Image Segmentation using Improved Genetic Algorithm

RoopaKumari, Neena Gupta, Narender Kumar

Abstract:Segmentation of image is a complex task. To recognize an image, segmentation is essential parts. During image segmentation, subsets of images on the basis of some features like gray levels values of pixels or position of pixels find out. This is an NP-complete problem, to find the solution to such problems is a computationally hard task. Some heuristic algorithm can be used to find out the solution to such a hard task. These algorithms find approximate solutions. Exact solution of such problems is not possible. Genetic algorithm can be considered a metaheuristic algorithm used the evolution of the population of solutions. This paper proposedan improved Genetic Algorithm that used to find multi-level thresholding segmentation of the image. The threshold value can be calculated by cumulative histogram and satisfactory result have been given by the experiments done on test images that are taken from Mnist datasets.

Keywords: Approximate Solutions, Evolution, Evolutionary Algorithm, Cumulative Histogram, Segmentation, Soft Computing, Multi-level Thresholding.

I. INTRODUCTION

Segmentation of an image is the essential part of object recognition in imaging system. It can be consider as the process of finding the subsets of an image on the basis of some features like intensity levels, the position of a pixel, colors etc. The target of segmentation will be to classify the pixels for extraction of some meaningful features from the image. Segmentation is used to locate edges, lines, points, and curves in an image. Segmentation of an image assigns a class label to every pixel in an image and the pixel with the same label share some feature and made a region on the basis of that characteristic. Segmentation has many applications such as CT scan and MRI to find tumors, diagnosis, measures tissues, surgery planning, etc. , object recognition,recognition of face and fingerprint, traffic control system, agricultural imaging, satellite imaging, robotics application, etc.

During recent years many techniques along with traditional techniques have been developed for segmentation of image such as edge detection techniques, region growing, region merging and splitting, graph-based [1-3], histogram-based [4-6], thresholding-based [7], fuzzy rule-based [8-9], contour detection-based [10], texture-based [11], pixel clustering-based [12]. Histogram based technique is implemented successfully in various areas out of these methods. Soft computing techniques also proposed for image segmentation for better optimization like fuzzy logic, artificial neural network, evolutionary computation, particle swarm optimization, because meta heuristic approaches deals with approximation and gives the solution to complex problems or soft computing is the use of inexact solutions to computationally hard broblem such as the solution of NP-Complete problems [13].

Image thresholding can be consider as one of the easy to implement, effective and best methods of image segmentation. It has been categorized into six groups by Sezgin and Sankur [14] on the basis of information i.e histogram-based methods, object-based methods, clustering-based methods, object attribute-based methods, spatial method, local method,entropy-based methods, and hybrid method.

Thresholdingbased on histogram methods are the simple and essential method that should be computed into one-dimensional histogram where peaks, valleys, curvatures are used to locate regions. Histogram can be grouped into a bi-modal histogram and multi-modal histogram. Histogram with two dominant modes or peaks is called bi-modal histogram. In this type of histogram, only one thresholding value is enough to partition the image. The multi-modal histogram has more than one mode or data peak of the probability distribution. Generally, an image has multiple reasons of interest so the multi-modal histogram is required to segment. But the drawback of histogram thresholding is that it will be hard to find significant peaks and valleys in an image so in this paper we try to overcome this drawback by using the cumulative histogram in place of the general histogram. The cumulative histogram is used to identify the optimised threshold value.

Several authors suggest various algorithms for segmentation[13]. Dinesh Maru proposed a genetic algorithm which provides a better solution then region growing and OTSU method. The proposed algorithm gets better PSNR and Maximum Absolute Error comparatively than the region growing and OTSU [15]. Mohan Muppidi introduced a new soft computing method for segmentation of both intensity level and color images by using fuzzy entropy-based criteria(cost function) of the genetic algorithm, and the evolutionary computational techniques [16]. Jito Di Gesu and GL. Bosco introduced a new image segmentation algorithm called Combined Genetic Segmentation based on a genetic algorithm. Here, the segmentation is considered as clustering of pixels and a similarity function based on spatial and intensity pixel features is used [17].

Revised Manuscript Received on October 20, 2019.

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AlaaSheta, Malik S. Braik proposed an algorithm using a genetic algorithm in an integrated manner with traditional image segmentation techniques to provide efficient segmentation and edge detection for selected natural images [18]. GL.Bosco described a new algorithm for image segmentation based on a genetic approach that allows considering the segmentation problem as a global optimization problem(GOP). Fitness function based on similarity is a function of both the intensity and spatial position of pixels [19]. Omar Banimelhem introduced an algorithm of image segmentation by using the thresholding technique with a genetic algorithm to find the optimal thresholds between the various objects and the background [20]. UjjawalMaulik had reviewed the major application of the genetic algorithm to the domain of medical image segmentation [21]. Vijai Singh presented an adaptive approach for color image segmentation using a genetic algorithm. In this algorithm, they also utilize the prior knowledge of RGB image to segment the image [22]. PayelGhosh introduced a genetic algorithm for combining the representation of learned information such as known shapes, regional properties and relative position of objects into a single framework to perform automated three-dimensional segmentation [23].

II. GENETIC ALGORITHM

Genetic algorithm is a natural influenced metaheuristic technique that mimics genes [20]. The genetic algorithm was developed by John Holland and regressively studied by Goldberg [24]and De Jong [25-27] which is a search-based optimization technique based on the evolutionary ideas of natural selection and principle of genetics. It is generally used to find optimal or near-optimal solutions to difficult problems.

Genetic Algorithm simulates the survival of the fittest among individuals over a consecutive generation for solving a problem. Each generation consists of a population of character strings that are like to the chromosome. Genetic Algorithm inspires one population of the chromosome to a new population by go through a process of evolution. Individuals in a population compete for resources and mates. Those individuals are best will produce more offspring than the poor ones. A simple Genetic Algorithm working can be described as given by Figure 1.

A. Initial population

The Firstly initial population can be initialized by randomly choosing the solutions of problems. It can also be defined as a set of chromosome. There are two primary methods to initialize a population i.e random initialization and heuristic initialization. Several important points when you deal with a genetic algorithm.

- It might lead to premature convergence if the diversity of the population should not maintain.
- If the population size is too large then it slows down the genetic algorithm.

B. Fitness Function

Fitness function governs or tells how to fit an individual. Fitness function is a type of objective function or a parameter selection where GA is used to modify the parameters of an existing image segmentation method to improve the output result. The segmentation algorithm quality measures by optimal fitness function and the fitness function of segmentation algorithm vary from image to image so there is no single or universally accepted fitness function for segmentation [20][28][29].

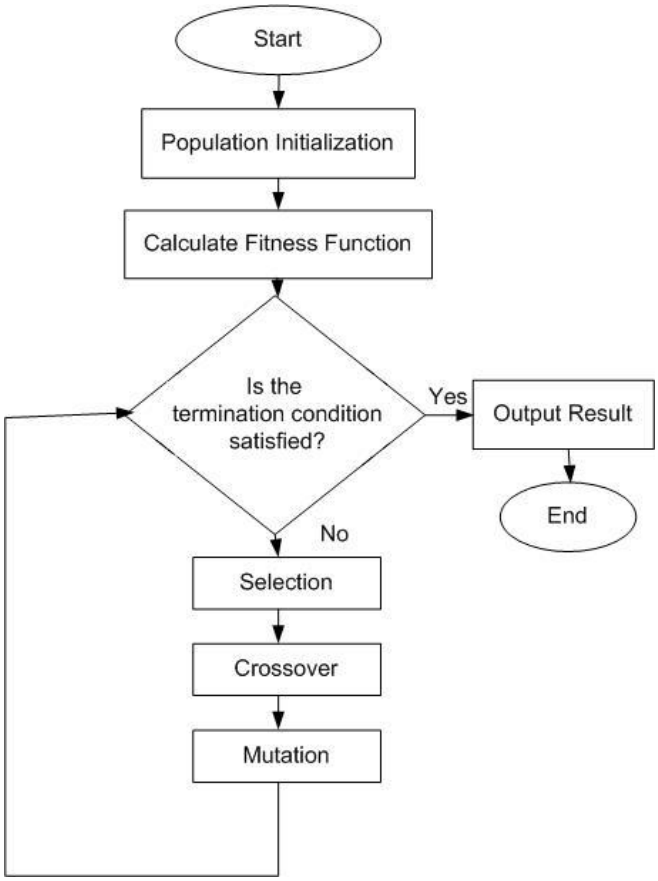

Figure 1: Flowchart for a Genetic Algorithm

C. Selection Process

Selection phase is the method to select the fittest individuals or chromosomes from the population and let them pass their genes to the next generation. Individuals or chromosomes with high fitness value have more chance of selection [30-31]

Various selection methods are:

- Roulette Wheel Selection
- Stochastic Universal Sampling (SUS)
- Tournament Selection
- Rank Selection
- Random Selection

D. Crossover Process

Crossover is a genetic operator that combines the genetic information of two individuals or parents to generate new offspring's from them. The crossover operator takes each pair of parents for mating. The crossover point is chosen randomly. Crossover probability (Pc) is a parameter that is used to define the performance of the crossover. If there is no crossover applied than, offsprings are exact copies of their parents i.e 0% probability and if the crossover is applied then offsprings are created by the part of both parents i.e 100% probability [30-32].

Some crossover techniques are:

- Single Point Crossover
- Two Point Crossover
- Multi Point Crossover
- Uniform Crossover

E. Mutation

The mutation is used to maintain and introduce genetic diversity within the population and prevent immature merging. Sometime crossover may be stuck in local minima problem then mutation should allow the algorithm to avoid local minima problem by preventing the population of the chromosome by flipping the gene. The mutation is the process of changing the gene values in a chromosome. The various mutation operations are:

- Flipping
- Interchanging
- Reversing

Which part of the chromosome mutated will be decided by the mutation probability (Pm). If mutation applied on one or more parts of a chromosome then Pm will be 100% and if nothing find than Pm will be 0% [30-31].

F. Termination Condition

The termination condition of a genetic algorithm is determined when a GA run will end or convergence condition is satisfied.

III. SEGMENTATION

The segmentation of a digital image X can be observed as a partition of its pixels, based on the gray value of the pixel. Image segmentation comes under the NP-Complete problem so that the exact solution is not possible of it, the only approximate solution with the help of some heuristic algorithm is possible.

Let the set of pixels of Digital Image$X = \{ x_0, x_1, \dots \dots \dots x_{N-1} \}$ with N number of pixels.

A partition $P = \{ P_0, P_1, \dots \dots \dots P_{K-1} \}$ where $1 \le K \le N$ is the set of the partition of K numbers of segments of image A such that

$$P_i \cap P_j = \Phi$$

$$\bigcup_{i=0}^{K-1} P_i = X$$

At the time of partitioning of image X a label $l_x \in \{0, 1, \dots \dots . K-1\}$is assigned to each element$x \in X$. Total number of possible partition is $K \times N$

Let M is the possible matrix of $K \times N$ such that

$$M = \{ M \in M_{K,N} \mid A_{i,k} \in \{0,1\}, \sum_{k}^{k=K} A_{i,k} = 1,$$

$$0 < \sum_{i}^{i=N} A_{i,k} < N, 0 \le k \le K, 0 \le i \le N \}$$

Each digital pixel $x \in X$ is represented as (i_x, j_x, g_x)

Here $i_x$is the x coordinate value, j_x is the $y$coordinate value, $g_x$is the gray level of the pixel.

The two pixels $(x, y) \in X$is based on the following similarity function.

$$s(x,y) = C_0 \times d_g(g_x, g_y) + C_1 \times d_E(x, g_y)$$

Where $C_0 \ge 0, C_1 \ge 0, C_0 + C_1 = 1$ and

$$d_g(g_x, g_y) = \frac{|g_x - g_y|}{\max(g_x, g_y)}$$

$$d_E(x,y) = \frac{1}{|N(i)|} \sum_{Z \in C_r(x)} \frac{|g_x - g_y|}{\max(g_x, g_y)}$$

Where $C_r(x)$ is the neighboring pixel of pixel x and r is the radius with center x and $N(i)$ is the number of neighboring pixels [28].

The next section gives the details of the proposed approach to optimize the segmentation. Section V represents the optimize results of the proposed CHGA Algorithm while Section VI represents the relevant conclusions.

IV. PROPOSED GENETIC ALGORITHM FOR IMAGE SEGMENTATION

For a given image X of size I×J, X (i,j) is the gray level value of a pixel (i,j). The implementation of the Genetic Algorithm of segmentation will consist of the following steps

A. Chromosome Coding:

The genetic chromosome is coded by an array of integers corresponding to input image X. Each integer element $l_x \in P$of the chromosome is corresponding to pixel X (i,j) of image X.

Let G is the set of genes of the chromosome of image X and P is the set of K segment then each gene G(i,j) of chromosome G is belong to set P as given below.

G_{11}	G_{12}	G_{13}	G_{14}
G_{21}	G_{22}	G_{23}	G_{24}
G_{31}	G_{32}	G_{33}	G_{34}
G_{41}	G_{42}	G_{43}	G_{44}

Figure 2: Representation of genes of chromosome of a given imageG(i.j) ∈ P ={0,1,2,…..K-1}

B. Initial Population:

The initial population of genetic algorithm is constructed using the cumulative histogram. Cumulative histogram can be used to find the initial threshold value. To construct the initial values of genes for different chromosomes, randomization near the boundary of the segments is taken place to assign the different values of genes to the chromosomes.

Procedure for cumulative histogram:

```
Cumulative_histogram(X,M,N)
Step1: Let an array hist[number of gray_level]
Step2: for m ← 0 to M
Step3:  for n ← 0 to N
Step4:      g ← X[m][n]
Step5:     hist[g] ←hist[g]+1
Step6: for g ← 1 to graylevel
Step7: hist[g] ←hist[g] +
       hist[g-1]
Step8: return hist
```

Procedure for multiple threshold:
Thresholdingis one of the simplest, essential and most widely used method for image region segmentation[29]. Here we find multiple threshold to optimize our segmentation result.

```
Multiple_threshold (hist, number_of_segments, gray_level,
M,N)
Step1: Let an array thres[number_of_segments +1]
Step2:thres[0] ← 0
Step3: thres[number_of_segments] ← number of
       gray_level-1
Step4:  seg←1
Step5: for g ← 1 to number of gray_level
Step6:      if(M*N*seg)/number_of_segments>hist[g-1]
            AND (M*N*seg)/number_of_seg<= hist[g]
Step7:    then set thres[seg] ← g
Step8: seg←seg + 1
Step9: return thres
```

Procedure for generate chromosomes:

```
Initial_population(X, thres, number_of_segments, pop_size)
Step1: for m ← 0 to M
Step2: for n ← 0 to N
Step3:for k← 0 to pop_size
Step4:for t← 0 to number_of_segments
Step5: if(X[m][n]>thres[t] AND X[m][n]<= thres[t+1])
Step6: then r ← 0
Step7:if(t==0 AND thres[t+1]- X[m][n]<5)
Step8: then r ←random(0,1)
Step9:elseif(t==(number_of_segments – 1) AND X[m][n] –
            thres[t] <5)
Step10: then r ←random(-1,0)
Step11:elseif(t!=0 AND X[m][n] –thres[t] <5)
Step12: then r ←random(-1,0)
Step13:elseif(t!=(number_of_segments -1) AND thres[t+1] –
            X[m][n]<5)
Step14: then r ←random(0,1)
Step15:chromosome[m][n][k] ←t+r
Step16: return chromosome
```

C. Fitness function

The Fitness function measures the goodwill for the algorithm. In the proposed algorithm fitness value $f_t$can be calculated

$$f_t = \frac{\sum_k^N \sum_i^{N_k} |x_{i,k} - C_k|}{\sum_k^N C_k}$$

Where $C_k$is the centroid of the kth segment and

$$C_k = \frac{\sum_i^{N_k} x_{i,k}}{N_k}$$

Where N_k is the number of pixel in the kth segment and $x_{i,k}$ is the gray value of the ith pixel of the kth segment
Procedure for calculating centroid for fitness function:

```
Centroid_calculation(X, M, N, pop_size, number_of_seg)
Step1: initialize centroid and cenc variable with two
dimensional array
Step2: for m ← 0 to M
Step3:  for n ← 0 to N
Step4:     for k← 0 to pop_size
Step5:      l ←chromosome[m][n][k]
Step6:     centroid[m][n][k] ← centroid[l][k] + X[m][n]
Step7:     cenc[l][k] ←cenc[l][k] + 1
Step8: centroid ←centroid / cenc
Step9: return centroid
```

Procedure for fitness_function

```
fitness_function (X, M, N, pop_size, centroid)
Step1: initialize fitness variable
Step2: for m ← 1 to M-1
Step3:  for n ← 1 to N-1
Step4:     for k← 0 to pop_size
Step5:      l ← chromosome[m][n][k]
Step6:            fitness[k][l]
                  ←fitness[k][1]+abs((img[m][n]-centroid[l
                  ][k]))
Step7: fitness[k][l] ← k
Step8: return fitness
```

After fitness calculation, fitness can be sort by bubble sort algorithm so that we can get the best fitness value that can be compete with the population.

D. Crossover:

For crossover operation, two random parents are chosen from chromosomes of a given population. Genes of the two parents are interchanged randomly. The new chromosomes generated are replaced with the chromosome of the worst fitness value of chromosomes of a given population. Half of the population is replaced with the new population.
Procedure of crossover

```
Procedure of crossover(pop_size,fitness,chromosome)
Step1: parent ←random(0,pop_size)
Step2: parent2= random(0,pop_size)
 Step3: if(parent1!=parent2)
 Step4:   worstfit←fitness[pop_size][0]
 Step5:   for m← 0 to M
Step6:for n ← 0 to N
Step7:       if(random(0,1)==0)
Step8:cromosome[m][n][worstfit]
        ←cromosome[m][n][parent1]
        else
Step9:cromosome[m][n][worstfit]←cromosome[m][n][pare
        nt2]
Step10: return chromosome
```

E. Mutation:

For mutation genes of chromosome is selected randomly and replaced with another gene whose value is increased or decreased by 1. Mutation probability at initial generation is high and decreases asthe number of generation is increases.
Procedure of mutation:

```
mutation(M, N, pop_size, number_of_segments,
        cromosome, bestfit, generation_number)
Step1: for m ← 0 to M
Step2:    for n ← 0 to N
Step3:      for k← 0 to pop_size
Step4: if(random(0,generation_number)==0 and bestfit!=k)
Step5:         r ←0
```

Step6: if(cromosome[m][n][k]=0)
Step7: r ←random(0, 1)
Step8: elseif(cromosome[m][n][k]= number_of_segments-1)
Step9: r ←random(-1, 0) else
Step10: r ←random(-1, 1)
Step11: cromosome[m][n][k]←cromosome[m][n][k]+r
Step12: return chromosome

Termination criteria:
The proposed genetic algorithm will be terminated as the fitness value become constant or the number of generation reached to the maximum value.

The Proposed Threshold Genetic Algorithm

Inputs:image X, Population size (Pop), Crossover rate, mutation rate, number of iterations, number of segments, gray_level
Outputs: segmented image

Step1: X ← Read Image, M← number of rows [X], N ←number of columns [X]
Step2: X_(g)← Convert Image into gray Image
Step3: hist← call Cumulative_histogram(X_(g),M,N)
Step4: thres←callMultiple_threshold(hist, number_of_segments, gray_level, M,N)
Step5:chromosome←callInitial_population(X, thres, number_of_segments, pop_size)
Step6: Repeat step 7 to 10 until termination criteria is meet
Step7: centroid ← call Centroid_calculation(X, M, N, pop_size, number_of_seg)
Step8: fitnessf_T←callfitness_function (X, M, N, pop_size, centroid)
Step9: chromosome←call crossover (pop_size,fitness,chromosome)
Step10: chromosome ←call mutation (M,N,pop_size, number_of_segments,cromosome,bestfit,generation_number)

V. RESULT AND DISCUSSIONS

Different images of gray color are tested with CHGA (proposed genetic algorithm) of Image Segmentation. The fitness values of genetic algorithm arefound out for different segments values for different images. To evaluate the performance which includes efficiency and convergence of CHGA algorithm, researchers selected " cameraman", "house", "mandril", "lake", "woman_darkhair" as standard test gray level images from Mnist datasets. All images are in tif format. The initial population size is 10 chromosome, but it is not fixed it varies according to the evaluation. The algorithm iterates for 1000 iterations. In general, threshold can be selected if the histogram of image peaks is foundtall, narrow, symmetric,narrow and separated by deep valleys [33]. This is the traditional method but in proposed algorithm (Cumulative Histogram Genetic Algorithm) threshold value can be selected by cumulative histogram.

Table 1: Evaluation Parameters used for segmented images

Evaluation Parameters	Formula
Mean Absolute Error(MAE)	$\mathrm{MAE} = \frac{1}{\mathrm{MN}}\sum\lvert \mathrm{X(i,j)} - \bar{\mathrm{X}}\mathrm{(i,j)}\rvert$ Where $\mathrm{X(i,j)}$ and $\bar{\mathrm{X}}\mathrm{(i,j)}$ is pixel values of images with M, N dimensions.
Root Mean Square Error(RMSE)	$\mathrm{RMSE} = \sqrt{\mathrm{MSE}}$ Where MSE is Mean Square Error
Peak Signal to Noise Ratio(PSNR)	$\mathrm{PSNR} = \frac{10\log 255^2}{\mathrm{MSE}}$ Where MSE is Mean Square Error
Normalized Absolute Error(NAE)	$\mathrm{NAE} = \frac{\sum\lvert \mathrm{X(i,j)} - \bar{\mathrm{X}}\mathrm{(i,j)}\rvert}{\sum\lvert \mathrm{X(i,j)}\rvert}$ where $\mathrm{X(i,j)}$ and $\bar{\mathrm{X}}\mathrm{(i,j)}$ is pixel values of images with M, N dimensions.

Table 2, 3 and 4 compare the existing method with CHGA (proposed method) on different parameters (Mean Absolute Error- MAE, Peak Signal to Noise Ratio- PSNR, Normalized Absolute Error- NAE and Root Mean Square Error-RMSE)as given in Table 1 for evaluation of different test images for different number of segmentations. From table 2 to table 4 CHGA method has been presented tabularresults for some of the test images on the proposed variations of the cumulative histogram with genetic algorithm and traditional histogram method. It is observed that CHGAmethod has MAE (Mean Absolute Error) value of 189.7458, 204.7886 and 204.4330 for two-level, three-level and four-level segmentations respectively, which are the lowest values among the considered histogram methods. This mirrored the minimum deviation from the segmented image and its input test image that may be given in Figure5. The proposed algorithm also revert the minimum value of NAE (Normalized Absolute Error), the statistical error parameter for two-level, three-level and four-level segments respectively. Since PeakSignal to Noise Ratio and Root Mean Square Error are inversely proportional to each other and the segmented results for all the test images are justifiable for all three levels of segmentation. Thus from tables 2 to table 4,it is testified that the CHGA method provides better segmentation results than the traditional histogram method and can be of use a better substitute in multilevel image thresholding segmentation.

Table2: Comparison of CHGA (proposed) algorithm and existing methods for two segments

Images	Existed method				CHGA(Proposed method)			
	MAE	PSNR	NAE	RMSE	MAE	PSNR	NAE	RMSE
Lake	189.9250	63.3456	0.9966	10.7400	189.7458	63.3471	0.9966	10.7392
House	171.0221	63.9960	0.8608	10.3963	158.4752	64.1389	0.8515	10.3223
Cameraman	205.1299	64.2542	1.1792	10.2630	201.14395	64.2836	1.0560	10.2479
Mandril	186.1508	64.7101	0.9807	10.0317	185.9672	. 64.7079	0.97547	10.0328
Woman_darkhair	190.4555	63.6843	0.9095	10.5597	173.3491	63.6713	0.9099	10.5666

Table 3: Comparison of CHGA (proposed) algorithm and existing methods for three segments

Images	Existed method				CHGA(Proposed method)			
	MAE	PSNR	NAE	RMSE	MAE	PSNR	NAE	RMSE
Lake	206.7558	63.5187	1.2176	10.6474	204.7886	63.5290	1.2100	10.6420
House	207.1678	65.7873	1.2947	9.5057	201.6982	65.5743	1.1563	9.6075
Cameraman	190.9302	65.1563	1.2004	9.8104	184.3752	64.9841	1.0927	9.8952
Mandril	189.8822	63.7108	1.2530	10.5457	165.9377	63.5831	0.9853	10.6132
Woman_darkhair	175.0622	63.8933	1.0396	10.4499	159.3872	63.7354	0.9475	10.5327

Table 4: Comparison of CHGA (proposed) algorithm and existing methods for four segments

Images	Existed method				CHGA(Proposed method)			
	MAE	PSNR	NAE	RMSE	MAE	PSNR	NAE	RMSE
lake	206.4475	63.5466	1.2180	10.6486	204.4330	63.5423	1.2104	10.6349
House	192.2263	62.3321	1.4185	11.3983	184.7551	62.2959	1.1443	11.3188
Cameraman	204.2095	64.4591	1.3617	10.1584	172.0556	64.0215	1.0824	10.3831
Mandril	189.9352	64.6032	1.2618	10.0855	161.2552	64.1895	1.0235	10.2962
Woman_darkhair	168.4738	64.6105	0.9528	10.0818	140.6022	64.8902	0.8932	9.9418

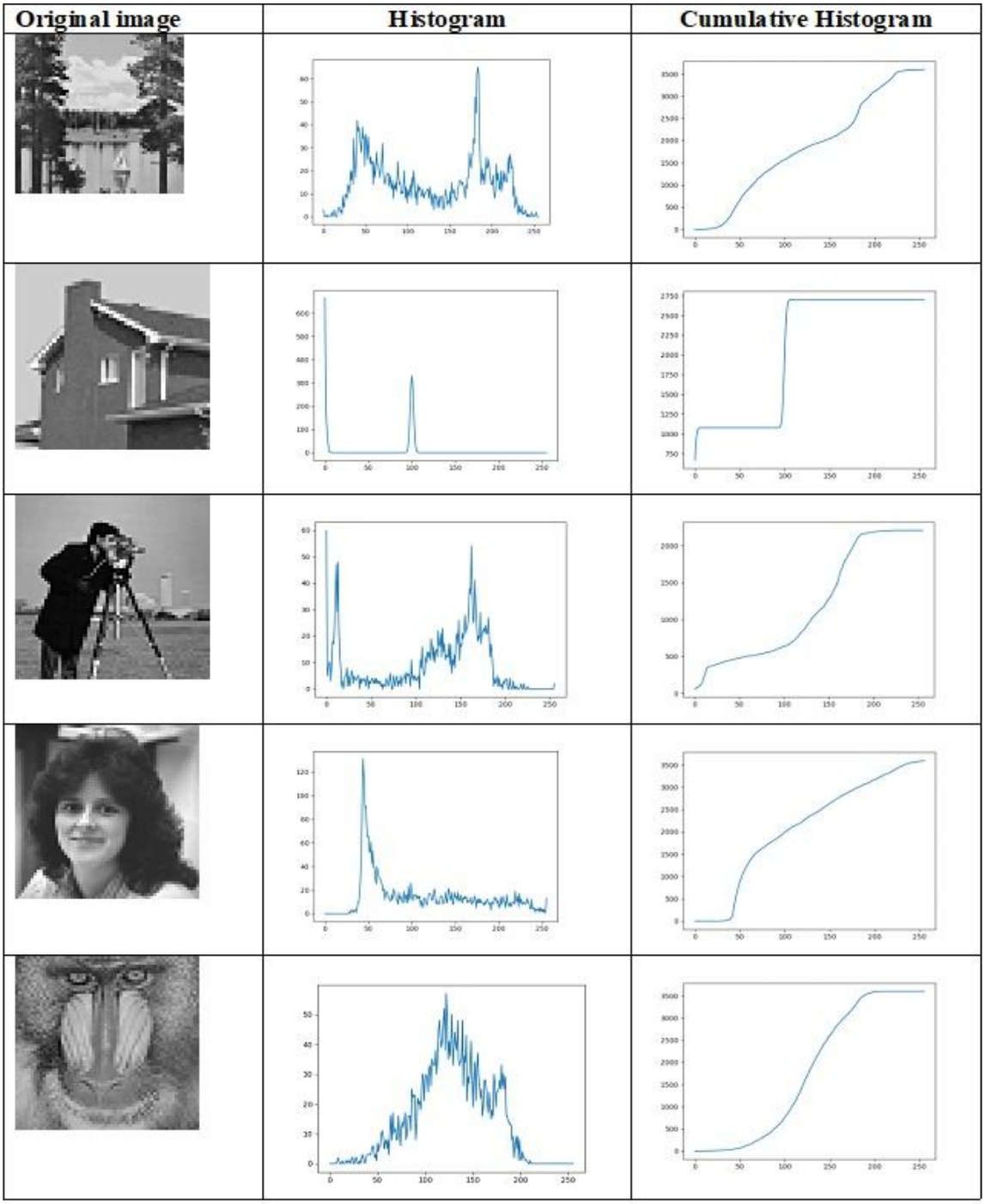

Figure 3: Histogram and cumulative Histogram for different Images

The test images ("cameraman", "lake", "house", "mandril", "woman_darkhair") and their corresponding histograms and cumulative histograms are described in Figure 3.

In CHGA algorithm,the cumulative histogram is used for multithresholding value up to dividing the x-axis of cumulative histogram into n region for n segments as showed in figure 4.The CHGA (proposed algorithm) is tested with different generation for the different number of segments. Segmented image for 2-level, 3-level, 4-level is displayed in Figure 5. The convergence of the proposed algorithm is shown by Figure 6,7 and 8 using a graph between fitness values and the number of generation for two segments, three segments, and four segments respectively.

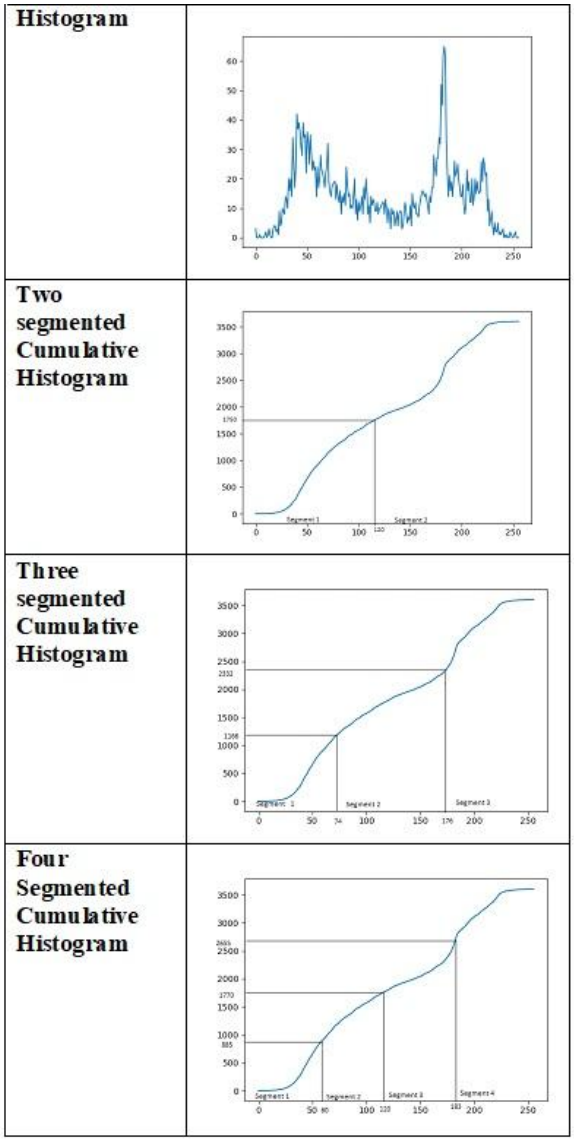

Figure 4: Histogram and cumulative Histogram for two, three and four segmented image

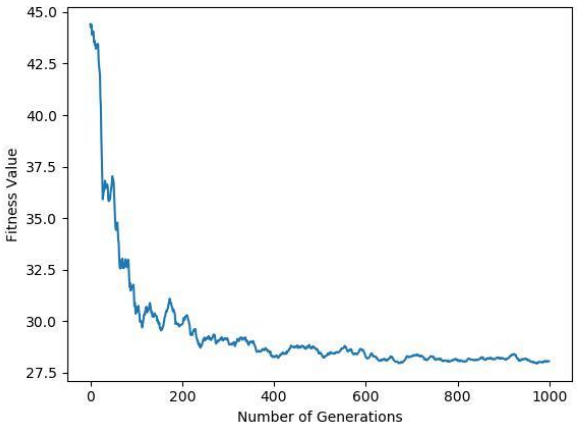

Figure 6:Convergence of algorithmfor Two Segments

Figure 5: Segmented Images with different number of segments

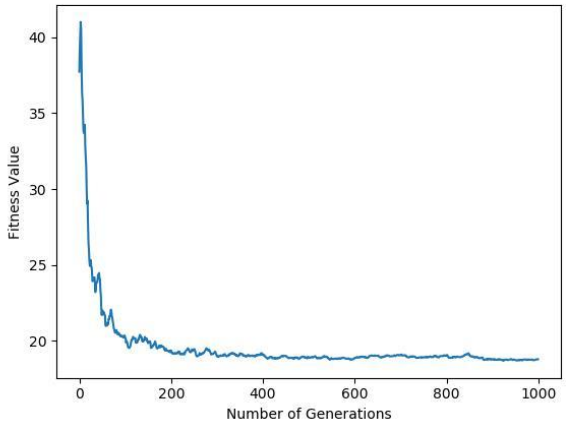

Figure 7: Convergence of algorithm for Three Segments

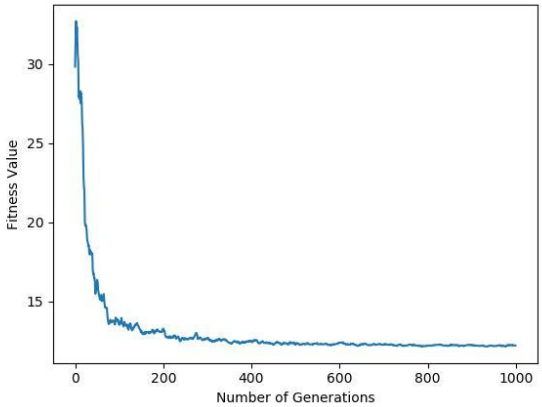

Figure 8: Convergence of algorithmfor Four Segments

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VI. CONCLUSION

The paper introduced an improved genetic segmentation algorithm. In this algorithm cumulative histogram is used to initialize the population for multi thresholding for segmentation. The performance of the CHGA Algorithm is verified by different images from Mnist datasets. After comparing the result of Cumulative Histogram Genetic Algorithm with an existing method gives improved performance. In the future, this algorithm can be implemented for colored images also.

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