, combining three objective functions i.e. Otsu's method,Tsalli's entropy and Kapur's entropy functions, the application of evolutionary algorithms is extensively studied for the multilevel-based color and gray scale image segmentation problem. The evaluation results of statistical tools show that the MCS algorithm with both three different objective functions namely Otsu's method, Kapur's and Tsalli's entropy function can be effectively used for segmenting color images based on multilevel thresholding approaches. However, MCS algorithm with Otsu's method as an objective function outperforms other approaches in terms of computational time but Kapur's entropy function in MCS algorithm is more efficient in terms of segmentation quality. Moreover, the result obtained by tools has found the proposed algorithm showed tremendous improvement when compared to the result obtained from other nature inspired algorithms and it minimizes the time complexity in terms of computational complexity i.e. CPU running time. The experimental outcomes achieved for different color and gray scale images demonstrate that the proposed method reveals to be favorable for both gray scale and color image segmentation more efficient for both lower level as well as the higher level of thresholding value which are one of the main limitations present in standard CS method as well as other nature inspired algorithms besides the time complexity and segmented quality.

FUTURE SCOPE

For future work, the proposed algorithm cab be extended for multi-objective optimization problems and also can be extended for developing some clustering approaches for application in some real life problems like satellite image segmentation ,gene expression data clustering ,cancer classification etc.

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