

An Improved Method for Image Thresholding based on the Valley-Emphasis Method

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Abstract—Thresholding is an important technique for image segmentation that extracts a target from its background on the basis of the distribution of gray levels. Many automatic threshold selection methods such as Otsu method provide satisfactory results for thresholding images with obvious bimodal gray level distribution. However, most threshold selection methods fail if the histogram is unimodal or close to unimodal. Valley-emphasis method partially resolves such problem by weighting the objective function of the Otsu method with the valley point in the histogram. In this study, we proposed an approach for improving the valley-emphasis method for optimal threshold selection by introducing a Gaussian weighting scheme to enhance the weighting effect. Experimental results indicate that the proposed method provides better and more stable thresholding results.

I. INTRODUCTION

Image thresholding is a popular technique for image segmentation because of its simplicity and computational efficiency [1]. The basic idea of image thresholding is to automatically select an optimal gray-level threshold value based on gray-level distribution, and compare each pixel in the image to the threshold value to separate objects of interest in an image from the background. Because of its wide applicability to other areas of image processing and applications, many automatic thresholding algorithms have been proposed in the literatures. In-depth survey and evaluation of various thresholding methods are given by Sahoo et al. [2], Lee et al. [3], Glasbey [4], and more recently, by Sezgin and Sankur [5].

Among the image thresholding techniques, the Otsu method [6] is one of the better threshold selection methods for general real world images with respect to uniformity and shape measures [2]. This method selects threshold values that maximize the between-class variances of the histogram. The Otsu method assumes that the gray level of the object and the background in an image distribution is Gaussian distribution with equal variances [7], thus it is optimal for thresholding a histogram with bimodal or multimodal distribution but fails if the histogram is unimodal or close to unimodal. Ng [8] revised the Otsu method for selecting optimal threshold values for both unimodal and bimodal distributions. The method, called valley-emphasis method, uses similar objective function as the Otsu method but give more weights to the valley points in the histogram. In other words, the

valley-emphasis method favors values that reside at the valley of two peaks, or at the bottom rim of a single peak. Therefore, the valley-emphasis method is able to select optimal threshold values for both bimodal and unimodal distributions. Recently, Fan and Lei [9] pointed out that the weighting effect of the valley-emphasis method might not be strong enough for cases where the variance of the object is very different from that of the background and thus fails to locate correct threshold value. They suggested that including the neighboring values around the valley points could improve the weighting effect. However, it is unclear how to determine the appropriate size for the neighborhood to achieve optimal thresholding results.

In this study, we proposed an approach for improving the valley-emphasis method for image thresholding by introducing a Gaussian weighting scheme in the objective function to enhance the weighting effect. The rest of the paper is organized as follows. Section 2 presents the algorithm and procedure for automatic threshold selection. Section 3 contains experimental results, and concluding remarks are given in section 4.

II. IMAGE THRESHOLDING METHODS

In this section, we briefly review the Otsu method and the valley-emphasis method for selecting optimal image threshold, and present the Gaussian weighting scheme for improving the valley-emphasis method.

A. Otsu Method

An image 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. Let the number of pixels with gray-level i be n_i , and n be the total number of pixels in a given image, the probability of occurrence of gray-level i is defined as:

$$p_i = \frac{n_i}{n} \quad (1)$$

The average gray-level of the entire image is computed as:

$$\mu_T = \sum_{i=0}^{L-1} ip_i \quad (2)$$

In the case of single thresholding, the pixels of an image are divided into two classes $C_1 = \{0, 1, \dots, t\}$ and $C_2 = \{t+1, t+2, \dots, L-1\}$, where t is the threshold value. C_1 and C_2 are normally corresponding to the foreground (objects of interest) and the background. The probabilities of the two classes are:

$$\omega_1(t) = \sum_{i=0}^t p_i \quad (3)$$

$$\omega_2(t) = \sum_{i=t+1}^{L-1} p_i \quad (4)$$

The mean gray-level values of the two classes can be computed as:

$$\mu_1(t) = \sum_{i=0}^t i p_i / \omega_1(t) \quad (5)$$

$$\mu_2(t) = \sum_{i=t+1}^{L-1} i p_i / \omega_2(t) \quad (6)$$

Using discriminant analysis, Otsu [6] showed that the optimal threshold t^* can be determined by maximizing the between-class variance σ_B ; that is:

$$t^* = \underset{0 \leq t < L}{\text{Arg Max}} \{ \sigma_B \} \quad (7)$$

$$= \underset{0 \leq t < L}{\text{Arg Max}} \{ \omega_1(t)(\mu_1(t) - \mu_T)^2 + \omega_2(t)(\mu_2(t) - \mu_T)^2 \}$$

Equation 7 could be further simplified as:

$$t^* = \underset{0 \leq t < L}{\text{Arg Max}} \{ \omega_1(t)\mu_1^2(t) + \omega_2(t)\mu_2^2(t) \} \quad (8)$$

From (8) we can see that Otsu method is simple and easy to realize thus makes it one of the most commonly used threshold methods in engineer practices with satisfactory results. However, Otsu method is optimal for thresholding a histogram with bimodal or multimodal distribution but fails if the histogram is unimodal or close to unimodal.

B. Valley-Emphasis Method

In the case of single object, the idea threshold value should lie at the valley of the two peaks (bimodal), or at the bottom rim of a single peak (unimodal), as shown in Fig. 1.

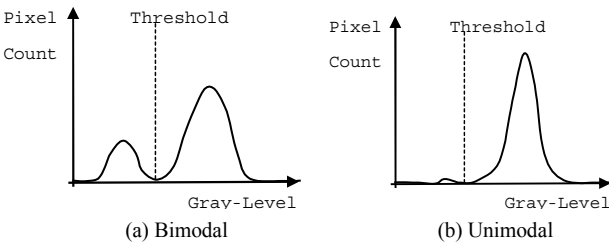


Fig. 1 Optimal threshold selection in gray-level histogram [8].

Based on this observation, Ng [8] proposed the valley-emphasis method to select a threshold value with a small probability of occurrence (p_i) which also maximizes the

between-class variance. They introduced a weighting term which is defined as inverse proportional to p_i :

$$W(t) = 1 - p_t \quad (9)$$

The optimal threshold is chosen by maximizing the revised objective function as:

$$t^* = \underset{0 \leq t < L}{\text{Arg Max}} \{ W(t)(\omega_1(t)\mu_1^2(t) + \omega_2(t)\mu_2^2(t)) \} \quad (10)$$

The first term in (10) is the weight and the second term is the between-class variance of the image. The smaller the p_t value, the larger the weight will be. This weight ensures that the resulting threshold will be a value that resides at the valley or bottom rim of the gray-level distribution.

C. Proposed Method

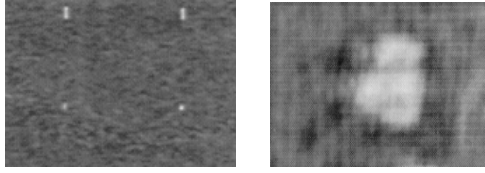
It was shown in [9] that the weighting term $(1-p_t)$ in (10) might not be significant enough for cases where the variance of the object is very different from that of the background and thus fails to determine correct threshold value. They suggested that including the neighboring values around the threshold value could improve the weighting effect. In this study, we propose a Gaussian weighting scheme that efficiently uses the neighborhood information for inclusion in the objective function. For each candidate threshold location t , a new weighting term is defined as:

$$W(t, \sigma) = 1 - \sum_x p_x e^{\left(\frac{(x-t)^2}{2\sigma^2} \right)} \quad (11)$$

It is one minus the sum of the grayscale probabilities around t multiplied with a Gaussian window of standard deviation σ . The Gaussian window is used to ensure that locations that are far from the candidate threshold location should receive less attention than those that are closer to the threshold location. This weight is more significant than the weight that uses only the probability at the threshold location as in the valley-emphasis method. In addition, the smoothing effect of the Gaussian window makes the new weight calculation less susceptible to noise. The appropriate value for sigma (σ) could be determined experimentally.

III. EXPERIMENTS

In the experiments, we tested the performance of applying the proposed Gaussian weighting scheme on the Otsu method and compared our results with the results of the valley-emphasis method. The test data consisted of a variety of 24 images including non-destructive testing (NDT) images and document images. Similar test images were also used in previous studies [5,8,9]. Fig. 2 shows samples of the test images and their corresponding ground truths.



(a) Sample test images



(b) Ground truths

Fig. 2 Sample test images and corresponding ground truths [5].

Quality of thresholding result is quantitatively evaluated by misclassification error (ME) measure, which regards image segmentation as a pixel classification process. The misclassification error is defined as [10]:

$$err = 1 - \frac{|B_0 \cap B_T| + |F_0 \cap F_T|}{|B_0| + |F_0|} \quad (12)$$

Where B_0 and F_0 denote the background and foreground of the original image, B_T and F_T denote the background and foreground of the test image, and $|\cdot|$ is the cardinality of the set. ME reflects the percentage of background pixels wrongly assigned to foreground, and conversely, foreground pixels wrongly assigned to background. The value of ME varies between 0 for a perfectly classified image and 1 for a totally erroneously classified one. A lower value of ME means better quality of corresponding thresholded image.

Fig. 3 shows the thresholding results using the original Otsu method (Otsu), Otsu with valley-emphasis weight (Valley), and Otsu with Gaussian weight (Our method) for a sample test image. We can see that the thresholding result of the proposed method is better than the Otsu method and the valley-emphasis method. The ME values for the Otsu method and the Valley method are 0.0609 and 0.0385 respectively, while the ME values for Our method (with $\sigma=5$) is 0.0151, which is much smaller than the that of the original Otsu method and the valley-emphasis method.

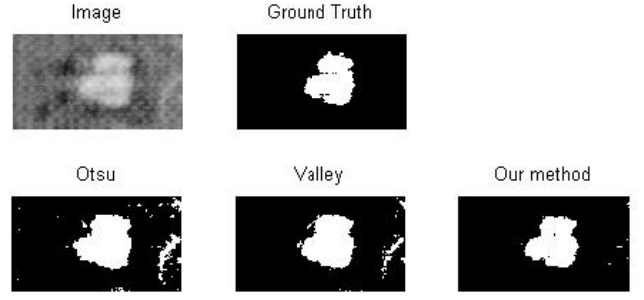


Fig. 3 Thresholding results.

Fig. 4 shows the histogram of sample test image and the Otsu objective function before and after applying the valley weight and the proposed Gaussian weight. The threshold value selected by Otsu method is 141, which is not at the valley (about 160) of the histogram. The threshold value selected by the valley-emphasis method is 148, which still deviate from the valley point. On the other hand, the proposed method reports a threshold value of 168, which is close to the valley point of the histogram. In addition, it is clear from Fig. 4 that the Gaussian weighting function is rather smooth while the valley weighting function is very noisy.

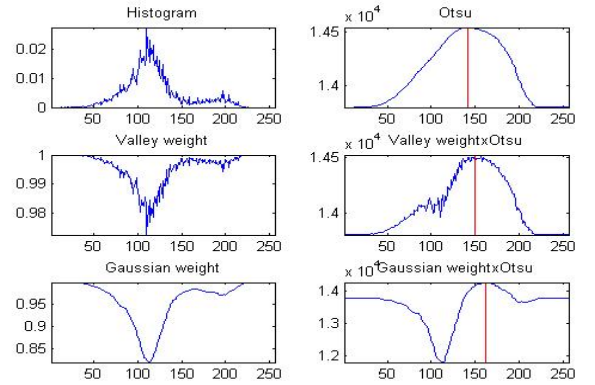


Fig. 4 Histogram and objective functions.

The average misclassification error of the 24 test images using the original Otsu method, Otsu with valley weight, and Otsu with Gaussian weight are shown in Table 1. The best result for the proposed method is about 0.0140 when the sigma value of the Gaussian weight is 6, which is about 12 times better than the original Otsu method, and about 2.7 times better than the valley-emphasis method.

TABLE I. AVERAGE MISCLASSIFICATION ERRORS.

Method	Misclassification Error
Otsu	0.1711
Valley-Emphasis	0.0377
Proposed ($\sigma=6$)	0.0140

Fig. 5 shows the average misclassification errors of the Gaussian weighting as a function of sigma. We can see that for the Otsu objective function, a Gaussian weight with sigma around 5 produces better thresholding results.

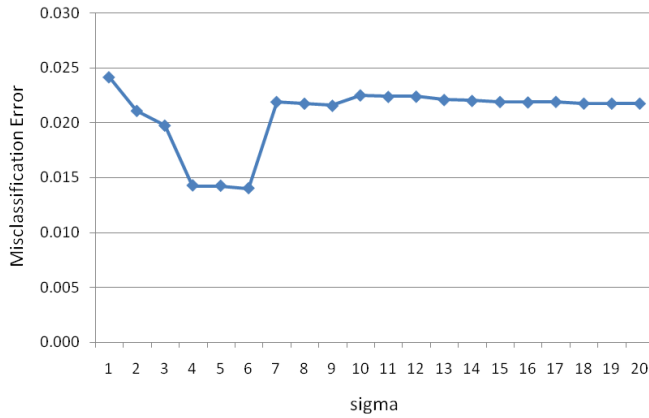


Fig. 5 Misclassification error of the proposed method as a function of sigma.

IV. CONCLUSIONS

In this study, we revised the valley-emphasis method and proposed a Gaussian weighting scheme to improve automatic threshold selection for both bimodal and unimodal gray level distributions. We tested the performance of the proposed method on 24 test images and the experimental results show that the proposed method gives better thresholding results than the original Otsu method and the valley-emphasis method. Gaussian weighting provides about 12 times improvement for the Otsu method, and about 2.7 times better than the valley-emphasis method. Future research will test the performance of the proposed Gaussian weighting scheme on other threshold selection methods, and extend the proposed method to multiple thresholding.

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