International Journal of Computer Applications (0975 – 8887)
Volume 66– No.22, March 2013

Segmentation of Noisy Binary Images Containing Circular and Elliptical Objects using Genetic Algorithms

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ABSTRACT
A segmentation technique basically divides the spatial domain, on which the image is defined in 'meaningful' parts or regions. The current approaches involving Genetic Algorithms (GAs) segment the regular-shaped images. In the proposed method, this drawback is overcome by applying GA to images containing circular and elliptical objects. The GA generated the initial population set randomly where each individual is a possible solution for image segmentation. The reproduction step of GA uses morphological operations at random. Over several generations, population is evolved to get near optimal results. The experimental results are presented for noisy images containing circular and elliptical objects. The results of the proposed method are compared with the standard image segmentation techniques. The proposed method enhances the image segmentation for higher density noise level.

General Terms
Image Processing, Pattern Recognition.

Keywords
Image Segmentation, Genetic Algorithm and Morphological Operators.

1. INTRODUCTION
Genetic algorithm is a search heuristic procedure based on natural evolution. It is used to generate solutions to difficult search and optimization problems. GA is inspired by natural evolution and uses a population-based approach with various operators that include selection, crossover and mutation. Genetic algorithm was developed by John Holland and his associates and is briefly characterized by three main concepts. First, a fitness function that determines a fitness of each individual chromosome. Second, a selection operation which selects individuals for recombination according to their fitness and third a recombination operation which creates new offsprings based on the genetic structure of their parents. Genetic algorithms are able to overcome many of the drawbacks of other optimization techniques namely exhaustive techniques, calculus based techniques and knowledge based techniques (heuristic methods, production rule system) [1]. They search from a population of individuals (search points) and do not require domain specific knowledge. Also, they use probabilistic rules rather than the deterministic rules. GAs have been used to solve various problems in computer vision, including image processing, image matching, object recognition and feature selection. The important parameters for successful application of GAs include population size and probabilities of the crossover and mutation operators.

Image segmentation is one of the steps in image analysis. GA based image segmentation has been used in various image analysis applications. Yu et al. [2] used a GA approach to segmentation of 2-D image using morphological operations. Bhandarkar and Zhang [3] proposed a stochastic annealing algorithm to replace the selection mechanism of GA to segment images. Rosenberger and Chehdi [4] have proposed a genetic algorithm method to multi components image segmentation. Bosco [5] proposed new method for image segmentation based on genetic algorithm. Paulinas and Usinskas [6] have covered a brief overview of application of genetic algorithms to image enhancement and segmentation. Ulbeh and Moustafa [7] proposed the new technique for noise reduction and image reconstruction of images. Pedtino and Saito [8] have proposed a new global optimization technique for image segmentation using morphological operations and genetic algorithm. Phulpagar and Kulkarni [9] have proposed a genetic algorithm technique for reconstruction of 2-D images containing regular-shaped objects.

In this paper, the GA-based approach has been extended for reconstruction of 2-D images containing circular and elliptical objects. The results obtained using GA-based approach are at times better than those obtained using the approach of existing techniques.

2. APPROACH OF IMAGE SEGMENTATION
Image segmentation is a process by which a given 2-D image is partitioned into nonoverlapapping regions, where each region is homogeneous and connected and the union of two spatially adjacent regions is heterogeneous. Each region in a segmented image needs to satisfy the properties of homogeneity and connectivity [10, 11]. A region is considered homogeneous if all of its pixels satisfy a homogeneity criterion defined over one or more pixel attributes such as color, intensity and texture etc. A region is considered as connected [12], if there exists a connected path between any two pixels within the region. In this paper, the images are considered to comprise of two constant gray levels and corrupted by the different types of noises (salt and pepper, Gaussian and Poisson), which may occur in noisy image transmission. The reconstruction of 2-D image is formed by using two constant gray levels and gray levels are varied from image to image.

SNR of 2-D image of size $M\times N$ is defined as the ratio of average signal power to average noise power. SNR is mean-squared error measures and its unit is decibel (dB).

$$\text{SNR (dB)} = 10\log_{10}\frac{\left(\sum_{(i=1,\ j=1)}^{(M,\ N)} A(i,\ j)^2\right)}{\left(\sum_{(i=1,\ j=1)}^{(M,\ N)} (A(i,\ j)-B(i,\ j))^2\right)} \quad (1)$$

Where, $A(i, j)$ denotes pixel (i, j) of the original image and

$B(i, j)$ denotes pixel (i, j) of the noisy image.

2.1 Image Segmentation Using GA

Assume the size of the binary image to be 64×64 pixels. Thus, the search space is $2^{64\times64}$. The image is divided into sub-images of size 16×16 pixels before performing image segmentation to increase the speed of the search process. The segmentation using GA is performed on 16×16 sub-images which are later combined to obtain the entire irregular-shaped segmented 2-D image. The length of the chromosomes is (L) fixed. It is equals to the numbers of pixels in a sub-image. A chromosome in GA represents a segmented 2-D image. The structure of the chromosome is a vector representing 2-D sub-image of size 16×16. Each gene of chromosome can have two possible values: 0 for background and 1 for foreground i.e. the object.

2.2 Initial Population Set

The initial population of GA is randomly generated. The set of individuals of the first generation represents the initial population in the search space as

$\{p_{1,1},\dots p_{i,j},\dots, p_{K,L}\}$ Where, $i = 1, 2, \dots, K,\ j = 1, 2, \dots, L.$

Where, p_i is randomly chosen individual, K is population size and L is chromosome size.

The initial population is randomly chosen. The GA convergence depends upon the size of populations, therefore the population size is an important factor in the application of GA.

2.3 Fitness Function

The fitness function returns the value associated with each individual indicating its fitness. Let the original noisy image be represented as $I = [\ I_1, I_2,\dots, I_L]$ and the chromosome is represented as $P_i = [p_{i,1}, p_{i,2},\dots, p_{i,L}]$, the fitness of each individual (P_i) is the difference between noisy image pixel and individual population value at that pixel.

The fitness function is defined as

$$\text{fitness}(P_i) = \frac{1}{(1+(\sum_{j=1}^{L=256}|P_{i,j}-I_j|/L))} \quad (2)$$

This fitness function is used to find out the fitness of each individual in the population.

2.4 Selection Function

After the evaluation of the fitness of individuals, the fitter individuals must be selected to be parents for producing offsprings, which form the populations of the successive generations. In this method, we have used roulette wheel selection [13], which is conducted by spinning a biased roulette wheel sized in proportion to the fitness of each chromosome.

2.5 Reproduction Operator

In GA, reproduction is another step that generates the population of qualified individuals in the successive generations. In this paper it consists of three functions i.e. morphological operations, cross-over and mutation.

2.5.1 Theoretical background of Morphological Operators

Morphology is a technique of image processing based on shapes. The value of each pixel in the output image is based on a comparison of the corresponding pixel in the input image with its neighbours. It has been used to process binary and grayscale images. To represent connectivity properties of an image, we applied morphological operation to selected individuals. Let P be an image and Q be a structuring element. The template size of the structuring element Q is a 3×3 or 5×5 with an appropriate intensity structure. The size and shape of Q depend on the solution of the segmented 2-D image. Basic binary morphological operators [10] are defined as follows:

Let A and B are two binary images. Translation of a set A, by x, denoted $(A)_x$, is given as

$$(A)_x = \{c | c = a + x, \forall\ a \in A\}$$

Reflection of a set B, denoted $\hat{B}$, is given as

$$\hat{B} = \{x | x = -b, \forall b \in B\}$$

Dilation and erosion are based on two set operations namely translation and reflection. Dilation adds pixels to the boundaries of objects in an image. Dilation of an input image A by a structuring element B is defined as follows:

$$A \oplus B = \{x | [(\hat{B})_x \cap A] \subseteq A\}$$

For example, if

$$A = \begin{bmatrix} 0\,0\,0\,0\,0 \\ 0\,1\,1\,1\,0 \\ 0\,1\,1\,1\,0 \\ 0\,1\,1\,1\,0 \\ 0\,0\,0\,0\,0 \end{bmatrix} \quad \text{then, } A \oplus \begin{bmatrix} 0\,0\,0 \\ 1\,1\,1 \\ 0\,0\,0 \end{bmatrix} = \begin{bmatrix} 0\,0\,0\,0\,0 \\ 1\,1\,1\,1\,1 \\ 1\,1\,1\,1\,1 \\ 1\,1\,1\,1\,1 \\ 0\,0\,0\,0\,0 \end{bmatrix}$$

$$\text{and } A \oplus \begin{bmatrix} 0\,1\,0 \\ 0\,1\,0 \\ 0\,1\,0 \end{bmatrix} = \begin{bmatrix} 0\,1\,1\,1\,0 \\ 0\,1\,1\,1\,0 \\ 0\,1\,1\,1\,0 \\ 0\,1\,1\,1\,0 \\ 0\,1\,1\,1\,0 \end{bmatrix}$$

Erosion removes pixels on object boundaries in an image. The erosion of an input image A by a structuring element B is defined as is the set of all points x such that B, translated by x, is contained in A,

$$A\ \Theta\ B = \{x | (B)_x \subseteq A\}$$

For example, if

$$A = \begin{bmatrix} 0\,0\,0\,0\,0 \\ 0\,1\,1\,1\,0 \\ 0\,1\,1\,1\,0 \\ 0\,1\,1\,1\,0 \\ 0\,0\,0\,0\,0 \end{bmatrix} \quad \text{then, } A\ \Theta \begin{bmatrix} 0\,0\,0 \\ 1\,1\,1 \\ 0\,0\,0 \end{bmatrix} = \begin{bmatrix} 0\,0\,0\,0\,0 \\ 0\,0\,1\,0\,0 \\ 0\,0\,1\,0\,0 \\ 0\,0\,1\,0\,0 \\ 0\,0\,0\,0\,0 \end{bmatrix}$$

$$\text{and } A\ \Theta \begin{bmatrix} 1\,0\,1 \\ 0\,1\,0 \\ 1\,0\,1 \end{bmatrix} = \begin{bmatrix} 0\,0\,0\,0\,0 \\ 0\,0\,0\,0\,0 \\ 0\,0\,1\,0\,0 \\ 0\,0\,0\,0\,0 \\ 0\,0\,0\,0\,0 \end{bmatrix}$$

Closing consists of dilation followed by erosion with the same structuring element. The closing of an input image A by a structuring element B is defined as follows:

$$A \odot B = (A \oplus B)\ \Theta\ B$$

For example, if

$$A = \begin{bmatrix} 0\,0\,0\,0\,0 \\ 0\,1\,1\,1\,0 \\ 0\,1\,1\,1\,0 \\ 0\,1\,1\,1\,0 \\ 0\,0\,0\,0\,0 \end{bmatrix} \quad \text{then, } A \odot \begin{bmatrix} 0\,0\,0 \\ 1\,1\,1 \\ 0\,0\,0 \end{bmatrix} = \begin{bmatrix} 0\,0\,0\,0\,0 \\ 1\,1\,1\,1\,1 \\ 1\,1\,1\,1\,1 \\ 1\,1\,1\,1\,1 \\ 0\,0\,0\,0\,0 \end{bmatrix}$$

$$\text{and } A \odot \begin{bmatrix}0&1&0\\0&1&0\\0&1&0\end{bmatrix} = \begin{bmatrix}0&1&1&1&0\\0&1&1&1&0\\0&1&1&1&0\\0&1&1&1&0\\0&1&1&1&0\end{bmatrix}$$

Morphological opening of an image is erosion followed by dilation using the same structuring element for both operations. Opening of an input image A by a structuring element B is defined as

$$A \circledcirc B = (A \Theta B) \oplus B$$

For example, if

$$A = \begin{bmatrix}0&0&0&0&0\\0&1&1&1&0\\0&1&1&1&0\\0&1&1&1&0\\0&0&0&0&0\end{bmatrix} \quad \text{then,} \quad A \circledcirc \begin{bmatrix}1&0&1\\0&1&0\\1&0&1\end{bmatrix} = \begin{bmatrix}0&0&0&0&0\\0&1&0&1&0\\0&0&1&0&0\\0&1&0&1&0\\0&0&0&0&0\end{bmatrix}$$

In order to evolve individual images containing circular and elliptical objects, we have selected a random morphological operator among the following set of morphological operators in reproduction step: dilation, erosion, opening, closing, opening followed by closing and closing followed by opening.

We also selected a structuring element at random from the following set.

$$\text{Set of SE's} = \left\{\begin{matrix}\begin{bmatrix}1&1&1\\1&1&1\\1&1&1\end{bmatrix}, \begin{bmatrix}0&0&0\\1&1&0\\0&1&0\end{bmatrix}, \begin{bmatrix}0&1&0\\1&1&1\\0&1&0\end{bmatrix}, \begin{bmatrix}0&0&0\\0&1&1\\0&1&0\end{bmatrix}, \begin{bmatrix}0&0&1\\0&0&1\\0&0&1\end{bmatrix}, \\ \begin{bmatrix}0&0&0\\1&1&1\\0&0&0\end{bmatrix}, \begin{bmatrix}0&0&1\\0&1&0\\1&0&0\end{bmatrix}, \begin{bmatrix}1&0&0\\1&1&1\\1&0&1\end{bmatrix}, \begin{bmatrix}1&1&0\\0&1&1\\0&0&1\end{bmatrix}, \begin{bmatrix}1&1&1\\0&1&0\\1&1&1\end{bmatrix}, \\ \begin{bmatrix}0&0&0\\0&1&1\\0&1&1\end{bmatrix}, \begin{bmatrix}0&1&0\\0&1&0\\0&1&0\end{bmatrix}, \begin{bmatrix}0&1&1\\1&1&0\\1&1&0\end{bmatrix}, \begin{bmatrix}0&1&1\\1&1&1\\1&1&1\end{bmatrix}, \begin{bmatrix}1&0&0\\1&0&0\\1&0&0\end{bmatrix}\end{matrix}\right\}$$

2.5.2 *Crossover Operator*

The crossover operator [13] creates two new offspring strings from two parent strings by swapping parts of parent chromosomes. Generally, two new offsprings are created from two parents. The crossover routines are one-point, two-point, *n*-point and uniform crossovers. In single-point crossover, a random a crossover point is selected and two offspring are formed by swapping parts of the chromosomes. The crossover operator is applied with probability p_c which is typically between 0.60 to 0.95. On the other hand, in two-point crossover operator, two crossover points are selected within a chromosome and then the alternative parts of two parent chromosomes are exchanged to produce two children.

2.5.3 *Mutation Operator*

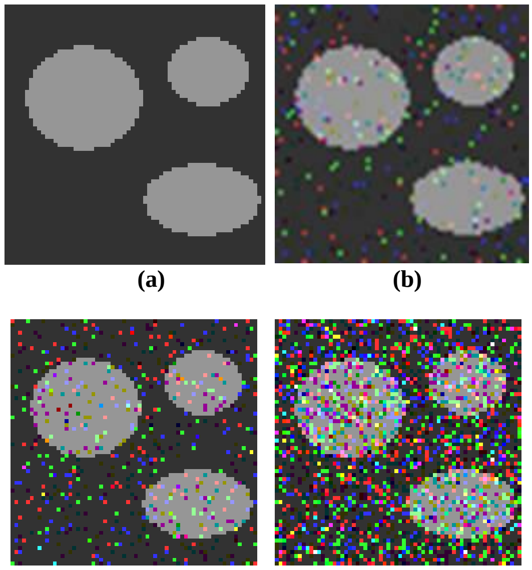
The mutation operator is implemented as a 3×3 median filter, where the central pixel in $n \times n$ window is replaced with the median of all the pixel values in the window. The mutation operator is applied with probability p_m which is typically very small (0.001 to 0.01). Also mask size is selected randomly from 3×3 and 5×5.

2.6 Termination Criterion

The program is terminated when the best fitness does not change the fitness value for *n* subsequent generations.

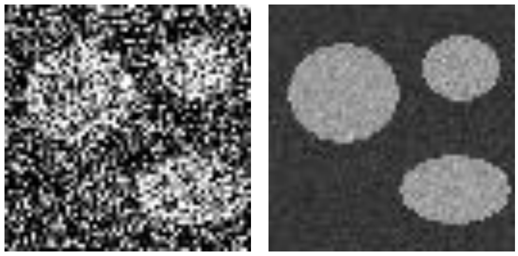
3. EXPERIMENTAL RESULTS

Let assume the synthetic images with two classes having pixel values 50 and 150. The number of objects in test image and their shapes are evolved. The salt and pepper noise is added with noise density of 0.03, 0.05 and 0.20 to the original image Figure 1(a) to obtain Figure 1(b-d) noisy images with SNR of 76 dB, 41 dB and 9 dB respectively. Figure 2 (a), (b) are corrupted images obtained by adding Gaussian noise of density 0.20 and Poisson to Figure 1(a).



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

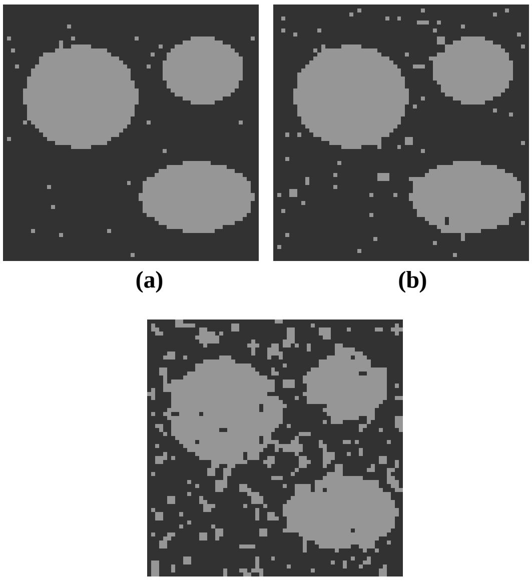
Figure 1: Original and salt and pepper noisy images. (a) original image, (b), (c) and (d) images with 76 dB, 41 dB, and 9 dB SNR respectively.



(a) (b)

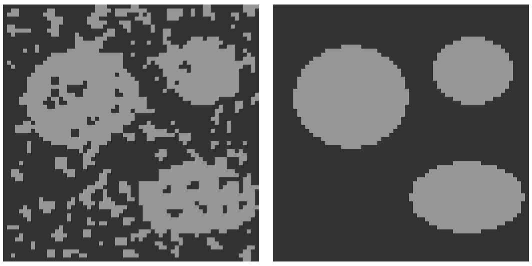
Figure 2: Gaussain and Poisson noises. (a) Gaussion image with 2.5436 dB SNR, (b) Poisson image at 8.5946 dB SNR.

Figure 3 and Figure 4 shows the results obtained using standard techniques of image segmentation. It may be observed that the quality of image segmentation decreases with the increasing noise density of salt and pepper and Gaussian noises. It shows the good segmentation for Poisson noise



(a) (b) (c)

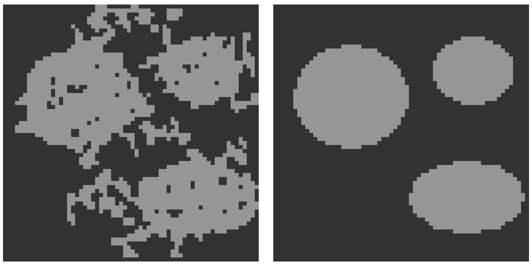
Figure 3: Results obtained by using iterative threshold method. (a), (b), (c) results obtained for Figure 1 (b), (c) and (d).



(a) (b)

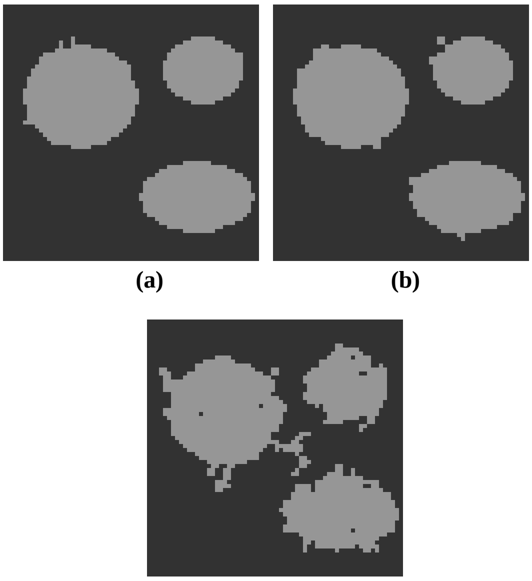
Figure 4: Results by using iterative threshold method. (a), (b) results for Figure 2 (a) and (b).

Figure 6 and Figure 5 shows the experimental results by region grow image segmentation technique. It shows that the quality of image segmentation is good for Poisson noise and for salt and pepper noise density level up to 0.03 with 76 dB SNR. Figure 6 (a), and Figure 5 (b), (c) shows image segmentation is poor.



(a) (b)

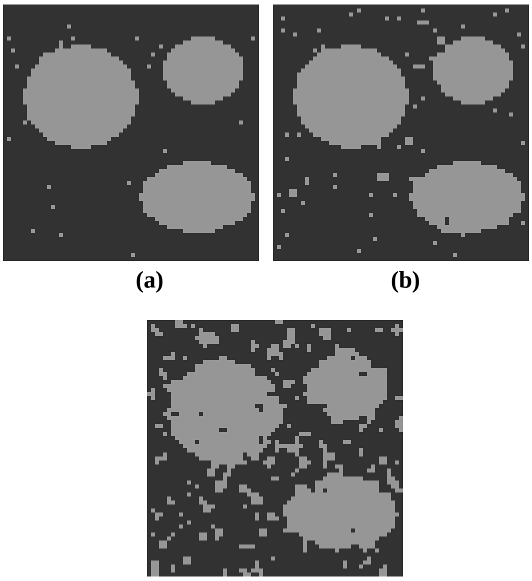
Figure 6: Results by using region grow method. (a), (b) results for Figure 2 (a) and (b).



(a) (b) (c)

Figure 5: Results obtained by using region grow method. (a), (b), (c) results obtained for Figure 1 (b), (c) and (d).

Figure 7 and Figure 8 shows the results obtained using fuzzy c-means (FCM) method. It may be observed that the segmentation of image is not good with the salt and pepper and Gaussian noises.

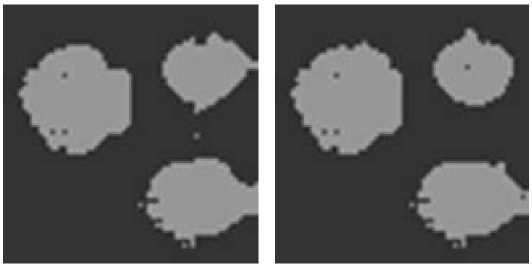


(a) (b) (c)

Figure 7: Results obtained by using FCM method. (a), (b), (c) results obtained for Figure 1 (b), (c) and (d).

Thus the problem with the some of the standard image segmentation techniques is that image segmentation quality decreases with increasing noise density level. The proposed method enhances the image segmentation for higher density level.

The proposed method is applied to the synthetic image of size 64×64 is divided into sub-images of size 16×16, thus each individual in GA is encoded as a matrix size 16×16. The GA parameters are set as follows, population size of 360, crossover probability in the range of 0.60 to 0.70 and a structuring element selected as a random from the given set of SE. Figure 9 (a) shows the results obtained using proposed GA with population size of 360 for Figure 1 (b) noisy image with 76 dB SNR. It may be observed that good segmentation is obtained after just 10 iterations and the accuracy of pixel classification is 92%. Fig. 9 (b) shows further improvement, with classification accuracy of 97% obtained after 72 iterations.



(a) (b)

Figure 9: Results of GA run for the reconstruction of image having salt and pepper noise of Figure 1 (b). (a) result obtained after 10 generations, (b) the result obtained after 72 generations.

Figure 11 shows graphs of GA convergence for this experiment, where error in the solution is plotted against the number of generations. We observe a very fast initial convergence upto 15 iterations followed by a very slow convergence.

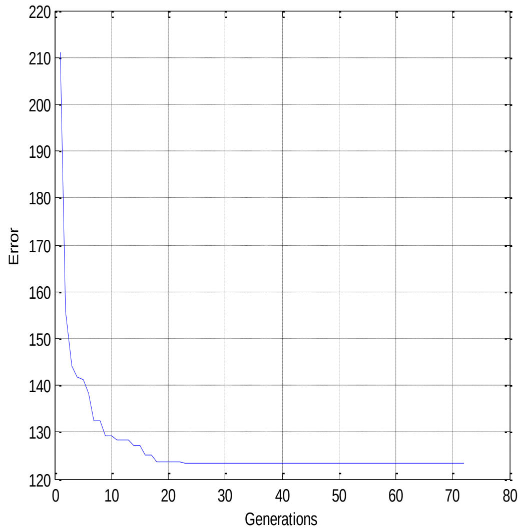
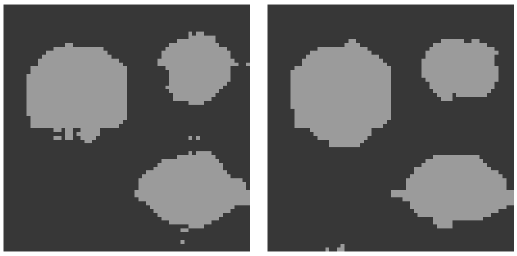


Figure 11: GA convergence for the reconstruction of Figure 1 (b) at 76 dB SNR.

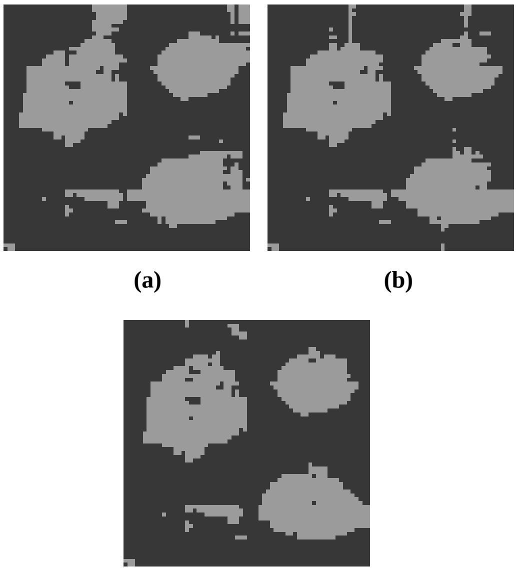
The proposed GA is also tested with higher density salt and pepper noise. Figure 1(c) and (d) show images with higher density of noise of 0.05 and 0.20 and Figure 10 (a), (b) shown the reconstructed images obtained after 120 and 100 iterations respectively.



(a) (b)

Figure 10: Results of GA run for image containing higher salt and pepper noise of Figure 1 (c) and (d). (a), (b) results obtained after 120 and 100 iterations respectively.

The proposed GA is next tested for the Gaussian and Poisson noises. The GA parameters are population size = 650, generations = 150, mutation probability = 0.06, crossover probability = 0.60 and for Figure 2 (a) with SNR = 2.5436 dB. The Figure 12 (a) through Figure 12 (c) show the segmented results obtained after 10, 20 and 150 generations respectively, where the segmentation result obtained after 150 generations has classification accuracy of 93%.

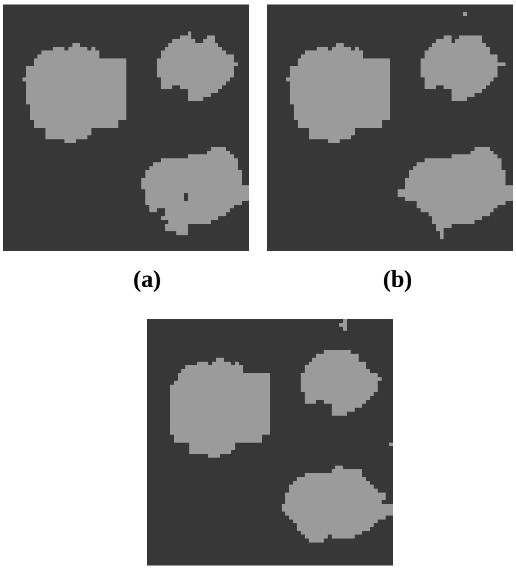


(a) (b)

(c)

Figure 12: Results of GA run for Gaussian noise. (a-c) results obtained after 10, 20 and 150 generations respectively

Figure 13 shows the experimental results with the proposed GA methodology using Poisson noise, for Figure 2 (b) at 8.5946 dB SNR. Figure 13 (a - c) shows the results obtained after 5, 10 and 150 generations respectively. The segmentation accuracy of 96% is obtained after 150 GA generations with 149 misclassified pixels. Thus, the experimental results show that the proposed method leads to some enhancement in the process of different types of noise reduction in the irregular shaped segmented images. The proposed GA methodology shows the classification of object and background pixel accuracy is in the range between 91% to 97%.



(a) (b)

(c)

Figure 13: Results of GA run using Poisson noise. at 8.5946 dB SNR, (a-c)results obtained after 5, 10 and 150 generations respectively.

Table 1 shows the comparison between the standard image segmentation methods and GA method.

4. CONCLUSION

GA approach has been proposed for the segmentation of binary images containing circular and elliptical objects and corrupted with different types of noise. The key to successful segmentation of such images is the choice morphological operators and structuring element at random. The proposed approach has been demonstrated to give good results for synthetic images having salt and pepper, Gaussian as well as Poisson noise with varying densities with accuracy of pixel classification between 91% to 97%. The proposed approach can be easily extended for images containing irregular shaped objects.

5. ACKNOWLEDGMENTS

We would like to thank the reviewers for their valuable suggestions.

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Result of image segmentation using image segmentation methods and GA technique

TABLE 1

Image With Size	Types of Noise	Density of Noise	SNR of Image	Misclassification of Pixels using Image Segmentation Methods and GA Technique			
				Iterative Threshold	Region Grow	FCM	GA
Figure 1 (a) (64×64)	salt and pepper	0.03	76 dB	33	20	31	137
		0.05	41 dB	94	36	91	136
		0.20	9 dB	491	212	446	126
	Gaussian	0.20	2.5 dB	702	629	3429	276
	Poisson	---	9 dB	1	13	0	149

7. BIOGRAPHIES

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