Image Segmentation based on Genetic Algorithm using Image Thresholding

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***Abstract*— The objective of this research is to use Genetic Algorithm with optimization parameter using threshold values to calculate the input parameter for the algorithm. Here, we show the results of three algorithm i.e. K-means, PSO, and GA and compare them on the basis of result which show the values for CDR, FDR, FRR and processing time. Selecting an optimal threshold value is the most critical step in the procedure of image thresholding. In a bimodal histogram which can be modelled as a combination of two Gaussian density functions assessing these densities in practice is simply unfeasible. The objective of this paper is to use Genetic Algorithm for the suboptimal estimation of the variances and means of these two Gaussian density functions; thereafter, the calculation of the optimal threshold value is straight forward. Experimental results shows on the basis of varied range of complex bimodal images that, proposed thresholding algorithm presents greater correct detection rate of object and background with respect to the other methods including particle swarm optimization (PSO) and K- Means. It also takes lower execution time than the PSO-based method, and also gives lower false acceptance and false rejection rate.**

***Keywords*—histogram-based thresholding, genetic algorithm, fitness function, object and background detection, PSO.**

I. INTRODUCTION

Segmentation refers to the process of partitioning a digital image into multiple segments or regions. The goal of segmentation is to simplify the representation of an image into something that is more meaningful and easier to analyze [1]. Segmentation is very challenging because of the multiplicity of objects in an image and the large disparity between them. Genetic Algorithm to solve the problem of image segmentation was treated as optimization problems based GA. Genetic algorithms are an optimization technique used in image segmentation. It mimics natural selection, allowing an algorithm to adapt. Solutions are represented by a population of individual chromosomes, usually represented as binary strings. A chromosome is made up of genes, each of which can represent a particular characteristic. Each individual in the population is given a fitness score based on how well they solve the particular problem. The higher the individual's fitness score, the greater their probability of breeding. Breeding creates the next generation through crossover and mutation. Crossover combines the chromosomes of two individuals, creating a new individual which is unlike either of the parents. Mutation which occurs only a small percent of the time randomly alters a new individual's chromosomes [2, 3]

In this paper, we apply Genetic Algorithm (GA) to find the threshold value adaptive and local histogram optimization function. We supposed that the intensity distributions of objects and background in an image can be assessed by Gaussian probability density functions. Thus, the histogram is fitted by a mixture of two Gaussian probability density functions for the given image. Then the GA algorithm is used to estimate the required parameters so that the difference between the estimated histogram and the image histogram reaches its minimum value. Thereafter, the optimal threshold is calculated by some straightforward relationships.

Experimental result on the benchmark image database shows that the threshold computation of proposed algorithm i.e GA is lower than the PSO and K-means. And also the Correct Detection rate of the proposed algorithm is higher among the other two thresholding method, while False acceptance rate and False rejection rate is lower.

In general, color segmentation methods could be classified as [4]:

1. Histogram thresholding (mode method) and color space clustering: In Histogram thresholding images are composed of regions with different grey level ranges, the histogram of an image can be

separated into a number of peaks (modes), each corresponding to one region, and there exists a threshold value corresponding to valley between the two adjacent peaks. Multiple histogram-based thresholding divided the color space by thresholding each component histogram.

2. Region based approaches: Region based approaches, including region growing, region splitting, region merging and their combination, attempt to group pixels into homogeneous regions.

3. Edge detection: In a monochrome image, edge is defined as a discontinuity in the gray level, and can be detected only when there is a difference of brightness between two regions. However, in color images, the information about edge is much richer than that in monochrome case.

4. Fuzzy techniques: The regions in an image are not always crisply defined, and uncertainty can arise within each level of image analysis and pattern recognition. Fuzzy set theory provides a mechanism to represent and manipulate uncertainty and ambiguity. Fuzzy operators, properties, mathematics and inference rules (IF-THEN rules) have found considerable applications in image segmentation.

5. Neural networks approaches: Artificial neural networks (ANN) are widely applied for pattern recognition. Their extended parallel processing capability and nonlinear characteristics are used for classification and clustering. ANN explore many competing hypotheses simultaneously through parallel nets instead of performing a program of instructions sequentially, hence ANN can be feasible for parallel processing. [4].

Some of these methods are subjected into two important errors:

1. They have no standard image segmentation method whenever they object to a more class images.

2. Having a more class image is a reality that presents some tenacious problems.

In an image containing only two principal grey level regions (e.g. "object" and "background"), the image histogram can be modelled as a mixture of two Gaussian density functions. Once the parameters of these two Gaussian density functions, the mean and the variance are estimated, the optimal threshold can be computed easily.

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Typically, experimental results presents that evolutionary methods generate correctly the parameter of models in image segmentation. The genetic algorithm (GA) is effectively used to the means and the variances of two Gaussian density functions in the histogram-based image thresholding. Proposed method gives exceptionally accurate results.

The rest of this paper is organized as follows. In Section 2, Presents an overview on Proposed Algorithm i.e GA. Section 3 presents our thresholding algorithm including its fitness function and Genetic for computing the optimal threshold value. The experimental results and discussions are given in Section 4 and finally, the paper is summarized and concluded in Section 5.

II THE PROPOSED ALGORITHM

This section shows the Proposed algorithm for computing the optimal threshold value. Firstly, it is required to approximate all the parameters of a parametric function from the image histogram. This problem can be solved by optimizing a fitness function that is minimized by Genetic optimization algorithm. Then, the optimal threshold is computed by the computed parameters.

Threshold Value and Fitness Function

The main input information is the image histogram for any histogram based image segmentation. For an image with M-1 gray levels, the image histogram can be declared as a discrete function, p(rk), as follows:

with M-1 gray levels, the image histogram can be declared as a discrete function, p(rk), as follows:

$$p(r_k) = \frac{n_k}{n} \quad (1)$$

Where

$$n = \sum_{r_{k=0}}^{M-1} n_k \quad (2)$$

$$\sum_{r_{k=0}}^{M-1} p(r_k) = 1$$

where r_k is the kth gray level (r_k [0,M-1]), nk is the number of pixels whose gray level is r_k and n is the total number of pixels in image; in other words, the histogram of an image is an approximation of a gray level r_k odds in an image. Histogram of an image for all values of k gives a general description from the image status without any information about its inside [7].

The histogram of a bimodal gray-level image can be approximated by mixing two probability density functions, $p_1(x)$and $p_2(x)$; then, the image histogram, p(x), can be computed by Equation 6:

$$P(x)= P1p_1(T) + P2p_2(T) \quad (3)$$

$$P1 +P2=1$$

where Pi denotes the prior probability of class i and x is a gray level between 0 to L-1.

Optimal threshold value T can be computed by minimizing total error probability and considering the Bayesian rule as Equation 6 [7] shows.

$$P1p_1(T) =P2p_2(T) \quad (4)$$

The main principle for histogram based image thresholding algorithm is to find threshold that is nearest to optimal threshold valve(Equation 4). In this paper, our aim is to segment the image into two regions (black and white zones) and find the suboptimal threshold for the thresholding.
Now to estimate p_1 (x) and p_2 (x), from equation (4) the value of p_1 (x) and p_2 (x) can be calculated. Considering p_1 (x) and p_2 (x) as two Gaussian probability density functions is one of the solutions. So, the histogram of a bimodal gray-level image can be approximated by mixing two Gaussian probability density functions by Equation 5:

$$p_{estimated}(x)=\sum_{i=1}^{2} Pi\, p_i(x) \quad (5)$$

where Pi denotes the prior probability of class i

pi(x) is Gaussian distribution function x of class i

$$\sum_{i=1}^{2} Pi \Big/ \sqrt{2\pi\sigma i}\, \exp \frac{-(x-\mu i)^2)}{2\sigma i^2} \quad (6)$$

μi and σi the mean and standard deviations of the ith distribution probability function

For a bimodal image , a root mean square (RMS) method is proposed to estimate the six parameters including P_1 μ_1,σ_1 for the first class and P_2, μ_2, σ_2 for the second class. The root mean square between the histogram function and the estimated Gaussian probability function is simplified as
Fitness function E is defined on the M-point image histogram. After computing the optimal values of the six parameters (P_1 μ_1,σ_1 andP_2, μ_2, σ_2), the optimal threshold value T can be computed by solving Equation 4 which leads the quadratic Equation 7 [7].

$$AT^2 +BT+C=0 \quad (7)$$

Although the above quadratic equation has two possible solutions, only one of them is a feasible one. In Equation 7, T is the threshold point and parameters A, B and C are computed by Equations 8 through 10, respectively [8]

$$A= \sigma_1^2 + \sigma_2^2 \quad (8)$$

$$B=2(\mu_1 \sigma_2^2 - \mu_2 \sigma_1^2) \quad (9)$$

$$C= (\sigma_1\mu_2)^2 - \sigma_2\mu_1)^2 +2\sigma_1\sigma_2 \ln(\sigma_2 P_1/\sigma_1 P_2) \quad (10)$$

where μ1 and σ1 are the mean value and the variance of one side of the bimodal image histogram, and μ2 and σ2 are the mean value and the variance of the other side of the bimodal image histogram. Both parameters μ and σ, describe the global properties of the histogram-based measurements. In order to optimize fitness function E and find the six parameters in Equation 6, it is essential to use a proper iterative optimization method [6].

Proposed Algorithm can be summarized as follow:

Step 1: Input the configuration parameters (Initial Population, Maximum Number of Generations etc.) for the Genetic Algorithm.

Step 2: Input the image.

Step 3: If the image is color convert it into gray level.

Step 4: Take the Histogram of the gray level image and convert it to Probability Distribution Function (PDF)

Step 5: Considering the PDF of gray image p(x) is mixture of p1(x) and p2(x) as two Gaussian probability densityfunctions

$$p(x) = P_1p_1(x) + P_2p_2(x)$$

$$p(x) = \frac{P_1}{\sigma_1\sqrt{2\pi}} e^{-\frac{(x-\mu_1)}{2\sigma_1^2}} + \frac{P_2}{\sigma_2\sqrt{2\pi}} e^{-\frac{(x-\mu_2)}{2\sigma_2^2}}$$

According to above equation we need to estimate the $\mu_1, \mu_2, \sigma_1, \sigma_2$.

Create the objective function such that the $\mu_1, \mu_2, \sigma_1, \sigma_2$ values should satisfy the following equation

$$p(x) - P_1 p_1(x) - P_2 p_2(x) = 0$$

Step 6: start the genetic algorithm to get these values and after getting these values calculate the segmentation threshold according to the equation below

$AT^2 + BT + C = 0$ By equation 8 through 10

Step 7: calculate the T and use it as segmentation threshold and perform segmentation.

III. Experimental Results

In order to appraise the performance of the Genetic algorithm, two different algorithms were compared including PSO and K- means based thresholding algorithms. The fitness function in the last two methods compared is the same as for our proposed algorithm only that they use K-Mean [5,6] and PSO [9,10] optimization algorithm.

All compared thresholding algorithms are applied on the USC-SIPI image database [11]. This benchmark image database contains 44 real complex images with different brightness, contrasts and sizes. The USC-SIPI image database is maintained primarily to support research in image processing, image analysis, and machine vision. The database is divided into volumes based on the basic character of the pictures. Images in each volume are of various sizes such as 256×256, 512×512, or 1024×1024 in pixels. All images are 8 bits/pixel for gray-level images, 24 bits/pixel for color images[11].

The major factor in the segmentation algorithms are accuracy and complexity. To calculate the accuracy and performance of the proposed algorithm in comparison with other algorithms, three performance metrics are defined. First is the correct detection rate (CDR) and is given in Equation 11. The false acceptance rate (FAR) is the percentage of detection moment in which false acceptance happens. The false rejection rate (FRR) is the percentage of recognition moments in which false rejection occurs. FAR and FRR are expressed in Equations 12 and 13, respectively and complexity can be measured by running time in the same condition

$$\text{CDR}=\frac{\text{Number of correctly classified samples in datase}}{\text{Tota number of samples in dataset}} \quad (11)$$

$$\text{FDR}=\frac{\text{Number of false accepted samples in dataset}}{\text{Total number of samples in dataset}} \quad (12)$$

$$\text{FRR}=\frac{\text{Number of false rejected samples in dataset}}{\text{Total number of samples in dataset}} \quad (13)$$

In order to compare the proficiency of the compared thresholding algorithms, including complexity and accuracy, we have implemented all algorithms in Matlab environment, run on a 1.6 GHz ,Core 2 Dou CPU, on Windows XP platform.

In order to compare the quality of proposed Algorithm four sample images are selected from dataset. Figure 1 through 4 illustrates the output images for all the compared thresholding algorithms

Following Parameters are used for GA and PSO Maximum Generations = 1000;
Initial Population = 16; Time Limit = 15 Sec

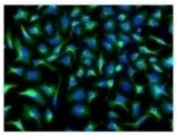
		
Original Image	Manually Segmented Image	
		
Segmentation by K-Means	Segmentation by PSO	Segmentation by GA

Figure: 1

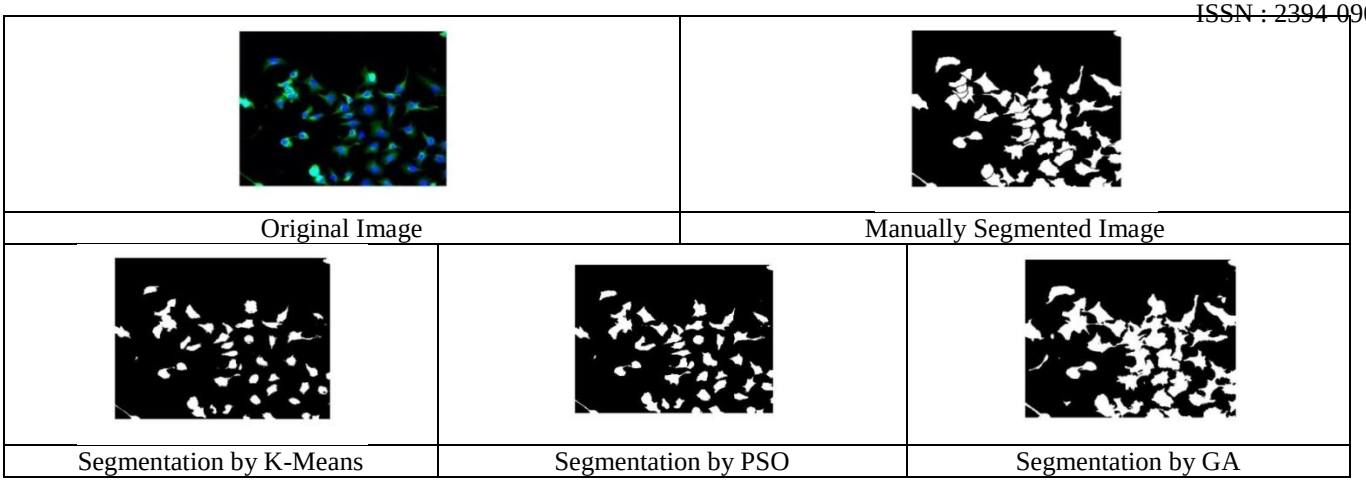


Figure: 2

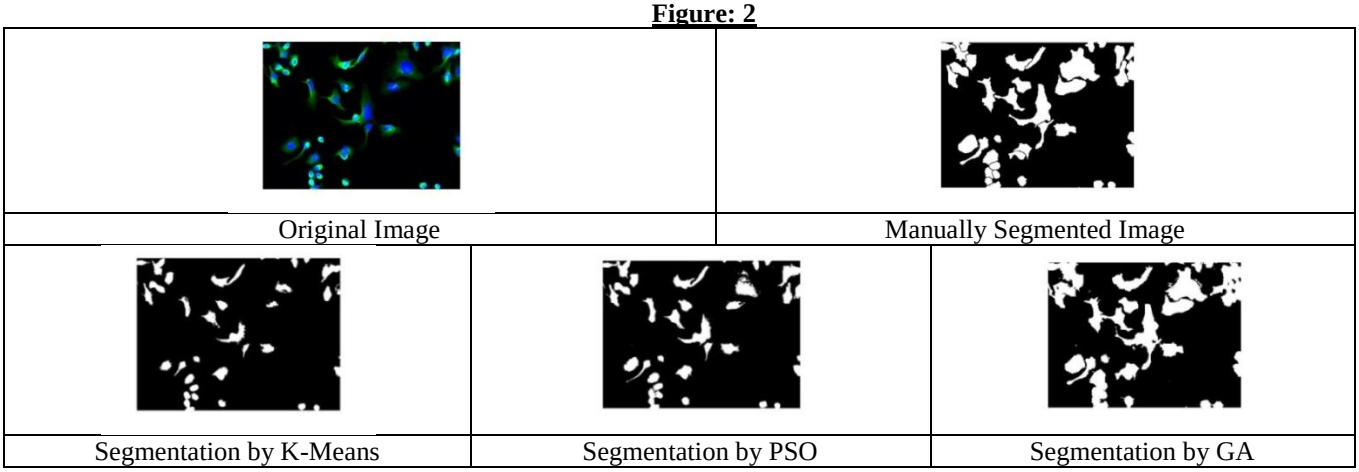


Figure: 3

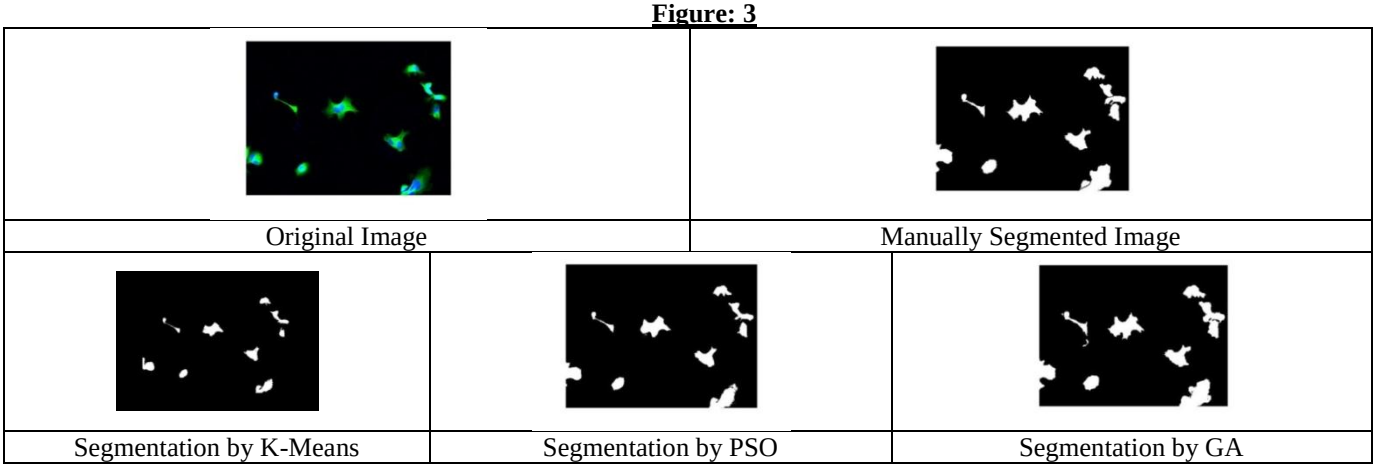
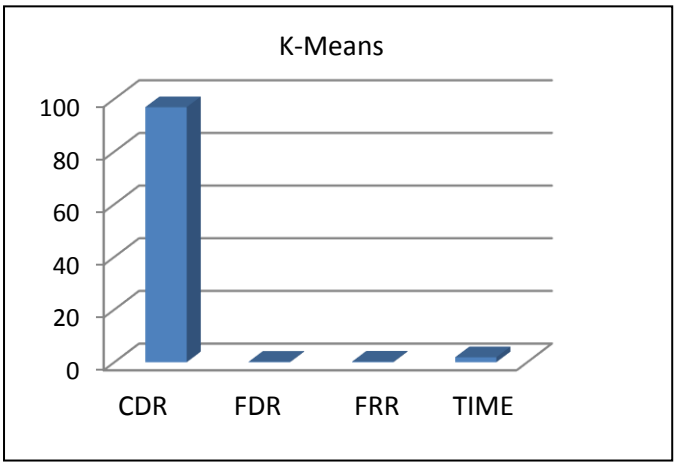
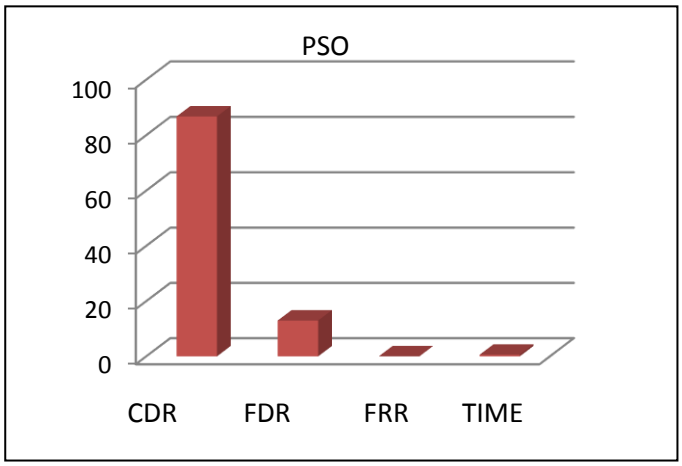


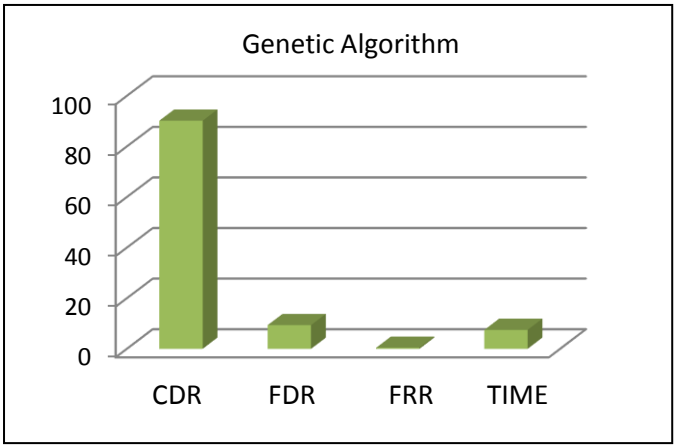
Figure:4

Image/ Criterion	**Image1**			**Image2**			**Image 3**			**Image 4**		
	K-means	**PSO**	**GA**	**K-means**	**PSO**	**GA**	**K-Means**	**PSO**	**GA**	**K-means**	**PSO**	**GA**
CDR	73.969	84.062	**96.694**	88.530	91.744	**95.988**	96.384	97.992	**98.989**	86.742	90.20	**96.883**
FAR	25.762	15.425	**2.088**	11.150	7.842	**0.0001**	3.595	1.974	**0.015**	12.970	9.375	**0.191**
FRR	0.2685	0.512	**0.217**	0.318	0.412	**0.209**	0.019	0.032	**0.023**	0.0286	0.418	**0.225**
Time(Sec)	0.2313	5.5157	**3.916**	0.646	3.127	**2.654**	0.063	5.065	**2.74**	0.574	7.495	**1.886**

Table 1: Accuracy and average execution time for different applied methods images On USC –SIPI images database







Graph to compare the performance metric i.e CDR, FDR, FAR and Processing Time (in sec) of the proposed algorithm in comparison with other algorithms for image 4. Similarly we can create graph for remaining three images also

V. Conclusion:

In this paper we use Genetic algorithm (GA) to find the threshold value based on the adaptive and local histogram optimization function, where we assumed that the intensity distributions of objects and background in an image can be estimated by Gaussian probability density functions. And thus the histogram of the given image is fitted by a mixture of two Gaussian probability density functions.

Thereafter, the Genetic Algorithm is then used to estimate the required parameters so that the difference between the estimated histogram and the image histogram reaches its minimum value. Then, the optimal threshold is computed by some basic relationships. Experimental results is then compared with the benchmark image dataset show that the computational cost of the proposed algorithm is lower than the threshold computation based on the K-Means and PSO, while the correct segmentation rates of the proposed algorithm are also the highest among all compared thresholding methods, while the false acceptance rate and the false rejection rate are lowest.

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