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A modified valley-emphasis method for automatic thresholding

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ABSTRACT

Otsu method is a commonly used technique for image thresholding selection, which can provide satisfactory results for thresholding an image with a histogram of clear bimodal distribution. This method, however, fails if the histogram is unimodal or close to unimodal. Ng (Ng, H.F., 2006. Automatic thresholding for defect detection. Pattern Recognition Lett. 27 1644–1649) proposed a modified method, called as valley-emphasis method, which weighs the objective function of the Otsu method with the valley point of the histogram for defect detection. In this paper, a revised valley-emphasis thresholding method is presented using the neighborhood information of the valley point. Experiment results show that the proposed method has the proper segmentation results in defect detection and provides better segmentation results than that of valley-emphasis method and Otsu method.

1. Introduction

Image segmentation is one of the most difficult, dynamic and challenging problems in image processing domain, and thresholding is a commonly used tool in image segmentation for extracting the object regions from their background (Sahoo, 1988). A widely used thresholding method, Otsu method (Otsu, 1979), is one of the best threshold selection methods for general real world images. By selecting threshold values of maximum between-class variances or minimum within-class variances for image histogram, this method can obtain satisfied segmentation results in many cases. Otsu method assumes that the gray level of the object and the background in an image distribution is Gaussian distribution with equal variances (Kittler and Illingwotth, 1985; Kurita et al., 1992). Generally speaking, the real world images do not have such character. Therefore, Otsu method fails to select the optimal thresholds in some cases, especially where the gray-level histogram is unimodal or close to unimodal. Many modified Otsu methods had been proposed, such as Morii (1994), Hou et al. (2006), and Ng (2006).

In order to effectively detect the defect in industry application, Hui-Fuang Ng proposed a revised Otsu method known as valley-emphasis threshold method, in which the valley point information was considered in the objective function. Valley-emphasis method can successfully detect the defects in an image. In this method, the optimal threshold is assumed to meet two conditions. First, the between-class variance of the thresholded image is maximum. Second, the threshold locates at the valley of the image histogram as close as possible.

However, in our experiments, we found that the valley-emphasis method failed in some cases, especially where the variance of the object is very different from that of the background. The reason is that valley-emphasis method only weighs the objective function with the valley-point value of the histogram. When the variance of the object is very different from that of the background, the weighing effect is weak, which made the valley-emphasis method doesn't work in such case.

In this paper, we consider not only the valley-point information but also the neighborhood gray information around the valley-point, which can intensify Hui-Fuang Ng's idea further. Experiment results show that our method can provide better segmentation results than Otsu method and the valley-emphasis method.

2. Valley-emphasis method

In this section, we firstly brief introduce the Otsu method for selecting an optimal image threshold. Let $F = \{f_1, f_2, \cdots, f_{M\times N}\}$ be a digital image of size $M \times N$, where f_i be the gray value of the ith pixel and $f_i \in [0, 1, \cdots, L-1]$. The amount of the pixels with the gray value g is denoted as $f(g)$. For the sake of convenience, we denote the set of all gray levels $[0, 1, \cdots, L-1]$ as G. The frequency $h(g)$ of the occurrence of gray-level g is defined as:

$$h(g) = \frac{f(g)}{M \times N}, \quad g = 0, 1, \ldots, L-1 \tag{1}$$

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

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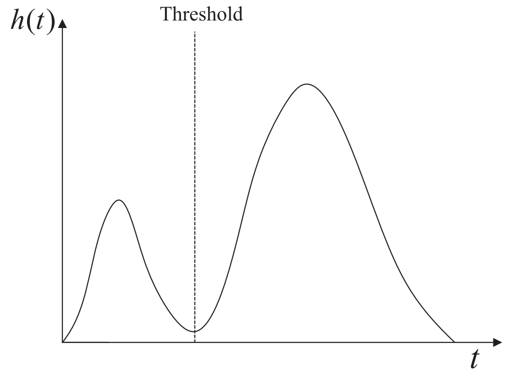

Fig. 1. Optimal threshold in gray-level histogram.

$$\mu_T = \sum_{g=0}^{L-1} g h(g) \tag{2}$$

In the case of single threshold t, the pixels of an image are divided into two classes c_0 and c_1 (object and background, or background and object), i.e., $c_0 = [0,\cdots,t]$, $c_1 = [t+1,\cdots,L-1]$. The probabilities of the two classes are:

$$p_0(t) = \sum_{g=0}^{t} h(g) \tag{3}$$

$$p_1(t) = \sum_{g=t+1}^{L-1} h(g) \tag{4}$$

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

$$\mu_0(t) = \sum_{g=0}^{t} g h(g)/p_0(t) \tag{5}$$

$$\mu_1(t) = \sum_{g=t+1}^{L-1} g h(g)/p_1(t) \tag{6}$$

Then, $p_0(t)\mu_0(t) + p_1(t)\mu_1(t) = \mu_T$, $p_0(t) + p_1(t) = 1$.

For the threshold t, using discriminate analysis, Otsu showed that the between-class variance $\sigma_B^2(t)$ of c_0 and c_1 is:

$$\sigma_B^2(t) = p_0(t)(\mu_0(t) - \mu_T)^2 + p_1(t)(\mu_1(t) - \mu_T)^2$$

$$= p_0(t)\mu_0^2(t) + p_1(t)\mu_1^2(t) \tag{7}$$

The optimal threshold t^* can be determined as:

$$t^* = Arg \max_{0<t<L-1} \sigma_B^2(t) = Arg \max_{0<t<L-1} \{p_0(t)\mu_0^2(t) + p_1(t)\mu_1^2(t)\} \tag{8}$$

The above Otsu method can be easily extended to multilevel thresholding of an image. For $M-1$ thresholds, which divide the image pixels in M classes, $c_1, c_2, \cdots, c_M$, the optimal thresholds $\{t_1^*, t_2^*, \ldots, t_{M-1}^*\}$ are chosen as follows:

$$\{t_1^*, t_2^*, \ldots, t_{M-1}^*\} = Arg \max_{0<t_1<t_2<\cdots<t_{M-1}<L-1} \left\{\sum_{k=1}^{M} p_k \mu_k^2\right\} \tag{9}$$

By the description, one can see that Otsu method is simple and easy to realize. Otsu method is one of the commonly used threshold methods in engineer practices since its good adaptability.

In the case of single thresholding, Otsu method works well when the image' histogram is close to bimodal distribution with equal variances. However, it gives the incorrect threshold value either when the diversity of the object variance and the

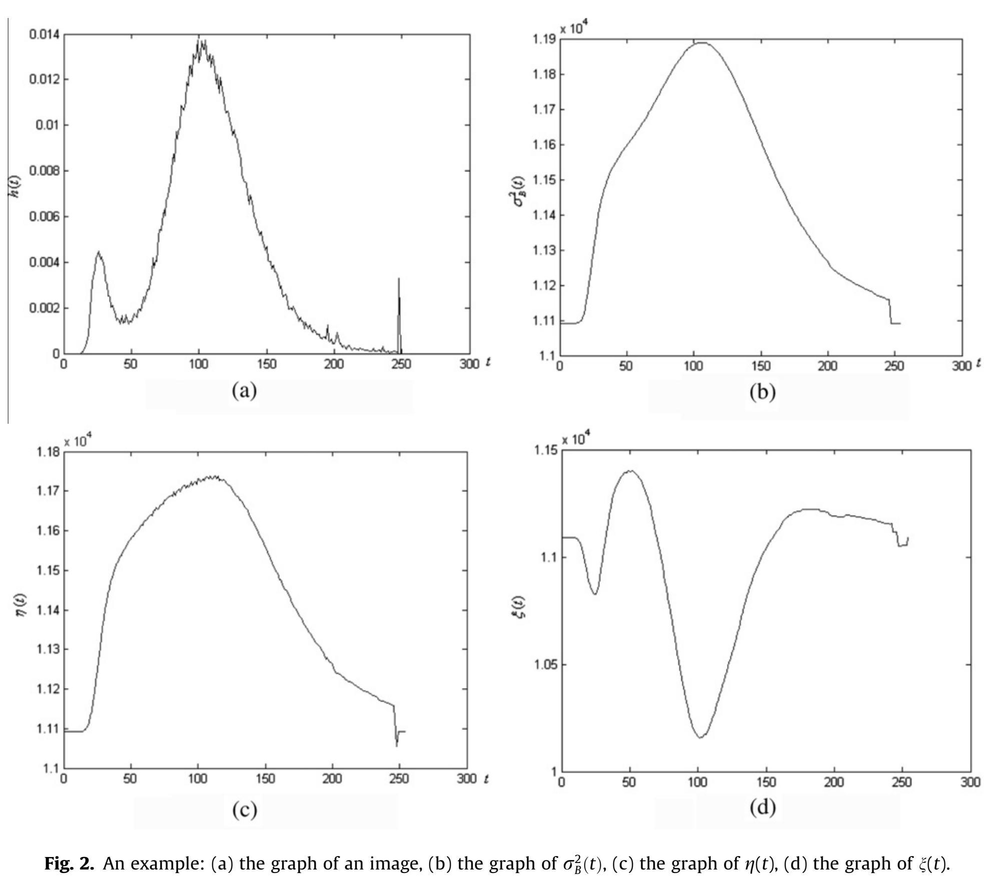

Fig. 2. An example: (a) the graph of an image, (b) the graph of $\sigma_B^2(t)$, (c) the graph of $\eta(t)$, (d) the graph of $\xi(t)$.

background variance is large or when the histogram is unimodal or close to unimodal. Hui-Fuang Ng proposed a weighted Otsu method which makes the threshold closer to the actual valley of the histogram.

In the case of single object, the ideal threshold should lie on the valley of the bimodal histogram, as demonstrated in Fig. 1. The probability of occurrence $h(t)$ at the threshold t should be small. Based on this thought, Hui-Fuang Ng proposed the valley-emphasis method to select a threshold value with a small probability of occurrence which maximizes the between-class variance. The objective function in this method is:

$$\eta(t) = (1 - h(t))(p_0(t)\mu_0^2(t) + p_1(t)\mu_1^2(t)) \tag{10}$$

The optimal threshold is then selected as:

$$\begin{aligned} t^* &= \arg \max_{0<t<L-1} \eta(t) \\ &= \arg \max_{0<t<L-1} \left\{(1 - h(t))(p_0(t)\mu_0^2(t) + p_1(t)\mu_1^2(t))\right\} \end{aligned} \tag{11}$$

In Eq. (10), the first term $1 - h(t)$ is the weight and the second term $p_0(t)\mu_0^2(t) + p_1(t)\mu_1^2(t)$ is the between-class variance of the image. The optimal threshold is selected to maximize the multiplication of the two terms, that is, each term should be the largest at the same time. For the weight $1 - h(t)$, the smaller the $h(t)$ (low probability of occurrence) is, the larger the weight value $1 - h(t)$ will be. It ensures that when the probability of occurrence is high (large value of $h(t)$), a smaller weight is made to the between-class variance, whereas, a larger weight is made to the between-class variance. That is the idea of the valley-emphasis method, which selects a threshold value that maximizes the between group variance and also resides at the bottom rim of the gray-level histogram.

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

$$\{t_1^*, t_2^*, \ldots, t_{M-1}^*\} = \arg \max_{0<t_1<t_2<\cdots<t_{M-1}<L-1} \left\{\left(1 - \sum_{j=1}^{M-1} h(t_j)\right)\left(\sum_{k=1}^{M} p_k\mu_k^2\right)\right\} \tag{12}$$

where the first term in (12) corresponds to the weight.

We can see that the idea of the valley-emphasis method is reasonable. Experiments of Hui-Fuang Ng also illustrated the validity of the method. However, the variation of the weight $1 - h(t)$ in valley-emphasis method might be smaller when the variance of the object is very different from that of the background, which may affect the weighting effect. We found that the valley-emphasis method fails in the case that the proportion of the object to the whole scene is small. As an example, Fig. 2a shows the histogram of an image, Fig. 2b shows the graph of between-class variance $\sigma_B^2(t)$ varies with the threshold t, Fig. 2c shows the graph of the object function $\eta(t)$ in valley-emphasis method varies with the threshold t. It can be seen that the optimal threshold should be near at $t = 50$ from Fig. 2a. It can also be seen from the histogram in Fig. 2a that the gray-level distribute as bimodal with two peaks has large diversity in variances. In this case, the maximum value of between-class variance in Otsu method deviates from the valley of the histogram, which is at $t \approx 100$ (Fig. 2b). The point value weight $1 - h(t)$ can not change the variation trend of $\sigma_B^2(t)$ .The optimal threshold of the valley-emphasis method is about $t \approx 100$, which still faraway the ideal optimal threshold. Therefore, the valley-emphasis method fails to segment the image in this case.

3. Neighborhood valley-emphasis method

From the above example, we know that the valley-emphasis method can still not improve the segmentation quality in some cases. This means that only using the valley point information is not enough. Therefore, we think neighborhood information at the valley point must be used to improve the segmentation quality. In this section, we proposed a revised valley-emphasis method named neighborhood valley-emphasis method. The new method weighs $\sigma_B^2(t)$ with the neighborhood information at the threshold point which made the method more available on the reasons that it considered not only the threshold but also the neighborhood information around the threshold point. The detail of neighborhood valley-emphasis method is described as follows.

For the one-dimensional histogram $\{h(g)\}$ of the image, the neighborhood gray value $\bar{h}(g)$ of the gray-level g is defined as:

$$\begin{aligned} \bar{h}(g) = [&h(g-m) + \cdots + h(g-1) + h(g) + h(g+1) + \cdots \\ &+ h(g+m)] \end{aligned} \tag{13}$$

Eq. (13) is the sum of the neighborhood gray probability in interval $n = 2m + 1$ for gray level g, where n is the neighborhood length, normally be odd number.

The objective function of the neighborhood valley-emphasis method is:

$$\xi(t) = (1 - \bar{h}(t))(p_0(t)\mu_0^2(t) + p_1(t)\mu_1^2(t)) \tag{14}$$

The optimal threshold is chosen by maximizing the following function:

$$\begin{aligned} t^* &= \arg \max_{0<t<L-1} \xi(t) \\ &= \arg \max_{0<t<L-1} (1 - \bar{h}(t))(p_0(t)\mu_0^2(t) + p_1(t)\mu_1^2(t)) \end{aligned} \tag{15}$$

The main modification to Eq. (10) is replacing $1 - h(t)$ by $1 - \bar{h}(t)$. The new weight $1 - \bar{h}(t)$ ensures that the best threshold will always be at a value which has not only a small probability but also a small sum of its neighborhood probability. Therefore, the optimal threshold might have more benefits at the valley of the gray-level distribution than valley-emphasis method.

Fig. 2(d) shows the graph of the objective function $\xi(t)$ varying with t. It can be found that the maximum value of $\xi(t)$ is near at the valley of the image gray-level histogram with $t \approx 50$, and $\xi(t)$ gets the minimum value when the gray level is near 100, i.e. $t \approx 100$. Therefore, the neighborhood valley-emphasis method can successfully segment the image when the variance of the object is very difference with that of the background. Moreover, the smooth ability of $\bar{h}(t)$ might make the neighborhood valley-emphasis method with better segment capacity for noisy image than that of the Otsu method and the valley-emphasis method.

Neighborhood valley-emphasis method can be generalized to multi-level thresholding. For $M - 1$ level threshold (M classes), the optimal thresholds $\{t_1^*, t_2^*, \ldots, t_{M-1}^*\}$ are given as:

$$\{t_1^*, t_2^*, \ldots, t_{M-1}^*\} = \arg \max_{0<t_1<t_2<\cdots<t_{M-1}<L-1} \left\{\left(1 - \sum_{j=1}^{M-1} \bar{h}(t_j)\right)\left(\sum_{k=1}^{M} p_k\mu_k^2\right)\right\} \tag{16}$$

where $\left(1 - \sum_{j=1}^{M-1} \bar{h}(t_j)\right)$ is the weight, $\bar{h}(t_j)$ is the neighborhood gray value of t_j. In theory, one can select different neighborhood length n_j for each threshold t_j. In this paper, in order to make the process simple, we only use the same neighborhood length n for each threshold t_j.

It should be note that $1 - \sum_{j=1}^{M-1} h(t_j)$ is always nonnegative in Eq. (12). However, $1 - \sum_{j=1}^{M-1} \bar{h}(t_j)$ might be negative in Eq. (16), especially when the neighborhood length n is too large. To avoid this undesirable phenomenon, n should be a smaller value in order to make most values of $1 - \sum_{j=1}^{M-1} \bar{h}(t_j)$ nonnegative. $n = 11$ is suggested for multilevel thresholding.

4. Experiment results

4.1. Simulation results

Experiments are simulated on PC with Matlab7, Intel Core 2.33 GHz CPU and 2G memory. In order to evaluate the performances of the proposed method, our experiments include two parts. One part is to compare our method with the valley-emphasis method using images in (Ng, 2006), which demonstrated that our method can also perform well to defect detection. The second part is to test the performances of our method, the valley-emphasis method and the Otsu method with different types of standard images, which testified that our method could get better performances than the other two methods in these cases.

Fig. 3 and Fig. 4 show the segmentation results of images in (Ng, 2006). Fig. 5 is a standard image, *sar1.gif*. Fig. 6 is a standard image with Gaussian noise, *number.tif*. Table 1 lists the optimal threshold values that are found for these images when the neighborhood length n equals to 3, 5, 7, 9,11 and 35 in the neighborhood valley-emphasis method, respectively.

In the neighborhood valley-emphasis method of single threshold, we use a function $\bar{h}(t)$ to weigh the objective function of the Otsu method. The neighborhood length will affect the optimal threshold of the images. In order to find out the appropriate value of n, we tested all the test images with different neighborhood sizes of $3,5,7,9,11,\ldots,35$, respectively. Here, we do not list all the segmentation thresholds vary with n. We find that when n increases to some value, the threshold will be inefficacy. To show the affect of large value of n to the threshold, we list the thresholds of different images with n equals 35 in Table 1. More detail study on the selection of n is given in Section 4.2. Considering the quality of the thresholded image, $n = 11$ is a better selection for the neighborhood valley-emphasis method. In the following experiments, $n = 11$ is used.

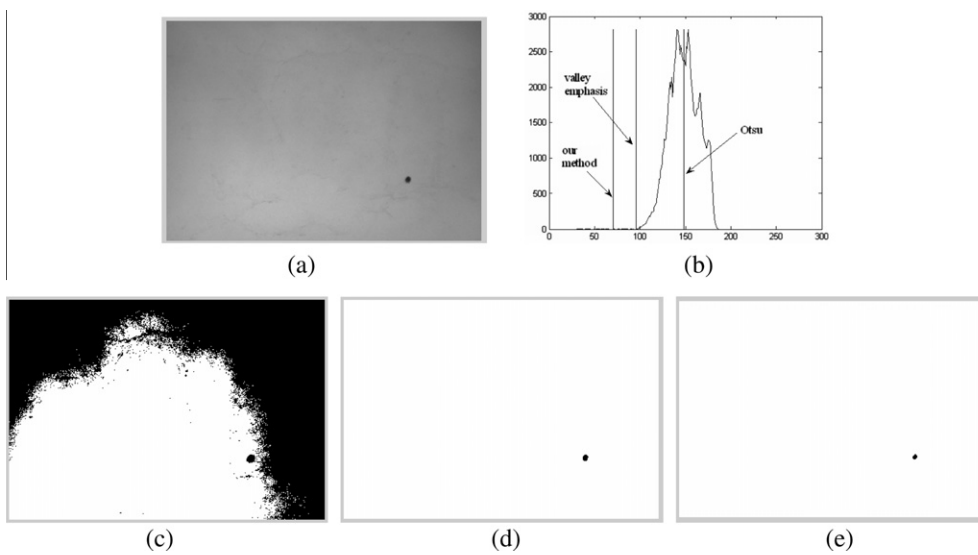

Fig. 3. Segmentation results for a small defect image: (a) original image, (b) histogram and threshold values, (c) Otsu segmentation result with threshold 148, (d) valley-emphasis segmentation result with threshold 96, (e) our segmentation result with threshold 71.

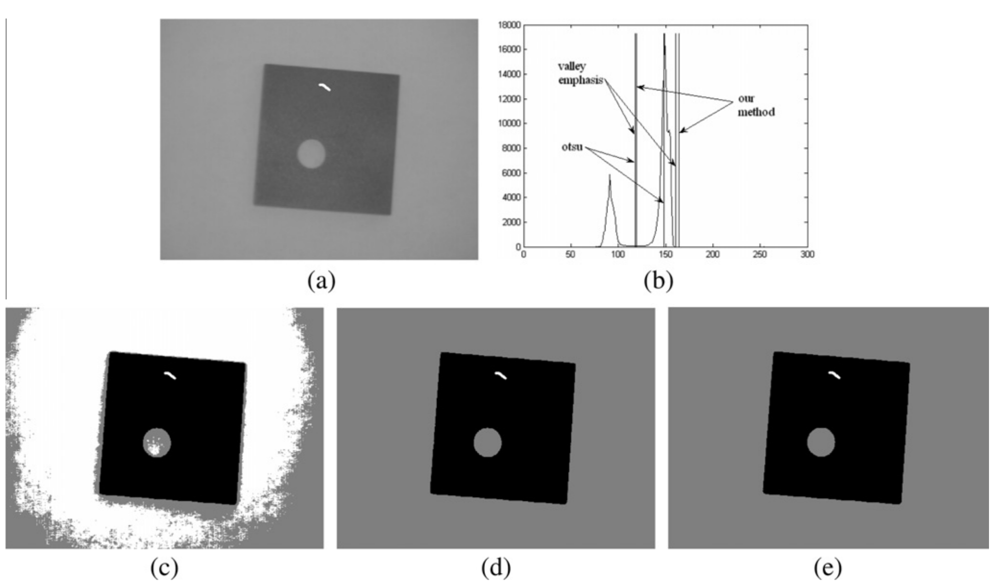

Fig. 4. Segmentation results for a part image: (a) original image, (b) one-dimensional histogram, (c) Otsu segmentation result with thresholds (118, 148), (d) valley-emphasis segmentation result with threshold (118, 161), (e) our segmentation result with threshold (120, 166).

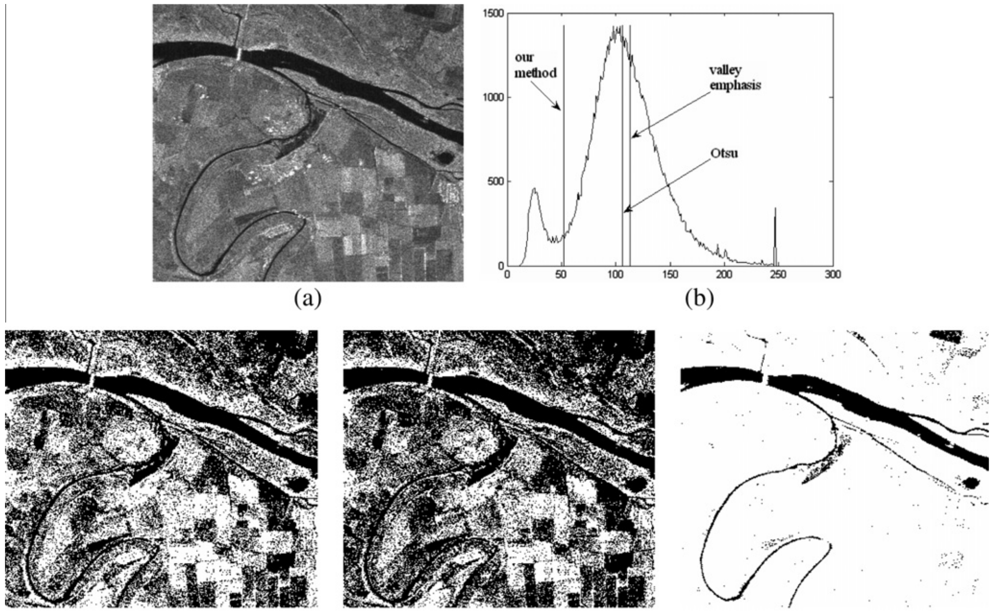

Fig. 5. Segmentation results for a sar1 image: (a) original image, (b) histogram and threshold values, (c) Otsu segmentation result with threshold 106, (d) valley-emphasis segmentation result with threshold 113, (e) our segmentation result with threshold 52.

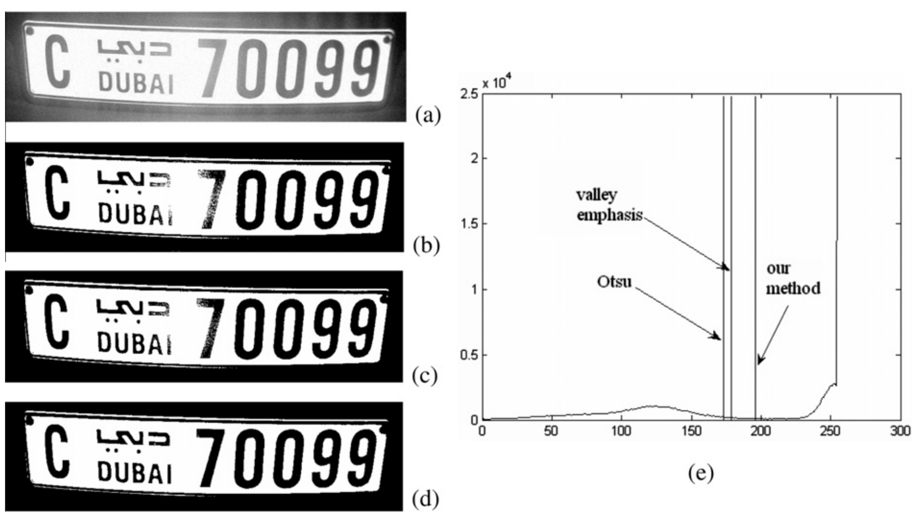

Fig. 6. Segmentation results for a number image: (a) original image, (b) Otsu segmentation result with threshold 176, (c) valley-emphasis segmentation result with threshold 182, (d) our method result with threshold 196, (e) histogram and threshold values.

Table 1
The optimal thresholds for various values of *n*.

	$n = 3$	$n = 5$	$n = 7$	$n = 9$	$n = 11$	$n = 35$
Defect image	89	69	68	71	71	1
Part image	(118, 162)	(120, 163)	(119, 164)	(120, 165)	(120, 166)	(119, 178)
Sar1 image	61	55	51	52	52	230
Number image	193	197	195	199	196	207

Fig. 3 shows the segmentation results for small defect image in (Ng, 2006) using the three methods respectively. As described in (Ng, 2006), Otsu method failed in this case and reported incorrect threshold. Valley-emphasis method successfully isolated the small defect in the image. Fig. 3(e) is the segmentation result provided by the proposed neighborhood valley-emphasis method. We can see that our method can also get proper segmentation result in this case.

Fig. 4 shows an image of a machine part with a small defect, which is the case of multilevel thresholding. Our aim is to separate the part from the background and also isolate the small defect from the part. Neighborhood valley-emphasis method and the valley-emphasis method worked well on the image and gave correct thresholds. Otsu method, however, performed poorly on this image.

We test the performances of the three methods for some standard images. Fig. 5 shows the results of sar1 image. Fig. 5(b) is the gray-level histogram of the image. The histogram demonstrates an unequal bimodal gray-level distribution, which has a small peak near the low gray value and a big peak at the high gray value. In this case, Otsu method gave the incorrect threshold. The threshold of the Otsu method is 106, near the middle of the big peak of the histogram. Fig. 5(d) shows the segmentation result of valley-emphasis method. As analyzed above before, the single point weight value can not change the trend of the $\sigma_B^2(t)$ .The optimal threshold of the valley-emphasis method is 113, which is far away from the valley of the gray level distribution. Fig. 5(e) shows the segmentation result of the proposed neighborhood valley-emphasis method. Our method successfully detects the river from the background and gives correct threshold 52, which resides at the valley of the gray-level histogram.

Fig. 6 shows an example of number image with a Gaussian noise whose mean value is 0 and variance is 0.001. All the three methods can segment the image basically, however, for the illuminated noise distributed nonuniformly in the middle of the image, Otsu method gets the worst segmentation result, valley-emphasis method gets better result and our method gets the best result.

4.2. The influence of the neighborhood length n in image thresholding

In our method, we have used the value $1 - \bar{h}(g)$ to weigh the objective function of the Otsu method in single threshold. In order to find out which length of n will produce an optimal threshold, we have tested all the test images with different lengths. In our experiment, we have considered neighborhood lengths of 3,5,7,9, 11,...,35, respectively. We found that $n = 3$ or 5 is not a good value for thresholding generally. And when n is too big, the threshold value might be invalid. For the defect image, when n is 35, the optimal threshold is 1, which can not segment the image well. For the number image, when n is 35, the optimal threshold is 207, which can segment the image well, but when n is increased to 105, the threshold is 1, and when n is less than 105, the variation of the thresholds is slight and the segmented results are basically similar. This means that the variation of the thresholds will be different with the value n to different images. But when n is in some interval, the thresholds are similar. As a conclusion, considering the image segmentation quality and based on our experiments, we suggest to select $n = 11$ as the neighborhood length for the proposed method.

5. Conclusions

In this paper, a revised valley-emphasis method named neighborhood valley-emphasis method is proposed based on the thought of valley-emphasis method presented by Hui-Fuang Ng. This novel method weighs the objective function defined in Otsu method with the neighborhood gray level of the threshold, and selects a threshold value that has small probabilities in its neighborhood area and also maximizes the between-classes variance in the gray-level histogram. Therefore, neighborhood valley-emphasis method is able to select optimal threshold for defect detection and images with large diversity between object variance and background variance.

The proposed method is robust for noisy image with Gaussian noise. Therefore, neighborhood valley-emphasis method is more suitable for actual applications.

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References

Hou, Z., Hu, Q., Nowinski, W.L., 2006. On minimum variance thresholding. Pattern Recognition Lett. 27, 1732–1743.

Kittler, J., Illingwotth, J., 1985. On threshold selection using clustering criteria. IEEE Trans. Systems Man Cybern. 15, 652–655.

Kurita, T., Otsu, N., Abdelmalek, N., 1992. Maximum likelihood thresholding based an population mixture models. Pattern Recognition 25, 1231–1240.

Morii, F., 1994. An image thresholding method using a minimum weighted squared-distortion criterion. Pattern Recognition 28, 1063–1071.

Ng, H.F., 2006. Automatic thresholding for defect detection. Pattern Recognition Lett. 27, 1644–1649.

Otsu, N., 1979. A thresholding selection method from gray-level histograms. IEEE Trans. System Man Cybernet. 9 (1), 62–66.

Sahoo, P.K., 1988. A survey of thresholding techniques. Comput. Vision Graph. Image Process. 41, 233–260.