AN EFFICIENT METHOD FOR ROTATION AND SCALING INVARIANT TEXTURE CLASSIFICATION

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ABSTRACT

This paper presents a new approach for texture classification using rotation and scaling invariant parameters. A test textured image can be correctly classified even if it is rotated and scaled. Based on a 2-D Wold-like decomposition of homogenenous random fields, the texture field can be decomposed into a deterministic component and an indeterministic component. The spectral density function(SDF) of the former is a sum of 1-D or 2-D delta functions. The 2-D autocorrelation function(ACF) of the latter is fitted to the assumed anisotropic ACF that has an elliptical contour. Invariant parameters applicable to the classification of rotated and scaled textured images can be estimated by combining the parameters representing the ellipse and those representing the delta functions. The effectiveness of this method is illustrated through experimemtal results on natural textures.

1 INTRODUCTION

The classification of textured images has been considered by many researchers, but few papers dealing with rotated and scaled textured images have been reported[2][3][5]. A desirable property that a classifier should have is invariance to rotation and scaling. This is of great importance in object recognition, because it is very difficult, or even impossible to ensure that the test image has the same orientation and scale as the known textured image. Kashyap[3] presented a rotation invariant AR model, but which can't be applied to the classification of scaled images. A high classification accuracy rate was reported by Cohen[2] even when the test images are rotated and scaled, but it is at the cost of higher computational complexity because of the calculation of the maximum likelihood functions along with the rotation and scaling of the spectral density function(SDF) of the test images. Liu[5] reported a classifier that can be applied to rotated and scaled images, but the classification accuracy rate are not very well. The aim of this paper is to present an efficient and simple method of the classification of rotated and scaled textures.

In image analysis, textures are broadly classified into two categories, stochastic textures and deterministic textures. Actually, most natural textures exist in between these two categories, such as raffia weave and woolen cloth. So in the analysis of these textures, we must consider both the stochastic and the deterministic characteristics of them.

In this paper we first present a mixed model which is applicable to most natural textured images. In the proposed model, the image is assumed to be a realization of a 2-D homogeneous random filed. Based on a 2-D Wold-like decomposition of homogeneous random fields[1], the texture field can be decomposed into two mutually orthogonal components: a deterministic component and an indeterministic component. The deterministic component is further decomposed into a harmonic component, and an evanescent component. Secondly, we estimate invariant parameters according to the model. The harmonic component and the evanescent component generate the periodic features and the global directional features of texture field, whose SDFs are a sum of 2-D delta functions and a sum of 1-D delta functions respectively. Parameters invariant to the rotation and scale changes of test textured images can be obtained from the positions of the 2-D delta functions and the direction of the 1-D delta functions, for example, the ratio(r_2/r_1) of the distances from two 2-D delta function locations to the origin and the included angle($\phi_2 - \phi_1$) between the directions of them. These invariant parameters can be used for the classification of rotated and scaled images. For the indeterministic component, an ACF model with three parameters ,the correlation intensity (ρ), the anisotropic degree(ε) and the maximum correlation direction(θ) of the ACF is used. The parameters ρ and ε are rotation invariant, and the parameters ε and θ are scaling invariant. Finally, these invariant parameters are applied to texture classification by defining a distance in the parameter

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space. Eighteen natural textures from the Brodatz album are used in our experiments and the classification accuracy rates are in the 95 percent range.

2 MODEL AND PARAMETER ESTIMATION

2.1 Image Model

An image can be modeled as a 2-D random field $\{x(m,n)\}$. Without loss of generality, we assume that $\{x(m,n)\}$ is a real, zero mean 2-D homogeneous random field. In this case, $\{x(m,n)\}$ can be represented by the sum of its orthogonal components based on 2-D Wold-like decomposition[1]:

$$x(m,n) = x_i(m,n) + x_d(m,n) \quad (1)$$

where $x_i(m,n)$ represents the indeterministic random field, $x_d(m,n)$ is the deterministic random field, which can be further decomposed by:

$$x_d(m,n) = x_h(m,n) + x_e(m,n) \quad (2)$$

where $x_h(m,n)$ is the harmonic random field and $x_e(m,n)$ is the evanescent random field.

The most general form of the harmonic field $x_h(m,n)$ is a countable sum of randomly weighted 2-D sinusoids.

$$x_h(m,n) = \sum_{i=1}^{p}\{C_i \cos 2\pi(m\omega_i+n\nu_i)+D_i \sin 2\pi(m\omega_i+n\nu_i)\} \quad (3)$$

where the $C_i's$ and $D_i's$ are mutually orthogonal random variables, $E[C_i^2] = E[D_i^2] = \sigma_i^2$, and (ω_i, v_i) are the spatial frequencies of the ith harmonic. Therefore, the SDF of $x_h(m,n)$ is a sum of 2-D delta functions.

$$S_h(\omega,\nu) = \sum_{i=1}^{p} A_i(\delta(\omega-\omega_i,\nu-\nu_i)+\delta(\omega+\omega_i,\nu+\nu_i)) \quad (4)$$

A typical form of the evanescent field $x_e(m,n)$ and its SDF which is a sum of 1-D delta functions can be given by:

$$x_e(m,n) = g(m)\sum_{i=1}^{q}\{A_i \cos 2\pi n\nu_i + B_i \sin 2\pi n\nu_i\} \quad (5)$$

$$S_e(\omega,\nu) = G(\omega)\sum_{i=1}^{q}\gamma_i\{\delta(\nu-\nu_i)+\delta(\nu+\nu_i)\} \quad (6)$$

After removing $x_h(m,n)$ and $x_e(m,n)$ from the test texture field, we assume that the remained indeterministic field $x_i(m,n)$ can be modeled by a simple partial differential equation on the continuous coordinates (x,y):

$$\{A\frac{\partial^2}{\partial x^2} + B\frac{\partial^2}{\partial y^2} + 2C\frac{\partial^2}{\partial xy} - 1\}x_i(x,y) = w(x,y) \quad (7)$$

$w(x,y)$: white noise with zero mean and variance σ^2.

Because the parameters A, B, C are not invariant parameters, they can not be used for the classification of rotated and scaled images directly. Instead, we will use the normalized ACF form of this model.

$$R(x,y) = \rho r K_1(\rho r) \quad (8)$$

$$r = \sqrt{(x\cos\theta + y\sin\theta)^2 + \varepsilon^2(-x\sin\theta + y\cos\theta)^2}$$

$K_1(\cdot)$ is the modified Bessel function of the second kind. Paremeter ρ, ε and θ represents the correlation intensity, the anisotropic degree and the maximum correlation direction of the field, respectively. Since ρ is rotation invariant, θ is scaling invariant and ε is rotation and scaling invariant, they can be applied to the classification of rotated and scaled images.

The SDF corresponding to the ACF in eq.(8) is:

$$S_i(\omega,\nu) = \frac{\rho^2}{\pi|\rho^2 + (\omega\cos\theta+\nu\sin\theta)^2 + 1/\varepsilon^2(-\omega\sin\theta+\nu\cos\theta)^2|^2} \quad (9)$$

This function is also useful to detect $x_h(m,n), x_e(m,n)$, as shown later.

2.2 Invariant Parameters

For the harmonic field $x_h(m,n)$, the positions of 2-D delta functions in its SDF $S_h(\omega,\nu)$ can be used to estimate invariant parameters. When p=1, the position of 2-D delta function (r_1, ϕ_1) is shown in Fig.1 with the contour of $S_i(\omega,\nu)$(the SDF of indeterministic field), we can easily get two invariant parameters: $\theta - \phi_1$ and ρ/r_1.

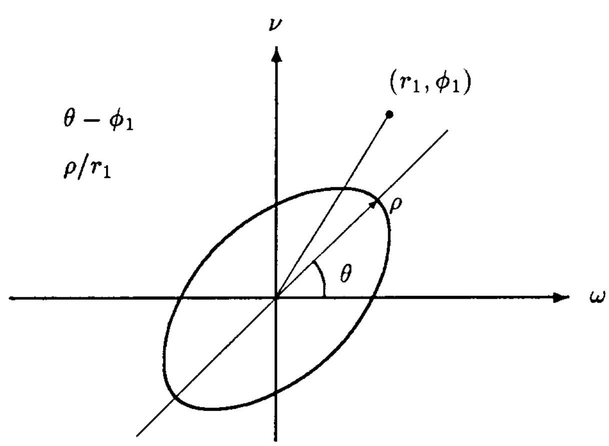

Fig.1 The position of 2-D delta function(p=1) and the contour of $S_i(\omega,\nu)$

Tabel 1: Invariant Parameters

	indeterministic	harmonic		evanescent
		$p \geq 2$	$p = 1$	$q = 1$
when rotated	ρ, ε	$r_1, r_2, \phi_2 - \phi_1, \theta - \phi_1$	$r_1, \theta - \phi_1$	$\theta - \psi$
when scaled	ε, θ	$r_2/r_1, \phi_1, \phi_2, \rho/r_1$	$\phi_1, \rho/r_1$	ψ
rotated and scaled	ε	$r_2/r_1, \phi_2 - \phi_1, \rho/r_1, \theta - \phi_1$	$\rho/r_1, \theta - \phi_1$	$\theta - \psi$

When $p > 1$, for simplicity, we only consider the two largest 2-D delta functions in (ω_1, ν_1) and (ω_2, ν_2) as shown in Fig.2. It is clear that r_1/r_2 and $\phi_2 - \phi_1$ are invariant parameters.

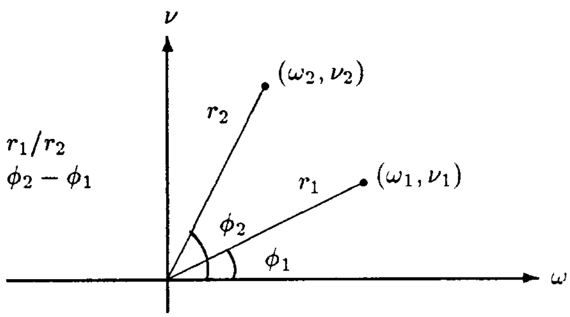

Fig.2 The positons of 2-D delta functions(p=2)

For the evanescent field $x_e(m,n)$, we consider the most simple case, its SDF $S_e(\omega,\nu)$ has only one 1-D delta function. In general, this 1-D delta function has an angle ψ in the (ω,ν) plane. The parameter ψ also can be used to estimate invariant parametes. All available invariant parameters are listed in Table 1.

2.3 Analysis Procedure and Parameter Estimation

First the least square method is used to estimate the parameters of ACF in eq.(9), that is, parameters ρ, ε and θ are estimated based on the minization of the square fitting error norm:

$$E_r = \sum \sum_{(k,l) \in S_r} |R_x(k,l) - R_a(k,l)|^2 \qquad (10)$$

where $R_x(k,l)$ is the ACF estimated from the available data $\{x(m,n)\}$ and $R_a(k,l)$ is the ACF assumed by eq.(9). S_r is the region of ACF fitting.

The harmonic field $x_h(m,n)$ can be detected and its parameters can be estimated by:

$$\frac{S(\omega_i,\nu_i)}{S_i(\omega_i,\nu_i)} \geq T, \quad i = 1,2 \qquad (11)$$

where $S(\omega,\nu)$ is the periodogram of the test textured image, $\{S(\omega_i,\nu_i), (\omega_i,\nu_i) \neq (0,0), i = 1,2\}$ are two largest peaks of the periodogram. $S_i(\omega,\nu)$ is the SDF with the parameters ρ, ε and θ given by eq.(9), and T is the threshold value we set by experience.

If eq.(11) holds, it means that (ω_1,ν_1) and (ω_2,ν_2) are the harmonic frequency points. If eq.(11) does not hold, it means that the test texture has no harmonic component. The evanescent field $x_e(m,n)$ can be detected and the parameter ψ can be estimated by eq.(12) in the almost same way.

$$\sum_{\omega_i = \tan(\psi)\nu_i} \frac{S(\omega_i,\nu_i)}{S_i(\omega_i,\nu_i)} \geq T_e \qquad (12)$$

The analysis procedure is shown in Fig.3.

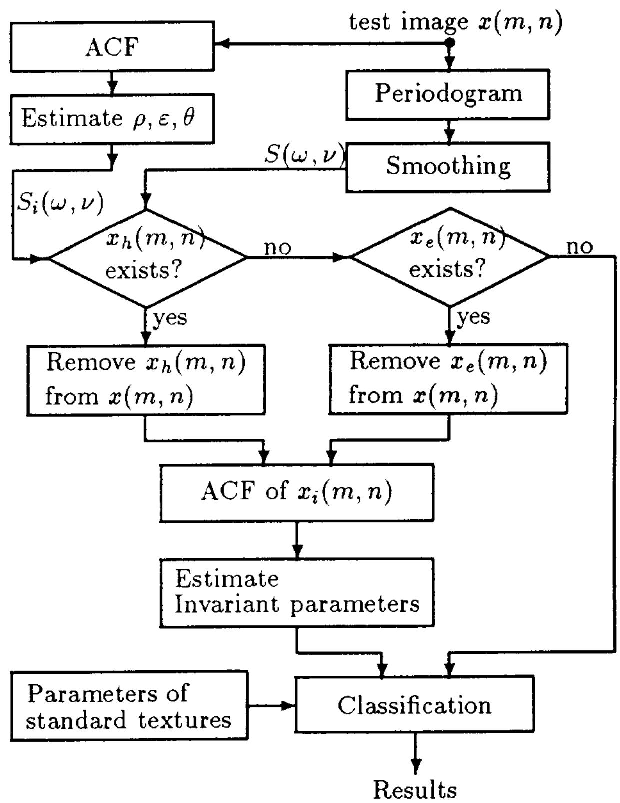

Fig.3 Block diagram of analysis procedure

3 EXPERIMENT RESULTS

Eighteen natural textured images from the Brodatz album are used.(D24, D93,D4,D5,D9,D12,D73,D92,D11, D17,D82,D84,D95,D37,D18,D98,D68,D15) Two examples of them are shown in Fig.4a(D18,raffia weave, contain harmonic field) and in Fig.4b(D15,straw, contain evanescent field) with their periodograms

Table 4: Classification results of rotated and scaled textures

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	Acc.%
1	25		2			3													83
2		30																	100
3			30																100
4				30															100
5					26			4											87
6	4		2			24													80
7					2		26	4											87
8					4		3	23											77
9									21			5	4						70
10										30									100
11									3		25	2							83
12									2		1	27							90
13									2				28						93
14														30					100
15															29	1			97
16															1	29			97
17																	30		100
18																		30	100

Average 91.3 %


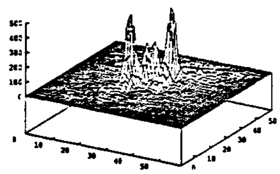

Fig.4a D18, raffia weave periodogram

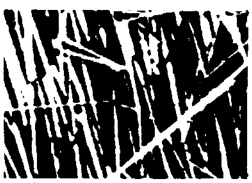
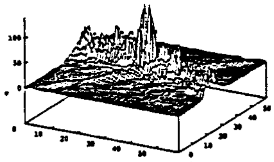

Fig.4b D11, straw periodogram

The test image denoted by $\#t$ is classified to $\#k$ texture if the distance D_{tk} defined in the invariant parameter space is minmium.

$$D_{tk} = \sum_{l=1}^{L} \frac{(p_{tl} - p_{kl})^2}{\sigma^2_{p_{kl}}}, \quad k = 1, 2 \cdots 18 \qquad (13)$$

where L is the number of the invariant parameters to be used. p_{tl} is the lth parameter estimated from the test image. p_{kl} is the known lth parameter value of the kth known textured image, and $\sigma^2_{p_{kl}}$ is its variance.

The leave-one-out strategy[3] is adopted to classification experiments. Three experiments were performed corresponding to: when the input textured images are rotated, the input images are scaled and the input images are rotated and scaled. The average classification accuracy rates are 99.1%, 97.5% and 91.3% respectively. Table 2 shows the classification result when the test textured images are scaled and rotated. The vertical numbers are the test texture numbers, the horizontal numbers are the standard texture's, and the diagonal numerals are correctly classified numbers, the off-diagonal numerals are the misclassified numbers.

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