A REAL-TIME ALGORITHM FOR ALUMINUM SURFACE DEFECT EXTRACTION ON NON-UNIFORM IMAGE FROM CCD CAMERA

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Abstract:

A novel real-time defect extraction framework is proposed for handling non-uniform images in high-speed aluminum strip surface inspection. The image is first preprocessed by Gaussian smoothing operator and Prewitt edge detection, which is robust to image non-uniformity. Afterwards, a fast adaptive segmentation algorithm is applied to further remove the effect of non-uniformity and enhance the edge detection. The final defect extraction image is achieved through morphological operations. The resultant method is computationally efficient and robust to non-uniformity. The proposed framework is evaluated on a large dataset of aluminum strip surface images obtained from the product line. The experimental results show that the proposed method achieves real-time defects extraction, and it outperforms the previous methods in accuracy.

Keywords:

Defect extraction; Surface inspection; Non-uniform image; Prewitt operation; Entropy

1. Introduction

The online surface inspection system is playing a more and more important role in the production of the metal strip [1, 2, 3]. Such a system can be used to timely control the product processing process. In addition, it provides us with a product report which can be used to improve the level of product management. For high-speed aluminum strip, a surface inspection system is commonly used to extract and measure the surface defect accurately in real-time. In general, a real-time surface inspection system gives priority to its efficiency. For example, Bindinganavler [3] selects the Roberts gradient operator for hot steel slab just because of the small amount of calculation, without considering the lighting effects and the impact of noise. However, the image scans from the typical CCD (Charge Coupled Device) camera in the product line are noisy. Therefore, their method can be affected by noise. Other approaches, like wavelet transform technique, the neural network technique, Gabor filter technique, and etc., have been proven robust to noise for defect detection for many kinds of products [4, 5, 6]. However, these algorithms are generally computational intensive to our task and hard to meet the real-time requirement [7]. Besides, these methods were designed for their special targets according to the surface properties of the corresponding different products, and they may not be suitable for detecting surface defect on aluminum strips. A prior work on defect detection on aluminum surface for high-speed aluminum strips is [7]. In [7], Zhaiming et al. proposed a method based on Kalman filters with a constant velocity (CV) model, called measurement-residual-based chi-square detector. We shall call it the chi-square detector henceforth. Their method is efficacious for most of the defects. However, their method cannot handle non-uniformity, and when the defects are relatively large, there would be false holes in the extracted regions.

Images obtained from CCD cameras are often non-uniform. To achieve the defect detection under non-uniformity, we propose to use the Prewitt edge detection [8] and the maxima of sum entropy of defect and background [9].

Our observation is that the non-uniformity of the image can be removed by edge detection. The compass Prewitt operator [8] can detect the edges in different orientations, and it allows for fast computation since it is based on convolution. We also adopt the entropy-based thresholding to enhance the results of edge detection given by Prewitt operation. According to the Shannon's entropy concept [10], the image of the normal aluminum surface is informationless and the entropy of the image is almost zero. If the defects appear on the aluminum surface, the corresponding image entropy will be larger for more informational regions. In recent years, many entropy-based thresholding methods have been proposed by researchers [11, 12], some are based on the Shannon's entropy concept. These methods aimed for computing the optimal threshold value. Basically, the entropy-based thresholding selects an optimal threshold value according to the statistical measure of the difference of image

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values. We adopt the segmentation method based on the one-dimensional entropy in this work for the sake of efficiency. Finally, we apply morphological operations to remove spurious edges and to extract the regions enclosed by the boundary edges.

This paper is organized as follows: section 2 describes our research background; section 3 introduces the proposed real-time defect extraction method; section 4 analyzes the experimental results; section 5 gives a conclusion.

2. Background

Our inspection system focused on the aluminum plate or strip surface. The system architecture is shown in Figure1. The speed of the aluminum strip is about 400m/min. The image acquisition system is equipped with four line scan CCD camera for aluminum top and bottom surface. Each one has 4096 element linear array with 18 kHz/s line scan rate. The camera has dual line scan technology that achieves ideal responsivity and throughput rates of 80 M pixels/s. Such system requires efficient image processing algorithms. Uniform light source of LED (Light Emitting Diode) linear light is used and bright illumination mode is chosen. In the ideal case, the image of smooth homogeneous surface of the aluminum strip has a uniform background, and the defect gray level is generally different from its background. However, there is local non-uniformity in images due to that the uniform light source has not been indeed uniform currently and the noise from CCD camera always exists.

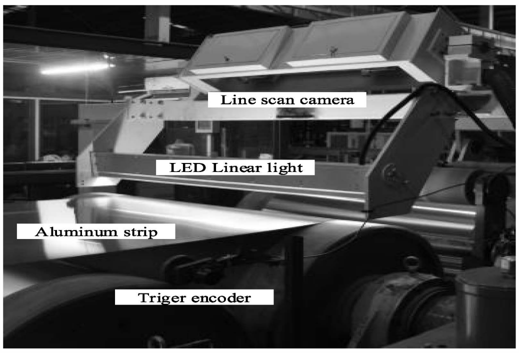

Figure1. System setup

3. Real-time defect extraction under non-homogeneity

In this section, we present our framework for real-time defect extraction. Our major concern is the computational cost. The flowchart of the defect extraction is shown in Figure 2.

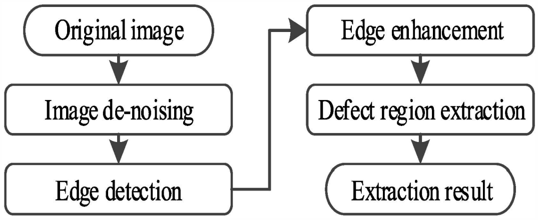

Figure 2. Extraction flowchart

Gaussian smoothing have been adopted for de-noising and Prewitt operation are used for edge detection. The edge detection can alleviate the effect of non-uniformity in the subsequent segmentation, while the de-noising can improve the accuracy of edge detection. We used these two filter-based approaches because they allow for fast on-chip implementation. The shape of the defect can be irregular, and the boundary edge can lies in various orientations. In order to detect as many as possible boundary edges, we use eight kernels, which are typically sensitive to eight possible directions (i.e. 0°, 45°, 90°, 135°, 180°, 225°, 315°), where 0° corresponds to the vertical direction[13, 14]. The eight orientations basically can be sufficient to ensure the completeness and continuity of the defect profile.

For image segmentation, image entropy has been used to describe how much information of the original unthresholded image is preserved in the thresholded image according to Shannon's theorization of information [10]. The optimal threshold value is computed by maximizing the sum of respective entropies of the target and the background [9]. The entropy of the histogram is a measure of the amount of information associated with the histogram. Unlike the conventional approaches, we use the thresholding technique for improving our edge detection given by Prewitt operation to further remove the effect of non-uniformity. We shall detail the formulation in the following.

For the image which has been filtered by Prewitt kernel, let us denote L as the gray-scale of the $M \times N$ image, the range of gray value as $[0, L-1]$, and h_i as the number of pixel with gray value i. The probability of occurrence of the gray value i is given by

$$p_i = \frac{h_i}{\sum_{i=0}^{L-1} h_i} = \frac{h_i}{M \times N} = \frac{h_i}{MN} \tag{1}$$

Let us denote d as the threshold, A as the boundary edge, and B as the background area. Then the probability of occurrence of the defect target and the background target are $P_A = \sum_{i=0}^{d} p_i$ and $P_B = \sum_{i=d+1}^{L-1} p_i$ respectively.

The one-dimensional entropies of the defect target and background are expressed as follows.

$$H(A(d)) = -\sum_{i=0}^{d}(p_i / P_A)\log_2(p_i / P_A) \tag{2}$$

$$H(B(d)) = -\sum_{i=d+1}^{L-1}(p_i / P_B)\log_2(p_i / P_B) \tag{3}$$

For the threshold value d, the information entropy of the image can de expressed as

$$H(d) = H(A(d)) + H(B(d)) \tag{4}$$

When $p_i = h_i / MN$, $P_A = \sum_{i=1}^{d} p_i$ and $P_B = \sum_{i=d+1}^{L-1} p_i$ are substituted into the equation (4) respectively, $H(d)$ is rewritten as

$$H(d) = -\frac{1}{a}\sum_{i=1}^{d} h_i \log_2 h_i - \frac{1}{MN-a}\sum_{i=d+1}^{L-1} h_i \log_2 h_i + \log_2\left(a(MN-a)\right) \tag{5}$$

Let $a = \sum_{i=1}^{d} h_i$, then $\sum_{i=d+1}^{L-1} h_i = MN - a$, $H(d)$ is then rewritten as follows:

$$H(d) = -\frac{1}{a}\sum_{i=1}^{d} h_i \log_2 h_i - \frac{1}{MN-a}\sum_{i=d+1}^{L-1} h_i \log_2 h_i + \log_2\left(a(MN-a)\right) \tag{6}$$

The optimal threshold value can be expressed as

$$d = \arg\max(H(d)). \tag{7}$$

The edge detection is enhanced by using the following rule with the threshold value d:

$$f(i) = \begin{cases} 0 & i \le d \\ 1 & i > d \end{cases}, \tag{8}$$

where the value 1 indicates the defect target and the value 0 indicates the background, then edge detection is enhanced.

The resultant edge detection results after thresholding may contain some random noise and it naturally leaves the defect regions as holes. We propose to use morphological operation to extract the defect regions from the edge detection result.

According to the inherent characteristics of the defects, two structuring element are chosen [8, 15]. We first remove noise dots or false defects using erosion operation with a square 3x3 erosion structure element as in [8]. Afterwards, we use the region filling algorithm [8] for hole-filling by the dilation operation with a symmetrical 3x3structure element, where the type of connectivity is 8-neighborhood. Finally, a diamond-shaped 5x5 structure element is used for eroding the small particle caused by the hole-filling to improve the final extraction accuracy. These three steps not only connect the parts of the defect, but they also remove the heterogeneous points in the target.

4. Experiment and analysis

To evaluate the proposed method, we use the image data from an aluminum plant. The proposed defect extraction algorithm has been implemented in our surface inspection system shown in Figure 1. An example of the proposed defect extraction method is shown in Figure 3. The result of every step in this extraction process is displayed, which illustrates this proposed method more clearly.

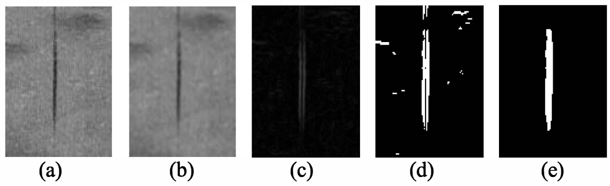

Figure 3. An example of the proposed method: (a) original image, (b) Gaussian smoothing, (c) edge detection, (d) edge enhancement, (e) morphology operation.

Table 1. Performance comparison of the proposed method and chi-square detector

Defect Type	Result	Extraction methods: Chi-square detector [7]	Extraction methods: Proposed method
Dent	CDR	0.959	0.961
	FAR	0.012	0.009
	MDR	0.041	0.039
Convexity	CDR	0.920	0.979
	FAR	0.019	0.018
	MDR	0.080	0.021
roller mark	CDR	0.968	0.998
	FAR	0.021	0.020
	MDR	0.032	0.002
Hole	CDR	0.997	0.999
	FAR	0.0301	0.034
	MDR	0.003	0.001
Scratch	CDR	0.989	0.998
	FAR	0.040	0.025
	MDR	0.011	0.002
Embedding object	CDR	0.966	0.967
	FAR	0.045	0.038
	MDR	0.034	0.033

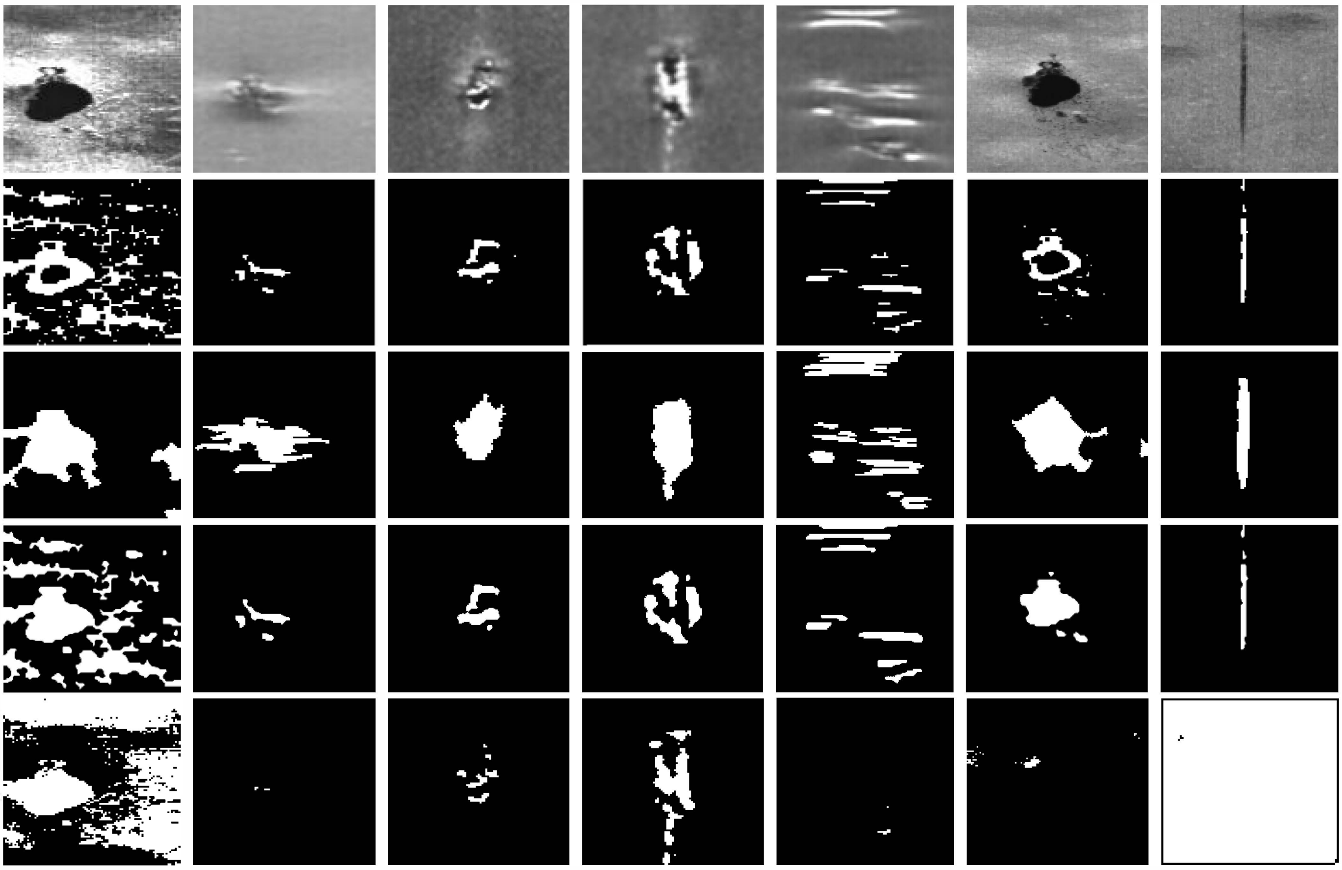

Figure 4. Performance comparison of defect extraction results using different method: 1st row - original images; 2nd row - the chi-square detector; 3rd row - the proposed method; 4th row - the chi-square detector followed by the proposed morphological algorithm; 5th row - the proposed method without Prewitt operation.

We compare our method with other related methods, including the chi-square detector [7], the chi-square detector followed by the proposed morphological algorithm, and the proposed method without the step of Prewitt operation. It is obviously seen from Figure 4 that the proposed method outperform the other methods.

We also present the quantitative results of the defect extraction. We adopt the measures used in [7], including the correct detection rate (CDR), the fake alarm rate (FAR), and the missed detection rate (MDR) as follows:

$$CDR = \frac{\text{the number of correctly detected defects}}{\text{the total number of the defects}} \tag{9}$$

$$FAR = \frac{\text{the number of the falsely detected defects}}{\text{the total number of the defects}} \tag{10}$$

$$MDR = \frac{\text{the number of the missed defects}}{\text{the total number of the defects}} \tag{11}$$

The data set contains 11539 defect images and 104 non-defect images. The quantitative results are shown in Table.1. For all defect types, compared with chi-square detector, we can observe the CDR of the proposed method is higher, and the MDR and FAR are generally lower.

Moreover, the computational time of the proposed method is much less than that of the chi-square detector. Like the chi-square detector, the statistics of computational time of the proposed method have been computed on the PC with

Intel E4500 CPU (2.2 GHz) for the images with size of 1024x768. The maximum computational time of the proposed method is 14.9ms, and the average processing time is only 6.5ms, while the average processing time of the chi-square detector is 42ms [7].

5 Conclusions

This paper describes a novel real-time defect extraction method for high-speed aluminum strip surface inspection, which is based on Prewitt edge detection and entropy-based image segmentation. The Prewitt edge detection is used for dealing with non-uniformities, and the entropy-based method for edge enhancement. The experiment results show that the method outperforms the previous methods for the aluminum inspection system.

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