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An Improved Image Segmentation Algorithm Based on Two-Dimensional Otsu Method

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Abstract: This paper presented an improved image segmentation algorithm based on 2D Otsu, in which two-dimensional histogram was mainly build by gray and neighborhood gray gradient of two tuples, and then calculated the biggest Otsu value of the object area and the background area in image, at last, got the threshold of the image. The experimental results indicate that we can get more smooth area of the image and more accurate shape of the image's edge, compared with Otsu method and the traditional 2D Otsu method.

Keywords: Image segmentation; Otsu; threshold selection; two-dimensional histogram.

I. Introduction

Image segmentation is an important research direction of image processing, which is widely applied to the fields of machine vision and image analysis and understanding. At present, many methods of image segmentation have been proposed, such as thresholding method, area growing, edge detection, texture analysis and so on. The thresholding method is a relatively common and simple effective method. In accordance with the use of information, the thresholding methods were divided into six categories by Sankur et al[1], including methods based on histogram shape, measurement space clustering, entropy, object attributes, spatial correlation and local gray-level surface.

Otsu method (Otsu) was proposed by Japanese scholar Otsu[2] in 1979.It is a global thresholding selection method based on spatial clustering, which is widely used because of its simple and effective. The one-dimensional Otsu method was improved by Li Zhe-xue[3] who proposed a fast multi-thresholding approach in order to improve the efficiency of segmentation. However, because the one-dimensional Otsu method only consider the pixel's gray-level information without considering the pixel's spatial neighborhood information, so it is difficult to obtain satisfactory segmentation results. The automatic thresholding of gray-level pictures via two-dimensional Otsu method was proposed by Liu Jian-zhuang[4]. The 2D Otsu method utilizes both the gray level information of each pixel and its spatial correlation information within the neighborhood. We can obtain satisfactory segmentation results when it is applied to the noisy images. The histogram is divided into four areas by two thresholds. But it is not accurate that the global probability distribution is replaced by the probability distribution of two areas which resulted in a partial loss of information. Many researchers have proposed their algorithms to improve thresholding method[5-10], which greatly improved the accuracy of image segmentation, but also increased the complexity of the algorithm.

This paper presented an improved image segmentation algorithm based on 2D Otsu. By using gray value-gradient value instead of gray value-mean value of spatial correlation pixel's gray value, we can get more smooth area of the image and more accurate shape of the image edge, for the decrease of valuable information losing of object area and background area.

II. Regional division in traditional 2D Otsu method

For a $M \times N$ picture, $f(x,y)$ is expressed as the gray value of each pixel whose coordinate is (x,y) in the image, $g(x,y)$ is expressed as the gray mean value of its spatial correlation pixels within the neighborhood, then:

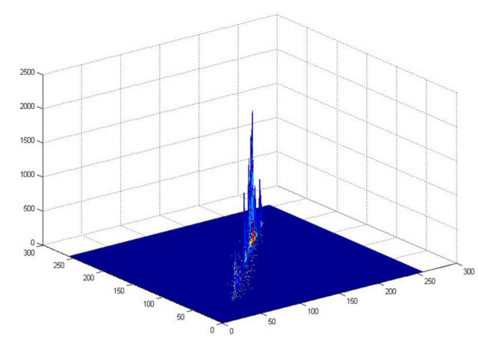
$$g(x,y) = \frac{1}{9}\sum_{m=-1}^{1}\sum_{n=-1}^{1} f(x+m, y+n) \qquad (1)$$

In which, $0<x+m<M, 0<y+n<N$.

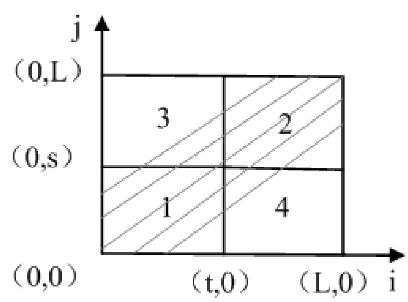
The gray value of each pixel is expressed as $f(x,y)=i$, its gray mean value is expressed as $g(x,y)=j$. They consist of the two-tuples which is expressed as (i,j) . Calculate appearance times of each two-tuples and express as C_{ij} , then the frequency of each two-tuples is formulated as:

$$P_{ij} = \frac{C_{ij}}{M \times N} \qquad (2)$$

(a)Original image



(b) Two-dimensional histogram



(c)Regional division

Figure 1.Lina's original image, two-dimensional histogram and its regional division

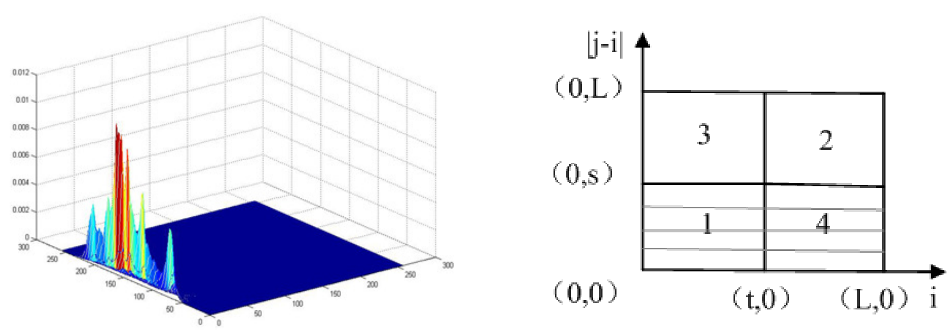
Taking i and j as independent variables, P_{ij} as the dependent variable, we can build the two-dimensional gray histogram. Figure 1(b) is the two-dimensional histogram of Lina who was shown in figure 1(a). Figure 1(c) shows that the two-dimensional histogram was divided into four areas by two thresholds.

As shown in figure 1(c), take (t,s) as the threshold for segmentation. The two thresholds divided the gray histogram into four areas. Since object pixels and background pixels are accounted for the largest proportion in the image, the pixel's gray levels of the object internal area and background internal area are relatively smooth; there is little difference between gray value and gray mean value. Then, in the two-dimensional histogram, the peak is mainly distributed in the diagonal of the plane. As a result of that, the area 1 and area 2 can be considered as the object area and the background area respectively, while the area 3 and area 4 can be considered as edge and noise respectively. So the probability distribution of the area 3 and area 4 is negligible. But the actual situation is that in area 3 and area 4 there are usually have object pixels and background pixels, which leads to a loss of valuable information. Especially when the image has more complex boundaries or noises, the segmented image through the traditional method has the following defects: the internal area is not smooth and the shape of the image edge is not clear.

III. Improved algorithm

III. A. Regional division algorithm

In this paper, we used gray value–gradient value instead of gray value–gray mean value to build the two-dimensional histogram. The gray value of the pixel whose coordinate is (x,y) in the image is expressed as $f(x,y)=i$, $g(x,y)=j$ is the gray mean value of its 3×3 neighborhoods, then the gradient value of this pixel can be expressed as $h(x,y)=|j\text{-}i|$. The new two-tuples (f,h), which consists of the two values of i and $|j\text{-}i|$, constructs the two-dimensional histogram of gray–gradient.



(a)New two-dimensional histogram *(b) New regional division*

Figure 2.Lina's new two-dimensional histogram and its regional division

Figure 2 (a) shows Lina's new two-dimensional histogram of gray–gradient. Figure 2 (b) is its regional division. We can see the probability distribution is mainly distributed in area 1 and area 4. The gradients of the object internal area and background internal area are smooth, which are mainly distributed in area 1 and area 4. The gradients of edges and noises are larger, which are mainly distributed in area 2 and area 3. Through this new regional division algorithm, we can reduce the loss of valuable information to maximum contain the object pixels and background pixels. The segmented image's edges would be comparatively clear and its internal region would be comparatively smooth.

III. B. The threshold selection analysis based on gray-gradient via 2D Otsu

If the currently selected threshold is (t,s), where t is the gray threshold and s is the gradient threshold, the image will be divided into two classes of C_o and C_b. ω_o is the probability distribution of object area and ω_b is the probability distribution of background area, then:

$$\omega_{\mathrm{o}} = P\left(C_o\right) = \sum_{i=1}^{s}\sum_{j=1}^{t} P_{ij} \tag{3}$$

$$\omega_b = P\left(C_b\right) = \sum_{i=s+1}^{L}\sum_{j=t+1}^{L} P_{ij} \tag{4}$$

μ_o and μ_b are the mean vectors of object area and background area respectively, they are calculated as:

$$\mu_o = (\mu_{o1,}\mu_{o2})^T = \left[\frac{\sum_{i=1}^{s}\sum_{j=1}^{t} iP_{ij}}{\omega_o}, \frac{\sum_{i=1}^{s}\sum_{j=1}^{t} jP_{ij}}{\omega_o}\right]^T \tag{5}$$

$$\mu_b = (\mu_{b1,}\mu_{b2})^T = \left[\frac{\sum_{i=s+1}^{L}\sum_{j=t+1}^{L} iP_{ij}}{\omega_b}, \frac{\sum_{i=s+1}^{L}\sum_{j=t+1}^{L} jP_{ij}}{\omega_b}\right]^T \tag{6}$$

μ_1 is the mean value of overall, which can be expressed as:

$$\mu_1 = (\mu_{11,}\mu_{12})^T = \left[\sum_{i=1}^{L}\sum_{j=1}^{L} iP_{ij}, \sum_{i=1}^{L}\sum_{j=1}^{L} jP_{ij}\right]^T \tag{7}$$

Dispersion matrix is defined as:

$$\sigma_{\mathrm{b}} = \omega_{\mathrm{o}}\left[(\mu_{\mathrm{o}} - \mu_1)\ (\mu_{\mathrm{o}} - \mu_1)^{\mathrm{T}}\right] + \omega_{\mathrm{b}}\left[(\mu_{\mathrm{b}} - \mu_1)\ (\mu_{\mathrm{b}} - \mu_1)^{\mathrm{T}}\right] \tag{8}$$

The trace of dispersion matrix, which is the measurement of discrete degree of background class and the object class, can be expressed as:

$$Tr(\sigma_b) = \omega_o\left[(\mu_{\mathrm{o}1} - \mu_{11})^2 + (\mu_{\mathrm{o}2} - \mu_{12})^2\right] + \omega_b\left[(\mu_{\mathrm{b}1} - \mu_{11})^2 + (\mu_{\mathrm{b}2} - \mu_{12})^2\right] \tag{9}$$

Maximize the value of the trace of dispersion matrix as the image's optimal threshold which is expressed as:

$$Tr(s^*,t^*) = Max\{Tr(\sigma_b)\} \text{ in which , } 0 \le s,t \le L-1 \qquad (10)$$

IV. Experiment and analysis

In order to verify the effectiveness of the proposed method, we have done a lot of experiments by matlab, comparing with one dimensional method and traditional 2D Otsu method. Figure 3, figure 4 and figure 5 are some typical images of experimental results.

(a)The original image *(b) one dimensional method* *(c) 2D Otsu method* *(d) our method*

Figure 3. image of Cell and its segmentation images

(a)The original image *(b) one dimensional method* *(c) 2D Otsu method* *(d) our method*

Figure 4. image of Chinese character and its segmentation images

(a)The original image *(b) one dimensional method* *(c) 2D Otsu method* *(d) our method*

Figure 5. image of License plate number and its segmentation images

Figure 3, figure 4, figure 5 are the segmentation results of experiment on three pairs of images, respectively, by using one dimensional method, traditional 2D method and our method. Table 1 shows the optimal thresholds respectively by using traditional 2D method and our method.

Table 1. Optimal thresholds statistics

Image	Optimal thresholds	
	Traditional method	Our method
Cell	(215,193)	(192,177)
Chinese character	(128,136)	(125,120)
License plate number	(103,108)	(102,86)

As shown in figure 3, because of the effect of liquid substances around the cell, OTSU method and 2D-OTSU method incorrectly consider the substance as the part of the cell, which lead to that segmented cell's boundaries are blurred. However our method can avoid this mistake segmentation. As shown in figure 4 and figure 5, paper and registration are affected by the uniform illumination, and the background region of segmented image containing a large block of the noise, even part of the text and background didn't completely separated, by using OTSU method and 2D-OTSU method separately. While using this improved method to segment the image, not only the target area is uniform and clear, but also the target and background region are segmented thoroughly.

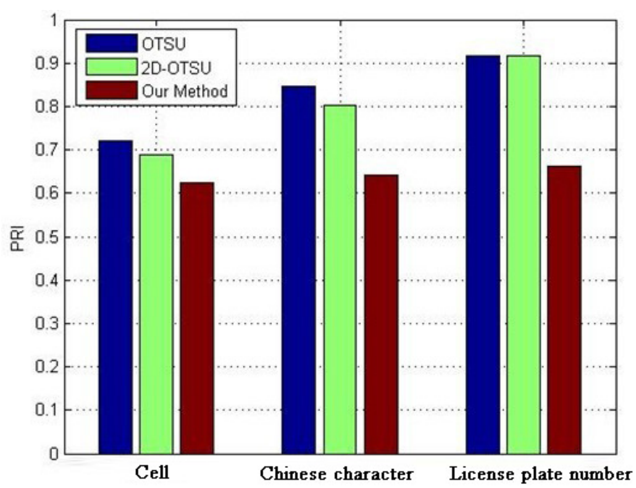


Figure 6. PRI of different images

In order to quantitative evaluate the quality of several segmentation methods, this paper calculates Probabilistic Rand Index (PRI) parameters[11] between segmented image and original image of each method. As shown in figure 6, PRI can be consistent with the human's visual habits; the smaller the value of PRI, the better the target image is divided.

Compared with the traditional method, our method can obtain more ideal segmentation image. Its background is smoother, and the object area and background area are segmented more thoroughly, which have removed the influence of the noise of light. Especially when the image has more complex edges or noises, our algorithm shows better segmentation performance. This is because that our algorithm maximized reduces the loss of image's valuable information, which can eliminate noise interference.

V. Conclusion

In view of the disadvantage of traditional 2D Otsu method, this paper presented an improved image segmentation algorithm based on new two-tuples. Experimental results show that, segmented image's edges are more clearly and accurately through our algorithm compared with traditional method. Especially when the image has more complex edges or noises, our algorithm is more accurate and effective.

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