TEXTURE CLASSIFICATION USING DUAL-TREE COMPLEX WAVELET TRANSFORM

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ABSTRACT

A new texture feature extraction method utilizing dual tree complex wavelet transform (DT-CWT) is introduced. The complex wavelet. transform is a recenbly developed tool that uses a dual tree of wavelet filters to find the real and imaginary parts of complex wavelet, coefficients (1). Approxin1ate shift. invariance, good directional selectivity, computational efficiency properties of DT-CWT make it a good candidate for representing the texture features. In this paper, we propose a methodfor efficiently using the properties of DT-CWT in finding the directional and spatial/freqiiency characteristics of the patterns and classifying different texture patterns in terms of these characteristics. Experimental results show that the proposed feature extraction and classification method is efficient, in terms of computational speed and retrieval accuracy.

1 INTRODUCTION

Efficient, texture representation is important. in search **and** retrieval of similar texture patterns from a large image database. There has been research on texture feature extraction by finding the spatial/frequency distribution of the patterns with tools like the Gabor filters (2), Teager filters (3), pyramid-structured wavelet transform (4), and tree-structured wavelet transform *(5)*. Tests indicate that the texture features which can efficiently define directional and spatial/frequency characteristics of the patterns lead to good texture analysis and classification results.

Gabor filters have been used in texture analysis due to their good directional selectivity in different frequency scales (2). Rut there are drawbacks with using the Gabor filters in practical applications. The selection of filters is dependent on the image frequency characteristics. The accurate implementation of a complete Gabor expansion would necessiatr an impractical number of filters. **Also** the discrete versions of the Gahor function should be obtained in order to be used for image applications.

In tree structured wavelet transform method, the given textured image is decomposed into **4** subimages in low-low, low-high, high-low and high-high subhands. After calculating the energies of each subimage, the decomposition is continued only for the subhands with energy greater than a given threshhold. The threshhold is chosen **as** a certain percentage of the largest. energy value **in** the same level. This method enables one to concentrate only on the frequency channels that are significant, for the particular pattern. Since the general assumption that the energy of an image is concentrated o11 the low-low hand is not valid for some texture patterns, this method gives better results than the pyramid-structured wavelet. transform method. However, directional selectivity is poor when real DWT **is** used for the subband decomposition and the texture patterns with similar spatial/frequency and different directional properties cannot, he differentiated. Also since small shifts in the input, signal can result, in large differences of DWT coefficients at different scales, same two patterns with small spatial shifts will produce distant, feature vectors.

Previous work shows that DT-CWT gives good results in image restoration and enhancement (1). Remarkable improvement over using real DWT for bhese image processing applications is obtained.

In this paper, we use DT-CWT for deromposiug a textured image into six bandpass subimages that are strongly oriented at 6 different. angles and two lowpass subimages. Since higher directional selectivity is obtained, the dominant, frequency channel and orientation of the pattern is detected with a higher precision. The dominant orientations are found by comparing the energies of the directionally tuned bandpass and the lowpass images. The complex wavelet decomposition is continued for the most, significant subimages.

This paper is organized as follows. In Section 2, the DT-CWT, its extension to two dimensions, and its properties are explained. The texture feature extraction and classification algorithms are explained in Section **3.** Efficiency comparisons with other feature extraction methods are performed and results are listed in Section **4.** Section **5** contains the discussion of the results.

2 DUAL TREE COMPLEX WAVELET TRANSFORM

In order to have directional selectivity with Mallat's efficient separable, iterative structure (6), it is necessary to use complex coefficient filters . Since short support complex FIR filters in a single tree cannot provide perfect reconstruction and good frequency characteristics, using two parallel fully decimated trees with real filter coefficients is proposed (1). The approximate shift invariance is obtained by having the downsampled outputs of first level filters of one tree one sample offset from the outputs of the other. This corresponds to doubling the sampling rate at each level of the tree, which gives 2:1 redundancy for one dimensional signals.

When odd length biorthogonal filters are used in one tree, even length filters are used in the other to have uniform intervals between samples from the two trees below first level. Filters are chosen to be linear phase so odd-length highpass filters have even symmetry and the even-length highpass filters have odd symmetry about their midpoints. So the impulse responses of these filters are like the real and imaginary parts of a complex wavelet.

Extension of the one dimensional DT-CWT to two dimensions enables us to obtain directional selectivity for texture patterns. The extension is performed by separable filtering. Real images have significant information in both first and second quadrants of the spectrum, so column filter outputs are also filtered by complex conjugates of the row filters. This gives 4:1 redundancy for two dimensional signals. The subsampled outputs of the row filters and their complex conjugates form six bandpass images, three in each quadrant, and these subimages are strongly oriented at $\pm 15^0, \pm 45^0, \pm 75^0$. The orientation is obtained since complex filters can separate positive and negative frequencies in both horizontal and vertical directions.

3 TEXTURE FEATURE EXTRACTION WITH DT-CWT

The idea of finding the frequency channels with most significant information and performing further decomposition in these channels is first proposed by Chang et al (5). Here, we extend the same algorithm for finding the most significant orientations of the texture pattern and continuing the decomposition only for the corresponding subimages. The decomposition algorithm is as follows:

1) Perform 2D-CWT to decompose the given pattern into 8 subimages (2 lowpass, 6 bandpass)

2) Find the averaged energy of each subimage by the following equation. (Subimages have real and imaginary parts)

$$E_k = \frac{1}{MN} \sum_{m=1}^{M} \sum_{n=1}^{N} |s_k(m,n)| \qquad (1)$$

where $s_k(m,n)$ is the k'th subimage (k = 1,2,..,8) and M,N are width and height of the subimage.

3) Stop the decomposition of a subimage if its energy is not large enough. The energy is compared with the largest energy in the same scale.
So if $E_k < K * E_{max}$, the decomposition is stopped for k'th subimage in that decomposition level.

4) Continue the decomposition for the remaining subimages and their corresponding mirrors in the adjacent spectral quadrant.

The decomposition should continue only while the subimages are large enough. The 2D-CWT energy distribution cannot effectively define the characteristics of the pattern when the subimage is too small.

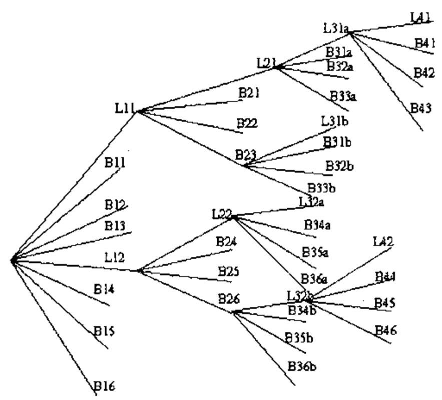

Figure 1: A decomposition example using the explained algorithm.

In Figure 1, a DT-CWT based decomposition is shown. Here, label L indicates lowband, and label B indicates bandpass subimages. After the second level of the decomposition, two significant subimages were found and decomposed in this example.

The classification is performed by using the means and standard deviations of the first L most significant complex subimages. The classification algorithm is as follows.

1) Find the first L subimages of the decomposed

texture pattern with largest averaged energy values.

2) Find the means and standard deviations of these subimages and form the feature vector including 2L complex feature elements.

3) For another texture pattern in the database, form its feature vector using the means and the standard deviations of its subimages corresponding to the same channels with the first pattern. If the corresponding subimage is not found in the decomposition, that texture pattern is not included in the candidate list.

4) Compute the normalized Euclidian distance between the feature vectors.

5) Repeat steps 3 and 4 for all patterns in the database. Sort the distances between the feature vectors of the query pattern and the other patterns in the database and choose the ones with closest feature vectors as the most similar texture patterns.

Normalized Euclidian measure is used in order to give each feature element the same weight in finding the distance.

4 EXPERIMENTAL RESULTS

To test the efficiency of this feature extraction method, Brodatz texture album with 116 images was used (7). Each image was divided into 16 portions of equal size, so a texture database of 1856 images was obtained. The image portions are of size 128x128, so in order to have large enough subimages in the highest level, 4 level DT-CWT was performed to these portions. For the dual filter tree, two linear phase biorthogonal filter sets with odd and even lengths were used. The odd and even filter sets were used alternately in the two trees to have symmetry. Also the filters are chosen so that they have good smoothness characteristics and rational coefficients. (13,19)-tap filters were formed by using the transformation of variables method (8) for the odd-length set. A (12,16)-tap filter set was formed according to the characteristics of the odd-length set, so that the impulse responses to inputs for the last two levels of both trees are as close as possible in mean squared distance sense. In Figure 3, a sample texture pattern from the Brodatz database is shown, and the directionally oriented bandpass subimages obtained from the topleft portion of the sample pattern can be seen in Figure 4. During subband decomposition, the threshhold was chosen as 40% of the largest energy in the same scale. This choice of threshhold gives a reasonable number of subimages to be further decomposed (between 1 to 3 for each level). While performing the classification, the most significant 16 subimages were used to form the feature vector of the query image, giving a feature vector of length 32.

Real-valued even-symmetric Gabor filters were implemented for efficiency comparisons (2) (according to the given classification algorithm and the Brodatz texture album). The directionally tuned Gabor filters were formed at 4 radial frequencies and 4 orientations $(0^0, 45^0, 90^0, 135^0)$ This gives 16 different Gabor filters and 32 feature vector elements were obtained from the means and standard deviations of the filter outputs. 4 level pyramid-structured wavelet decomposition was performed on the image portions to obtain 13 subimages and feature vectors of length 26 were formed. Tree structured wavelet transform with 4 levels was used and the most significant 12 subimages were selected, giving feature vectors of length 24.

Normalized Euclidian distance method was used for the classification with all feature extraction methods. The retrieved images are the 15 images having the nearest feature vector to the query image feature vector. The image portions that are originally from a different image are regarded as false retrievals and the percentage of correct retrievals over all image portions in the database is called the retrieval rate.

The feature vector length and retrieval rate comparisons for different feature extraction methods is displayed in Table 1 for the particular texture classification experiment.

Feature Extraction Method	Feature Vector Length	Retrieval Rate
DT-CWT	32	79.73%
Gabor Filters	32	75.37%
Pyramid-structured wavelet transform	26	68.82%
Tree-structured wavelet transform	24	69.64%

Table 1: Efficiency comparisons of different feature extraction methods

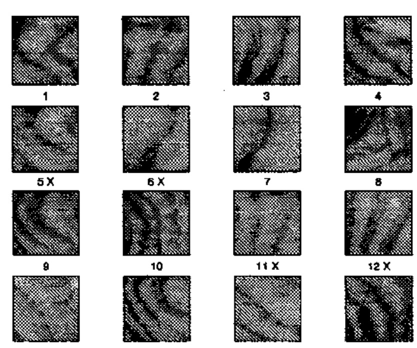

Figure 2: Retrieved image portions from the database (False retrievals are indicated by X)

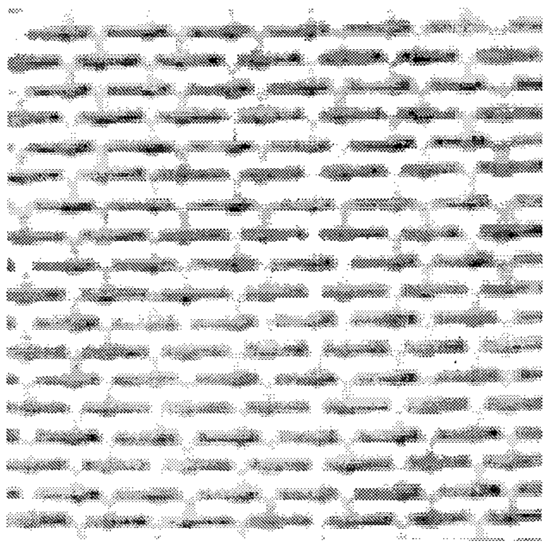

Figure 3: A sample texture pattern from Brodatz texture database

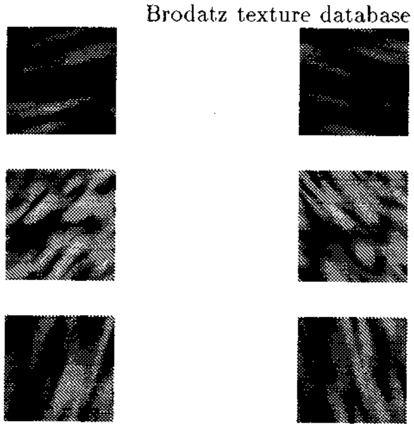

Figure 4: Directionally selected bandpass subimages obtained from a portion of the texture pattern

5 DISCUSSION OF THE RESULTS

According to the unsupervised classification method and the Brodatz texture database used in the experiments, DT-CWT method produced the most efficient results in terms of retrieval rate. The fact that the significant subimages are directly related with the most important visual properties of the texture pattern enables the patterns retrieved from other images (false retrievals) to be very similar to the query pattern. In Figure 2, we see that the false retrievals are also very much like the given pattern. Also, the feature extraction methods that have directional selectivity properties are successful, since completely different texture patterns may have similar frequency distributions while their directional behaviours are much different. So when a combination of both properties are utilized, the retrieval rate increases.

Since the feature extraction is performed by adding limited redundancy, independent of the number of levels, to highly efficient maximally decimated discrete wavelet transform, the extraction method is computationally efficient. Although, perfect reconstruction is not necessary in texture analysis, this property can be used in further applications.

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