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Defect detection in magnetic tile images based on stationary wavelet transform

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ABSTRACT

A novel approach using stationary wavelet transform (SWT) is proposed for automatically detecting low-contrast defects under various light conditions in magnetic tile images. In this method, the uneven background was removed by Sobel operation. Then the index low-pass filtering and the nonlinear enhancement were respectively used to eliminate the interference and enhance the target in subbands produced by SWT. To verify the validity of the proposed algorithm, extensive experiments were conducted in a novel machine vision based system. As the result shows, the proposed method achieves an accuracy rate of 92.86% in detecting various defects in magnetic tile surfaces with the average operation time of 0.5190 s, and is superior to traditional methods in terms of the high reliability and accuracy.

1. Introduction

Magnetic tile is an important component of permanent magnet motor and plays an important role in the performance and life circle of the motor [1]. As the surface defects pose a serious threat to its quality, the defect detection process becomes a key part of the production process. Currently, this task depends mainly on skilled workers, which exposes the weaknesses of high cost and low accuracy. Thus, the automation of detection is becoming increasingly urgent for the development of magnetic tile industry.

Among the numerous candidates of non-destructive testing (NDT) techniques, machine vision has been widely applied to industrial production due to the advantages of low cost, fast speed and strong adaptability, whose application now mainly focuses on measurement [2–3] and surface feature detection [4–7]. For the detection of surface features, the relevant researches can be generally categorized into three types, namely, spatial approaches, spectral approaches and joint spatial-frequency approaches. The spatial approaches always be directly applied to feature extraction and noise removal. Zou et al. [8] used Kalman filtering to detect the trajectory continuity of defects in radiographic image of spiral pipe, which proves effective in reducing the false alarm rate. Wang et al. [9] applied multiple thresholds and Hough transform to detect weld defects, which is effective for noisy and low contrast X-ray images. However, since the spatial approaches depend mainly on the gray level of each pixel, they are insensitive to the information of gradient and periodicity, which limits their application in complex background. In contrast, the spectral approaches are more effective in extracting these features by modifying the spectral distribution. Ogawa et al. [10] utilized Fourier transform magnitudes as texture features and enabled missing texture reconstruction by retrieving their phases based on the error reduction algorithm. Their method realizes accurate texture feature estimation and achieves successful reconstruction of the missing intensities. Nevertheless, the spectral approaches adopt an undifferentiated strategy towards specific frequency components regardless of background or target, which leads to the loss of local details. Consequently, they are only suitable for objects that exhibit a high level of homogeneity. By combing the strengths of spatial approaches and spectral approaches, the joint spatial-frequency approaches become better alternatives for feature extraction. Tong et al. [11] employed Gabor filters to tackle the woven fabric inspection issue, where the composite differential evolution was used to optimize the parameters of Gabor filters and the defects could be segmented from background using the optimal Gabor filters. Their method is demonstrated to be superior to existing models in terms of detection accuracy. But as each Gabor filter takes effect to one specific frequency and orientation, it is not suitable for the object with indefinite directionality. Benefiting from the property of multi-scale, a series of multi-resolution analysis (MRA) techniques have been extensively applied to surface feature detection in the past few years. Typical examples include wavelet

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[12], curvelet [13], contourlet [14] and shearlet [15]. Sun et al. [16] presented a novel non-uniform background removal algorithm based on multi-scale wavelet transform (WT) for automated pavement distress identification, where the non-uniform brightness of pavement images were corrected by reconstructing the low-wavenumber components through inverse WT and the defects were extracted from uniform background using threshold. Their method is effective in removing the non-uniform background, but causes the loss of target components. Zhong et al. [17] applied curvelet transform (CT) to water reflection recognition, where a novel curvelet feature space based on the characteristics of motion blur in water reflection images was constructed to detect water reflection images and reflection axis. This method is reliable in water reflection classification, but does not address the issue of target segmentation. In Li et al. [18], non-stochastic surfaces were decomposed into multiple sub-images by nonsubsampled contourlet transform (NSCT), then the real edges were determined by comparing the positions of the edge candidates at different scales. Although their method proves valid for feature identification, it is too slow for on-line inspection. Duval-Poo et al. [19] discussed the shearlet cascade edge detection (SCED) algorithm, which estimated the edge energy by reasoning on the behavior of shearlet coefficients at different scales of a given point of the image, and identified the edges using the functions of non-maxima suppression and threshold. The algorithm suffers very little from false edge, but performs poorly in identifying continuous interference.

For the detection of magnetic tile surface defect, not much work has been done in this field. Li et al. [20] proposed a new algorithm for detecting cracks with dark colors and low contrasts in magnetic tile images using fast discrete Curvelet transform (FDCT) and texture analysis. In their method, the original images were first decomposed based on FDCT. Then textures in each subband were eliminated with the threshold calculated by texture feature measurements. Finally, the crack defects contours were extracted by employing Canny operator. The method can effectively eliminate the grinding texture, but it is only available to detect the crack defects and requires a strict lighting condition for image acquisition. More recently, Xie et al. [21] proposed a shearlet transform based defect detection method for magnetic tile images. It applied shearlet transform (ST) to enhance the contrast between the defect area and normal area and segmented the defects by means of threshold. Their method is effective in averting the effects of uneven background and grinding textures, and can detect the defects efficiently. However, the method neglects the effect of noise and sets the parameters by experience, which greatly reduces its accuracy. As magnetic tile is produced in quantity and require strict quality, both high accuracy and high efficiency are demanded in the detection procedure, and the works mentioned above fail to meet the requirements simultaneously.

In this paper, a novel approach based on stationary wavelet transform (SWT) is proposed for automatically detecting low-contrast defects under various light conditions in magnetic tile images. Compared with other MRA techniques, SWT is more efficient to implement and preserves more detail information in decomposition coefficients by eliminating the subsampling process in WT, which are perfect for the detection task in this work. Besides, the proposed approach takes full account of various interference, and adopts operations with low computational cost, including Sobel operation, index low-pass filtering and nonlinear enhancement, to fulfill the efficiency requirement of online inspection. The remainders of this paper are outlined as follows. Section 2 briefly introduces the properties of SWT. Section 3 illustrates the defect detection algorithm in detail. Section 4 presents the experimental platform, showing the experimental results and making a discussion. Finally, we conclude the whole paper in Section 5.

2. Stationary wavelet transform

In traditional WT, signal is convolved with filters and down-sampled to obtain the decomposition of the next level. Size of the new signal is the 1/4 of the approximation signal at upper level, so WT is non-redundant [22]. In comparison, SWT, proposed by Nason and Silverman [23], exhibits the properties of redundancy and shift invariance on the basis of multi-scale and multi-direction. Instead of implementing the down-sampling operation after applying the low-pass and high-pass filters to the signal, SWT does not decimate the original signal and modifies the filters at each level by padding them out with zeros. As a result, the new signal has the same size as the approximation signal at upper levels and the shift invariance is achieved at the cost of redundant decomposition. As more details can be preserved in redundant decomposition, SWT is ideal for the defects detection of magnetic tiles that involve various defects with low contrast. Moreover, despite its redundancy, SWT exhibits low computational cost [24]. For the reasons above, SWT is selected in this study. Given an image $f(x, y)$ of size $M \times N$. For discrete stationary wavelet transform (DSWT), decomposition at level j is as follows:

$$\begin{cases} L_{j+1}(a, b) = \sum_k \sum_l h_k^j h_l^j L_j(a + k, b + l) \\ W_{j+1}^h(a, b) = \sum_k \sum_l g_k^j h_l^j L_j(a + k, b + l) \\ W_{j+1}^v(a, b) = \sum_k \sum_l h_k^j g_l^j L_j(a + k, b + l) \\ W_{j+1}^d(a, b) = \sum_k \sum_l g_k^j g_l^j L_j(a + k, b + l) \end{cases} \tag{1}$$

where $a = 1, 2, 3, \ldots, M$ and $b = 1, 2, 3, \ldots, N$. h_k^j and h_l^j are low-pass filters. g_k^j and g_l^j are high-pass filters. L_j and L_{j+1} are the low frequency subband at level j and $j+1$, respectively. W_{j+1}^h, W_{j+1}^v and W_{j+1}^d represent the horizontal detail coefficients, the vertical detail coefficients and the diagonal detail coefficients, respectively. The decomposition process of DSWT is shown in Fig. 1.

For inverse DSWT, the equation is:

$$\begin{aligned} \tilde{L}_j(a, b) = & \sum_k \sum_l \tilde{h}_k^j \tilde{h}_l^j \tilde{L}_{j+1}(a + k, b + l) \\ & + \sum_k \sum_l \tilde{g}_k^j \tilde{h}_l^j \tilde{W}_{j+1}^h(a + k, b + l) \\ & + \sum_k \sum_l \tilde{h}_k^j \tilde{g}_l^j \tilde{W}_{j+1}^v(a + k, b + l) \\ & + \sum_k \sum_l \tilde{g}_k^j \tilde{g}_l^j \tilde{W}_{j+1}^d(a + k, b + l) \end{aligned} \tag{2}$$

where $\tilde{h}_k^j$ and $\tilde{h}_l^j$ are the reconstruction low-pass filters. $\tilde{g}_k^j$ and $\tilde{g}_l^j$

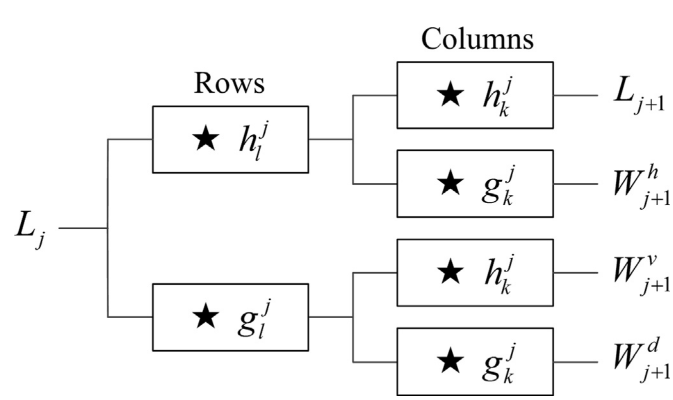

Fig. 1. DSWT decomposition filter bank structure.