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Directional statistical Gabor features for texture classification

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ABSTRACT

In texture classification, methods using multi-resolution directional (MRD) filters such as Gabor have not often shown significantly better performance than simple methods using local binary patterns, although they have a robust theoretical background and high computational complexity. We expect that this is because such methods usually make use of only the modulus parts of complex-valued MRD-filtered images and do not fully utilize their phase parts and other directional information. This letter presents a rotation-invariant feature using four types of directional statistics obtained from both the modulus and phase parts of Gabor-filtered images. First, modulus statistics, scale-shift cross-correlations, and orientation-shift cross-correlations are computed over all directions for each pixel of Gabor-filtered images, and global autocorrelations are computed over all pixels of each Gabor-filtered image. Global means and standard deviations for the three types of directional statistics and directional means and standard deviations for the global autocorrelations are then computed to form a feature vector. Experimental results with Brodatz, STex, CUReT, KTH-TIPS, UIUC, UMD, ALOT, and Kylberg databases show that the proposed method yields excellent performance compared with several conventional methods.

1. Introduction

Techniques for classification of image textures can be widely applied to various image processing fields such as texture image retrieval, image segmentation, biometrics, and face recognition [1,2]. Recent research works have presented texture classification methods using multi-resolution directional (MRD) filters such as Gabor and wavelet filters [3–6], which are based on the characteristics of the human visual system. It is well known that most mammalian cortical simple cells yield the behaviour of multiscale filtering with orientation selectivity or MRD filtering. In particular, the receptive field profiles have been shown to be well matched with the impulse responses of Gabor filters, which achieve the lowest bound on the product of effective spatial extent and frequency bandwidth [7,8].

Wavelet transforms using separable filters are a special case of two-directional (horizontal and vertical) MRD filters. Some of them extract energy distributions [9], refined histogram signatures [10], or SVD (singular value decomposition) distribution parameters [11] of wavelet sub-band images. Others seek bit plane signatures [12] of absolute wavelet sub-band images.

Numerous approaches using simple directional gradients are also found in the MRD filtering literature. Simple directional gradient here means the grey-level difference of a neighbour pixel along each direction to a centre pixel [13]. It can be viewed as one of the outputs of Haar MRD high-pass filters with two taps, 1 and -1, along all. The local binary pattern (LBP) suggested by Ojala et al. [2] is considered a sign configuration of simple directional gradients at a pixel. Many of them adopt multi-resolution schemes. After LBPs for an image are binary-coded, the histogram or co-occurrence of the LBP codes is commonly used for the texture feature [14]. Some typical variants of the LBP are uniform LBP (ULBP) [15], dominant LBP (DLBP) [16], and completed LBP (CLBP) [17].

Many advanced methods using LBP that produce successful performance have also been reported recently, some of which are labelled DLBP [18], median robust extended LBP (MRELBP) [19], and scale-selective LBP (SSLBP) [20]. In SSLBP, dominant patterns are first found from CLBP histograms for each scale, and the dominant pattern of the maximal frequency over all scales for each histogram bin is then searched for a scale-invariant feature. This feature shows excellent performance that is robust even to scale variation.

In this letter, we concentrate on feature extraction using Gabor filtering. Although Gabor filters possess beneficial attributes that mimic the behaviour of mammalian cortical simple cells and support wider regions than Haar MRD filters, Gabor features rarely show performance superior to LBP-based features. One can expect that this is because most conventional Gabor features contain en-

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ergy statistics features that utilize only the modulus parts of Gabor filter outputs and do not include other statistical features using both modulus and phase parts.

Because rotation invariance may be an important property of texture features, many Gabor features have been presented for rotation-invariant texture classification. In [22], rotation-invariant Gabor filters were used, which are the results of averaging Gabor filters over all directions. In [3], 2D DFTs of mean and standard deviation feature matrices were utilized, whose components are the global means and standard deviations of Gabor response magnitudes along directions and scales. In [4], the classification was executed such that the covariate shift of the Gabor feature is minimized. In [5], local binary patterns were extracted from the magnitudes of Gabor-filtered images.

In this paper, we present a rotation-invariant feature using four types of directional statistics obtained from both the modulus and phase parts of Gabor-filtered images. First, modulus statistics, scale-shift cross-correlations, and orientation-shift cross-correlations are computed over all directions for each pixel of Gabor-filtered images, and global autocorrelations are computed over all pixels of each Gabor-filtered image. Next, global means and standard deviations for the directional statistics and directional means and standard deviations for the global autocorrelations are computed to form a feature vector. Experimental results with Brodatz [23], STex [24], CUReT [25], KTH-TIPS [26], UIUC [27], UMD [28], ALOT [29], and Kylberg [30] databases (DBs) show that the proposed method yields excellent performance compared with several conventional methods.

The rest of the paper is organized as follows. Section 2 presents the proposed directional statistical Gabor feature and texture classification method. Section 3 describes the experimental results, and Section 4 concludes the paper.

2. Proposed texture classification using directional statistical Gabor features

In this section, we first describe directional and global statistics using Gabor-filtered images and how to construct our proposed features from the Gabor statistics. We then explain the texture classification method that uses the Gabor features.

2.1. Directional and global statistics using Gabor-filtered images

Consider an image $\{I(p) \mid p \in \mathbf{P}\}$, where $I(p)$ denotes the grey level of a position or pixel p on a two-dimensional plane, and $\mathbf{P}$ is the set of all image pixels. Let $\{h_{s,\theta}(p) \mid p \in \mathbf{P}, s \in \mathbf{S}, \theta \in \mathbf{\Theta}\}$ be a set of MRD filters along direction θ at scale s. The sets of scales and directions are given as $\mathbf{S} = \{1, b, \dots, b^{M-1}\}$ and $\mathbf{\Theta} = \{0, \phi, \dots, (N-1)\phi\}$, where b denotes the scale base, ϕ the directional spacing of $\phi = 2\pi/N$, and M and N the number of scales and the number of directions, respectively. Although most Gabor-based methods work with one-half of the full number of directions, here we consider the full number of directions in $[0, 2\pi)$ to obtain rotation-invariant directional statistics. Thus, N is even so that there will be the same number of directions in each of $[0, \pi)$ and $[\pi, 2\pi)$.

We then use a set of Gabor filters to obtain an MRD image representation $\{f_{s,\theta}(p) | p \in \mathbf{P}, s \in \mathbf{S}, \theta \in \mathbf{\Theta}\}$ as

$$f_{s,\theta}(p) = I(p) * h_{s,\theta}(p) \tag{1}$$

$$= \sum_{q \in \mathbf{R}_s} h_{s,\theta}(q)\, I(p-q) \tag{2}$$

where the symbol $*$ stands for a convolution operation and $\mathbf{R}_s$ a filter support region for each scale s. For simplicity, the input image and a Gabor-filtered image are expressed as I and $f_{s,\theta}$ when they are considered as individual images.

Among various forms of Gabor filters, we choose the ones used by Han and Ma [22], which are rewritten in the form of

$$h_{s,\theta}(p) = \frac{\|\kappa_{s,\theta}\|^2}{2\pi\sigma_x\sigma_y} \exp\Bigg[-\frac{1}{2\sigma_x^2}\left(\kappa_{s,\theta} \cdot p\right)^2 - \frac{1}{2\sigma_y^2}\left(j\kappa_{s,\theta} \cdot p\right)^2 - j2\pi W\left(\kappa_{s,\theta} \cdot p\right) \Bigg] \tag{3}$$

where σ_x and σ_y characterize the spatial extent and frequency bandwidth of the Gabor filters, and W denotes their center frequency. The operation $\cdot$ is the inner product between two vectors. The wave vector $\kappa_{s,\theta}$ is defined as

$$\kappa_{s,\theta} = s^{-1} e^{j\theta}. \tag{4}$$

The set of Gabor filters (3) is commonly used in texture classification owing to its relatively good performance. The Gabor parameters σ_x, σ_y, and b are determined from the upper and lower centre frequencies, $U_h (= W)$ and U_l, preselected.

We consider two types of statistics to obtain an efficient feature vector. These are defined by

$$\left\langle F\left(f_{s,\theta}(p)\right)\right\rangle_{\mathbf{\Psi}} = \frac{1}{|\mathbf{\Psi}|} \sum_{\psi \in \mathbf{\Psi}} F\left(f_{s,\theta}(p)\right) \tag{5}$$

where F denotes a function, $\mathbf{\Psi}$ is $\mathbf{\Theta}$ or $\mathbf{P}$, $|\mathbf{\Psi}|$ is the size of $\mathbf{\Psi}$, and ψ is an element of $\mathbf{\Psi}$. If $\mathbf{\Psi}$ is $\mathbf{\Theta}$, then these are called directional statistics, and if $\mathbf{\Psi}$ is $\mathbf{P}$, then they are called global statistics. Because we see that

$$\left\langle F\left(f_{s,\theta}(p)\right)\right\rangle_{\mathbf{\Theta}} = \left\langle F\left(f_{s,\theta+n\phi}(p)\right)\right\rangle_{\mathbf{\Theta}} \tag{6}$$

for any rotation $n\phi$ with an integer n, we can say that any directional statistics (6) are rotation invariant for each pixel.

If we extract the global mean and standard deviation for each MRD image, we obtain a feature vector of dimension $2MN$ that is not rotation invariant. To acquire a rotation-invariant one, we may first compute a directional statistical image for each MRD-filtered image and then obtain their global means and standard deviations, which form a feature vector of dimension $2M$. As a result, we gain rotation invariance but lose directional configuration details.

To obtain a feature vector that exposes various views of texture characteristics well, we suggest four types of directional statistics for Gabor-filtered images that utilize their phase parts as well as their modulus parts. They include first-order statistics such as the mean and second-order statistics such as normalized correlations. For two complex-valued functions $g_1(\psi)$ and $g_2(\psi)$ of a variable $\psi \in \mathbf{\Psi}$, we define a second-order correlation as

$$\underset{\mathbf{\Psi}}{\mathrm{COR}}(g_1(\psi),\ g_2(\psi)) = \Re\left\{ \frac{\langle g_1(\psi) g_2^*(\psi)\rangle_{\mathbf{\Psi}}}{\left[\langle |g_1(\psi)|^2\rangle_{\mathbf{\Psi}} \langle |g_2(\psi)|^2\rangle_{\mathbf{\Psi}}\right]^{1/2}} \right\} \tag{7}$$

$$= \frac{\langle g_1^R(\psi) g_2^R(\psi) + g_1^I(\psi) g_2^I(\psi)\rangle_{\mathbf{\Psi}}}{\left[\langle \left|g_1^R(\psi)\right|^2 + \left|g_1^I(\psi)\right|^2\rangle_{\mathbf{\Psi}} \langle \left|g_2^R(\psi)\right|^2 + \left|g_2^I(\psi)\right|^2\rangle_{\mathbf{\Psi}}\right]^{1/2}} \tag{8}$$

where the symbol $*$ denotes a complex conjugation, $|\cdot|$ the modulus, and $\Re$ the real part. The symbols $g_i^R(\psi)$ and $g_i^I(\psi)$ denote the real part and the imaginary part of $g_i(\psi)$, respectively.

Referring to the form of (8), we define a higher-order correlation to be extended as

$$\underset{\mathbf{\Psi}}{\mathrm{COR}}\left(g_1(\psi), g_2(\psi), \dots, g_n(\psi)\right) = \frac{\langle \prod_{i=1}^n g_i^R(\psi) + \prod_{i=1}^n g_i^I(\psi)\rangle_{\mathbf{\Psi}}}{\left[\prod_{i=1}^n \left\langle \left|g_i^R(\psi)\right|^n + \left|g_i^I(\psi)\right|^n \right\rangle_{\mathbf{\Psi}}\right]^{1/n}} \tag{9}$$

where $\prod$ denotes the product of all elements, and n is the order of the correlation.