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Pattern Recognition Letters 29 (2008) 664–672

Pattern Recognition Letters

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Optimum Gabor filter design and local binary patterns for texture segmentation

Ma Li [a], R.C. Staunton [b,*]

[a] *School of Automation, Hangzhou Dianzi University, Hangzhou 310018, PR China*
[b] *School of Engineering, University of Warwick, Gibbit Hill Road, Coventry CV4 7AL, UK*

Received 14 November 2006; received in revised form 30 November 2007
Available online 15 December 2007

Communicated by R. Davies

Abstract

We present a novel approach to multi-texture image segmentation based on the formation of an effective texture feature vector. Texture sub-features are derived from the output of an optimized Gabor filter. The filter's parameters are selected by an immune genetic algorithm, which aims at maximizing the discrimination between the multi-textured regions. Next the texture features are integrated with a local binary pattern, to form an effective texture descriptor with low computational cost, which overcomes the weakness of the single frequency output component of the filter. Finally, a K-nearest neighbor classifier is used to effect the multi-texture segmentation. The integration of the optimum Gabor filter and local binary pattern methods provide a novel solution to the task. Experimental results demonstrate the effectiveness of the proposed approach.

Keywords: Texture segmentation; Gabor filter; Local binary pattern; K-nearest neighbor; Immune genetic algorithm

1. Introduction

Gabor filters have been successfully applied to the fields of image processing and image analysis, including edge detection, texture segmentation, and image enhancement (for example, see Tsai et al., 2001; Yang et al., 2003). The goal of texture segmentation is to partition an image into meaningful regions based on the surface textures of objects. Mathematically modeling image textures for the segmentation problem is very difficult as the textures are usually characterized by two-dimensional variations in intensity.

In the past decade, both Gabor filters and local binary patterns (LBP) have been separately recognized as texture detectors with good performance as shown by Ojala et al. (2002), Topi et al. (2000) and Wu et al. (2001). The former has optimal join localization both in the spatial and frequency domains, while the latter is widely used as a nonparametric statistical texture indicator. In recent years the filter-design approach to texture segmentation has been introduced in an effort to reduce the computational complexities of the previous filter-bank approaches as shown in (Yang et al., 2003). Classifiers utilizing the wavelet and Fourier domains have also been researched that provide good discrimination between textures (see for example, Choi et al., 1999). However the proposed approach is to effectively combine what we will describe below as macro-features detected with the Gabor filter with micro-features from the LBP.

There has been much research into optimum Gabor filter design by genetic algorithm (GA) and by simulated annealing (SA). For example, see Tsai et al. (2001), but both have problems such as premature convergence to local minima, and both require substantive iterations. Recently, biological immune system models have been introduced into the traditional GA to enhance its evolu-

* Corresponding author. Tel.: +44 2476 523980; fax: +44 2476 418922.
E-mail addresses: mali@hdu.edu.cn (M. Li), R.C.Staunton@warwick.ac.uk (R.C. Staunton).

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doi:10.1016/j.patrec.2007.12.001

tionary performance as demonstrated by Chen and Zhang (2004). In our approach, we have used the immune genetic algorithm (IGA) to effectively tackle the issue of premature convergence by utilizing its ability to maintain concentration and diversity as demonstrated by Li et al. (2005).

It has been shown that a single optimized Gabor filter can be a highly effective discriminator for separating multi-textured images. However it has also been shown by Tsai et al. (2001), that performance degrades with an increasing number of texture classes within the image. In order to improve the segmentation performance, we have employed the LBP operator described by Topi et al. (2000) as a complementary tool to extract texture features from the Gabor filtered textured images. Finally our proposed approach uses a K-nearest neighbor (K-NN) classification to select and bound the individually textured regions. Our results have shown that the proposed combined classifier enabled a better discrimination between textures than either of the previous classifiers operating individually, and that it has worked well for a larger number of differently textured segments within the image.

The novelty of the proposed method concerns two aspects: (1) we use an IGA with affinity and diversity estimation to search for the optimum Gabor filter. This enabled the filter parameters to not only be found more quickly, but also with a reduced possibility of the selection process being stuck in a local minimum at the conclusion of the analysis, which would result in a sub-optimal filter being designed and (2) we use the combined texture features from a LBP statistical histogram and the averaged intensity output images from the optimized Gabor filter as features for a further K-NN classification. In the proposed method, the IGA based Gabor filter parameter search is implemented as a pre-processing stage that results in strong responses to individual texture patterns. The K-NN classifier as described by Hotta et al. (2004) produces texture partitions and the final feature extraction.

This paper is organized as follows. Section 2 describes the design of the adaptive Gabor filter. Section 3 gives illustrations of how the IGA operates and how it provides parameters for the Gabor filter. The combined feature formation using the outputs of the LBP and the Gabor filter as inputs to the K-NN classifier is discussed in Section 4. Experimental results from the proposed method are discussed in Section 5, and conclusions are provided in the final section.

2. A single Gabor filters for texture segmentation

2.1. The Gabor function and Gabor filter

The Gabor filter has been extended to 2D operation by Daugman (1985). A 2D Gabor filter is an oriented complex sinusoidal grating modulated by a 2D Gaussian function:

$$h(x,y) = g(x,y)\exp[2\pi \mathrm{j}(Ux+Vy)] = h_{\mathrm{R}}(x,y) + \mathrm{j}h_{\mathrm{I}}(x,y) \tag{1}$$

where (U,V) is a single spatial frequency, $g(x,y)$ is the Gaussian function with scale parameter σ, and $h_{\mathrm{R}}(x,y)$ and $h_{\mathrm{I}}(x,y)$ are the real and imaginary parts of $h(x,y)$, respectively.

$$g(x,y) = \frac{1}{2\pi\sigma^2}\exp\left\{-\frac{x^2+y^2}{2\sigma^2}\right\} \tag{2}$$

The Gabor filter is a bandpass filter centered on frequency (U,V), with a bandwidth determined by σ. The parameters of the Gabor filter are represented by the spatial frequency U, V and the scale, σ. Usually, a radial frequency $f=\sqrt{U^2+V^2}$, with orientation $\theta = \tan^{-1}(V/U)$, are used in polar coordinates to specify the filter (f,θ,σ). The Gabor filtered output of an image $i(x,y)$ is obtained by the convolution of the image with the specified Gabor function. The local energy measure at a point (x,y) is defined as

$$E(x,y|f,\theta,\sigma) = C_{\mathrm{R}}^2(x,y|f,\theta,\sigma) + C_{\mathrm{I}}^2(x,y|f,\theta,\sigma) \tag{3}$$

where

$$C_{\mathrm{R}}(x,y|f,\theta,\sigma) = \sum_{l=-w}^{w}\sum_{m=-w}^{w} i(x+l,y+m)h_{\mathrm{R}}(l,m)$$
$$\text{and}\quad C_{\mathrm{I}}(x,y|f,\theta,\sigma) = \sum_{l=-w}^{w}\sum_{m=-w}^{w} i(x+l,y+m)h_{\mathrm{I}}(l,m) \tag{4}$$

represent the discrete convolution of the real and imaginary components of $h(x,y)$ with the image over a given neighborhood with a fixed window size of $M = 2w+1$. The resulting feature image, $E(x,y)$, contains a distribution of local energy measures, which depends strongly on the choice of the design parameters (f,θ,σ) of the single Gabor filter.

2.2. Problem statement

Based on the discussion above, the problem of multi-texture segmentation can be stated as follows: consider the input image $i(x,y)$ to be composed of multiple disjointed regions with distinct textures $t_i(x,y)$, $i = 1,2,\ldots,L$. It is assumed that samples of each texture are available in advance, and the number, L, of different textures is given. Then the first stage of the proposed approach is to search for an optimal Gabor filter that will provide the greatest discrimination between the energy distributions of the differently textured regions in the feature image defined above. The next stage of the feature extraction concerns combining the output of a LBP texture indicator with the averaged intensities from the Gabor filtered image. In the final stage, a K-NN classification is applied to yield the labeled regions in the segmented images, each of which contain one of the L possible textures.

2.3. Design model for the Gabor filter

The optimum Gabor filter is the one with the highest sensitivity to the different patterns in each textured region.