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Feature extraction using dual-tree complex wavelet transform and gray level co-occurrence matrix

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ABSTRACT

This paper introduces a new feature extraction method for texture classification application. In the proposed method, dual-tree complex wavelet transform is first performed on the original image to obtain sub-images at six directions. After that gray level co-occurrence matrix of each sub-image is calculated and the corresponding statistical values are used to construct the final feature vector. The experimental results demonstrate that our proposed method has the property of robustness, and can achieve higher texture classification accuracy rate than the conventional methods.

1. Introduction

Texture classification aims to assign an unknown sample image to one of a set of known texture classes, which is fundamental to many applications such as automatic industrial inspection, biomedical image processing, aerial imagery segmentation and content based image retrieval. To obtain better classification performance, it is essential to extract texture features with good discrimination power. A number of feature extraction methods have been proposed over the years, which can be classified into three main categories: i.e., model based methods, statistical methods and signal processing methods [1].

Haralick et al. introduced the concept of gray level co-occurrence matrix (GLCM), and extracted statistical features for texture image classification [2]. As a traditional statistical feature extraction method, GLCM has been commonly used in many applications. Partio et al. applied GLCM for rock texture image retrieval, and the results showed that the GLCM features outperform Gabor wavelet features [3]. Wu et al. employed GLCM to extract the texture features of aerial insulator images for segmentation [4], and Wang et al. employed GLCM for 18 different fruit category identification [5]. Siqueira et al. extended the GLCM to multiple scales through Gaussian scale-space representation and image pyramid, which outperforms the original GLCM for texture description [6]. Furthermore, Subrahmanyam et al. presented the modified GLCM for color image retrieval [7]. Note that GLCM features can also be extracted from transformed image instead of original image. Jhanwar et al. presented a content based image retrieval system by using motif co-occurrence matrix (MCM) derived from the motif transformed image [8]. Since MCM captures the third order image statistics in the local neighborhood, it is better than the conventional methods for feature extraction. Zhang et al. first obtained GLCM from Prewitt edge images, and then calculated statistical parameters of GLCM to generate feature vector [9]. Moreover, several researchers tried to enhance the GLCM based method by fusing other extracted features [10,11].

The favorite signal processing method for feature extraction includes Gabor, wavelet transform, Contourlet, etc. Gabor filters have been used for texture segmentation, and perfect reconstruction of the input image can be achieved [12]. The energies calculated in a window around each pixel can be taken as texture features. Moreover, Gabor wavelets have been applied for rotation invariant texture classification [13,14]. The input image can be first decomposed into multiple scales and orientations. After that, texture features could be extracted by calculating the mean and variance of the Gabor filtered image. Besides using Gabor feature, Irtaza et al. introduced hybrid texture features to maximize the performance of image retrieval [15]. Ganesan et al. proposed wavelet based method by using an integration of the crude wavelets with rotational invariance [16,17]. In such method, the first- and second-order statistical parameter and entropy were calculated as texture features. Note that the consistent estimator of texture model parameters could also been applied for feature extraction, which may provide greater accuracy and flexibility in capturing texture information [18,19]. Moreover, several researchers applied discrete wavelet transform (DWT) and other

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approaches jointly to extract more meaningful texture features [20–22]. Since the Contourlet transform overcomes the limitation of DWT in capturing the geometry of image edges, it could be applied to capture some smooth features (such as the contours and lines in image) [23–25]. Kingsbury et al. proposed the dual-tree complex wavelet transform (DTCWT), which has the advantages of efficient computation, approximately shift invariance and good directional selectivity [26,27]. Therefore, it can effectively address the problem of conventional Gabor filters and DWT. Celik et al. applied DTCWT for texture classification [28]. In their proposed method, feature vector was constituted by variance and entropy at multiple scales and directional sub-bands of the transformed domain. Furthermore, Kennel et al. extracted representative texture features by computing textons obtained from DTCWT decomposition [29].

In this paper, we proposed a new feature extraction method for effective and efficient texture classification. DTCWT was first used to decompose the texture image into sub-images at different directions. After that, GLCMs of each sub-image were calculated, and the statistical features of GLCMs were extracted for final classification. Since the proposed method utilizes both local mutual occurrence of patterns and global directional texture information, one can obtain elaborate description of texture image. The rest of this paper is organized as follows. Section 2 gives brief review of DTCWT and GLCM. The proposed feature extraction method is described in Section 3. Section 4 analyzes the experimental results and Section 5 addresses the conclusion.

2. DTCWT and GLCM

2.1. DTCWT

DWT suffers from the drawback of shift variance, i.e., a small shift of the input signal causes significant fluctuations in energy distribution of wavelet coefficients. Kingsbury has proposed DTCWT to address the problem, which calculates the complex transform of a signal using two separate DWT decompositions (tree a and tree b) [26]. If the filters used in one tree are specifically designed different from those in the other, it is possible for the first DWT to produce the real coefficients and the second DWT to produce the imaginary coefficients. In DTCWT, an image signal $f(x, y)$ is decomposed by using a complex scaling function and six complex wavelet functions as follow

$$f(x,y)=\sum_{l\in Z^2}A_{j_0,l}\phi_{j_0,l}(x,y)+\sum_{k\in\alpha}\sum_{j=1}^{j_0}\sum_{l\in Z^2}D_{j,l}^{k}\varphi_{j,l}^{k}(x,y) \tag{1}$$

where j_0 is the number of decomposition level,$A_{j_0,l}$ and $D_{j,l}^k$ are scaling coefficients and wavelet coefficients respectively. $\phi_{j_0,l}(x,y)$ denotes the scaling function and $\varphi_{j,l}^k(x,y)$ denotes six wavelet functions which are oriented at $k\in\alpha=\{\pm\pi/12, \pm\pi/4, \pm 5\pi/12\}$. Therefore, it can produce six directionally selective sub-bands for each scale. The impulse responses of the filters for the six directional sub-bands are shown in Fig. 1.

Considering the two-dimensional wavelet $\varphi(x,y)=\varphi(x)\varphi(y)$ associated with the row–column implementation of the wavelet transform, if $\varphi_g(t)$ is approximately the Hilbert transform of $\varphi_h(t)$, i.e., $\varphi_g(t)\approx H\{\varphi_h(t)\}$, one can obtain the following six wavelets:

$$\varphi_i(x,y)=\frac{1}{\sqrt{2}}(\varphi_{1,i}(x,y)-\varphi_{2,i}(x,y)) \tag{2}$$

$$\varphi_{i+3}(x,y)=\frac{1}{\sqrt{2}}(\varphi_{1,i}(x,y)+\varphi_{2,i}(x,y)) \tag{3}$$

for $i=1$, 2, and 3, where the two separable two-dimensional wavelet bases are defined as follows:

$$\varphi_{1,1}(x,y)=\phi_h(x)\varphi_h(y),\ \ \varphi_{2,1}(x,y)=\phi_g(x)\varphi_g(y) \tag{4}$$

$$\varphi_{1,2}(x,y)=\varphi_h(x)\phi_h(y),\ \ \varphi_{2,2}(x,y)=\varphi_g(x)\phi_g(y) \tag{5}$$

$$\varphi_{1,3}(x,y)=\varphi_h(x)\varphi_h(y),\ \ \varphi_{2,3}(x,y)=\varphi_g(x)\varphi_g(y) \tag{6}$$

In fact, the DTCWT is implemented by taking sum/difference of two separable wavelet filter banks in a quad-tree structure with 4:1 redundancy [27]. Since each of the above six wavelets are aligned along a specific direction, the DTCWT can capture more image information than the conventional wavelet transform.

2.2. GLCM

GLCM has been introduced by Haralick, which transforms an image into a matrix according to the relationship of pixels in the original image. The mutual occurrence of pixel pairs for a specific distance oriented at a particular direction need to be calculated. After that, the statistical features can be extracted for texture image classification [5]. The GLCM with distance d and orientation θ of a $N_x\times N_y$ image is defined as $G_d^\theta=[g_d^\theta(i,j)]_{q\times q}$, where q is the gray level quantization. The elements of the GLCM with four orientations can be calculated as follows

$$g_d^0(i,j)=\#\{((k,l),(m,n))\,|\,k-m=0,\,|l-n|=d,I(k,l)=i,I(m,n)=j\} \tag{7}$$

$$\begin{aligned}g_d^{\pi/4}(i,j)=\#\{&((k,l),(m,n))\big|k-m=d,\,\big|l-n\big|=d \text{ or } k-m\\&=-d,\big|l-n\big|=-d,I(k,l)=i,I(m,n)=j\}\end{aligned} \tag{8}$$

$$g_d^{\pi/2}(i,j)=\#\{((k,l),(m,n))\,|\,|k-m|=d,\,l-n=0,I(k,l)=i,I(m,n)=j\} \tag{9}$$

$$\begin{aligned}g_d^{3\pi/4}(i,j)=\#\{&((k,l),(m,n))\big|k-m=d,\,l-n=-d \text{ or } k-m\\&=-d,l-n=d,I(k,l)=i,I(m,n)=j\}\end{aligned} \tag{10}$$

where $(k,l),(m,n)\in N_x\times N_y$. $I(k,l)$ and $I(m,n)$ are the pixel intensity at position (k,l) and (m,n) of the input image.

Fig. 2 shows an example of GLCM calculation. In Fig. 2 (a) original 4×4 image with 4 (from 0 to 3) gray levels is shown. G_1^0, $G_1^{\pi/4}$ and $G_1^{\pi/2}$ can be calculated according to Eqs. (7)–(9) respectively, and the results are shown in Fig. 2(b)–(d).

3. The Proposed feature extraction method

As mentioned in Section 2, DTCWT has property of good directional selectivity, which can decompose the texture image from

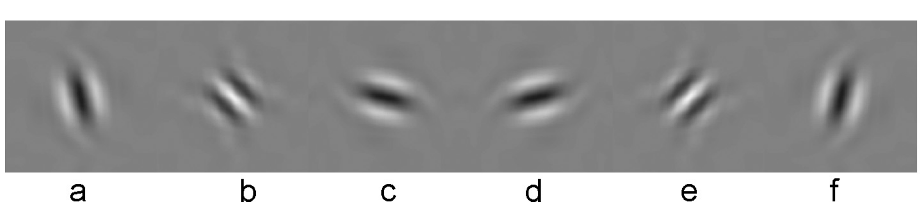

Fig. 1. Impulse response of DTCWT filters at different directions. (a) $-5\pi/12$, (b) $-\pi/4$, (c) $-\pi/12$, (d) $\pi/12$, (e) $\pi/4$, and (f) $5\pi/12$.