Multilevel Global Segmentation of Digital Images

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Abstract— The digital image processing has been applied in several areas and, in an initial stage, the segmentation is used to separate the image in parts that represents an object of interest that may be used in a specific study. In this context, this project aims to presents an adaptable segmentation method that can be applied to different type of images, providing a better segmentation. The proposed method is based in a model of automatic multilevel thresholding and considers techniques of group histogram quantization, analysis of the histogram slope percentage and calculation of maximum entropy to define the threshold. The technique was applied to segment the cell core and potential rejection of tissue in myocardial images of biopsies from cardiac transplant. The results are significant in comparison with those provided by one of the best known segmentation methods available in the literature.

Keywords-digital images; segmentation; thresholding

I. Introduction

The biological vision system is one of the most important means of exploration of the world to the humans, performing complex tasks with great ease such as analysis, interpretation, recognition and pattern classification. For this reason many studies attempt to produce artificial vision systems with the same efficiency of the biological system, that is still a highly complex task [1].

One possibility to represent an artificial vision system efficiently is to use appropriate methods of segmentation, considered as a first step for analyzing an image, it allows to separate the objects in parts, according to some criterion of uniformity [2]. For high quality segmentation systems, digital image processing is used in a primary stage of thresholding to separate the object of the rest of the image.

The thresholding consists in identifying in an image, a threshold of intensity in which the object distinguishes better of the back of the image, and in most cases, the choice of threshold takes a subjective criterion of a human operator. Several methods had been proposed to do this automatically based on different criteria in the image, such as those proposed in [3], [4], [5], [6], [7] e [8]. However, in many cases it is not achieved a threshold that provides a good segmentation of the entire image. For such situations are applied techniques of variables and multilevel thresholding based on analytical studies, using the parameters of statistical distribution of gray levels, or graphics, using the histogram display the gray level image.

For this, [9] proposed a methodology where the algorithm automatically gets the multilevel threshold, by analyzing the histogram. The method finds the histogram valleys, which are the places where the thresholds and therefore the subdivision of the image are concentrated. However the method proves effective in cases where the image and the histogram are well defined, for cases where the image is not presented optimally, with noise, distortion and nonstandardized histograms, the method does not produce an effective threshold that identifies the objects in the image quality. In this context, the paper presents an improved version of the model of multilevel automatic thresholding described in [9] to prevent the identification of not significant thresholds and allow more control during the step of feature extraction in artificial vision systems.

II. Metodology

As in [9] we used a methodology to detect the multilevel thresholds, however in order to define more precisely the amount of desired objects and their respective thresholds, we added some techniques such as division of the histogram into groups and analysis of the percentage of slope. We also adapted the method of valleys analysis. Another possibility is to set the filter size that is a parameter who defines how the filter will smooth the image.

A. *Histogram Quantification*

To evaluate the histogram in specific groups, the user should set the size of the group. If the given value is 1 then the process analyzes pixel by pixel. For values greater than 1, the value used in the process of iteration of the algorithm is the value that was defined by the user. To illustrate, consider a group of 10 figures and 256 gray levels. The first group will include the gray levels from 0 to 9, the second from 10 to 19 and so on, until the latter is 250 to 255, with 6 levels of gray.

B. Valleys Analysis

The identification of the histogram valleys is very important, because in these valleys the thresholds are concentrated, and therefore the division of classes. The algorithm identifies automatically these valleys using the transition of the histogram values signals, which is done in the following way:

- First you compare the first group's value, which was determined in the histogram segmentation, with this group's last value. If the first is lower it means that the histogram values are increasing and the signal is positive. On the other hand, the histogram values are decreasing and the signal is negative.
- The next step is to identify the sign of the next group, every time there is a transition from a negative to positive, a valley is identified.

Once you found the first valley, you pass to the next step, the analysis of the percentage of slope.

C. Analysis of the slope percentage

The determination of thresholds based on an analysis of vouchers may include differences in cases where there is a distribution of values in the histogram, without valleys or valleys insignificant, with little variance. For the type of image analyzed, we identified that an effective threshold would be near to the base of a group that has a considerable percentage of slope. This minimum percentage of slope is set by the user, who may adjust according to the type of image.

This approach involves calculating the slope achieved by the difference of the average of the last three values of the group with the first three. If this difference is greater than the parameter set, the scanning of the slope percentage is interrupted and go to the step of identifying the threshold. If the difference is smaller, the histogram scan continues until the difference of means is greater. This strategy avoids identifying groups and trace thresholds for classes with little variation, separating objects with common characteristics.

D. Threshold identification using maximum entropy

Having established a group with valley, the threshold identification is calculated by determining the maximum entropy, which is achieved from probabilistic calculations. In this context, we consider an image as a result of a random process, where the probability pi corresponds to the probability of a pixel of the image taking a value of intensity i (i = 1, .., n) [4], as shown in (1) and (2). The gray level with the highest entropy is identified as a threshold. After identifying the threshold, we return to the stage of analysis of the valleys until the entire histogram has been processed.

$$H = -\sum_{i=1}^{n} p_i * \log p_i \qquad (1)$$

$$p_i = \frac{n_i}{N} \qquad (2)$$

where H is the entropy of the image, n is the total number of outputs, i.e., the number of gray levels of image; p_i is the probability of gray level i to be found in the image; n_i represents the number of pixels with intensity i and N is the total number of pixels in the image.

E. Images Processed and Compared Parameters

We used for study, medical heart imaging, that present some specific characteristics, which are found in the following object classes, core, fibrous tissue, muscle and tissue rejection, and also because they are subject to an existing study to analyze the degree of rejection in heart transplants. A total of 120 images were processed with proposed algorithm.

To analyze the results, we compared three items, namely: the thresholds outlined, that are the points that are the division of the objects or classes, the average gray level for each class, and the total score for each class, as well as differences of the thresholds. The average gray levels and of the total of points are computed by the difference between the methods regarding the total possible of the image, for example, in the thresholds and gray levels, there are 256 possible gray levels, so the difference is calculated regarding 256. For the total points, it's calculated regarding the total of points of the image, for example, an image 800x600 pixels has 480,000 points. Thus, the calculation can be done according (3).

$$d = \frac{(a-b)*100}{c} \qquad (3)$$

where d is the difference, a is the value of the first method, b is the value of the second method and c is the value of the total possible gray levels (for the calculation of the thresholds and average gray levels), or the total points of the image (for the total points calculation).

III. Tests and Results

In the studied images we used four different input parameters, the image format to be processed, the size of the histogram division group, the filter size and the percentage of slope to be used to identify thresholds. To demonstrate the method and the results, it is compared the proposed method with one of the best known, [3]. As an example, was used the Figure 1, with the following input parameters: the image format = jpg, size of the histogram division group = 10, filter size = 5 and percentage of slope = 35%. These parameters can be adjusted depending on the type of image, in order to obtain an optimal segmentation. The results and the differences, comparing the thresholds, the average gray level and total points are shown in Tables I, II and III, respectively.

It is possible to verify that thresholds presented by [3] provided a significant difference in the thresholds, in the average gray levels and in the total points of each class. These characteristics may indicate that only regions of interest were selected, making the processing performed by patters recognition algorithms. To exemplify visually the results obtained with 120 images processed, the Figures 2 and 3 shows the results obtained from the segmentation by maximum entropy and the Figure 4 shows the result with the Otsu's method.

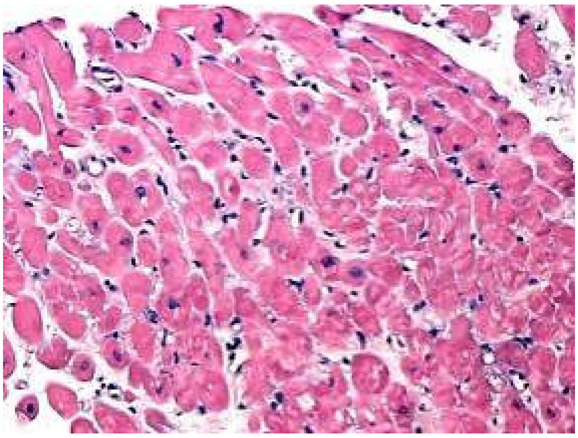

Figure 1. Original Image.

TABLE I. COMPARISON BETWEEN THE AVERAGE THRESHOLDS OBTAINED BY THE TECHNIQUE OF MAXIMUM ENTROPY THRESHOLDING AND OTSU (1978)

	Thresholds	
Otsu	139	203
Maximum Entropy	70	240
Diference	26.95%	14.45%

TABLE II. COMPARISON BETWEEN THE AVERAGE GRAY LEVELS OBTAINED BY THE TECHNIQUE OF MAXIMUM ENTROPY THRESHOLDING AND OTSU (1978)

	Average Gray Level		
	Class 1	**Class 2**	**Class 3**
Otsu	104.91	172.44	232.38
Maximum Entropy	41.12	165.99	243.55
Diference	24.92%	2.52%	-4.36%

TABLE III. COMPARISON BETWEEN THE AVERAGE TOTAL POINTS OBTAINED BY THE TECHNIQUE OF MAXIMUM ENTROPY THRESHOLDING AND OTSU (1978)

	Total Points		
	Class 1	**Class 2**	**Class 3**
Otsu	52160	277376	150464
Maximum Entropy	13823	408421	57756
Diference	7.99%	-27.30%	19.31%

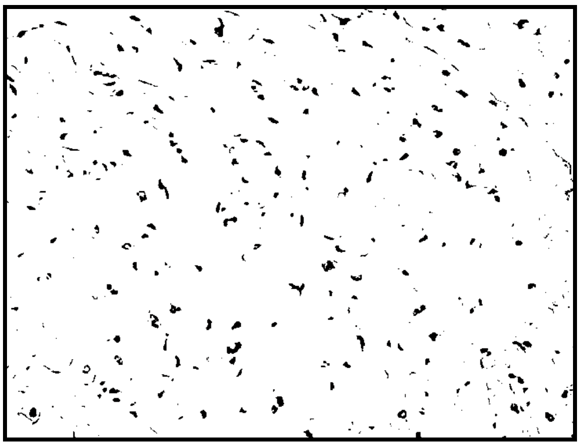

Figure 2. Result of image processing shown in Fig 1, showing the cell core or tissue rejection (class 1) obtained with the maximum entropy.

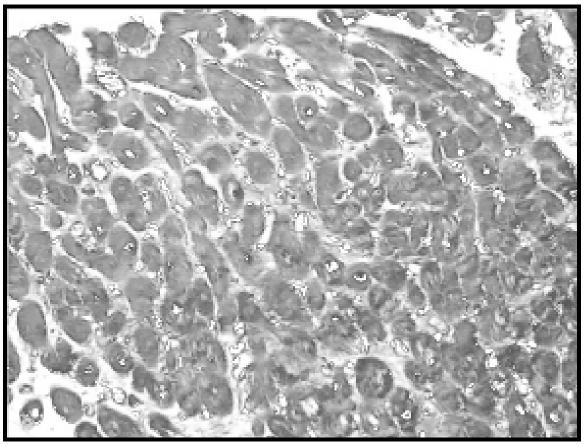

Figure 3. Result of image processing shown in Fig 3, showing cardiac muscle (class 2) with the maximum entropy.

The third class is composed of fibrous tissue, however, it is the tissue rejection or cell core that is used to compare with [3], because this is the aim of the study. As observed, the segmentation by [3] identified, in some areas, as cell nucleus or tissue rejection where, in fact, occur the presence of heart muscle. This difference in the segmentation can significantly disrupt the diagnosis of the image.

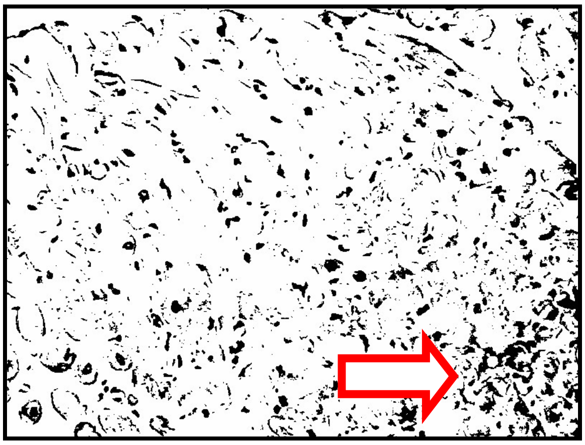

Figure 4. Image (Fig. 1) processed with the Otsu's method (1978). The indication shows cardiac muscle (class 2) included as the cell core or tissue rejection (class 1).

IV. CONCLUSIONS

According to used method, it was possible to find the images thresholds, and, therefore, segmenting them, presenting satisfactory results. Compared with the method shown in [3], for the studied images, the proposed technique shows better results because it allows the adjustment of parameters such as group size and slope percentage of the histogram, factors that influence the threshold values. Another important aspect is that the technique is based on the valleys analysis and in the characteristics of the histogram, and not only in probabilistic calculations. The method used in [3] includes false regions for the analysis of rejection, including not relevant information to the processing. This can lead to an erroneous diagnosis of the analyzed image.

The proposed technique identifies clearly cell core, fibrous tissue, muscle and tissue rejection, in myocardial images of biopsies from heart transplant patients, with advantages over one of the best known and widespread method in the literature. These characteristics are significant aspects of the developed technique, and it allows the application to other image types, since the input parameters are adjustable to the studied case. This versatility and quality of results make the developed technique a considerable alternative to be applied during the stage of feature extraction in artificial vision systems

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