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Comparative Study on Thresholding

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Abstract*— Criterion based thresholding algorithms are simple and effective for two-level thresholding. However, if a multilevel thresholding is needed, the computational complexity will exponentially increase and the performance may become unreliable. In this approach, a novel and more effective method is used for multilevel thresholding by taking hierarchical cluster organization into account. Developing a dendogram of gray levels in the histogram of an image, based on the similarity measure which involves the inter-class variance of the clusters to be merged and the intra-class variance of the new merged cluster . The bottom-up generation of clusters employing a dendogram by the proposed method yields good separation of the clusters and obtains a robust estimate of the threshold. Such cluster organization will yield a clear separation between object and background even for the case of nearly unimodal or multimodal histogram. Since the hierarchical clustering method performs an iterative merging operation, it is extended to multi-level thresholding problem by eliminating grouping of clusters when the pixel values are obtained from the expected numbers of clusters. This paper gives a comparison on Otsu's & Kwon's criterion with hierarchical based multi-level thresholding..

***Keywords*— segmentation, thresholding, clustering, inter- class variance, intra-class variance dendogram**.

I. INTRODUCTION

The goal of image segmentation is to extract meaningful objects from an input image. Image segmentation is one of the most difficult low level computer vision task .The efficiency of any computer vision solution depends on the output of segmentation Process. All the subsequent task of computer vision, including feature extraction, model matching and object recognition, heavily depends on the quality of the image segmentation process. Thresholding is a simple but effective tool for image segmentation. Due to its simplicity thresholding is more practical for real-time implementation. The purpose of this operation is that objects and background are separated into non overlapping sets. The output of the thresholding operation is a binary image and in many applications of image processing, the use of binary images can decrease the computational cost of the succeeding steps compared to gray-level images. The purpose of this operation is that objects and background are separated into non overlapping sets. The output of the thresholding operation is a binary image and in many applications of image processing, the use of binary images can decrease the computational cost of the succeeding steps compared to gray-level images.

In 1979 Otsu [03] suggested minimizing the weighted sum of within–class variance of the foreground and background pixels to establish an optimum threshold. Minimization of within-class variance is tantamount to the maximization of between class-variance of two data sets. This method gives satisfactory results when the numbers of pixels in each class are close to each other. The function formulated by Otsu's [03] is one of the most referred thresholding method. but the criterion function proposed by Kwon's [14] not only involved the histogram of the image but also the information on spatial distributation of pixels. This criterion function optimizes intra-class similarity to achieve the most similar class and inter-class similarity to confirm that every cluster is well separated. The similarity function used all pixels in two clusters as denoted by their coordinates. The threshold value is obtained by taking hierarchical cluster organization into account by developing a dendogram of gray levels in the histogram of an image.

II. CLUSTERING

Clustering can be considered as a task to organize a data set into a number of groups such that patterns within a cluster are more similar to each other than the patterns (features) belonging to different clusters. In other words, clustering is an important technique for discovering an inherent structure in any given data sheet. Literature is very rich in clustering algorithms. All though purposed clustering algorithms proposed in literatures can be broadly divided into two categories.

(i) Hierarchical clustering.
(ii) Partitioned clustering.

Hierarchical clustering builds a cluster hierarchy or, in words, a tree of clusters, which is also known as dendogram. Where as, Partitioned clustering obtains a single partition of the data rather than a cluster structure such as the dendogram produced in hierarchical technique. In this chapter, we developed a multi thresholding algorithm using hierarchical clustering.

A. *Hierarchical clustering*

Hierarchical clustering builds a cluster hierarchy or, in words, a tree of clusters, which is also known as dendogram. There are two approaches to achieve hierarchical clustering as follows;

(i) Agglomerative
(ii) Divisive

Agglomerative clustering executes in a bottom top fashion, which initially treats each data point as a singleton cluster and then successively merges clusters until all points have been merged into a single remaining cluster.Divisive clustering, in the other hand, initially treats all the data points in one cluster and then split them gradually until the desired numbers of clusters are obtained. Proposed Multiclass thresholding method is based on agglomerative clustering approach.

B. *Proposed Hierarchical Clustering Based multiclass Thresholding*

In this approach, a dendogram has been developed from the gray level histogram based on the similarity measure which involves the inter-class variance of the cluster to be merged and the intra-class variance of the new merged cluster. The bottom-up generation of clusters employing a dendogram by the proposed method yields a good separation of the clusters and obtains a robust estimate of the threshold. Such type of clustering approach will yield a threshold to clearly separate the object and the background from a complex scene. Since, this approach initially treats each non empty gray level in the histogram as a single cluster and then successively merges clusters until all points have been merged therefore, this approach is suitable for multi level thresholding problem.

C. *Cluster merging strategy and threshold detection*

Let C_k be the k^{th} cluster of gray levels in the ascending order and T_k be the highest gray level in the cluster C_k. Consequently, the cluster Ck contains gray levels in the range $[T_{k-1}+1, T_k]$, if we define $T_0 = -1$. The proposed algorithm of cluster merging is summarized as follows

Step 1. It is assumed that the target histogram contains K different non-empty gray levels. At the beginning of the merging process, each cluster is assigned to a particular gray level i.e. the number of cluster is k and one and each cluster contains only one gray level.

Step 2. The following two steps are repeated (k- t) times for t-level thresholding.

2.1. The distance between every pair of adjacent clusters is computed. The distance indicates the dissimilarity of the adjacent clusters.

2.2. The pair of the smallest distance is found, and these clusters are unified into one cluster. The index of clusters C_k and T_k are reassigned since the number of cluster is decreased one by the merging.

Step 3. Finally t clusters, C_1, C_2, Ct , ….,are obtained. The gray levels $T_1, T_2, ..., T_{t-1}$, which are the highest gray levels of the clusters, are the estimated thresholds. For the usual two-level thresholding, t = 2 and the estimated threshold is T1, i.e., the highest gray level of the cluster of lower brightness. For multiclass thresholding t = n where, "n" is the number of classes. For example in case of three class problem t = 3 and the estimated thresholds are T1 and T2 where, T2 is greater than T1. The highest gray level of the cluster of lowest brightness is T1 and T2 is the highest gray level of the center cluster that is between highest brightness and lowest brightness clusters.

D. *Distance measurement*

The proposed definition of the distance between two adjacent clusters in the histogram is based on both the difference between the means of the two clusters and the variance of the resultant cluster by the merging. To measure the above two characteristics, we regard the histogram as a probability density function. Let h(z), z =0 ,1 , ..., L-1, be the histogram of the target image, where z indicates the gray level and L is the number of available gray levels including empty ones. The histogram h (z) indicates the occurrence frequency of the pixel with gray level z. If we define p (z) as p(z)=h(z)/N, where N is the total number of pixels in the image, p(z) is regarded as the probability of the occurrence of the pixel with gray level z. We also define a function P (C_k) of a cluster C_k as follows:

$$P(C_k) = \sum_{z=T_{k-1}+1}^{T_k} p(z), \sum_{k=1}^{k} p(c_k) = 1$$

(2.1)

This function indicates the occurrence probability of pixels belonging to the cluster Ck . The distance between the clusters C_{k1} and C_{k2} is defined as

$$Dis(C_{k1},C_{k2}) = \sigma_1^{\,2}(C_{k1} \cup C_{k2})\sigma_A^{\,2}(C_{k1} \cup C_{k2}). \qquad (2.2)$$

The two parameters in the definition correspond to the inter-class variance and the intra-class variance respectively. The inter-class variance, $\sigma_1^{\ 2}$ (C_{k1}, C_{k2}), is the sum of the square distances between the means of the two clusters, and the total mean of both clusters, and defined as follows

$$\sigma_1^{\ 2}(C_{k1} \cup C_{k2}) = \frac{P(C_{k1})}{P(C_{k1}) + P(C_{k2})}[m(C_{k1}) - M(C_{k1} \cup C_{k2})]^2 + \frac{P(C_{k2})}{P(C_{k1}) + P(C_{k2})}[m(C_{k2}) - M(C_{k1} \cup C_{k2})]^2$$

$$= \frac{P(C_{k1})P(C_{k2})}{(P(C_{k1}) + P(C_{k2}))^2}[m(C_{k1}) - M(C_{k1} \cup C_{k2})]^2 \quad (2.3)$$

Where m (C_k) denotes the mean of cluster C_k, defined as follows.

$$m(C_k) = \sum_{Z=T_k-1}^{T_k} zp(z) \qquad (2.4)$$

And M ($C_{k1} \cup C_{k2}$) denotes the global mean of the clusters C_{k1} and C_{k2}, defined as follows.

$$M(C_{k1} \cup C_{k2}) = \frac{P(C_{k1})m(C_{k1}) + P(C_{k2})m(C_{k2})}{P(C_{k1}) + P(C_{k2})} \quad (2.5)$$

The intra class variance, $\sigma_A^{\ 2}(C_{k1} \cup C_{k2})$, is the variance of all pixel values in the merged cluster, and defined as follows.

$$\sigma_A^{\ 2}(C_{k1} \cup C_{k2})$$

$$= \frac{1}{P(C_{k1}) + P(C_{k2})} \times \sum_{Z=T_{k1-1}+1}^{T_{k2}} [(z - M(C_{K1} \cup C_{k2}))^2 p(z)] \quad (2.6)$$

The distance between the clusters C_{k1}, C_{k2} and C_{k3} is defined as

$$\mathrm{Dist}(C_{k1}, C_{k2}) = \sigma_1^{\ 2}(C_{k1} \cup C_{k2})\sigma_A^{\ 2}(C_{k1} \cup C_{k2}). \quad (2.7)$$

III. SIMULATION

The proposed HCBT is validated with the following images. The original image with histogram and the corresponding segmented images using Otsu's, Kwon's and HCBT multiclass thresholding approaches are shown and the differentiation can be visualized in Fig.-3.1, ig.-3.2, Fig.-3.3, Fig.-3.3 The detected threshold values are tabulated in the Table.-3.1.

Fig 3.1

(a) Original Image

Fig 3.2

(a) Original Image

Fig 3.3

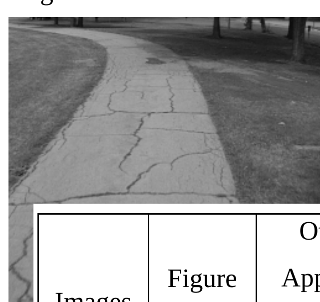

Fig 3.4

Images	Figure No	Otsu's Approach		Kwon's Approach		HCBT Approach	
		T1	T2	T1	T2	T1	T2
Home	3.1	120	182	64	266	141	193
Leena	3.2	91	148	98	223	70	132
Road	3.3	75	121	72	74	72	116

(Threshold value for three class problem by Otsu's, Kwon's and proposed HCBT Approach)

IV. RESULTS AND DISCUSSIONS

We have considered four multiclass scene images to validate our multiclass thresholding model. The home image in Fig.- 3.1 (a) has a histogram in Fig.- 3.1 (b). From the histogram it could be presumed that the number of classes may be more than three. In our work we have assumed the number of classes in an image is three. The segmented images using Ostu's, Kwon's multiclass thresholding and the HCBT as shown in the Fig. – 3.1 (c), (d) and (e) respectively. Know's multiclass thresholding produced the thresholds 64 and 66. From Fig.- 3.1 (d), it is clear that, Know's method failed to segment the image where as the Otsu's Multi thresholding algorithm produced thresholds 120 and 182 and HCBT multiclass thresholding approach produced thresholds 141 and 193. Comparing the segmented images of Otsu's and HCBT based approaches as shown in Fig. 3.1 (c) and (e). We could conclude that both are comparable to each other where as there are more misclassified pixels in the lawn area i.e. bottom of the image.

Leena image which was used in many literatures is shown in Fig 3.2 (a)and the corresponding histograms shown in the Fig. 3.2 (b). Fig 3.2 (c), (d) and (e) shows the three class segmented image of the Leena image using Ostu's, Kwon's and HCBT multiclass threshold approaches respectively. The threshold values detected are 91 and 148, 98 and 223, 70 and 132 with Ostu's Kwon's and HCBT based thresholding algorithms respectively. From the segmented images, it is observed that HCBT approach produced better results than the Ostu's approach where as Kwon;s approach segmented the image like a two class image. From Fig 3.2 (c), it could be observed that, there are lot of misclassification at the face, cap and body region, where as there are low amount of misclassification in the result obtained by HCBT as shown in Fig. 3.2 (d). HCBT method produced more misclassified pixels at the hair of the Leena Images.

Fig. 3.3 (a) shows a road image and the corresponding grey level distribution is shown in the Fig. 3.3 (b). Fig 3.3 (c), (d) and (e) show the three class segmented images of the Fig 3.3 (a) using Ostu's, Kwon's and HCBT approaches respectively. The threshold values detected by Ostu's approaches are 75 and 121. Kwon's approaches are 72 and 74 and HCBT approaches are 72 and 116. From Fig. 3.3 (c), (d), and (e) it could be observed that HCBT approach produced better result than the Ostu's and Kwon's multiclass thresholding approach. Both Ostu's and Kwon's segmented the images into nearly two classes.

The Sunrise image which is a low contrast image as shown in the Fig. 3.4 (a) having considered for testing of these three approaches. The histogram of the sunrise image shown in the Fig 3.4 (b) reflects a complex histogram having more than three dominant modes. The threshold values detected with Ostu's, Kwon's and HCBT approach are 77 & 141, 55 & 52 and 131 & 186 respectively. From Fig. 3.4 (d), it could be clearly observed that Kwon's approach failed to segment it into three classes due to the low distance between the two thresholds. Ostu's approach also failed to segment properly that is the size of the sun and the reflected sun in the water. In the segmented image the size of the sun is larger than the size in the original image. The segmented image produced by the HCBT approach produced a result with more effectively for future analysis.

V. PERCENTAGE OF MISS CLASSIFICATION ERROR

Percentage of Misclassification error (PME) reflects the percentage of background pixels wrongly assigned to foreground, and conversely, foreground pixels wrongly assigned to background. Miss classification error (ME) can be simply expressed as:

$$ME = 1 - \frac{|B_0 \cap B_k| + |F_0 \cap F_k|}{|B_0| + |F_0|}$$

PME = ME X 100%

Where B_O and F_O denote the background and foreground of the original (ground-truth) image, B_k and F_k denote the background and foreground area pixels in the test image, and |.| is the cardinality of the set. The PME varies from 0 for a perfectly classified image to 1 for a totally wrongly binarized image. Table 4.1

Image Name	Otsu's Method	Kwon's Method	Hcbt Approach
Home	15.66%	87.64%	13.94%
Lady	23.20%	59.23%	03.20%
Road	37.76%	37.87%	06.10%
Sun rise	59.74%	81.25%	17.57%

(Percentage of Misclassification Error for 3 Classes)

VI. CONCLUSIONS

In this dissertation, the problem of object and background classification using thresholding approach has been addressed. Histogram based thresholding has been popularized due to its simplicity for real time implementation. For a two class problem, the histogram represents the gray level distribution of the object class and the background class. The problem becomes complex when there will be substantial amount of overlapping between these two class gray level distribution. When there are more than one object class to be detected from the background, multiclass thresholding approach could be the solution for the segmentation. In this paper the consideration given to Otsu's and Kwon's approaches, for the extension of the multilevel thresholding problem. The complexity increases when these global thresholding approaches extend to multiclass thresholding. Here the hierarchical clustering based multiclass thresholding is introduced by using dendogram which is constructed from the histogram of the image. The final conclusion is that the hierarchical based multiclass thresholding outperform the multi-class thresholding approaches of the Otsu's and Kwon's criteria.

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