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# Image Segmentation Based on 2D Otsu Method with Histogram Analysis

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***Abstract*—Image segmentation plays an important role in image analysis and computer vision system. Among all segmentation techniques, the automatic thresholding methods are widely used because of their advantages of simple implement and time saving. Otsu method is one of thresholding methods and frequently used in various fields. Two-dimensional (2D) Otsu method behaves well in segmenting images of low signal-to-noise ratio than one-dimensional (1D). But it gives satisfactory results only when the numbers of pixels in each class are close to each other. Otherwise, it gives the improper results. In this paper, 2D histogram projection is used to correct the Otsu threshold. The 1D histograms are acquired by 2D histogram projection in x and y axes and a fast algorithm for searching the extrema of the projected histogram is proposed based on the wavelet transform in this paper. Experimental results show that the proposed method performs better than the traditional Otsu method for our renal biopsy samples.**

***Keywords-image segmentation; 2D Otsu method; 2D histogram projection; wavelet transform***

## I. INTRODUCTION

Image segmentation is one of the basic techniques of image processing and computer vision. It is a key step for image analysis, comprehension and description. Among all the segmentation techniques, thresholding segmentation method is the most popular algorithm and is widely used in the image segmentation field.

The basic idea of automatic thresholding is to automatically select an optimal or several optimal gray-level threshold values for separating objects of interest in an image from the background based on their gray-level distribution.

Over the past years, many technologies have been proposed for selecting the threshold automatically. Sezgin and Sankur [1] provide an exhaustive description and the comparison of the performance measures over many image thresholding techniques. Automatic thresholding techniques can be roughly categorized as global thresholding and local thresholding. Otsu thresholding technique [2] is one of the global thresholding method and has been cited as an effective technique [3,4,5]. In Trier and Jain's study [4], four global thresholding techniques were compared and Otsu method performed the best , followed, in order, by Kapur et al.'s Entropy technique [6], Abutaleb's entropy technique [7], and Kittler and Illingworth's minimum error technique [8]. However, some issues are still on in this method. One of them is its sensitivity to the object size [9]. Say in brief, if the object proportion is much less than background, the pixels in background will be wrongly classified as object; on the contrary, if the object proportion is much more than background, the pixels in object will be wrongly classified as background.

As for our renal biopsy samples, the object size is much less than background, the wrong classification of pixels by traditional Otsu method will lead to the failure segmentation. To solve this problem, a histogram analysis based on wavelet transform is proposed to correct the Otsu threshold in this paper.

## II. TWO-DIMENSIONAL OTSU METHOD

### *A. Two-dimensional Histogram*

An image with size $M \times N$ can be represented by a 2D gray level intensity function $f(x,y)$. The value of $f(x,y)$ is the gray level, ranging from 0 to $L$-1, where $L$ is the number of distinct gray levels. In a 2D thresholding method, the gray level of a pixel and its local average gray level are both used. The local average gray level is also divided into the same $L$ values, let $g(x,y)$ be the function of the local average gray level, then

$$g(x,y)=\frac{1}{n^2}\sum_{i=-n/2}^{n/2}\sum_{j=-n/2}^{n/2} f(x+i,y+j) \qquad (1)$$

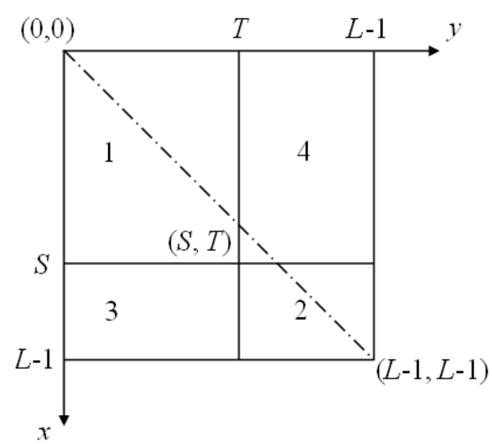


Figure 1. The top view of 2D histogram

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Where $n \le min\{M, N\}$.

Let $r_{ij}$ be the total number of occurrence (frequency) of the pair $(i, j)$ which represents pixel $(x, y)$ with $f(x, y) = i$ and $g(x, y) = j$, $0 \le r_{ij} \le M \times N$, then the joint probability mass function $p_{ij}$ is given by

$$p_{ij} = \frac{r_{ij}}{M \times N} \tag{2}$$

Where $i, j = 0, \cdots, L-1$, $\sum_{i=0}^{L-1}\sum_{j=0}^{L-1} p_{ij} = 1$.

The 2D histogram of the image is $\{p_{ij}\}$. Figure 1 shows the top view of 2D histogram. It covers a square region with size $L \times L$. The x-coordinate ($i$) represents gray level and the y-coordinate ($j$) represents the local average gray level. The 2D histogram is divided into four quadrants at a vector $(S, T)$, where $0 \le S, T \le L-1$. The dash dot line is the diagonal of 2D histogram. The pixels interior to the objects or the background should contribute mainly to the near-diagonal elements because of the homogeneity. Because for the pixels interior to the objects and background, the gray level of a pixel and its local average gray level are similar. For pixels in the neighborhood of an edge between the objects and the background, the gray level of a pixel differs fairly from its local average gray level. Therefore, quadrants 1 and 2 contain the distributions of background and object classes, whereas the off-diagonal quadrants 3 and 4 contain the distributions of pixels near edges and noises.

### B. Two-dimensional Otsu Method

Now suppose that the pixels are partitioned into two classes $C_0$ and $C_1$ (background and objects) by a threshold pair $(s, t)$, then the probabilities of class occurrence are given by

$$P_0(s,t) = \sum_{i=0}^{s}\sum_{j=0}^{t} p_{ij} \tag{3}$$

$$P_1(s,t) = \sum_{i=s+1}^{L-1}\sum_{j=t+1}^{L-1} p_{ij} \tag{4}$$

and the corresponding class mean levels are

$$\mu_0 = (\mu_{00}, \mu_{01})^T = \left(\frac{\sum_{i=0}^{s}\sum_{j=0}^{t} i \cdot p_{ij}}{P_0}, \frac{\sum_{i=0}^{s}\sum_{j=0}^{t} j \cdot p_{ij}}{P_0}\right)^T \tag{5}$$

$$\mu_1 = (\mu_{10}, \mu_{11})^T = \left(\frac{\sum_{i=s+1}^{L-1}\sum_{j=t+1}^{L-1} i \cdot p_{ij}}{P_1}, \frac{\sum_{i=s+1}^{L-1}\sum_{j=t+1}^{L-1} j \cdot p_{ij}}{P_1}\right)^T \tag{6}$$

The total mean level vector of the 2D histogram is

$$\mu_T = (\mu_{T0}, \mu_{T1})^T = \left(\sum_{i=0}^{L-1}\sum_{j=0}^{L-1} i \cdot p_{ij}, \sum_{i=0}^{L-1}\sum_{j=0}^{L-1} j \cdot p_{ij}\right)^T \tag{7}$$

Because of assumption that the occurrences of image data in off-diagonal quadrants of 2D histogram can be neglected, it is easy to be verified that

$$P_0 + P_1 \approx 1, \mu_T \approx P_0\mu_0 + P_1\mu_1 \tag{8}$$

The between-class variance matrix is defined as

$$S_B = \sum_{k=0}^{1} P_k[(\mu_k - \mu_T)(\mu_k - \mu_T)^T] \tag{9}$$

By using the trace of $S_B$ as the measurement of between-class variance, there is

$$\begin{aligned} t_r S_B &= P_0[(\mu_{00} - \mu_{T0})^2 + (\mu_{01} - \mu_{T1})^2] \\ &\quad + P_1[(\mu_{10} - \mu_{T0})^2 + (\mu_{11} - \mu_{T1})^2] \\ &= \frac{(\mu_i(s,t) - P_0\mu_{T0})^2 + (\mu_j(s,t) - P_0\mu_{T1})^2}{P_0(1-P_0)} \end{aligned} \tag{10}$$

Where

$$\mu_i(s,t) = \sum_{i=0}^{s}\sum_{j=0}^{t} i \cdot p_{ij}$$

$$\mu_j(s,t) = \sum_{i=0}^{s}\sum_{j=0}^{t} j \cdot p_{ij}.$$

A threshold vector $(S, T)$ is selected by maximizing $t_r S_B$

$$t_r S_B(S,T) = \max_{0<s,t<L-1}\{t_r S_B(s,t)\} \tag{11}$$

In this paper, we use the following fast recursive algorithm to realize the above method.

$$P_0(s,1) = P_0(s-1,1) + p_{s1} \tag{12}$$

$$\begin{aligned} P_0(s,t) &= P_0(s,t-1) + P_0(s-1,t) \\ &\quad - P_0(s-1,t-1) + p_{st} \end{aligned} \tag{13}$$

$$\mu_i(s,1) = \mu_i(s-1,1) + s \cdot p_{s1} \tag{14}$$

$$\begin{aligned} \mu_i(s,t) &= \mu_i(s,t-1) + \mu_i(s-1,t) \\ &\quad - \mu_i(s-1,t-1) + s \cdot p_{st} \end{aligned} \tag{15}$$

$$\mu_j(s,1) = \mu_j(s-1,1) + t \cdot p_{s1} \tag{16}$$

$$\begin{aligned} \mu_j(s,t) &= \mu_j(s,t-1) + \mu_j(s-1,t) \\ &\quad - \mu_j(s-1,t-1) + t \cdot p_{st} \end{aligned} \tag{17}$$

## III. Two-dimensional Histogram Analysis

Because Otsu method will give the improper results when the object size is very different from background [10], we use the 2D histogram projection to correct the Otsu threshold. For our renal biopsy samples, the object we want has a high gray level. If we project the 2D histogram in x and y axes, the last peak must be object. So after projection, the valleys corresponding to the last peak in x and y axes are regarded as the auxiliary threshold. The final threshold $(S_{final}, T_{final})$ is calculated as

$$(S_{final}, T_{final}) = (\frac{S_{otsu} + S_{hist}}{2}, \frac{T_{otsu} + T_{hist}}{2}) \qquad (18)$$

Where $(S_{otsu}, T_{otsu})$ is the threshold by Otsu method; $(S_{hist}, T_{hist})$ is the threshold by histogram analysis.

To eliminate the influence of the pseudo valley, use wavelet transform to obtain the smoothed histogram without tiny changes. Then put a search window with fixed width *w* in the smoothed histogram and calculate the differences of the adjacent elements in this window.

There are five cases we may meet, as shown in Figure 2, the first column is the local histogram in search window with *w*=10 and the second is the differences in this window.

- First, the local histogram in the window increases monotonically and all calculated differences are non-negative.
- Second, the local histogram in the window decreases monotonically and all differences are non-positive.
- Third, there exists a peak in the window and the differences change from positive to negative.
- Fourth, there exists a valley in the window and the differences change from negative to positive.

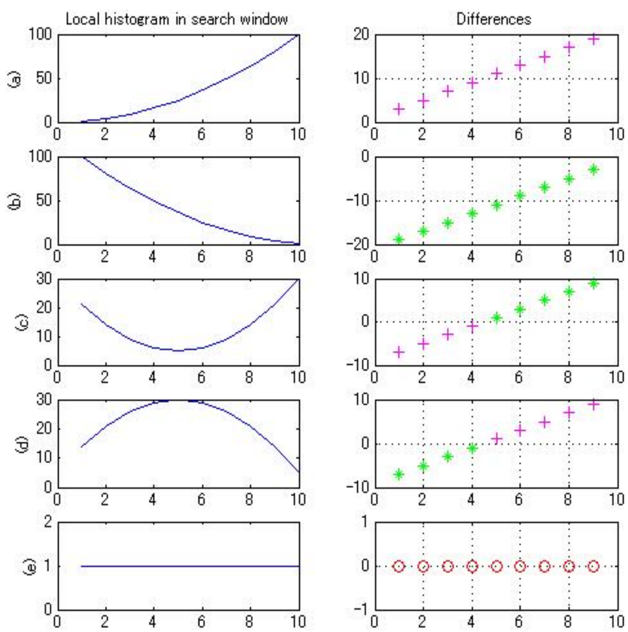



Figure 2. Five cases

- Fifth, there is no change in the window and all differences are equal to 0. In this case, the further three situations need to be considered, as shown in Figure 3.
  - ✧ One, the sign of the last element in previous window is positive and the sign of the first element in next window is negative, there exists a peak in current window.
  - ✧ Two, the sign of the last element in previous window is negative and the sign of the first element in next window is positive, there is a valley in current window.
  - ✧ Three, if the sign of the last element in previous window and the sign of the first element in next window are same or equal to 0, there is no peak or valley in the current window.

Based on above analysis, through moving the window with step *w*/2 in whole histogram, all peaks and valleys can be detected. Finally, backtrack the position to the corresponding extrema in the original histograms, and then we can get all valleys and peaks.

For our application, only the last valley is used as auxiliary threshold. In Figure 2 and 3, the magenta '+' denotes that the difference is positive, green '∗' denotes negative and red '×' denotes zero.

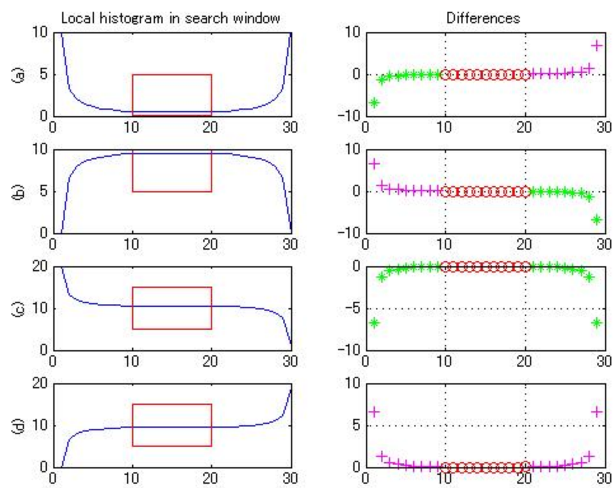
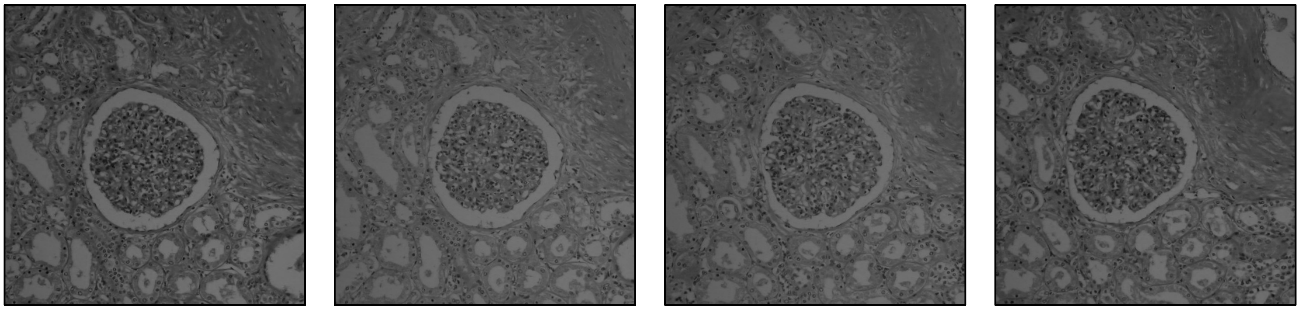



Figure 3. Three further cases with window width 10
(The red rectangle is the current search window; (c) and (d) belong to the third case because the sign of difference has no change)

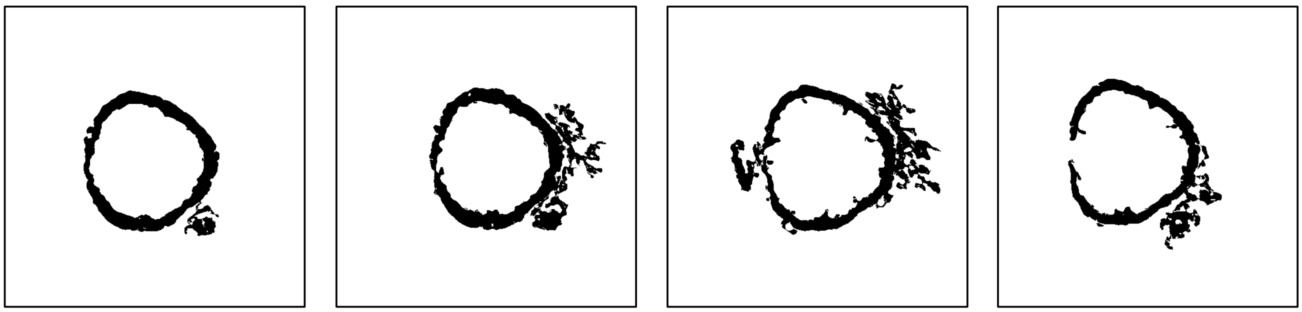
## IV. Experimental Results

The proposed method is tested using the renal biopsy image sequence. All the algorithms are implemented on a personal computer with CPU of 1.83GHz using MATLAB7.0 programming language.

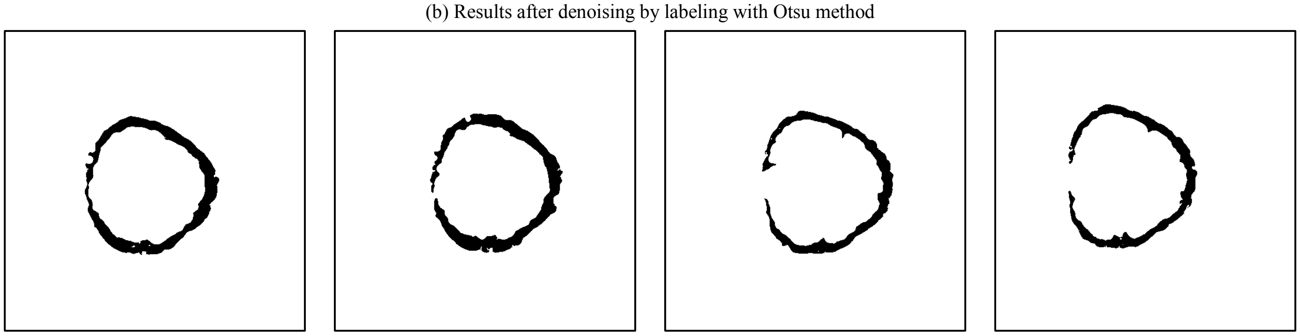
The original gray level images shown in Figure 4(a) consists $512 \times 512$ pixels. Figure 4(b) gives the Otsu results after denoising. We can see that some unexpected noises attach to the object and become an obstacle for subsequent processing.



(a) Original images from renal biopsy image sequence



(b) Results after denoising by labeling with Otsu method



(c) Results after denoising by labeling with our method

Figure 4. Comparison between Otsu method and our method

This problem is solved by our method, shown in Figure 4(c). The noises can be removed completely.

## V. CONCLUSION

This paper introduces a 2D histogram projection analysis to solve the problem of traditional Otsu method. Using this method, the problem of its sensitivity to the object size can be overcome. It is very helpful for the subsequent processing and improves the success ratio of image segmentation.

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