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Editor's Choice Article

Invariant texture classification using a spatial filter bank in multi-resolution analysis☆

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ABSTRACT

This paper proposed a new method based on spatial filter banks and discrete wavelet transform (DWT) for invariant texture classification. The method used a multi-resolution analysis method like DWT and applied the proposed filter bank on different resolutions. Then, a simple fusion of features on different resolutions was used for invariant texture analysis. A comprehensive study was done to examine the effectiveness of the proposed method. Different datasets with different properties were used in this paper such as Brodatz, Outex, and KTH-TIPS for the evaluation. Local binary pattern (LBP) methods have been one of the powerful methods in recent years for invariant texture classification. A comparative study was performed with some state-of-the-art LBP methods. This comparison indicated promising results for the proposed approach as compared with the LBP methods.

1. Introduction

Textures are one of the most important features in image processing and machine vision. Remote sensing, medical image segmentation, etc. are different areas where texture analysis is frequently used. Many authors proposed different methods for texture analysis. Texture classification, segmentation, and synthesis are three main categories of texture analysis. In [1] texture classification is divided into four main groups, including statistical methods, filter-based techniques, model-based schemes, and structural approaches.

Statistical features are normally extracted from the first order and the second order statistics of texture. Moreover, second order statistical methods are divided into three categories, namely the gray-level difference methods, the spatial gray-level difference techniques using analysis of co-occurrence matrix (GLCM) proposed in [2], and the gray-level run schemes. Wouwer et al. [3] proposed wavelet co-occurrence signatures, then they extracted the GLCM features from different channels of wavelet decomposition. Local binary patterns (LBPs) proposed by Ojala et al. [4] is one of the most important statistical features that has attracted much attention in recent years. In this method, at first, a neighborhood around each pixel is defined, then it exploits the relationship between neighborhood pixels. Many extensions of this approach have lately been proposed, which have good robustness against rotation, illumination, and noise [5,6].

Using spatial filter banks for texture analysis has been proposed by different authors. Leung and Malik [7] proposed a spatial filter bank, including 48 different filters for illumination and posed invariant texture classification. Later on, Varma and Zisserman [8,9] used a different filter bank for texture classification. They proposed a special filter bank, namely the maximum response sets (MR8) in [8] for rotation and scale invariant texture classification. Their filter bank consisted of 38 filters, which contained 2 isotropic filters, such as Gaussian and Laplacian of Gaussian, and also two anisotropic filters at 3 different scales and 6 different orientations. These methods intrinsically had a problem that lost frequency information in texture analysis. Ghita et al. [10] presented a good comparison between the LBP and different filter bank methods on different datasets with a variation of texture sizes and orientations.

Spatial-frequency filters like discrete wavelet transform (DWT), complex wavelet transform (CWT), and Gabor wavelets are powerful tools for texture analysis. Chang and Kuo [11] proposed a tree structure wavelet transform on the DWT. In this method, until the energy of each decomposed image is low as compared with other channels, the DWT is applied. Next, l_1-norm energy was extracted from different channels, then it was used for texture classification. Kashyap and Khotanzad [12] proposed a model-based method for rotation invariant texture classification. This model was among the first methods in this field. Translation invariant wavelet transform and Radon transform were used in [13] to extract rotation invariant features for texture classification. The Radon transform was used to convert rotation to translation, then their proposed features were extracted using a translation invariant wavelet transform. Classification process was performed by K-nearest neighbor classifier (KNN) with different Ks. In [14] the same authors

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proposed another idea that initially tried to estimate the rotation angle of the texture using the Radon transform, and after that image could be converted into the principal direction of 0°.

Furthermore, DWT was also used for extraction of invariant texture features. Porter and Canagarajah [15] proposed combining channel scheme on DWT to achieve features that were robust to the rotation of textures. These features were almost independent of directionality of textures. They proposed 4 different wavelet features that were extracted from l_1-norm of combination of LH and HL channels in three levels of decomposition and also LL channel in the last level. Mantalkar et al. [16] extended this method and proposed different combining schemes, then they extracted 14 different features such as standard deviation and energy features. Log-polar transform was used in [17] for extracting rotation and scale invariant features.

Kingsbury [18] proposed a dual-tree complex wavelet transform (DT-CWT) approach which was made of the Gabor filters with complex coefficients, hence it had two advantages like directional selectivity and shift invariant, as compared with DWT. Hill et al. [19] extended the idea of combining channels in [15] to the DT-CWT with 6 different channels in each level of decomposition. Xie et al. [20] presented a multi-channel filter bank based on the Gabor filters for rotation and scale invariant texture classification. Contextual information is a very important feature in image processing. Random field models like Gibbs, Markov, and Gaussian random field can properly model spatial relationship between pixels [21,22].

The conventional wavelet based methods are effective and powerful tools for texture analysis; however, they have basic shortcomings for invariant texture classification. The 2D-DWT suffers from intrinsic problem like lack of directionality, which highly complicates the processing of geometric image features, including ridges and edges. Also, they have moderate ability to deal with illumination invariant texture classification. Moreover, the spatial filter banks have a good ability to deal with the geometric image features, although they mostly have high running time because of using a lot of anisotropic filters at different orientations. Spatial filter bank methods have good results for invariant texture classification such as rotation and illumination [8]. Furthermore, spatial filter banks just consider images at one scale; therefore, they lose the frequency and spectral information of textures.

For these reasons, this paper tries to incorporate appropriate properties of the spatial filter bank methods into the DWT in order to alleviate their shortcomings. This paper proposes a combination of wavelet and spatial filter bank for invariant texture classification. A spatial filter bank is proposed, and then it is applied on different resolutions of texture. The DWT is used for multi-resolution analysis. Wavelet features extracted from the DWT are sensitive to rotation. Moreover, the rate of these changes is higher in anisotropic textures as compared with isotropic textures. By rotating the texture image, the detailed images are strongly changed. Therefore, the proposed feature vector only used LL channels for feature extraction and ignored the detailed channels. Finally, a fusion of features in different resolutions is applied for texture classification. A minimum Mahalanobis distance classifier is used for classification section. In addition, different wavelet bases are used and their results are reported.

2. Discrete wavelet transform and related features

Wavelet transform is a mathematical function that produces a multi-resolution representation of images. Wavelet transform attracts much attention in many areas like image compression, segmentation, and texture classification. Wavelet transform can produce a spatial-frequency analysis of signals. 1D continuous wavelet transform (CWT) is represented by Eq. (1).

$$CW(a,b) = \frac{1}{\sqrt{a}}\int s(t)\varphi\left(\frac{t-b}{a}\right)dt \tag{1}$$

where $s(t)$ is signal and φ is wavelet function and also a and b are scale and translation parameters, respectively. The wavelet function $\varphi_{a,b}(t)$ can be created by a mother wavelet function $\varphi(t)$ using the following form that is a dilated and shifted version of the mother wavelet function.

$$\varphi_{a,b}(t) = \frac{1}{\sqrt{a}}\varphi\left(\frac{t-b}{a}\right). \tag{2}$$

The base functions of a DWT are captured via sampling from CWT, which can be expressed in Eq. (3).

$$\varphi_{n,m}(t) = \; = 2^{-n/2}\,\varphi\left(2^{-n}t-m\right),\; m,n\in N. \tag{3}$$

Some of the mother wavelets, such as the Mexican Hat, Symlet, Biorthogonal, and Daubechies are proposed with different properties. Moreover, The CWT is not so efficient for implementation; therefore, DWT has been proposed because it has a simple and easy implementation. This paper used wavelet bases, such as the Symlet, Biorthogonal, and Daubechies for multi-resolution analysis. Based on the results, changing wavelet bases have a small effect on final results, although the Symlet 4-tap obtains higher results than the other methods in most of datasets.

A 2D-DWT is computed by the 1D-DWT. The filters are applied along rows and columns of the image. This property in the implementation of wavelet transform is a main reason which makes it sensitive to rotation. After applying wavelet transform, each image is divided into four sub-images, including low horizontal and low vertical frequency (LL), high horizontal and low vertical frequency (HL), low horizontal and high vertical frequency (LH), and high horizontal and high vertical frequency (HH) that consisted of low resolution image, horizontal detail, vertical detail, and diagonal detail, respectively. This procedure can be applied for several times on a low resolution image.

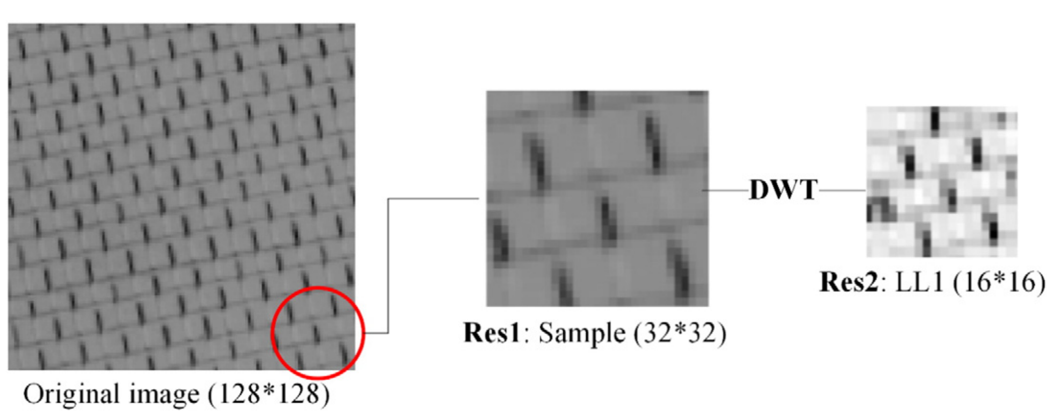

Fig. 1. Two different resolutions used in this paper.