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# MEDICAL IMAGE RETRIEVAL USING ROTATED COMPLEX WAVELET FILTERS WITH HARALICK TEXTURE FEATURES

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**ABSTRACT**

In this paper, a set of two-dimensional (2-D) rotated complex wavelet filters (RCWFs) are designed with coefficients complex wavelet filter, which gives texture information strongly oriented in six different directions. The 2-D RCWFs are non-separable and improve characterization of oriented textures. Most of the texture image retrieval systems are struggle providing retrieval result with high retrieval accuracy and less computational complexity of retrieval. To address this problem, we propose an approach for texture image retrieval by using a set of dual-tree rotated complex wavelet filter (DT-RCWF) and dual-tree-complex wavelet transform (DT-CWT) jointly by using Haralick Texture Features are obtains in 12 different directions. In decomposed image the features are obtained on each subband. Our proposed method results improves retrieval rate (85%) when comparing with other existing methods and traditional discrete wavelet transform based approaches.

**Keywords:** CBIR, dual tree- complex wavelet transform, Dual tree-rotated complex wavelet filters, haralick texture features.

## 1. INTRODUCTION

Image retrieval system is a computer system for browsing, searching and retrieving images from a large database of digital images. The image retrieval can be classified into two types. They are content based retrieval (CBIR) and text based image retrieval (TBIR). Content-based image retrieval (CBIR), also known as query by image content(QBIC) and content-based visual information retrieval (CBVIR) is the application of computer vision techniques to the image retrieval problem, that is, the problem of searching for digital images in large databases. "Content-based" means to analyzes the contents of the image rather than the metadata such as keywords, tags, or similes associated with the image. The term "content" in this context might refer to colors, shapes, textures, or any other information that can be derived from the image itself. Text-based image retrieval uses traditional database techniques to manage images. Through text descriptions, images can be organized by topical or semantic hierarchies. However, since automatically generating descriptive texts for a wide spectrum of images is not feasible, most text-based image retrieval systems require manual annotation of images. Most of the systems use CBIR systems. The CBIR systems use low-level image features such as color, texture, shape, edge, etc., for image indexing and retrieval.

In CBIR, texture feature is due to its presence in many real world images: for example, clouds, trees, bricks, hair, fabric etc., earlier methods [4], [10] 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 summarized as follows.

1) Design of two-dimensional (2-D) rotated complex wavelet filters to efficiently handle texture images. The design yields texture features oriented in 12 different directions.
2) Formulation of new texture-retrieval algorithm using the proposed filters.

In [6] *et al.* modified wavelet transform called the tree-structured wavelet transform or wavelet packets for texture analysis and classification. The transform, we are able to zoom into any desired frequency channels for further decomposition. In contrast, the conventional pyramid structured wavelet transform performs further decomposition only in low frequency channels. They develop a progressive texture classification algorithm which is not only computationally attractive but also has excellent performance. In other sections we present design and implementation of 2-D rotated complex wavelet filters. The texture image retrieval application using DT-RCWF and DT-CWT with HTF using intuitionistic fuzzy set is proposed.

## 2. WAVELET TRANSFORM

In mathematics, a wavelet series is a representation of a square-integrable (real-or complex-valued) function by a certain orthonormal series generated by a wavelet. Nowadays, wavelet transformation is one of the most popular candidates of the time-frequency-transformations. This article provides a formal, mathematical definition of an orthonormal wavelet and of the integral wavelet transform. The integral wavelet transform is the integral transform defined as

$$[W\varphi f](a,b) = \frac{1}{\sqrt{|a|}}\int_{-\infty}^{\infty} \varphi\left(\frac{x-b}{a}\right) f(x)dx$$

The wavelet coefficients are then given by

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$C_{jk} = [W_\varphi f](2^{-j}, k2^{-j})$

**Continuous wavelet transform**

The continuous wavelet transform (CWT) uses inner products to measure the similarity between a signal and an analyzing function. In the Fourier transform, the analyzing functions are complex exponentials, $e^{j\omega t}$. The resulting transform is a function of a single variable, ω. In the short-time Fourier transform, the analyzing functions are windowed complex exponentials, $w(t)e^{j\omega t}$, and the result in a function of two variables. The STFT coefficients, $F(\omega,\tau)$, represent the match between the signal and a sinusoid with angular frequency ω in an interval of a specified length centered at τ. In the CWT, the analyzing function is a wavelet, ψ. The CWT compares the signal to shifted and compressed or stretched versions of a wavelet. Stretching or compressing a function is collectively referred to as *dilation* or *scaling* and corresponds to the physical notion of *scale*. By comparing the signal to the wavelet at various scales and positions, you obtain a function of two variables. The two-dimensional representation of a one-dimensional signal is redundant. If the wavelet is complex-valued, the CWT is a complex-valued function of scale and position. If the signal is real-valued, the CWT is a real-valued function of scale and position. For a scale parameter, a>0, and position, *b*, the CWT is:

$$C(a,b;f(t),\psi(t)) = \int_{-\infty}^{\infty} f(t)\frac{1}{\sqrt{a}}\psi^*\left(\frac{t-b}{a}\right)dt$$

where ∗ denotes the complex conjugate. Not only do the values of scale and position affect the CWT coefficients, the choice of wavelet also affects the values of the coefficients.

**Discrete wavelet transform**

In numerical analysis and functional analysis, a discrete wavelet transform (DWT) is any wavelet transform for which the wavelets are discretely sampled. As with other wavelet transforms, a key advantage it has over Fourier transforms is temporal resolution: it captures both frequency and location information (location in time).

**Dualtree- complex wavelet transform (DT-CWT)**

The Dual Tree-Complex Wavelet Transform is a relatively recent enhancement to the discrete wavelet transform (DWT), with important additional properties: It is nearly shift invariant and directionally selective in two and higher dimensions. It achieves this with a redundancy factor of only substantially lower than the undecimated DWT. The multidimensional (M-D) dual tree-complex wavelet transform is nonseparable but is based on a computationally efficient, separable filter bank (FB).

## 3. PROPOSED METHOD

RCWF sets provide important complementary information to the DT-CWT filter set by extracting texture features in 6 different directions which are 45Â° apart from decomposition directions of DT-CWT. To make usual segmentation via the Fuzzy c-means (FCM) using the Mean Shift Algorithm. The proposed technique is analised on a range of textured images including composite texture images, artificial texture images as well as real scene images. Directional 2D RCWF are obtained by rotating the directional 2D DT-CWT filters by $45^0$ so that decomposition is performed along new direction, which are apart from decomposition $45^0$ directions of CWT. The size of a filter is (2N-1)X(2N-1), where N is the length of the 1-D filter. The decomposition of input image with 2-D RCWF followed by 2-D down sampling operation is performed up to the desired level. The computational complexity related with RCWF decomposition is the same as that of standard 2-D CWT, if both are implemented in the 2-D frequency domain. The set of RCWFs retains the orthogonal property. The six sub bands of 2D DT-RCWF gives information strongly oriented at ($-30^0$, $0^0$, $30^0$, $60^0$, $90^0$, $120^0$).

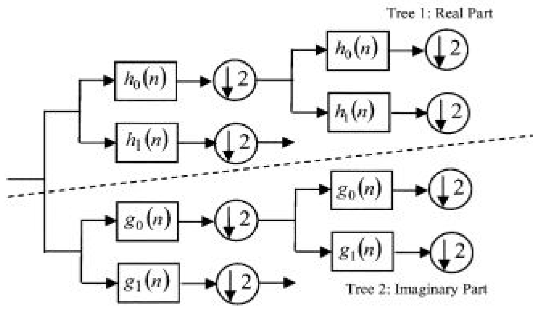


**Figure-1.** Dimensional dual tree complex wavelet transform.

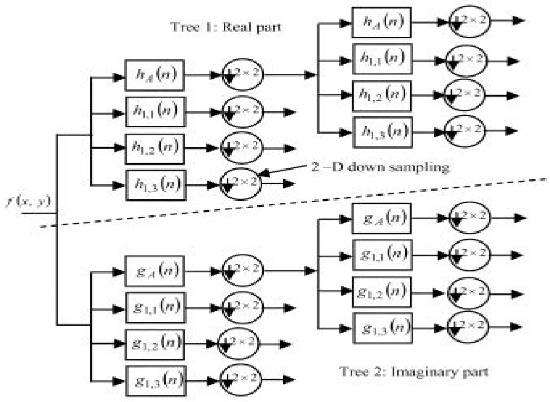


**Figure-2.** Dimensional dual tree complex wavelet transform.

We design the new set of 2-D-rotated complex wavelet filters. 2-D-RCWFs are nonseparable and give complementary information to the DT-CWT by making use of its orientation selectivity. For designing 2-D directional RCWF, first we get the 2-D directional complex wavelet filters and then those filters are rotated by 45. Kokare and Biswas *et al*. 2005 have used rotated discrete wavelet filters that are obtained by rotating the standard 2D-DWT filters (RWF). Computational complexity is same as that of the standard 2D-DWT filters decomposition, if both are implemented in 2D frequency domain. The methods to design the 2D rotated wavelet filters are shown in below,

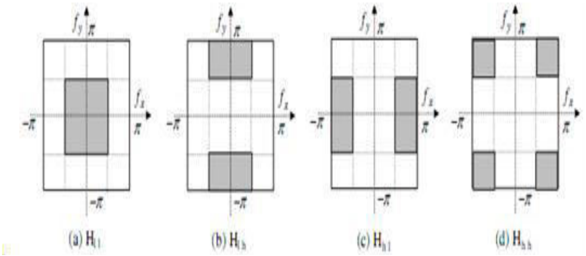

**Figure-3.** Frequency domain partition resulting from the one level DWT decomposition.

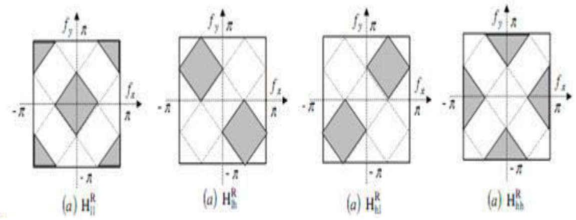

**Figure-4.** Frequency domain partition resulting from the one level RWT decomposition.

The haralick texture features, the basis for these features is the gray level co-occurrence matrix. This matrix is square matrix with dimension $N_g$, where $N_g$ denoted as number of gray levels in the image. Element [*i*,*j*] of the matrix is generated by counting the number of times a pixel with value *i* is adjacent to a pixel with value *j* and then dividing the entire matrix by the total number of such comparisons made. Each entry is considered to be the probability that a pixel with value *i* will be found adjacent to a pixel of value *j*.

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$$G = \begin{bmatrix} p(1,1) & p(1,2) & \cdots & p(1,N_g) \\ \vdots & & \ddots & \vdots \\ p(N_g,1) & p(N_g,2) & \cdots & p(N_g,N_g) \end{bmatrix}$$

Since adjacency can be defined to occur in each of four directions in a 2D, square pixel image (horizontal, vertical, left and right diagonals), above four such matrices are calculated.

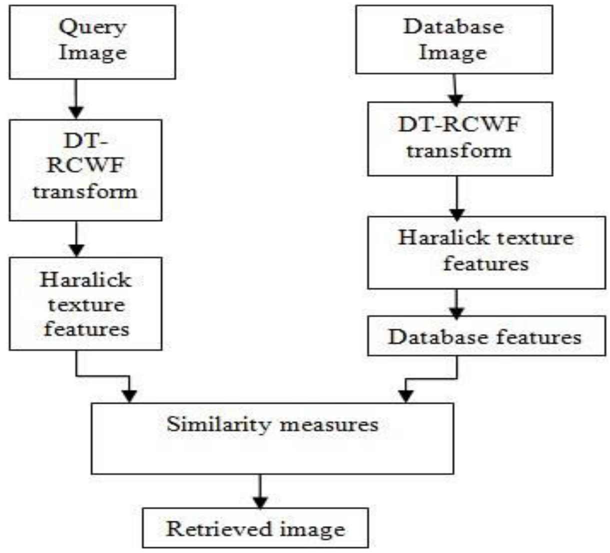


**Figure-5.** Block diagram of image retrieval using DT-RCWF.

## 4. RETRIEVAL ALGORITHM

This section verifies the performance of the proposed approach using rotated complex wavelet filters with HTF using MD. The greatest retrieval rate is obtained by using this proposed method. To realize the performance of the proposed method, the four sample images are taken from a set of brain, breast, bones and phantom images. In database, it contains only 100 images. Each image can be decomposed using wavelet transform. Apply the HTF (Entropy, Energy, Variance, Standard deviation, Correlation) in each subband of decompose image.

**Algorithm for feature extraction and similarity matching database image feature extraction**

i=1
While i ≤ 100
Do Wavelet Decomposition
Extract Haralick Texture Features
(Energy, Entropy, Variance, standard deviation, Correlation)
accumulate Data
Inc i
End

**Steps for query image feature extraction**

Obtain Input
Do Wavelet Decomposition
Extract Haralick Texture Features
(Energy, Entropy, Variance, standard deviation, Correlation)

**Distance measure**

While i ≤ 100
Energy distance = Mahalanobis (Energy Q, Energy of database images)
Entropy distance = Mahalanobis (Entropy Q, Entropy of database images)
Variance distance = Mahalanobis (Variance Q, Variance of database images)

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Standard deviation distance = Mahalanobis (Standard deviation Q, Standard deviation of database images)
Correlation distance = Mahalanobis (Correlation Q, Correlation of database images)

Sort Ascending order of combined Energy, Entropy, Variance, Standard deviation, Correlation

## 5. PERFORMANCE EVALUATION

Better retrieval rate has been obtained by using the proposed method. In order to study the performance of the proposed method, the four sample images have been taken from a set of MRI images. The top hundred retrieved images for the MRI breast database images are considered for validating the performance of the proposed technique. The top twenty retrieved images for MRI breast categories are depicted in Figure. Table shows comparison of the retrieval efficiency of the proposed approaches with the existing approach like GMM with KLD (Kullback-Leibler Distance), Wavelet+PCA+HTF with MD, wavelet+PCA with MD.

Retrieval efficiency defined in terms of precision and recall is expressed in equation. If the number of images retrieved is lower than or equal to the number of relevant images, this value is the retrieval efficiency (precision), otherwise it is the retrieval efficiency (recall) of a query.

$$\text{Retrieval Efficiency} \quad (\text{Precision}) = \frac{\text{No.of relevant} \quad \text{images} \quad \text{retrieved}}{\text{Total} \quad \text{No.of} \quad \text{images} \quad \text{retrieved}} \tag{1}$$

$$\text{Retrieval Efficiency} \quad (\text{Recall}) = \frac{\text{No.of relevant} \quad \text{images} \quad \text{retrieved}}{\text{Total} \quad \text{No.of} \quad \text{relevant} \quad \text{images}} \tag{2}$$

The average retrieval efficiency of our proposed method gives 85% whereas existing methods gives accuracy of 81%, 80.5% and 77%. The obtained retrieval results using wavelet and PCA with HTF produces good retrieval rate when compare to the existing approaches.

**Table-1.** Comparison of the proposed methods retrieval efficiency with existing methods.

| Approach | Proposed methods | Existing methods | | |
|---|---|---|---|---|
| | Rotated Wavelet filters HTF+MD | Wavelet+PCA+HTF+MD | Wavelet+PCA+MD | GMM+ KLD |
| Retrieval Efficiency (%) | 85% | 81% | 80.5% | 77% |

## 6. SIMULATION RESULTS

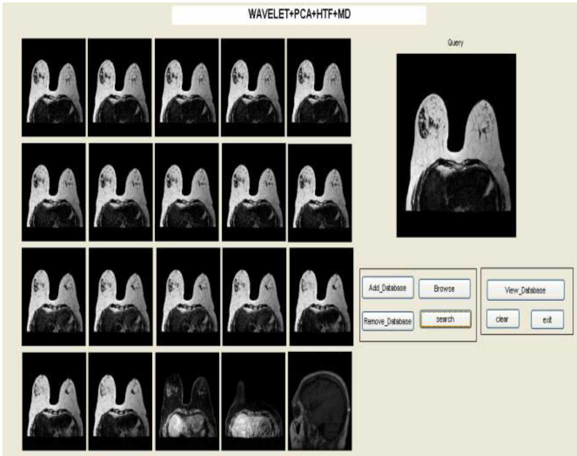


**Figure-6.** Simulation result of MRI image retrieval.

**Table-2.** Comparison of the average precision for the proposed methods with existing methods for top hundred matches.

| No. of Top images considered | Average precision for Proposed Approaches | Average precision for Existing Approaches (%) | | |
|---|---|---|---|---|
| | Rotated complex Wavelet filters+ HTF + MD | Wavelet+ PCA+HTF +MD | Wavelet+ PCA+MD | GMM +KLD |
| 10 | 1 | 1 | 1 | 1 |
| 20 | 0.96 | 0.93 | 0.90 | 0.89 |
| 30 | 0.91 | 0.89 | 0.88 | 0.84 |
| 40 | 0.87 | 0.83 | 0.81 | 0.79 |
| 50 | 0.86 | 0.80 | 0.75 | 0.73 |
| 60 | 0.84 | 0.78 | 0.74 | 0.71 |
| 70 | 0.78 | 0.77 | 0.70 | 0.70 |
| 80 | 0.72 | 0.68 | 0.67 | 0.65 |
| 90 | 0.66 | 0.64 | 0.62 | 0.60 |
| 100 | 0.65 | 0.60 | 0.61 | 0.59 |

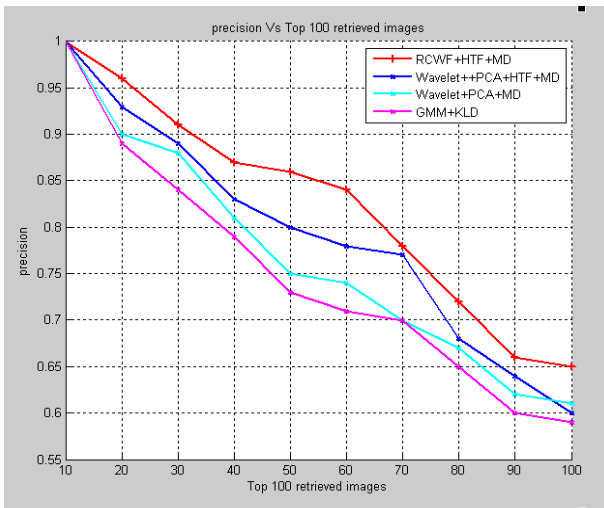


**Figure-7.** Average precision of MRI DB for various proposed and existing methods.

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**Table-3.** Comparison of the average recall for the proposed methods with existing methods for top hundred matches.

| No. of Top images considered | Average recall for Proposed Approaches | Average recall for Existing Approaches (%) | | |
|---|---|---|---|---|
| | Rotated complex Wavelet filters+ HTF + MD | Wavelet+ PCA+HTF +MD | Wavelet+ PCA+MD | GMM +KLD |
| 10 | 80 | 77 | 74 | 71 |
| 20 | 82 | 78 | 75.6 | 73 |
| 30 | 83 | 78.8 | 77 | 76 |
| 40 | 84 | 79.4 | 78.2 | 76.2 |
| 50 | 84.4 | 79.8 | 78.6 | 76.9 |
| 60 | 84.6 | 80 | 79 | 77 |
| 70 | 85 | 80.6 | 79.2 | 77.4 |
| 80 | 85.3 | 81.4 | 79.8 | 77.8 |
| 90 | 85.6 | 81.8 | 80 | 78 |
| 100 | 87 | 82 | 81 | 79 |

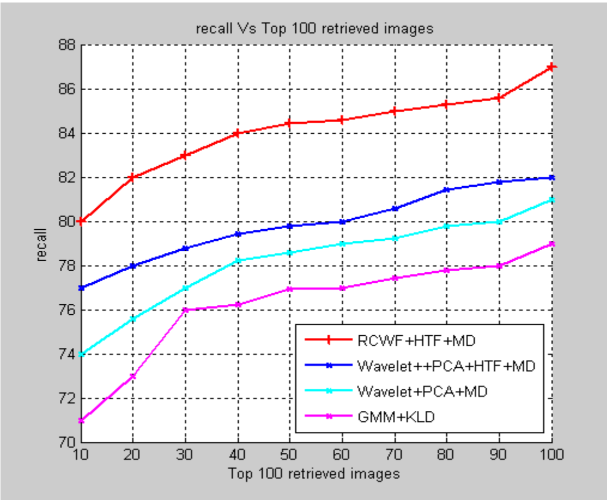


**Figure-8.** Average recall of MRI DB for various proposed and existing methods.

## 7. CONCLUSIONS

The results of our proposed method were compared with other previous reported. Our proposed method was found to perform better than those existing methods. In this project texture image retrieval method has the retrieval accuracy is more, and the computational complexity is less. It can improve the retrieval rate from 81% to 85%. In terms of feature extraction time for query image, the GMM and KLD are most expensive. Proposed method also retains comparable levels of computational complexity compared with existing methods.

Further research could be carried out on extending the proposed method to other pattern recognition applications. Furthermore, robust isotropic rotation invariant texture feature can be obtained easily with proposed method for characterizing textures in rotation invariant applications. One can extend proposed method easily to obtain rotation, translation, and scale invariance in pattern recognition usage. In this paper, we processed the retrieval on the database, it contains only the minimum number of images. In future it can be applied to many number of database images.

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