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A Survey on Threshold Based Segmentation Technique in Image Processing

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Abstract
The present paper describes the study of the threshold techniques in image segmentation. Image segmentation is one of the fundamental approaches of the digital image processing. Image segmentation is used widely in many applications. Several general purpose algorithms and techniques have been developed for image segmentation. Segmentation applications are involving detection, recognition and measurement of features. The purpose of image segmentation is to partition an image into meaningful regions with respect to a particular application. Segmentation techniques can be classified as either contextual or non-contextual. Thresholding is a Non-Contextual Approach. This method is based on a threshold value to turn a gray-scale image into a binary image. In Histogram Dependent Technique, a histogram is computed from all of the pixels in the image and this paper enumerates and reviews a comparative performance of threshold technique as Histogram Dependent Technique (HDT) based on Global Threshold, Local Threshold and Adaptive Threshold one another

Keywords*: Digital image processing, Image segmentation, Non-Contextual Approach threshold technique, Histogram Dependent Technique (HDT), adaptive threshold technique*

1. Introduction

The objective of digital image processing is extracting useful information from images without human assistance. The segmentation process for images with complicated structure is one of the most difficult problems in image processing and has been an active area of research for several decades. Segmentation divides an image into its constituent regions or objects. Segmentation of images is a difficult task in image processing. Still under research. Segmentation allows extracting objects in images. Segmentation is unsupervised learning.

Firstcategory is to partition an image based on a bruptchanges in intensity, such as edges in an image.Secondcategory is based on partit ioning an image into regions that are similar according to predefined criteria [1].This paper taken the study of these second category threshold techniques. Survey of some of the methods found in Weszka [19], Sahoo et al. [18], and Lee et al. [29].

2. Threshold

Thresholding is the simplest method of image segmentation. From a gray scale image, thresholding can be used to create binary images. Binary images are produced from color images by segmentation. Segmentation is the process of assigning each pixel in the source image to two or more classes. If there are more than two classes then the usual result is several binary images. In image processing, thresholding is used to split an image into smaller segments, or junks, using at least one color or gray scale value to define their boundary. The advantage of obtaining first a binary image is that it reduces the complexityof the data and simplifies the process of recognition and classification.

The most common way to convert a gray level image to a binary image is to select a single threshold value (T) [44].

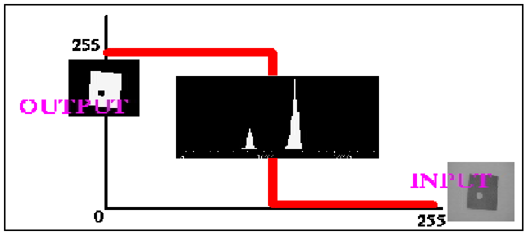

Figure 1: Thresholding non-contextual approach

The input to a thresholding operation is typically a gray scale or color image. In the simplest implementation, the output is a binary image representing the segmentation. Black pixels correspond to background and white pixels correspond to foreground (or vice versa). This method of segmentation applies a single fixed criterion to all pixels in the image simultaneously [28].
Image Segmentation = divide image into (continuous) regions or sets of pixels. The pixels are partitioned depending on their intensity value.
Segment image into foreground and background.
g(x, y) = 1 if f(x,y) is foreground pixel = 0 if f(x, y) is background pixel
In real applications histograms are more complex,
with many peaks and not clear valleys and it is not always easy to select the value of T.

$$g(x, y) = \begin{cases} 0 & f(x, y) < T \\ 1 & f(x, y) => T \end{cases} \quad (1)$$

This technique can be expressed as:
T=T[x, y, p(x, y), f(x, y]
Where $f(x, y)$ is the gray level and p (x, y) is some local property.
F(x, y) >T called an object point otherwise the point is called a background point.[1].
There are three types of thresholding algorithms.

- Global thresholding
- Local thresholding
- Adaptive thresholding

In adaptive thresholding, different threshold values for different local areas are used.

3. Global Thresholding

The global threshold applicable when the intensity distribution of objects and background pixels are sufficiently distinct. In the global threshold, a single threshold value is used in the whole image. The global threshold has been a popular technique in many years [6][7][8]. . When the pixel values of the components and that of background are fairly consistent in their respective values over the entire image, global thresholding could be used.
Global Thresholding = Choose threshold T that separates object from background.
If $g(x, y)$ is a threshold version of $f(x, y)$ at some global threshold T,

$$g(x,y) = \begin{cases} = 1 & \text{if } f(x,y) \geq T \\ = 0 & \text{otherwise} \end{cases} \quad (2)$$

There are a number of global thresholding techniques such as: Otsu, optimal thresholding, histogram analysis, iterative thresholding, maximum correlation thresholding, clustering, Multispectral and Multithresholding.

3.1. Threshold Selection based on Histogram based

The histogram based techniques is dependent on the success of the estimating the threshold value that separates the two homogenous region of the foreground and background of an image.
The (HDT) is suitable for image with large homogenous and will separate regions where all area of the objects and background are homogenous and except the area between the objects and back-ground.
Histogram based thresholding is applied to obtain all possible uniform regions in the image [10].
Let P1 and P2 be the gray value of the peaks of the histogram. The threshold value T is given by

T= (P1+P2)/2
Or T may be the gray level at the minimum between the two peaks.
T= min H (u)
U€ [P1, P2]
Where H (u) is the histogram value at gray level u between P1 and P2
The histogram based techniques is dependent on the success of the estimating the threshold value that separates the two homogenous region of the object and background of an image.

3.2. Threshold Selection based on Iterative

Iterative methods give better result when the histogram doesn't clearly define valley point. This method doesn't require any specific knowledge about the image. Iterative method has the ability to improve the anti-noise capability.
Ridler and Calvard [15] have described an iterative heuristic thresholding technique which is implicitly based on the assumptions described above. The initial threshold value, t0, is set equal to the average
brightness, 0. Thereafter, the new threshold value tk+1for the (k + 1)-th iteration is given by (this for- mutation is actually given in Trussell's comment [17] on the paper by Ridler and Calvard [15].
Where $(^{t}k^{)}$ and $_{2}{}^{(t}k)$ are the a posteriori mean values of the gray values below and above the previous threshold t_k, respectively, and G is the number of gray levels.
This iterative algorithm is a special one dimensional case of K-means clustering that converges at a local minimum. But the main disadvantage is, a different initial estimate for T may give a different result.

3.3. Threshold Selection based on Otsu's method

This method is used to overcome the drawback of iterative thresholding i.e. calculating the mean after each step. In this method identify the optimal threshold by making use of histogram of the image [11]. Otsu's method is aimed in finding the optimal value for the global threshold.
The main drawback of Otsu's method of threshold selection is that it assumes that the histogram is bimodal. This method fails if two classes are of different sizes and also with variable illumination.

3.4. Thresholding based on Maximum correlation

Brink [21] has demonstrated a thresholding method based on maximizing the correlation between the original gray level image and the threshold image
The gray levels of the two classes in the threshold image may be represented by the two a posteriori average values below and above the threshold.
However, as pointed out by Cseke and Fazekas [24] this optimization criterion is identical to the one used by Otsu, despite their deferent approach.

3.5. Multithresholding Methods

The global thresholding methods, such as Otsu [20], Pun [25, 26], Kapur et al [31], moment preserving [34], minimum error [27] can be extended to the case of Multithresholding.
Multilevel thresholding is a process that segments a gray-level image into several distinct regions. This technique determines more than one threshold for
the given image and segments the image into certain brightness regions, which correspond to one background and several objects. The method works very well for objects with colored or complex backgrounds, on which bi-level thresholding fails to produce satisfactory results.

3.6. Threshold Selection based on Clustering

The purpose of clustering is to get meaningful result, effective storage and fast retrieval in various areas.

3.6.1. Fuzzy c means clustering

Fuzzy c-means (FCM) is a data clustering technique in which a dataset is grouped into n clusters with every data point in the dataset belonging to every cluster to a certain degree [4]. of the MRI signal.
Fuzzy c-means (FCM) clustering [27, 34, and 36] is an unsupervised technique that has been successfully applied to feature analysis, clustering, and classifier designs in fields such as astronomy, geology, medical imaging, target recognition, and image segmentation. Fuzzy C-means its improvement methods algorithm and strategies for remote sensing image segmentation can offer less iterations times to converge to global optimal solution. . Its good effect of segmentation can improve accuracy and efficiency of remote sensing image threshold segmentation [32].

3.6.2. K-Means clustering

K-means clustering is an efficient method of threshold selection. Using this algorithm, the image is divided into k segments using (k-1) thresholds and minimizing the total variance within each segment. One of the most popular heuristics for solving the k-means

problem is based on a simple iterative scheme for finding a locally minimal solution [39]. This algorithm is often called the k-means algorithm [21], [38].
Clustering based on k-means is closely related to a number of other clustering and location problems. These include the Euclidean k-medians (or the multisource Weber problem) [38], [45] in which the objective is to minimize the sum of distances to the nearest center and the geometric k-center problem [42] in which the objective is to minimize the maximum distance from every point to its closest center. There are no efficient solutions known to any of these problems and some formulations are NP-hard [4].For further information on clustering and clustering algorithms, see [43]. This method works well if the spreads of the distributions are approximately equal, but it does not handle well the case where the distributions have differing variances.

4. Local Thresholding

A single threshold will not work well when we have uneven illumination due to shadows or due to the direction of illumination. The idea is to partition the image into *m x m* sub images and then choose a threshold.

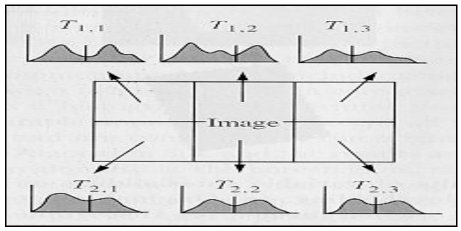

Figure 2: Sub images of an image

Tij for each sub image.
Local thresholding can be used effectively when the gradient effect is small with respect to the chosen sub image size. local thresholding technique, the threshold value T depends on gray levels of f(x, y) and some local image properties of neighboring pixels such as mean or variance [5]. Threshold function T(x, y) is given by

$$g(x, y) = \begin{cases} 0 & \text{if } f(x, y) < T(x,y) \\ 1 & \text{if } f(x, y) \geq T(x, y) \end{cases} \qquad (3)$$

Where $T(x, y) = f(x, y) + T$
First the gray level histogram for a sub image is approximated by a sum of two Gaussian distributions, then the threshold is obtained by minimizing the classification error with respect to the threshold value. Some experiments on this method were done in [13]

5. Adaptive Thresholding

Global thresholding method is not suitable whenever the background illumination is uneven. Adaptive thresholding typically takes a grayscale or color image as input and, in the simplest implementation, outputs a binary image representing the segmentation. For each pixel in the image, a threshold has to be calculated. If the pixel value is below the threshold it is set to the background value, otherwise it assumes the foreground value. In adaptive thresholding, different threshold values for different local areas are used
There are two main approaches to finding the threshold: (i) the Chow and Kaneko [23[approach and (ii) local thresholding. The assumption behind both methods is that smaller image regions are more likely to have approximately uniform illumination, thus being more suitable for thresholding.. Adaptive thresholding is used to separate desirable foreground image objects from the background based on the difference in pixel intensities of each region. The drawback of this method is that it is computational expensive and, therefore, is not appropriate for real-time applications.
An alternative approach to finding the local threshold is to statistically examine the intensity values of the local neighborhood of each pixel. The statistic which is most appropriate depends largely on the input image. Simple and fast functions include the mean of the local intensity distribution, local adaptive thresholding, on the other hand, selects an individual threshold for each pixel based on the range of intensity values in its local neighborhood. This allows for thresholding of an image whose global intensity histogram doesn't contain distinctive peaks.
Chow and Kaneko [22, 23] suggest the use of a 7 X 7 window for local thresholding. In their method, the original image is divided into 7 x 7 sub images and a threshold is computed for each sub image. However, a threshold is not computed for sub images with unimodal gray level histogram. For X-ray angiograms Fernando and Monro [30] suggest a local thresholding method.

6. Conclusion

Otsu method works well for some images and give poor results for certain types of images. The results from Otsu have too much of noise in the form of the background being detected as foreground. The main advantage is the simplicity of calculation of the threshold. Since it is a global algorithm it is well suited only for the images with equal intensities. The method does not work well with variable

illumination This might not give a good result for the images with lots of variation in the intensities of pixels. The drawback of adaptive thresholding is that it is computational expensive and, therefore, is not appropriate for real-time applications.
The study also reviews the research on various research methodologies applied for image segmentation and various research issues in this field of study. This study aims to provide a simple guide to the researcher for those carried out their research study in the image segmentation

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