Parallel Genetic Algorithm Based Thresholding for Image Segmentation

P. Kanungo
NIT, Rourkela
IPCV Lab.
Department of Electrical Engineering
p.kanungo@yahoo.co.in

P. K. Nanda
NIT Rourkela
IPCV Lab.
Department of Electrical Engineering
pknanda_d13@rediffmail.com

Abstract

Threshold plays a vital role in classification of objects and background in a given scene and hence segmentation. Determination of optimal threshold is hard for images exhibiting overlapping histogram distributions. In this paper, we propose a novel strategy of determining the threshold from histogram distributions. A feature image is generated from the given image and the optimal threshold is determined using the histogram of the featured pixels. The featured pixels are generated by considering a fixed window around a pixel. The histogram distributions are discrete in nature and hence Genetic Algorithm (GA) and Parallel Genetic Algorithm (PGA) based clustering algorithms are proposed to determine the optimal thresholds for two and three class problems. The optimal thresholds, thus determined could segment the noisy image. The efficacy of the proposed scheme is compared with that of the Otsu's approach. Results obtained by the proposed scheme was comparable to that Otsu's and in some noisy cases our method could be better than the latter one. Satisfactory results could also be obtained even for histograms with overlapping class distributions.

1. Introduction

Selection of proper threshold is one of the key issues in segmentation of images. There has been persistent research effort to obtain proper threshold for images having two or more classes [1-4]. In spite of the several reported results, determination of optimal thresholds still remains a challenging task for noisy images and images corresponding to overlapping class distributions. In a generic sense, bi-level thresholding classify the image into two groups, one including those pixels with their gray values equal to and below a certain threshold, and the other including those with gray values below the threshold. Multi-thresholding divides the whole range of gray values into several sub ranges. Often, the shape of the histogram [5-9] has been used as one of the key parameters to devise thresholding techniques.

Histograms for images having two classes, has a deep and sharp valley between the two peaks arising due to object and background respectively. For such histograms, the threshold could be chosen at the bottom of this valley [2]. Often, in case of real images it is hard to detect the valley precisely, because (i) valley could be flat and broad and (ii) the two peaks could be extremely unequal in height, often producing no traceable valley. Rosenfeld et al. [3] proposed the valley sharpening techniques which restricts the histogram to the pixels with large absolute values of derivatives, S. Watanable et al. [11] proposed the difference histogram method, which selects threshold at the gray level with the maximal amount of difference. These utilize information concerning neighbouring pixels or edges in the original picture to modify the histogram so as to make it useful for thresholding. Another class of methods deal directly with the gray level histogram by parametric techniques. The histogram is approximated in the least square sense by a sum of Gaussian distributions, and statistical decision procedures are applied [11]. However, such methods are tedious and computationally involved.

In this paper, optimal threshold is determined using the histogram of the featured pixels as opposed to the original histogram. The feature value of a given pixel is determined by considering a window around the pixel and selecting the average value depending upon σ (standard deviation) of the window. Gaussian distribution is assumed over each window. The featured image is generated based on the featured value of the pixels. The shape of the histogram of the feature image is used to determine the optimal threshold. In this regard, we have proposed GA and PGA based crowding algorithm to maintain stable subpopulations and hence determine the peaks of the featured histogram. Thereafter, the valleys between the successive peaks are found out based on GA based search strategy. The valleys, thus determined, correspond to the optimal thresholds. The overlapping class distributions in the original histogram could be reduced partially thus facilitating the determination of the having two and three classes are presented to validate our approach.

2. Problem statement

The notion of thresholding has been applied to many computer vision problems including classification of object and background in a given scene. The segmentation of such an image acts as a precursor of object recognition etc. The histogram of such a scene exhibit bi-modality feature in the class distributions. Analogously, two objects and a background in an image corresponds to tri-modality feature of the histogram. Segmentation of such images greatly depends upon the precise determination of the optimal thresholds. In the past many threshold based image segmentation algorithms have been proposed [1-8]. The inherent bottleneck is the error occurring due to the overlapping of the class distributions of the histogram. In order to address the issue, in this work, the shape information of the histogram of the featured pixels is considered instead of the original histogram. The feature pixels are generated as follows. A window of a given size, say for example (3x3) is considered around the pixel and the distribution of pixels over the window is assumed to be Gaussian. Hence, the likelihood estimates of the first and second moment become

$$\hat{\mu}_{w_{ij}} = \frac{1}{N_w}\sum_{k=1}^{N_w} x_k \quad and \quad \hat{\sigma}_{w_{ij}} = \frac{1}{N_w}\sum_{k=1}^{N_w}(x_k - \hat{\mu}_{w_{ij}})^2 \tag{1}$$

The first moment of the pixel is considered as the feature value if the following condition is satisfied.

$$if \ \left| x_{ij} - \hat{\mu}_{w_{ij}} \right| \le \hat{\sigma}_{w_{ij}} \quad then \quad x_{ij} = \hat{\mu}_{w_{ij}} \tag{2}$$

Where x_{ij} is the gray value corresponding to the $(i,j)^{th}$ pixel, $\hat{\mu}_{w_{ij}}$ and $\hat{\sigma}_{w_{ij}}$ are the average value and standard deviation of the Gaussian distributed pixels over the window centered at $(i,j)^{th}$ pixel and N_w is the number of pixels in the window. Thus another image, consisting of featured pixels is generated. Figure 1 shows the histogram of a two class image. It is seen from the figure 1 that there are distinct overlapping of the class distributions. The histogram of the featured image generated using (1) is shown in figure 2 that exhibits clearly bimodality with minimum overlapping. Thus optimal thresholds can be determined using figure 2.

Hence, we propose GA based clustering to determine the optimal threshold using this discrete histogram. Usual search algorithm might determine threshold as suboptimal solution because of the discrete nature of the histogram. Hence a GA and PGA based algorithms are proposed to determine niches (peaks) followed by determination of the valley. This valley corresponds to the optimal threshold.

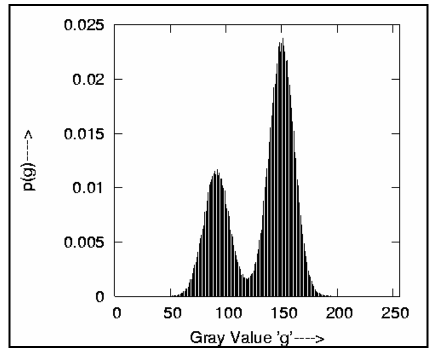

Fig. 1. Normalized histogram of the original image

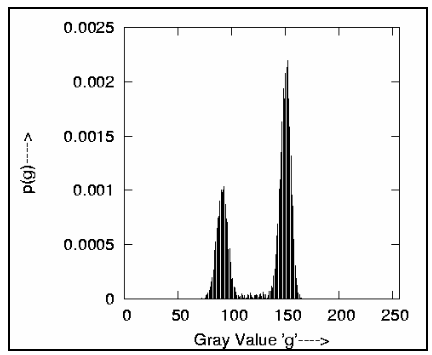

Fig. 2. The featured based normalized histogram of the image

3. Segmentation using threshold operators

As mentioned in Section 2, optimal threshold may be used to segment images. Optimal threshold is determined as follows. Given a histogram with multimodal features, the two peaks corresponding to two classes are determined using the proposed GA based crowding schemes. This algorithm determines the two peaks by maintaining stable sub population at the respective peaks of the multimodal histogram. Once the peaks are determined, the valley or the minima between these peaks are determined by GA. The two steps combinedly thus determines the valleys and hence the thresholds for segmentation.

3.1. GA class model

Usually GA are used for function optimization and hence determining the global optimal solution. In case of nonlinear multimodal function optimization, the problem of determining the global optimal solution as well as local optimal solution reduces to determining the niches in the multimodal functions. Thus the problem boils down to clustering the population elements around the given niches. Some effort has been directed in this direction for last couple of years where new strategies and algorithms are proposed [12].

3.2. Crowding method

In the deterministic crowding, sampling occurs without replacement [12-13]. We will assume that an element in a given class is closer to an element of its own class than to elements of the other classes. A crossover operation between two elements of same class yield two elements of that class, and the crossover operation between two elements of different class will yield either: (i) one element from both the classes, (ii) one element from two hybrid classes. For example, for a four class problem, the crossover operation between two elements of class AA and BB may results in elements either belonging to the set of classes AA, BB, or AB, BA. Hence the class AB offspring will compete against the class AB parents, the class BA offspring will compete with class BA parents. Analogously for a two class problem, if two elements of class A randomly paired, the offspring will also be of class A, and the resulting tournament will advance two class A elements to the next generation. The random pairing of two class B elements will similarly result in no net change to the distribution in the next generation. If an element of class A gets paired with an element of class B, one offspring will be from class A, and the other from class B. The class A offspring will compete against class A parent, the class B offspring against the class B parent. The end results will be that one element of the both classes advances to the next generation no net change.

3.2. GA for optimal threshold

Once the stable subpopulation is maintained at the peaks of the multimodal function, the problem is to determine the valley between the two successive peaks. The two peaks correspond to two gray levels and in between these two gray values the minimum of the function is found out. The fitness function here is the discrete histogram itself

$$\textit{Fitness function} \quad f(g) = p(g) \tag{3}$$

Where $p(g)$ denotes the featured histogram distribution. We have employed basic GA to determine the minimum of the objective function which is the fitness function itself.

3.4. GA based algorithm

Our proposed algorithm consists of determining the all the peaks of the histogram distribution and in the sequel to find out the minima in between each pair of peaks. The salient steps of the algorithm are:

(i) Initialize randomly a population space of size N_p (each element corresponds to a gray value between 0 and 255) and their classes are determined.

(ii) Choose two parents randomly for crossover and mutation operation with crossover probability P_c and mutation probability P_m. Compute the fitness of parents and off-springs. The fitness function is the normalized featured histogram function p(g).

(iii) The offspring generated complete with the parents based on the concept of tournament selection strategy.

(iv) After selection the selected elements are put in their respective classes.

(v) Step (ii), (iii) and (iv) are repeated for all elements in the population.

(vi) Steps (v) is repeated till the convergence is met i.e. the elements of respective classes are equally fit.

(vii) The peaks will be determined from the converged classes of step (vi)

(viii) Initialize randomly a population space of size N_v between the two peaks (i.e. between the two corresponding gray values).

(ix) Choose two parents randomly for crossover and mutation operation with crossover probability P_c and mutation probability P_m. Compute the fitness of parents and off-springs. The fitness function is the featured normalized histogram function p(g).

(x) The fittest two elements between the parents and offspring are selected for the next generation in the selection strategy.

(xi)Step (ix), (x) are repeated for all elements in the population.

(xii) Step (xi) is repeated till the convergence is met.

(xiii) The converged value is the gray value corresponding to the valley between the two peaks. The image is then segmented using this value as threshold.

3.5. PGA for optimal threshold

The Objective of designing parallel GA is two fold: (i) reducing the computational burden and (ii) improving the quality of the solutions. The design of PGA involves choice of multiple populations where the size of the population must be decided judiciously. These populations may remain isolated or they may communicate exchanging individuals. This process of dividing the entire population into sub-populations and then providing the mechanism of interaction between them is known as coarse grained parallelism. The process of communications between individual demes is known as migration. The coarse grained PGA is broadly based on the island model and stepping stone model. In an island model the population is partitioned in to small subpopulations by geographic isolation and individuals can migrate to any other subpopulation. In this parallel scheme, the population is divided into demes and the demes evolve for convergence. After some generations migration is carried out to achieve convergence. We have adopted the following Interconnection Island model for the PGA algorithm. We have adopted the good-bad based migration policy. In our problem we considered four demes D1, D2, D3 and D4 and the interaction network model is shown in fig 3. Tournament selection mechanism is applied to all demes. We have employed a new crossover operator known as Generalized Crossover (GC) operator [9].

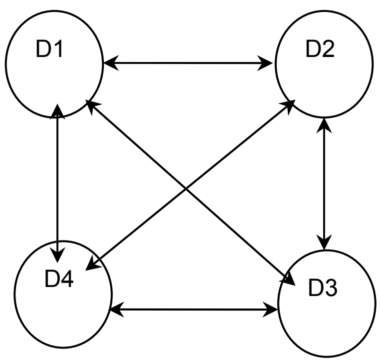

Fig. 1. Interconnection of demes

3.6 PGA based algorithm

The steps of the parallelized crowding scheme are the following.

1. Initialize randomly a population space of size N_p (each element corresponds to a gray value between 0 and 255) and their classes are determined.
2. Divide the population space into fixed number of sub-populations and determine the class of individuals in each sub-population.
3. i. In the given sub-population, choose two elements at random for Generalized Crossover (GC) and Mutation operation with crossover probability P_c and mutation probability P_m.

   ii. Evaluate fitness of each parents and offspring. The fitness function is the featured normalized histogram function p(g).

   iii. The tournament selection mechanism is a binary tournament selection among the two parents and offsprings, the set which contains the individual having highest fitness among the four elements is selected to the set of parents for the next generation.

   iv. Repeat steps i, ii & iii for all the elements in the sub population.

   v. Repeat steps i, ii, iii & iv for a fixed number of generations
4. Step 3 is repeated for each sub-population.
5. Migration is allowed from each deme to every other deme. The individuals are migrated based on the selected migration policy. Numbers of elements to migrate are determined from the selected rate of migration. The elements migrate with migration probability P_{mig}.
6. Repeat steps 3, 4 & 5 till convergence is achieved. The algorithm stops when the average fitness of the total population is above pre-selected threshold.
7. The peaks will be determined from the converged classes of step 6.
8. Initialize randomly a population space of size N_v between the two peaks (i.e. between the two corresponding gray values).
9. Use GA (step 3 is repeated till the convergence is achieved) to find the valley between the two peaks. (PGA can be used for determining the valley points between the peaks).
10. Use the valley points gray value to segment the image.

4. Results and discussions

Images of both two and three classes are considered in our simulation. The corresponding histograms exhibit bimodal and tri-modal features. Fig 4(a) shows an indoor image of size (256x256), and the corresponding histogram is shown in Fig 4(b). It is clear from Fig. 4(b) that histogram distribution possesses bimodality. The featured image is generated as follows. A window of size (3x3) is considered around each pixel x_{ij} and the first moment $\hat{\mu}_{w_{ij}}$ and the variance $\hat{\sigma}_{w_{ij}}$ is computed assuming Gaussian distribution over the window. If $\left|x_{ij} - \hat{\mu}_{w_{ij}}\right| \le \hat{\sigma}_{w_{ij}}$ then the pixel is replaced $\hat{\mu}_{w_{ij}}$, otherwise the pixel value remains unchanged. The histogram of the featured image is shown in Fig. 4 (c). Close observation indicate that there are changes in the histogram. GA and PGA based clustering algorithm are employed to detect the peak and valleys. The “X” symbol indicate the cluster of population in the peaks. The parameters used for GA are: Generation=1000, Probability of Crossover P_c=0.8, Probability of Mutation P_m=0.001, population size N_p= 400 and N_v=100. The parameters used for PGA are: Generation=1000, Migration period is after 10 generation, Number of demes is 4, Probability of Crossover Pc=0.8, Probability of Mutation Pm=0.001, population size N_p = 400 and N_v=100, Probability of migration P_{mig}=0.8, Migration rate is (R_{mig}) = 4%.

Fig. 4 (a)

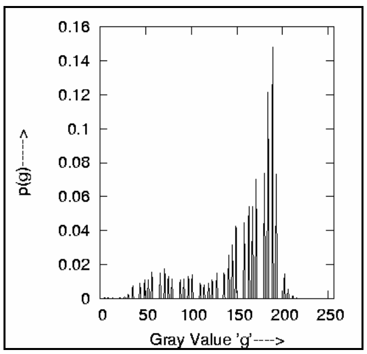

Fig. 4 (b)

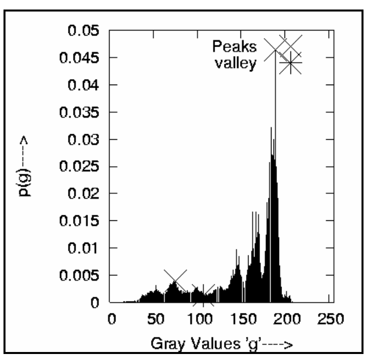

Fig. 4 (c)

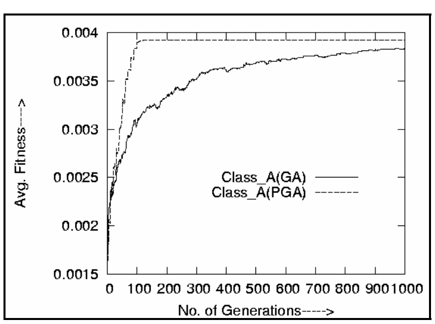

Fig. 4 (d)

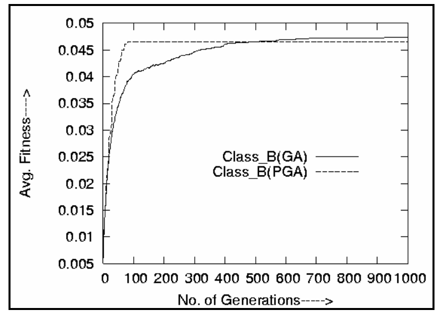

Fig. 4 (e)

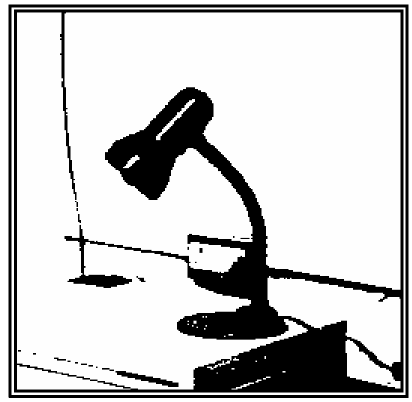

Fig. 4 (f)

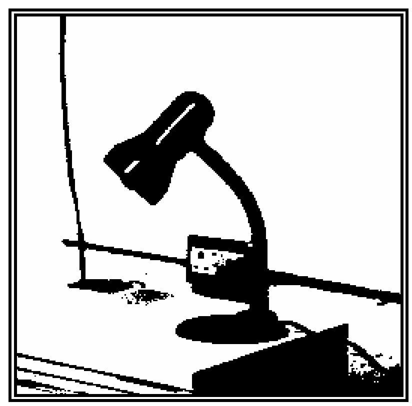

Fig. 4 (g)

Fig. 4 (a) Original image of size 256x256, (b) Normalized histogram of the image 4(a), (c) Featured histogram of the image 4(a) with detected peaks and valley (Peaks are at 71 and 189, valley at 114), (d) Average fitness vs generations of class A for both PGA and GA, (e) Average fitness vs generations of class B for both PGA and GA, (f) Segmented image using the proposed method (threshold T=114), (j) Segmented image using Otsu's method (T=123).

Fig. 5 (a)

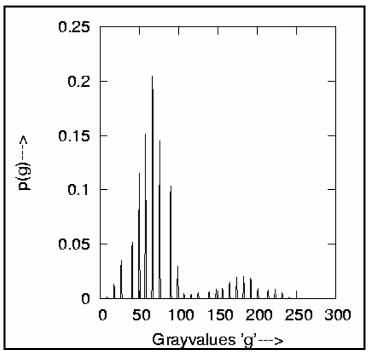

Fig. 5 (b)

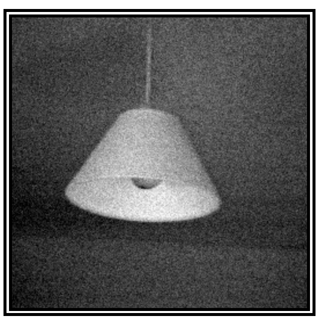

Fig. 5 (c)

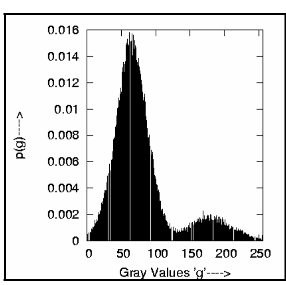

Fig. 5 (d)

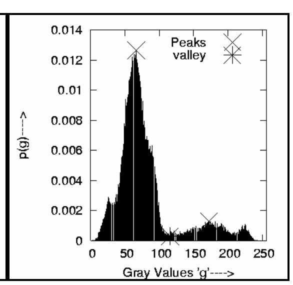

Fig. 5 (e)

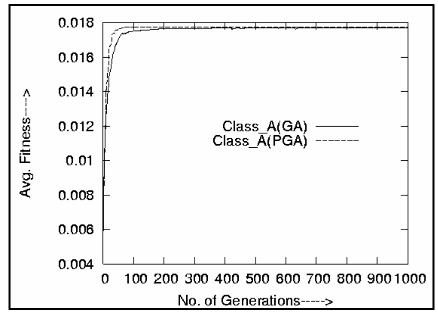

Fig. 5 (f)

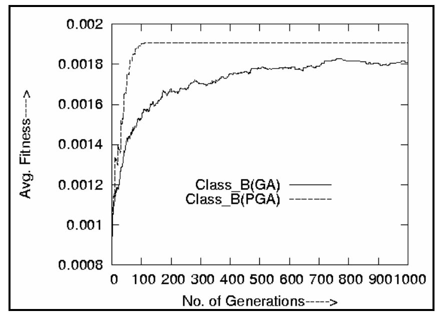

Fig. 5 (g)

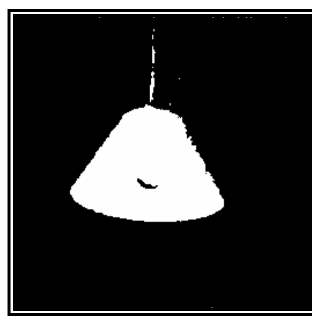

Fig. 5 (h)

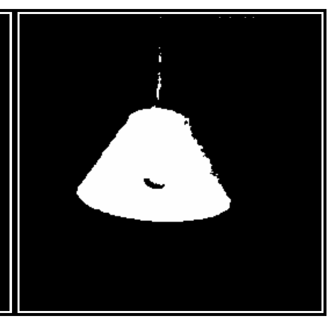

Fig. 5 (i)

Fig. 5: (a) Original image of size 256x256, (b) Normalized histogram, (c) Noisy version of original image having SNR 16 dB, (d) Normalize histogram of image Fig. 5(c), (e) Featured histogram of the image Fig. 5(c) and detected peaks and valley (peaks at 66 and 172 and valley at 116), (f) Average fitness vs generations of class A for both PGA and GA, (h) Average fitness vs generations of class B for both PGA and GA, (i) Segmented image using the proposed method(T=116), (j) segmented image using Otsu's method (T=126).

Fig. 6 (a)

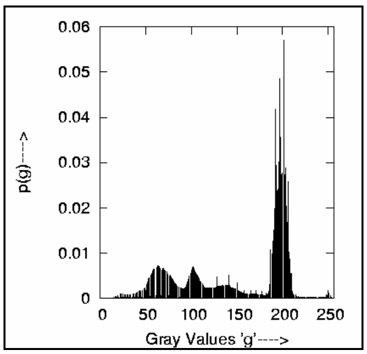

Fig. 6 (b)

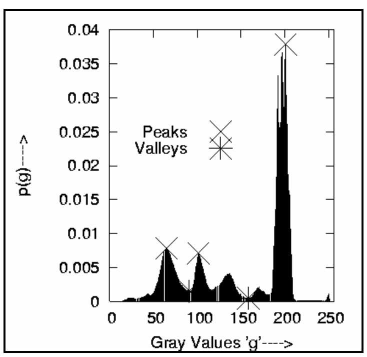

Fig. 6 (c)

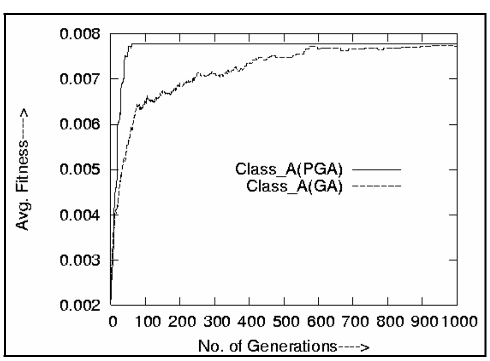

Fig. 6 (d)

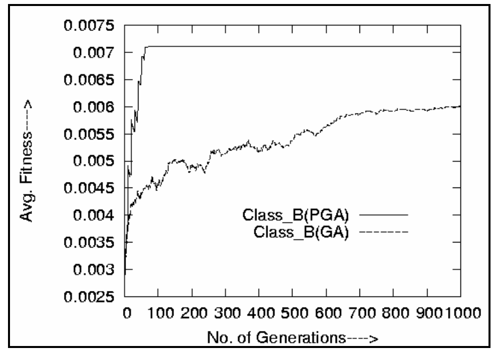

Fig. 6 (e)

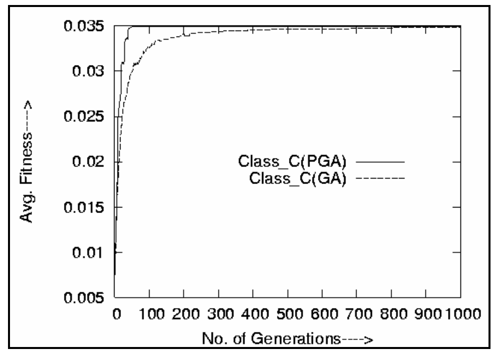

Fig. 6 (f)

Fig. 6 (g)

Fig. 6: (a) Original image of size 1600x1200, (b) Normalized histogram of the original image, (c) Featured histogram of the image Fig. 6(a) and detected peaks and valleys (peaks are at 64, 102 and 201 and valleys are at 87 and 181), (d) Average fitness vs generations of class A for both PGA and GA, (e) Average fitness vs Generations of class B for both PGA and GA, (f) Average fitness vs Generations of class C for both PGA and GA, (g) Segmented image using the proposed method (T_1=87 and T_2=181)

The peaks are detected at gray values of 71 and 189. The valley is found to be at a gray value of 114 and hence the threshold. The rate of convergence is shown in Fig 4(d) and Fig 4(e) for Class A and Class B respectively. Since this is a two class problem Class A and Class B refers to the object and background respectively. It is observed from both these figures that GA converges at around 1000 generations where as PGA takes 100 generations. Thus, PGA is found to be almost 10 times faster that of GA. The optimal threshold value of 114 is used for segmentation and the segmented result is shown in Fig 4(f). It can be seen from Fig (f) that except a few misclassifications, the object and background have been segmented. Fig 4(g) shows the result obtained by Otsu's approach. Comparing Fig 4(f) and Fig 4(g) it is observed that the results are comparable. Although, here the result is comparable, the efficacy of our method is quite evident in case of noisy images as shown in Fig 5.

Fig 5(a) shows the original image and the corresponding histogram is shown in Fig 5(b). There is bimodality feature observed with the histogram. The noisy image of SNR 16 dB is generated and is shown in Fig 5(c). We define SNR as

$$SNR_{dB} = 10\log_{10}\frac{\sum_{ij} x_{ij}^2}{\sum_{ij} n_{ij}^2} \qquad (4)$$

The histogram of the noisy image is shown in Fig. 5(d). Overlapping of the class distributions are observed in Fig 5(d) which is reduced in case of the histogram of the featured pixels as shown in Fig 5(e). GA and PGA are employed to detect the peaks and valley. The detected peaks are at 66 and 172 and the valley at 116 respectively. As observed in previous example, PGA is faster than that of GA. This phenomenon is shown in Fig 5(f) and 5(g). The optimal threshold value is used for segmentation and the segmented result is shown in Fig 5(h). Fig 5(i) shows the result obtained by Otsu's approach. Even though the result obtained by our approach is visually comparable to that of Otsu's approach, the misclassification error of our approach is 0.67% where as 0.77% is the error in case of Otsu's approach. Since, the error is very close to each other the results are also comparable. We define the misclassification error as

$$ME=(N_{mc}/N_t)\times 100 \qquad (5)$$

Where N_{mc} is the total number of misclassified pixels and N_t is the total number of pixels in the image.

We have also considered an image having three classes of size (1600x1200) as shown in Fig 6(a).The corresponding histogram is shown in Fig 6 (b) which shows three clear modes. The histogram of the featured pixels is shown in Fig 6(c), where there is clear tri-modality. GA and PGA are employed to detect the peaks and valleys. The valleys are found to be at 87 and 181 gray values. The parameter of GA and PGA are same as those used for the two class problems. In this case also, PGA is found to converge faster than that of GA. This effect is shown in Fig 6 (d), (e) and (f). The optimal thresholds are used to segment the images and the segmented image is shown in Fig 6(g). This is clear that proper segmentation could be achieved except a few misclassified points .Thus two and three class images could be segmented using the proposed scheme.

5. Conclusions

In this work, a new approach is proposed to determine the optimal thresholds for two and three class image segmentation. The shape information of the histogram corresponding to the featured pixels is used to compute the optimal threshold. The first moment over a window around a pixel is considered as the feature value of the pixel. Gaussian distribution is assumed over each window and the consideration of the featured value depends upon the standard deviation of the window. This notion helps to reshape the histogram i.e. the shape of the featured histogram is more useful. The peaks are determined from the normalized histogram using the GA and PGA based crowding. Because of the discrete nature of the histogram the peaks are detected by GA and PGA based concepts. Subsequently the valley corresponding to the optimal threshold determined. The proposed scheme yielded satisfactory results for two and three class problems. Results obtained by the proposed scheme are quite comparable to that of Otsu's approach. The performance of the proposed scheme is found to be better in case of noisy images. The noisy case for a two class has been presented, but it also worked for other classes. Parallel genetic algorithm converged faster and takes very less time and hence will be suitable for real time application. Current work focuses on devising adaptive threshold scheme for classification of objects and background.

Acknowledgment

This research work has been supported by the Ministry of Human Resource and Development (MHRD), India project on "Real-Time Image Processing using soft computing Approach".

References

[1] K. S. Fu and J. K. Mui, "A Survey on Image segmentation", *Pattern Recognition*, vol. 13, 1981, pp. 3-16.

[2] M. Sezgin and B. Sankur, “Survey over image thresholding techniques and quantitative performance evaluation”, *Journal of Electronic Imaging*, vol. 13, no. 1, 2004, pp. 146-165.
[3] N. R. Pal and S. K. Pal, “A Review on Image Segmentation Techniques”, *Pattern Recognition*, vol. 26, no. 9, 1993, pp.1277-1294.
[4] P. K. Sahoo, S. Soltani and A. K. C. Wong, “A Survey of Thresholding Techniques”, *Computer Vision, Graphics, and Image Processing*, vol. 41, 1988,pp.133-260.
[5] J. Kittler and J. Illingworth, “Minimum Error Thresholding”, *Pattern Recognition*, vol. 19, no. 1, 1986, pp. 41-47.
[6] J. M. S. Prewitt and M. L. Mendelsohn, “The analysis of cell images”, *Ann. N. Y. Acad. Sci*., vol. 128, 1966, pp. 1035-1053.
[7] J. S. Weszka, R. N. Nagel, and A. Rosenfeld, “A threshold selection technique”, *IEEE Trans. Comput*., vol. C-23, 1974, pp. 1322-1326.
[8] N. Otsu, “A Threshold Selection Method from Gray-Level Histograms”, *IEEE Trans. Syst., Man, Cybern.*, vol. SMC-9 (1), 1979, pp. 62-66.
[9] S. Watanable and CYBEST Group, “An automated apparatus for cancer processing: CYBEST”, *Comp. Graph. Image processing*, vol. 3, 1974, pp. 350-358.
[10] P. K. Nanda & P. Kanungo, “Parallelized Crowding Scheme Using a New Interconnection Model”, *in Proc. of 2002 AFSS, International conference on Fuzzy Systems*, Calcutta, India, February, 2002, LNAI 2275, Springer-Verlag, pp. 436-443.
[11] P. K. Nanda & P. Kanungo, “Parallel Genetic Algorithm based Crowding Scheme Using Neighbouring Net Topology”, *in Proc. 6th international conference on Information Technology*, Bhubaneswar, India, December 2003, pp. 583-585.
[12] S. W. Mahfoud, “Simple Analytical Models of Genetic Algorithms for Multimodal Function Optimization”, *Technical Report, Illinois Genetic Algorithm Laboratory*, IlliGAL report No. 93001, Feb. 1993.
[13] S. W. Mahfoud, “Cross over Interaction among Niches”, *in Proc. 1st IEEE Conference on Evolutionary Computation*, World Congress on Computation Intelligence, 1994, pp.188-193.