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Ocular Fundus Image Segmentation using Cuckoo Search Algorithm

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ABSTRACT

Retinal Fundus image segmentation is challenging due to the presence of faintly interrelated optic nerve disk, fovea, and blood vessels. Among them most relevant and region of interest is blood vessels for ophthalmologists for proper disease diagnostic purpose. In this paper, we proposed a computationally effective image segmentation algorithm for fundus image segmentation known as Cuckoo Search algorithm The proposed algorithm evaluated to be most promising, and computationally effective for segmenting fundus images. Convergence rate evaluations also reveals that the proposed algorithm outdoes others in achieving stable universal optimum thresholds. The trial outcomes help ophthalmologists for proper diagnostic on retinal diseases like Glaucomatous and diabetic retinopathy and inspire interrelated researches for more accuracy and efficiency in image segmentation of fundus images.

Keywords

Image Segmentation, Fundus images Protocol, Cuckoo algorithm, Otsu's method, Kapur's entropy method, Tsallis entropy.

INTRODUCTION

Fundus is the base or bottom of anything. In medicine, it is a wide-ranging term for the innermost lining of a hollow organ. The ocular fundus is the innermost lining of the eye comprising of the Sensory Retina, Bruch's Membrane, the Choroid, and the Retinal Pigment Epithelium.

Retina is the inner most part of human eye that senses the external illumination. Light falls on retina and lots of opto-sensitive tissues transform these signals into electric signals and communicate these signals to the brain for clarification. Optical-disc seems as an elliptical bright section on retinal fundus image from where all retinal blood vessels enters retina. The outline of blood vessels in retina are unique to every person which is significant from the viewpoint of biometric examination [1]. Diabetic retinopathy is the one amongst other

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foremost reasons of blindness in the adult population. Initial detection of diabetic retinopathy via screening programs and succeeding treatment is crucial in order to evade visual blindness. The early symptoms of diabetic retinopathy as demonstrated in retinal images embraces micro-aneurysms, exudates, and hemorrhages. Clinicians usually use retinal fundus images for the showing differential analysis of retinal diseases for example lesions, retinal edema, exudates, age-related macular degeneration, diabetic retinopathy malarial retinopathy, cataracts, glaucoma, estimation of strokes in patients of hypertension and so on [2-4]. The increasing ubiquity of diabetes and less number of clinical experts, increase the requirement for automatic approaches to lessen the workload of physicians [5] also making the diagnosis consistent and robust. Color fundus imaging has arisen as the favored technique by the medical community for complete large scale retinal disease recognition due to their affluence of acquisition and decent visibility of retinal structures.

In the literature, a no. of approaches for segmenting the cataracts, optical disk, exudates, blood vessels etc. have been recommended. It is well recognized fact that the segmentation of color image proves to be more useful than the segmentation of gray scale image, as color image expresses much more image features than gray scale image. In this paper we are using various thresholding techniques to find fitness function for segmenting fundus images, used thresholding approaches are kapur'sthresholding, Ostu'sthresholding and Tsallis entropy and the algorithm used for segmenting is cuckoo search algorithm. In the later part of this paper we are going to discuss them in detail.

THRESHOLDING TECHNIQUES

Thresholding is a vital part of image segmentation, where we wish to isolate objects from the background. It is also an important component of robot vision. It is used to remove unnecessary detail from an image, to concentrate on essentials.

OTSU's METHOD

Otsu's method also wellknown as between class variance method is a non parametric segmentation technique which aims to hike the inter class variance which in turn minimizes with in class variance amount between the pixels of each class (Otsu, 1979). For multilevel thresholding segmentation problem, we can outline $\mu_0 , \mu_1 \dots \mu_m$as the average intensity pixel value of class $0, 1 \dots m$resp., $\mu_T$as the global average, $p_i$as the pixel intensity probability where $i$varies from 0 to 255 and Nsignifying the tot no. of different intensity levels. The between class variance function is specified as

$$\sigma_0^2 = \omega_0(\mu_0 - \mu_T)^2,$$
$$\sigma_1^2 = \omega_1(\mu_1 - \mu_T)^2,$$
$$\sigma_j^2 = \omega_j(\mu_j - \mu_T)^2,$$
$$\sigma_m^2 = \omega_m(\mu_m - \mu_T)^2$$

Where,

$$\mu_0 = \frac{\sum_{i=0}^{t_1-1} i p_i}{\omega_0},$$
$$\mu_1 = \frac{\sum_{i=t_1}^{t_2-1} i p_i}{\omega_1},$$

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$$\mu_j = \frac{\sum_{i=t_j}^{t_{j+1}-1} ip_i}{\omega_1},$$

$$\mu_m = \frac{\sum_{i=t_m}^{N-1} ip_i}{\omega_1}, \tag{3}$$

Hence the segmentation method tries to maximize $f(t)$ which is the summation of the between class variance func. to find the optimal threshold values as given below in the Eq (4)

$$\underset{t}{\rightarrow} *= a \quad m \quad (f(t)),$$

Where

$$f(t) = \sum_{i=0}^{m} \sigma_i^2 \tag{4}$$

This method is relevant for both color satellite and gray scale images.

KAPUR'S ENTROPY METHOD

The idea of maximizing the Kapur entropy measure for image segmentation ascends from the detail that an image is comprised of foreground and a background region in an image which pay towards the probability distribution of the intensity values (Kapur, Wong, and Sahoo, 1985). The entropies of both the regions are distinctly evaluated and their sum is maximized. An optimal threshold value is then calculated which maximizes the summation of the entropy. The same thought can be simply protracted to multilevel image thresholding which can be statistically expressed as

$$H_0 = -\sum_{i=0}^{t_1-1} \left(\frac{p_i}{\omega_0}\right) \log_2\left(\frac{p_i}{\omega_0}\right);$$

$$H_1 = -\sum_{i=t_1}^{t_2-1} \left(\frac{p_i}{\omega_1}\right) \log_2\left(\frac{p_i}{\omega_1}\right);$$

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

$$H\,m = -\sum_{i=t_m}^{N-1} \left(\frac{p_i}{\omega_m}\right) \log_2\left(\frac{p_i}{\omega_m}\right);$$

where$\omega_0 = \sum_{i=0}^{t_1-1} p_i$;

$$\omega_1 = \sum_{i=t_1}^{t_2-1} p_i;$$

$$\omega_j = \sum_{i=t_j}^{t_{j+1}-1} p_i ;$$

$$\omega_m = \sum_{i=t_m}^{N-1} p_i ; \tag{5}$$

where$H_0,\ H_1,\ \ldots H_m$are the entropy values of $m+1$ dissimilar classes or regions and probability of the pixel intensity value denoted by p_i where intensity i varies from 0 to 255 and in the gray scale image $N$is the tot no. of different intensity levels. Same methodology can be used for color image segmentation by processing RGB channels distinctly.

TSALLIS ENTROPY

Tsallis entropy is presented by ConstantinoTsallis basically it is the simplified form of Boltzmann Gibbs entropy measure. A simplified form of Tsallis entropy measure to a non-extensive system administered by an entropy formula given in Eq. (6) can be expressed using the idea of multifractal theory by Tsai in 1985.

$$S_q = \frac{1-\sum_{i=1}^{k} p_i^q}{q-1} \tag{6}$$

where$p_i$ranges from 0 to 1 which signifies the probability of the modelled system to be in state i. In the case of grey level image it signifies the no. of different intensity levels. The parameter $q$which elasticities the measure of non-extensively system under deliberation it is known as Tsallis parameter. By using pseudo additivity entropy rule we can have

$$S_q(f_g^c + b_g^c) = S_q(f_g^c) + S_q(b_g^c) + (1-q)\,.\,S_q(f_g^c)\,.\,S_q(b_g^c)$$

Where

$$c = \begin{cases} 1,2,3, & f \quad c \quad in \quad (R \quad) \\ 1, & fo \quad g \quad - s \quad in \end{cases} \tag{7}$$

where$b_g$and f_g signifies the background and foreground of an image. This technique can be used for segmenting color and grey scale images. Multilevel i.e. *m*-level image thresholding by Tsallis entropy technique by Agrawal et al. in 2013 and in 2014 Bhandari et al. thus can be expressed as

$$S_q^{c_0}(t) = \frac{1-\sum_{i=0}^{t_1-1}\left(\frac{p_i^c}{\sum_{i=0}^{t_1-1} p_i^c}\right)}{q-1}$$

$$S_q^{c_1}(t) = \frac{1-\sum_{i=t_1}^{t_2-1}\left(\frac{p_i^c}{\sum_{i=t_1}^{t_2-1} p_i^c}\right)}{q-1}$$

$$S_q^{c_j}(t) = \frac{1-\sum_{i=t_j}^{t_{j+1}-1}\left(\frac{p_i^c}{\sum_{i=t_j}^{t_{j+1}-1} p_i^c}\right)}{q-1}$$

$$S_q^{c_j}(t) = \frac{1-\sum_{i=t_m}^{N-1}\left(\frac{p_i^c}{\sum_{i=t_m}^{L-1} p_i^c}\right)}{q-1} \tag{8}$$

generating the optimal threshold values as

$$[\vec{t_0^*}, \quad \vec{t_1^*}, \ldots \vec{t_m^*}] = a \quad m \quad [S_q^{c_0}(t) + S_q^{c_1}(t) \ldots S_q^{c_m}(t) + (1-q)\,.\,S_q^{c_0}(t)\,.\,S_q^{c_1}(t)\,.\,S_q^{c_m}(t)]$$

subject to

$$|P^{c_0} + P^{c_1}| - 1 < S^{c_0} < 1 - |P^{c_0} + P^{c_1}|;$$
$$|P^{c_1} + P^{c_2}| - 1 < S^{c_1} < 1 - |P^{c_1} + P^{c_2}|;$$

$$|P^{c_{m-1}} + P^{c_m}| - 1 < S^{c_m} < 1 - |P^{c_{m-1}} + P^{c_m}|; \tag{9}$$

$P^{c_0}, P^{c_1}, \ldots P^{c_m}$can be evaluated from the probability distribution of pixel values against threshold values $\overrightarrow{t_0^*}$, $\overrightarrow{t_1^*}$, ... $\overrightarrow{t_m^*}$ respectively.

specified as,

$$P^{c_0} = \sum_{i=0}^{t_1-1} p_i^c\,;\; P^{c_1} = \sum_{i=t_1}^{t_2-1} p_i^c\,; \ldots P^{c_m} = \sum_{i=t_m}^{L-1} p_i^c \tag{10}$$

CUCKOO SEARCH (CS) ALGORITHM

It is also a meta experimental optimization algorithm progressed by captivating imitation policy of certain Cuckoo species developed by Deb and Yang in 2009. They lay eggs in other birds nest and even take away host eggs to upsurge the probability of their eggs to be hatched. These birds displays mainly of three types of blood parasitism: (a) Nest takeover (b) Cooperative breeding (c) Intra-specific. certain species of host birds merely throw out cuckoos eggs or even left their own nest and lay up a new one when alien eggs have been revealed.

Some species of Cuckoo are very clever. They even copycat the texture and color of the host bird eggs. which lessens the probabilities of getting caught. For shortening the whole procedure, we assume these 3 situations 1. One egg will be put up at a time by each cuckoo in any nest selected arbitrarily. 2. Nest having the best quality eggs are passed over to the upcoming generation. 3. The probability of host species determining cuckoo's egg lying within the probability range of $p_a \in [0, 1]$ and the tot no. of nests is being fixed. The Cuckoo search procedure initializes its first iteration with a arbitrarily engendered solution set attained by Eq. used in ABC procedure. Once the cuckoo's egg has been identified by host species in its nest, it will abdicate the nest or thrown out that very egg away which is realized in this algorithm by substituting $p_a$of the tot. no. of nests with new one. Each & every egg resembles to a viable solution and thereby its fitness value have been evaluated. A novel solution is designed using the idea of $L\acute{}evy$flight which is given in below Eq.

$$x_i(t + 1) = x_i(t) + \alpha \oplus L\acute{}e \quad (\lambda) \tag{18}$$

whereα is the size of step. $L\acute{}evy$flight put on arbitrary walks and follows $l\acute{}evy$distribution where in the step sizes given by

$$L\acute{}e \quad (\lambda) = t - \lambda; 1 < \lambda \leq 3 \tag{19}$$

The nonlinear equation for variance of $l\acute{}evy$flight is given in below Eq. which assists to explore large unidentified search gaps more proficiently as equated with models of linear equation.

$$\sigma^2(t) \sim t^{2-\beta}; 1 \leq \beta \leq 2 \tag{20}$$

The iterative procedure lasts till it attains the universal optimal. This rather evades the problem of being caught in local optimum which generally seems in PSO algorithm. The flowchart of CS algorithm is specified in above flowchart Fig. 1.

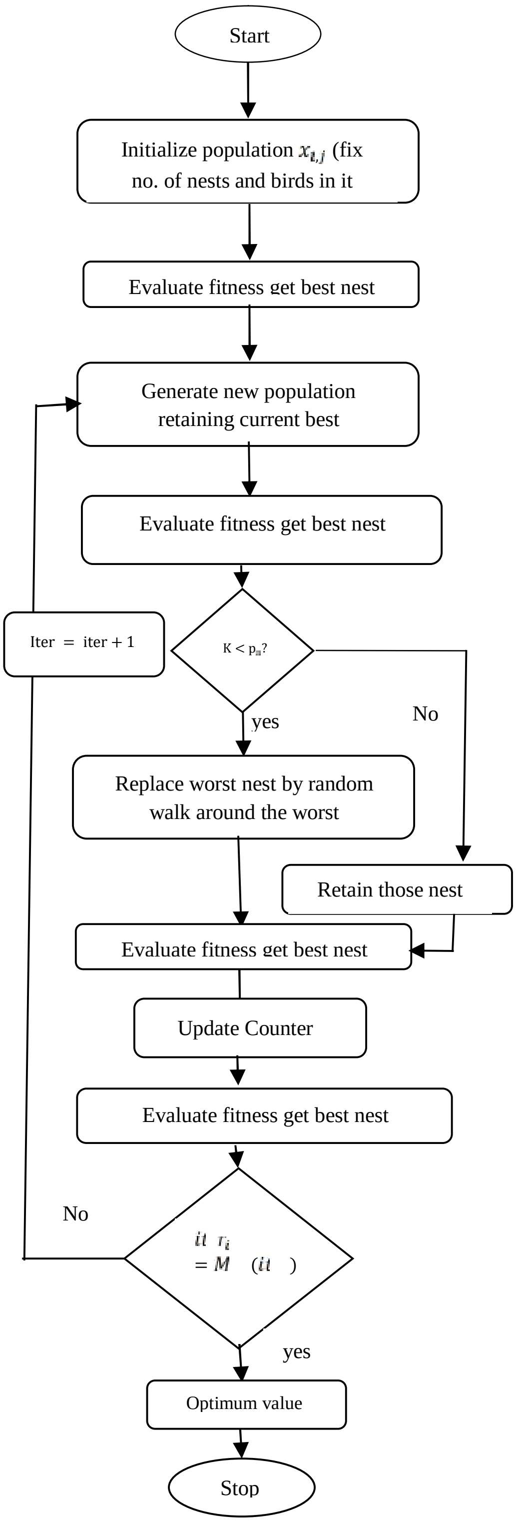

Fig. 1. Flowchart of CS algorithm.

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EFFICIENT CUCKOO SEARCH ALGORITHM (CS*McCULLOCH)*

As our main focus is on refining the of cuckoo search algorithm's convergence rate making it more effectual in time constraint situations, a novel method is projected for modelling *l´evy*flight approach in Cuckoo Search technique. The algorithm proposed in 1976 by Chambers, Stuck and Mallows grants a less expensive way of engendering constant random variables which can be cast-off for modeling *l´evy*flight. Several approaches were deduced for creating stable random no.'s in which most of them depend on taking the inverse distribution set of pseudo random no.'s homogenously distributed in the range (0,1). Performance of such approaches are rational when we need quite a large no. of simulations. Apart from being arithmetically expensive, it presented imprecisions in every iteration which will get broadcasted to the Monte-Carlo outcomes. Henceforth for problems in real-world with small or moderate size a novel method was put fwd. by Chambers et al. in 1976 which is arithmetically faster. In 2005, Leccardi emphasized on arithmetical efficiency of this approach over others in relative study of all 3 algorithms for *l´evy*noise without corrupting other parameters related to performance. Our work merges this method for *l´evy*flight generation with Cuckoo Search algorithm for segmenting fundus images. In 1976, Chambers et al. introduced algorithm which was later on encoded by *J.H. McCulloch* for real-world applications, and hereafter labelled as *McCulloch's* algorithm, which returns an m matrix of random no.'s categorized by scaling parameter c,an exponent value α, a location specifying parameter δ and skewness measure β Liable on the value of α we can clarify diverse cases for this algorithm.

Algorithm 1: Proposed *CS McCulloch* algorithm.

1 Population Initialization: $x_{i,j}$; $i \in \{1,2,....N\}, j \in \{1,2,....n\}$ via eq.$x_{i,j} = x_m^j + r$ $(0,1)(x_m^j - x_m^j)$;

2 Fitness value computation for a defined objective function: (x); $x = [x_1, x_2 \dots x_n]^T$;

3 if *(ITER <MAXITER)* **then**

4 Generate new solution space by retaining the current best;

5 Fitness value computation; Memorize best nest;

6 if $k < p_a$ **then**

7 Step size α generation using *McCulloch's* method via eqn. (32);

8 Replace worst nest by *L´evy*flight via eqn. (18);

9 Fitness value computation; Memorize best nest;

10 Update the Counter;

11 Find best fitness value so far;

12 else

13 Retain those nests;

14 end

15 end

16 Find the optimum solutions;

1. $\alpha =$ 1 resembles to the Cauchy case with its median value as δ

$$s_z = c\, t \quad (\varphi) + \delta$$

2. $\alpha =$ 2resembles to the Gaussian case with its mean as δ and variance given by $2c^2$ (β has no effect).

$$s_z = 2c\sqrt{\omega}\, s \quad (\varphi) + \delta$$

3. $\alpha >$ 1 gives the mean of the distribution to be δ for all values of β, where

$\omega = -\log_1 (r \quad (m, n))$and

$$\varphi = (r \quad (m,n) - \frac{1}{2})\pi$$

For $\beta = 0$ symmetric case and $\alpha \neq 1(\alpha \in [0, 0.1 \ldots 2])$, the algorithm uses the method portrayed in Eq. (31) to calculate step sizes.

$$s_z = c \frac{\sin\left[\alpha \quad + \tan^{-1}\left(\beta \tan\left(\frac{\alpha}{2}\right)\right)\right]\left[\cos\left((1-\alpha)\varphi - \tan^{-1}\left(\beta\left(\tan\left(\frac{\alpha}{2}\right)\right)\right)\right)\right]^{\frac{1}{\alpha}-1}}{\left[\cos\left(\tan^{-1}\left(\beta\left(\tan\left(\frac{\alpha}{2}\right)\right)\right)\right)\right]^{\frac{1}{\alpha}}(\cos(\varphi))^{\frac{1}{\alpha}}\omega^{\frac{1}{\alpha}-1}} + +\delta \sim s_\alpha(c, \beta, \delta)$$

which reduces to

$$s_z = c\left[\frac{c \quad (1-\alpha)\varphi}{\varphi}\right]^{\frac{1}{\alpha}-1}\left[\frac{\sin(\alpha \quad)}{\cos\varphi}\right]^{\frac{1}{\alpha}} + \delta$$

where s_z represents the step size.

The value of α essential to be preserved within the limit 0 to 2 in order to evade excess. So, in our applied set of experiments α is limited to a value $0 \leq \alpha \leq 2$. A β value greater than 0 outcomes the distribution to get tilted towards right. In our set of researches, we have selected $\alpha = 0.5$ and $\beta = 0$ subsequently it generated improved outcomes which outfits our setup. The step size engendered by this method is used to update the solution set which signifies the eggs in the nests for Cuckoo Search algorithm to novel set of values for the next iteration.

RESULTS & DISCUSSION

Table 1. ***Healthy Eye*** **image segmentation**

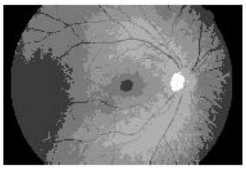
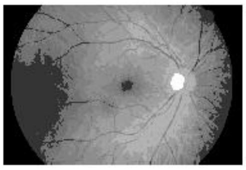
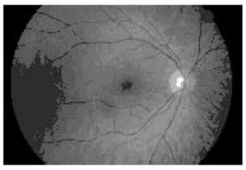
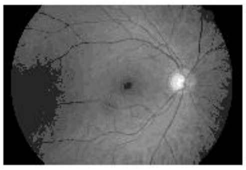
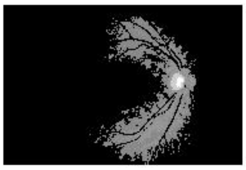
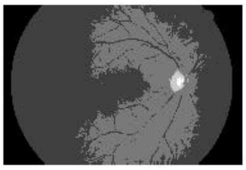
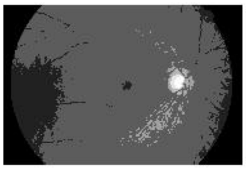
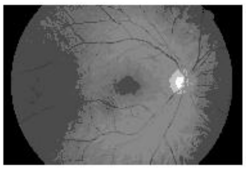
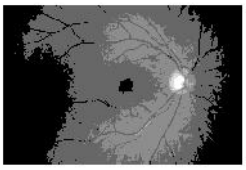
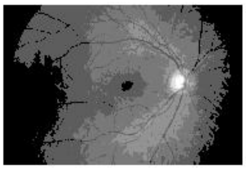
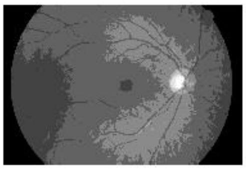
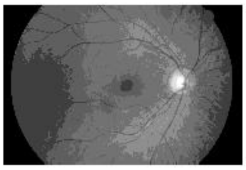
Obj. Func.	Thresholding Level (n)			
	5	7	9	11
Otsu				
Kapur				
Tsallis				

Table 2.Comparison of threshold values

n	Objective Function		
	Otsu	**Kapur**	**Tsallis**
5	4487106123175	124138184186231	88120152185217
7	288194107117130180	255359111167188234	82107130152175200225
9	397786100109120131165186	212980141161197200222252	14355986121151174200224
11	36778997109115128144173245249	54656796104111121159162171227	14355786103128150165182202230

Table 3.*GlaucomatousEye* image segmentation

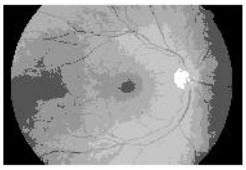
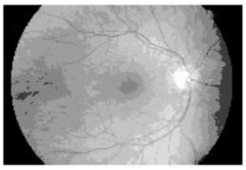
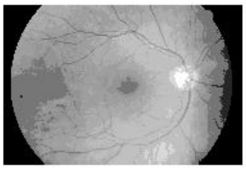
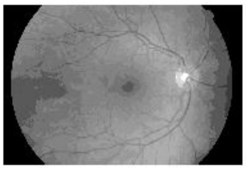
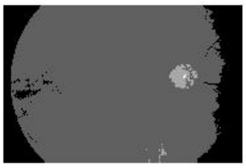
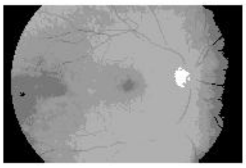
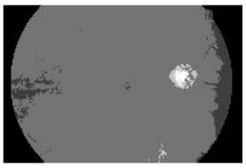
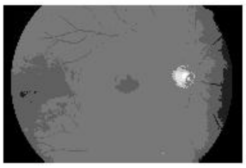
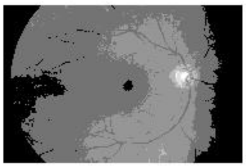
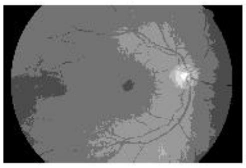
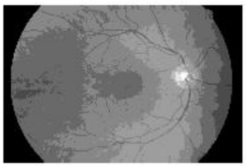
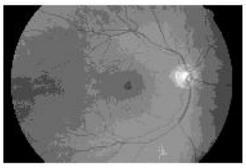
Obj. Func.	Thresholding Level (n)			
	5	**7**	**9**	**11**
Otsu				
Kapur				
Tsallis				

Table 4.Comparison of threshold values

n	Objective Function		
	Otsu	**Kapur**	**Tsallis**
5	458092104135	71124188216233	77100124148170
7	32708293102114133	65788495138200218	155278104124148173
9	2265828895102106120141	284073124144150155161217	1030517292107129156174
11	4160788896103111116143171255	1236784130150152159178197249	1028527593104124136152164179

Table 5.*Diabetic RetinopathyEye* image segmentation

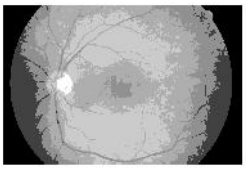
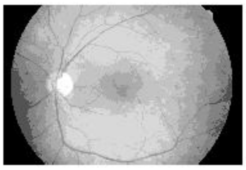
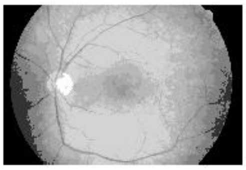
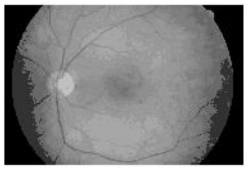
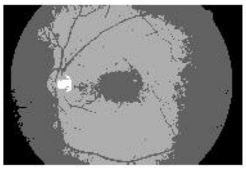
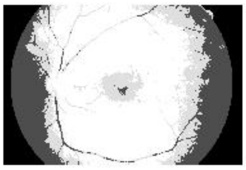
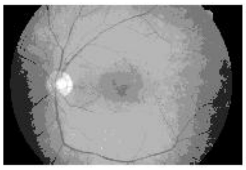
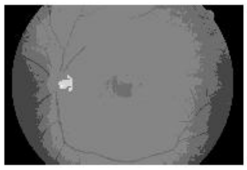
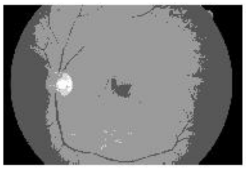
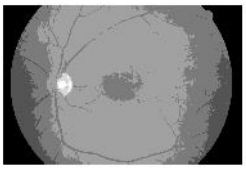
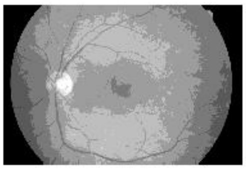
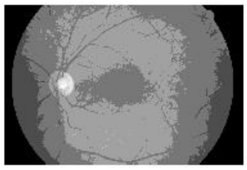
Obj. Func.	Thresholding Level (n)			
	5	**7**	**9**	**11**
Otsu				
Kapur				
Tsallis				

Table 6.Comparison of threshold values

n	Objective Function		
	Otsu	**Kapur**	**Tsallis**
5	368096112141	59105151154199	165394130155
7	44697991103114135	10133189102205225	12325377101135160
9	2870829110011011 4138255	2374911041111311 39156195	832547394114131142153
11	36758591991021091191371822 55	10194550799515217618218622 8	83152801081311431561712552 55

Threshold values for segmenting fundus retinalimage using various objective functions such as Tsallis entropy measure,Kapur's entropyand Otsu's between class variance. CS algorithm initiates its iteration with a random set of solutions attained by using

$$x_{i,j} = x^{j}_{m} + r(0,1)(x^{j}_{m} - x^{j}_{m})$$

eachspecifying an egg in a nest. Population size required to be fixed first by setting theeggs in each nest and total no. of nests. No. of eggs in a nest can be evaluated according to the no. of different threshold values we required for multi-level image segmentation. In our trials, we have taken 50 no. of nests and the no. of eggs in each nest as 5,7,9,11 resp. we have fixed no. of iterations to be 150. The control constraints like the probability of searching the cuckoos egg, $p_a$is taken as 0.25 and the step size or scaling factor for arbitrary walk generation is fixed to 3/2 which harvest the best outcomes. Cuckoo search algorithm was tested for 03 different objective fitness functions which embracesTsallis entropy, Kapur's entropy and Otsu's between class

variance for segmenting retinal fundus images of healthy eye and of patients facing retinal diseases like Glaucomatous and diabetic retinopathy. relatively performance metric values are portrayed in above Tables. For a givenspecifiedretinalfundus image under trails, it is very much cleared that the quality metric standards is having its optimal values for trials which in turn increases the variance between classes. As the no. of levels for multilevel segmentation increases Tsallistechniqueseems to beon upper hold. Essentialrunning time of CPU for optimization algorithmusingKapur's entropy as objective fitness function is seems to be less when compared with Otsu's or Tsallis technique. Computational complication for segmenting fundusimage is reliably low for researches usingTsallis entropy as the objective function. Asq is the Tsallis parameter index which shows the range of non-extensity of the system, in our set of trials the value of q was taken to be 0.25 ($q \in [0, 1]$) which resembles to sub extensive Tsallis entropy state which was experimentally demonstrated to be more apt for our situation.

CONCLUSION

Nature-motivated Cuckoo search optimization algorithms faces the problem in simulation time complication increases exponentially with increase in the no. of thresholds for image segmentation. Cuckoo Search algorithm engages levy flights to universally explore the search space for searching optimum values for thresholding. Levy flight modelling thus plays a vibrant role in monitoring the convergence rate of Cuckoo Search algorithm. In this paper, a computationally much efficient modified form of Cuckoo search algorithm i.e. CS McCulloch has been presented for segmenting fundus images. The projected CS McCulloch algorithm alters the levy flight generation approach in CS algorithm by integrating computationally effectual McCulloch's technique for steady random no. generation. CS McCulloch algorithm were exploited to maximize three different objective functions which includes Tsallis entropy, Kapur's entropy and Otsu's between class variance. Performance evaluating parameters verifies enhancement in the performance.

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