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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). 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 result depends on the variation of the spatial intensity distribution of the light that passes through the defective photos.

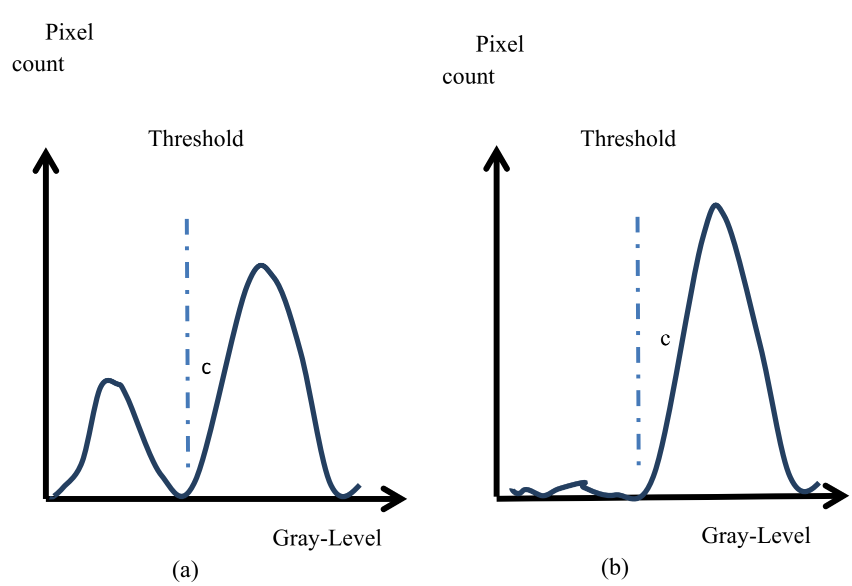

Figure 1 Optimal threshold selection in gray-level histogram: (a) bimodal and (b) unimodal.

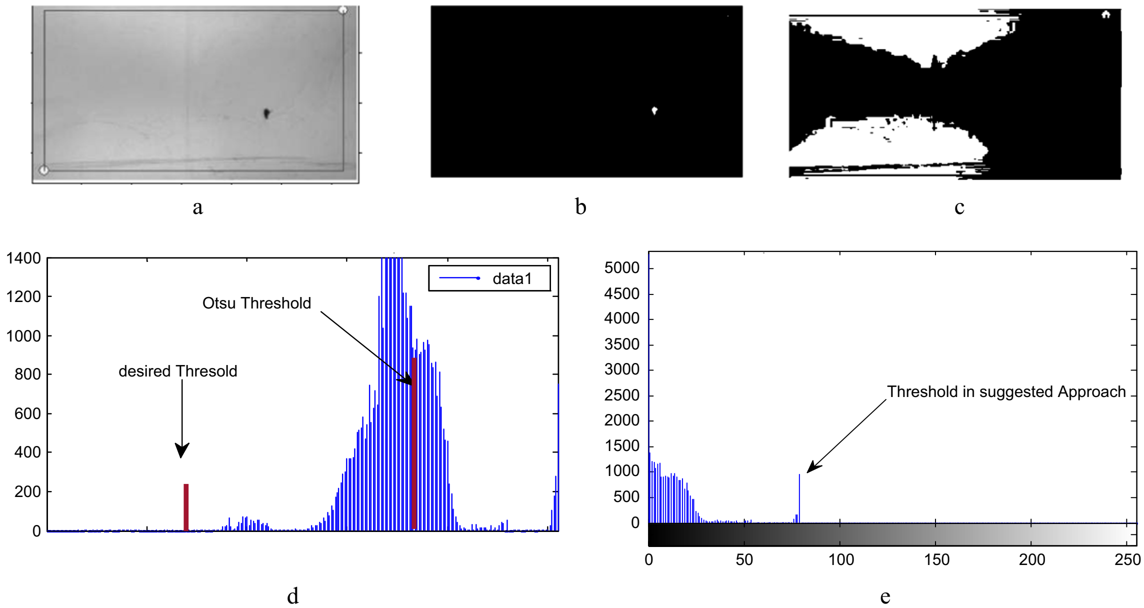

Figure 2 The problem with the Otsu method in thresholding small defects: (a) original image; (b) new approach threshold result; (c) Otsu threshold result; (d, e) histogram and threshold values.

Alternatively, an automated thresholding method was studied by Aminzadeh and Kurfess (2015). The aim of this study was to determine the gray-level ranges of the background and defects despite their sizes, characteristics, or modes. This method also requires many preprocessing stages and noise removal while studying the regions of the images to select the appropriate threshold values.

Unlike the methods that use assumptions, such as the valley-based thresholds or those which study the difference between the background and defective regions of the histograms to find the appropriate threshold values, this study proposes a new algorithm for selecting the optimal unique threshold value for unimodal, bimodal, or multimodal distributions.

The idea of the proposed method is based on the subtraction mask built on the mean value of pixel intensities in the entire underlying image from the image itself. To find the general thresholding value, the extreme value in the histogram of the resulting defective regions, which lie on the boundary limits between the background and defective region (foreground), was calculated and selected as the threshold value. The proposed automatic defect-detection method uses this unique general threshold value to segment objects of interest (defective regions) from the background despite their sizes, characteristics, or modes.

In general, the threshold value should be located at the valley or at the bottom rim of the gray-level distribution of the histogram of the original defective image which will match the extreme end of the defective region of the histogram (Bhardwaj et al., 2015).

This study is organized as follows: Section 2 presents the proposed thresholding algorithm. Section 3 provides details on obtaining the threshold value. Sections 4 presents the experimental results. Finally, Section 5 presents the conclusions.

2. Proposed algorithm

Considering the following fundamental facts:

1. The basic idea of thresholding states that global thresholding is an appropriate segmentation technique for images that contain objects that occupy a different range of gray levels than that of the background.
2. In most applications, the intensity of defects does not belong to a single gray-level range and may appear to be both darker and brighter than the background.
3. The best threshold values lie at the boundary of the gray-level ranges associated with defects and background (Zhang and Bresee, 1995; Nixon, 2008).

These ideas are conveniently used in this study to propose a new method for automatic threshold selection for defect-detection applications.

The proposed algorithm comprises the following steps:

1. Creating a background mask from the mean gray-level values of the entire original image (defective image).
2. Sharpening the original image to increase the contrast along the boundaries between the defective regions and the background.
3. Subtracting the mask from the image itself, thus extracting the features of the defective regions.
4. Calculating the histogram for the resulting image (basically containing the features of the defects).
5. Finding the extreme (highest gray level) value of the histogram.
6. Selecting this value as the thresholding value to separate the defects from the background.

The main advantage of using the mask of the mean intensity values is that it allows the separation of the defective regions from their background, thus isolating the defective histogram completely from the histogram of the original image, as shown in Fig. 2.

The proposed method allows the determination of the required thresholding value that can be easily used to separate the background (defect-free regions) as well as the defective regions (regions containing defects) automatically.

The proposed method is proven very effective on several standard images of surface defects with scratches, bumps, and pits in textile manufacturing, metal processing, and in a number of other industries. The flowchart of the proposed method is shown in Fig. 3.

3. Automatic threshold selection

In step 2 of the proposed algorithm, the sharpening process was applied on the original image (defective image) to increase the contrast of image pixels around the boundary between the background and the defective regions (foreground). As shown in Fig. 4, the image sharpening technique uses a blurred, negative image to create a mask of the original image. This unsharpened mask is then combined with the positive (original) image, creating an image that is less blurry than the original.

The Gaussian blur was applied as an image-blurring filter based on the Gaussian function. For one dimension, the Gaussian function is given by Shapiro and Stockman (2001) and Nixon (2008):

$$G(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{x^2}{2\sigma^2}} \tag{1}$$

In two dimensions, the Gaussian function is the product of two such Gaussians, one in each dimension (Shapiro and Stockman, 2001; Nixon, 2008):

$$G(x, y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \tag{2}$$

In the horizontal axis, x is the distance from the origin. In the vertical axis, y is the distance from the origin. σ is the standard deviation of the Gaussian distribution.

When applied in two dimensions, the Gaussian function yields a surface whose contours are concentric circles with a Gaussian distribution from the center point. The resulting distribution values are used to form a convolution matrix applied to the original image (Shapiro and Stockman, 2001; Nixon, 2008).

This process pushes the gray-level intensity at the boundary edges far inside the color map of the object, increasing the variance in color at the boundaries, as shown in Fig. 4 and consequently facilitating the thresholding process of the foreground objects from the background.

The resulting image from step 3 contains the same original scene with the newly reassigned gray level values, which are far from those of the original values, with separable background and foreground. In other words, the step subtracting the mean value mask from the sharpened original image creates a new image remapped in gray-level scale values.

Theoretically, the global thresholds (T) for image segmentation can be represented by the following expression (Nixon, 2008):

$$T = \mu + z \cdot \sigma \tag{3}$$

The parameter μ represents the mean gray level of the entire image pixels. The parameter σ represents the standard deviation of the mean gray levels in the defective image (original). Factor z could be selected by trial and error to determine the strictness of the defect-detection test (Nixon, 2008; Aminzadeh and Kurfess, 2015).

In the proposed method, the threshold value equal to the extreme value of the histogram of the image resulting in step 3, which can be automatically calculated easily, was selected. This value is exactly located at the boundary limits of the region between the foreground and the background.

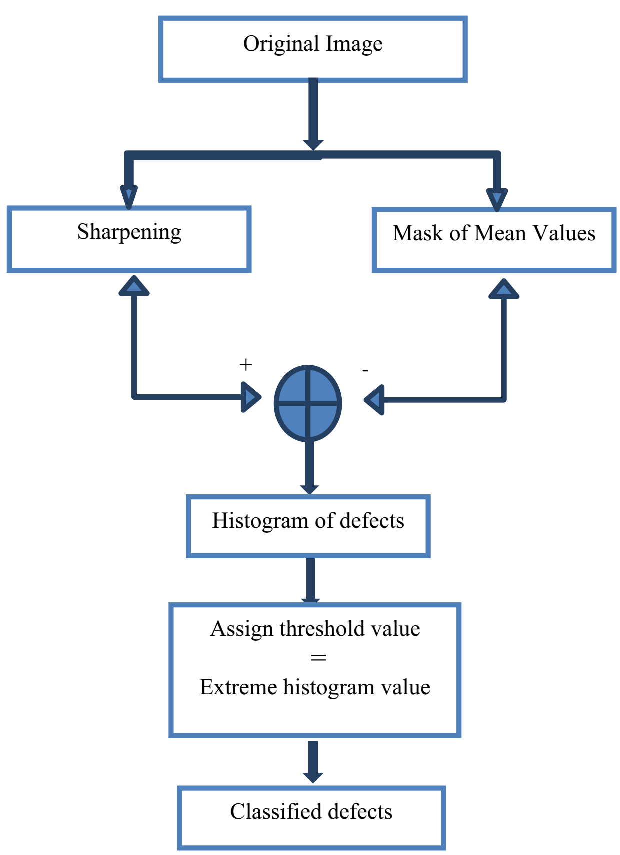

Figure 3 Flowchart of proposed method.

4. Experimental results

In the experiments, the performances of both the proposed and the Otsu methods (with its modifications) were tested on several common defect-detection standard images. For each defect-detection test application, three categories were selected: no, small, and large defect objects. Thresholding was applied to all images using the proposed and the Otsu methods (or valley-emphasis method).

For the images of clear bimodal distribution, the method of the present study provided a threshold value that was comparable to the value generated by the Otsu and valley-emphasis methods (Ng et al., 2013; Aminzadeh and Kurfess, 2015). Fig. 5 shows an example of a threshold for a test image with

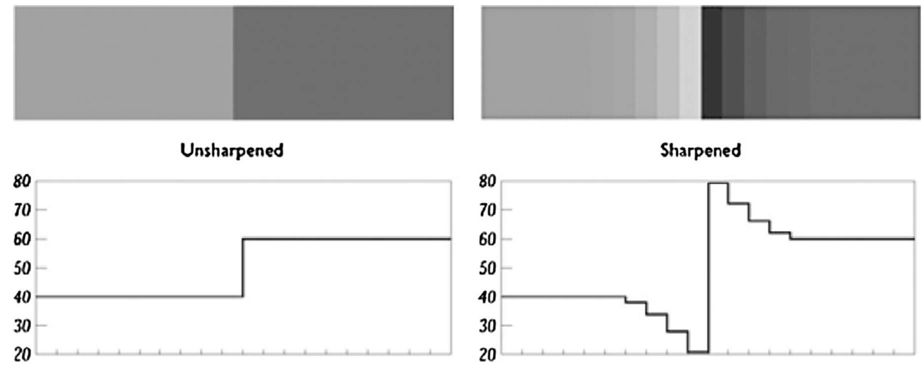

Figure 4 Effect of sharpening process.

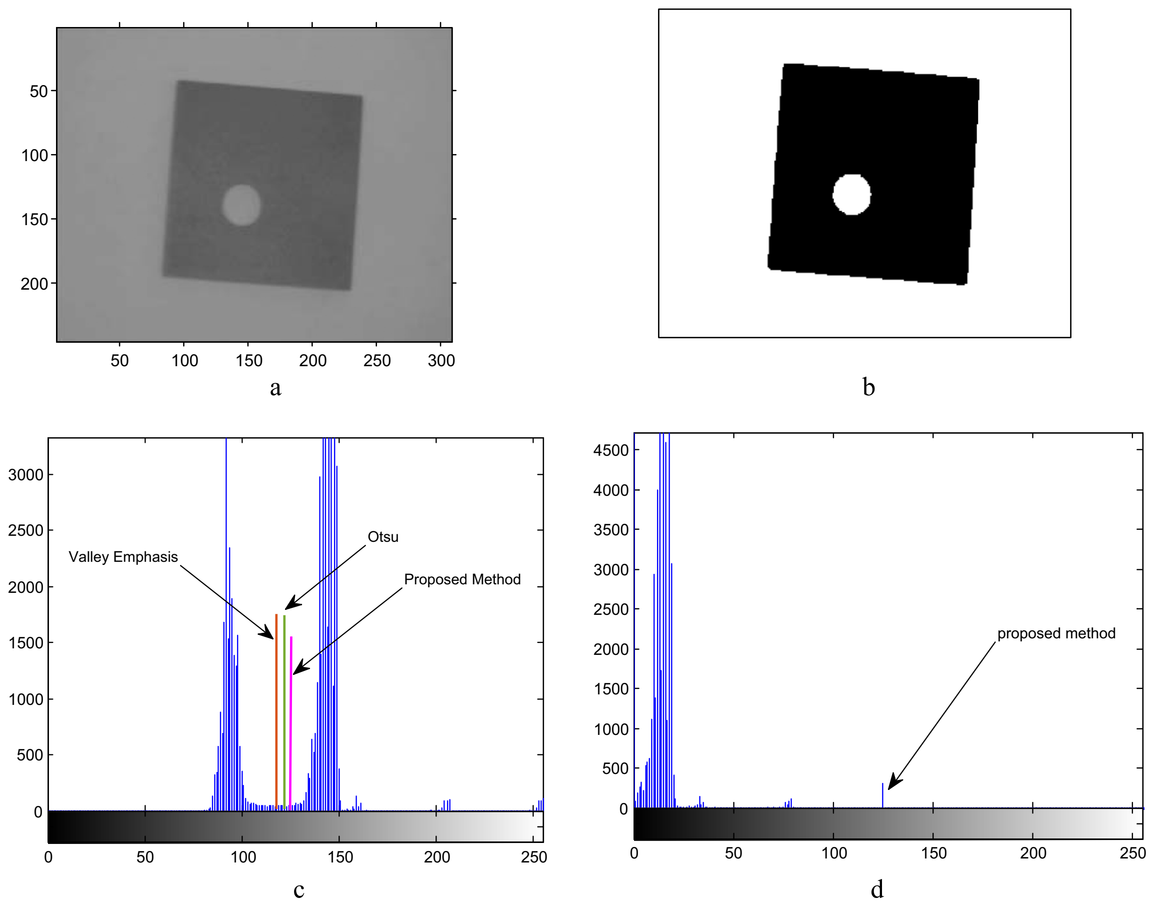

Figure 5 Threshold for a test image with a bimodal distribution: (a) test image, (b) thresholding result, (c, d) histogram with threshold values.

a bimodal distribution. The threshold values returned by the Otsu, valley-emphasis, and the proposed methods were 121, 117, and 125, respectively.

In the following experiments, the performance of the proposed method was tested on multilevel thresholding. Fig. 6a is an image of a machine part with a small defect. The aim was to isolate the part from the background and to also isolate the defect from the part. Fig. 6b shows the threshold result of the proposed method, which was identical to the valley-emphasis method that uses trilevel thresholding. Obviously, the proposed method worked well with the images that had no obvious multimodal gray-level distribution.

In contrast, the Otsu method performed poorly on image of the part (Fig. 6c) because it required clear multimodal gray-level distribution (Yang et al., 2012; Nixon, 2008; Zhang and Bresee, 1995). The threshold values computed by the three methods are shown in Figs. 6d and 6e. The advantage of the proposed method is its ability to separate all entities in the

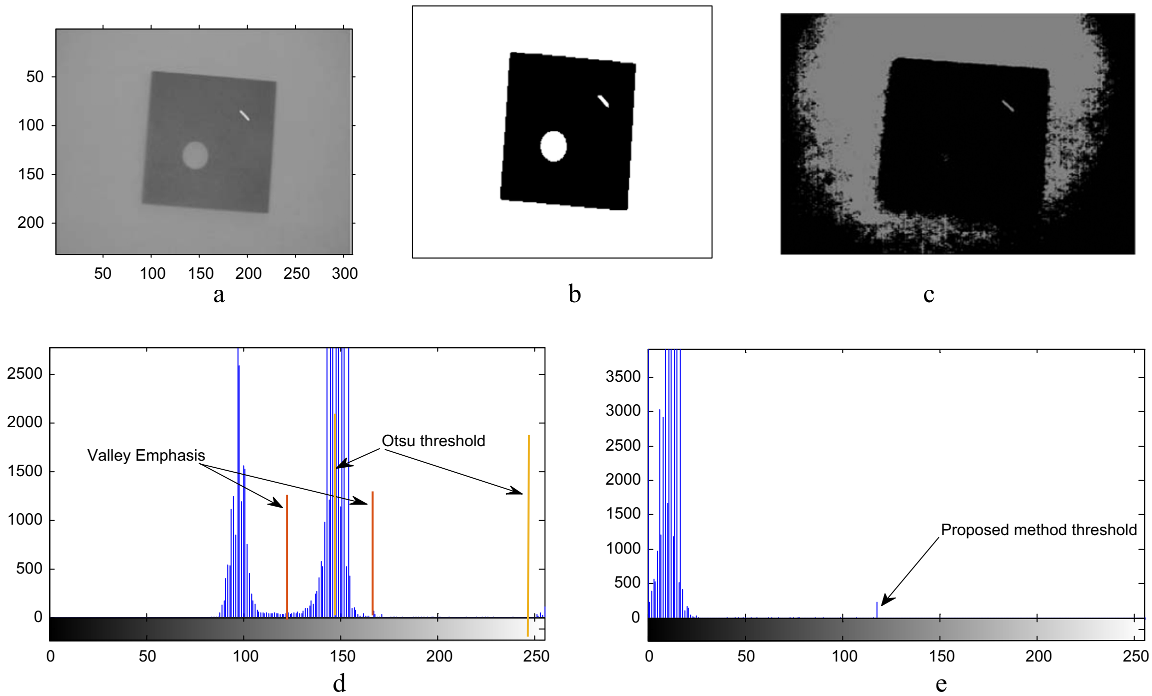

Figure 6 Proposed, Otsu, and valley-emphasis threshold results: (a) part image; (b) the proposed and valley-emphasis trilevel threshold result; (c) Otsu trilevel threshold result; (d) histogram and threshold values.

image using the general threshold, unlike the Otsu method and all other methods based on it, such as the valley-emphasis method, which use multiple thresholds to separate the defects from the background in the case of bimodal or multimodal distributions.

Fig. 7 shows an image of a surface with two defects as well as its histogram. Fig. 7(b) presents the result of the single- and bilevel Otsu segmentations. Despite the preprocessing and noise removal, the segmentation result was still far from satisfactory. The bilevel Otsu segmented the defects but mistakenly segmented large portions of the background as well. The result of the application of the proposed method is shown in Fig. 7 (c). Obviously, the proposed method was able to easily calculate and select the appropriate threshold value required to separate the defects from the background with minimum misclassification error compared with other known methods. Bilevel and multilevel thresholds use more than one threshold with less or equivalent results. Fig. 7(e) shows the histogram of the defective regions as a result of subtracting the mean mask from the original image. Fig. 7(f) shows the enlarged end of the defects histogram, which was used by the method to find the threshold value (equal to 83 in this case).

The examples show that the proposed algorithm in most cases, where the Otsu thresholding fails in the case unimodal defects, yields greatly improved results than the other known methods. Meanwhile, the valley-emphasis and background histogram extent methods, which applied improvements to the Otsu method, required many preprocessing and region selections to obtain good results. Nevertheless, they also failed to use the general threshold in the case of multimodal defects. When applied on different kinds of images, the proposed approach showed very good results, especially in the case of small and very small defects, the detection of which is generally more important than very large defects.

5. Conclusion

In this study, a new automated method for defect-detection thresholding was proposed. The method effectively separates the defective region histogram by comparing a mask based on the mean of pixel intensity values with the sharpened copy of the image itself. The threshold value is selected as the extreme edge of the defect histogram. Experiments on different kinds of defective images were conducted where the background can have a uniform or non-uniform gray-level distribution and can even include textures and patterns of low sharpness and contrast as depicted in the sample images.

The significant advantage of the proposed approach is its applicability to a large variety of images of different sizes and characteristics and its ability to detect and isolate both small and large defects from the background.

The results show the priority of the proposed method over other known methods because the proposed method successfully segments different objects of the foreground from their background using the resulting general threshold. The results obtained indicated that the proposed approach is a simple and effective defect-detection method.

Conflict of interest

The authors declare that there is no conflict of interests regarding the publication of this article.

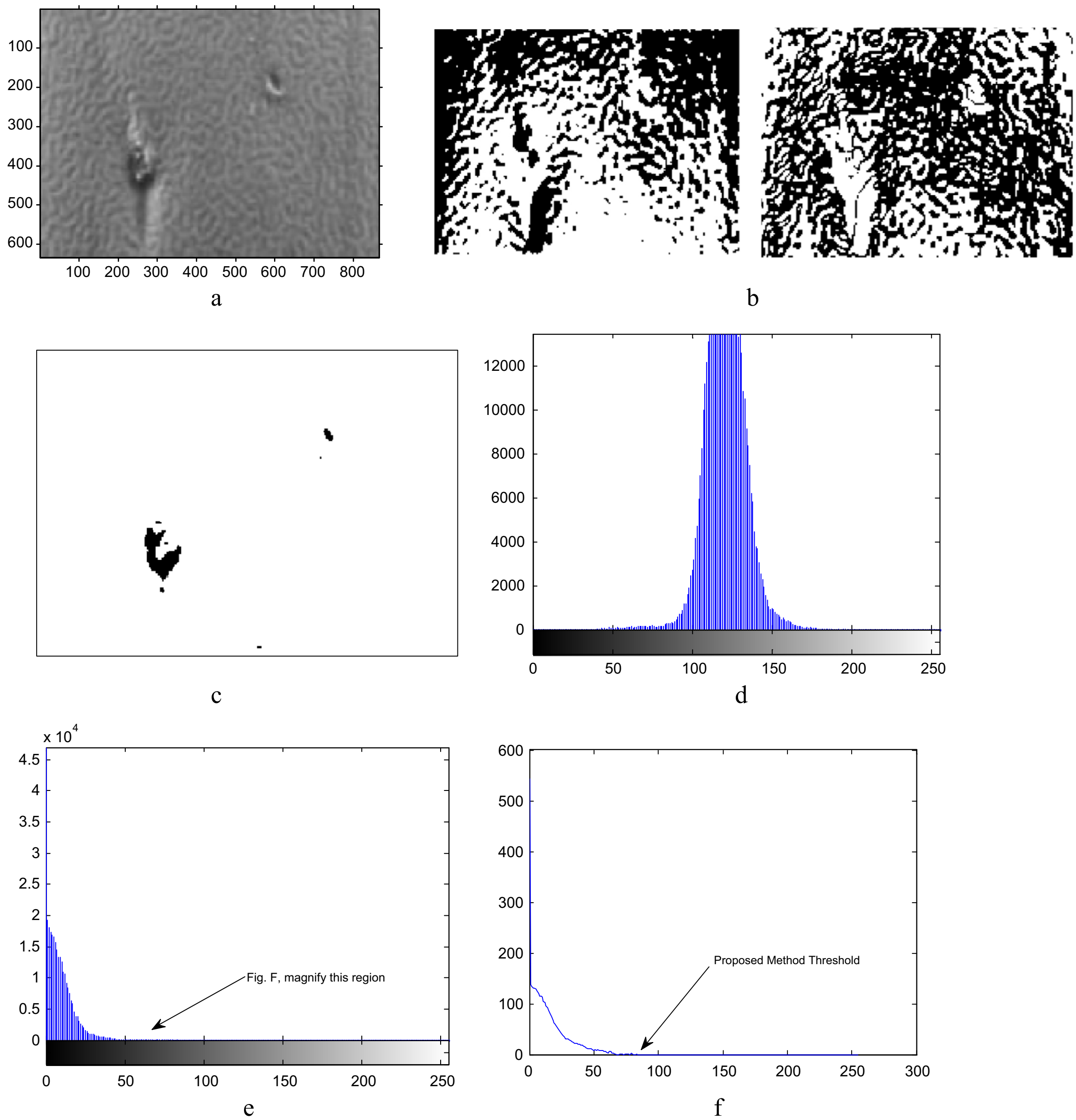

Figure 7 Test image of a surface with two defects: (a) test image; (b) result of the Otsu thresholding: single level (left) and bilevel (right); (c): result of proposed method; (d) the image histogram; (e) redrawing Fig. 7(e) using SQRT function to illustrate small values (f).

Author contributions

All authors jointly worked on deriving the results and approved the final manuscript.

Source code

The Matlab code for our proposed method with additional images are available on the link: http://darkion.net/index/codes/0–33.

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