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New banknote defect detection algorithm using quaternion wavelet transform

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ABSTRACT

In order to improve the accuracy of detection of defects in banknote sorting, a new algorithm is proposed to detect cracks and scratches on banknote images. The quaternion wavelet transform and the least squares method are used for the banknote image registration. The features of the defects that are robust to gray intensity changes are constructed using edge information captured by the Kirsch operator. The banknote image is divided into several subzones of fixed size. The level of defect of the banknote image is estimated based on the defective features of each sub-zone. The experimental results show that the proposed algorithm is robust even with low quality banknote images and can obtain a high recognition rate and high stability. The proposed algorithm has already been used in a practical banknote sorting system.

1. Introduction

As the economy and society develops, there is a growing requirement for banknote processing systems in financial institutions and banks. Defect detection plays an important role in financial transactions, and feature extraction is an essential step within any banknote sorting system.

In recent years, there are some banknote defect feature extraction algorithms have been proposed. Takeda et al. [1] applied Fourier power spectra as feature in banknote classification. Frosini et al. [2] proposed new banknote classification method by using neural network model based on low cost sensors. In [3], Takeda proposed new feature extraction method by using masks, and then applied genetic algorithm to optimize the mask. Liu et al. [4] divided each banknote image into different blocks. The feature vector is obtained by computing the average gray value of each region of banknote image. Choi et al. [5] investigate new approach to feature extraction for banknote classification by using wavelet transform. Hamid et al. [6] proposed a robust paper currency recognition method based on Hidden Markov Model. Chi et al. [7] proposed a system based on multiple-kernel support vector machines for banknote recognition. Farid et al. [8] applied color and texture features for Mexican banknotes classification. In [9], Faiz proposed a component-based framework by using speeded up robust features. Jin [10] proposed a algorithm for the detection of cracks and scratches based on homogeneity features of banknote image.

The wavelet transform is an important tool for image processing [11–13]. Selesnick et al. [14] has proposed new multi-scale analysis tool in the hyper-complex space which has one magnitude. Chan et al. [15] has proposed image de-noising methods by using quaternion wavelet filters and customized thresholds corresponding to a given noisy image. As proved in [16,17], the multiresolution analysis is straight forwardly extended to the QWT. The QWT is widely used in many applications including image segmentation [18,19], edge detection [20,21], image registration [22] and texture classification [23,24].

The paper is organized as follows: In Section 2, the theory of QWT is reviewed. The new framework of banknote image registration based on QWT is proposed in Section 3. In Section 4, the new banknote defect detection algorithm is proposed. The experimental results and analysis are discussed in detail in Section 5. Finally, the conclusion is given in Section 6.

2. Quaternion wavelet transform

A standard wavelet transform (DWT) can provide a scale-space analysis of an image. It can yield a matrix that has each coefficient related to a sub-band and to a position in the image. However, DWT suffers from four fundamental shortcomings: shift variance, oscillations, aliasing and lack of directionality. To solve these problems, this paper uses the quaternion wavelet transform (QWT) to provide a richer scale-space analysis for 2-D signals, which can be considered to be similar to a local 2D quaternion Fourier transform (QFT). In contrast with DWT, it is almost shift

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invariant and provides a magnitude-phased local analysis of images. We also briefly review some basic theory on quaternion algebra and construction of the QWT.

The quaternion $q = a + bi + cj + dk \quad (a, b, c, d \in \Re)$ which is generalization of the complex algebra was proposed by Hamilton in 1843. The orthogonal imaginary numbers have multiplication rules as follows:

$$\begin{cases} i^2 = j^2 = k^2 = -1 \\ ij = k, \quad kj = i, \quad ki = j \end{cases} \tag{1}$$

Its polar representation for a quaternion is $q = |q| e^{i\phi} e^{j\theta} e^{k\psi}$, where $|q|$ denote magnitude, ϕ, θ, ψ are three local phases. Each local phase angle is defined with the range of $[-\pi, \pi]$, $[-\pi/2, \pi/2]$ and $[-\pi/4, \pi/4]$ respectively. In [26], a quaternion analytical signal can be defined as follows:

$$f_A(x, y) = f(x, y) + iH_1 f(x, y) + jH_2 f(x, y) + kH_T f(x, y) \tag{2}$$

where (H_1, H_2) and H_T are the partial and total Hilbert transform, respectively. The 2D Hilbert transform is equivalent to a 1D Hilbert transform along rows and/or columns. The 2D analytic wavelets are constructed as separate products, taking the 1D Hilbert transform pair of wavelets $(\psi_h \psi_g = H\psi_h)$ and the scaling function $(\varphi_h \varphi_g = H\varphi_h)$ into consideration. Similar to the quaternion analytic signal, the QWT is constructed using a real separable scaling function φ and mother wavelets ψ^V, ψ^H, ψ^D which are oriented in the vertical, horizontal and diagonal directions respectively. They are defined as follows:

$$\begin{cases} \psi^V = \varphi_h(x)\psi_h(y) + i\varphi_g(x)\psi_h(y) + j\varphi_h(x)\psi_g(y) + k\varphi_g(x)\psi_g(y) \\ \psi^H = \psi_h(x)\varphi_h(y) + i\psi_g(x)\varphi_h(y) + j\psi_h(x)\varphi_g(y) + k\psi_g(x)\varphi_g(y) \\ \psi^D = \psi_h(x)\psi_h(y) + i\psi_g(x)\psi_h(y) + j\psi_h(x)\psi_g(y) + k\psi_g(x)\psi_g(y) \\ \varphi = \varphi_h(x)\varphi_h(y) + i\varphi_g(x)\varphi_h(y) + j\varphi_h(x)\varphi_g(y) + k\varphi_g(x)\varphi_g(y) \end{cases} \tag{3}$$

The magnitude of QWT represents the features at any spatial position in each frequency sub-band, and the three phases (ϕ, θ, ψ) describe the textural information and local shift of the image signal. The QWT coefficients are computed using separate 2D dual tree filter banks. $h_j^q, g_j^q \; (j = 1, 2)$ are the quaternion filters along the rows and columns, respectively. They can be used to generate four possible combinations of quaternion filters such as $h_j^q h_j^q, h_j^q g_j^q, g_j^q h_j^q$ and $g_j^q g_j^q$. Fig. 1 shows the decomposition process which down-samples the two primary levels of the QWT by a factor of two, from fine to coarse. $A_i^q (i = 1, 2)$ are the approximate components of the QWT and $B_i^q (B = H, V, D, i = 1, 2)$ denote the detailed components of the QWT. The decomposition structure of QWT at a scale $S = 2$ is illustrated in Fig. 2.

3. Banknote image registration

There are substantial differences between banknote images with the same face value, due to deviation of the banknote image size and the effects of temperature, humidity and creasing. There can be different tilt angles when the banknote image samples are being acquired. Hence, banknote image registration is a key step in the banknote defect detection process.

3.1. Registration framework using QWT

Based on the characteristics of a banknote image, only stretching and shift transformations can occur during the coordinate conversion from the reference image to the test image. The relationship between the corresponding pixels is defined as follows:

$$\begin{pmatrix} x_{ai} \\ y_{ai} \end{pmatrix} = \begin{pmatrix} a_1 & 0 \\ 0 & a_2 \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix} + \begin{pmatrix} b_1 \\ b_2 \end{pmatrix} \tag{4}$$

where $A = (a_1, a_2)$ are the horizontal and vertical scale coefficients, and $B = (b_1, b_2)$ are the shift coefficients. Let $\tau = \{A, B\}$ denote the mapping transformation model which satisfies $\tau(x, y) = (x_{ai}, y_{ai})$.

QWT is used for the time-frequency analysis by using the scaling function and the wavelet basis function. The decomposition coefficients are defined as follows:

$$\begin{cases} \varphi(m, n) = \sum_k \sum_l h(k - 2m)h(l - 2n)f(k, l) \\ \psi^H(m, n) = \sum_k \sum_l h(k - 2m)g(l - 2n)f(k, l) \\ \psi^V(m, n) = \sum_k \sum_l g(k - 2m)h(l - 2n)f(k, l) \\ \psi^D(m, n) = \sum_k \sum_l g(k - 2m)g(l - 2n)f(k, l) \end{cases} \tag{5}$$

where φ are the approximation coefficients and ψ^H, ψ^V and ψ^D are the detailed coefficients. Let $f(m, n)$ be the original banknote image, the processed banknote image is then $f(2m, 2n)$ by QWT due to down-sampling by a factor of two. Let τ denote the stretching transformation so $f(2m, 2n)$ is expressed as $f(2m + 2b_1, 2n + 2b_2)$. Assuming that $u = k - 2m$ and $v = l - 2n$ and substitute these values into Eq. (5). The low frequency component is represented as follows:

$$\sum_k \sum_l h(k - 2m)h(l - 2n)f(m, n) = \sum_u \sum_v h(u)h(v)f(u + 2m, v + 2n) \tag{6}$$

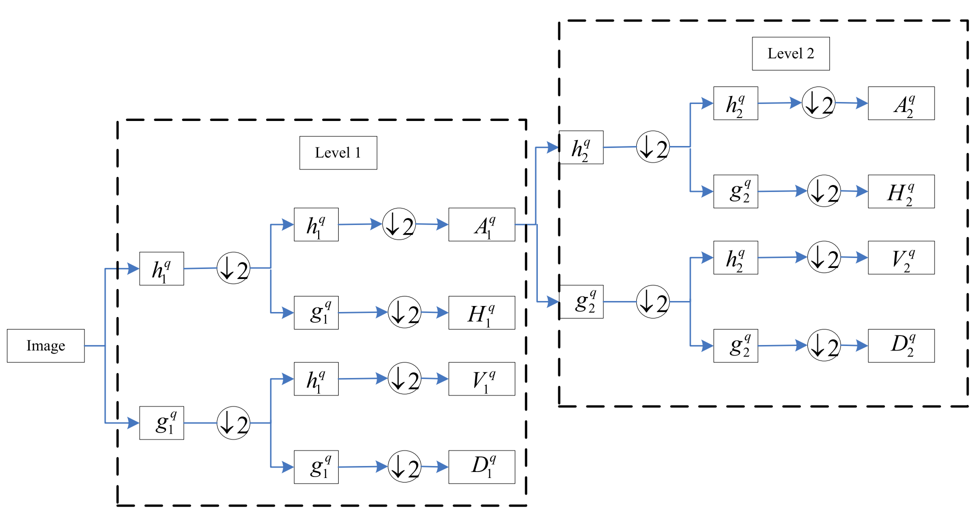

Fig. 1. Two levels of quaternion wavelet transform.