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Detection of surface crack defects on ferrite magnetic tile

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ABSTRACT

A new approach is proposed for automatically detecting crack defects with dark colors and low contrasts in magnetic tile images using the fast discrete curvelet transform (FDCT) and texture analysis. In this methodology the original images were first decomposed and reconstructed based on the FDCT. Then the thresholds of decomposition coefficients were calculated by texture feature measurements. With these thresholds the surface textures in the images can be eliminated. Finally by extracting contours from the reconstructed images, the expected images without textures but with crack defects contours were obtained. Experimental results show that the proposed method could eliminate the contours of the textures, and extract from the image cracks longer than 0.8 mm.

1. Introduction

Magnetic tiles made of ferrite material are commonly used in permanent magnet motors in industrial automatic control devices, such as automobiles and machine tools. Cracks on the surfaces of the magnetic tiles, however, can be easily generated during the manufacturing process. They directly influence the performances and lives of the devices in which they are mounted.

Ferrite magnetic tiles are manufactured using the sintering technique that mainly consists of three steps. The first step is to press the magnetic powder to form solid masses. The second step is to sinter these masses in kilns with controlled atmosphere to obtain magnetic tiles. After sintering, the last step is to grind the magnetic tiles which produce the regular linear and arc textures on the end surfaces and the outer arc surfaces. Cracks are inevitably produced during the process, and their common forms are shown in Fig. 1. Fig. 1(a) shows a crack in one of the end faces and Fig. 1(b) shows a crack in the outside arc surface. Grinding textures interfering with the cracks increase the difficulty in defect detection by human eyes or non-destructive testing (NDT) systems.

At present, the magnetic tile defects are mainly detected by manual work, which is of low efficiency and precision, requiring strong intensity of labor. At the same time, missing and false detection frequently happen. An automatic detection system with low cost and high reliability is required.

The method proposed in this paper is basically a NDT one. There are many NDT methods for ferrite magnetic titles: eddy current testing [1,2], ultrasonic testing [3], magnetic particle testing [4,5], penetrant testing [6], etc. The eddy current and ultrasonic testing are usually more suitable for large-size plates. In magnetic particle and penetrant testing, the process is more complex than machine vision systems in magnetic tile defects detection.

With both the rapid expansion of production scale of enterprise and the advance of the level of the industrial automation, researchers all over the world have studied and proposed many optical NDT techniques for industrial production, such as mathematical morphology [7,8], template matching [9], wavelet transform [10,11], independent component analysis (ICA) [12], watershed algorithm [13,14], Markov random field model [15], neural network [16,17], and support vector machine (SVM) [18–20]. But because the cracks in magnetic tile surfaces are usually very small, the ferrite material itself is dark in hue and the contrast of magnetic tile image is low, there is a rare automatic detection system applied to the magnetic tile non-destructive detection.

The aim of this work is to develop an automatic detection system for defect detection in ferrite magnetic tile surfaces. Automatic detection of magnetic tile defects in real-time image usually consists of two steps: (1) image extraction and (2) defect segmentation. By analyzing the surface crack defects in magnetic tiles, we can enhance the image contrast by reasonably designing the illumination and separating the defects from normal surface efficiently. In this paper, a suit of the automatic checkout equipment is designed for crack defects detection. The image acquisition system is integrated into the convey system on the production line. This research proposes a hybrid method of texture analysis method and the FDCT method to identify and extract defects. The influence of the grinding

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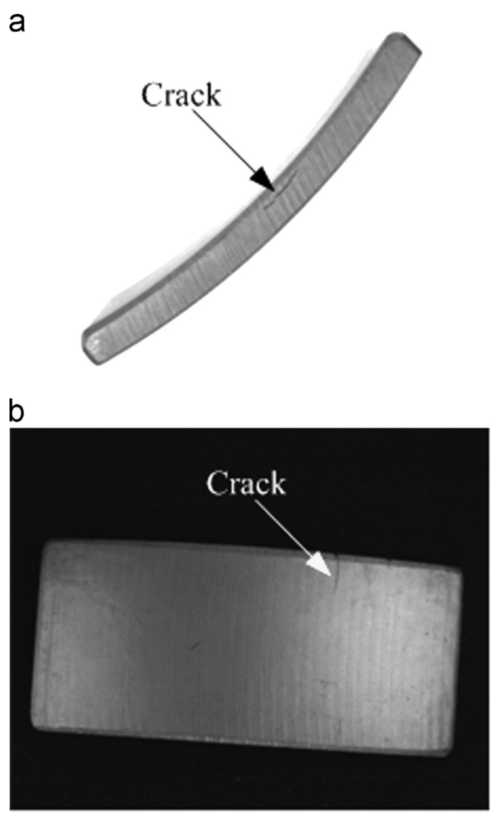

Fig. 1. Magnetic tile images with defects: (a) a crack in the end face and (b) a crack in the outside arc surface.

textures can be eliminated by changing FDCT reconstructed coefficients for further defects identification and detection. The system can provide an effective solution to magnetic tile defects detection industry.

The rest of this paper is organized as follows. Section 2 presents the algorithms of removing texture by using the FDCT and the gray level co-occurrence matrix. Section 3 presents the application of our method to the magnetic tile defects detection, showing the experimental results and making a discussion. Finally, Section 4 gives the conclusion.

2. Theory and methods

2.1. The fast discrete curvelet transform

The magnetic tile surfaces have their regular grinding textures which seriously affect the crack defects detection. In order to eliminate the effect of grinding textures, in this paper, we propose a method based on the FDCT [21,22] to reconstruct the magnetic tile images, which can eliminate the textures and then extract crack defects.

Candès [23,24] proved that the threshold processing method of the discrete curvelet coefficients provided an essentially optimal representation of typical objects that are C2 except for discontinuities along piecewise C curves. He also presented two digital implementations of a new mathematical transform, namely the second generation curvelet transform in two and three dimensions in the year 2005 [25]. The first digital transformation is based on unequally spaced fast Fourier transforms (FDCT_USFFT), while the second is based on the wrapping of specially selected Fourier samples (FDCT_WARP). In this paper, we use the FDCT_WARP algorithm to reconstruct the magnetic tile images.

In Cartesian coordinates, $f[t_1,t_2]$ $(0 \le t_1,t_2 \le n)$ is an input, the discrete curvelet transform coefficients are defined as

$$c^D(j,l,k) := \sum_{0 \le t_1,t_2 < n} f[t_1,t_2]\overline{\varphi^D_{j,l,k}[t_1,t_2]}, \tag{1}$$

where $\varphi^D_{j,k,l}$ are the digital curvelet wave forms and j, l, and k indicate scales, directions and positions, respectively.

A band-pass function is selected to be

$$\psi(\omega_1) = \sqrt{\phi(\omega_1/2)^2 - \phi(\omega_1)^2}, \tag{2}$$

where we define

$$\psi_j(w_1) = \psi(2^{-j}w_1) \tag{3}$$

The function is used to implement the multi-scale segmentation. For each $\omega=(\omega_1,\ \omega_2)$, $\omega_1>0$:

$$V_j(S_{\theta l}\omega) = V(2^{\lfloor j/2 \rfloor}\omega_2/\omega_1 - l), \tag{4}$$

where $S_{\theta_l} = \begin{bmatrix} 1 & 0 \\ -\tan\theta_l & 1 \end{bmatrix}$ is the shear matrix, and the distance of θ_l is not equal while the distance of slope is the same.

The curvelet decomposition coefficients from the lowest scale to the highest scale represent a coarse-to-fine process. A direction subblock coefficient of a certain level represents the feature of this direction by dividing angles in the middle scale.

The study object of this paper is a low-contrast image with regular texture features. The curvelet decomposition coefficients have multi-resolution and multidirectional characteristics, which we use to remove certain coefficients in order to eliminate the texture features in the reconstructed images. Then the Canny operator can be used to extract crack defects precisely.

2.2. Texture feature measurement

The second-order statistics method is the most commonly used method in the texture description. The spatial gray level dependence matrix which is also called co-occurrence matrix is most famous. It can reflect the gray comprehensive information about the direction, adjacent interval and ranges in the image. For a two-dimensional digital image $f(x,y)$, its size is $M \times N$ and the gray level is N_g. The gray level co-occurrence matrix for some certain spatial relationship can be represented as

$$P(i,j) = \#\{(x_1,y_1),(x_2,y_2) \in M \times N | f(x_1,y_1)=i, f(x_2,y_2)=j\} \tag{5}$$

where $\#(x)$ is the number of elements in the collection of x, P is a matrix with the size $N_g \times N_g$. If the distance between (x_1,y_1) and (x_2,y_2) is d, the angle between them and X-axis is θ, then the gray level co-occurrence matrix $P(i,j,d,\theta)$ with different distances and angles can be presented.

The principle of selecting the texture feature measurement functions is that the values of the functions change to the opposite trend of the change of density of the textures. This principle may serve as a reference in determining the regions of curvelet coefficients. Haralick [26] defined 14 second-order statistics functions calculated from the gray level co-occurrence matrix, we used four of them to measure texture features as follows:

$$\text{Variance} = \sum_{i=0}^{quant_k} \sum_{j=0}^{quant_k} P(i,j)(i - \text{mean}^2), \tag{6}$$

$$\text{Entropy} = -\sum_{i=0}^{quant_k} \sum_{j=0}^{quant_k} P(i,j) * \ln P(i,j), \tag{7}$$

$$\text{Homogeneity} = \sum_{i=0}^{quant_k} \sum_{j=0}^{quant_k} P(i,j)/(1+(i-j)^2), \tag{8}$$