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Defect detection based on extreme edge of defective region histogram

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Abstract Automatic thresholding has been used by many applications in image processing and pattern recognition systems. Specific attention was given during inspection for quality control purposes in various industries like steel processing and textile manufacturing. Automatic thresholding problem has been addressed well by the commonly used Otsu method, which provides suitable results for thresholding images based on a histogram of bimodal distribution. However, the Otsu method fails when the histogram is unimodal or close to unimodal. Defects have different shapes and sizes, ranging from very small to large. The gray-level distributions of the image histogram can vary between unimodal and multimodal. Furthermore, Otsu-revised methods, like the valley-emphasis method and the background histogram mode extents, which overcome the drawbacks of the Otsu method, require preprocessing steps and fail to use the general threshold for multimodal defects. This study proposes a new automatic thresholding algorithm based on the acquisition of the defective region histogram and the selection of its extreme edge as the threshold value to segment all defective objects in the foreground from the image background. To evaluate the proposed defect-detection method, common standard images for experimentation were used. Experimental results of the proposed method show that the proposed method outperforms the current methods in terms of defect detection.

1. Introduction

Defect detection in industrial artifacts has attracted specific attention in computer vision applications. The widely used technique for these purposes is automatic thresholding (Sezgin, 2004; Ng, 2006; Sezgin and Sankur, 2001). An optimal gray-level threshold value is selected in automatic thresholding to separate objects in an image from the background according to their intensity distribution. Sezgin (2004) recently gave a well-studied survey and evaluation of various thresholding methods.

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Automatic thresholding techniques can be roughly categorized into global and local thresholding (Kwon, 2004; Fan and Lei, 2012). Global thresholding selects a single threshold value from the image histogram, while local thresholding selects multiple threshold values based on their localized intensity information. The global thresholding algorithm is fairly easy to implement but its result is dependent on good (uniform) illumination (Ng et al., 2013).

The Otsu method is considered as one of the best threshold algorithms for general purpose images (Gonzalez and Woods, 2008). This method divides an image into two-class background and foreground in the case of single thresholding or divide the image pixels into multiple classes in the case of multilevel thresholding. The Otsu method selects the threshold values that maximize the class variances of the image histogram as a cost function (Ng, 2006; Ng et al., 2013). It works well in the case of bimodal or multimodal histogram distribution (Pak et al., 2015). However, it was proven optimal for thresholding large objects from the background but fails when the histogram is unimodal or close to unimodal (Yang et al., 2012; Wang and Liao, 2002; Aminzadeh and Kurfess, 2015). In defect-detection applications, the defects can have different shapes and sizes, ranging from very small to large. Moreover, defect-detection applications range from no defect to small and large defects, which make the gray-level distributions range from unimodal to bimodal distributions. Therefore, the Otsu method requires revisions to handle both unimodal and bimodal distributions and effectively detect defects. The gray-level distributions of the image histogram can vary between unimodal and multimodal as shown in Fig. 1.

The following example shows the inability of the Otsu method to detect small defects. As shown in Fig. 2(c), the Otsu method yields an incorrect threshold value and fails to isolate the contaminant. The Otsu method fails because the histogram demonstrates a unimodal distribution because the defect size is very small compared with the background size. The desired and the Otsu threshold values are shown in Fig. 2(d) (Bhardwaj et al., 2015; Shapiro and Stockman, 2001; Nixon, 2008; Zhang and Bresee, 1995).

To overcome this limitation, several modifications have been made to the original Otsu method. Ng (2006) revised the original Otsu method by automatically selecting the threshold values, which are close to the valley points in the histogram, and called it the valley-emphasis method. This approach simplified the selection of optimal threshold values for both the bimodal and unimodal distributions. Moreover, Ng et al. (2013) proposed an improved valley-emphasis method by applying the Gaussian weighting algorithm that efficiently enhanced the objective function of the Otsu method.

Another modified valley-emphasis method (Fan and Lei, 2012) covered the limitation in the case where the variance of the object is different from that of the background. This method does not provide satisfactory results in the case of images with large overlaps between modes or with no observable valleys. In addition, this method requires many preprocessing steps and prior knowledge about the defects to find the optimal thresholds.

Ng et al. (2013) modified the Otsu threshold values to be located as close as possible to the valley points in the image histogram. This method suggested that such threshold value exists at the valley of the two peaks (bimodal) or at the bottom rim of the single peak (unimodal) in the case of single thresholding as demonstrated in Fig. 1. The Ng et al. (2013) method is based on the principle that the probability of occurrence at the threshold value has to be small. Therefore, the valley-emphasis method selects a threshold value that has a small probability of occurrence (valley in the gray-level histogram), and the method also maximizes the group variance like the Otsu method.

Bhardwaj et al. (2015) assessed the limitations of the valley thresholding method and proposed a new approach that uses light to enhance the imaging of a defective photo. This approach applies the valley-emphasis method after light passes through the photo to identify defective objects. The detection

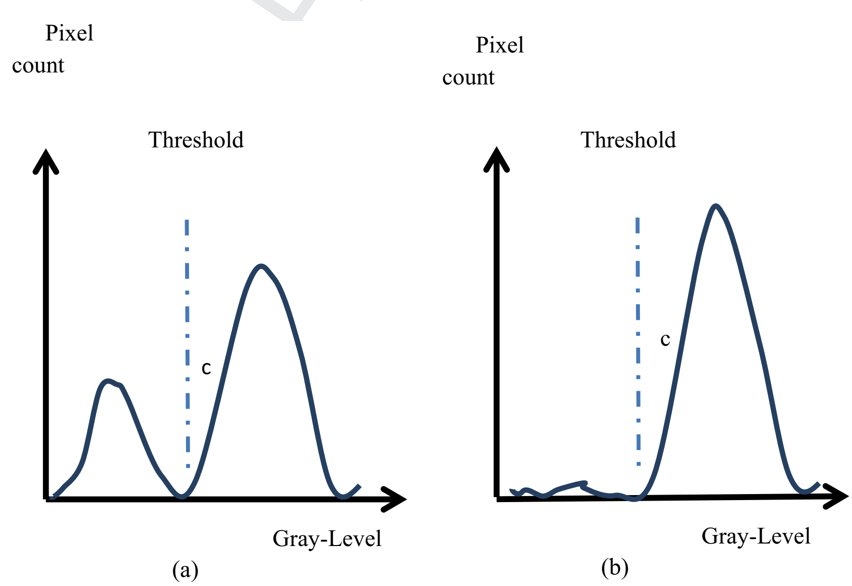

Figure 1 Optimal threshold selection in gray-level histogram: (a) bimodal and (b) unimodal.