

Classification of Objects and Background Using Parallel Genetic Algorithm Based Clustering

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Abstract

In this paper, two novel strategies have been proposed to segment the object and background in a given scene. The first one, known as Featureless (FL) approach, deals with the histogram of the original image where Parallel Genetic Algorithm (PGA) based clustering notion is used to determine the optimal threshold from the discrete nature of the histogram distribution. In this regard, we have proposed a new interconnection model for PGA. The second scheme, the Featured Based (FB) approach, is based on the proposed feature histogram distribution. A feature from the given image is extracted and the histogram corresponding to the derived feature is used to determine the optimal threshold of the original image. The proposed PGA based clustering is used to determine the optimal threshold. The performance of both the schemes is compared with that of Otsu's and Kwon's method and FB method is found to be the best among the three techniques.

Key Words: Image segmentation, Parallel Genetic Algorithm, Clustering, Thresholding

1 Introduction

It is important in image processing to select an appropriate threshold of gray level for extracting object from the background. Image thresholding is a necessary step in image analysis and applications [1]-[4]. In its simplest form, thresholding means to classify the pixels of a given image into two groups (e.g. objects and background), one containing pixels with gray values above a certain threshold, and the other including those with gray values equal to and less than the threshold. This is called bi-level thresholding. In multilevel thresholding, one can select more than one threshold and use them to divide the whole range of gray values into several sub ranges. Most of the thresholding techniques[5] -[8] utilize shape information of the histogram of the given image to determine appropriate threshold.

In an ideal case, for images having two classes, the histogram distribution has a deep and sharp valley between two peaks representing objects and back ground, respectively. Therefore, the threshold can be chosen as the bottom of this valley [4]. However, for most real pictures, it is often difficult to detect the valley precisely, because; (i) valley could be flat and broad, and (ii) the two peaks could be extremely unequal in height.

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Rosenfeld et al. [3] proposed the valley sharpening technique which restricts the histogram to the pixels with large absolute values of derivatives. S. Watanabe et al. [5] proposed the difference histogram method which selects threshold at the gray level with the maximal amount of difference. These methods utilize information concerning neighbouring pixels or edges of the original picture to modify the histogram so as to make it suitable for determination of optimal threshold. Another class of methods deals directly with the gray level histogram by parametric techniques. The histogram is approximated by sum of Gaussian distributions in the least square sense, and statistical decision procedures are applied [8]. However, such methods are tedious and computationally involved. Recently, the notion of cluster analysis has been employed for determination of optimal threshold [9, 10]. A new similarity measure based on the inter class and intra class variance of the clusters has been proposed by Arifin et al. [10]. Qiao et al. [11] have proposed a variance and intensity contrast based thresholding scheme for segmenting small objects in a given scene.

We have proposed two methods to determine the optimal threshold for classification. The first one, called Feature Less (FL) approach, exploits the shape information of the discrete histogram distribution of the original image to determine the optimal threshold. The optimal threshold corresponds to the valley of the histogram landscape. In the histogram landscape, each mode is assumed to correspond to one class of the image. For example, histogram having two modes (two peaks and one valley) correspond to two classes in the given image. Therefore, the problem is cast as classification problem. The second approach, called Feature Based (FB) approach, deals with the histogram of the "feature pixels" rather than the original pixels. The optimal threshold for the given image is obtained by determining the valley of the modified histogram.

Often, because of the irregular nature of discrete histogram distribution, the conventional exhaustive method may obtain incorrect threshold leading to poor classification. In case of discrete histogram distribution, exhaustive search for the minimum gray value may lead to pseudo thresholds because the exhaustive search may obtain minimum value at the initial portion or the final portion of the histogram distribution. Hence, we propose a clustering technique to detect peaks corresponding to different modes of the histogram. Irregularity in the distribution, for example, could be the presence of a small kink in one of the peaks of the distribution thereby misleading one peak as two peaks. In this research work, a Parallel Genetic Algorithm (PGA) based clustering technique is proposed to detect the peaks and, in the sequel, the valley between the successive peaks is obtained by exhaustive search method. In order to accelerate convergence, a new interconnection model is proposed for PGA. The proposed FL approach yields satisfactory results, but the performance is found to deteriorate with overlapping class distributions that results from either the type of the image or the presence of noise. In order to take care of such cases, a Feature Based (FB) approach is proposed which deal with histogram having overlapping class distributions. In this approach, feature of the image is extracted and the histogram corresponding to the feature pixels is considered as opposed to the histogram of the original image. This modified histogram is used to determine the optimal threshold to segment the original image. The process of determination of valley of the feature histogram is the same as that of the FL approach. PGA based clustering algorithm is used to determine the peaks and the valley is obtained by the exhaustive search method. The valley, thus obtained, is used as the threshold to segment the original image. FL and FB methods are validated for images with two as well as three classes. FB approach is compared with FL, Otsu's [7] and Kwon's [9] approaches and it is found that the FB approach is the best among these four methods.

2 Proposed Approaches

2.1 Featureless (FL) Approach

In this approach, the shape of the discrete histogram distribution is considered to determine the optimal threshold. For example, it is observed from Fig. 1(a) that there are two distinct modes corresponding to two classes of the given image. The optimal threshold that corresponds to the valley of the landscape is obtained as follows. First, the peaks of the histogram distribution are determined by PGA based crowding and then the valley point, in between the two peaks, is determined by exhaustive search method. Analogously, for a three class problem,

the histogram distribution will have three modes and two valleys. PGA based clustering algorithm is used to determine the peaks. Thereafter, the two consecutive valley points corresponding to two thresholds are found out by exhaustive search method.

2.2 Featured Based (FB) Approach

By and large, histogram distributions for noisy scenes have overlapping class distributions. In such situations, the FL approach yields approximate results with large percentage of misclassification error. This could be due to the overlapping class distributions. In order to minimize the overlapping of the class distributions, a Feature Based (FB) approach is proposed. This approach deals with the histogram distribution corresponding to feature pixels only. Feature from the original image is extracted as follows. A window of a given size is considered around a pixel and the distributions of the pixels over the window is assumed to be Gaussian. The first moment of this distribution over the window is considered as the feature and this is governed by the second moment (variance) of the distribution. With Gaussian assumption, it is known that the likelihood estimates of the first and second moment over a window size w is

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

The first moment of the pixels is considered as the feature value if the following condition is satisfied; i.e.,

$$\text{if } |x_{ij} - \hat{\mu}_{w_{ij}}| \leq \hat{\sigma}_{w_{ij}}/K \quad \text{then } x_{ij} = \hat{\mu}_{w_{ij}}, \quad (2)$$

where K is a positive constant bounded between 1 and w (window size) to take care of edge and non-edge pixels, x_{ij} is the gray value of the $(i, j)^{th}$ pixel, $\hat{\mu}_{w_{ij}}$ is the mean value, $\hat{\sigma}_{w_{ij}}$ is the standard deviation, and N_w denotes the number of pixels in the window. The features corresponding to all the pixels of the whole image are extracted and histogram of the feature pixels is considered. In the FB approach, the optimal threshold for the original image is obtained from the modified histogram. The modified histogram is found to either reduce the degree of overlapping or remove the overlapping between class distributions. The proposed PGA based clustering algorithm is used to determine the peaks and thereafter the valley is determined by exhaustive search method. Fig. 1(a) shows the histogram distributions having two modes that correspond to two classes of the given image. It is clear from Fig.1(a) that there is appreciable amount of overlapping between two modes. The feature values corresponding to every pixel of the image are extracted and the histogram is found out for the feature values of the pixels. The histogram, thus obtained, is shown in Fig.1(b) and it is observed that the overlapping of two class distributions has been reduced substantially. The optimal threshold for the original image is obtained by determining the valley of Fig.1(b).

3 GA class model

Usually GAs are used for function optimization and hence determine the global optimal solution. In case of nonlinear multimodal function, each mode corresponds to a solution and use of basic GA would yield one global optimal solution. If it is necessary to determine global as well as local optimal solutions, the basic GA fails. For example, for a nonlinear multimodal function, determination of all the solutions reduces to finding out the niches of the function. Thus, this is not an usual optimization problem. The niches, corresponding to solutions can be determined by GA based clustering techniques [12, 13, 14]. In our case, determination of all the peaks of the histogram is equivalent to determining the niches. Here, the GA based clustering maintains subpopulation at every peak and hence the gray values corresponding to peaks are determined.

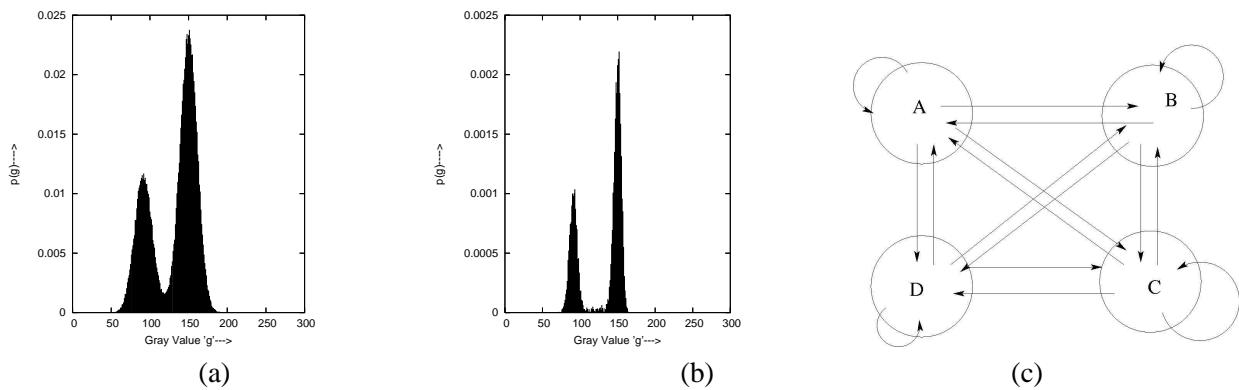


Figure 1: (a) Normalized histogram of the image, (b) Featured based normalized histogram, (c) Interconnection model used in PGA

3.1 Crowding method

In the deterministic crowding, sampling occurs without replacement [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 the same class yield two elements of that class, and the crossover operation between two elements of different classes will yield either: (i) one element from both the classes, or (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 result will be that one element of both the classes advances to the next generation and hence no net change.

3.2 GA based algorithm

It is mentioned in Section 2 that the histogram landscape of the original image is used in FL based approach and histogram of the feature pixels is used in FB approach. For two class image the histogram has two modes and for three class problem the corresponding histogram has three modes. First, the peaks of the histogram are detected by the GA based clustering and thereafter, the valley is detected by exhaustive search. The fitness function for GA based clustering is the histogram itself. Hence, fitness function $f(g) = p(g)$ $g \in [0, L]$, where g denotes the gray value, $p(g)$ corresponds to either discrete histogram distribution of the original pixels or the feature pixels.

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.
- (iii) The offspring generated compete with the parents based on the concept of binary tournament selection strategy.
- (iv) After selection the selected elements are put in their respective classes.
- (v) Steps (ii), (iii) and (iv) are repeated for all elements in the population.

- (vi) Step (v) is repeated till the convergence is met i.e. the elements of respective classes are equally fit.
- (vii) Exhaustive search algorithm is used to determine the valley point and hence the threshold.

3.3 PGA based algorithm

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 may communicate by exchanging individuals. This process of dividing the entire population into sub-populations and then providing a 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. We have used the Island model and in an Island model, the population is partitioned into 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 among demes is carried out to achieve convergence. A new interconnection model having the notion of self migration is proposed as shown in Fig 1(c). Besides, the interconnection between demes, a self loop has been introduced to take care of intrademe migration. This helps in accelerating the convergence and also improves the quality of the solution. We have adopted the good-bad (GB) based migration policy [14, 15]. In our problem, we considered four demes D1, D2, D3 and D4 and the interaction network model as shown in Fig 1(c). Tournament selection mechanism is applied to all demes. A new crossover operator known as Generalized Crossover (GC) operator [14] has been used in the PGA.

The steps of the parallelized crowding scheme are enumerated as follows.

- (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 parent and offspring.
(iii) The tournament selection mechanism is a binary tournament selection among the two parents and offspring, 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 and iii for all the elements in the sub population.
- (v) Repeat steps i, ii, iii and 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. Number of elements to migrate is determined from the selected rate of migration R_{mig} . The elements migrate with migration probability P_{mig} .
- (6) Self Migration is allowed in each deme based on the selected migration policy and the selected rate of self-migration R_{smig} with a probability P_{smig}
- (7) Repeat Steps 3,4,5 and 6 till convergence is achieved. The algorithm stops when the average fitness of the total population is above pre-selected threshold.
- (8) The peaks will be determined from the converged classes of Step 7.
- (9) The valley points in between the peaks will be determined by exhaustive search method.

4 Simulation

In simulation, images corresponding to two as well as three classes have been considered and the corresponding histogram distributions have two and three modes. Fig. 2(a) shows the original image and the corresponding

Window Size (WS)	Sample Images					
	Image1		Image2		Image 3	
	T	ME in %age	T	ME in %age	T	ME %age
3x3	107	0.8942	126	0.5748	106	0.4593
5x5	107	0.8942	129	0.5748	119	0.3403
7x7	110	0.8942	127	0.5748	121	0.3403
9x9	116	0.8286	130	0.5748	112	0.0000
11x11	107	0.8942	129	0.5748	114	0.0000
13x13	104	0.8942	108	1.4148	114	0.0000
15x15	110	0.8942	110	1.2904	118	0.3403

Table 1: Threshold values and misclassification error for different window size using the FB approach

Sample images	Threshold Selection Methods							
	Otsu's Approach		Kwon's Approach		FL Approach		FB Approach	
	T	ME %age	T	ME %age	T	ME %age	T	ME %age
Image 1	123	2.8595	122	1.762	114	0.0	116	0.8286
Image 2(SNR 22dB)	121	0.705	119	0.759	119	0.759	111	0.5748
Image 3(SNR 22dB)	126	0.6165	109	0.162	129	0.8240	106	0.2472

Table 2: Performance evaluation of Otsu's, Kwon's, FL and FB approach for two class images

Sample images	Threshold Selection Methods											
	Otsu's Approach			Kwon's Approach			FL Approach			FB Approach		
	T_1	T_2	ME %age	T_1	T_2	ME %age	T_1	T_2	ME %age	T_1	T_2	ME %age
Image 4	96	155	11.2503	101	197	76.6708	88	171	13.0600	112	167	5.5298
Image 5	100	160	2.3787	125	127	14.9711	99	154	1.5349	115	140	2.9010

Table 3: Performance evaluation of Otsu's, Kwon's, FL and FB approach for three class images

discrete histogram distribution as shown in Fig.2(b) has two prominent modes and hence a two class image. FL approach uses the histogram shown in Fig.2(b) and the PGA based clustering is used to detect the peaks. The peaks are found to be at gray values 71 and 189 as shown by " × " in Fig.2(b). Thereafter, exhaustive search method is used to find out the valley point and the valley is found to be at a gray value 114 as shown by " * " in Fig.2(b). This valley is the optimal threshold of the original image and is used to segment the image. The segmented image is shown in Fig.2(g) and the segmented image obtained by Otsu's approach is shown in Fig.2(h). This is a two class problem and it is seen from Fig.2(h) that there are misclassified pixels near the base of the rod and at the back of lamp leading to more misclassification error. The misclassification of these pixels is absent in Fig.2(g) that is obtained by FL approach. The ground truth image is constructed manually and the misclassification error for segmented images is computed as follows

$$ME = 1 - \frac{|B_O \cap B_T| + |F_O \cap F_T|}{|B_O| + |F_O|}; \quad (3)$$

where B_O and F_O denote the background and foreground of the original image and B_T and F_T denote the background and foreground of the test image. The parameters used for GA are: No. of Generations =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: No. of Generations=1000, Migration period is 10 generations, Number of demes $d_m=4$, Probability of Crossover $P_c = 0.8$, Probability of Mutation $P_m = 0.001$, Population size $N_p = 400$ and $N_v = 100$, Probability of Migration $P_{mig} = 0.8$, Migration Rate $R_{mig} = 4\%$, Probability of Self Migration $P_{smig} = 0.8$ and Self Migration Rate $R_{smig} = 2\%$. The rate of convergence of GA and

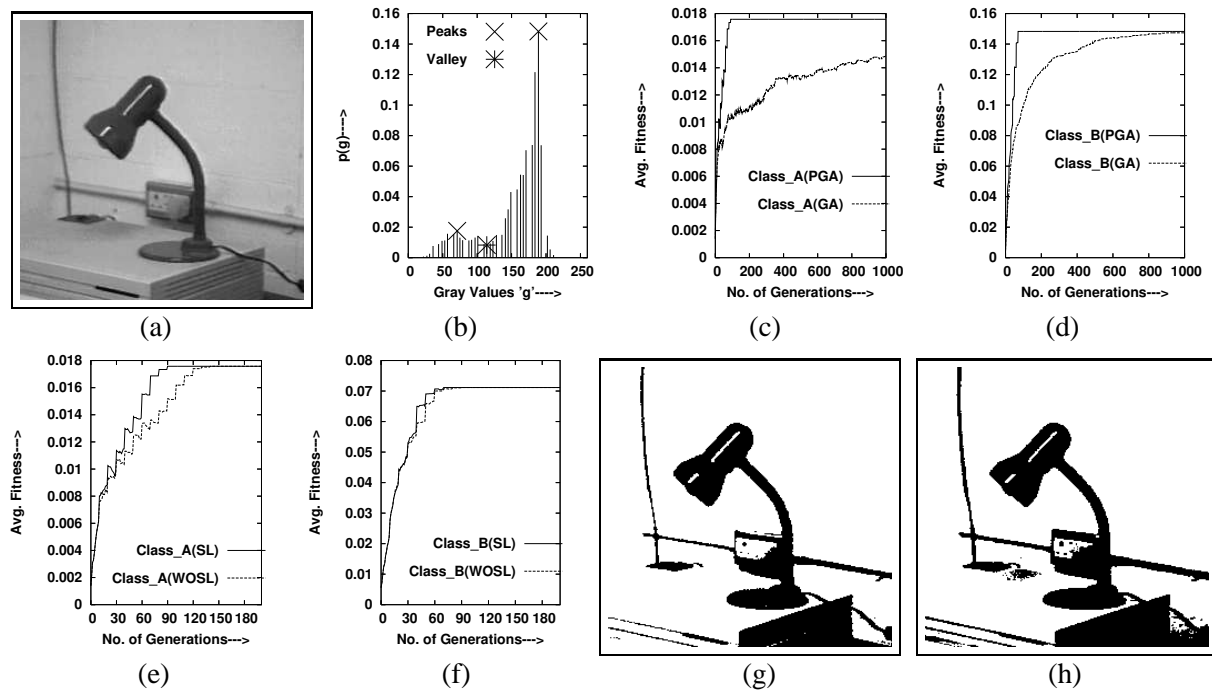


Figure 2: (a) image 1, (b) Histogram with detected peaks and valley, (c) Average fitness vs generation of class "A" PGA and GA, (d) Average fitness vs generation of class "B" PGA and GA, (e) class "A" with self loop(SL) and without self loop(WOSL), (f) class "B" with self loop(SL) and with out self loop(WOSL), (g) Segmented image using FL, (h) Segmented image using Otsu's approach.

PGA for class A and class B is compared in Fig.2(c) and 2(d) respectively. From Fig.2(c), it is clear that GA converges at 1000 generations while PGA converges around 100 generations. PGA is based on the Island model and we have proposed a fully interconnected model by introducing a new notion of self migration, called self loop (SL) in each deam. PGA with the proposed interconnection model is found to converge faster than that of model without self loop (WOSL). This is observed from Fig.2(e) and 2(f) for class A and class B respectively.

The proposed FB approach is also validated for two and three class images. From Section 2.2 it is clear that the feature depends upon the proper choice of the window size. The optimum size of window is determined empirically based on the percentage of misclassification error. We have considered three images and the effect of size of the window on percentage of misclassification error (PME) is plotted in Fig.3, the corresponding values are tabulated in Table-1. As observed from Fig 3, the PME is minimum for a window size (9x9). Hence, window size 9x9 is considered to extract features in FB based approach. The same 'table lamp and rod' image is considered again as shown in Fig.4(a) and corresponding histogram is shown in Fig.4(b). The feature values for each pixel is extracted and the histogram corresponding to feature pixels is shown in Fig.4(c). As seen from Fig.4(c), feature histogram exhibits clear modes. GA and PGA based clustering algorithms are used to detect peaks at 73 and 188 as shown by "x" in Fig.4(d) and the valley is determined at gray value 116 as shown by "*" in Fig.4(d). The parameters of GA and PGA are the same as that of FL approach. The threshold of 116, thus obtained, is used to segment the original image and the segmented image is shown in Fig.4(i). The ground truth image is drawn manually and based on (3) the percentage of misclassification is found to be 0.828%. Figs. 4(j) and (k) show the segmented images obtained by Otsu's and Kwon's approach respectively. As observed from Fig.4(j) and (k), there are misclassified pixels near the base of the rod and at the back of the table. The PME is more in case of Otsu's and Kwon's approach than that of FB approach. It is also visually apparent that the segmented image obtained by FB approach is better than that of Otsu's and Kwon's approach. The proposed FB approach has also been tested with noisy images as shown in Fig.5(a)

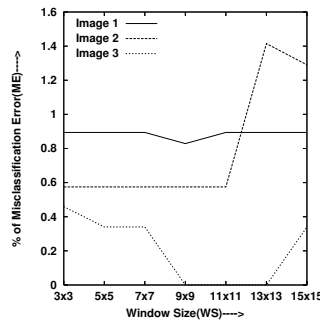


Figure 3: Percentage of Misclassification versus window size (Image 1, 2 & 3 are Fig4(a),5(a) & 6(a))

and Fig.6(a). For the original image of Fig.5(a), the noisy version with SNR 22dB is shown in Fig.5(b). We define SNR as $SNR_{dB} = 10 \log_{10} \left(\frac{\sum_{ij} x_{ij}^2}{\sum_{ij} n_{ij}^2} \right)$. The histogram of the noisy image is shown in Fig.5(c) and it is observed from the histogram that two modes corresponding to two classes have appreciable amount of overlapping. After extracting feature of the pixels, it is observed that the feature histogram does not have overlapping between the class distributions. The PGA based clustering algorithm when applied on the histogram of Fig.5(c) resulted in peaks at gray values of 92 and 151 and the corresponding threshold at 119. The segmented image of FL approach is shown in Fig.5(e). But, the PGA based algorithm with histogram of Fig.5(d) found peaks at gray values 89 and 150 and the corresponding valley is found to be at 111. This threshold value (111) is used to segment the original image and segmented image is shown in Fig.5(f). The results obtained by Otsu's approach and Kwon's approach are shown in Fig.5(g) and (h). As observed from Table-2 the percentage of misclassification error is minimum in case of FB approach albeit visible similarity among the segmented images of different method. The other noisy image considered is shown in Fig.6(b). The results obtained by FL, FB, Otsu's and Kwon's approach are shown in Fig.6(e),(f),(g) and (h). As seen from these figures, FB approach yielded results with sharp edge and the rod portion of the image could be fully preserved. Because of some misclassified pixels, the PME of FB is close to the other methods. Nevertheless, visual appearance shows that the edges and the full length of the rod could be well preserved in case of FB approach.

The proposed schemes are also tested for images having three classes. The first three class image considered is shown in Fig.7(a) and the corresponding histogram is shown in Fig.7(b). The histogram exhibit three predominant modes and also few other modes. In FL approach, the histogram of Fig.7(b) is used and the PGA based algorithm detected peaks and the two valleys are found at 88 and 171. These two thresholds are used to segment the image and the segmented image is shown in Fig.7(d). In FB approach, the feature pixels are extracted and the corresponding histogram is shown in Fig.7(c). It is observed that there are distinct modes and the thresholds are found to be at gray values 112 and 167. The segmented image is shown in Fig.7(e) and the PME is found to be 5.5%. Results obtained using Otsu's and Kwon's approach are shown in Fig.7(f) and 7(g). Based on the ground truth image, FB approach has least PME among all the methods. This is also because of thresholds in FB approach are quite different from the rest of the approaches. The second three class image considered is shown in Fig.8(a) and the peaks and valleys are shown by "×" and "*" in Fig.8(b) and 8(c). The segmented images for FL and FB approaches are shown in Fig.8(d) and (e). Comparing FL and FB approach, FB approach could preserve edges properly while the results by FL have distorted edges. Segmented images obtained by Otsu's and Kwon's approach are shown in Fig.8(f) and (g). From Table-3, it is observed that the PMEs in case of FL and FB approaches are less than Kwon's approach and comparable to Otsu's approach. In case of two class problem, FB approach is found to be the best one for histograms having overlapping class distributions and noisy images. In case of three class problem, FB approach also yielded better results than that of Otsu's and Kwon's approaches. The algorithms are implemented in a machine with Intel PIV,3GHz,512MB RAM,800MHz FSB and 1MB L2 Cache specifications. For two class problem 0.5 sec was required for PGA,

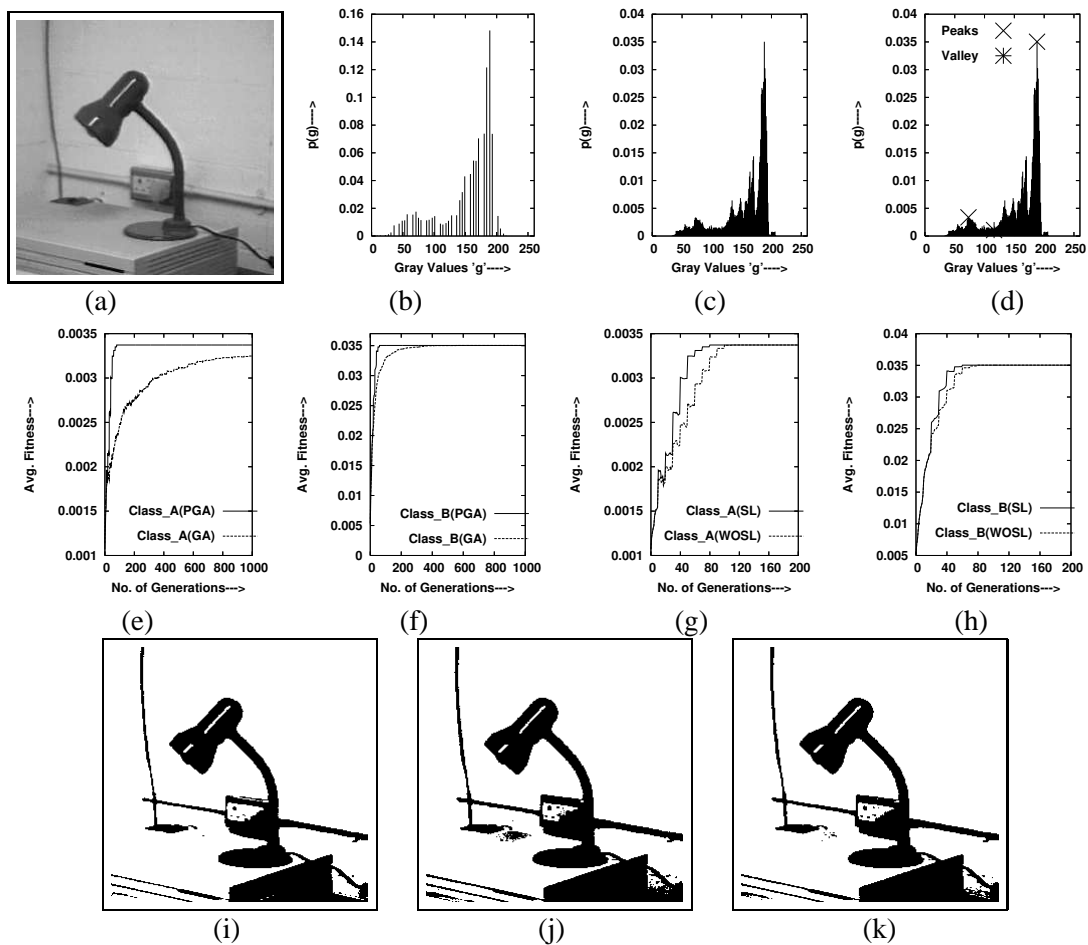


Figure 4: (a) Image 1, (b) Histogram, (c) Featured histogram, (d) Detected peaks and valley, (e) Average fitness vs generations of class "A" PGA and GA, (f) Average fitness vs generations of class "B" PGA and GA, (g) class "B" with SL and WOSL, (h) Segmented image using the FB, (j) Segmented image using Otsu's approach, (k) Segmented image using Kwon's method.

2sec for GA, 0.2 sec for otsu and 0.05sec for Kwon's method. For three class problem, PGA is executed in 1 sec, GA in 4sec, Otsu's in 1sec and Kwon's in 1.6sec. Thus it is observed that with increase in class the proposed approach takes less time than that Otsu's approach.

5 Conclusions

We have proposed two schemes. The FL approach deals with the original histogram distributions and the FB approach deals with the histogram of feature pixels. The peaks are found out by PGA based clustering algorithm and the valleys are determined by exhaustive search. In PGA a new interconnection model is proposed to accelerate the convergence as well as the quality of solution. It is observed that the proposed model with a new crossover operator yielded better results. FB approach is found to be the best among the Otsu's and Kwon's methods. In case of noisy images and overlapping class distributions of the histogram, FB approach could yield segmentation results with less percentage of misclassification error. PGA based clustering is found to converge faster than that of GA based clustering. For two class problem, in a given platform, FB approach consumes more time but with increase in number of classes the rate of increase of time in FB is less than that of Otsu's and Kwon's approaches. Hence, FB approach is suitable for small as well as large number of classes. Current

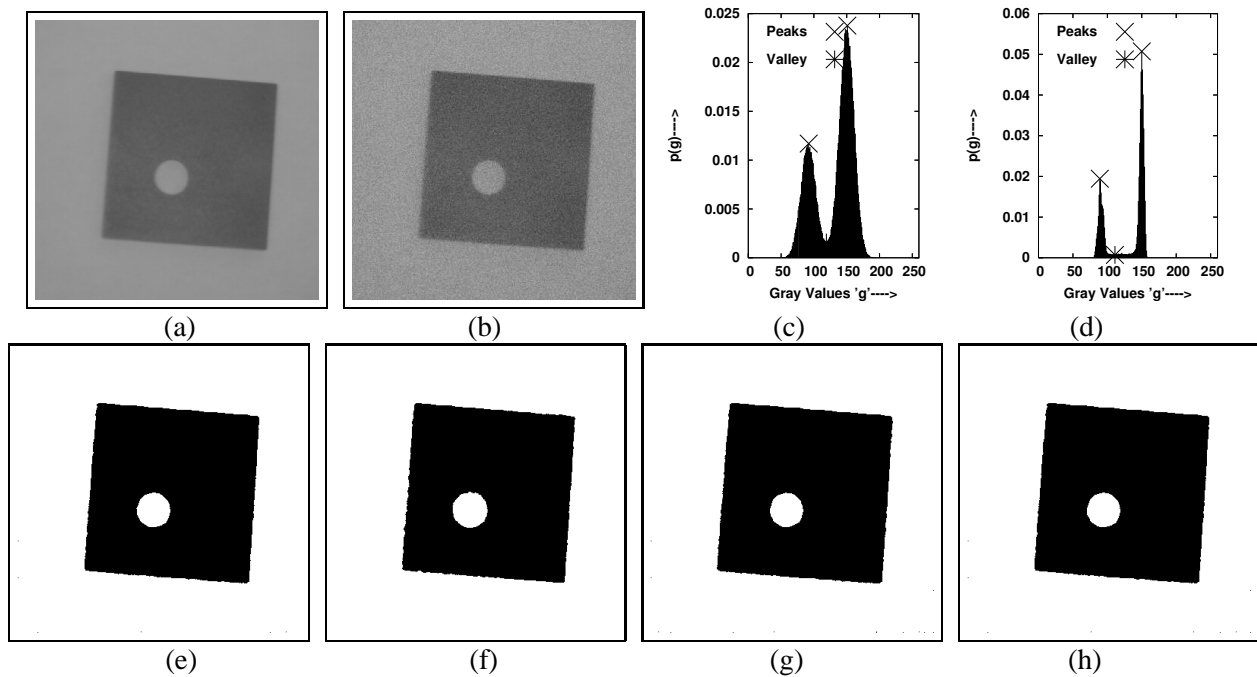


Figure 5: (a) Image 2, (b) Noisy version of image 2 with SNR 22dB, (c) Histogram of (b) with detected peaks and valley, (d) Featured histogram of (b) with detected peaks and valley, (e) Segmented image using FL, (f) Segmented image using FB, (g) Segmented image using the Otsu's Approach, (h) Segmented image using the Kwon's Approach.

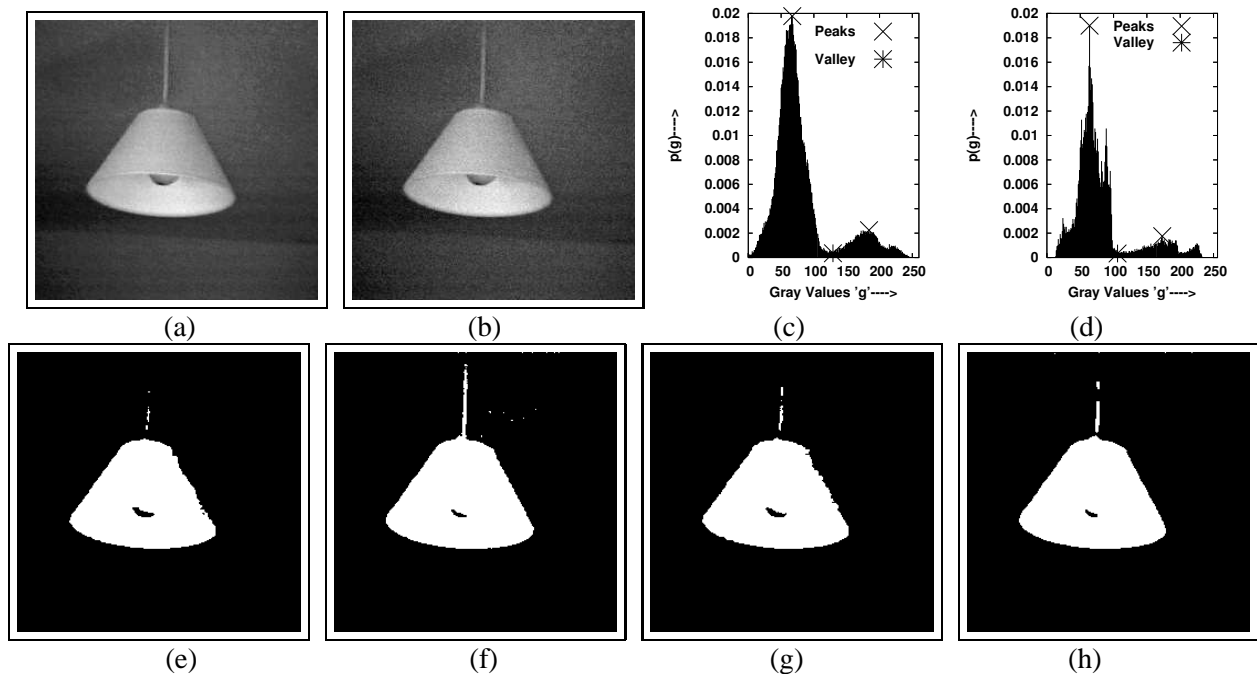


Figure 6: (a) Image 3,(b) Noisy version of image 3 with SNR 22dB,(c) Histogram of (b) with detected peaks and valley,(d) Featured histogram of (b) with detected peaks and valley,(e) Segmented image using FL,(f) Segmented image using FB,(g) Segmented image using the Otsu's Approach,(h) Segmented image using the Kwon's Approach

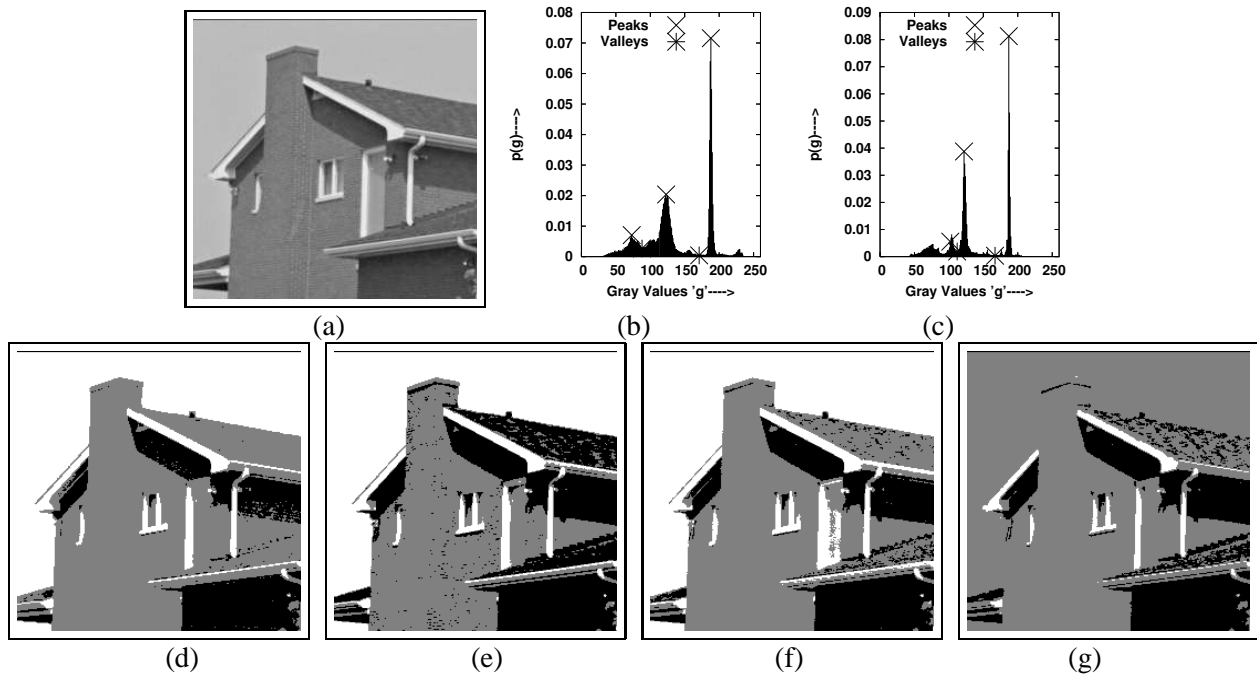


Figure 7: (a) Image 4, (b) Histogram with detected peaks and valleys, (c) Featured histogram with peaks and valleys, (d) Segmented image using FL, (e) Segmented image using FB, (f) Segmented image using Otsu's approach, (g) Segmented image using Kwon's approach.

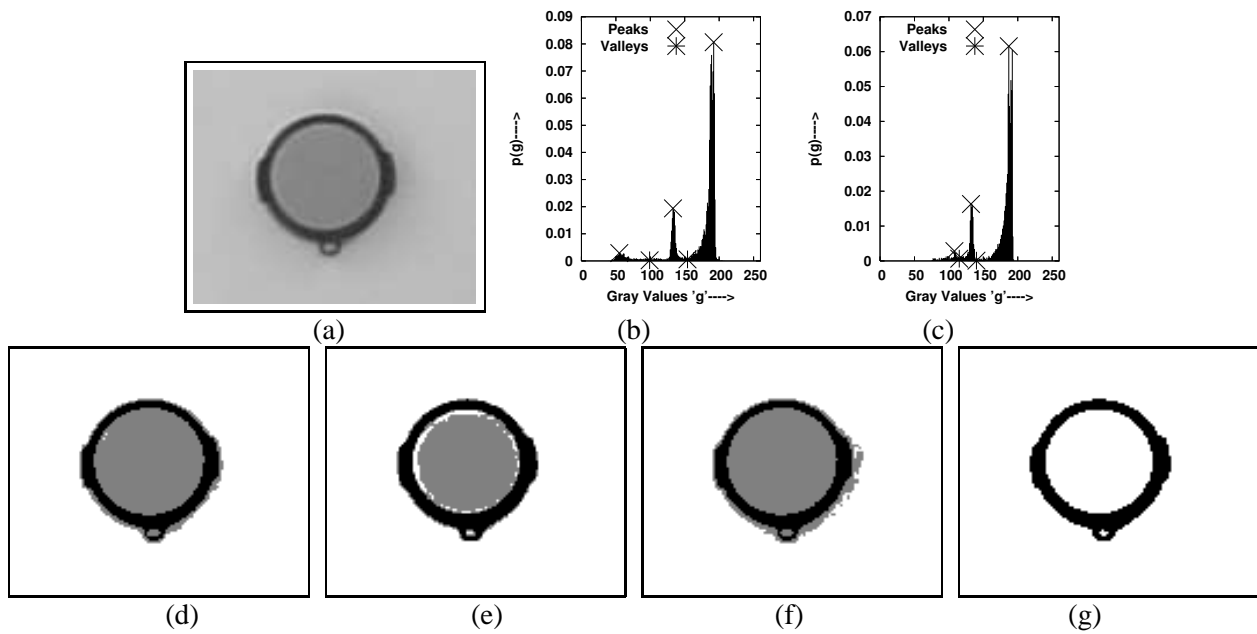


Figure 8: (a) Image 5, (b) Histogram with detected Peaks and valleys, (c) Featured histogram with Peaks and Valleys, (d) Segmented image using the FL, (e) Segmented image using FB, (f) Segmented image using Otsu's approach, (g) Segmented image using Kwon's approach.

work focuses on incorporating new feature and also weighted features to reduce the percentage of misclassified pixels.

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