Multilevel Image Segmentation Based On Firefly Algorithm

K. Vennila and K. Thamizhmaran

Abstract---Multilevel image segmentation is time-consuming and involves large computation. The Firefly Algorithm (FA) has been applied to enhancing the efficiency of multilevel image segmentation. Threshold values are the values chosen from the intensity values of the image ranges from 0 to 255. In this work OTSU based firefly algorithm is applied for the gray scale images. OTSU'S between-class variance function is maximized to obtain optimal threshold level for gray scale images. The existence Darwinian Particle Swarm Optimization (DPSO) gives small swarm size and few numbers of iterations. In FA, the performance assessment of the proposed algorithm is carried using prevailing parameters such as Objective function, Standard deviation, Peak-to-Signal Ratio (PSNR), and Best cost value and search time of CPU. The experimental results show that the proposed method can efficiently segment multilevel images and obtain better performance than DPSO.

Keywords---OTSU, Firefly Algorithm, DPSO, Peak-to-Signal Ratio, PSNR.

I. INTRODUCTION

DIGITAL images can be viewed as two dimensional matrix or two variables function. It consists of discrete points called pixels. In color images, each pixel has three values: red, green and blue. Each value has a range between 0 and L-1, where L is the number of levels of precision. On the other hand, gray level images are composed of pixels where each pixels has only one value between 0 and L-1 called gray level. For many image processing problems, it would be simple and more efficient to deal with gray level images than with the color images. For that reason, color images are often converted to gray level images before applying image processing algorithms. The most widely adopted gray level is 256 (i.e. the value of each pixel is between 0 and 255).

Multilevel thresholding divides the pixels into several groups. The pixels of the same group have gray levels within a specified range. However, the problem gets more complex when the segmentation is achieved with greater details by employing multilevel thresholding. Then the image segmentation problem becomes a multiclass classification problem where pixels having gray levels within a specified range are grouped into one class. Usually it is not simple to determine exact locations of distinct valleys in a multimodal histogram of an image, that can segment the image efficiently and hence the problem of multilevel thresholding is regarded as an important area of research interest among the research communities worldwide.

Multi-thresholding approach generalizes the image thresholding by finding multiple thresholds which aim to separate multiple objects. In general, for segmenting an image that has 'n' objects and background 'n' threshold can be used. To find the thresholds that best separate objects, it is easier to deal with statistics of the image instead of the image itself. Image histogram statistics is one dimensional representation that shows the frequency of each gray level in the image. It is computed by counting number of pixels that have the same gray level.

Converting color images into gray level images and then using the one dimensional histogram of the image makes thresholding-based segmentation process an easy and computationally efficient task, which can be used in many real time applications. There are many methods to find thresholds from image histogram. In the case of one threshold, we can try all the values between 0 and L-1 and then we choose the value that gives the best segmentation to use it as a threshold.

However, for multiple thresholds segmentation, trying all the possible combination needs L × (L-1) ×…. × (L-t+1) trails where t is the number of thresholds. In natural images, one can see that same objects have similar pixels and different object has unsimilar pixels, this suggest that the measure that will be taken into consideration is the inter-class variance and intra-class variance. The computational complexity and the existence of goodness measure in the case of multiple thresholds motivated the use of an efficient search algorithm.

II. BACKGROUND

An improved quantum-inspired genetic algorithm for image multilevel thresholding segmentation was done by Zhang et al (2014). Segmentation of SAR images using improved artificial bee colony algorithm and neutrosophic set was done by Hanbay and Talu (2014). Firefly inspired algorithm for discrete optimization problems an application to manufacturing cell formation was done by Hafezalkotob et al (2013). Automatic detection of common surface defects on oranges using combined lighting transform and image ratio methods was done by Rao et al (2013). A comparison of nature inspired algorithms for multi-threshold image segmentation was done by Osuna-Enciso et al (2013). A novel hybrid approach using wavelet, firefly algorithm and fuzzy ARTMAP for day-ahead electricity price forecasting was done by Haque et al (2013). An efficient method for segmentation

Manuscript received on February 22, 2017, review completed on February 23, 2017 and revised on March 02, 2017.

K. Vennila is with the Department of ECE, Annamalai University, Annamalai Nagar, Tamil Nadu, India. E-Mail: vennilaeceau@gmail.com

K. Thamizhmaran is with the Department of ECE, Annamalai University, Annamalai Nagar, Tamil Nadu, India. E-Mail: tamil10_happy@rediff.com.

Digital Object Identifier: BB032017005.

of images based on fractional calculus and natural selection was done by Ghasmi et al (2012). Firefly algorithm for solving non-convex economic dispatch problems with valve loading effect Hosseini et al (2012). Optimal multilevel thresholding using bacterial foraging algorithm was done by Sathya and Kayalvizhi (2011). Optimal segmentation of brain MRI based on adaptive bacterial foraging algorithm was done by Sathya and Kayalvizhi (2011). A novel multi-threshold segmentation approach based on differential evolution optimization was done by Cuevas et al (2010). A firefly algorithm for multimodal optimization was done by Yang (2009). Application of ahybrid ant colony optimization for the multilevel thresholding in image processing was done by Liang and Chen et al (2006). Image segmentation algorithms applied to wood defect detection was done by Funck and Zhong et al (2003)

III. Problem Description

The basic objective is to the recently developed Firefly Algorithm has been shown to outperform the longstanding Particle Swarm Optimization, and this work aims to verify those results and improve upon them by comparing the two algorithms with a large scale application. A direct hardware implementation of the Firefly Algorithm is also proposed, to speed up performance in embedded systems application and it performs large number of iterations. In DPSO the swarm size is small and it performs only little number of iterations. The emission source localization proves quite the challenge, and the FA actually outperforms the PSO in noisy situation. Each particle is simply moved from one location to another. This mutation is performed in a directed manner, such that each particle is moved from its previous location to a new, hopefully better, location. The location update process is drawn with vectors. Each particle knows its position, velocity, and personal best location found so far, and the global best but the time consumption is more in DPSO.

IV. Proposed Scheme

The firefly algorithm is based on three main principles:

1. All fireflies are unisex, implying that all the elements of a population can attract each other.
2. The attractiveness between fireflies is proportional to their brightness. The firefly with less bright will move towards the brighter one. If no one is brighter than a particular firefly, it moves randomly. Attractiveness is proportional to the brightness which decreases with increasing distance between fireflies.
3. The brightness or light intensity of a firefly is related with the type of function to be optimized. In practice, the brightness of each firefly can be directly proportional to the value of the objective function.

This algorithm is based on two key ideas: the light intensity emitted and the degree of attractiveness that is generated between two fireflies.

The light intensity of firefly i, I_i depends on the intensity I_0 light emitted by firefly i and the distance r between firefly i and j. In, the light intensity I_i varies with the distance r_{ij} monotonically and exponentially. That is

$$I_i = I_O \, e^{-\gamma r_{ij}}$$

Where γ is the light absorption coefficient. In theory, $\gamma \in [0;+\alpha[$, but in practice γ can be taken as 1. Since the attractiveness β_{ij} of the firefly i depends on the light intensity seen by an adjacent firefly j and its distance r_{ij} , then the attractiveness β_{ij} is given by:

$$\beta_{ij} = \beta_O \, e^{-\gamma r_{ij}}$$

Where β_0 is the attractiveness at $r_{ij}=0$.

$$r_{ij} = \|x_i - x_j\|_2$$

The movement of a firefly i towards another brightest firefly j is given by:

$$x_i = x_i + \beta_{ij}(x_j - x_i) + \alpha\epsilon_{ij}$$

Where ϵ_{ij} is a random parameter generated by a uniform distribution and α is a parameter of scale.

In this work, the light intensity of a firefly i ,I_i is determined by its objective function value.

The pseudo code of the Firefly Algorithm for bound constrained optimization problems can be summarized as follows:

Initialize Population of *m* fireflies χ_i, i=1,2,…….*m*

Compute Light Intensity f(χ_i),for all i=1,2………..*m*

While (stopping criteria is not met) **do**

for *i= 1 to m*

for *j= 1 to m*

if f(χ_i) > f(χ_j) **then**

Move firefly i towards j using (4.4)

end if

end for

end for

Update Light intensity f(χ_i) for all *i=1,2,……….m*

Rank the fireflies and find the current best

end while

With the purpose of separating multiple objects from background, multilevel image segmentation is formulated. Otsu thresholding is a classical and efficient algorithm for image segmentation. In consequence, Otsu thresholding is selected to solve image segmentation problem in this work. The core idea of the Otsu thresholding algorithm is searching a threshold to maximize the between-class variance.

Suppose that there are N pixels with L gray levels in an image; the probability distribution of the gray level i (i =0, . . . , $L-1$) can be defined by pi=h_i /N, where $\Sigma_{i=0}^{L-1} pi$= 1and hi represents the number of pixels with the specific gray level i. Hence, the mean value of the total image is $\mu_T=\Sigma_{i=0}^{L-1} ipi$. Let a threshold t partition the image into two classes: class C_1 including the pixels $i \leq t$ and class C_2 including the pixels $i >$

t. Define the probability of C_1 and C_2 to be $\omega_1 = \Sigma_{i=0}^{t} pi$ and $\omega_2 = \Sigma_{i=t+1}^{L-1} pi$. Then, mean values of the two classes can be calculated as,

$$\mu_k = \sum_{i=0}^{t_k} \frac{ip_i}{\omega_k},$$

$$\omega_k = \sum_{i=0}^{t_k} p_i,$$

In this situation, the maximum variance between two classes can be defined as

$$\sigma^2 = \omega_1(\mu_1 - \mu_T)^2 + \omega_2(\mu_2 - \mu_T)^2$$

To solve the multilevel Otsu thresholding problem, an image needs to be classified into j classes (C_1, C_2 , C_j) with the set of thresholds (t_1, t_2, . . . , t_{j-1}). In a similar way, the maximum between-class variance with multilevel thresholds can be defined as

$$\sigma^2_{mul} = \sum_{k=1}^{j} \omega_k (\mu_k - \mu_T)^2$$

With,

$$\mu_k = \sum_{i=0}^{t_k} \frac{ip_i}{\omega_k} \qquad \omega_k = \sum_{i=0}^{t_k} p_i, \qquad k=1,$$

$$\mu_k = \sum_{i=t_{k-1}+1}^{t_k} \frac{ip_i}{\omega_k},$$

$$\omega_k = \sum_{i=t_{k-1}+1}^{t_{k-1}} p_i, \qquad 1 < k < j,$$

$$\mu_k = \sum_{i=t_{k-1}+1}^{t_{L-1}} \frac{ip_i}{\omega_k}$$

$$\omega_k = \sum_{i=t_{k-1}+1}^{L-1} p_i, \qquad k=j,$$

In other words, the problem of multilevel otsu thresholding can be understand as searching a set of thresholds ($t_1, t_2, \ldots\ldots\ldots t_{j-1}$) that can maximize the between-class variance.
The optimization problem is defined as

$$(\hat{t_1}, \hat{t_2}, \ldots\ldots\ldots\ldots\ldots, \widehat{t_{j-1}}) = max\ \sigma^2_{mul}$$

V. Simulation Results

The Proposed digital image segmentation using Firefly algorithm is developed using MATLAB with input image. The results obtained by the proposed method are compared with the Darwinian Particle Swarm Optimization. The entire images are resized to dimension of (256 x 256). The quality metrics are evaluated for different input images such as PSNR, Threshold, std Val, Best cost, µ value and time (sec).

The input cameraman image Fig.1 shows that the threshold values for the output image m=2, 3, 4, 5. The tabular column value represents that the different threshold values, std val, PSNR, Best cost, µ value and time (sec) for different m values .Fig. 2 seems to be comparison of comparison of different output cameraman image with the PSNR value. The comparison of computational time in (sec) for various output cameraman image for different m-value.

Input Image (Cameraman)

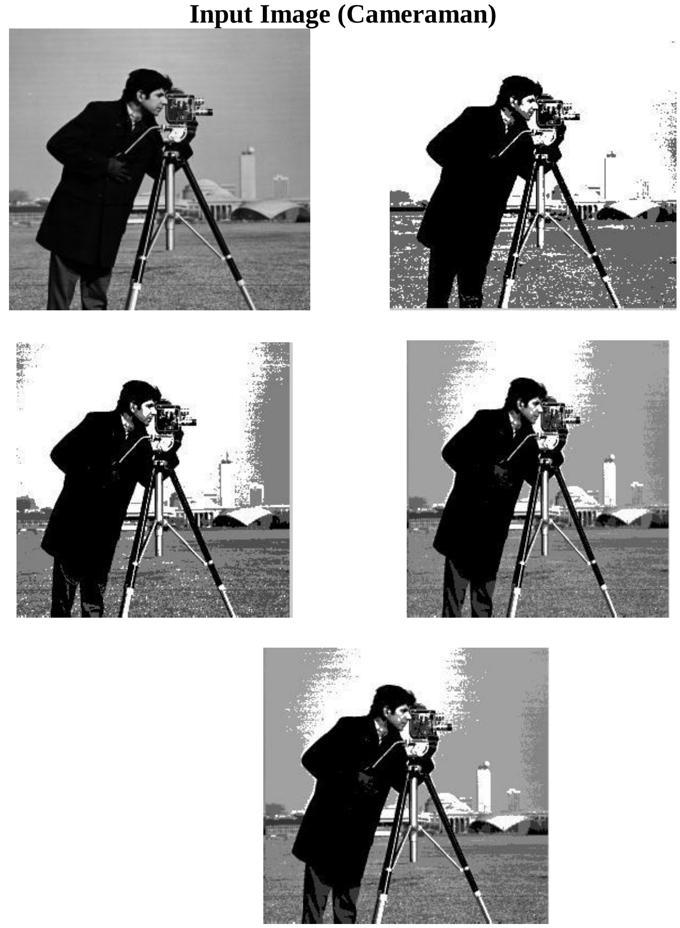

Fig. 1 Input and Output Images for Various Threshold Level m=2, 3, 4 and 5 (a) Input Image, (b) Output Image m=2, (c) Output Image m=3, (d) Output Image m=4 and (e) Output Image m=5

TABLE 1
DIFFERENT THRESHOLD, STD VAL, PSNR, BEST COST, M VALUE AND TIME(S) FOR DIFFERENT M VALUES FOR CAMERAMAN IMAGE

Input image	m	Thres hold	Std val	PSNR	Best cost	µ value	Tim e (s)
Camera man	2	70,14 4	0.0345	11.539 2	3650. 335	3.6503 e+03	2.79 3
	3	59,11 9,156	1.1866	13.039 9	3725. 715	3.7256 e+03	2.92 3
	4	42,95, 140,1 70	0.2596	16.802 5	3780. 686	3.7807 e+03	4.33 9
	5	36,82, 122,1 49,17 3	2.0453	18.036 4	3812. 009	3.8117 e+03	5.67 0

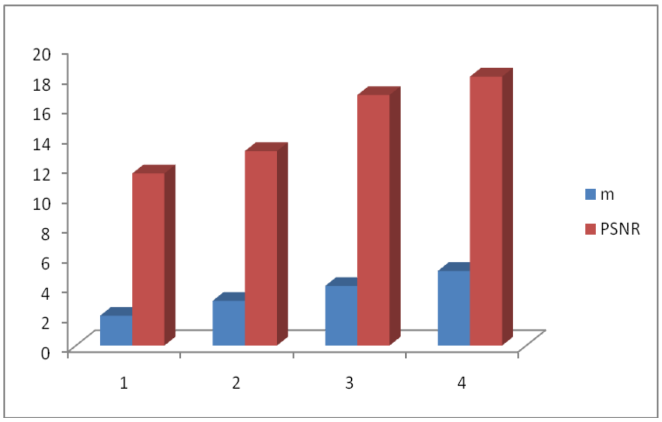

Fig. 2 Comparison of Different Output Cameraman Image with PSNR Value

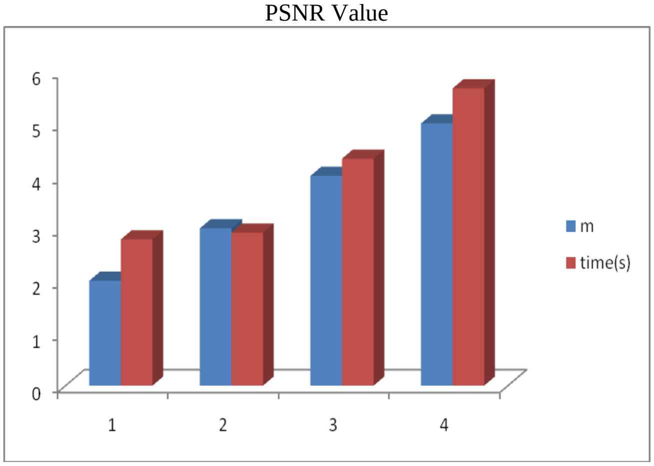

Fig. 3 Comparison of Computational Time in (sec) for Various Output Cameraman Image for Different m – Value

From Table1 The different threshold, std val, PSNR, Best cost, µ value and time in (sec) for different m values for cameraman image shows that the performance is better than DPSO. From Fig2.The bar graph showing that the increasing m level makes the increasing in PSNR values showing that the better quality of the segmented image and from Fig3. The bar graph showing that the increasing m value makes the computational time increases.so,that the thresholding levels is increasing to make the timing increases.

VI. CONCLUSION

A multilevel image thresholding approach based on the proposed firefly algorithm.Otsu based multilevel thresholding between-class variance function is maximized to obtain optimal optimal threshold level for grayscale images. cameraman images is used to verify the proposed method. The performance parameters such as objective function, Standard deviation, PSNR, Bestcost value and search time of CPU. The experimental results reveal that the proposed method can efficiently segment multilevel images and obtain better performance than DPSO.

REFERENCES

[1]. Hanbay, and Talu (2014) "Segmentation of SAR images using improved artificial bee colony algorithm and neutrosophic set", Applied Soft Computing, Vol. 21, pp. 433-443.
[2]. Li et al (2013) "Automatic detection of common surface defects on oranges using combined lighting transform and image ratio methods", Postharvest biology and technology, Vol. 82, pp. 59-69.
[3]. Mandal, et al (2013) "A novel hybrid approach using wavelet, firefly algorithm, and fuzzy ARTMAP for day-ahead electricity price forecasting", IEEE Transactions on Power Systems, Vol. 28, No. 2, 1041-1051.
[4]. Sayadi, et al (2013) "Firefly-inspired algorithm for discrete optimization problems: an application to manufacturing cell formation", Journal of Manufacturing Systems, Vol. 32, No. 1, 78-84.
[5]. Li, et al (2013) "Automatic detection of common surface defects on oranges using combined lighting transform and image ratio methods", Postharvest biology and technology, Vol. 82, pp. 59-69.
[6]. Yang, et al (2012) Firefly algorithm for solving non-convex economic dispatch problems with valve loading effect", Applied soft computing, Vol. 12, No. 3, pp. 1180-1186.
[7]. Sathya, and Kayalvizhi, (2011) "Optimal multilevel thresholding using bacterial foraging algorithm", Expert Systems with Applications, Vol. 38, No. 12, pp. 15549-15564.
[8]. Sathya and Kayalvizhi (2011) "Optimal segmentation of brain MRI based on adaptive bacterial foraging algorithm", Neuro computing, Vol. 74, No. 14, pp. 2299-2313.
[9]. Yang, "Firefly algorithms for multimodal optimization", International Symposium on Stochastic Algorithm, pp. 169-178
[10]. Liang, "Application of a hybrid ant colony optimization for the multilevel thresholding in image processing.", International Conference on Neural Information Processing, pp. 1183-1192