ENERGY REPRESENTATION BASED 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 recent developed theory of time-scale space decomposition—a general class extending wavelet transform, an energy distribution based multiscale texture analysis method is proposed. The multiscale texture analysis technique gives textural energy representation between spatial space and scale space, and provides 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 area 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 multi-channel 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 exist 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 the multiscale decomposition of textural energy, a multiscale texture analysis method is proposed, technique for multiscale texture feature fusion is advanced, finally some experiments are given.

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 \(\{a_{nm}\}\) 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 filter 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 discrimination 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

\[
G(x,y) = g(x', y') \exp[2\pi i (u x + v y)]
\]  

where

\[
(x', y') = (x \cos \phi + y \sin \phi, -x \sin \phi + y \cos \phi),
\]

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

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

\[
B = \log \left[ \left( \frac{1 + 0.1874}{c_f} \right) \left( \frac{1 - 0.1874}{c_f} \right) \right]
\]

where \( B \) is the spatial frequency bandwidth (octaves), \( \sigma \) is the standard deviation corresponding to the Gaussian envelope, and \( f^* \) 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. TIME-SCALE ENERGY DISTRIBUTION

The simultaneous representation of signals in time (or space) and spatial-frequency variables has been widely used in time-varying signal processing application. Recently, Rioul and Flandrin(Rioul and Flandrin, 1992) define a new general class of time-scale distribution, which describes signal energy distribution in both time and scale planes, a general formulation can be written as

\[
\Omega_{f}(x,a,\Pi) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \Omega_{f}(\tau,v)w_{\Pi}(\tau,v)\overline{w_{\Pi}(\tau,v)}d\tau dv
\]

where \( \Pi(x,a) \) is some arbitrary time-scale characterization function and where

\[
w_{\Pi}(x,u) = \int_{-\infty}^{\infty} f\left( x + \frac{u}{2} \right) f\left( x - \frac{u}{2} \right) e^{j2\pi u x} du
\]

is the well-known Wigner-Ville distribution(WVD), the function \( f^* \) denotes the complex conjugate of \( f \).

For a particular point on the signal, \( \Omega_{f}(x,a,\Pi) \) gives the local spectrum centered at \( x \) providing the scale information as a function of location. In fact, this general time-scale distribution includes all bilinear energy distributions that covariant under time and scale shifts.

Suppose \( w_{\Pi}(x,a) \) be the WVD of wavelet \( w_{\Pi}(\tau) \), then if we let \( \Pi(x,a) = w_{\Pi}(x,a) \) in (5), we get a simple example of time-scale energy distribution as

\[
\Omega_{f}(x,a,\Pi) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \Omega_{f}(\tau,v)w_{\Pi}(\tau,v)\overline{w_{\Pi}(\tau,v)}d\tau dv = |\mathcal{W}T(x,a)|^2
\]

where \( |\mathcal{W}T(x,a)|^2 \) is the squared modulus of the wavelet transform. So it is easy to get energy density distribution of the wavelet transform from (5), we call time-scale distribution (5) as an extended wavelet transform.

### 4. ENERGY DISTRIBUTION BASED MULTISCALE TEXTURE ANALYSIS

Figure 1. Flow Chart of the Energy Distribution Based Multiscale Texture Analysis Method

Figure 1 shows the flow chart of our energy representation based multiscale texture analysis method proposed in this paper.
Because of the outstanding ability to represent signal, the extended wavelet transform based multiscale decomposition is integrated in our method, which directly gives the energy distribution of image texture over scale planes locally, and window size is correspondingly changed according to the size of analysis scale and texture attribute.

4.1 Selection of Multiscale Characterization Function

In order to capture textural feature effectively, selected characterization 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 multiscale characterization function may be considered as the textural detector of the form

\[ G(x, y) = g(x, y)\sin(2\pi(x\cos\theta - y\sin\theta) + \phi) \]  \hspace{1cm} (8)

or

\[ G(x, y) = g_s(x, y)\sin(2\pi(x\cos\theta - y\sin\theta) + \phi) \]  \hspace{1cm} (9)

where

\[ g(x, y) = \exp\left(-\frac{1}{2}\left(\frac{x-x_0}{\alpha\sigma}\right)^2 + \left(\frac{y-y_0}{\sigma}\right)^2\right) \]  \hspace{1cm} (10)

is the Gaussian envelope, \( g_s(x, y) \) is the first deviation of \( g(x, y) \), \( \phi = 0, \pi/2 \).

Because the WVD of 2D gabor function is

\[ W_g(x, y, u, v) = 4\pi\sigma_u\sigma_v \exp\left(-\frac{x^2}{\sigma^2_u} + \frac{y^2}{\sigma^2_v}\right) \exp\left(-4\pi^2(\sigma_u^2 + \sigma_v^2)\right) \]  \hspace{1cm} (11)

In order to be compatible with the computed energy response of wavelet transform, multiscale characterization function can also be chosen as the form of

\[ \Pi(x, y, u, v) = \frac{\sqrt{\alpha\beta}}{\pi} \exp\left(-\frac{(x - x_0)^2}{2\alpha^2} - \frac{y^2}{2\beta^2}\right) \]  \hspace{1cm} (12)

or

\[ \Pi(x, y, u, v) = \frac{\sqrt{\alpha\beta}}{\pi} \exp\left(-\frac{(x - x_0)^2}{2\alpha^2} - \frac{y^2}{2\beta^2}\right) \exp(-\sqrt{\alpha\beta} g_s(x, y)) \]  \hspace{1cm} (13)

where \( g_s(x, y) \) is the first deviation of Gauss function.

To simplify our description, we now consider such a multiscale decomposition where the basic function is the same as (8):

\[ \Pi(x, y, f, \theta) = \exp\left(-\frac{f^2}{2\sigma_f^2} + j2\pi f(x\cos\theta - y\sin\theta)\right) \]  \hspace{1cm} (14)

The corresponding family of multiscale characterization function (wavelet function) is

\[ \Pi(x - x_0, y - y_0, a, f, \theta) = a^{-1} \left(\frac{x - x_0}{a}, \frac{y - y_0}{a}, a f, \theta\right) \]  \hspace{1cm} (15)

For practical application, (15) is discretized as

\[ \Pi(x - m, y - n, a', a' f, \theta) = a'^{-1} \left(\frac{x - m}{a'}, \frac{y - n}{a'}, a' f, \theta\right) \]  \hspace{1cm} (16)

where \( a \in R, \theta \in [0, \pi], m, n, j \in \mathbb{Z} \).

4.2 Multiscale Energy Decomposition

Let \( \alpha = 2', \) from (5), multiscale decomposition at frequency \( f = \sqrt{u_0^2 + v_0^2}, \) direction \( \theta \) is then defined by

\[ \Omega(x_0, y_0, 2', f, \theta) = \int \int \Pi(x, y, u, v) \left(\frac{x - x_0}{2'}, \frac{y - y_0}{2'}\right) f, \theta dx dy \]  \hspace{1cm} (17)

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

4.3 Multiscale Textural Primitive Planes

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

4.4 Computing Textural Features

we computer standard deviations from the decomposable value, amplitude, or average absolute deviation from the standard deviation, 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.

4.5 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 (Jixian Zhang, 1994).

(1) Local competitive interactions: competitive interactions help in noise suppression and reducing the effects of illumination. These steps can be modeled by non-linear lateral inhibition between features. Two types of such interactions are identified: competition between spatial neighbors within each orientation, and competition between different orientations at each spatial position.

(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/edges increases (hence these are often referred to as end detectors). These cells appear to play an important role in localizing line-ends and texture boundaries.

(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.

5. TEXTURE DENSITY COMPUTATION

The 2D energy distribution based multiscale decomposition describes the distribution of the image energy over space, direction and frequency. At a given location \((x,y)\) in the image plane, our multiscale decomposition procedure can be used to compute the energy content of the image signal at that location. The change of the energy content with respect to position can then be related to the texture gradient for the computation of surfacen orientation. In the spatial-scale domain the high density texture has high spatial frequencies and therefore the change in spatial frequency contents over the image space is directly related to the texture gradient. With this observation, the energy distribution \(\Omega(x,y,\lfloor f \rfloor,f,\theta)\) described by our multiscale decomposition can be used to compute texture density.

From our multiscale decomposition, it follows that the total energy at \((x,y)\) is

\[
E(x,y) = \sum_{\lfloor f \rfloor} \sum_{\theta} \Omega(x,y,\lfloor f \rfloor,f,\theta)
\]

The low frequency energy content at \((x,y)\) is determined by

\[
E_{\lfloor f \rfloor}(x,y) = \sum_{\theta} \sum_{\lfloor f \rfloor} \Omega(x,y,\lfloor f \rfloor,f,\theta)
\]

where \(S\) is the low frequency band in the spatial-frequency domain given by \(S = \{f: 0 < f < f_{\ell}\}\) and \(f_{\ell}\) is a predetermined threshold value. Therefore texture density is defined as

\[
d(x,y) = 1 - E(x,y) / E(x,y)
\]

It is clear that \(0 \leq d \leq 1\) is a function that describes the high frequency energy distribution over space.

6. EXPERIMENTS AND ANALYSIS

The performance of our energy distribution based 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\(\mu m\), entire image size is 256\(\times\)512 pixels, size of every image block is 128\(\times\)128 pixels. The following principles are used in our experiments: 1) we chose formula (13) in direction \(0^\circ, 45^\circ, 90^\circ\) as our basic wavelets for the multiscale decomposition, their parameters of bandwidth \(B=1.5\) octave, \(\alpha = \lambda \sigma \), \(\alpha = \sigma \), \(\beta = \beta = 4 \pi , m = n = f = 1.75\), \(\alpha = 2^f (f \in Z)\); 2) we define the initial overlapping window size as 5\(\times\)5 for our decomposition in scale \(2\); 3) the decomposed value and amplitude in scale \(2\) are used as the textural primitives, then the standard deviations (SDVs) are computed as textural features, the SDVs are computed in overlapping window 15\(\times\)15 by our edge-preserving and noise-smoothing procedure.

After the processing of above-mentioned steps, a spatial restraint-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 \(2\) is shown in table 2. In order to compare with other method, laws' texture energy method and cooccurrence 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 ES55, ES85, RS55, RS85 filters are employed, while in the cooccurrence 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 percent recognition accuracy is improved using our multiscale method.

<table>
<thead>
<tr>
<th>Texture</th>
<th>Multiscale method</th>
<th>Laws energy</th>
<th>Cooccurrence matrix</th>
</tr>
</thead>
<tbody>
<tr>
<td>grass lawn</td>
<td>79.0</td>
<td>27.6</td>
<td>34.4</td>
</tr>
<tr>
<td>raffia weave</td>
<td>86.8</td>
<td>67.5</td>
<td>47.7</td>
</tr>
<tr>
<td>beach sand</td>
<td>66.8</td>
<td>26.5</td>
<td>17.7</td>
</tr>
<tr>
<td>woolen</td>
<td>92.3</td>
<td>83.5</td>
<td>87.6</td>
</tr>
<tr>
<td>pigskin</td>
<td>85.2</td>
<td>50.1</td>
<td>48.3</td>
</tr>
<tr>
<td>leather</td>
<td>88.0</td>
<td>92.2</td>
<td>58.4</td>
</tr>
<tr>
<td>water</td>
<td>94.7</td>
<td>92.3</td>
<td>64.5</td>
</tr>
<tr>
<td>wood grain</td>
<td>91.8</td>
<td>77.1</td>
<td>63.2</td>
</tr>
<tr>
<td>average</td>
<td>85.6</td>
<td>64.6</td>
<td>52.2</td>
</tr>
</tbody>
</table>

Table 2: Classified Accuracy in our Experimental Images (%)
Experiments are also fulfilled in some real aerophotographs and again the performance of our multiscale approach is showed.

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 the extended wavelet transform. Our proposed method can give representation between spatial space and scale space, detect different scale texture features, and correspond to the visual texture perception. Experiments showed the ability to recognize texture image effectively.

References from Journals:


References from Books:


References from Other Literature: