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Image Segmentation Based on Framework of Two-dimensional Histogram and Class Variance Criterion

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Abstract

Histogram thresholding is one of the most popular image segmentation techniques. Variance-based thresholding is a famous method in which. In this paper, a new method based the framework of two-dimensional gray level histogram and class variance criterion is proposed. The methodology for image segmentation using two-dimensional histogram and variance criterion is elaborated firstly. Then the algorithm of the presented scheme is realized through recursion. Finally, the proposed method is tested on synthetic and real-world images. Experimental results show that the proposed method is better to overcome the shortcomings of the conventional variance-based methods, and the effectiveness of the proposed method is demonstrated by the experiments.

Keywords: *image segmentation, histogram thresholding, class variance criterion, two-dimensional histogram, recursion*

1. Introduction

Image segmentation is the foundation of image analysis, image understanding, and other image processing tasks [1]. However, there is not a universal method for all images since the complicacy of nature images. So, it is still a challenging task to put forward a new and effective image segmentation method. In many image segmentation methods, the thresholding based on the information of image histogram is a very popular technology for image segmentation since its simplicity and effectiveness [1]. Due to the solid foundation of statistical theory, the maximum between-clusters variance method (Otsu) [2] and the minimum error thresholding (MET) [3] methods are two best known methods among thresholding approaches. The idea of the maximum between-clusters variance method originates from the analysis of variance (ANOVA) theory. Otsu presented this method through maximizing the between-clusters variance between image background and foreground to obtain the optimal threshold for image segmentation. The idea of the MET method originates from Bayes error theory. This method is presented by Kittler and Illingworth in 1986. Firstly, the distribution model of image histogram is simulated by mixture normal distribution, and then the optimal threshold for image segmentation is calculated through Bayes error theory.

In the process of imaging, the interference by some noises is inevitable. The performances of the thresholding methods which only use the information of original histogram are poor on some cases since these methods neglect the influence of pixels' spatial distribution. To improve the performance of thresholding method, many means those considering the spatial relationship of pixels have been presented. The two-dimensional histogram method, as one of those ways, is one of the most famous means used to reach to improve the performance of thresholding method [4-14].

Since the success of ANOVA in science and engineering application, the Otsu method which originates from ANOVA theory become more and more popular in image thresholding segmentation. The improved versions of Otsu method, which extending

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through two-dimensional histogram have been put forward in recent years [5-11]. The effectiveness of every two-dimensional Otsu methods has been demonstrated in many literatures. However, a remarkable drawback of Otsu method has still not been overcome. The drawback is the optimal thresholds obtained by Otsu method will partial to the part which has dominant distribution in gray level histogram. So, if the variances of distributions of image foreground and background differ bigger, the good segmented results will not be obtained by Otsu method [15]. The MET method use mixed normal distribution to fit the model of gray level histogram distribution. However, the MET method will produce the model deviation problem because of the complicacy of imaging [16], *i.e.* the simulation model can not match the true model. The method presented in [13, 14] extended the MET method based on two-dimensional normal distribution, and overcome the drawback exist in the one-dimensional MET method. At the same time, the authors of [13, 14] also demonstrated that their method can remedy the drawback exist in Otsu method to a certain degree. However, their method is still a method based on mixed normal distribution. So, the model deviation problem will existed in their method. Based on the ANOVA theory, a minimum class variance (MCV) thresholding method was presented by Hou et al. in 2006 [15]. The main drawback of one-dimensional Otsu method is overcame by the MCV method. However, the performance of MCV method is also affected by the noise existed in the process of imaging. To overcome the drawback of the Otsu and MCV method, we proposed an extension of MCV method based on two-dimensional histogram in this paper.

The remainder of this paper is organized as follows. In Section 2, we briefly review the image thresholding methods based on class variance criterion. Section 3 introduces the two-dimensional histogram framework and proposes segmentation scheme under this framework. Section 4 applies the suggested approach to the segmentation of synthetic and some real-world images. Section 5 concludes the paper.

2. Review of Class Variance Criterion for Image Thresholding

Let I denotes the image with gray levels $G=\{0,1,2,\ldots,L-1\}$, and size of $M\times N$, where L denotes the number of gray levels. If we use h_i to denote the frequency of gray level i occurred in image I, then the normalized histogram p_i of image I can be denoted as $p_i=h_i/(M\times N)$, $i=0,1,\ldots,L-1$.

Assume that t is an optimal threshold for thresholding, the histogram of image can be divided in two parts, i.e. $C_1=\{0,1,\ldots,t\}$ and $C_2=\{t+1,t+2,\ldots,L-1\}$. For C_1 and C_2, the class probabilities about them can be defined as $\omega_0=\sum_{i=0}^{t} p_i$, $\omega_1=\sum_{i=t+1}^{L-1} p_i$, class means $m_0=\sum_{i=0}^{t} ip_i \Big/ \omega_0$, $m_1=\sum_{i=t+1}^{L-1} ip_i \Big/ \omega_1$, and class variances $\upsilon_0=\sum_{i=0}^{t}(i-m_0)^2 \Big/ \omega_0$, $\upsilon_1=\sum_{i=t+1}^{L-1}(i-m_1)^2 \Big/ \omega_1$, respectively.

Based on the above definition, the minimum class variance method for image thresholding is presented by Hou et al. [15]

$$t^* = \min_{t\in G}(\upsilon_0+\upsilon_1) \tag{1}$$

If we consider the effect of class probabilities in the process of thresholding, the method to be equivalent to Otsu method [2] can be obtained, i.e.

$$t^* = \min_{t\in G}(\omega_0\upsilon_0+\omega_1\upsilon_1) \tag{2}$$

Both theoretical analysis and experiments have verified the validity of MCV method to overcome the drawback of Otsu method. However, the performance of MCV method is still affected by the noise information since the MCV method leave out of consideration the relation of spatial distribution of pixels. In order to improve the performance of MCV method, we extended the MCV method based on two-dimensional histogram in this paper.

3. The Proposed Method

3.1. Thresholding Using Two-dimensional Histogram and Class Variance Criterion

In this paper, we use the histograms of original image and the mean image of original image to construct the two-dimensional histogram. The mean image of original image can be obtained by smooth filtering to original image. Let $f(x, y)$ denotes the pixel value at point (x, y) in original image, $g(x, y)$ denotes the pixel value at (x, y) in mean image, then

$$g(x,y)=\left\lfloor \frac{1}{w\times w}\sum_{i=-a}^{a}\sum_{j=-a}^{a} f(x+i, y+j) \right\rfloor \tag{3}$$

Where $\lfloor\,\rfloor$ denotes the floor function; w denotes the width of neighboring window, generally w is a odd number, and $a=(w-1)=2$; obviously, $g(x, y)\in G$. Let h_{ij} denotes the frequency of $f(x, y)=i$ and $g(x, y)=j$ in original and mean image, then the normalized two-dimensional histogram of image I can be defined as $p_{ij} = h_{ij}=(M\times N)$, $i, j = 0, 1,\ldots,L - 1$. Obviously, $\sum_{i=0}^{L-1}\sum_{j=0}^{L-1} p_{ij} = 1$. The two-dimensional histogram of image I is an $L\times L$ matrix shown as Figure 1.

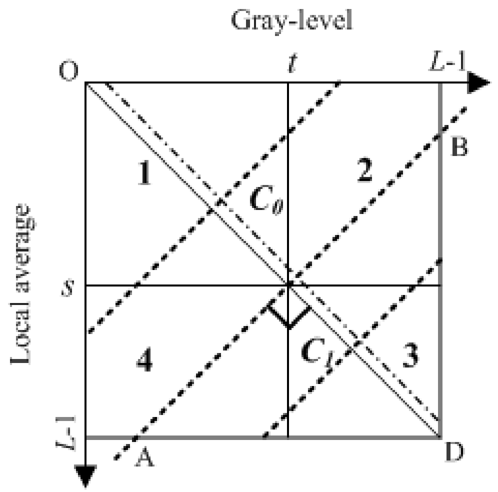


Figure 1. Two-dimensional Histogram and Its Partition

Assume that (s,t) is a pair of thresholds in two-dimensional histogram, the two-dimensional histogram is divided into four parts in conventional two-dimensional thresholding method, *i.e.* area 1, 2, 3, and 4 shown as Figure 1. Where area 1 denotes the background or foreground information, area 3 denotes the foreground or background information of image; area 2 and 4 denote the edge and noise information of image. Since the information included in area 2 and 4 is less, this information is ignored in the process of thresholding in conventional two-dimensional histogram method. Since the area 2 and 4 are neglected in the process of thresholding in conventional two-dimensional method, there are a few pixels that are misclassified inevitably.

In order to eliminate adverse effect to segmentation performance brought by misclassified pixels, the authors of references [8, 12, 14] presented a new way to divided the two-dimensional histogram, *i.e.* linear-type partition; the authors of reference [9] presented another partition mode, *i.e.* oblique partition. While comparing these two new partition ways carefully we see that their essence thought is same. As shown in Figure 1, the two-dimensional histogram is divided into two parts, *i.e.* C_0 and C_1, by a straight line

AB when the new way is used to partition two-dimensional histogram. The straight line passes point (s,t), and is perpendicular to the principal diagonal OD of two-dimensional histogram.

When the new way is used to partition two-dimensional histogram, the partition of two-dimensional histogram is no longer by a point, but by a straight line. The geometric equation of the straight line is $i+j=s+t$, the optimal straight line exists in the lines those parallel to AB. In this paper, we adopt the new way to partition the two-dimensional histogram. In order to construct the criterion to select the optimal threshold line, we define the class probabilities about C_0 and C_1 as follows

$$\omega_0 = \sum_{i+j\le s+t} p_{ij}, \quad \omega_1 = \sum_{i+j>s+t} p_{ij} \tag{4}$$

Class means

$$m_0 = (m_{0i}, m_{0j})^T = \left(\sum_{i+j\le s+t} ip_{ij}, \sum_{i+j\le s+t} jp_{ij} \right)^T \Big/ \omega_0 \tag{5}$$

$$m_1 = (m_{1i}, m_{1j})^T = \left(\sum_{i+j>s+t} ip_{ij}, \sum_{i+j>s+t} jp_{ij} \right)^T \Big/ \omega_1 \tag{6}$$

Total mean about two-dimensional histogram

$$m_t = (m_{ti}, m_{tj})^T = \left(\sum_{i=0}^{L-1}\sum_{j=0}^{L-1} ip_{ij}, \sum_{i=0}^{L-1}\sum_{j=0}^{L-1} jp_{ij} \right)^T \tag{7}$$

Obviously, $m_t=\omega_0 m_0+\omega_1 m_1$. When an image is segmented by the proposed method, the class variances about regions C_0 and C_1 are defined as follows.

$$\upsilon_0 = \sum_{i+j\le s+t} p_{ij} \left[(i-m_{0i})^2 + (j-m_{0j})^2 \right] \Big/ \omega_0 \tag{8}$$

$$\upsilon_0 = \sum_{i+j>s+t} p_{ij} \left[(i-m_{1i})^2 + (j-m_{1j})^2 \right] \Big/ \omega_1 \tag{9}$$

The total variance is defined as $\upsilon=\upsilon_0+\upsilon_1$. The optimal thresholds can be calculated by minimizing the total variance υ, i.e.

$$(s^*, t^*) = \min_{(s,t)\in G} (\upsilon) \tag{10}$$

When the optimal thresholds are obtained, the image can be segmented by

$$r(x,y) = \begin{cases} 0, & if \quad f(x,y)+g(x,y) \le s^* + t^* \\ 1, & if \quad f(x,y)+g(x,y) > s^* + t^* \end{cases} \tag{11}$$

Where $r(x,y)$ denotes the pixel value at point (x,y) in segmented image.

3.2. The Implementation of Algorithm of the Proposed Method

When the two-dimensional histogram is divided by the approach that adopted in the proposed method, the optimal thresholds points concentrate to the principal diagonal OD and the secondary diagonal that parallel to OD, as show in Figure 1. If we observe the threshold line $i+j=s+t$ carefully, we can see that the sum of the values of coordinate of the threshold point (s,t) is located in the region [0,2(L-1)], i.e. $0\le s+t\le 2(L-1)$. If we let $s+t=th$, the threshold point (s,t) lies on the line OD when th is an even number, and point (s,t) lies on the line that parallel to OD and on its right when the th is an odd number. From Equation (8) and (9), we can find that we must traverse the two-dimensional histogram to compute the class probability and class mean about C_0 and C_1 at every calculation of the variance of two-dimensional histogram. At the implementation of algorithm, it will cost a lot of calculation time. To reduce the computation time, we design four lookup tables about the class probability and class mean of C_0 and C_1 through recursion. In order to construct four lookup tables, let $W0(th)$, $W1(th)$, $X0i(th)$, $X0j(th)$, $X1i(th)$, and $X1j(th)$ as the zeroth and first order moments about C_0 and C_1, then

$$W0(0) = P_{00},\ \ W0(th) = W0(th-1) + \sum_{i+j=th} p_{ij} \tag{12}$$

$$X0i(0) = 0,\ \ X0i(th) = X0i(th-1) + \sum_{i+j=th} ip_{ij} \tag{13}$$

$$X0j(0) = 0,\ \ X0j(th) = X0j(th-1) + \sum_{i+j=th} jp_{ij} \tag{14}$$

$$W1(th) = 1 - W0(th) \tag{15}$$

Let Xti and Xtj as the total first moment of two-dimensional histogram

$$Xti = \sum_{i=0}^{L-1}\sum_{j=0}^{L-1} ip_{ij},\ \ Xtj = \sum_{i=0}^{L-1}\sum_{j=0}^{L-1} jp_{ij} \tag{16}$$

then there are $X1i(th)=Xti-X0i(th)$, $X1j(th)=Xtj-X0j(th)$. In addition, let $M0(th)$ and $M1(th)$ as the mean vectors of C_0 and C_1, then

$$M0(th) = (m_{0i}(th), m_{0j}(th))^T = \left(\frac{X0i(th)}{W0(th)}, \frac{X0j(th)}{W0(th)}\right)^T \tag{17}$$

$$M1(th) = (m_{1i}(th), m_{1j}(th))^T = \left(\frac{X1i(th)}{W1(th)}, \frac{X1j(th)}{W1(th)}\right)^T \tag{18}$$

In the processing of image segmentation, the four lookup tables of $W0$, $W1$, $M0$ and $M1$ are set up by abovementioned recursion formula firstly. Thus, in the process of search of optimal thresholds, there is no need for traversal of two-dimensional histogram at every calculation of variance. So the time can be saved in the run of algorithm. After the lookup tables are set up, let *min_var* as the initial minimal class variance, then the algorithm for image thresholding can be realized by pseudocode as follows

```
for n=0:2(L-1)-1
    V0 = Σ_{i+j≤n} p_ij[(i−m_0i(n))^2 + (j−m_0j(n))^2]/W0(n);
    V1 = Σ_{i+j>n} p_ij[(i−m_1i(n))^2 + (j−m_1j(n))^2]/W1(n);
    V=V0+V1;
    if (V<min_var)
        min_var=V;
        th=n;
    endif
endfor
```

Through the abovementioned computation, the sum th^* of the optimal thresholds (s,t) can be obtained. If th^* is an even number, let $a=th^*/2$, then the optimal thresholds vector $(s^*,t^*)=(a, a)$. If th^* is an odd number, let $a=(th^*-1)/2$, then $(s^*, t^*)=(a, a+1)$.

4. Experimental Results and Analysis

In order to verify the effectiveness of the proposed method, the two-dimensional Otsu method presented in [7], two-dimensional Otsu method presented in [8,9], two-dimensional MET method presented in [14], two-dimensional cross entropy method in [12], and the MCV method in [15] are used to compare with the proposed method. For convenience, the referenced methods are called as 2d_Otsu_1, 2d_Otsu_2, 2d_MET, 2d_MCE, and 1d_MCV, the proposed method is called as 2d_MCV. In this paper, all algorithms are coded by Matlab language. All algorithms are run on a computer with Intel(R) Core^{TM} Duo CPU T8100 @ 2.10GHz, 2GB RAM. The widows for generating the two-dimensional histogram is set as w=3.

4.1. Performance Evaluation

For the performance evaluation of image segmentation methods, there is no an absolutely effective objective criteria. In order to quantitative analysis of segmentation performance of every methods, the criteria, misclassification error (ME), which is widely used in many references [17,18], is selected as the objective evaluation criterion of segmentation methods in this paper.

$$ME = 1 - \frac{|B_O \cap B_T| + |F_O \cap F_T|}{|B_O| + |F_O|} \tag{19}$$

Where B_O and F_O denote the true background and foreground of image, B_T and F_T denote the background and foreground of segmented image respectively. |•| is the number of the elements of the set •. From Equation (19), it can be seen that the smaller the value of ME, the better the performance of segmentation algorithm.

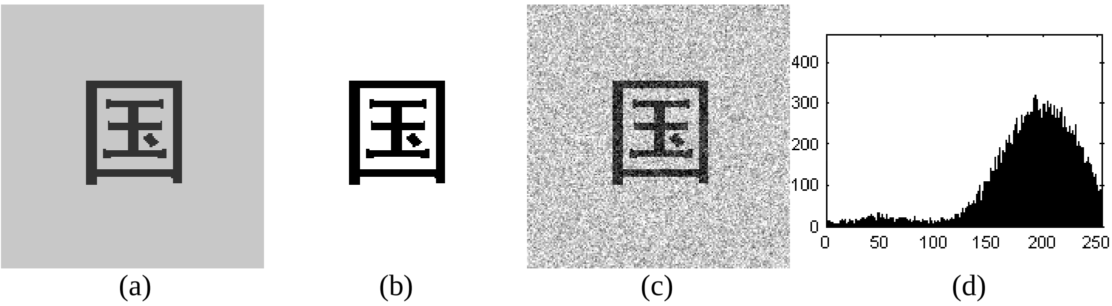


Figure 2. The Synthetic Image and Its Noise-added Image with Gaussian Noise; (a) Original Synthetic Image, (b) Ground Truth Image, (c) Noise-added Image, and (d) Histogram of Noise-added Image

The first experiment is carried on a synthetic image, the foreground of the synthetic image is constituted by a Chinese character, its pixels gray level is 50, background gray level is 200, and the size of the image is 170×170. Figure 2 shows the original, ground truth, and noise-added image of the synthetic. The noise that added on the synthetic image is Gaussian noise with 0 mean, and standard deviation 0.02.

Figure 3 shows the segmented results of noise-added image by methods referenced in this paper. From Figure 3, we can see that the result obtained by the proposed method is better than other methods. While for the two two-dimensional Otsu methods, two-dimensional cross entropy method, and the two-dimensional MET method, there is more noise in the segmented results. For one-dimensional MCV method, the object is separated. However, there are many pixels that are classified as background, and the Chinese character become incomplete.

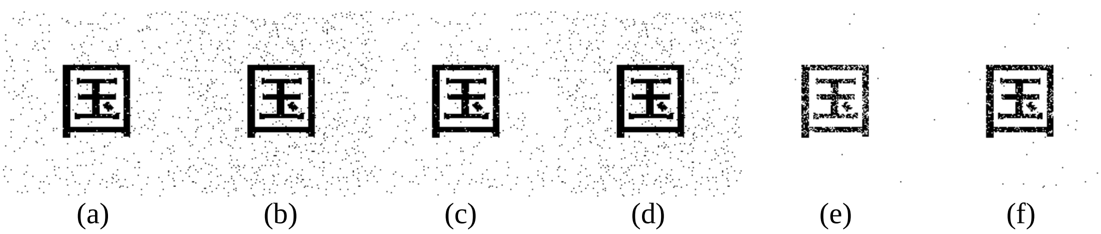


Figure 3. The Segmented Results of Synthetic Noisy Image by (a) 2d_Otsu_1, (b) 2d_Otsu_2, (c) 2d_MCE, (d) 2d_MET, (e) 1d_MCV, and (f) 2d_MCV Method

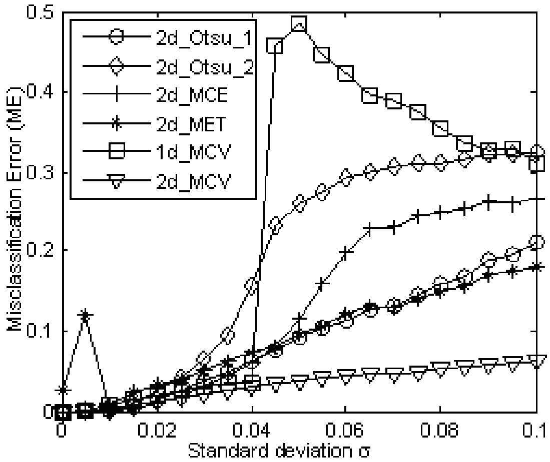


Figure 4. Variation Curve of ME Values

Table 1 list the optimal threshold(s), number of pixels that are misclassified by the referenced methods. From Table 1, it can be seen that the number of pixels that are misclassified by the proposed method is the fewest. Second fewest is the two-dimensional cross entropy method. The numbers for the two two-dimensional Otsu methods, two-dimensional MET method, and the one-dimensional MCV method are bigger than other method.

Table 1. The Threshold(s) and Number of Misclassified Pixels of Noise-Added Image

Method	2d_Otsu_1	2d_Otsu_2	2d_MCE	2d_MET	1d_MCV	2d_MCV
Threshold(s)	(208,121)	(131,132)	(115,116)	(130,131)	72	(88,88)
Misclassified pixels	428	750	333	703	548	318

In order to illustrate the noise tolerance of every method preferably, we carry out a series of experiments on synthetic images with 0 mean and standard deviation σ is increasing step by step. Figure 4 shows the variation curves of ME of every method of tests on each noise-added image. Gaussian noise has randomness. To overcome the influence of the randomness to ME, the ME values shown in Figure 4 are the average of 10 MEs that obtained by algorithm independent run 10 times on each noise level.

From Figure 4, we can see that variation curve of ME for the proposed method is smooth and steady to each noise level. The maximum of ME for the proposed method does not exceed 0.1. While for other methods, the variation curves of ME have larger fluctuation. From Figure 4, it can be seen that the proposed method has better capability of anti-noise.

4.2. Real-world Images

In order to demonstrate the performance of the referenced methods preferably, we test the methods on many real-world images. Due to the limit of space, a part results are shown in this section. Images shown in Figure 5 are an infrared human image with size of 240×320 and its segmented results by different methods. From Figure 5, we can see that the results obtained by 2d_Otsu_1, 2d_MCE, and 2d_MET are worse than other methods. The human targets in Figure 5(a) do not be separated basically. For 2d_Otsu_2 method, there are more residual noise on the left bottom and top right of segmented result. The results obtained by 1d_MCV and the proposed method are better than other methods.

Although some parts of the human body appear broken, the defect can be remedied by simple morphological operator.

(a) (b) (c) (d) (e) (f) (g)

Figure 5. The Segmented Results of Infrared Human Image; (a) Original image, and Results by (b) 2d_Otsu_1, (c) 2d_Otsu_2, (d) 2d_MCE, (e) 2d_MET, (f) 1d_MCV, and (g) 2d_MCV Method

Figure 6 shows a licence plate image added Gaussian noise with 0 mean, and standard deviation 0.01, the size is 193×600, and the segmented results. From Figure 6, we can see that there are more residual noise in the results obtained by two-dimensional Otsu method, two-dimensional cross entropy method, and the two-dimensional MET method. In the results obtained by the one-dimensional MCV method and the proposed method, the objects are separated from background well, and few residual noise.

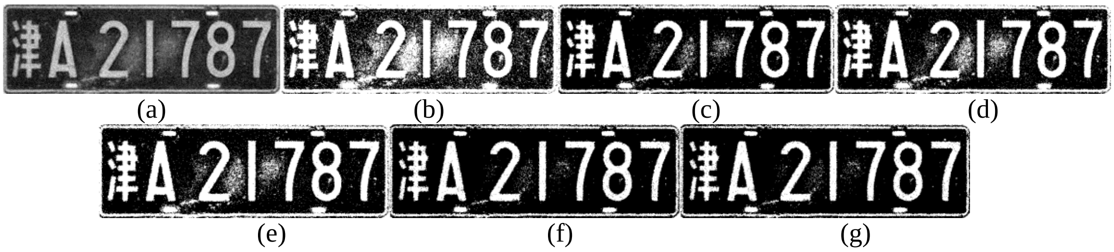
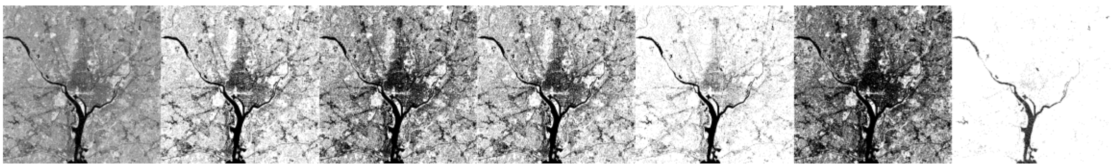


Figure 6. The Segmented Results of Licence Plate Image; (a) Original image, and Results by (b) 2d_Otsu_1, (c) 2d_Otsu_2, (d) 2d_MCE, (e) 2d_MET, (f) 1d_MCV, and (g) 2d_MCV Method

Figure 7 shows a SAR image with size of 1024×1026 and its segmented results. The original SAR image is added Gaussian noise with 0 mean, and standard deviation 0.02. From Figure 7 we can see that the object of the SAR image does not separated by the two-dimensional Otsu method, two-dimensional cross entropy method, the two-dimensional MET method, and the one-dimensional MCV method basically. The best result is obtained by the proposed method. For the proposed method, the river is separated from the background well.



(a) (b) (c) (d) (e) (f) (g)

Figure 7. The Segmented Results of SAR Image. (a) Original image, and Results by (b) 2d_Otsu_1, (c) 2d_Otsu_2, (d) 2d_MCE, (e) 2d_MET, (f) 1d_MCV, and (g) 2d_MCV Method

5. Conclusions

This paper presents a new method for gray image segmentation. Based on the framework of two-dimensional gray level histogram and variance criterion, this method presents a scheme for image segmentation and a realized algorithm through recursion.

One major contribution of this paper is the improvement of the variance-based thresholding method under the presented scheme. This makes the proposed method be able to overcome the weakness of the conventional variance-based methods.

We applied the proposed segmentation method on both simulated and real images. The results of the proposed method are compared with those of conventional variance-based method, cross entropy method, and the minimum error thredholding method. The results of synthetic image segmentations show that the proposed performs better than the other methods. Moreover, the experimental results on real-world images show that the proposed method is valid for realistic applications.

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