

13—6 A Novel Multilevel Thresholding Method Based on Finding the Consistent Peak of Correlation Function

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Abstract

In this paper a novel multilevel thresholding method is proposed based on selecting the consistent peak of correlation function over the interested histogram region. The histogram is separated into two more regions up to the cost function is reached minimum. In the separation process of the histogram, a novel dichotomisation method is used. In general, correlation function of an image histogram may have some peak points. In the method proposed by Yen, threshold is placed in the maximum point of the correlation function. In our proposed method not only the maximum of the correlation function is considered but also other local maximums are taken into consideration. The main contribution of this method is to evaluate the all peaks' location of TC function as candidate threshold location. These points may have some important information in the sense of segmentation by human eye. The proposed method has been tested on some set of images and satisfactory results have obtained.

1. Introduction

Image thresholding is a fundamental process in image processing and computer vision applications. Furthermore a multilevel thresholding technique plays an important role, especially in those imaging problems where the prime objectives are to establish crisp boundaries in order to partition the image into its meaningful regions and extract its features [1].

Thresholding techniques can be classified as bilevel and multilevel thresholding. The object(s) in the scene can be extracted from background by bilevel or multilevel thresholding methods roughly, depends on the nature of the scene [2].

The multilevel thresholding techniques can also be classified into two categories. In the first category, the method defines the number of thresholds and threshold values automatically. But in the second category, the number of thresholds

is pre-defined dependent of the nature of the scene. This type of methods calculates only the locations of the thresholds.

2. Automatic Thresholding Criterion

An automatic thresholding criterion was proposed devoted to multilevel thresholding purpose in reference [3]. This method uses the cost function in the following equation.

$$C(k) = r * (Dis(k))^{1/2} + (\log_2(k))^2 \quad (1)$$

The first term of $C(k)$ measures the cost incurred by the discrepancy between the thresholded and original images, and the second measures the cost resulted from the number of bits used to represent the thresholded image. The square root of discrepancy - $Dis(k)$ has a similar meaning to the standard deviation of random variable. In this equation $r=0.8$ is a constant [3] and k is the classification number that the gray-levels are classified. Optimum class number k^* is determined by the following equation.

$$C(k^*) = \min \{C(k)\} \quad (2)$$

The interested image histogram region is separated into two classes sequentially up to minimum of cost function is reached [3]. In the dichotomisation process of the histogram, MCC (Maximum Correlation Criterion) based bilevel thresholding is used [3]. In each step choosing the distribution with the largest variance and applying MCC to it this selected distribution can be further dichotomised into two more distributions.

2.1. Maximum Correlation Criterion (MCC) based bilevel thresholding

Let X be a discrete random variables with finite or countable infinite range, ($R=\{x_0, x_1, \dots\}$) and P_i

denote $\text{Prob}\{X=x_i\}$. The correlation function of X is defined by the following equation [3].

$$C(X) = -\ln \sum_{i \geq 0} P_i^2 \quad (3)$$

Let's define the notation for the thresholding purpose.

$f(x,y)$: NxN image,

$h(i)$: i^{th} gray-level of the image histogram,
 $p_i=h(i)/(N^2)$: probability of the i^{th} gray-level,

$$P(s) = \sum_{i=0}^{s-1} p_i : \text{the total probability up to } (s-1)^{\text{th}} \text{ gray-level},$$

A: the distribution between $(0,s-1)$ gray-levels,
B: the distribution between $(s,m-1)$ gray-levels.

The total amount of correlation provided by distributions A and B can be defined in the following equation [3].

$$TC(s) = C_A(s) + C_B(s) = -\ln \sum_{i=0}^{s-1} \left(\frac{P_i}{P(s)} \right)^2 - \ln \sum_{i=s}^{m-1} \left(\frac{P_i}{1-P(s)} \right)^2 \quad (4)$$

In order to obtain maximum correlation contributed by the object and background in the image, $TC(s)$ is maximised. The maximum correlation criterion is to determine the threshold - s^* which satisfy the following equation [3].

$$TC(s^*) = \max\{TC(s)\} \quad s=0,1,2,\dots,m-1 \quad (5)$$

3. The Proposed Multilevel Thresholding Method

The flow diagram of the proposed multilevel thresholding method is shown in Fig 1. It uses the main structure of Yen's method [3] but it differs in the dichotomisation process of the histogram region having the largest variance. In this technique not only the global maximum of the total correlation function defined in equation (4) is considered but also other local maximums of the total correlation function are taken into consideration for each dichotomisation process.

It is observed that the peak's locations of the total correlation function have some important information in the sense of finding homogenous regions. In the proposed method threshold is placed one of the peak points of the correlation function. The peak's location is selected as the threshold value that creates the lowest class variance. Let's define the extra notation related with the proposed method.

- r : The number of peaks of total correlation function over the interested histogram region,
- T : $\{t_1, t_2, \dots, t_r\}$, candidate threshold values of the interested histogram region,
- σ_{1,t_i}^2 : The class variance of the first distribution dichotomised by the threshold value t_i ,
- σ_{2,t_i}^2 : The class variance of the second distribution dichotomised by the threshold value t_i , ($i=1,2,\dots,r$).
- s^{**} : The threshold value obtained by the proposed method for the dichotomisation process.
- s^{**} must satisfy the following rule.

$$s^{**} = \{t_i^{**} \mid \sigma_{1,t_i}^2 = \min[(\sigma_{1,t_1}^2, \sigma_{2,t_1}^2), (\sigma_{1,t_2}^2, \sigma_{2,t_2}^2), \dots, (\sigma_{1,t_r}^2, \sigma_{2,t_r}^2)]\} \quad (5)$$

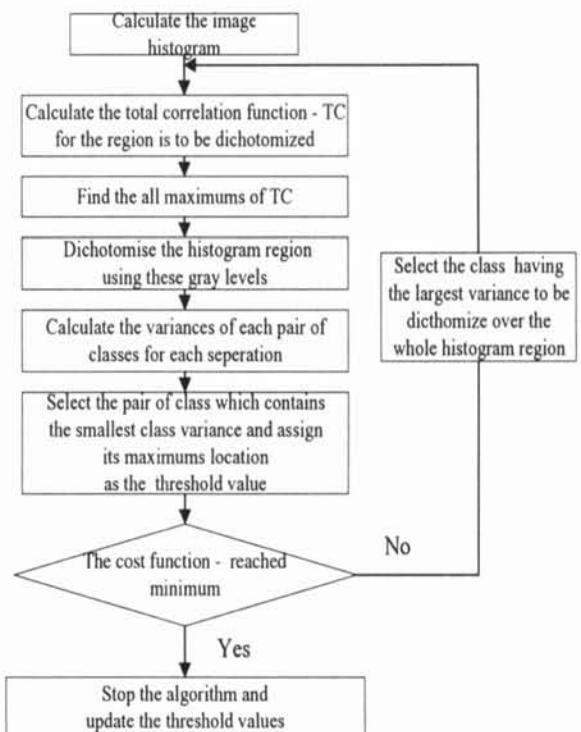


Fig.1. The flow diagram of the proposed method.

Using the proposed method, homogenous regions having low variance can be extracted from the scene without the cost function is reached minimum. This is important in the automatic inspection of the pathological images since cancerous cell images may contain small areas having approximately homogenous distributions in the different gray-level locations. It is also

important in the visual quality inspection of the industrial products.

An example total correlation function of the muscle cell image (See Fig 3.a.) is depicted in Fig.2. to demonstrate an example dichotomisation process. As shown in this figure there are 2 major peak points represented with t_1 , t_2 and their associated classification variance pairs are given in Table 1. In this dichotomisation step the proposed method dichotomise the histogram with $s^{**}=t_2=226$ since the minimum classification variance is occurred in this dichotomisation ($\sigma^2_{2,t_2}=27.3$). However the Yen's [3] method insert the threshold on t_1 . So, the region between t_2 and 255 can not be extracted from the scene without the cost function reached the optimal classification number.

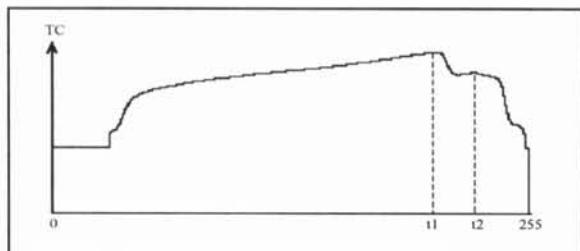


Fig.2. The Total Correlation function of the muscle cell image (see Fig.3.a.) for the first dichotomisation process.

Table 1. The classification variance pairs of muscle cell image for the first dichotomisation process.

Dichotomisation Process	Class variances	
	σ^2_{1,t_1}	σ^2_{2,t_2}
Dichotomisation with $t_1=207$	4341.3	97.6
Dichotomisation with $t_2=226$	3817.2	27.3

4. Results

The proposed multilevel thresholding method was tested on some biomedical and microscopic material images. It is observed that the proposed method gives good threshold values and stops the iteration when it is reached to optimum class number generally.

A muscle cell and microscopic material images are shown in Fig.3.a and Fig.4.a respectively. The image histograms is depicted in Fig 3.b and

Fig.4.b. The result images thresholded by the Yen's method are shown in Fig.3.c. and Fig 4.c. The results of the proposed method are also shown in Fig3.d. and Fig 4.d. There are some other thresholded image results is given in Fig.5. and Fig.6.

When a comparison is made between Yen's and the proposed method, it can be seen that the proposed method can find the diagonal lines in the Fig.3.a against the Yen's method couldn't find it. In addition to these result Yen's method finds only 1 threshold for the Fig.4.a. But the proposed method segments this image effectively as shown in Fig.5.d.

Moreover the proposed method segments the image very consistently as compared with the segmentation result of human eye. Actually it was subjective to authors perception of what a good thrseholde image should look like. Threshold values obtained by different methods are shown in the following table.

Table 2. Threshold values obtained by various methods.

	<i>Yen's Method</i>	<i>The Proposed Method</i>	<i>Human eye</i>
<i>Fig.3.</i>	117, 207	107,202,226	101,196,225
<i>Fig.4</i>	126	123,161,185	116,170,195
<i>Fig.5</i>	137,185	68,137,185	80,140,190
<i>Fig.6</i>	62,105, 164,215	62,111, 163,213	73,136, 176,210

5. References

- [1] M. Fleury, L. Hayat, A.F. Clark, "Parallel entropic auto-thresholding", Image and Vision Computing, 1996, Vol:14, pp:247-263.
- [2] P.K.Sahoo, S.Soltani, A.K.C. Wong and Y.C. Chen, "A Survey of Thresholding Techniques", Comp. Vis., Graph. Image, Proc., 1988, 41, pp:233-260.
- [3] J.C. Yen, F.J. Chang, S. Chang, "A New Criterion for Automatic Multilevel thresholding", IEEE Transaction on Image Processing, pp:370-378, no:3, vol:4, March, 1995.

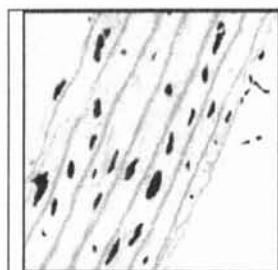


Fig.3.a. An original muscale image.

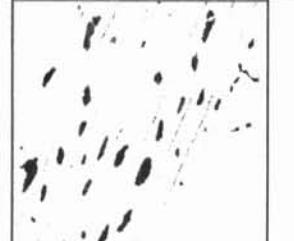
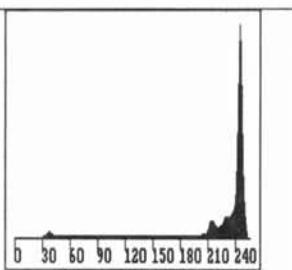


Fig.3.c. MLT results with the Yen's method.

Thresholds: 117,207

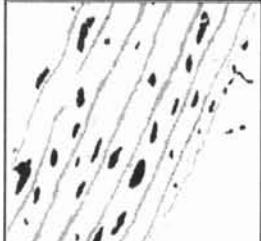


Fig.3.d. MLT results with the proposed method.

Thresholds: 107,202,226

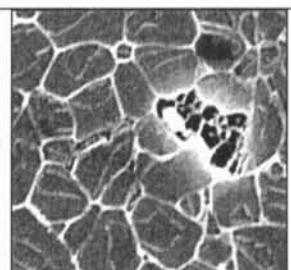


Fig.4.a. An original microscopic material image.

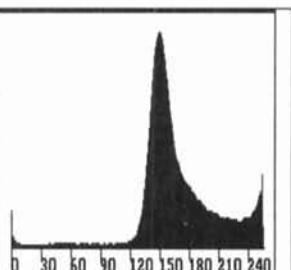


Fig.4.c. MLT results with the Yen's method

Thresholds: 126



Fig.4.d. MLT results with the proposed method.

Thresholds: 123,161,185

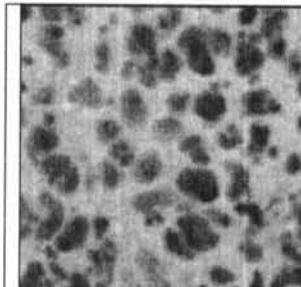


Fig.5.a. An original Microscopic material image.

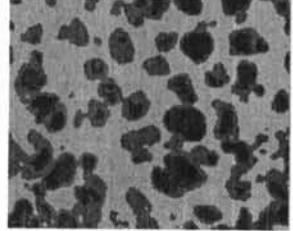
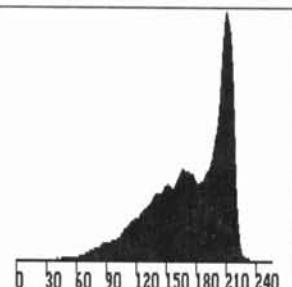


Fig.5.c. MLT results with the Yen's method.

Thresholds: 137,185

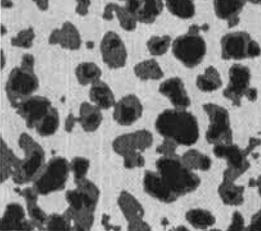


Fig.5.d. MLT results with the proposed method.

Thresholds: 68,137,185

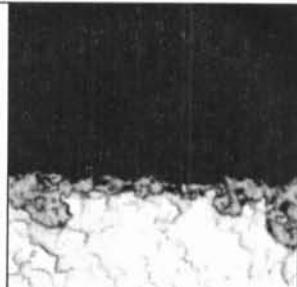


Fig.6.a. An original material plating region image.

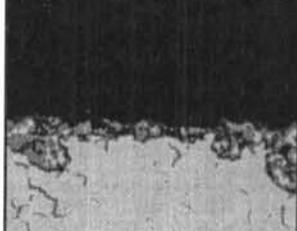
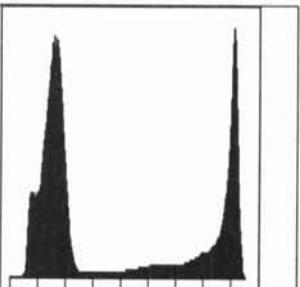


Fig.6.c. MLT results with the Yen's method.

Thresholds:
62,105,164,215

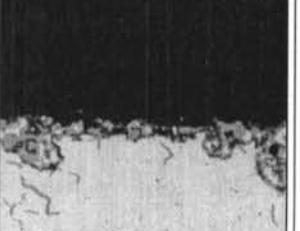


Fig.6.d. MLT results with the proposed method.

Thresholds:
62,111,163,213