MULTISCALE APPROACH TO IMAGE TEXTURE

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ABSTRACT:

It is important to consider the role of scale for texture analysis since its multiscale attribute of image texture. In this paper, a textural detector based on 2D Gabor function and visual textural perception is established first, then based on the textural detector and wavelet theory of multiscale decomposition and fractal geometry, a multiscale texture analysis method is proposed, and technique for multiscale textural feature fusion is advanced according to the lateral inhibition and end-inhibition in neurodynamics. The multiscale texture analysis technique gives representation between spatial space and Fourier space, and provide a hierarchical analysis framework for image texture. They can detect different scale texture features, correspond to the visual texture perception, and have the ability to recognize texture image effectively.

1. INTRODUCTION

Image texture analysis has become fundamental means in the areas of computer vision and image analysis. So far many methods have been developed for the description of textural features (Deren Li and Jixian Zhang,1993), however, most of them. extract textural features only in some one scale and ignore its multiscale attribute of image texture, general-purpose, universally accepted method is still unavailable.

Inspired by a multi-channel filtering theory for processing visual information in the early stages of the human visual system, multi-channel filtering approach to texture analysis is developed, however following issues are unsolved: (1) mathematical functional indication and the number of multichannel filters; (2) detection of suitable texture features and integration among these features in filtered images; (3) relationship among filtered images.

According to our proposed methodology (Jixian Zhang,1994), image texture is regarded as the spatial distribution of grey levels of neighboring pixels, it has hierarchical attribute, multiscale attribute, shift-invariant attribute and stochastical and deterministic duality. Image texture analysis method should existed in a hierarchical framework, while extraction of image texture feature should consider its multiscale attribute. In this paper, a textural detector based on 2D Gabor function and visual textural perception is established first, then based on the textural detector and wavelet theory, a multiscale texture analysis method is proposed, and technique for multiscale texture feature fusion is advanced, finally some experiments are gived.

2. MODEL OF VISUAL TEXTURAL DETECTOR

According to the preattentive theory, visual discrimination of image texture is achieved by two steps: (1) detection of local feature difference---- texton (or textel); (2) discrimination based on statistical feature of detected textons(Julesz 1986). It is important to find the function of textural detector for image texture analysis, which should not only has the ability to detect any kinds of textels effectively, but also correspond to the visual texture perception.

Two-dimensional (2D) Gabor representation gives an attractive framework for a unified theory and mathematical description of the spatial receptive fields of visual cortex (Daugman 1988), such filters simultaneously capture all the fundamental properties of linear neural receptive fields in the visual cortex: spatial localization, spatial frequency selectivity, and orientation selectivity. Any image can be expanded by a finite set of 2D elementary Gabor functions and the expansion coefficients $\{a_{mn}\}$ provide a compact representation of the image. Experiments by Fogel and Sagi (1989) showed that, by using 2D Gabor filters, results to discriminate textural elements used in Krose's psychophysical data are in high correlation with the results for the human visual system by Krose, the discriminability orders are almost the same. Therefore we can conclude that 2D Gabor filters can be regarded as texture discriminator. 2D Gabor function is desirable representation of textural detector, it not only satisfies the requirement of visual texture perception, gives good statistical description of textons, but also provides a reasonable explanation of texture descrimination in theory and experiment from the viewpoint of psychophysics and physiology. Now we give following theorem:

Theorem: Visual detection or catch of textural primitive distribution in retinal image can be described or represented by oriented 2D Gabor function G(x,y) (1), we known the oriented 2D Gabor function as textural detector

$$G(x,y) = g(x',y')\exp[2\pi j(u_0 x + v_0 y)] \tag{1}$$

where

$$(x',y') = (x\cos\varphi + y\sin\varphi, -x\sin\varphi + y\cos\varphi), \tag{2}$$

$$g(x,y) = \frac{1}{2\pi\lambda\sigma}\exp\left[-\frac{\left(x/\lambda\right)^2 + y^2}{2\sigma^2}\right] \tag{3}$$

The selection of parameters in textural detector (1) is in accordance with following formula (Jixian Zhang ,1994; Fogel and Sagi, 1989):

$$B = \log_2\left[(1 + 0.1874/\sigma f_0)/(1 - 0.1874/\sigma f_0)\right] \tag{4}$$

where B is the spatial frequency bandwidth (octaves), σ is the standard deviation corresponding to the gaussian envelope, and f_0 is the optimal spatial frequency.

As textural detector, the Gabor implementation effectively unifies the solution of the conflicting problems of determining local textural structures (features, texture boundaries) and identifying the spatial extents of textures contributing significant spectral information, e.g., the densities of oriented and/or elongated textons.

3. TEXTURAL DETECTOR BASED MULTISCALE TEXTURE ANALYSIS

Figure 1 shows the flow chart of the multiscale texture analysis method proposed in this paper. Because of the outstanding ability to represent signal, approach to wavelet multiscale decomposition is integrated in our method, and window size is correspondly changed according to the size of analysis scale and texture attribute.

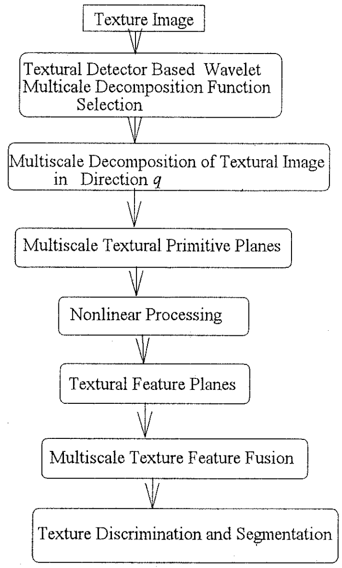

Figure 1. Flow Chart of the Multiscale Texture Analysis Method

3.1 Selection for Multiscale Decomposable Function

In order to capture textural feature effectively, selected wavelet function for multiscale decomposition should be compatible with the textural detector. A 2D Gabor function satisfies the condition of wavelet and is therefore an admissible wavelet (Mallat,1989). In the view of our point, the wavelet decomposable function may be considered as the textural detector of the form

$$G(x,y) = g(x,y)\sin(2\pi f(x\cos\theta - y\sin\theta) + \varphi) \tag{5}$$

or

$$G(x,y) = g_\theta(x,y)\sin(2\pi f(x\cos\theta - y\sin\theta) + \varphi) \tag{6}$$

where

$$g(x,y) = \exp\left[-\frac{1}{2}\left(\left(\frac{x-x_0}{\lambda\sigma}\right)^2 + \left(\frac{y-y_0}{\sigma}\right)^2\right)\right] \tag{7}$$

is the Gaussian envelope, $g_\theta(x,y)$ is the first deviation of $g(x,y)$, $\varphi = 0, \pi/2$.

To simplify our description, we now consider such a multiscale decomposition where the basic wavelet $\psi(x,y,\theta)$ is the same as (5)

$$\psi(x,y,\theta) = \exp\left(-\frac{x^2/\lambda^2 + y^2}{2\sigma^2} + j2\pi f(x\cos\theta - y\sin\theta)\right) \tag{8}$$

The corresponding family of wavelet function is

$$\psi_\alpha(x-x_0,y-y_0,\theta)=\alpha^{-1}\psi\left(\frac{x-x_0}{\alpha},\frac{y-y_0}{\alpha},\theta\right) \quad (9)$$

For practical application, (9) is discretized as

$$\psi_{\alpha^j}(x-m,y-n,\theta)=\alpha^{-j}\psi\left(\frac{x-m}{\alpha^j},\frac{y-n}{\alpha^j},\theta\right) \quad (10)$$

where $\alpha\in R,\theta\in[0,\pi],m,n,j\in Z$.

3.2 Multiscale Decomposition of Texture Image

Let $\alpha=2^j$, multiscale decomposition in θ direction through wavelet transform is then defined by

$$W_{2^j}f(x_0,y_0,\theta)=\iint f(x,y)\,\psi_{2^j}(x-x_0,y-y_0,\theta)dxdy \quad (11)$$

Here the Mallat's multiresolution decomposition algorithm (Mallat 1989) is employed for our purpose of multiscale decomposition.

3.3 Multiscale Textural Primitive Planes

After multiscale decomposition, we define the decomposable value, amplitude, phase angle and standard deviation etc. as textural primitives, which consist of the basis for computing textural features.

3.4 Nonlinearity

Each texture primitive plane is subjected to a nonlinear transformation, we use the following bounded nonlinearity

$$N(t)=th(\alpha t)=\frac{1-e^{-2\alpha t}}{1+e^{-2\alpha t}} \quad (12)$$

where α is a constant. Nonlinear transformation is computed in a window $\alpha_{2^j}(x,y)$.

3.5 Computing Textural Features

After nonlinear transformation of the textural primitive planes, we computer standard deviations from the decomposable value, amplitude, or average absolute deviations from the standard deviation, phase angle in overlapping window $n\times n$ through edge-preserving and noise-smoothing procedure (Jixian Zhang, 1994; Jixian Zhang and Deren Li ,1995) as textural features. We can also compute local fractal dimension, textural density as texture measures.

4. FRACTAL FEATURE IN MULTISCALE TEXTURE ANALYSIS

Fractal dimension is a powerful feature of texture for the description of its coarseness and complexity which may integrate some measures described by other methods. Textural image can be regarded as a process of fractional Brownian motion (fBm), fBm is described by the scalar parameter H, which is related to fractal dimension D=3-H.

In 1-dimensional space, Flandrin (Flandrin, 1992) showed that for any j, the wavelet coefficients of fBm give rise to time sequences which are self-similar and stationary under orthonormal wavelet decomposition.

$$E\left[\tilde{W}_{2^j}(n)\tilde{W}_{2^j}(m)\right]=\frac{\sigma^2}{2}\left\{-\int_{-\infty}^{+\infty}r_\psi\left[\tau-(n-m)\right]|\tau|^{2H}d\tau\right\} \quad (13)$$

where

$$\tilde{W}_{2^j}(n)=(2^j)^{(-H+1/2)}W_{2^j}(n),r_\psi(\tau)=A_\psi(1,\tau) \quad (14)$$

$$A_\psi(\alpha,\tau)=\sqrt{2}\int_{-\infty}^{+\infty}\psi(\tau)\psi(\alpha t-\tau)dt \quad (15)$$

$W_{2^j}(n)$ are the wavelet coefficients for scale 2^j, $\psi(\tau)$ is the basic wavelet.

According to above theorem, fractal feature in our multiscale texture analysis is computed through following two methods.

4.1 General Fractal dimension

We compute general fractal dimension as the result of all used scales, let n=m, from (10) we get following equation:

$$Var(W_{2^j}(n))=\frac{\sigma^2}{2}V_\psi(H)(2^j)^{2H+1}=C(2^j)^{2H+1} \quad (16)$$

where

$$Var(W_{2^j}(n))=E(W_{2^j}(n)W_{2^j}(n)),\quad V_\psi(H)=-\int_{-\infty}^{+\infty}r_\psi(H)|\tau|^{2H}d\tau$$

It follows that

$$\log_2(Var(W_{2^j}(n)))=(2H+1)j+constant \quad (17)$$

Therefore, the fBm index H (and hence D) can be easily obtained from the slope of this variance plotted as a function of scale in a log-log plot.

4.2 Local Fractal Dimension

Local fractal dimension is considered as a function of scales, from (16), we obtain local fractal dimension as

$$D(2^j) = \log_2\left(Var\left(W_{2^{j+1}}(n)\right)\right) - \log_2\left(Var\left(W_{2^j}(n)\right)\right) \tag{18}$$

5. MULTISCALE TEXTURE FEATURE FUSION

Fusion of multiscale texture features is following feature extraction and is according to the lateral inhibition and end-inhibition in neurodynamics. Both competitive fusion and cooperative fusion are developed.

5.1 Local Competitive Interactions

Competitive interactions help in noise suppression and reducing the effects of illumination (Grossberg, 1987; Manjunath, 1993). These steps can be modeled by non-linear lateral inhibition between features. Two types of such interactions are identified: competition between spatial neighbors with each orientation, and competition between different orientations at each spatial position.

5.1.1 Competition Between Spatial Neighbors with Each Orientation: A cell of prescribed orientation excites like-oriented cells corresponding to its location and inhibits like-oriented cells corresponding to nearby locations at the next processing stage (Grossberg, 1987).

Let $Y_i(s,\theta)$ be the output of a cell at position s = (x, y) in a given scale with a preferred orientation θ, $I_i(s,\theta)$ be the excitatory input to that cell from the previous processing stage (texture measures in multiscale analysis), N_s be the local spatial neighborhood of s. These interactions are modeled by non-linear lateral inhibition between features as

$$\Delta X(s,\theta) = -a_{s,\theta}X(s,\theta) + I(s,\theta) - \sum_{s' \in N_s} b_{s,s'}Y(s',\theta) \tag{19}$$

$$Y(s,\theta) = g[X(s,\theta)] \tag{20}$$

where (a, b) are positive weights, g(x) is a non-linear function such as $g(x) = 1 / (1 + \exp(-\beta x))$.

5.1.2 Competition between different orientations at Each spatial position: This competition defines a push-pull opponent process. If a given orientation θ at position s = (x, y) is excited, then other orientation $\theta'(\theta \neq \theta')$ is inhibited (especially in perpendicular orientation) and vice versa.

Still, let $Y_i(s,\theta)$ be the output of a cell in this step, the output from previous competition $Y_i(s,\theta)$ be the input $I(s,\theta)$ to that cell. The competitive dynamics is represented by

$$\Delta X(s,\theta) = -a_{s,\theta}X(s,\theta) + I(s,\theta) - \sum_{\theta' \neq \theta} b_{\theta,\theta'}Y(s,\theta') \tag{21}$$

$$Y(s,\theta) = g[X(s,\theta)] \tag{22}$$

5.2 Competition Between Scale Interactions

Scale interactions are used for the representation of end-inhibition property exists among hypercomplex cells in the visual cortex of mammals. These cells respond to small lines and edges in their receptive field, and their response decreases as the length of lines or edges increases (hence these are often referred to as end detectors) (Manjunath, 1993). These cells appear to play an important role in localizing line-ends and texture boundaries.

If $Q_{ij}(s,\theta)$ denotes the response of such a cell at position s = (x, y) receiving inputs from two channels i and j ($\alpha > \alpha'$) with preferred orientation θ, then

$$Q_{ij}(s,\theta) = g\left(\alpha_1 I_i(s,\theta) - \alpha_2 I_j(s,\theta)\right) \tag{23}$$

5.3 Cooperative Fusion

This final stage involves grouping similar orientations. The cooperative fusion process receives inputs from the competitive stage and from end-detectors described in local competitive interactions and scale interactions. If $Z_i(s,\theta)$ represents the output of this process, then

$$Z_i(s,\theta) = g\left(\int d_i(s-s')Y_i(s',\theta) + Q_{ij}(s',\theta)\right)ds' \tag{24}$$

$$d(s=(x,y),\theta) =$$

$$\exp\left(-(2\sigma^2)^{-1}\right)\left[\lambda^2(x\cos\theta + y\sin\theta)^2 + (-x\sin\theta + y\cos\theta)^2\right] \tag{25}$$

$d_i(s,\theta)$ represents the receptive field of $Z_i(s,\theta), \theta$ is the preferred orientation , θ is the corresponding orthogonal direction, and λ is the aspect ratio of the Gaussian.

6. EXPERIMENTS AND ANALYSIS

The performance of the proposed multiscale analysis method is illustrated on following eight textures from Brodatz (Brodatz, 1966) texture album: grass lawn, raffia weave, beach sand, woolen, pigskin, leather, water, wood grain. The scan resolution is 85 μm, entire image size is 256×512 pixels, size of every image block is 128×128 pixels. The following principles are used in our experiments: 1). we chose formula (6) in direction $0°, 45°, 90°$ as our basic wavelets for the multiscale decomposition, their parameters of bandwidth B=1.5 octave, f_0 = 1.75, $\alpha = 2^j (j \in Z)$; 2). we define the initial overlapping window size as 5×5 for our decomposition in scale 2^0; 3). the decomposed value and amplitude in scale 2^j are used as the textural primitives, then the standard deviations (SDVs) after their nonlinearity are computed as textural features, the SDVs are computed in overlapping window 15×15 by our edge-preserving and noise-smoothing procedure.

After the processing of above-mentioned steps, a spatial restrain-based probabilistic relaxation technique (Jixian Zhang, 1994) is developed for the segmentation and recognition of these textural images. The results of classified accuracy in scale 2^1 is shown in table 2. In order to compare with other method, laws' texture energy method and cooccurrance matrix method are used for the segmentation of our experimental textural images, and their results are also shown in table 2. In laws' energy method, the E5L5, E5S5, R5R5, L5S5 filters are employed, while in the cooccurrance method, measures of the energy, correlation, local homogeneity, inertia are used as textural features. It is easy to see from table 2 that more than 20 percentage recognition accuracy is improved using our multiscale method.

Experiments are also fulfilled in some real aeriophotographs and again the performance of our multiscale approach is showed.

	Multiscale method	Laws energy	Cooccurrance matrix
grass lawn	71.5	27.6	34.4
raffia weave	86.9	67.5	47.7
beach sand	74.1	26.5	17.7
woolen	92.7	83.5	87.6
pigskin	90.1	50.1	48.3
leather	92.1	92.2	58.4
water	95.2	92.3	64.5
wood grain	91.4	77.1	63.2
average	86.8	64.6	52.7

Table 2 Classified Accuracy in our Experimental Images (%)

7. CONCLUSIONS

Because of its multiscale attribute of image texture, it is important to consider the role of scale for texture analysis. In this paper, we have developed a common hierarchical framework which provides a multiscale approach to image texture based on the visual texture perception and wavelet theory of multiscale decomposition. Our proposed method can give representation between spatial space and Fourier space, detect different scale texture features, and correspond to the visual texture perception. Experiments showed the ability to recognize texture image effectively.

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