OTSU'S MULTI LEVEL THRESHOLDING USING MODIFIED FIREFLY ALGORITHM

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CERTIFICATE

This is to certify that **Shweta Mittal (2k14/ISY/15)** has carried out the major project titled "**Otsu's Multilevel Thresholding using Modified Firefly Algorithm**" in partial fulfilment of the requirements for the award of Master of Technology degree in Information Systems by **Delhi Technological University**.

The major project is bonafide piece of work carried out and completed under my supervision and guidance during the academic session 2014-2016. To the best of my knowledge, the matter embodied in the thesis has not been submitted to any other University/Institute for the award of any degree or diploma.

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ABSTRACT

Segmentation plays a crucial role in most tasks requiring image analysis. Basically segmentation is the process of partitioning an image into multiple segments. Segmentation changes the representation of image into a more meaningful and easier to analyze one. Pixels with the same characteristics are grouped together. Image segmentation can be done using several techniques. Here we are using the threshold selection method. Threshold selection is a significant technique for image segmentation and is broadly applied in many fields like computer vision, character recognition, analysis of medical images etc. Here, we are using the modified firefly algorithm for threshold selection embedded with the otsu's method. The intra cluster variance is minimized for threshold selection so that pixels with more similarity and hence less intra cluster variance are grouped together. The firefly algorithm is a meta heuristic algorithm which is inspired by the flashing behavior of fireflies. It has been used here as firefly has a high convergence rate.The minimization of intra cluster variance is the fitness function taken in firefly.The results have also been compared to other evolutionary algorithms like particle swarm optimization and ant colony optimization which shows better performance of modified firefly algorithm. .

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Chapter 1

INTRODUCTION

Image segmentation plays a vital role in different image processing techniques. Segmentation is the process of splitting an images into its constituent regions depending upon certain property or characteristics. Each pixel in a region is similar to another in certain aspect such as intensity, texture, color, etc. In segmentation the basic goal is to extract meaningful information and make things easier to visualize and analyze.

There are various areas in which segmentation has its utility such as machine vision, medical imaging, automatic traffic control system, face recognition, , expert system and also for dealing with images obtained from satellite, etc. Due to the various applications in the field of medical Medical Images segmentation is of great significance nowadays.

1.1 BACKGROUND

Various image segmentation techniques have been proposed and have been applied to a number of applications in the real world[17] . We are here concerned mainly with thresholding where thresholds i.e the pixel intensities are found and then based on the thresholds evaluated the image is segmented or divided.. This method helps to segment an image into background and foreground. The clarity of the image can be increased by increasing the number of levels of thresholds. This is done by increasing the number of thresholds and this is called as multilevel thresholding.

The main purpose is to find the threshold pixels optimally. Otsu's method[1] is used to automatically perform clustering-based image thresholding. The algorithm is efficient to bi level thresholding[11] but with increase in number of thresholds the computational complexity of the algorithm increase.Therefore, the firefly algorithm[4] is embedded with otsu's to reduce the complexity as it has a high convergence rate[6].The intra cluster variance is minimized to threshold the image. The minimization of intra cluster variance is taken as fitness function for FA.

1.2 MOTIVATION

Thresholding is an important technique for image segmentation. Because the segmented image obtained from thresholding has the advantage of smaller storage space, fast processing speed and ease in manipulation, compared with a gray level image containing 256 levels, thresholding techniques have drawn a lot of attention during the last few years. The aim of an effective segmentation is to separate objects from the background and to differentiate pixels having nearby values for improving the contrast. In many applications of image processing, image regions are expected to have homogeneous characteristics (e.g., gray level, or color), indicating that they belong to the same object or are facets of an object, implying the possibility of effective segmentation.

Otsu's method is efficient for bi-level thresholding but the computation time grows exponentially with the number of thresholds. Therefore, we are using the modified FA to reduce the time space complexity in finding optimum thresholds.

1.3 GOAL OF MASTER THESIS

The main aim of this thesis work is to combine otsu's techniques of thresholding and some evolutionary algorithms that provide a faster and efficient approach for image thresholding. Our main point of focus is on modified firefly algorithm . The approach has been compared to other evolutionary algorithms like particle swarm optimisation and ant colony optimisation for evaluation. The results are evaluated for higher number of thresholds as well.

1.4 THESIS ORGANIZATION

Chapter two gives details of the work that has been done previously in the current field and describes the thresholding techniques. This chapter also gives details about applications of image segmentation.Description of firefly algorithm, otsu's method and modified firefly algorithm is given.

Chapter three presents the proposed approach used for thresholding. The approach used combines the otsu's multi level thresholding with modified firefly algorithm. Also the pseudo code for the proposed approach has been given.

Chapter four presents the results obtained from the proposed approach and compare the results against other algorithms. The Berkley dataset is used here as the standard set taken for reference.

Chapter five gives the conclusion to the thesis and some further ideas for future work that can be carried out has also been presented.

Chapter 2

LITERATURE REVIEW

Image segmentation approaches can be broadly classified into two classes. First is based on similarity and the second one is based on Discontinuity.

In segmentation based on similarity, the image is subdivided into several regions, each region having similar properties based on certain predefined criteria. There are various techniques in similarity based approach like region growing, clustering and thresholding.

In discontinuity based segmentation, the image is partitioned on the basis of sudden changes in the pixel intensities. Edge detection is a technique used in discontinuity based segmentation..

2.1 Thresholding based segmentation

2.1.1 Thresholding

Thresholding is the simplest method of image segmentation. In this approach, the thresholds or the pixel intensities are found out according to which the image is divided based on the thresholds.number of thresholds vary according to the number of levels the image is required to be segmented. The thresholding can be local , global or adaptive. In global thresholding a in their respective values over the entire image, global thresholding could be used. In adaptive thresholding single threshold for all the image pixels is used. When the pixel values of the components and that of background are fairly consistent, different threshold values for different local areas are used. The current approach is very effective. It helps to divide the image into foreground and background according to the threshold. The value of the threshold can be calculated manually or algorithms are also there to do so.

2.1.2 Various Thresholding Methods

Thresholding can be bi level or multi level depending on the number of segments. In bi-level thresholding, image is segmented into two different regions. The pixels with gray values greater than a certain value T are classified as object pixels, and the others with gray values lesser than T are classified as background pixels[9].

Multilevel thresholding is a process that segments a gray level image into several distinct regions. This technique determines more than one threshold for the given image and segments the image into certain brightness regions, which correspond to one background and several objects.

The method works very well for objects with colored or complex backgrounds, on which bi-level thresholding fails to produce satisfactory results.

The various techiques are grouped in the following:

- Methods based on the shape of histogram, in which , for example, the valleys, peaks and curvatures of the smoothened histogram are analyzed
- Methods based on clustering , where the sample grey levels are grouped into two parts as the background and foreground.
- Methods based on Entropy use the algorithms that make use of the entropy of the background and foreground regions, the cross-entropy between the binarized and original image etc.
- Methods based on Object Attribute search for a measure of similarity between the gray-level and the binarized images, like fuzzy shape similarity, etc.
- **Spatial** methods use high-order probability distribution and correlation between pixels
- **Local** methods adapt the threshold value over each pixel to the local image characteristics. In these , a different T value is selected for every pixel in the image.

Several thresholding methods have been proposed like:
Otsu's Method[1]
Kapur's Method[2]
Niblack's Method[12]
Here we will be working on otsu's method.

2.2 APPLICATIONS OF IMAGE SEGMENTATION

Some of the various applications in which image segmentation use can be found are:

1. **Machine Vision**: Machine vision provides for automatic inspection based on imaging. The primary uses include automatic inspection and industrial robotc guidance.
2. **Content based Image Retrieval**: This is used to find and return images from a large database with the use of queries. "content-based" means that the search done is based on the content of the input image rather than the keywords or key or token. The term "content"

here implies the characteristics of the image like shape, color, texture or any other thing that can be evaluated from the image.

3. **Object detection** :It is correlated with computer vision and image processing that works in locating certain objects in an image or a video. It has applications in various areas like

- Face detection
- Pedestrian detection

4. **Medical imaging**: In medical imaging segmentation provides a technique for viewing internal representation of the human body for the better analysis and also helps in diagnosing the disease.

- Simulating Virtual surgery
- Tumor Detection
- Studying anatomical structure
- Tissue volume measurement
- Surgery Planning

2.3 OTSU'S THRESHOLDING

In the fields of image processing and computer vision , **Otsu's Thresholding**,[1] that was named after Nobuyuki Otsu is used to automatically perform image thresholding based on clustering or, the reduction of an image from a gray level image to a binary image. The algorithm assume that the image contains two categories of pixels following bi-modal histogram i.e the foreground pixels and the second category background pixels.[11] It then calculates the threshold that optimally separates the pixels into two classes so that their combined spread or intra-class variance is minimal, or equivalently (the sum of the pairwise squared distances being constant), so their inter-class variance is maximal.

In Otsu's method we do exhaustive search for finding the threshold that minimizes the intra-class variance i.e. the variance within the class , defined as the weighted sum of variance of the two classes. In bi-level thresholding, the pixels are divided into two groups or classes at a threshold (or into multiple groups based on threshold levels) and the variance between them is calculated. Variance is an important factor in symmetrical distribution of grayscale images. There are two types of Variance- Inter cluster variance and Intra cluster variance.

Intra cluster variance is the difference within the members of a cluster, and Inter cluster variance is the difference between two(or more) clusters. The lesser the intra cluster variance shows the lesser difference between members in a cluster. In our approach, we have used Intra cluster variance for optimizing threshold.

The image size is M × N and the image gray level is L. Let, an image is represented by L gray levels. The gray level range is 0 ~ L-1. The pixel number of grayscale level *i* is n_i Thus, the number of the image pixels

is:

$$n = \sum_{i=0}^{L-1} n_i = M \times N$$

For normalized Histogram, the probability distribution is:

$$p_i = \frac{n_i}{n} \quad , \qquad \sum_{i=0}^{L-1} p_i = 1 \tag{1}$$

The image is divided into two classes with the standard threshold t. The class c1 includes the pixel $i \leq t$ and the class c2 includes the pixels $i > t$. The cumulative probability of c1 is calculated as follows:

$$w_1 = \Pr(c_1) = \sum_{i=0}^{t} p_i \tag{2}$$

The cumulative probability of c2 is calculated as follows:

$$w_2 = \Pr(c_2) = \sum_{i=t+1}^{L-1} p_i \tag{3}$$

The mean levels is given as:

$$\mu_1 = \sum_{i=0}^{t} i \Pr(i/c_1) = \sum_{i=0}^{t} i p_i / w_1 \tag{4}$$

$$\mu_2 = \sum_{i=t+1}^{L-1} i \Pr(i/c_2) = \sum_{i=t+1}^{L-1} i p_i / w_2 \tag{5}$$

Variance of class c1 and class c2 is calculated as follows:

$$\sigma_1^2 = \sum_{i=0}^{t} (i-\mu_1)^2 \Pr(i/c_1) = \sum_{i=0}^{t} (i-\mu_1)^2 p_i / w_1 \tag{6}$$

$$\sigma_2^2 = \sum_{i=t+1}^{L-1} (i-\mu_2)^2 \Pr(i/c_2) = \sum_{i=t+!!}^{L-1} (i-\mu_2)^2 p_i / w_2 \tag{7}$$

Intra-cluster variance is calculated as follows:

$$\sigma_w^2 = w_1 \sigma_1^{\ 2} + w_2 \sigma_2^2 \tag{8}$$

Inter-cluster variance is calculated as follows:

$$\sigma_B^2 = w_1(\mu_1 - \mu_T)^2 + w_2(\mu_2 - \mu_T)^2 = w_1 w_2(\mu_1 - \mu_2)^2 \qquad (9)$$

The best threshold value Th should satisfy the condition after the image is divided into two categories c1and c2:

$$\eta|_{Th} = max\left[\frac{\sigma_B^2}{\sigma_W^2}\right] \qquad (10)$$

The threshold obtained by OTSU is used to segment the image [22], . When it segments the image with complex target area, the OTSU method should be extended to two or more thresholds [18]. At that point, the image is divided into n categories c1, c2, c3,…,cn by Th1, Th2,….,Thn. The intra-cluster variance of these thresholds is given by:

$$\sigma_w^2 = w_1\sigma_1{}^2 + w_2\sigma_2^2 + w_3\sigma_3^2 + \text{..........} w_n\sigma_n^2 \qquad (11)$$

Inter-cluster variance is given by:

$$\sigma_B^2 = w_1(\mu_1 - \mu_T)^2 + w_2(\mu_2 - \mu_T)^2 + w_3(\mu_3 - \mu_T)^2 + \text{.......} w_n(\mu_n - \mu_T)^2 \qquad (12)$$

Here in this approach we will be using intra cluster variance minimisation .

2.4 FIREFLY ALGORITHM

2.4.1 Description

Firefly algorithm formulated by Xin-She Yang[6], is an nature–inspired algorithm and is among the most powerful algorithms for optimization. The Firefly algorithm (FA) may also be considered as a typical swarm-based approach for optimization. Here the search algorithm is inspired by the flashing behavior of fireflies. There are two important factors in the Firefly algorithm that are

1. Variation of light intensity
2. Formulation of attractiveness

FA is used in variety of applications like Job Shop Scheduling, Clustering, PID Controller tuning etc. FA has high convergence speed along with less computation rate as compared to other evolutionary algorithms. Therefore it reduces the total runtime taken and gives good results.

What are fireflies?

Lampyridae is a family of insects in the beetle order Coleoptera.These are winged beetles, and commonly called fireflies or lightning bugs as they have ability to emit light.Light production in fireflies is due to a type of chemical reaction called bioluminescence. The main purpose of a firefly's flash is to send signal system for attracting other fireflies. The large groups of fireflies are known to synchronise their flashes.This phenomenon is said as phase synchronization.

The intensity of light drops exponentially as the distance between the emitting firefly and receiving one increases.That is the light intensity I decreases with the increase in distance r in terms of I.Also the environment can absorb pats of the light and thus further decrease the intensity of the emitted light. These properties influences on communicating abilities of fireflies and are used to simulate behavior of fireflies in our algorithms.

Rules of Firefly Algorithm

Xin-She Yang formulated the firefly algorithm[5] by assuming the following points :

1. All fireflies are unisex, so that any firefly is attracted to all other fireflies;
2. Attractiveness is directly proportional to their brightness, for any two fireflies, the less brighter one will be attracted by (and thus will move towards) the more brighter one; however, the intensity decreases with the increase in their mutual distance
3. If there is no firefly which is brighter than a given firefly, it will tend to move randomly.

Attractiveness

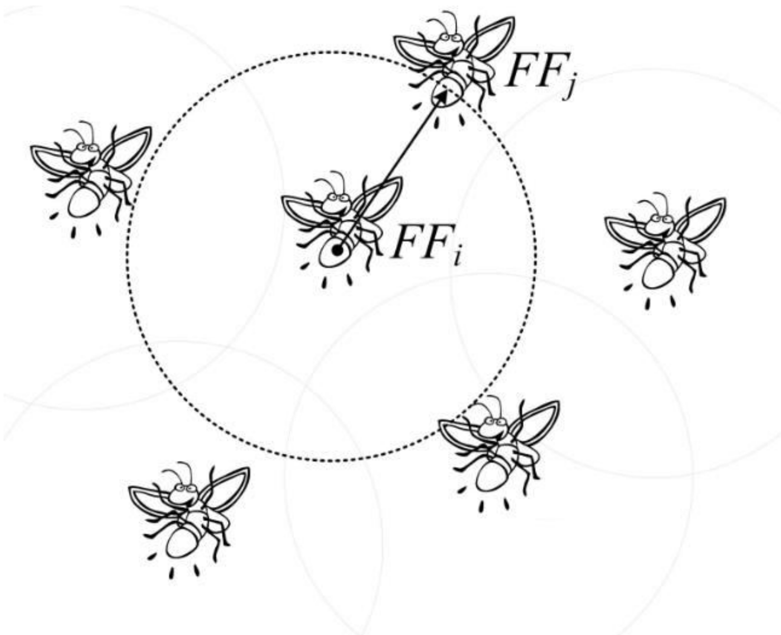


Fig 2.1 Attractiveness within fireflies

The light intensity changes as per the inverse square law.

$$I(r) = I_s / r^2 \tag{13}$$

where *Is* is the intensity at the source. Next step is to add the light absorption coefficient. That is

$$I(r) = I_0 \, e^{-\gamma r2} \tag{14}$$

where I_0 gives the original light intensity. For avoiding the singularity attained at r=0 in the expression I_s/r^2. To approximate the mixed effect of both inverse square law and absorption following Gaussian form is used [10]

$$I(r) = I_0 \, e^{-\gamma r2}$$

The attractiveness of any firefly is directly proportional to the light intensity as seen by the adjacent fireflies, so attractiveness β of a firefly can now be given by:

$$\beta(r) = \beta_0 \, e^{-\gamma 2} \tag{15}$$

where the β_0 is the attractiveness at $r = 0$ and γ is the light absorption coefficient at the source.

Distance and Movement

The distance or separation between any two Fireflies say *i* and *j* at x_i and x_j respectively, is given by the Cartesian distance which is calculated as:.

$$R_{ij} = \|x_i - x_j\| = \sqrt{\sum_{k=1}^{d} \left(x_{i,k} - x_{j,k}\right)^2} \tag{16}$$

Firefly i movement towards any other more attractive Firefly j is given by:

$$X_i = X_i + \beta_0 e^{-\gamma r_{ij}^2} \ (X_i - X_j) + \alpha(rand - \frac{1}{2}) \tag{17}$$

where the second term arises due to the attraction while the third term comprises of a randomization parameter α. Rand is random number generator uniformly distributed in range[0, 1].The variation of the attractiveness is characterised by the parameter γ, also its value helps in calculating the speed of convergence of the FA.

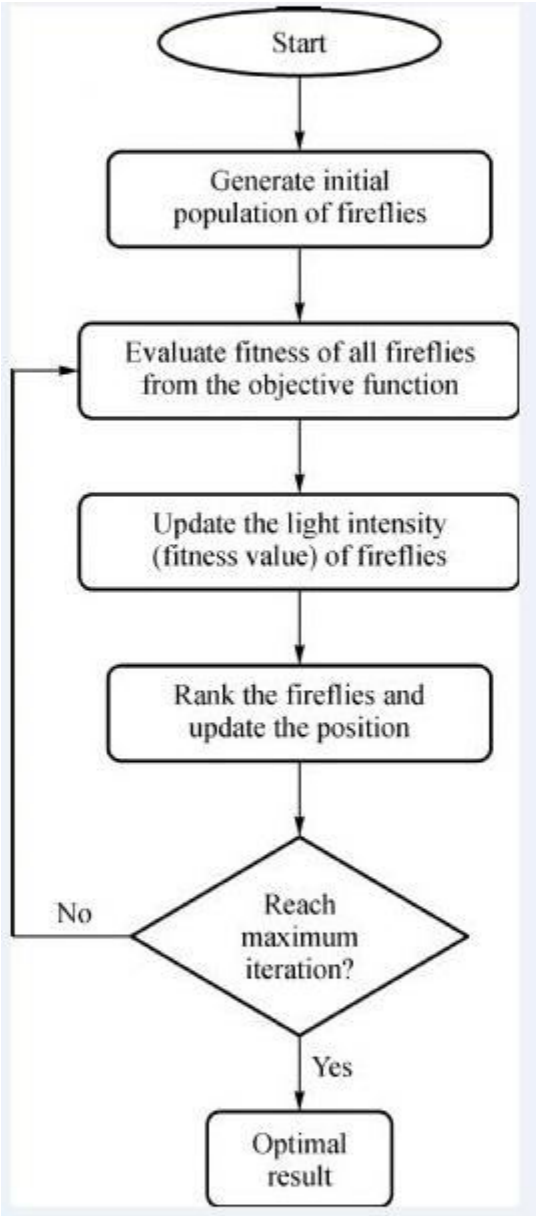
2.4.2 Algorithm

```
Begin
        Objective function f (x); x = (x1;.....xd)
        Generate an initial population of fireflies xi (i = 1;2;.....;n)
        Light intensity Ii at xi is determined by f (xi)
        Define the light absorption coefficient
        While (t <MaxGeneration)

        For i = 1 : n all n fireflies
                For j = 1 : n all n fireflies
                        If(Ij> Ii)
                                Move firefly i towards j in d-dimension
                        End if
                Attractiveness varies with distance r via β0 e^(−γr²)
                Evaluate new solutions and update light intensity
                End for j
        End for i
        Rank the fireflies and find the current best
End while
Postprocess results and visualization
End
```

2.4.3 Flow Chart

Fig 2.2 Flow Chart of Firefly Algorithm



α β

2.5 MODIFIED FIREFLY ALGORITHM

This algorithm was proposed by Mehrnoosh Shafaati and Hamed Mojallai in 2012 [16]. This algorithm enhances the exploitation quality of the algorithm by gradually reducing the randomness. This increases the global exploration chances of fireflies.[14] In F A, the solution keeps on changing while approaching the global optima. This randomness of the F A was reduced in Modified Firefly by redefining the randomization parameter α by:

$$\alpha=\alpha_{\infty} +(\alpha_0 - \alpha_{\infty})e^{-t} \tag{18}$$

where t : $[O,t_{max}]$ is the pseudo time for simulation, ao is the initial randomization parameter, a_{∞} is the final value and t_{max} is the maximum number of generations.

Chapter 3

PROPOSED APPROACH

In this work, otsu's algorithm is combined with modified firefly algorithm to increase the computational efficiency and to increase the explorartion.As firefly has high convergence rate[7] and by gradually decreasing the randomnesss parameter the exploration range gets increased[14] the images produced by thresholding are of good visual quality. The results are then compared with other evolutionary algorithms like particle swarm optimisation and ant colony optimization[21].The proposed approach comes out to be be better than those .

3.1 OTSU'S THRESHOLDING USING MODIFIED FIREFLY ALGORITHM

The OTSU's thresholding uses the exhaustive approach to find the thresholds by calculating the minimum intra-variance within the classes. This approach suits well for finding the bi-level thresholding but for finding multi-level threshold, the multi OTSU method is very time consuming as it will require a larger number of iterations to check for all the possibilities in order to find the optimal threshold. The computation time grows exponentially with the number of thresholds. Specifically, the computational complexity of an exhaustive search is O (L^N-1) where L is the number of intensity levels and N-1 is the number of thresholds which produces N-level segmented image. It would limit the OTSU method applications. To increase the efficiency of OTSU'S method, the proposed method uses the FA because as mentioned earlier FA has higher convergence rate and high computational speed which helps in optimizing the OTSU method.

The thresholding peocess here is formulated as an optimization process. We model the optimum threshold in terms of a modified Firefly Algorithm. Each firefly represents the potential solution of the optimum thresholds, and equation of intra cluster minimising is considered as the fitness function. The difference between the OTSU method and the FA-based OTSU algorithm is that the former finds the solution by testing the thresholds in the range of gray level one by one, thus making it an exhaustive method. On the other hand, the latter obtains the solution by the cooperation of the fireflies and, therefore, will shorten the computation time, particularly in multilevel thresholding. For this purpose, we define the fireflies as points where each dimension of a firefly represents intensity from a range of gray intensity levels 0-255, i.e. d-dimensional vectors. The dimension of individual firefly depends upon the number of thresholds. We will then spread the fireflies over the whole of the intensity range and initially the position of all the fireflies is random so that they can cover the whole range. Then, calculate the mean, probability and variance. After all the computations, the fitness function is evaluated according to the equation. Then the positions of the fireflies are updated. This process continues for the maximum number of iterations

3.1.1 PSEUDOCODE

- Begin
- Define Objective function f (x) : Intra Cluster variance

  $f(x) = w_q\sigma_1^2 + w_2\sigma_2^2 + w_3\sigma_3^2 + ...w_d\sigma_d^2$

  where d depends upon the number of thresholds
- Initialize population: random X where each firefly has d-dimensions and each dimension represent an intensity level(candidate threshold)
- Determine the intra-cluster variance for each firefly in X by first calculating cumulative probability(w) and then variance for each dimension of each firefly and then putting the values in fitness function
- Define the light absorption coefficient
- While(max number of generations)
    - Foreach firefly i in X
        - Foreach firefly j in X
            - If $f(X_j)<f(X_i)$
                - Determine the distance between ith firefly and jth firefly using Euclidean distance given as:

                  $$R_{ij} = \|x_i - x_j\| = \sqrt{\sum_{k=1}^{d}\left(x_{i,k} - x_{j,k}\right)^2}$$

                - Determine the Attractiveness which varies with distance r:

                  $$\beta(r) = \beta_0 \, e^{-\gamma 2}$$

                - Update α using

                  $$\alpha=\alpha_\infty +(\alpha_0 - \alpha_\infty)e^{-t}$$

                - Move firefly i towards j

$$X_i = X_i + \beta_0 e^{-\gamma r_{ij}^2} \ (X_i - X_j) + \alpha(rand - \frac{1}{2})$$

- Evaluate new solutions by calculating minimum intra cluster variance and update the light intensity

Rank the fireflies; find the current best

o End of while

End

Chapter 4

EXPERIMENTAL RESULTS

Following configuration is taken while implementing the project.

- Processor: Intel Core i3
- Hard Disk Capacity: 512 Gb
- Main Memory: 4 GB
- Clock Speed: 2.40 GHz
- Software Used: MATLAB R2010a

The Berkeley[22] database images has been used for the segmentation purpose. The Berkeley database provide an empirical basis for research on image segmentation and boundary detection. The results have been quantitatively measured using two coefficients an compared against the ground truth.

The experimental results obtained from the proposed approach are shown next. The images as mentioned above have been taken from the Berkeley dataset. The segmentation has been done upto 6 levels.

Image No

I1 I2 I3

(a)

(b)

(c)

(d)

(e)

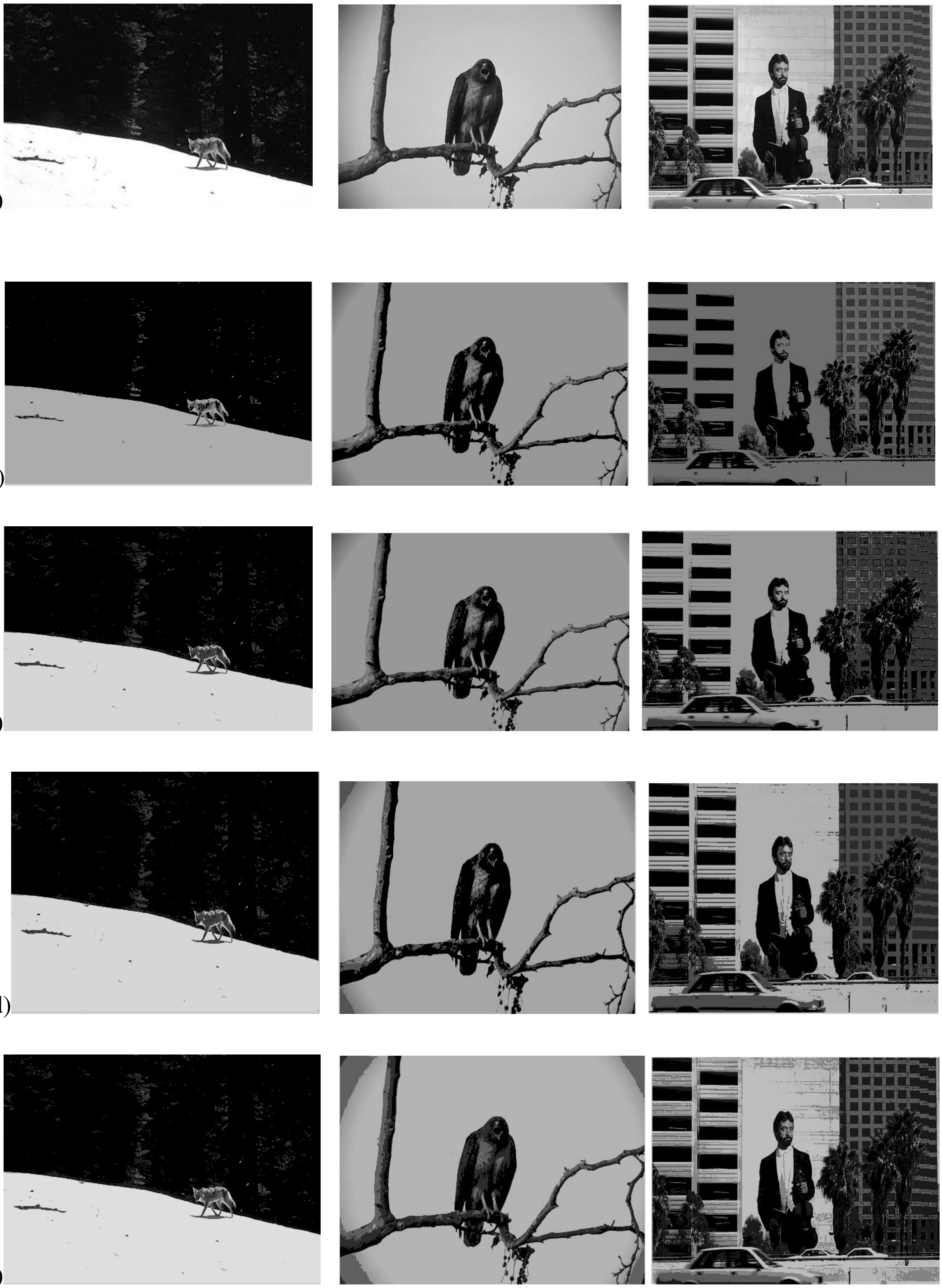


Fig 4.1 Results using Proposed Approach (a)Original Image (b) 3-level segmented image (c) 4-level segmented image (d) 5-level segmented image (e) 6-level segmented image

Fig 4.2 Results using Proposed Approach (a)Original Image (b) 3-level segmented image (c) 4-level segmented image (d) 5-level segmented image (e) 6-level segmented image

I7 I8 I9

(a) (b) (c) (d) (e)

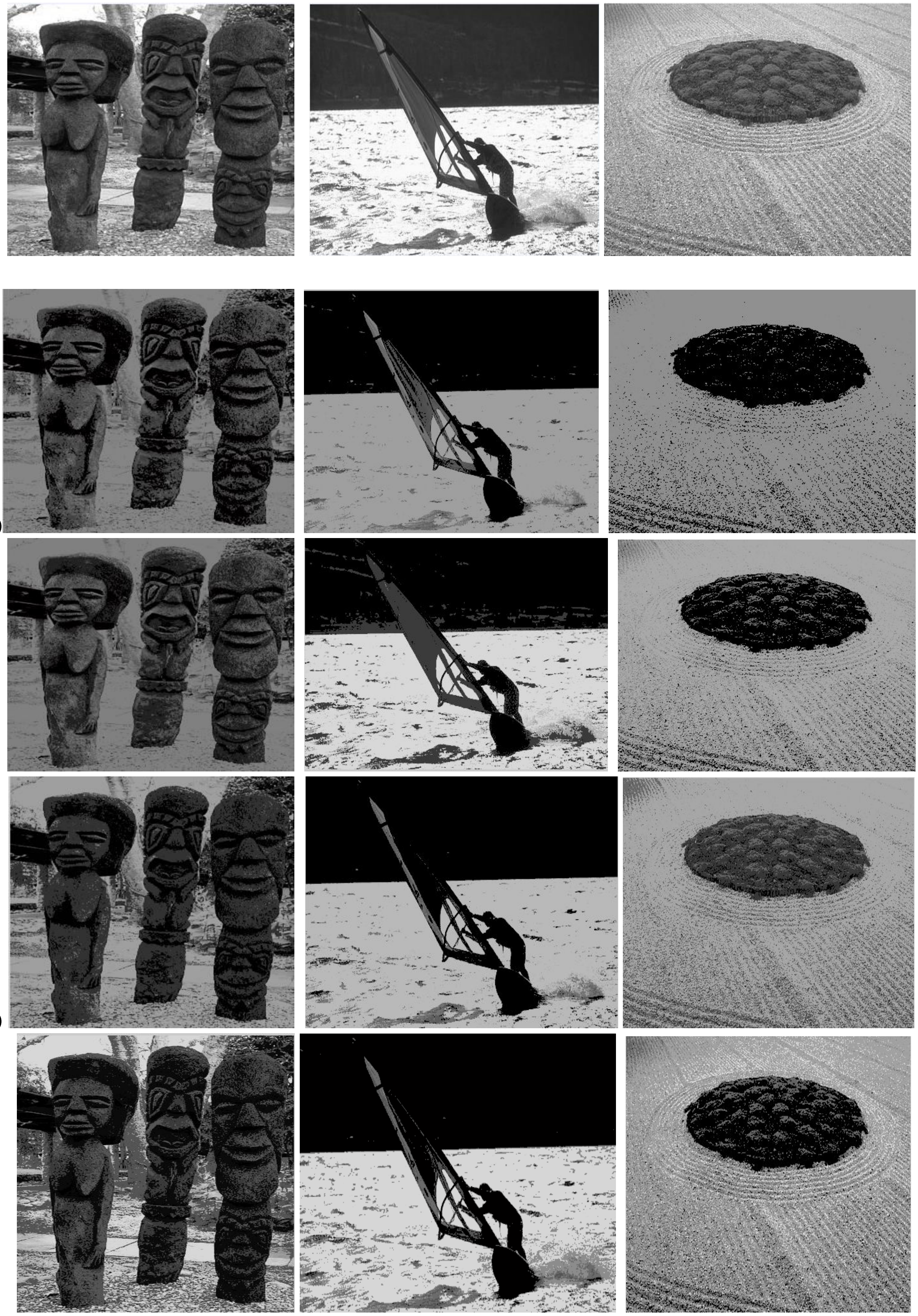


Fig 4.3 Results using Proposed Approach (a)Original Image (b) 3-level segmented image (c) 4-level segmented image (d) 5-level segmented image (e) 6-level segmented image

The thresholding has been applied to the images in a way like for example image I_3 the optimum thresholds obtained are 53,108 and 155 in 4-level segmented image, we divide the pixels of the whole image such that the pixels with the intensities from 0 to 53 are assigned an intensity 0, pixels with the intensities from 53 to 108 are assigned an intensity 53, pixels with the intensities from 108 to 155 are assigned an intensity 108 and pixels from 155 to 255 are assigned an intensity 155.

The segmentation is done for 4-level, 5-level and 6-level. From the results it can be seen that with the increase in number of thresholds the details of image becomes more clear.

Table I

Threshold intensity values

Image	3-level threshold	4-level threshold	5-level threshold	6-level threshold
I1	70,171	45,120,217	30,65,163,214	21,50,111,165,205
I2	69,155	54,80,180	76,90,125,170	25,56,76,140,180
I3	42,140	53,108,155	41,73,159,175	29,45,79,97,165
I4	87,145	80,99,148	47,73,120,167	46,79,97,127,208
I5	76,133	36,88,165	23,98,157,197	26,59,113,150,224
I6	74,164	77,128,154	57,88,137,173	55,86,100,146,184
I7	76,150	63,98,136	40,81,152,213	32,78,115,144,183
I8	74,167	88,132,228	64,140,204,236	78,123,165,197,214
I9	66,165	78,114,178	50,81,109,179	89,136,163,204,228

The table gives the values of thresholds for 4-level, 5-level and 6-level segmentation.

Comparison with PSO & ACO

In order to show the efficiency of the proposed approach as compared with other evolutionary algorithms, the results are compared with Particle Swarm Optimization(PSO) and Ant Colony Optimization. The results show that the visual quality of segmented images is better as obtained from the other two algorithms.Hence showing the efficiency of our proposed approach over them.

The same Berkeley dataset images have been used for comparison as used above.

Fig 4.2 Comparison with PSO & ACO (a through i ,a’ through I’ and a’’ through I’’ represent 5-level segmented image in our approach,using PSO and through ACO and similarly a2 to i2,a2’ to i2’,a2’’ to i2’’ represents images in 6-level segmentation)

(a)

(a’)

(a’’)

(a2)

(a2’)

(a2’’)

(b)

(b’)

(b’’)

(b2)

(b2’)

(b2’’)

©

(c’)

(c’’)

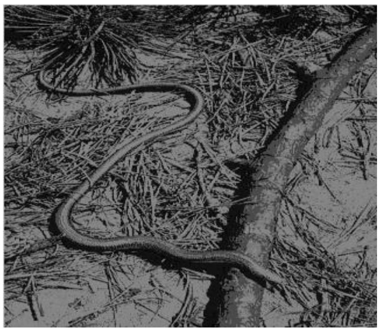

(c2)


(c2’)

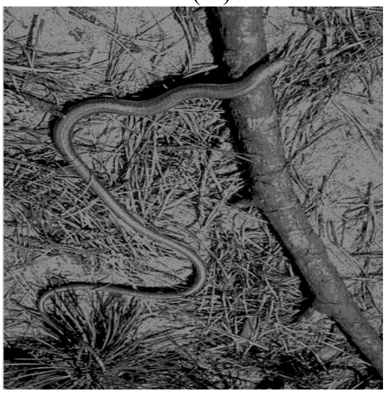

(c2’’)

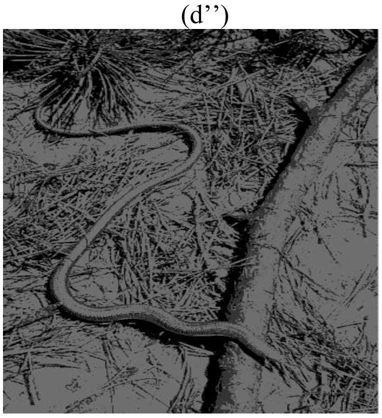

(d)


(d’)


(d’’)


(d2)


(d2’)


(d2’’)


(e)


(e’)


(e’’)


(e2)

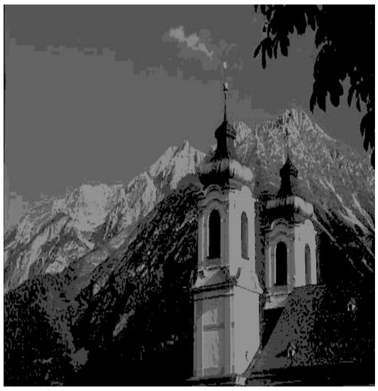

(e2')


(e2'')

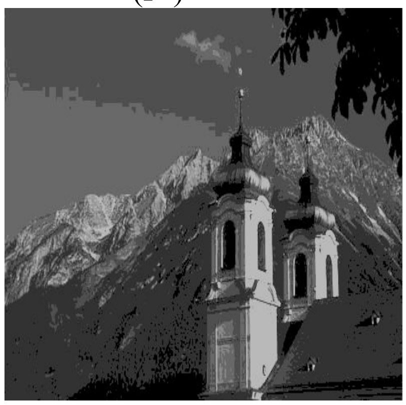

(f)


(f')


(f'')


(f2)


(f2')


(f2'')


(g)


(g')


(g'')

(g2)

(g2’)

(g2’’)

(h)

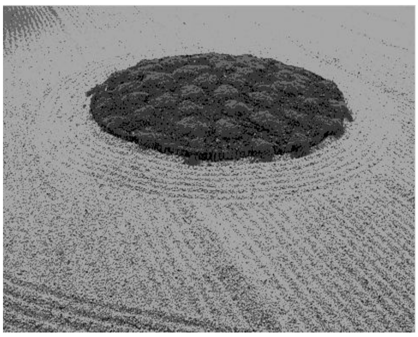
(h’)

(h’’)

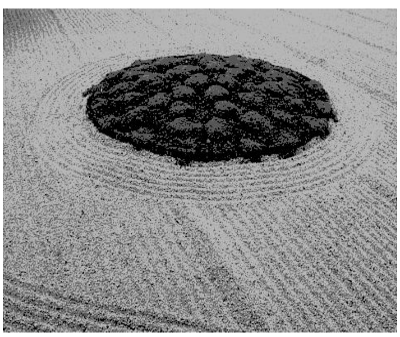
(h2)

(h2’)

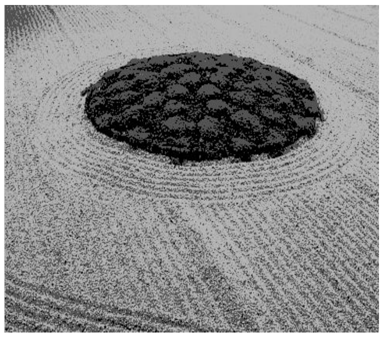
(h2’’)



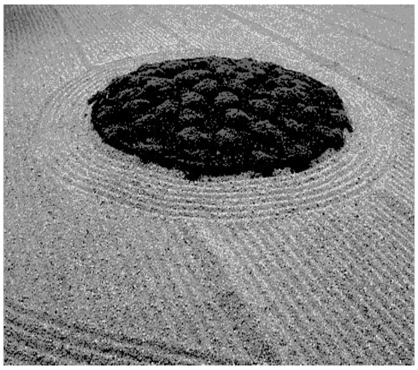
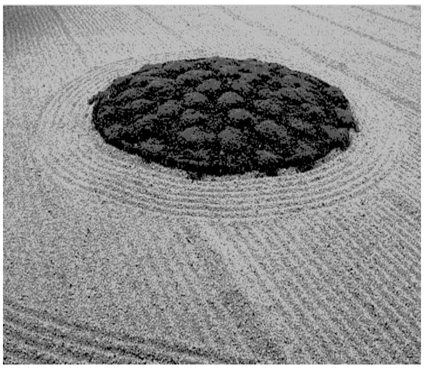
(i)



(i’)



(i’’)

(i2) (i2’) (i2’’)

To measure the accuracy of results of segmentation , several quantitative evaluation schemes can be used.[23][24] .We have here used Dice coefficient and Jaccard coefficient as the quantitative measure.These coefficients are described:

1. Dice Coefficient:

It is calculated as follows and requires two sets i.e P and Q

D(P,Q)=2(|P and Q|)/(|P|+|Q|)

Where,

|.| is for the size of set.

Dice coefficient’s values lies between the range of [0,1]. 0 is for no match and 1 is for complete match. In terms of segmentation, P stands for segmented image and Q stands for the ground truth..

2. Jaccard’s Coefficient

J(P,Q)=(P intersection Q)/(P union Q)

Jaccard similarity measure’s value also is in between the range 0 and 1. 0 signifies no match/overlap and 1 signifies full match/overlap. Dice coefficient and Jaccard similarity are related to each other as follows:

D=2*J/(1+J)

.**TABLE II: Dice Coefficient**

MODIFIED FIREFLY			PSO			ACO		
	Dice Coefficient					Dice Coefficient		
Image #	**5 seg**	**6 seg**	**Image#**	**5 seg**	**6 seg**	**Image#**	**5 seg**	**6 seg**
I1	0.8192	0.8526	I1	0.6464	0.6851	I1	0.6172	0.6201
I2	0.9734	0.9767	I2	0.9501	0.9562	I2	0.9412	0.9467
I3	0.9016	0.9152	I3	0.8540	0.8565	I3	0.8181	0.8476
I4	0.9512	0.9603	I4	0.9223	0.9331	I4	0.9112	0.9115
I5	0.9318	0.9481	I5	0.9238	0.9321	I5	0.9218	0.9311
I6	0.9439	0.9530	I6	0.9354	0.9412	I6	0,9246	0.9351
I7	0.9103	0.9376	I7	0.8990	0.9207	I7	0.8522	0.9112
I8	0.8690	0.9164	I8	0.7286	0.7384	I8	0.7254	0.7297
I9	0.9735	0.9788	I9	0.9511	0.9645	I9	0.9501	0.9589

Dice Coefficient is the volume overlap metric that is used to quantitatively evaluate the segmentation results using the segmentation volumes pairs. The algorithm was implementes on different images of standard dataset(Berkley dataset).

From the results obtained we can see that there is significant difference between the result obtained from our approach as compared to other algorithms used i.e. PSO and ACO . The proposed approach shows better results.

If the value is close to 1, then the image is considered to be segmented more clearly . in general, for good segmentation, the value of the dice coefficient >0.7.

Similar to Dice Coefficient is another measure called the Jaccard's similarity measure. Although, Dice Coefficient is comparativey more famous than jaccard ratio . We have shown below approximate results using Jaaccard's ratio also so as to have a better outlook of the classification system used and compared.

$J=D/(2-D)$
where,

J- Jaccard's ratio

D- Dice coefficient

.TABLE III: Jaccard Coefficient

MODIFIED FIREFLY			PSO			ACO		
			Jaccard Coefficient			Jaccard Coefficient		
Image #	**5 seg**	**6 seg**	**Image#**	**5 seg**	**6 seg**	**Image#**	**5 seg**	**6 seg**
I1	0.8167	0.8679	I1	0.6464	0.6851	I1	0.6387	0.6390
I2	0.9745	0.9799	I2	0.9501	0.9562	I2	0.8635	0.8854
I3	0.8916	0.9045	I3	0.8409	0.8535	I3	0.8331	0.8484
I4	0.9167	0.9463	I4	0.9056	0.9321	I4	0.9012	0.9219
I5	0.9797	0.9817	I5	0.9276	0.9378	I5	0.9187	0.9265
I6	0.9834	0.9877	I6	0.9812	0.9870	I6	0.9476	0.9578
I7	0.8443	0.8967	I7	0.8167	0.8461	I7	0.7915	0.7985
I8	0.9278	0.9346	I8	0.9217	0.9399	I8	0.9182	0.9241
I9	0.9895	0.9964	I9	0.9473	0.9683	I9	0.9292	0.9408

The above tables II and III shows the dice coefficient and the Jaccard Index and the values of our proposed approach are greater than PSO and ACO. The values obtained are quite close to 1 and hence show quality results.

From both the tables and segmented results we can see that our proposed approach works better than PSO which in turn is better than ACO.

Chapter 5

CONCLUSION

In the work presented, image multi level thresholding .is done using modified firefly algorithm embedded with the otsu's method . The step by step algorithm for the proposed approach has been presented. A higher number of thresholds has also been used to justify the use of proposed approach for multi level thresholding. The firefly algorithm is a meta heuristic algorithm which is inspired from the flashing behavior of fireflies and is used to give optimal solution. It has been used here as firefly has a high convergence rate. The minimization of intra cluster variance is the fitness function taken in firefly from the otsu's method. This is so because the pixels belonging to the same cluster should have less intacluster variance.The results obtained have been compared to other evolutionary algorithms like Ant Colony Optimization and Particle Swarm Optimization. The Berkeley dataset was used to segment the images to test the accuracy. The proposed approach gave better results to the compared algorithms. In future, to further improve the accuracy and efficiency of the algorithm the work of thesis can be extended. Also this work dealt with some bio inspired algorithms can be extended to be done with more algorithms/hybrid of them.

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