ROTATION INVARIANT TEXTURE FEATURES USING ROTATED COMPLEX WAVELET FOR CONTENT BASED IMAGE RETRIEVAL

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ABSTRACT

New rotationally invariant texture feature extraction method is introduced that utilizes the dual tree rotated complex wavelet filters (DT-RCWF) and dual tree complex wavelet transform (DT-CWT) jointly. A new two-dimensional rotated complex wavelet filter is designed with complex wavelet filter coefficient. Decomposing image with DT-RCWF and DT-CWT jointly gives shift invariant subbands oriented in twelve different directions. Isotropic rotationally invariant features are extracted from these subbands. The performance of image retrieval with proposed features on *rotated* and *nonrotated* image database is compared with existing method. The experimental results show that the proposed rotation-invariant texture features are more robust and outperform the other existing methods.

1. INTRODUCTION

With the advances in information technology there is explosive growth of the multimedia databases, which demands effective and efficient tools that allow users to search and browse through such a large collection. As the databases grow larger, the traditional keyword based method to retrieve a particular image becomes tedious and inadequate. To solve these problems, content-based image retrieval (CBIR) approach has emerged as promising alternative. In CBIR, images are indexed by their own visual contents. Comprehensive and extensive literature survey on CBIR can be found in [1-2].

Feature extraction and matching are very important components in CBIR. Queries can be based on many features such as texture, colour, shape and their combinations. Importance of texture feature is due to its presence in many real world images: for example clouds, trees, bricks, hair, fabrics etc., all of them have textural characteristics. The majority of existing work on texture analysis assumes that all images are acquired from the same viewpoint. This assumption is not realistic in practical applications. The performance of these methods becomes worse when this underlying assumption is no longer valid.

Several authors have proposed rotation invariant texture features. A comparative study of rotation invariant texture analysis methods was given by Fountain et.al. [3]. Chen and Kundu [4] modeled the features of wavelet subband as hidden Markov model (HMM). Haley and Manjunath [5] used magnitude of a discrete Fourier transform in the rotation dimension of features obtained with a multiresolution filtering. All these rotation invariant texture analysis methods were designed for the classification problems, where the classes are defined a *priori*. Therefore these methods are not suitable for the retrieval applications, where each database image forms a separate class and must be trained individually. To address these problems, recently Do and Vetterli [6] proposed a wavelet domain HMM for rotation invariant texture characterization and retrieval. In [7] Pun proposed a rotation invariant polar-wavelet texture features for CBIR. In his method rotation invariant features are obtained by transforming image into polar form, which is followed by an adaptive row shift invariant wavelet packet transform.

In this paper, we propose effective and robust rotation invariant texture features for CBIR. The approach followed herein is novel in the following respects:

1. For better dealing with oriented textures new 2-D rotated complex wavelet filters are designed with dual tree complex wavelet filter coefficients.
2. Decomposing image with DT-RCWF and DT-CWT jointly gives orientation information in twelve different directions (6 with each) at each scale.
3. Robust isotropic rotationally invariant features are extracted from these subbands. Retrieval results of the proposed method outperform the existing methods.

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This paper is organized as follows. In section 2 design of complex rotated wavelet filter is presented. The isotropic rotation invariant texture features are proposed in section 3. Experimental results are given in section 4, which is followed by the conclusion in section 5.

2. DUAL-TREE ROTATED COMPLEX WAVELET FILTERS.

Discrete wavelet transform (DWT) has poor directional selectivity and it lacks shift invariance. It is found that both the above problems can be solved effectively by the complex wavelet transform (CWT) by introducing limited redundancy into the transform. In CWT, filters have complex coefficients, which generate complex output samples. However, a perfect reconstruction becomes difficult for complex wavelet decomposition beyond level 1, when the input to each level becomes complex. To overcome this, Kingsbury [8] have recently developed the DT-CWT.

2.1. Dual-Tree Complex Wavelet Transform

The DT-CWT decomposes a signal in terms of a complex shifted and dilated mother wavelet. The DT-CWT is implemented using separable transforms and by combining subband signals appropriately [9]. Although it is non-separable yet it inherits the computational efficiency of separable transforms. Specifically, the 1-D DT-CWT is implemented using two filter banks in parallel operating on the same data as illustrated in figure 1. A complex-valued wavelet $\psi(t)$ can be obtained as

$$\psi(t) = \psi_h(t) + j\,\psi_g(t) \tag{1}$$

Where $\psi_h(t)$ and $\psi_g(t)$ are both real-valued wavelets. Thus far, the dual tree does not appear to be a complex transform at all. However, when the outputs from the two trees in figure 1 are interpreted as the real and imaginary parts of complex coefficients, the transform effectively becomes complex.

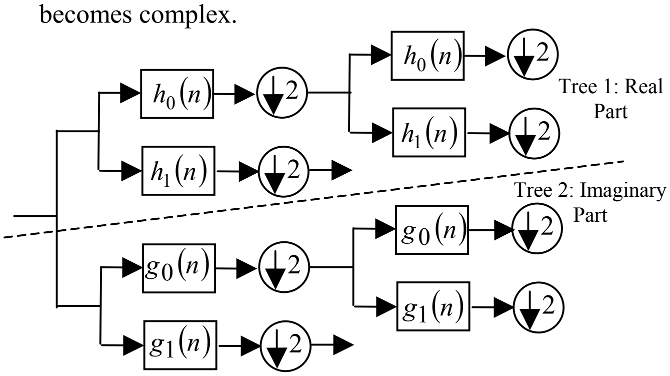


Figure 1. The 1-D dual-tree complex wavelets transform.

2.2. Directional 2-D Rotated Complex Wavelet Filters

For designing directional 2-D rotated complex wavelet filters (2D-RCWF), first we obtain the directional 2-D complex wavelet filters and then rotated those by 45°.

2.2.1. Directional 2-D wavelets

If $\psi_g(t)$ is approximately the Hilbert transform of $\psi_h(t)$, then the oriented nonseparable 2-D wavelet is implemented by combining the subbands of two separable 2-D DWTs. The scaling and directional wavelet are obtained by defining a 2-D separable wavelet basis via

$$\phi_1(x,y) = \phi_h(x)\,\phi_h(y) \qquad \phi_2(x,y) = \phi_g(x)\,\phi_g(y) \tag{2}$$

$$\psi_{1,1}(x,y) = \phi_h(x)\,\psi_h(y) \quad \psi_{2,1}(x,y) = \phi_g(x)\,\psi_g(y) \tag{3}$$

$$\psi_{1,2}(x,y) = \psi_h(x)\,\iota_h(y) \quad \psi_{2,2}(x,y) = \psi_g(x)\,\phi_g(y) \tag{4}$$

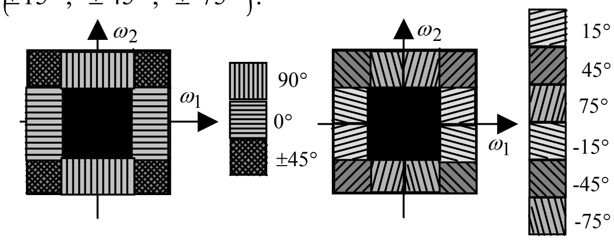
$$\psi_{1,3}(x,y) = \psi_h(x)\,\psi_h(y) \quad \psi_{2,3}(x,y) = \psi_g(x)\,\psi_g(y) \tag{5}$$

Then the six wavelets defined by

$$\psi_i(x,y) = \psi_{h,i}(x,y) + \psi_{g,i}(x,y) \tag{6}$$

$$\psi_{i+3}(x,y) = \psi_{h,i}(x,y) - \psi_{g,i}(x,y) \tag{7}$$

($1 \le i \le 3$) are directional as illustrated in figure 2 (b). A wavelet transform based on these six wavelets can be implemented by taking sum and difference of two separable 2-D DWTs. The resulting directional wavelet transform is two-times redundant. The inverse requires taking sum and difference, dividing by 2, and the separable inverse DWTs. The six subbands of the 2D DT-CWT gives information strongly oriented at $\{\pm 15^0,\ \pm 45^0,\ \pm 75^0\}$.



(a) Standard real wavelet (b) Complex wavelet

Figure 2: Partition of frequency domain resulting from the one level decomposition.

2.2.2. Rotated Complex Wavelet Filters (RCWF)

2-D complex wavelet filters can be obtained from the products of 1-D wavelet and scaling functions as given in equations (2)-(5). Characterization of specific directional information of texture image improves retrieval performance. This is also supported by our experimental results given in section 4. That is made possible by using nonseparable oriented wavelet transform obtained with rotated wavelet filters. RCWF sets are obtained by rotating 2-D complex wavelet filters by 45° so that the decomposition is performed along the new directions, which are 45° apart from decomposition directions of CWT. The size of a filter is $(2N-1)\times(2N-1)$, where N is the length of the 1-D filter. The decomposition of input image with 2-D RCWF can be performed by filtering a given image $f(x,y)$ with 2-D RCWFs followed by 2-D down sampling operations. The computational complexity associated with the RCWF decomposition is the same as that of standard 2-D CWT, if both are implemented in the 2-D frequency domain. Partition of frequency domain resulting from single level RCWF decomposition is shown in figure 3. The set of RCWF's retains the orthogonality property, since it holds following condition:

$$\frac{1}{2\pi}\int_{-\infty}^{\infty} S_i(\omega)\overline{S_j(\omega)}\, d\omega = 0, \quad (i \neq j) \tag{8}$$

where $S_i(\omega)$ is the Fourier transform of the 2-D filter. The six subbands of the 2D DT-RCWF give information strongly oriented at $\{-30^0, 0^0, 30^0, 60^0, 90^0, 120^0\}$ as shown in figure 3. This characteristic of RCWF sets provides important complementary information to the CWT filter set in extracting texture features in twelve different directions by considering them jointly for CBIR.

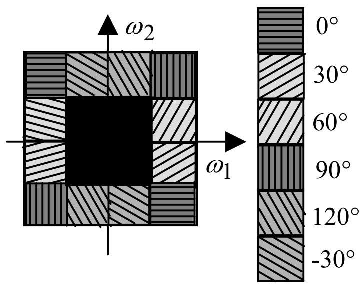


Figure 3: Partition of frequency domain resulting from the one level RCWF decomposition

3. ROTATION INVARIANT FEATURE EXTRACTION AND IMAGE MATCHING

In our experiments, all the texture images are decomposed into twelve bandpass oriented subbands using DT-CWT and DT-RCWF with low-low subbands at each scale being recursively decomposed for three levels. This gives 12×3 oriented subbands with four residual low-low pass images. Channel energies using L_1 norm and standard deviation were extracted from each subband except low-low subbands.

$$E_k = \frac{1}{N^2}\sum_{i=1}^{N}\sum_{j=1}^{N} |\, x_k(i,j) \,| \tag{9}$$

$$\sigma_k = \left[\frac{1}{N\times N}\sum_{i=1}^{N}\sum_{j=1}^{N}\left(x_k(i,j)-\mu_k(i,j)\right)^2\right]^{\frac{1}{2}} \tag{10}$$

where E_k is the energy and σ_k is the standard deviation for the k^{th} subband of dimension $N\times N$ with coefficients $x_k(i,j)$ and mean value $\mu_k(i,j)$.

Isotropic rotationally invariant features are produced by summing separately the energies and standard deviation values from each of the subbands at each scale. This gives the feature vector of length 6.

3.1. Similarity Measurement

A *query* image is any one of the image from image database. Features of query image are extracted in same way as the database image. For similarity measurement between *query* image and *database* image one can use Euclidean distance metric but in this distance metric each feature vector elements are squared before summation, which places great emphasis on those features for which the dissimilarity is large. This has been taken care of in Canberra distance metric [10] by normalizing the individual feature vector elements before finding the distance between the two images. If f_d and f_q are the feature vectors of database and query image respectively of dimension n, then the Canberra distance is given by

$$\text{Canberra}\,(f_d, f_q) = \sum_{i=1}^{n}\frac{\left|f_{d_i}-f_{q_i}\right|}{\left|f_{d_i}\right|+\left|f_{q_i}\right|} \tag{11}$$

The distances are stored in increasing order and the closest set of patterns is retrieved. The numbers of ground truth images for each query image in the database are 16. The performance is measured in terms of the average retrieval rate, which is defined as the average percentage number of patterns belonging to the same class as the query pattern in the top 16 matches.

4. EXPERIMENTAL RESULTS

To check the effectiveness of proposed method, we used same texture database, which was used by Do and Vetterli [6]. It consists of thirteen 512×512 Brodatz textures images that were rotated to various degrees before being digitized [11]. From these images *non-rotated* image database is created by dividing each 0° version of the original textures into sixteen 128×128 non-overlapping subimages. Next we construct *rotated* image database by taking four non-overlapping 128×128 subimages each from the original images at 0°, 30°, 60° and 120°. Both database sets contain 208 images each. The *non-rotated set* serves as the ideal case, where all images in a same class have the same orientation, for the *rotated set*.

We conducted two different sets of experiments on different databases. Table 1 shows the comparison of performances in percentage of retrieving relevant image for the *non-rotated* set without using rotation invariant features, and the *rotated set* using rotation invariant features. In the first set of experiments *non-rotated* database is used. The result of proposed method is compared with standard DWT (with normalized Euclidean distance as similarity measure) and the vector wavelet domain HMM (WD_HMM) as reported in [6].

In the second series of experiments, we have tested the rotation invariant property of proposed method obtained with isotropic rotation invariant features. In this experiment we used *rotated database* set. Results have been compared with the isotropic rotationally invariant features extracted from DWT developed by Porter [12] and rotation invariant property obtained with the vector steerable WD_HMM as reported in [6]. Experimental results from Table 1 shows that on both the databases the proposed rotation-invariant texture features outperform the other existing methods. Retrieval accuracy is improved by 10% as compared to DWT on both the database set, 7% and 4% as compared to WD_HMM on *nonrotated set* and *rotated set* respectively.

TABLE 1
Retrieval Accuracy

Texture Name	Non-rotated database set			Rotated database set		
	DWT	SWD_HMM	DTCWT+DTRCWF	DWT	SWD_HMM	DTCWT+DTRCWF
Bark	100.0	68.86	81.25	93.75	88.67	100.0
Brick	56.25	89.62	81.25	56.25	75.47	81.25
Bubble	100.0	65.09	100.0	75.00	65.00	87.50
Grass	68.75	100.0	81.25	100.0	100.0	100.0
Leather	93.75	97.16	100.0	75.00	100.0	87.50
Pigskin	93.75	82.20	93.75	75.00	87.73	93.75
Raffia	75.00	68.86	100.0	87.50	76.88	100.0
Sand	87.50	88.67	100.0	100.0	85.84	100.0
Straw	43.75	87.73	87.50	62.50	98.00	68.75
Water	100.0	83.96	93.75	100.0	84.90	100.0
Weave	100.0	97.16	100.0	100.0	99.00	100.0
Wood	100.0	93.39	100.0	56.25	89.62	68.75
Wool	100.0	99.00	93.75	87.50	80.00	93.75
Avg.	**83.17 %**	**86.41 %**	**93.71 %**	**82.21 %**	**86.77 %**	**90. 86 %**

5. CONCLUSION

We have introduced a new two-dimensional rotated complex wavelet filters. Decomposing image with dual tree complex wavelet transform and dual tree rotated complex wavelet filters jointly captures orientation information in twelve different directions. Furthermore robust isotropic rotation invariant texture feature are obtained and tested for image retrieval application. Additionally the proposed method is shift invariant, which inherits from DT-CWT. These are very useful properties of proposed method and can be applied to many pattern recognition applications. Our results on large databases are encouraging and, which outperform the other existing methods.

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