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Texture Image Retrieval Using A Set of Dual-Tree Rotated Complex Wavelet Filter And Dual-Tree-Complex Wavelet Transform

Sachin S. Mahulkar[1], Dr. Ajay P. Thakare[2], Ajaykumar K. Kakde[3]

[1]Dept. of Electronics & Telecommunication Engineering, Sipna College of Engineering and Technology, Amravati. India

[2] Professor and Head, Dept. of Electronics & Telecommunication Engineering Sipna College of Engineering and Technology, Amravati. India

[3] Dept. of Electronics & Telecommunication Engineering, Cusrow Wadia Institute of Technology, Pune.India

Abstract: *Most of the texture image retrieval systems are still incapable of providing retrieval result with high retrieval accuracy and less computational complexity. This is the limitation of conventional image retrieval system. To overcome this problem, we propose a new approach of extracting texture features for texture image retrieval by using a combined set of dual-tree rotated complex wavelet filter (DT-RCWF) and dual-tree-complex wavelet transform (DT-CWT) together, which obtains texture analysis in 12 different directions. A set of two-dimensional (2-D) rotated complex wavelet filters (RCWFs) are designed with complex wavelet filter coefficients, which gives texture information strongly oriented in six different directions (450 apart from complex wavelet transform). The 2-D RCWFs are non-separable and oriented, which improves characterization of oriented textures. The information provided by DT-RCWF complements the information generated by DT-CWT. Features are obtained by computing the energy and standard deviation on each subband of the decomposed image. To check the retrieval performance, texture database D of 500 texture images is created. Experimental results on database D consisting of 500 texture images are categorized into 5 different classes indicates that our method significantly improves retrieval performance by considering African, bus and dinosaur category examples is 81.25%, 87.50%, and 87.50% respectively by using DT-RCWF +DT-CWT, compared with from 25%, 25% and 25% of traditional approach of Gabor wavelet-based features, respectively. Experimental result also shows retrieval time for query image using proposed method is 0.08 second which is very less than that using Gabor wavelets based method having 0.146 second. The proposed method also retains comparable levels of computational complexity.*

Keywords: *Texture image retrieval, Content based image retrieval, Complex wavelets transform, Rotated complex wavelet filters.*

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I. INTRODUCTION

We are living in the digital age of information, a digital Renaissance. Image retrieval (IR) has become an important research area in digital world where digital image collections are rapidly being created and made available to large number of users through the World Wide Web. Content-based image retrieval (CBIR) has been very operational research area as long as from 1970. However, as the databases grow larger, the traditional keywords based method to retrieve a particular image becomes inefficient and suffers from following limitations.

i. For a large data set, it requires more skilled labor and need very large, sophisticated keyword systems.
ii. It is difficult to express visual content like color, texture, shape, and object within the image precisely.
iii. Further, the keywords increase linguistic barrier to share image data globally.

To overcome these limitations, content based image retrieval is a promising alternative approach. The main advantage of CBIR is its ability to support visual queries. The challenge in CBIR is to develop the methods that will increase retrieval accuracy and reduce the retrieval time. As an important feature, texture acts as an important role in image analysis [1], object detection [2] and remote sensing image analysis [3]. Earlier methods [6], [7] for texture image retrieval suffer from two main drawbacks. They are either computationally expensive or retrieval accuracy is poor. In this paper we concentrate only on the problem of finding good texture features for CBIR, which are efficient both in terms of accuracy and computational complexity. The main contributions and novelty of this paper are design of a set of dual tree rotated complex wavelet filters (DT-RCWF) is used jointly with dual tree complex wavelet transform (DT-CWT) for texture analysis in twelve different directions. DT-CWT can represent image texture efficiently in six directions [4] because of approximate shift invariance, good directional selectivity, computational efficiency and low redundancy properties. To utilize image texture information in more orientations, 2-D RCWF using complex wavelet filter coefficients [5] can be used to give texture information strongly oriented in six different directions (45^0apart from DT-CWT).

Therestofthispaperisorganizedasfollows.InsectionII,wepresentournewmethodology.Webrieflydiscussthe complexwavelettransforminSectionsIII.InSectionIV,wepresentdesignandimplementationof2Drotatedcomplexw aveletfilters.Experiments and discussion are given in SectionV. Finally, the conclusion is given in SectionVI.

II. OUR METHODOLOGY

To improve the retrieval performance both in terms of retrieval accuracy and retrieval time, in this paper, we have designed a new set of 2-D RCWF using complex wavelet filter coefficients in such a way that it gives texture information strongly oriented in six different directions (45^0 apart from DT-CWT). The 2-D RCWF are non-separable and oriented, which improves characterization of oriented textures. We have used dual-tree rotated complex wavelet filter (DT-RCWF) and DT-WCT jointly to extract texture features in 12 different directions (in six directions with each), which improves retrieval performance. Our approach has twofold advantages over Gabor wavelet based approach. First, the retrieval accuracy is more because of characterizing texture images in 12 different directions, and secondly the computational complexity is less than Gabor wavelet based approach, which is an important requirement for online application. Additionally the proposed method is shift invariant, which it inherits from DT-CWT. For large-scale evaluation our retrieval results are checked on two different sets of large databases D1 and D2. The retrieval performance of proposed method outperforms the other existing methods consistently on both the databases.

III. COMPLEX WAVELET

The problem related to real discrete wavelet transform (DWT) is poor directional selectivity and lacks of shift invariance. These problems can be solved effectively by the complex wavelet transform (CWT) by introducing limited redundancy into the transform. In CWT, filters have complex coefficients and generate complex output samples.

A. DT-CWT

Real DWT has poor directional selectivity and it lacks shift invariance. Drawbacks of the DWT are overcome by the complex wavelet transform (CWT) by introducing limited redundancy into the transform. But still it suffer from problem like no perfect reconstruction is possible using CWT decomposition beyond level 1, when input to each level becomes complex. To overcome this, Kingsbury [8] proposed a new transform DT-CWT. The DT-CWT uses a dual tree of real part of wavelet transform instead using complex coefficients. This introduces a limited amount of redundancy and provides perfect reconstruction along with providing the other advantages of complex wavelets. The DT-CWT is implemented using separable transforms and by combining subband signals appropriately. Even though 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 Fig. 1. Thus far, the dual tree does not appear to be a complex transform at all. However, when the outputs from the two trees in Fig. 1 are interpreted as the real and imaginary parts of complex coefficients, the transform effectively becomes complex. DT-CWT has six directions ($+15^0$, -15^0, $+45^0$, -45^0, $+75^0$, -75^0,) as shown in Figure 2.

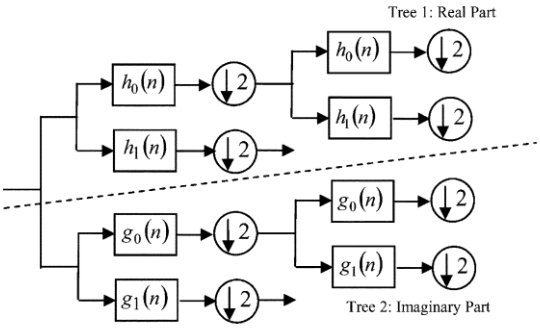

Fig. 1. The 1-D dual-tree complex wavelets transform.

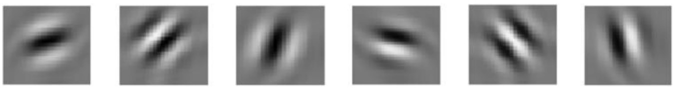

Fig. 2. Impulse response of six wavelet filters of DT-CWT.

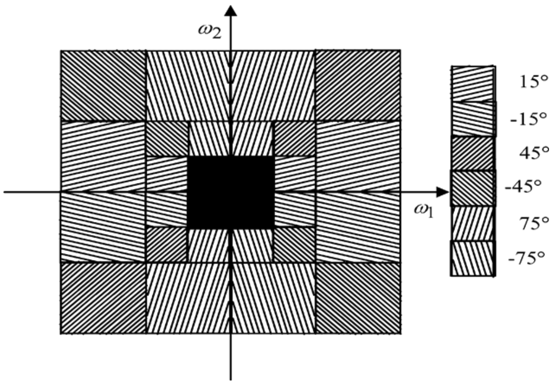

Fig. 3. Two levels Frequency-domain partition resulting from complex wavelet transform decomposition.

IV. DIRECTIONAL ROTATED COMPLEX WAVELET FILTERS

Edge information is very important in characterizing texture properties. In the texture retrieval application, in many cases, characterization of specific directional information of an image improves retrieval performance. Some of the important developments in the recent wavelet research have been the implementation of 2-D multiscale transforms that represent edges more efficiently than does the standard real wavelet transform. Examples include curvelets[9], directional filter banks and pyramids [10], complex wavelet filters [11],the steerable pyramids [12], rotated wavelet filter [13] and the complex dual- tree wavelet transforms. These transforms give superior results for image processing applications compared to the standard real wavelet transform. In this paper, we design the new set of 2-D-rotated complex wavelet filters which are 2D-RCWFs nonseparable and give complementary information to the DT-CWT by making use of its orientation selectivity. For designingdirectional2-DRCWF,first we obtain the directional 2-D complex wavelet filters and then those filters are rotated by 45^0.

A. RCWF

Directional 2-D RCWF is obtained by rotating the directional 2-D 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)*(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 with 2-D RCWFs followed by 2-D down sampling operations. The computational complexity associated with the CRWF decomposition is the same as that of standard 2-D CWT, if both are implemented in the 2-D frequency domain. The set of RCWF's retains the orthogonality property. The six subbands of the 2D DT RCWT gives information strongly oriented at (-30^0, 0^0, $+30^0$, $+60^0$, $+90^0$, $+120^0$)

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, as can be seen in Figure 4.

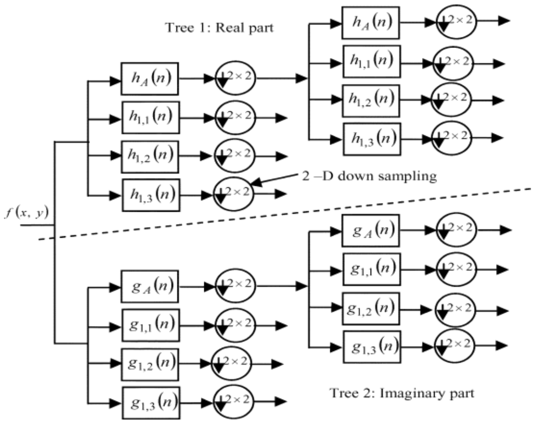

Fig.4. The 2-D Dual Tree – Rotated Complex Wavelets Filter.

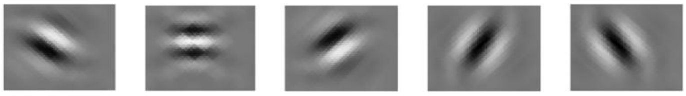

Fig.5. Impulse response of six Rotated Complex Wavelet Filters.

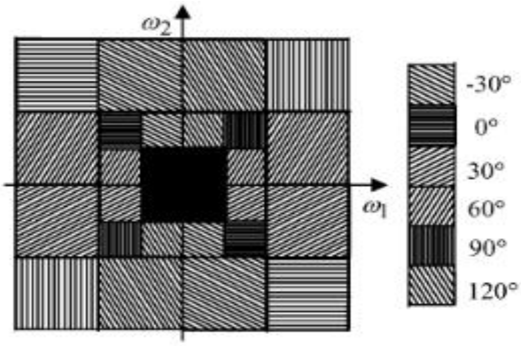

Fig.7. Two levels Frequency-domain partition resulting from RCWF decomposition.

B. The Directional Selectivity with RCWF and DT-CWT

The two dimensional, rotated complex wavelet filters and dual-tree complex wavelet transform allow us to distinguish between a feature oriented at an angle α and one oriented at angle -α. For example, the DT-CWT has separate subbands for features at $\pm15^0$whereas the real wavelets transform lumps these into one "horizontal" subband (see Figs. 2). An edge in an image at 15^0causes the DT-CWT coefficients in the "$+15^0$"subband to be large, while an edge at -15^0 causes the DT-CWT coefficients in the "-15^0" subband to be large. In contrast, both of these edges would cause the real coefficients in the "0^0" (horizontal) subband of the DWT to be large. Similarly RCWF has separate subbands for features at 30^0 and 60^0 (see fig.5) whereas the real wavelet transform lumps this information into $\pm45^0$ subband. Thus, the 2-D DT-CWT and RCWF provide us with greater directional selectivity in the direction {($+15^0$, $+45^0$, $+75^0$, -15^0, -45^0, -75^0), (0^0, $+30^0$, $+60^0$, $+90^0$, $+120^0$, -30^0)} than the DWT whose directional selectivity is in only three directions {0^0, $\pm45^0$, 90^0}. By providing explicit information about orientations at a broader range, the RCWF and DT-CWT allow us to distinguish between and characterize images that are different in more subtle ways.

V. Experiments And discussion

To check the retrieval efficiency of proposed method we have used following texture database in our experiment and results are presented separately.

A. Texture Image Database

The texture database D used in our experiment consists of 500 different textures images from Corel image database. These 500 images are categorized into 5 different classes. These categories are African, Beach, Monument, Bus and Dinosaur. Each category consists of 100 images.

Retrieval results such as average retrieval accuracy, retrieval time, and retrieval accuracy as a function of number of the top images considered, and the retrieval example obtained from the two sets of experiments are given below.

B. Average Retrieval Accuracy

Table I Accuracy comparison between base and proposed approach

Category	Base DWT, Gabor WT	Proposed DT-RCWF+DT-CWT
	Accuracy %	
African	25	81.25
Beach	25	87.50
Monument	31.25	81.25
Bus	25	87.50
Dinosaur	25	87.50

Table II Precision and Recall comparison between base and proposed approach

Category	Base DWT, Gabor WT		Proposed DT-RCWF+DT-CWT	
	Precision %	Recall %	Precision %	Recall %
African	80	25	86.66	81.25
Beach	80	25	93.33	87.50
Monument	80	25	86.66	81.25
Bus	80	25	93.33	87.50
Dinosaur	80	25	93.33	87.50

Tables I and II provides a detailed comparison of average retrieval accuracy, precision and recall for given database. Table I gives detailed comparison of retrieval accuracy obtained using standard real DWT, Gabor WT, and combination of DT-RCWF and DT-CWT. Table II gives detailed precision and recall comparison between base and proposed approach obtained using standard real DWT, Gabor WT, and combination of DT-RCWF and DT-CWT. Following are the main observations.

1. Feature sets, set1 and set2 derived using [12], perform better on databases
2. Our proposed method (combination of DT-CWT and DT- RCWF) outperforms other existing methods. Retrieval performance is improved compared with standard real DWT-based approach. This is because the DT-RCWF provides complementary texture information to the DT-CWT by making use of its orientation selectivity. Also, combination of DT-RCWF and DT-CWT based features are more expressive in characterizing textures than the DWT-based ones.

C. Retrieval Time

Experimental result shows retrieval time for query image using proposed method is 0.08 second which is very less than that using Gabor wavelets based method having 0.146 second. In terms of feature extraction time for query image, the Gabor wavelet is most expensive. Proposed method also retains comparable levels of computational complexity. Feature extraction time for query image using proposed method is 3 times less than that using Gabor wavelets based method.

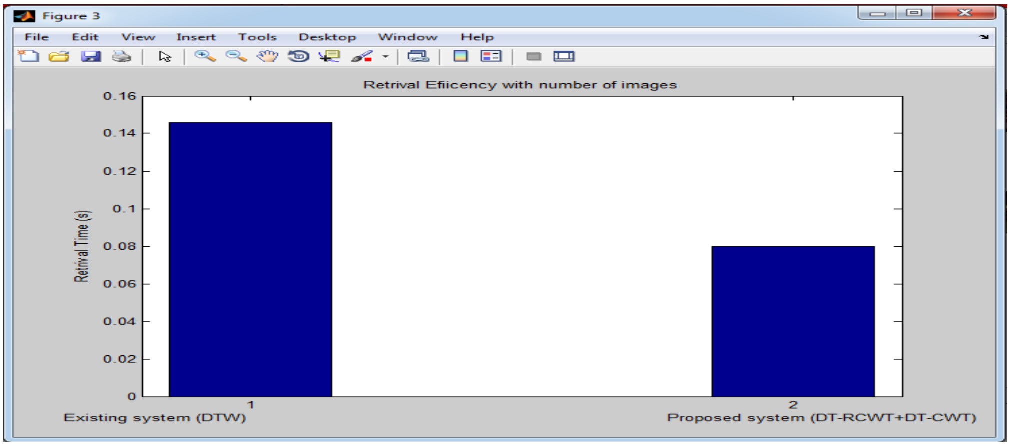

Fig. 8 Average retrieval rate of database according to number of top relevant images considered.

D. Retrieval Effectiveness

Following [6], we evaluated the performance in terms of the average rate of retrieving relevant images as a function of the number of top retrieved images. Fig.9. shows a graph illustrating this comparison according to the number of top matches considered for database. From Fig.9 it is clear that the new method is superior to standard real DWT and Gabor wavelet based method. The proposed method always outperforms the earlier methods. This consistency is also seen in Fig. 9, when experiments are conducted on image database having different texture.

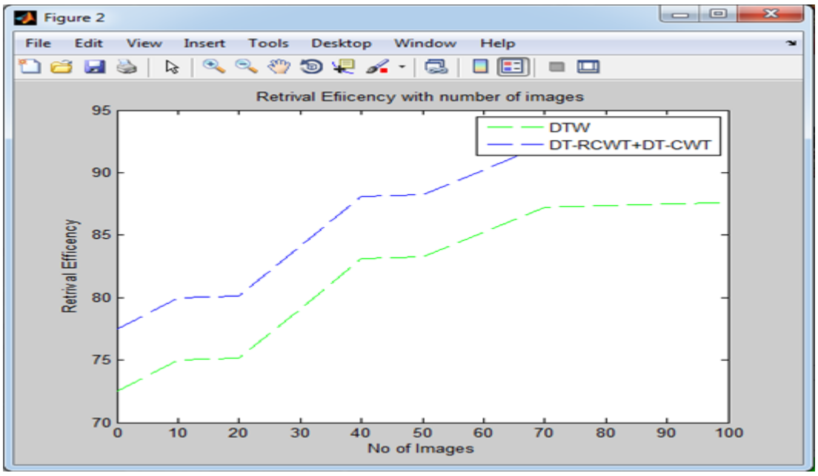

Fig. 9 Average retrieval efficiency of database according to number of top images considered.

E. Image Retrieval Example

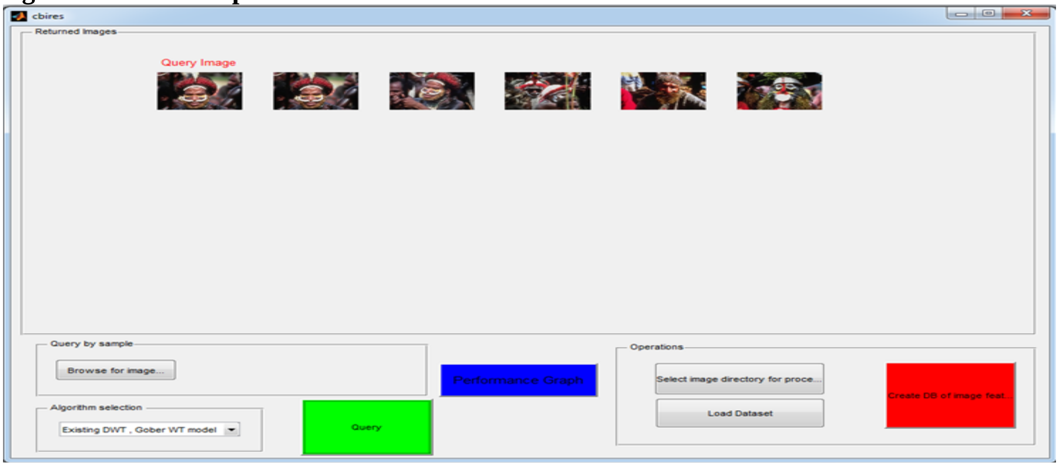

Fig. 10 (a) Retrieval of images from database of African category using real DWT, Gabor Wavelet

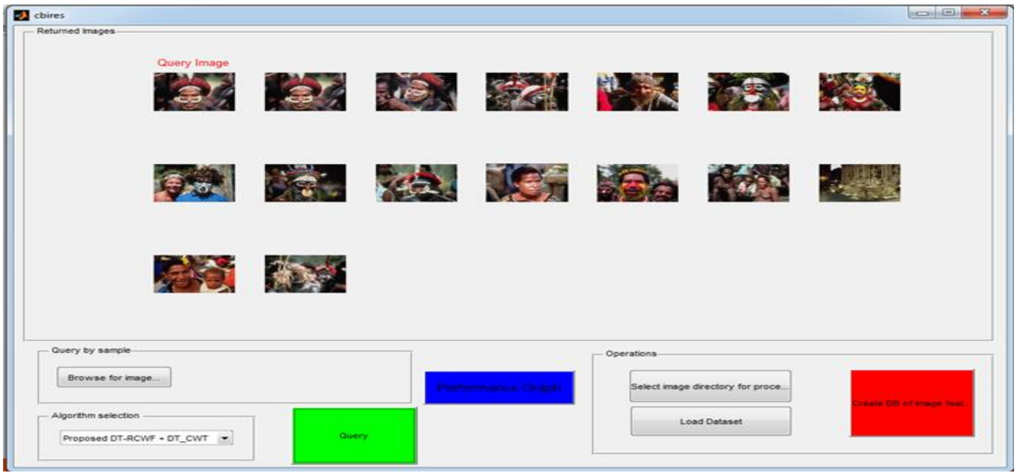

Fig. 10 (b) Retrieval of images from database of African category using DT-RCWF+DT-CWT

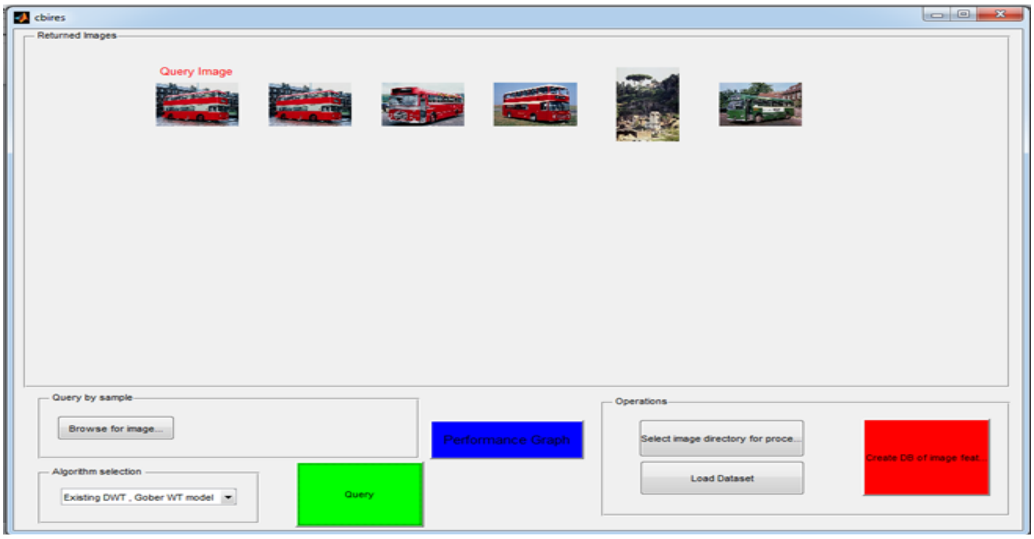

Fig.11.9.4 (a) Retrieval of images from database of Bus category using real DWT, Gabor Wavelet

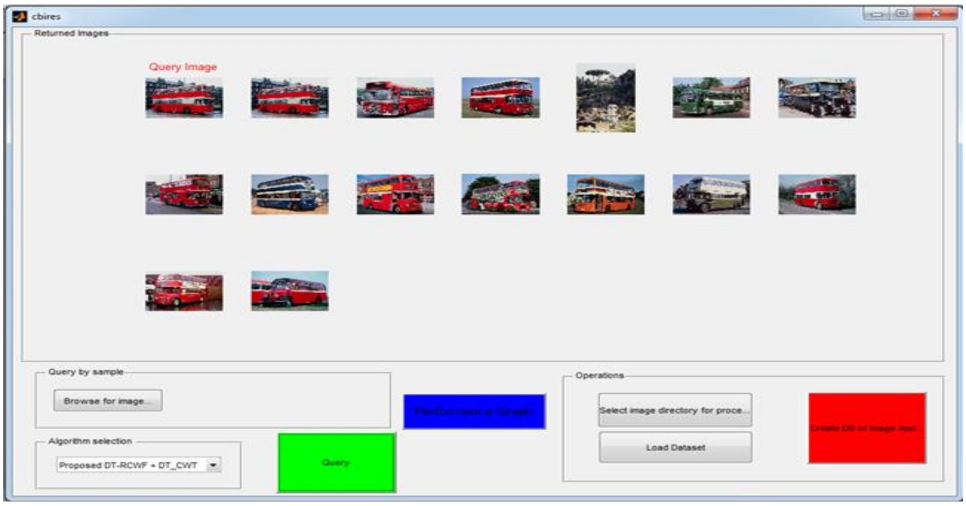

Fig.11(b) Retrieval of images from database of Bus category using DT-RCWF+DT-CWT

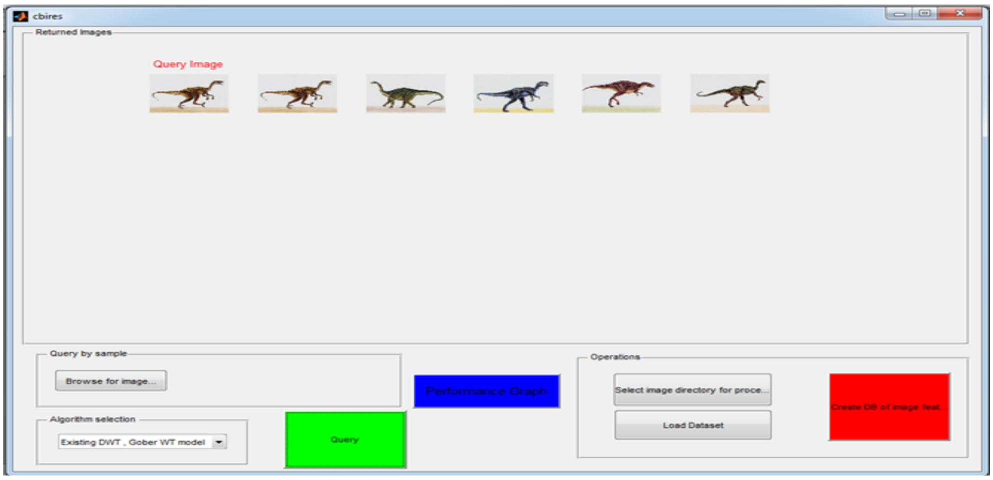

Fig. 12.9.5 (a) Retrieval of images from database of Dinosaur category using real DWT, Gabor Wavelet

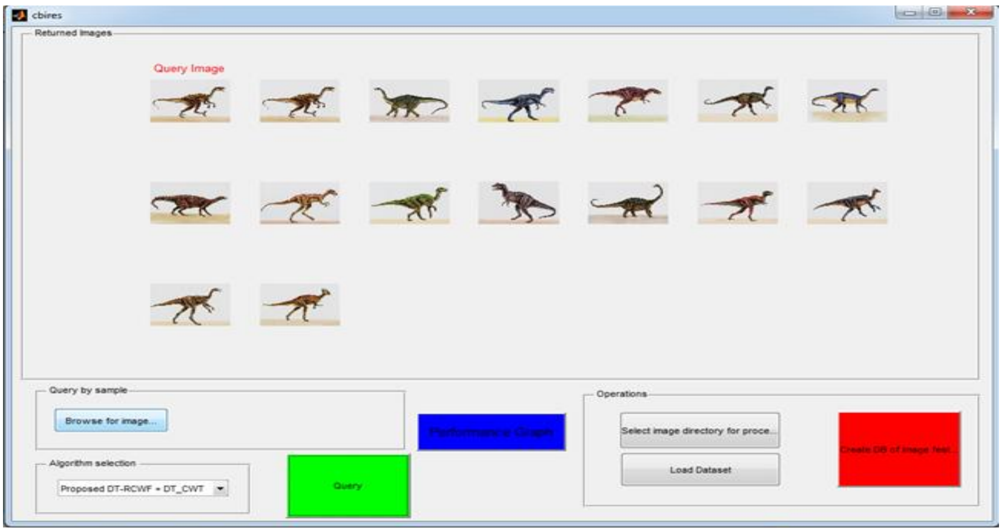

Fig. 12 (b) Retrieval of images from database of dinosaur category using DT-RCWF+DT-CWT

Three retrieval examples from different texture category of database are shown in Figs. 10, 11 and 12 respectively. Fig. 10 shows retrieval example of texture image number 38 (African texture) from database D, which is directional and oriented texture. In this example, DT-RCWF+ DT-CWT based texture image retrieval is shown together with the results given by the real DWT and the Gabor wavelet. Images are displayed from top left to right in increasing order of distance from query image.

An example shown in Fig. 10 demonstrates the superior qualitative and quantitative performance of the DT-RWCF + DT-CWT features. There are 16 ground-truth images of each class in the database. In Fig. 10(a) shows that though among 16 top matches, 4 (25%) out of 16 ground truth images of the same class are retrieved using DWT based features, but fails to find other similar images and retrieves perceptually very different images from the query image in top 16. In Fig. 10(b), the new method retrieves perceptually very similar images in top 16, and also there are 13 (81.25%) ground-truth images of that class in top 16. Fig. 10 shows retrieval example of African texture image from database D, which is complex texture and difficult to describe. All these thee retrieval example also demonstrates the superior qualitative and quantitative performance of the DT-RWCF+ DT-CWT features over the other features. Retrieval accuracy of African, bus and dinosaur category examples is 81.25%, 87.50%, and 87.50% respectively by using DT-RCWF +DT-CWT, which is superior improved compared with 25%, 25% and 25% of Gabor wavelet-based features, respectively.

VI. CONCLUSION

The texture database D used in our experiment consists of 500 different textures images from Corel image database. These 500 images are categorized into 5 different classes. These categories are African, Beach, Monument, Bus and Dinosaur. Each category consists of 100 images.

We have introduced new 2-D rotated complex wavelet filters. The 2-D RCWFs are non-separable and oriented, which improves characterization of oriented textures. Decomposing image with dual-tree complex wavelet transforms and dual-tree rotated complex wavelet filters jointly captures orientation information in 12 different directions. Texture image retrieval application is presented using the new 2-D dual-tree rotated complex wavelet filters and dual-tree complex wavelet transform jointly. Experimental results on database D consisting of 500 texture images are categorized into 5 different classes indicates that our method significantly improves retrieval performance by considering African, bus and dinosaur category examples is 81.25%, 87.50%, and 87.50% respectively by using DT-RCWF +DT-CWT, compared with from 25%, 25% and 25% of traditional approach of Gabor wavelet-based features, respectively.

The results of our proposed method were also compared with previous reported methods on corresponding databases and our proposed method was found to perform better than those existing methods. Proposed texture image retrieval method has twofold advantages over Gabor wavelet based approach. First, the retrieval accuracy is more, and secondly the computational complexity is 3.3 times less than Gabor wavelet-based approach. These are important requirement for online application. Additionally the proposed method is shift invariant, which it inherits from DT-CWT.

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