

# Image Segmentation Using Thresholding and Genetic Algorithm

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## Abstract

**In this paper the problem of image segmentation is addressed using the notion of thresholding. A new approach based on Genetic Algorithm (GA) is proposed for selection of threshold from the histogram of images. Specifically GA based crowding algorithm is proposed for determination of the peaks and valleys of the histogram. Experimental results are provided for histogram with bimodal feature, however, this technique can be extended to multi threshold selection for histograms with multimodal feature.**

## Index Terms

Segmentation, Genetic Algorithms (GAs)

## 1 Introduction

It is important in picture processing to select an adequate threshold of gray level for extracting object from there background. Image thresholding is a necessary step in many image analysis 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 including those pixels with their gray values above a certain threshold, and the other including those with grey values equal to and below the threshold. This is called bi-level thresholding. Generally, one can select more than one threshold, and use them to divide the whole range of gray values in to several sub ranges. This process is called multilevel thresholding. Most thresholding techniques [5]-[8] utilize shape information of the histogram of given image while selecting thresholds.

In an ideal case, for images having two class, the histogram has a deep and sharp valley between two peaks representing objects and back ground respectively. Thus the threshold can be chosen at the bottom of this valley [5]. 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, often producing no traceable

valley. Rosenfeld et. al [6] proposed the valley sharpening techniques which restricts the histogram to the pixels with large absolute values of derivatives, S. Watanable et. al.[9] proposed the difference histogram method, which selects threshold at the gray level with the maximal amount of difference. These utilize information concerning neighboring 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 grey 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 [8]. However, such methods are tedious and computationally involved.

In our proposed method we used GA to find out the peaks and valley in bimodal class of images. GAs are used for function optimization process and hence determining the global optimal solutions. In last couple of years there were new strategies and algorithms proposed to detect the global as well as local solutions in a nonlinear multimodal function optimization [14]-[18]. Crowding originally proposed by Dejong (1975) helps to maintain multiple peaks (Global as well as Local) in multimodal function optimization problem. We have considered the images whose histogram has two peaks. Crowding method will help us to detect the two peaks. After getting the two peaks we can use GA to find out the valley bottom between these peaks. Here we have considered both types of image having flat valley as well as sharp valley in the histogram. Our discussion is confined to the elementary case of threshold selection where only the gray-level histogram suffices without other a priori knowledge. Our algorithm does not require any valley sharpening techniques.

## **2 Problem Statement**

The problem considered is to extract objects from their background. Thresholding is a popular tool for segmenting grey level images. The approach is based on the assumptions that object and background pixels in the image can be distinguished by their gray level threshold. The dominant values of object and background intensities the original grey levels image can be transformed in to a segmented image of two classes (for example; one object and the other background). Although the method appears to be simple, it is an important and basic one with wide applicability. We have only considered the histogram without any priory information. For a two class problem the aim is to determine a threshold at the grey value in the valley between the two peaks of the histogram. Determination of these two peaks is not an obvious task. Prewitt et al.[5] proposed the mode method. In which they

chose thresholds at the valleys (or antimodes) on the histogram. The automatic selection scheme involved some smoothing of the histogram data, searching for modes, and placing thresholds at the minima between them. Their method relied heavily on the structure of the gray level histogram, which contained peaks and valleys corresponding to gray level subpopulation of the image. Object and background regions (represented by histogram peaks) were assumed to be of fairly constant gray level, and to differ in average gray level. Edges were composed of intermediate grey levels and were less populated than either object or back grounds. Heuristic search method also fails to find the two peaks. Also it is difficult to find the exact threshold point if the valley is flat. However, the bottom of the valley is some thing difficult to locate.

Several methods have been proposed for transforming the histogram so that the valley is deepened, or is converted to peak. Thus, correct threshold may be selected efficiently. In our proposed method we applied GA to find the two peaks. Genetic Algorithms are used for getting the global solution. But in this problem we need global as well as local solutions i.e. determining the niches in the multimodal function. To maintain stable sub-population by replacing population with like individuals is known as Crowding method. We have used crowding mechanism to maintain subpopulation at the two peaks. After getting the two peaks we used the GA to determine the valley bottom between the peaks. GA used here to get the global solution. We found that this method works even if the valley is flat. We do not need any valley sharpen method to depend the valley of histogram. Experimental results presented here are only for two class images. The histogram of these images have two distinct peaks. Our proposed method is works efficiently if the histogram of the given image has clearly two modes of any size i.e the image has a two class image. Our proposed algorithm fails to segment properly if there are more than two class in an image (histogram has more than two peaks).

### **3 GA Based Class Model**

Usually GAs are used for optimization of nonlinear multimodal function and hence determines the global optimal solution. In case of nonlinear multimodal function optimization, the problem of determining the global optimal solution as well as the local solution reduces to determining the niches in the multimodal function. Thus the problem boils down to determining the niches of the multimodal function. Substantial efforts has

been directed in this direction for last couples of years [14-18], where new strategies and algorithm are proposed.

### 3.1 Crowding Method

To maintain stable sub-population by replacing population with like individuals can be broadly called crowding method. Crowding, originally proposed by Dejong in the year 1975 is motivated by analogy with competition for limited resourced among similar member of a natural population. Dissimilar population member often occupy different environmental niches. Older members of the niche will be replaced by the fittest of the younger member. Stochastic replacement error prevents the basic crowding algorithm from maintaining more than two peaks of multimodal fitness.

Deterministic crowding eliminates replacement error and maintains multiple peaks. It works by randomly pairing the population to yield  $n/2$  pairs for  $n$  individuals in the Population. Each pair of parent yields two children by undergoing crossover and mutation and these two children compete with the parent. In tournament selection, the pair containing the maximally fit element wins.

In the deterministic crowding, sampling occurs without replacement. We will assume that an element in a given class is closer to its own class than to elements of other class. Our previous assumption is that a crossover operation between two elements of same class yields two elements of that class, and crossover operation between two elements of different classes yield one element of the both classes. Therefore, if two elements of class-A gets 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 form class-A, and the other from class-B. the class-A offspring will compete against the class-A parent, the class-B offspring against the class-B parent. The end result will be that one element of the both classes advances to the next generation, and hence no net change. Since each element receives exactly one trial, the mean and variance for the number of population elements in class-A after one generation are  $\mu_A=I_A$  and  $\sigma_A=0$ .

### 3.2 Salient Steps of the Proposed Algorithm.

- (i) Initialize randomly a population space of size  $N$  (each element corresponds to a gray value between 0 to 256) 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 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  $n$  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 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.

## 4 Results and Discussion

In simulation, we have considered images whose histograms exhibit bimodal feature. Fig 1.(a) is the original image of size 507x284, whose normalized histogram is shown in Fig. 1(b). From Fig. 1 (b), it is observed that there are two clearly separated peaks having unequal heights. The distributions of the two sets of gray values are not analogous. Selection of a global threshold now reduces to determine a suitable gray value in between the peaks of the histogram. The proposed crowding algorithm is used to determine the two peaks. The parameters of the proposed algorithm are (i) number of population elements “ $N$ ”

is 20 (ii) crossover probability  $P_c = 0.9$  (iii) mutation probability  $P_m$  follows a decaying exponential function with starting value 0.05. The valley point between the two peaks in the histogram, in other words the optimal threshold is obtained by searching the minimum gray value in between the gray values corresponding to two peaks. This minimum point is determined by employing Genetic Algorithm (GA). Fig. 1(d) shows the detected peaks and valleys using the proposed algorithm. Here, the peaks are at gray value 91 and 148 and valley is at gray value 117. Using the gray value 117 as threshold value segmentation of the original image is carried out and the segmented image is shown in Fig. 1(d). From Fig 1(d), it can be observed that the object and background is clearly distinguished.

Fig 2(a) shows the original image of size 238x238 and the corresponding histogram is shown in Fig. 2(b). From this histogram it can be seen that the two modes are clearly separated by a long valley. Fig 2(c) shows the peaks and valley detected by the proposed algorithm. Peaks are at gray values 2 and 187 and the valley is at gray value 58. The segmented image is shown in Fig. 2(d) by taking gray value 58 as threshold.

Fig. 3(b) shows the histogram of another image shown in Fig. 3(a). The peaks and valleys found by our proposed algorithm are shown in Fig. 3(c). Thus the threshold is selected to be 98 and the segmented image using this threshold is shown in Fig. 3(d). Thus in this case also proper segmentation could be achieved.

Fig. 4(b) shows the histogram of the image shown in Fig. 4(a). From this histogram we can see that the two peaks are quite uneven in size and they are separated by a flat valley. Fig. 4(c) shows the peaks and valley detected by the proposed algorithm. Taking the valley point gray value 136 as threshold the original image is segmented and the segmented image is shown in Fig. 4(d). Here the object is clearly segmented from the background.

Fig 5(a) is the original image of size 255x255 and the corresponding normalized histogram is shown in Fig. 5(b). From the histogram we can observe that there are three peaks. So this image consists of three classes. When the proposed two class algorithm is applied to this image it yields the two peaks at 122 gray value and other at 216 and 195 as the valley point for threshold which is shown in Fig. 5(c). After thresholding at this gray value 195 the image is shown in fig 5(d). It can be seen that there are some misclassification, the black dots in background and white dots in the object. This problem can be solved by modifying the algorithm for more than two classes.

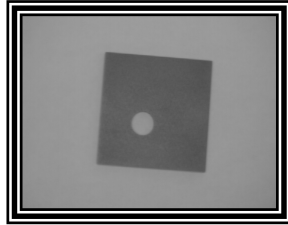


Fig. 1(a). Original Image of size 507x284

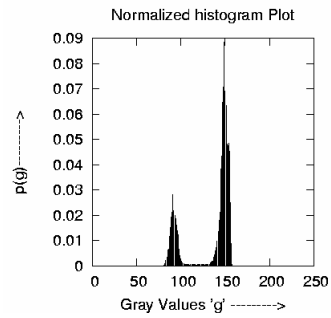


Fig. 1(b). Normalized Histogram of Fig 1(a)

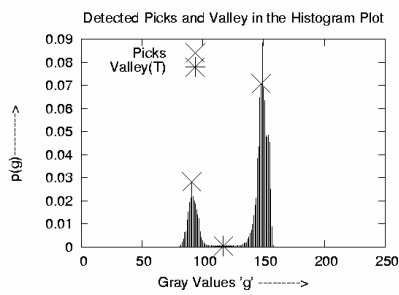


Fig. 1(c). Picks(91,148) and valley(117) detected using GA

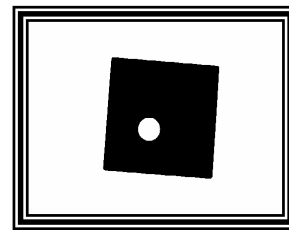


Fig. 1(d). Segmented Image after putting Threshold at the valley(117)

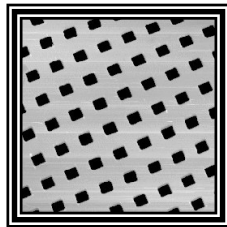


Fig. 2(a). Original Image of size 238x238

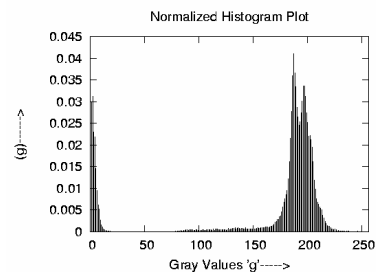


Fig. 2(b). Normalized Histogram of Fig. 2(a)

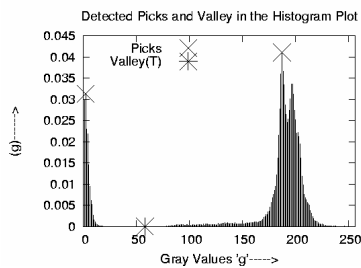


Fig. 2(c). Picks(2,187) and valley(58) detected using GA

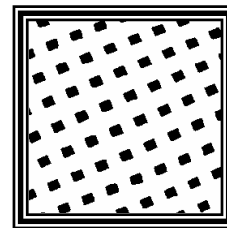


Fig. 2(d). Segmented Image after putting Threshold at the valley (58)



Fig. 3(a). Original Image of size 320x240

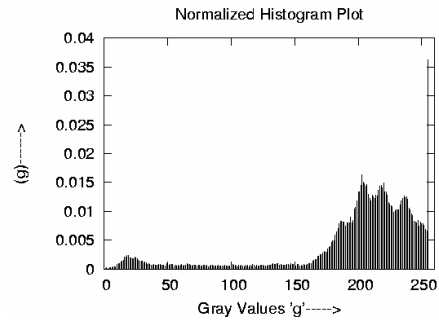


Fig. 3(b). Normalized Histogram of Fig. 3(a)

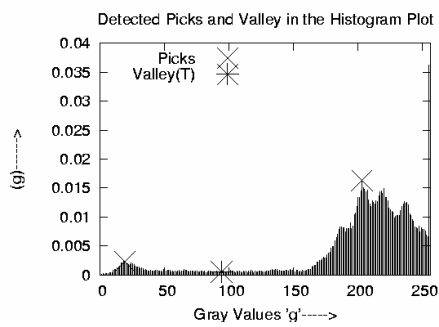


Fig. 3(c). Picks (19,203) valley(98) detected using GA



Fig. 3(d). Segmented Image after putting Threshold at the valley (98)

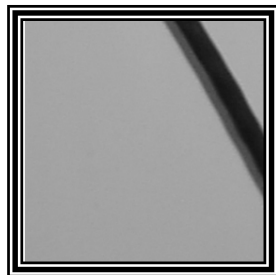


Fig. 4(a). Original Image of size 256x256

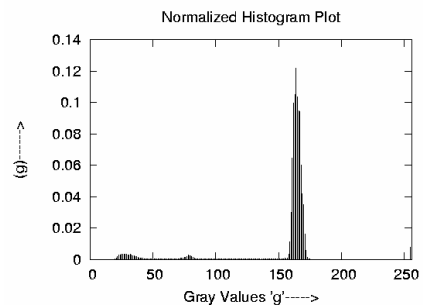


Fig. 4(b). Normalized Histogram of Fig. 4(a)

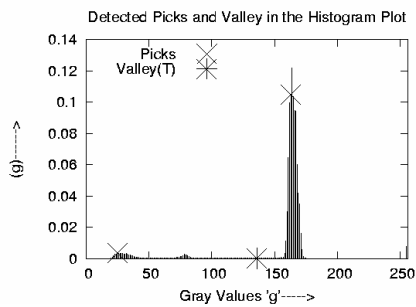


Fig. 4(c). Picks(25,163) and valley(136) detected using GA

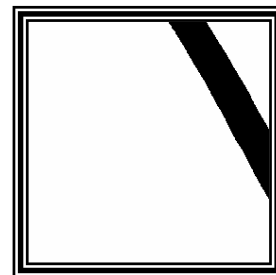


Fig. 4(d). Segmented Image after putting Threshold at the valley (136)





Fig.5(a). Original Image of size 255x255

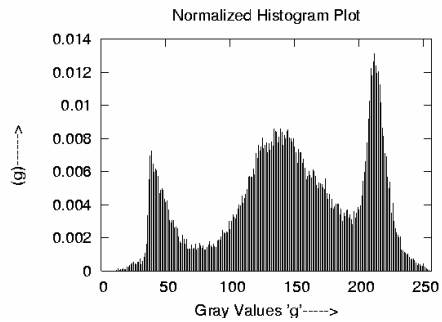


Fig. 5(b). Normalized Histogram of Fig. 5(a)

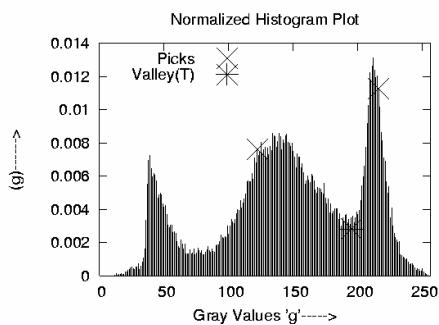


Fig. 5(c). Picks(122,216) and valley(195) detected using GA

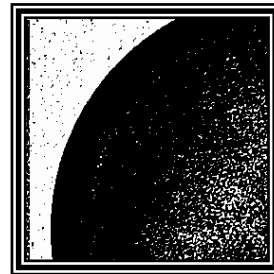


Fig. 5(d). Segmented Image after putting Threshold at the valley (195)

## 5 Conclusion

The problem of separating object from the background in a given image is considered. Hence, the problem boils down to determining the threshold using histogram of the given image. Often, in practice, the histograms do not show two clearly separated classes rather overlapping classes. Many methods have been suggested in the past for such kind of problem but still for overlapping classes, it is hard to determine a global threshold. Hence, attempts have been made by proposing a new approach to determine the global threshold for image segmentation. The algorithm is found to produce satisfactory results for images having histograms with bimodal feature. The algorithm fails for images having histograms with tri-modal features. Currently, attempts are made to address two class images with noises and images requiring multiple thresholds.

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