Pattern Recognition Letters 36 (2014) 135–143

Contents lists available at ScienceDirect

Pattern Recognition Letters

journal homepage: www.elsevier.com/locate/patrec

Gabor wavelets combined with volumetric fractal dimension applied to texture analysis

Alvaro G. Zuñiga [a], Joao B. Florindo [b], Odemir M. Bruno [b,*]

[a] University of São Paulo, Institute of Mathematics and Computer Science, Scientific Computing Group, São Carlos, SP, Brazil
[b] University of São Paulo, São Carlos Institute of Physics, Scientific Computing Group, São Carlos, SP, Brazil

ARTICLE INFO

Article history:
Received 2 January 2013
Available online 11 October 2013

Communicated by A. Petrosino

Keywords:
Texture analysis
Volumetric fractal dimension
Gabor wavelets
Feature extraction

ABSTRACT

Texture analysis and classification remain as one of the biggest challenges for the field of computer vision and pattern recognition. On this matter, Gabor wavelets has proven to be a useful technique to characterize distinctive texture patterns. However, most of the approaches used to extract descriptors of the Gabor magnitude space usually fail in representing adequately the richness of detail present into a unique feature vector. In this paper, we propose a new method to enhance the Gabor wavelets process extracting a fractal signature of the magnitude spaces. Each signature is reduced using a canonical analysis function and concatenated to form the final feature vector. Experiments were conducted on several texture image databases to prove the power and effectiveness of the proposed method. Results obtained shown that this method outperforms other early proposed method, creating a more reliable technique for texture feature extraction.

1. Introduction

Texture analysis and classification have a huge variety of applications. Although it has been widely studied it remains open for research and in fact, is one of the biggest challenges for the field of computer vision and pattern recognition. There are a lot of different methods to deal with texture analysis, which can be grouped into four classes: (i) structural methods – where textures are described as a set of primitives; (ii) statistical methods – textures are characterized by non-deterministic measures of distribution, using statistical approach; (iii) model-based – textures are described as mathematical and physical modeling; and (iv) spectral methods, based on the analysis in the frequency domain methods, such as Fourier, cosine transform or wavelets. In the last approach, lay one of the well known and very succeed texture method: the Gabor filter, in which a feature extraction enhancement is proposed in this work.

The Gabor filter was proposed by Dennis Gabor in 1946 and extended by 2D and applied to image textures by Daugman (1980, 1985) in the 80's. Daugman's work main motivation was to model mathematically the receptive fields (response of neuronal cells set) of the cortical cells in the primate brain. Besides the biological motivation, the Gabor Filter has a very good performance for texture processing and still remains one of the best methods for texture analysis. Gabor texture technique consists on the convolution of an image with several multi-scale and multi-orientation filters. For each convolution, a transformed space is created, and the feature extraction is performed in each space. Usually, the feature vector is composed concatenating the energy measure of each convoluted image (Rajadell et al., 2009). This way, each convoluted image is represented by a single statistical value that is far from representing adequately the rich information present in the Gabor space. This issue has motivated the research in the field and the proposal of this work.

One of the simplest Gabor enhancement was proposed by Bandzi et al. (2007), Clausi and Deng (2005) and Shahabi et al. (2006), which uses other basic statistical descriptors that proves to work better than energy in some situations. Another approach proposed is the use of GLCM (Haralick et al., 1973) applied over the convoluted images to extract simple features achieving good results. Tou et al. (2007, 2009), proposed a simple yet powerful method to calculate the covariance matrix of all the convoluted images. More recently, the success of the Linear Binary Patterns (LBP) operator (Ojala et al., 2002) in several computer vision fields motivated the adaptation of this operator on the Gabor process yielding the best results found on the literature.

In addition fractal dimension has been successfully used in texture feature extraction (Backes and Bruno, 2012; Backes et al., 2009). The fractal descriptors represent the spatial relations between pixel intensities, even small changes between texture patterns produce significant changes on the signature. In this paper,

* Corresponding author. Tel.: +55 16 3373 8728; fax:+55 16 3372 2218.
E-mail addresses: agomez423@gmail.com (A.G. Zuñiga), jbflorindo@ifsc.ursa.usp.br (J.B. Florindo), bruno@ifsc.usp.br (O.M. Bruno).
URL: http://scg.ifsc.usp.br.

0167-8655/$ - see front matter
http://dx.doi.org/10.1016/j.patrec.2013.09.023

we propose the use of volumetric fractal dimension to extract the fractal descriptors of the Gabor convoluted images with the use of canonical analysis to decorrelate the signature descriptors and reduce dimensionality. The introduced approach is validated using several image texture datasets, and the results analyzed and compared against the best feature extraction methods for Gabor space found in the literature.

The paper is split into 9 sections. Next section gives a short overview of the Gabor wavelets method. Section 3 presents a brief description of the different methods implemented to compare their performance against the proposed technique. Section 4 explains the Volumetric fractal dimension method in detail. Section 5 presents the combinational approach of Gabor wavelets with volumetric fractal dimension. Section 6,7 and 8 shows the experiments conducted and the results obtained. Finally, Section 9 draws conclusions and future directions.

2. Gabor wavelets

Since the discovery and description of the visual cortex cells of mammalian our understanding of how the human brain process texture has advanced enormously. Daugman (1980, 1985) shown that simple cells in the visual cortex can be modeled mathematically using Gabor functions. These functions (Gabor, 1946) approximate cortex cells using a fixed gaussian. Later, Daugman proposed a two-dimensional Gabor wavelet (Daugman, 2004) for its application on image processing and it has been widely used in the field for its biological and mathematical properties. The 2D Gabor function is a local bandpass filter that achieves optimal localization in both spatial and frequency domain and allows multi-resolution analysis by generating multiple kernels from a single core function.

The Gabor wavelets are generated by dilating and rotating a single kernel with a set of parameters. Based on this concept, we use the Gabor filter function as the kernel to generate a filter dictionary. The two-dimensional Gabor transform is a complex sine wave with frequency W modulated by a Gaussian function. Its form in space $\mathbf{g}(x,y)$and frequency domains $\mathbf{G}(u,v)$, is given by Eqs. (1) and (2):

$$\mathbf{g}(x,y) = \left(\frac{1}{2\pi\sigma_x\sigma_y}\right)\exp\left[-\frac{1}{2}\left(\frac{x^2}{\sigma_x^2}+\frac{y^2}{\sigma_y^2}\right)+2\pi jWx\right] \tag{1}$$

$$\mathbf{G}(u,v) = \exp\left\{-\frac{1}{2}\left[\frac{(u-W)^2}{\sigma_u^2}+\frac{v^2}{\sigma_v^2}\right]\right\} \tag{2}$$

A self-similar filter dictionary can be obtained by dilating and rotating $\mathbf{g}(x,y)$ using the generating function proposed in Manjunath and Ma (1996).

$$g_{mn} = a^{-m}\mathbf{g}(x',y') \tag{3}$$

where $a > 1$ and m,n are integer values that specify the number of scales and orientations respectively $m = 0,1,\ldots,M-1$ and $n = 0,1,\ldots,N-1$, where M represents the total number scales and N the total number of orientations. The x' and y' parameters are defined by:

$$x' = a^{-m}(x\cos\theta + y\sin\theta) \tag{4}$$

$$y' = a^{-m}(-x\cos\theta + y\sin\theta) \tag{5}$$

where $\theta = \frac{n\pi}{N}$, the scaling factor a^{-m} is needed to ensure that the energy is independent from m. The parameters necessary to generate the dictionary could be selected empirically. However, in Manjunath and Ma (1996), the authors present a suitable method to compose a filter dictionary that ensures a maximum spectrum coverage with the lowest redundancy possible. Based on this approach, we use the following equations to describe how to obtain the ideal sigmas.

$$a = \left(\frac{U_h}{U_l}\right)^{\frac{1}{M-1}} \tag{6}$$

$$\vartheta_u = \frac{(a-1)U_h}{(a+1)\sqrt{2\ln 2}} \tag{7}$$

$$\vartheta_v = \frac{tan\left(\frac{\pi}{2N}\right)\left[U_h - 2ln\left(\frac{\vartheta_u^2}{U_h}\right)\right]}{\sqrt{2ln2 - \frac{(2ln2)^2\vartheta_u^2}{U_h^2}}} \tag{8}$$

where $W = U_h$ and U_h and U_l represent the minimum and maximum central frequencies respectively.

3. Gabor descriptors

The Gabor wavelet representation of an image is the convolution of this image with the entire filter dictionary. Formally, the convolution result of an image $\mathbf{I}(\mathbf{x},\mathbf{y})$ and a Gabor wavelet dictionary $\boldsymbol{\varphi}_{f_u,m,n}$ named as *Gabor images* on the rest of the paper can be defined as follows:

$$gi_{m,n}(x,y) = \mathbf{I}(\mathbf{x},\mathbf{y}) * \boldsymbol{\varphi}_{f_u,m,n}(x,y) \tag{9}$$

where $\boldsymbol{\varphi}_{f_u,m,n}$ denotes the Gabor wavelet with central frequency f_u, scale m and orientation n. The number of images generated depends on the number of scales and orientations used. For example, four scales and six orientations will generate 24 Gabor images. The feature vector F is composed by extracting single or multiple features from each generated image using image descriptors. A general process to describe this is shown in Fig. 1.

A classical and simple approach to obtain the feature vector F is just calculating the energy of each Gabor image by

$$\mathbf{F} = [e(\mathbf{gi}_{1,1}), e(\mathbf{gi}_{1,2}),\ldots,e(\mathbf{gi}_{1,n}), e(\mathbf{gi}_{2,1}), e(\mathbf{gi}_{2,2}),\ldots,e(\mathbf{gi}_{m,n})] \tag{10}$$

where $e = \iint f(x,y)^2$ (Daugman, 1985). Although it is largely used in the literature, this approach does not achieve a efficiently information of the Gabor images. It has motivated the development of the methods to extract more efficiently the Gabor images information. In the following subsections a brief overview of the most important methods found on the literature is presented.

The non-orthogonal Gabor filters produce different effects depending on the texture characteristics. It does not exist an ideal combination of parameters that ensures the maximum performance. Whilst the work presented in Manjunath and Ma (1996) help reducing the redundancy of the filters still some parameters like scales orientations and central frequencies are determined empirically. Thus, central frequencies variations seem to have a low impact on the results. They are fixed to 0.05 and 0.4 to reduce the number of variables for the experiments. In order to determine Gabor + method combination that obtains the best results for each combination, we performed eight experiments per method for each database. Each of those experiments represents a variation in the number of scales and orientations used in the Gabor wavelet process ranging from 2 to 6 scales and 3 to 6 orientations combined in an incremental framework: $2\times6, 3\times4, 3\times5, 4\times4, 4\times6, 5\times5, 6\times3, 6\times6$ being scale $\times$ orientation.

For the purpose of comparison, the experiments are replicated using several state of the art techniques found in the related literature.