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Texture classification based on EMD and FFT*

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Abstract: Empirical mode decomposition (EMD) is an adaptive and approximately orthogonal filtering process that reflects human's visual mechanism of differentiating textures. In this paper, we present a modified 2D EMD algorithm using the FastRBF and an appropriate number of iterations in the shifting process (SP), then apply it to texture classification. Rotation-invariant texture feature vectors are extracted using auto-registration and circular regions of magnitude spectra of 2D fast Fourier transform (FFT). In the experiments, we employ a Bayesion classifier to classify a set of 15 distinct natural textures selected from the Brodatz album. The experimental results, based on different testing datasets for images with different orientations, show the effectiveness of the proposed classification scheme.

Key words: Texture classification, Empirical mode decomposition (EMD), Fourier transform, Auto-registration, Rotation-invariant

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INTRODUCTION

Multi-scale is one of the main features of natural images, a series of methods for representing the quality of images are presented, such as multi-scale technique based on diffusion equation (Perona and Malik, 1990), image pyramid (Burt and Adelson, 1983) and wavelet (Mallat, 1989). Bidimensional empirical mode decomposition (BEMD) (Nunes *et al*., 2005; Linderhed, 2004) is a new multi-scale analysis method proposed recently. The difference between BEMD and traditional multi-scale analysis method is that BEMD is totally data-driven.

There are many researches on the mechanism of human's differentiating textures from visual view. For example, some people regard high order statistical quantities of textures and think that textons and their statistical quantities are right features. Recently, the output of multi-scale and multi-direction filters such as wavelet and Gabor filters is considered to explain the mechanism of human's differentiating textures (Tomita and Tsuji, 1990). We know that human's differentiating textures depend on the highest spatial frequency, the second highest spatial frequency and other frequencies after adaptively decomposing multi-texture images (Liu and Peng, 2005). EMD decomposition reflects this human's visual perception. Therefore, we present a new texture classification method using 2D EMD.

Texture classification is a fundamental and yet difficult task in machine vision and image processing. Most image processing techniques need to know where the objects of interest are. Texture classification can offer this kind of information. Many schemes proposed for texture classification involve co-occurrence matrix (Haralick *et al*., 1973), an analysis of the image spectrum using Wigner distribution and Gabor filter, etc. (Bodnarova *et al*., 2002; Kumar and Pang, 2002), fractals (Clausi, 2002; Charalampidis and

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Kasparis, 2002), rotational invariant operators (Clausi, 2002), the extraction of the structural and stochastic components of an image (Kasparis *et al*., 2001; Hsu and Wilson, 1998), model-based method (Chellappa *et al*., 1993), and so on. Markov random field (MRF) models, which fall under model-based category (Chellappa *et al*., 1993), capture local characteristics of an image by assuming a local conditional probability distribution. MRF model parameters have been proposed to be texture features. But finite model parameters can hardly represent complex texture information. In addition, it takes too much time to select model parameters. Recently, Haley and Manjunath (1999) employed a complete space-frequency Gabor wavelet model for rotation-invariant texture classification with very promising results. However, high computational complexity for feature extraction is required. Kim and Udpa (2000) proposed the rotated wavelet filters by rotating 45° the standard 2D discrete wavelet filter for texture classification. But, these rotated filters are not invariant to different rotation angles. Directional empirical mode decomposition was applied to texture classification (Liu *et al*., 2004). But it decomposes the image into Intrinsic Mode Functions (IMFs) using 1D EMD and does not employ the 2D correlation of image. In addition, there is no general method to find the direction of texture, although it is very important in texture recognition.

Therefore, we propose an effective scheme for rotation invariant texture classification using 2D EMD and FFT. A feature vector extracted from each circular region of 2D IMFs' FFT is constructed for rotation of invariant texture classification. The proposed scheme has been well tested using the Bayes classifier to classify a set of 15 distinct natural textures selected from the Brodatz album.

The outline of this paper is organized as follows. In the next section, we introduce the modified 2D EMD based on FastRBF (Carr *et al*., 2001; 2003) and an appropriate number of iterations in the SP. Then we present our proposed scheme for extracting the rotation invariant. The classification results for different kinds of textures sets are presented in the following section. Comparisons of the classification performance of our proposed method with other rotation-invariant texture classification methods are also discussed in this section. Conclusions and future works are presented in the final section.

MODIFIED 2D EMD ALGORITHM

The reasons of introducing EMD to texture processing are as follows: (1) The obtained Intrinsic Mode Functions (IMFs) by EMD (Huang *et al*., 1998) can be seen as results of filter bank for some kinds of signals resembling those involved in wavelet decomposition (Flandrin *et al*., 2004); (2) EMD decomposes signals according to the local scales computed by identifying the distance between adjacent extrema, which is different from traditional adaptive filtering techniques such as wavelet/wavelet packet and nonlinear diffusion; (3) EMD decomposes the spatial frequency components into a set of IMFs where the highest spatial frequency component of each spatial position is in the first IMF and the second highest spatial frequency component of each spatial position is in the second IMF, etc. This reflects human's visual mechanism of differentiating textures

BEMD has its unique priorities for adaptively extracting the frequency component of image. But envelope calculation using RBF (Nunes *et al*., 2005; Linderhed, 2004) consumes time and space too much. So, in this section, we focus on the interpolation procedure and on the number of iterations that defines the sifting process to accelerate BEMD. We replace the stopping criterion by an appropriate number of iterations in the SP to obtain a fast 2D EMD. In 2D EMD, We simply extract the extrema points by comparing the candidate data point with its nearest 8-connected neighbors. Spline interpolation based on FastRBF (Carr *et al*., 2001; 2003) is applied to implement 2D EMD. The sifting process to find the IMFs of an image $I(m,n)$ comprises the following steps (Nunes *et al*., 2005; Linderhed, 2004):

Step 1: Find the positions and amplitudes of all local maxima and minima in the signal $h_{1,0}=I(m,n)$.

Step 2: Create the upper and lower envelopes by FastRBF interpolation (Carr *et al*., 2001; 2003) of the local maxima and minima. Denote the upper and lower envelopes $e_{\mathrm{upper}}(m,n)$ and $e_{\mathrm{lower}}(m,n)$ respectively.

Step 3: Calculate the mean of the upper and lower envelope:

$$e_{\mathrm{mean}}(m,n)=[e_{\mathrm{upper}}(m,n)+e_{\mathrm{lower}}(m,n)]/2.$$

Step 4: Subtract the envelope mean signal from the input signal

$$h_{l,k}(m,n)=h_{l,k-1}(m,n)-e_{\text{mean}}(m,n).$$

This is one iteration of the sifting process. The next step is to check whether $h_{l,k}(m,n)$ is an IMF or not. We apply the appropriate number of iterations in the SP to build IMFs by replacing the proposed stopping criterion (Linderhed, 2004). We notice that, in every case, the average median of $|e_{\text{mean}}(m,n)|$ decreases very rapidly for the fifth iterations and then decreases much slower. The error curve of IMF iteration is shown in Fig.1. This suggests that the appropriate number of iterations can be determined using the existing method (Damerval *et al*., 2005). The number of iterations given by this criterion is independent of the kind of images. We adopt the appropriate number of iterations, that is, K=10 in this paper.

Step 5: When the stopping criterion is met, the IMF $c_l(m,n)$ is defined as the last result in Step 4.

$$c_l(m,n)=h_{l,k}(m,n).$$

After the IMF is found, define the residue $r_l(m,n)$ as

$$r_l(m,n)= h_{l,0}(m,n)-c_l(m,n).$$

Step 6: The next IMF is found by starting over from Step 1, now with the residue as the input signal:

$$h_{l+1,0}(m,n)=r_l(m,n).$$

Steps 1~6 can be repeated for all $h_{l+1,0}$. The 2D EMD is completed when the residue, ideally, does not contain any extrema points. The signal can be expressed as the sum of IMFs and the last residue

$$I(m,n)=\sum_{j=1}^{L}c_j(m,n)+r_L(m,n).$$

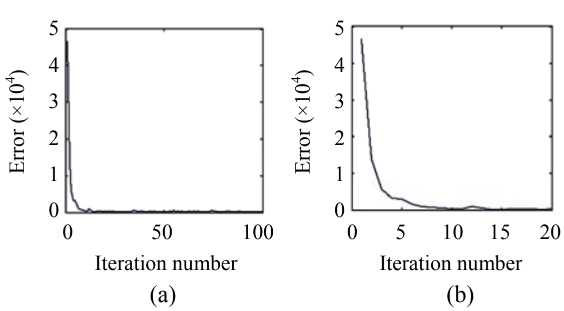

Fig.1 Error curve of IMF iterations in the SP
(a) N=100; (b) N=20

The woman image is decomposed with the 2D EMD method described above. The image's four IMFs and the last residue are shown in Fig.2. The last residue has only very few extrema points.

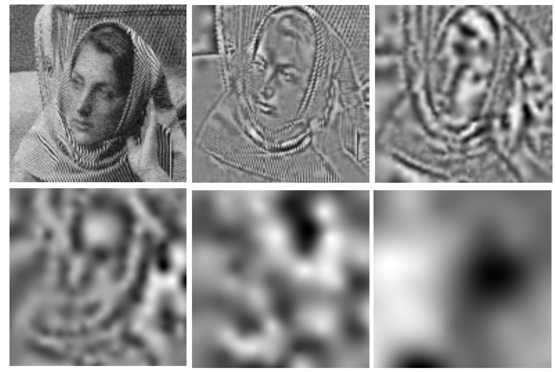

Fig.2 2D empirical mode decomposition of woman image

FEATURE EXTRACTION AND CLASSIFICATION

We decompose each texture image into J IMFs and a residue by the modified 2D EMD, and then apply 2D FFT to each IMF. From the 2D FFT, we know that even though the edges of image may have various orientations and their locations in the image may be random, the contribution of all edges with the same orientation will result in the orientation being perpendicular to the edges in the magnitude of Fourier transform. This special phenomenon is called auto-registration of the magnitude spectra. The auto-registration also means a redistribution of contributions of all patterns of the texture, according to the orientations of edges and the frequency locations of patterns rather than spatial locations of them. This method is very effective because of easily handled texture rotation. The basic properties of Fourier transform show that the rotation of the original image will result in the corresponding rotation of Fourier spectra.

In order to extract rotation invariant feature vectors, we introduce circular feature regions and divide each IMF's Fourier magnitude spectra into M circular regions with one circle and $M-1$ cirques using the centroid coordinate. Let W and H denote the width and height of image respectively, then the radius of circular regions is defined as:

$$r=\begin{cases}W/2M, & W\le H;\\ H/2M, & W>H.\end{cases}$$

We compute the total energy E_i (i=1, …, M) of each circular region, then obtain the ratio of energy u_i between circular regions and normalize them. A feature vector is now constructed using u_i as feature components. In the experiments, we use J IMFs and M circular regions, resulting in a feature vector

$$\boldsymbol{f}=\{u_i^j\},\ i=1,\ ...,\ M;\ j=1,\ ...,\ J.$$

We employ the Bayes classifier (Theodoridis, 1999; Campisi *et al*., 2004) to classify texture. The Bayes decision function D_n is defined as

$$D_n=(\boldsymbol{f}-\boldsymbol{f}_n)\boldsymbol{C}_n^{-1}(\boldsymbol{f}-\boldsymbol{f}_n)+\ln|\boldsymbol{C}_n|,$$

where $\boldsymbol{f}$ is the feature vector of an unknown texture image, $\boldsymbol{f}_n$ and $\boldsymbol{C}_n$ are the mean vector and covariance matrix of the data in class n respectively. The texture is assigned to the class k, if $D_k<D_n$ for all $k\neq h$. The texture classification algorithm including the training phase and the classification phase (Theodoridis and Koutroumbas, 1999; Campisi *et al*., 2004) is detailed as follows.

Let us consider N=15 texture classes. In the training phase, we first select m "typical" finite samples of the texture, that is m different parts all capturing the same relevant characteristics of the texture itself. The m samples composing the class should be chosen to yield a small model mismatching error; whose effect on the feature vector can be further reduced by averaging the N samples composing the class, so finally we will obtain the mean feature vector $\boldsymbol{f}_n$, which "globally" represents the texture class.

The classification phase extracts the feature vector $\boldsymbol{f}$ and compares it with the representative feature map $\boldsymbol{f}_n$, using a suitable distance metric criterion. Then to decide which texture the unknown texture belongs to.

The concrete texture classification algorithm is shown as follows:

(1) Decompose texture into J IMFs and a residue by the modified 2D EMD.

(2) Compute the FFT magnitude of each IMF.

(3) Circular regions are applied to the magnitude of FFT to get the rotation invariant feature vector $\boldsymbol{f}$.

(4) Employ the Bayes classifier to classify texture.

EXPERIMENTAL RESULTS

To demonstrate the performance of the proposed texture feature in differentiating textures, we use a set of textures extracted from the Brodatz album. Fifteen classes have been considered (N=15); samples are shown in Fig.3.

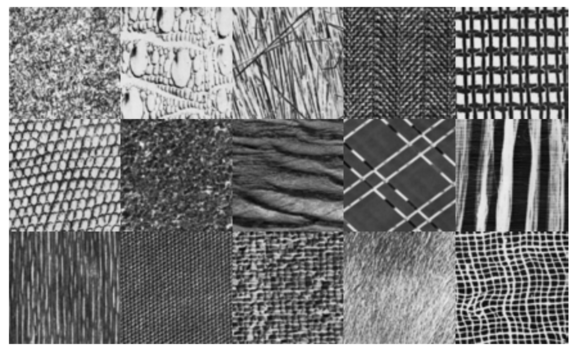

Fig.3 Texture samples
From left to right: First row: D9, D10, D15, D17, D20; Second row: D22, D29, D37, D49, D51; Third row: D68, D84, D77, D93, D103

Experiment 1 We performs test on not rotated textures with J=2, M=8. Textures (576×576) are segmented into 80 nonoverlapping samples (64×64). We carry out the training phase by selecting m=30 texture samples from the 80 subimages. The remaining 50 texture samples are used to perform the classification tests. The average percentages of correct classification for not rotated texture are given in Table 1.

Experiment 2 This experiment relates to rotated textures with J=2, M=8. For each class, the training set is composed by textures at angles 0°, 30°, 60°, 110°, and 160°. For each angle, m=30 non-overlapping samples (64×64) are considered. The textures to classify are obtained both from the original images and after rotations at angles 20°, 70°, 90°, 120°, and 150°. For each rotation angle, 20 classification tests were performed. The average percentages of correct classification of rotated texture are also given in Table 1.

Experiment 3 We compare our method with two other texture classification methods: model based approach (Campisi *et al*., 2004) (MI), rotation-invariant wavelet method (Porter and Canagarajah, 1997) (WA). The results are also given in Table 1.

Experiment 4 This experiment relates to rotated textures with J=2, M=16. Here, the test set of Experiment 2 is used. Table 2 gives the percentages of correct classification for rotated texture samples with different textures and different angles. We found that our method is not stable for all textures. For instance, the percentages of correct classification of the textures D15, D37 and D68 are lower than those of the other textures. This is a disadvantage of our method.

CONCLUSION AND FUTURE WORK

A novel rotation invariant texture classification scheme based on 2D EMD and Fourier model has been proposed. 2D EMD decomposes images into the highest frequency, the second highest frequency, etc. which reflects the mechanism of human's differentiating textures. We extend 2D EMD using FastRBF and the appropriate number of iterations in the SP to obtain fast 2D EMD. We apply auto-registration and circular regions of the magnitude spectra of 2D FFT to extract rotation-invariant feature vectors for texture classification. In the experiments, we employ the Bayes classifier to classify a set of 15 distinct natural textures selected from the Brodatz album. The experimental results, based on different testing datasets for images with different orientations, show the effectiveness of the proposed classification scheme. Comparisons of the classification performance of our proposed method with other rotation-invariant texture classification methods are also given in this paper. In the future, the following problems will be considered: first, what are the results when we use a different number of circular regions and more IMF, such as M=32, 64, three or four IMFs; second, how to implement other invariance for 2D EMD, for example, the scale invariance.

Table 1 Percentage of correct classification for rotated and not rotated texture samples using our approach (EMD), moment invariants (MI), and the wavelet based method (WA)

Texture	Not rotated			Rotated		
	EMD	MI	WA	EMD	MI	WA
D9	81%	82%	88%	79%	79%	76%
D10	83%	82%	82%	80%	82%	83%
D15	74%	85%	78%	78%	78%	73%
D17	99%	96%	95%	93%	93%	83%
D20	94%	98%	90%	77%	96%	83%
D22	76%	86%	88%	77%	80%	67%
D29	97%	90%	70%	96%	86%	85%
D37	70%	90%	69%	81%	89%	67%
D49	100%	84%	86%	99%	78%	88%
D51	93%	90%	83%	80%	87%	73%
D68	81%	92%	85%	82%	89%	74%
D77	100%	90%	90%	100%	86%	85%
D84	82%	86%	87%	81%	81%	52%
D93	77%	84%	85%	74%	79%	77%
D103	100%	84%	72%	96%	79%	68%
Average	87.1%	87.9%	83.2%	84.8%	84.1%	75.6%

Table 2 Percentage of correct classification for rotated textures samples (at different angles) using EMD method. J=2, M=16

		D9	D10	D15	D17	D20	D22	D29	D37	D49	D51	D68	D77	D84	D93	D103
20°	EMD	90%	75%	65%	100%	100%	90%	80%	65%	100%	100%	75%	100%	75%	85%	100%
70°	EMD	90%	85%	65%	100%	100%	85%	90%	65%	100%	100%	65%	100%	85%	90%	100%
90°	EMD	100%	90%	60%	100%	100%	95%	100%	75%	100%	65%	65%	100%	100%	95%	100%
120°	EMD	95%	80%	70%	95%	100%	85%	80%	65%	100%	80%	70%	100%	100%	75%	100%
150°	EMD	95%	85%	75%	100%	100%	85%	85%	70%	100%	65%	85%	100%	90%	85%	100%

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