Rotation Invariant Texture Classification Using Circular Gabor Filter Banks

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Abstract. This paper presents a new method for rotation invariant texture classification based on the circular Gabor wavelets. A circular Gabor filter bank is proposed to decompose an image into multiple scales and be rotation invariant. By the mean and variance of the circular Gabor filtered image, a discriminant can be found to classify rotated images. In the primary experiments, comparatively high correct classification rates were obtained using a large test sample set.

1 Introduction

Texture analysis is a fundamental issue in image analysis and computer vision. The Gabor function can be appropriately considered as an orientation and scale tunable detector. The banks of Gabor filters are a group of wavelets, which one can capture the signal or feature at a specific frequency and a specific orientation. There are several approaches based on Gabor filters, which focus on the rotation invariant texture in [1-3]. But, most of them only work well on a small database and need a lot of samples for training.

The motivation of this paper is to classify rotation-invariant textures in a large texture database. The proposed algorithm is based on circular Gabor filter responses, in which each texture has the corresponding global features. Then, a similarity measure is used to compare the unknown samples with the feature of known textures. The primary experiments have proven this approach performs well in applications.

2 Circular Gabor Wavelet and Classification

For the filter to be rotation invariant, it is necessary that the sinusoidal grating varies in all orientations. In the circular Gabor filter, both Gaussian and grating vary only in a radial direction from origin, such that the filter is completely circularly symmetric. The circular Gabor filter is defined as[1]:

$$Cg(x, y) = \frac{1}{2\pi\sigma^2} \exp\left[-\frac{(x^2 + y^2)}{2\sigma^2}\right] \cdot \exp\left[j2\pi W(\sqrt{x^2 + y^2})\right] \quad (1)$$

Where W is the required centered frequency of the circular Gabor filter, and $\sigma = \sigma_x = \sigma_y$. The frequency domain representation of the circular Gabor filter is given by:

$$CG(u, v) = \frac{\sqrt{2\pi}}{2} \alpha \cdot \exp\left[-\frac{(\sqrt{u^2 + v^2} - W)^2}{2\alpha^2}\right], \quad \alpha = \frac{1}{2\pi\sigma} \quad (2)$$

2.1 Circular Gabor Wavelet and Parameter Selection

A class of self-similar functions like the wavelet is considered as the circular Gabor filter bank or circular Gabor wavelet in the following discussion. Let $Cg(x, y)$ be the mother Gabor wavelet, then this self-similar filter dictionary can be obtained by appropriate dilations and rotations of $Cg(x, y)$ through the generating function:

$$Cg_m(x, y) = a^{-m} Cg(x', y'), \quad a > 1, \quad m = 1, \dots, S \quad (3)$$

$$x' = a^{-m}x, \text{ and } y' = a^{-m}y$$

Where a is a scale factor, and the factor a^{-m} is meant to ensure that the energy is independent of m . S is the number of scales in the multiresolution decomposition.

Let W_l and W_h denote the lower and upper center frequencies of interest. Then, the design strategy is to ensure that the half peak magnitude cross-sections of the filter responses in the frequency spectrum touch each other. This results in the following formulas for computing the filter parameters σ and W :

$$a = (W_h/W_l)^{1/(S-1)}, \text{ or } W_h = W_l \cdot a^{(S-1)}, \quad \sigma = (3\sqrt{2\ln 2})/(2\pi W_h) \quad (4)$$

2.2 Texture Representation and Rotation Invariant Measurement

Given an image $I(x, y)$ of size $M * N$, its discrete circular Gabor transform is given by convolution:

$$H_m(x, y) = \sum_p \sum_q I(x-p, y-q) Cg_m^*(p, q), \quad m = 1, \dots, S \quad (5)$$

Where p, q is the filter mask size, $Cg_m^*(p, q)$ is the complex conjugate of Cg_m .

It is assumed that the texture regions are spatially homogeneous. The mean μ_m and standard deviation σ_m of the magnitude of the transform coefficients are used to construct global features to represent the homogeneous textures.

$$\mu_m = \frac{\sum_M \sum_N |H_{mn}(x, y)|}{M * N}, \sigma_m = \frac{\sqrt{\sum_x \sum_y (|H_m(x, y)| - \mu_m)^2}}{M * N}, m = 1, \dots, S \quad (6)$$

Now, the direct distance metric can be defined between the query image Q and a target image T in the database as:

$$d_m^\mu(Q, T) = |\mu_m^Q - \mu_m^T|, d_m^\sigma(Q, T) = |\sigma_m^Q - \sigma_m^T| \quad (7)$$

Three differential factors can be defined as:

$$df_\mu = \frac{\sum_{m=1}^S (d_m^\mu)^2}{\sum_{m=1}^S (\mu_m^T)^2}, df_\sigma = \frac{\sum_{m=1}^S (d_m^\sigma)^2}{\sum_{m=1}^S (\sigma_m^T)^2}, df_D = \sum_{m=1}^S (d_m^\mu)^2 + \sum_{m=1}^S (d_m^\sigma)^2 \quad (8)$$

Actually, the texture similarity measurement is accomplished by defining the differential measurement:

$$df = \min(df_\sigma * df_\mu * df_D) \quad (9)$$

This similarity measurement is rotation invariant, and is smallest if Q is the same as or very similar to T .

3 Experiments

The experiments are carried out on a texture database from the Brodatz texture album, which is comprised of 111 texture images. Each center portion of size 256×256 from each respective texture image is used in the training phase. Texture classification is done with a total of 1998 rotated texture images in steps of 10° up to 180° for various scale values of Gabor decomposition (scale is from 2 up to 10). The center frequencies for Gabor filters are 0.02-0.48 and are separated by one octave. In Table 1, the results of comparisons with other main methods [2-3] are given. Other schemes need a large training for each class of images. However, the proposed approach only needs a sample of each class for training at 0 angle, then can work well. Nevertheless, the proposed approach can deal with 111 classes with a correct classification rate of more than 97%, only using scale=7 and 14 features.

Table 1. The performance comparisons between the proposed approach and other schemes

Method	Samples			The number of features	Correct classification rate
	Number of classes /total of images	Number of each class for training	Number of each class for testing		
Space-frequency model [3]	109/ (872*2=1744)	8	8	—	80.4%
Arivazhagan's method [2]	112/ (112*36=4032)	1	36	100	93.7%
Proposed approach	111/ (111*18+111=2109)	1	18	14	97.7%

4 Conclusions

A rotation invariant texture classification scheme based on the circular Gabor filter is developed for a reasonably large (111 classes) texture databases. By the mean and variance of the Gabor filtered image, a discriminant can be found to classify rotated images. The primary experiments have proven that the proposed approach is effective for rotation invariant texture classification.

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