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Pattern Recognition Letters 27 (2006) 1644–1649
Pattern Recognition Letters
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# Automatic thresholding for defect detection

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Received 26 January 2005; received in revised form 25 February 2006
Available online 14 June 2006

Communicated by Y.J. Zhang

**Abstract**

Automatic thresholding has been widely used in the machine vision industry for automated visual inspection of defects. A commonly used thresholding technique, the Otsu method, provides satisfactory results for thresholding an image with a histogram of bimodal distribution. This method, however, fails if the histogram is unimodal or close to unimodal. For defect detection applications, defects can range from no defect to small or large defects, which means that the gray-level distributions range from unimodal to bimodal. For this paper, we revised the Otsu method for selecting optimal threshold values for both unimodal and bimodal distributions, and tested the performance of the revised method, the valley-emphasis method, on common defect detection applications.


*Keywords:* Automatic thresholding; Defect detection

## 1. Introduction

Automatic thresholding is an important technique in image segmentation and machine vision applications. The basic idea of automatic thresholding is to automatically select an optimal gray-level threshold value for separating objects of interest in an image from the background based on their gray-level distribution. This thresholding technique has been widely used in the industry for automated visual inspection of defects (Newman, 1995). The technique is often referred to as contrast sensing in the machine vision industry. Because of its wide applicability to other areas of image processing and applications, there is a considerable body of work on automatic threshoding to draw from. In-depth survey and evaluation of various thresholding methods are given by Sahoo et al. (1988), Lee et al. (1990), Glasbey (1993) and more recently, by Sezgin and Sankur (2004).

Automatic thresholding techniques can be roughly categorized into global thresholding and local thresholding. Global thresholding selects a single threshold value from the histogram of the entire image. Local thresholding uses localized gray-level information to choose multiple threshold values; each is optimized for a small region in the image. Global thresholding is simpler and easier to implement but its result relies on good (uniform) illumination. Local thresholding methods can deal with non-uniform illumination but they are complicated and slow. For automated visual inspection applications, where non-uniform illumination is usually not an issue due to controlled lighting conditions, global thresholding is commonly used for its simplicity and speed.

Among the global thresholding techniques, the Sahoo et al. (1988) study concluded that the Otsu method (Otsu, 1979) was one of the better threshold selection methods for general real world images with respect to uniformity and shape measures. This method selects threshold values that maximize the between-class variances of the histogram. The Otsu method is optimal for thresholding large objects from the background; in other words, it is good for thresholding a histogram with bimodal or multimodal distribution. The Otsu method, however, fails if the histogram is unimodal or close to unimodal. Because defect

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doi:10.1016/j.patrec.2006.03.009

detection applications range from no defect to small and large defects, the gray-level distributions range from unimodal to bimodal. As a result, to successfully detect defects in the automatic visual inspection applications with the Otsu method, we need to revise the method so that it will handle both unimodal and bimodal distributions equally well. The objectives of this study were to revise the Otsu method for selecting optimal threshold values for both unimodal and bimodal distributions, and to test the performance of the revised method on common defect detection applications.

## 2. Automatic threshold selection

In this section, we briefly review the Otsu method for selecting optimal image threshold. We show the problem of using the Otsu method in thresholding small defects in an image. Later, we will present the valley-emphasis method, a revised version of the Otsu method for detecting small to large defects.

### 2.1. The 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:

$$p_i = \frac{n_i}{n} \tag{1}$$

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

$$\mu_{\mathrm{T}} = \sum_{i=0}^{L-1} \mathrm{i}p_i$$

In the case of single thresholding, the pixels of an image are divided into two classes $C_1 = \{0,1,\ldots,t\}$ and $C_2 = \{t+1,\ t+2,\ldots,L-1\}$, 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:

$$\omega_1(t) = \sum_{i=0}^{t} p_i \quad \text{and} \quad \omega_2(t) = \sum_{i=t+1}^{L-1} p_i \tag{2}$$

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

$$\mu_1(t) = \sum_{i=0}^{t} \mathrm{i}p_i/\omega_1(t) \quad \text{and} \quad \mu_2(t) = \sum_{i=t+1}^{L-1} \mathrm{i}p_i/\omega_2(t) \tag{3}$$

Using discriminant analysis, Otsu (1979) showed that the optimal threshold $t^*$ can be determined by maximizing the between-class variance; that is:

$$t^* = \mathrm{Arg}\,\underset{0\leqslant t<L}{\mathrm{Max}}\{\sigma_{\mathrm{B}}^2(t)\} \tag{4}$$

where the between-class variance $\sigma_{\mathrm{B}}$ is defined as:

$$\sigma_{\mathrm{B}}^2(t) = \omega_1(t)(\mu_1(t)-\mu_{\mathrm{T}})^2 + \omega_2(t)(\mu_2(t)-\mu_{\mathrm{T}})^2 \tag{5}$$

An equivalent, but simpler formulation for the Otsu method is given in Liao et al. (2001). The simplified formula for obtaining optimal threshold $t*$ is computed as follows:

$$t^* = \mathrm{Arg}\,\underset{0\leqslant t<L}{\mathrm{Max}}\{\omega_1(t)\mu_1^2(t) + \omega_2(t)\mu_2^2(t)\} \tag{6}$$

The Otsu method described here can be easily extended to multilevel thresholding of an image (Otsu, 1979; Liao et al., 2001). For $M-1$ thresholds, which divide the image pixels into $M$ classes, $C_1 \sim C_M$, the optimal thresholds $\{t_1^*, t_2^*, \ldots, t_{M-1}^*\}$ are chosen by maximizing the between-class variance as follows:

$$\{t_1^*, t_2^*, \ldots, t_{M-1}^*\} = \mathrm{Arg}\,\underset{0\leqslant t_1<\ldots<t_{M-1}<L}{\mathrm{Max}}\left\{\sum_{k=1}^{M} \omega_k\mu_k^2\right\} \tag{7}$$

The Otsu method works well when the images to be thresholded have clear peaks and valleys—in other words, it works for images whose histograms show clear bimodal or multimodal distributions. For the defect detection applications, defects range from small defects to large defects. Histograms of images containing small defects do not show clear bimodal distributions, as is illustrated in the following example. Fig. 1 shows an application to detect contamination in liquid. Fig. 1a shows the test image, and Fig. 1d shows the histogram of the image. Because the contaminant (dark spot) is small comparing to the background, the histogram demonstrates a unimodal distribution. The desired threshold should be the value that separates the small contaminant from the background (Fig. 1b). However, the Otsu method gives the incorrect threshold value and fails to isolate the contaminant, as shown in Fig. 1c. The desired threshold value and the Otsu threshold value are shown in Fig. 1d.

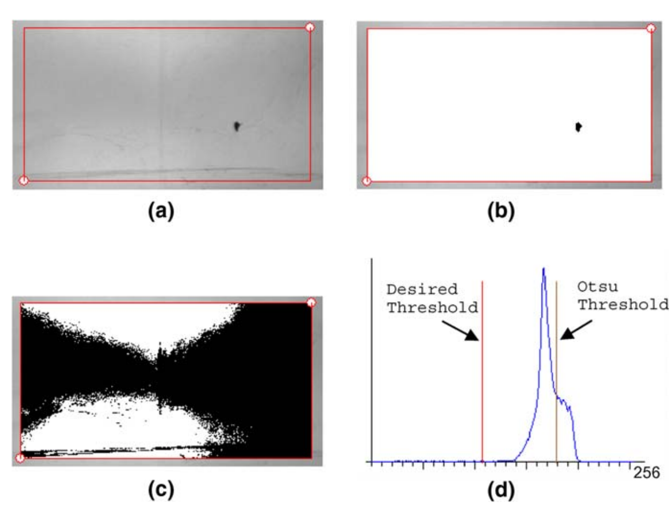


Fig. 1. Problem with the Otsu method in thresholding small defects: (a) original image; (b) desired threshold result; (c) Otsu threshold result; (d) histogram and threshold values.

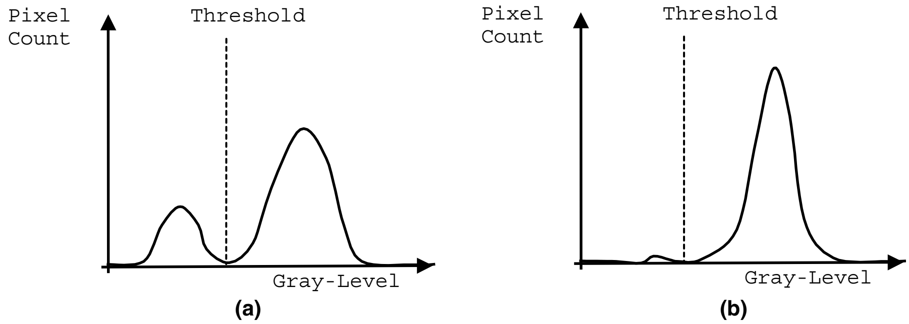


Fig. 2. Optimal threshold selection in gray-level histogram: (a) bimodal; (b) unimodal.

*2.2. The valley-emphasis method*

The objective of automatic thresholding is to find the valley in the histogram that separates the foreground from the background, as demonstrated in Fig. 2. For the case of single thresholding, it is clear from Fig. 2 that such threshold value exists at the valley of the two peaks (bimodal), or at the bottom rim of a single peak (unimodal). The important observation here is that the probability of occurrence at the threshold value ($p_t$) has to be small.

With this observation in mind, we propose an improvement to the Otsu method for selecting threshold values, the valley-emphasis method. The idea of the valley-emphasis method is to select a threshold value that has a small probability of occurrence (valley in the gray-level histogram), and also maximize the between group variance, as in the Otsu method. The formulation for the valley-emphasis method is:

$$t^* = \operatorname{Arg}\operatorname*{Max}_{0\leqslant t<L}\{(1-p_t)(\omega_1(t)\mu_1^2(t)+\omega_2(t)\mu_2^2(t))\} \tag{8}$$

The key to the valley-emphasis formulation is the application of a weight, $(1-p_t)$, to the Otsu threshold calculation. The smaller the $p_t$ value (low probability of occurrence), the larger the weight will be. This weight ensures that the result threshold will always be a value that resides at the valley or bottom rim of the gray-level distribution. Using the valley-emphasis method on the contamination application shown in Fig. 1, we were able to find the correct threshold value that isolates the contaminant in the test image (Fig. 1b). The valley-emphasis method does not attempt to split a peak in unimodal distribution as the Otsu method does (see Fig. 1d). A peak in the histogram normally corresponds to a single entity in the image.

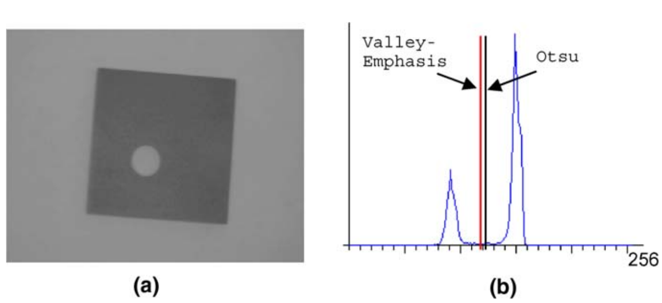


Fig. 3. Threshold selections for a test image with bimodal distribution: (a) test image; (b) histogram and threshold values.

For images that have apparent bimodal distribution, the valley-emphasis method should give a threshold value that is comparable to the value generated by the Otsu method because both methods attempt to maximize the between-group variance of the histogram. Fig. 3 shows an example of using both methods in finding threshold value for an image that has bimodal gray-level distribution. The threshold values returned by the Otsu method and the valley-emphasis method are 121 and 117, respectively.

It is straightforward to generalize the valley-emphasis method to handle multi-level thresholding. For $M-1$ level threshold (M classes), the optimal thresholds $\{t_1^*, t_2^*, \ldots, t_{M-1}^*\}$ are given as:

$$\{t_1^*, t_2^*, \ldots, t_{M-1}^*\} = \operatorname{Arg}\operatorname*{Max}_{0\leqslant t_1<\ldots<t_{M-1}<L}\left\{\left(1-\sum_{j=1}^{M-1}p_{t_j}\right)\left(\sum_{k=1}^{M}\omega_k\mu_k^2\right)\right\} \tag{9}$$

where the first term in (9) corresponds to the weight.

## 3. Experiments

In the experiments, we tested the performance of the valley-emphasis method and the Otsu method on several common defect detection applications. For each experiment, we evaluated the misclassification errors of the two methods defined as (Yasnoff et al., 1977):

$$\mathrm{err} = 1 - \frac{|B_\mathrm{o}\cap B_\mathrm{T}| + |F_\mathrm{o}\cap F_\mathrm{T}|}{|B_\mathrm{o}| + |F_\mathrm{o}|} \tag{10}$$

where $B_\mathrm{o}$ and $F_\mathrm{o}$ denote the background and foreground area pixels of the manually thresholded image, $B_\mathrm{T}$ and $F_\mathrm{T}$ denote the background and foreground area pixels in the image that are thresholded using either the valley-emphasis method or the Otsu method, and $|.|$ is the cardinality of the set. This error reflects the percentage of wrongly assigned pixels, which ranges from zero for no error, to one for completely wrong. For each defect detection application, 10 test images that ranged from no defect to small and large defects were first thresholded manually, and then by the

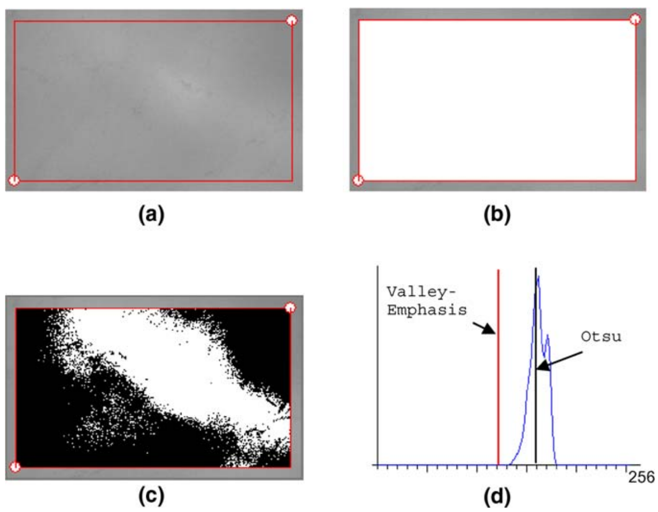


Fig. 4. Valley-emphasis and Otsu threshold results for contamination detection: (a) image with no contaminant; (b) valley-emphasis threshold result; (c) Otsu threshold result and (d) histogram and threshold values.

valley-emphasis method and the Otsu method, and their misclassification errors computed. The final misclassification error for a method was calculated as the average of the 10 error values.

We have seen that the proposed valley-emphasis method gave the proper threshold value for isolating small contaminants for a contamination detection application in the last section. Another example is shown in Fig. 4, where there is no contaminant in the image being inspected. The valley-emphasis method gave the appropriate threshold value and did not report any defect (Fig. 4b). The Otsu method, however, gave the incorrect threshold value and reported false defect result (Fig. 4c). The histogram and the threshold values reported by the valley-emphasis method and the Otsu method are shown in Fig. 4d. For the contamination detection application, the average misclassification errors were 0.004 for the valley-emphasis method and 0.583 for the Otsu method.

Fig. 5 shows an example of detecting defects on the ceramic body of electronic component. The valley-emphasis method successfully isolated the small defect in the upper-right corner of the ceramic body (Fig. 5b). The Otsu method was able to detect the defect but it also reported false defects on the ceramic body as seen in Fig. 5c. The histogram of the image and the threshold values are shown in Fig. 5d. For the ceramic body defect detection application, the average misclassification errors were 0.007 for the valley-emphasis method and 0.110 for the Otsu method.

Another common defect detection application is metal sheet scratch inspection. Fig. 6a shows an image of metal sheet with scratches. The differences in gray-level between the scratches and the metal sheet were rather small, which can be seen from the image histogram in Fig. 6d. The threshold results for the valley-emphasis method and the Otsu method were shown in Figs. 6b and c, respectively. The valley-emphasis method performed better for thresholding the defects on the test images. The average classification errors for this application were 0.006 for the valley-emphasis method, and 0.192 for the Otsu method.

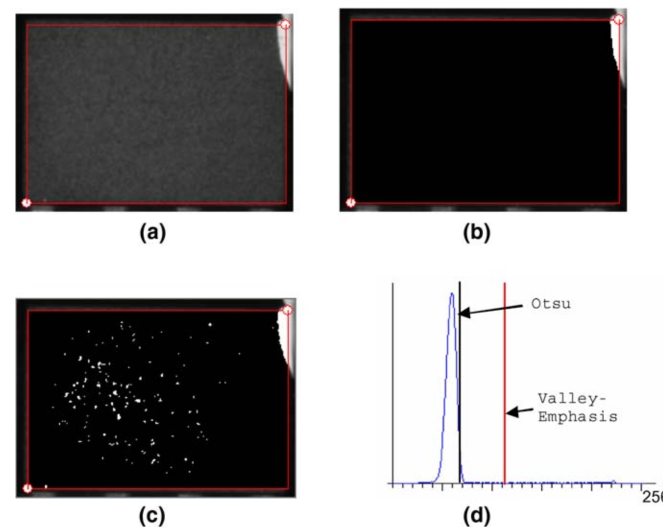


Fig. 5. Valley-emphasis and Otsu threshold results for ceramic body defect detection: (a) ceramic body image; (b) valley-emphasis threshold result; (c) Otsu threshold result; (d) histogram and threshold values.

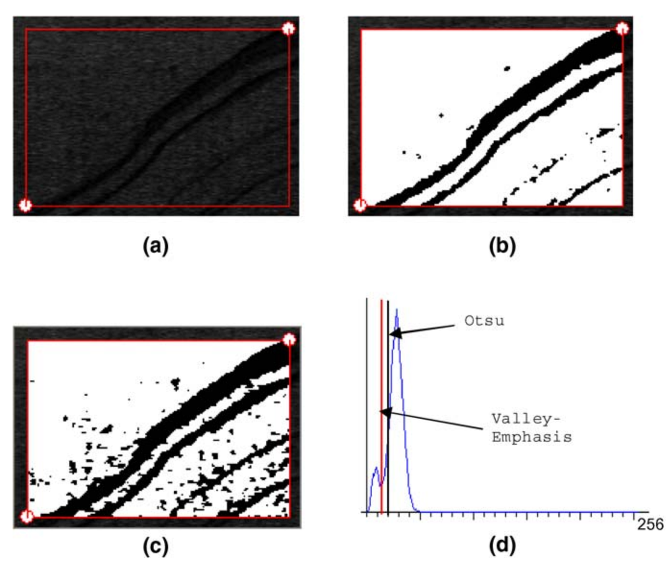


Fig. 6. Valley-emphasis and Otsu threshold results for metal sheet scratch inspection: (a) metal sheet image; (b) valley-emphasis threshold result; (c) Otsu threshold result; (d) histogram and threshold values.

The average misclassification errors for the valley-emphasis method and the Otsu method are summarized in Table 1. The valley-emphasis method outperformed the Otsu method for all three defect detection applications. The misclassification errors for the valley-emphasis method are very small comparing to the Otsu method. Note that the Otsu method has significantly larger misclassification errors for the contamination detection application. This is because in our contamination detection experiment, most of the test images contain little contaminants or no

Table 1
Average misclassification errors for the valley-emphasis method and the Otsu method for three common defect detection applications

| Application | Misclassification error | |
|---|---|---|
| | Otsu | Valley-emphasis |
| Contamination inspection | 0.583 | 0.004 |
| Ceramic body inspection | 0.110 | 0.007 |
| Metal sheet inspection | 0.192 | 0.006 |

contaminant. The Otsu method performs poorly on such images.

In the following experiments, we examine the performance of the valley-emphasis method on multilevel thresholding. Fig. 7a shows a house image and the histogram of the image is shown in Fig. 7d. The histogram demonstrates a tri-modal gray-level distribution. Figs. 7b and c are the threshold results of the valley-emphasis method and the Otsu method using tri-level thresholding. We can see that both methods worked well for the house image, which had clear multimodal gray-level distribution, and the valley-emphasis method produced similar result as the Otsu method.

Fig. 8 shows another experiment of multilevel thresholding. Fig. 8a is an image of a machine part with a small defect. Our aim was to separate the part from the background and also to isolate the small defect from the part. Fig. 8b shows the threshold result of the valley-emphasis method using tri-level thresholding. The valley-emphasis method worked well on the image even though the image did not have obvious multimodal gray-level distribution. The Otsu method, however, performed poorly on the part

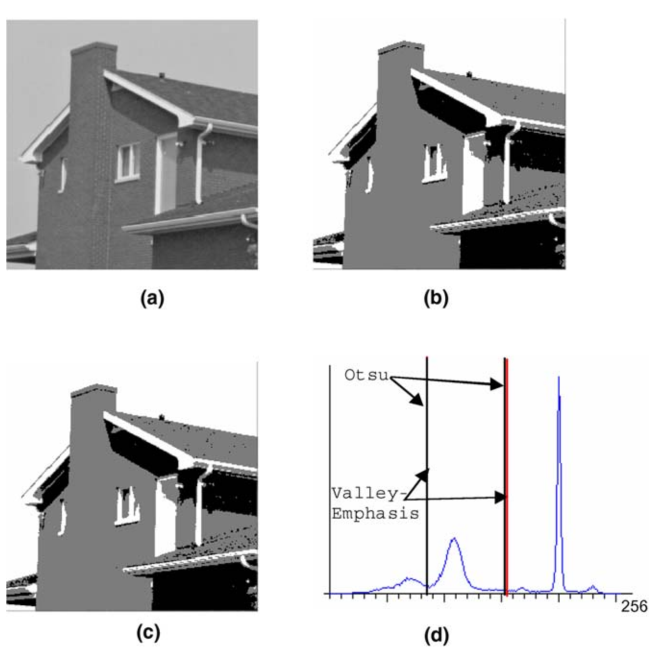


Fig. 7. Valley-emphasis and Otsu threshold results for a house image: (a) house image; (b) valley-emphasis tri-level threshold result; (c) Otsu tri-level threshold result; (d) histogram and threshold values.

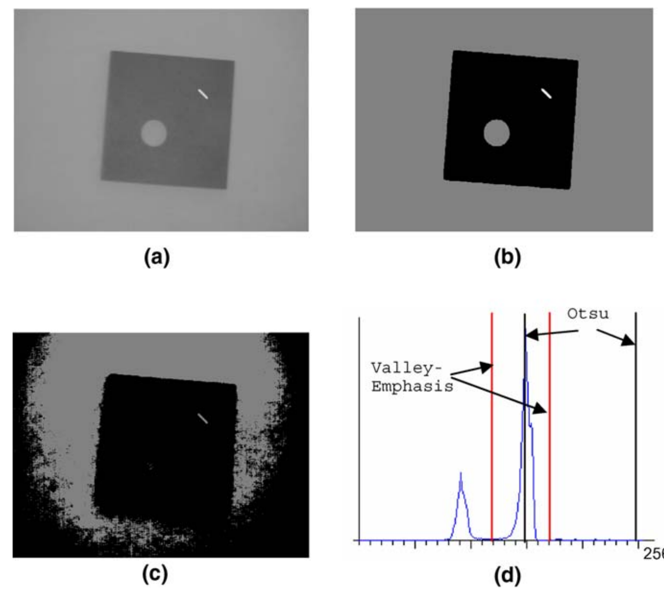


Fig. 8. Valley-emphasis and Otsu threshold results for a part image: (a) part image; (b) valley-emphasis tri-level threshold result; (c) Otsu tri-level threshold result; (d) histogram and threshold values.

image (Fig. 8c) because it requires clear multimodal gray-level distribution. The threshold values computed by the two methods are shown in Fig. 8d.

## 4. Comments and conclusions

In this paper we have presented the valley-emphasis method, a revised version of the Otsu method, to automatically select the optimal threshold value for defect detection applications. The method selects a threshold value that has small a probability of occurrence and also maximizes the between group variance in the gray-level histogram. The small probability of occurrence requirement ensures that the resulting threshold value will always be a value that resides 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. This is essential for defect detection applications because defects range from no defects through small and large defects. We have demonstrated the effectiveness of the proposed method on various defect detection applications such as contamination inspection, ceramic body defect detection, and metal sheet scratch inspection. The experiment results suggest that valley-emphasis method is effective for selecting threshold values for defect detection applications.

The proposed method is simple and fast. The class probabilities and means in (8) can be computed recursively (Liao et al., 2001). For a $640 \times 480$ gray-scale image, the processing time is about 2.5 ms running on a PC with 2.6 GHz Pentium 4 processor and 512MB RAM. Therefore, the proposed method is suitable for real-time inspection applications.

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