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Research Paper

MEDICAL IMAGE RETRIEVAL USING TEXTURE FEATURES BY DISCRETE WAVELET TRANSFORM AND ROTATED COMPLEX WAVELET TRANSFORM

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In this work, efficient medical image retrieval is made possible by using texture features. The texture features used are discrete wavelet transform and rotated complex wavelet transform. The discrete wavelet transform uses Haar wavelet. The reason is, because of its easy computation. A two dimensional (2-D) Rotated wavelet are designed with complex wavelet filter coefficients, which gives texture information strongly oriented in six different directions (45° apart from complex wavelet transform). This texture image retrieval system is capable of providing retrieval result with high retrieval accuracy and less computational complexity. Proposed a novel approach for texture image retrieval by using two approaches, one by using Discrete Wavelet Transform (DWT) and second by a set of Dual-Tree Rotated Complex Wavelet Filter (DT-RCWF). The information provided by DT-RCWF and DWT were analyzed in detail. Features are obtained by computing the energy on each sub band of the decomposed image. To check the retrieval performance, Texture database is created using images like ultrasound, CT and MRI of 600 images. The algorithm of DWT and RCWF was applied on these databases and their performances were evaluated. The retrieval rate of DWT outperforms RCWF. RCWF shows less retrieval rate in precision and recall values as 60%and 30% comparing while traditional discrete wavelet transform based approach with 80% and 70% while retrieving the medical image. The proposed method also retains comparable levels of computational complexity.

Keywords: Medical image retrieval, Discrete wavelet transform, Rotated complex wavelet transform, Texture features

INTRODUCTION

The use of medical imaging, particularly CT and MR imaging, has scored in the last several decade. With increased scrutiny of the costs of medical care, imaging has been highlighted as an area of particular growth and cost.

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Though further primary data collection is critical for defining the scope of incidental findings and understanding current practice patterns related to their workup, resource requirement for identifying the long term costs, risks and benefits of incidental findings are percussively high in most settings. The combined approach of primary data collection and economic modeling of our transform based retrieval has the potential to yield.

Advances in computerized tomography technology have revolutionized the non invasive imaging technology evolution. They provide faster acquisition time increased anatomic coverage, and decreased need for sedation. When one, endeavors to device an appropriate imaging algorithm for the investigation; three key factors have to be considered. First the imaging modalities should be as quick and accurate as possible. Second the result of this test should positively direct pattern management and help dictate treatment. The third factor is nature of investigation tools should not have any negative effect on health, or at least, that effect should be minimized. The natural inclination would be to immediately use the most accurate and sensitive test. Some of the imaging strategies used is chest radiography, echocardiography vascular ultrasound, esophagography, MRI-MRA, CTA, catheter angiography or a combination thereof may be performed for diagnostics evaluation. The incidental findings on radiographic studies will help us in diagnosis. Discovery of such findings with cross-sectional imaging believed to be beneficial by leading to early detection of subclinical disease and probably for better outcomes. An incidentally discovered mass of lesions, detected by CT, MRI or other imaging modality for clinical treatment with intervention in image processing provides us an excellent result.

With traditional radiology screening techniques, visually analyzing medical images is laborious, time consuming, expensive and each individual scan is prone to interpretation error. Additionally, visual analysis of radiographic images is subjective; one rater may choose a particular lesion as a candidate, while another radiologist may find this lesion as insignificant. Consequently, some lesions are being missed or misinterpreted. To reduce reanalyze the images after the physician). Such methods are advantageous not only because they are cost effective, but also because they are designed to objectively quantify pathology in a robust, reliable and reproductive manner.

Content Based Image Retrieval (CBIR) technology has been proposed for the management of increasing large image collection, to aid clinical care, biomedical research, and education. Based on the literature we conclude that there is wide spread enthusiasm for CBIR in the engineering research community. But the application of this technology for solving practical medical problems is yet to be realized. CBIR exploits the visual content in image data. It is proposed to benefit the management of increasingly large biomedical image collections as well as to aid clinical medicine, research and education. It is used to index images based on the characteristics of their visual content, to retrieve images by their similarity to characteristics. Application of CBIR depends on intensity, color, texture, shape, size, location or a combination of these. Sketching a cartoon, selecting an example image, or a combination of both methods, is typically used to form query. The retrieved results are usually rank-ordered by some criteria, other methods, such as clustering of similar images, have been used to organize the result as well. In CBIR, images are indexed by its own visual contents, such as color, texture, and shape. 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. Application of CBIR depend on many different techniques and technologies applied at several stages in the indexing and the retrieval area, such as image segmentation and feature extraction, feature indexing and database method; image similarity computation methods; pattern recognition and machine learning methods; image compression and networking for image storage and data transmission. On growth of large medical image databases, the traditional keywords based method to retrieve a particular image becomes inefficient and suffers from the following limitations, it is difficult to express visual content like color, texture, shape, and object within the image precisely, for a large dataset, it requires more skilled labor and need very large, sophisticated keyword systems. Further, the keywords increase linguistic barrier to share image data globally. To overcome several of these limitations, Content-Based Image Retrieval (CBIR) approach has emerged as a promising alternative. CBIR is very active research topic in recent years.

For example the CT appearance of a variety of splenic lesions overlaps considerably, when a splenic lesion is detected on CT, it often cannot be characterized completely without basic clinical correlation. High quality evidence regarding the burden of imaging-detected incidental findings in a wide spectrum of clinical and patient scenarios. Equipped with such information, clinicians and will be able to make better decision about the appropriateness of imaging procedure in future healthcare practices. It is difficult to express visual; content like color, texture, shape and object within the image precisely. For a large dataset, need very large, sophisticated keyword systems. Keywords increases linguistic barrier to share image data globally. The novelty and the main contribution of this paper are design and formulation of new texture- retrieval algorithm using the proposed method. The main contributions and novelty of this paper are summarized as follows; design of two-dimensional (2-D) Discrete wavelet transform and (2-D) rotated complex wavelet filters to efficiently handle texture images.

TEXTURE BASED IMAGE RETRIEVAL

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, Teager filters, Pyramid-structured wavelet transform, and tree structured wavelet transform. 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.

Discrete Wavelet Transform

The Discrete Wavelet Transform (DWT) is gaining momentum as a feature extraction and/or classification tool, because of its ability to localize structures with good resolution in a computationally effective manner4. The result is a unique and discriminatory representation, where important and interesting structures (edge, details) are quantified efficiently by few coefficients. These coefficients may be used for feature themselves, or features may be computed from the wavelet domain that describes the needs in the data. DWT is gaining momentum as a feature extraction and/or clarification tool, since its ability to localize structures with good resolution in a computationally effective manner. And it offers a multi resolution representation, by decomposing the image using various scale frequency resolutions, which is achieved by changing the size of the window. The wavelet transform utilizes both wavelet []r and scaling []k functions. The wavelet function is used to localize the high frequency content, whereas scaling function to examine low frequency. In order to perform the wavelet transforms for discrete images, implementation of DWT using filter bank is widely used. Haar transforms is the wavelet consisting of square shaped functions. It transforms signals from the space domain to a local frequency domain. A Haar wavelet decomposes an image using both low-pass filtering and high-pass filtering, working first on image columns and then on image rows.

For a Haar wavelet

$$h_\phi = [h_\phi(0), h_\phi(1-0)] = h_\phi(1) = \left[\frac{1}{\sqrt{2}}, \frac{1}{\sqrt{2}}\right] \quad ...(1)$$

Then,

$$h_\phi(0) = (-1)^\circ [h_\phi(1-0)] = h_\phi(1) = \frac{1}{\sqrt{2}} \quad ...(2)$$

$$h_\phi(1) = (-1)^1 [h_\phi(1-1)] = -h_\phi(1) = \frac{1}{\sqrt{2}} \quad ...(3)$$

Wavelet function ϕ(x) can be described as

$$\psi(x) = \begin{cases} 1 & 0 \le x \le \frac{1}{2} \\ -1 & \frac{1}{2} < x < 1 \\ 0 & elsewhere \end{cases} \quad ...(4)$$

Scaling function $\phi(x)$ can be described as:

$$\phi(x) = \begin{cases} 1 & 0 \le x \le \frac{1}{2} \\ 0 & elsewhere \end{cases} \quad ...(5)$$

Haar transforms decomposes signal in to an average (approximation) component and a detail (fluctuation) component. A signal with 2^n sample values, the first average sub signal a^1 (a_1, a_2, …..,$a_{n/2}$) for a signal length of N is given as follows

$$a = \frac{y_{2n-1} - y_{2n}}{\sqrt{2}} \quad n = 1, 2, ... \quad ...(6)$$

And the first detail sub signal

$$d = \left(d_1 d_2 d_3 \ldots \ldots \ldots \ldots d_{\frac{N}{2}}\right) \text{ is given as:}$$

$$d_n = \frac{y_{2n-1} - y_{2n}}{\sqrt{2}} \quad n = 1, 2, ... \quad ...(7)$$

The transform is applied to all rows of the matrix, the approximation part of each row transform is arranged in the first column and the corresponding detail parts in the last n columns. The matrix by dimension (number of rows/2) $\times$ (number of columns/2) as shown in the matrix. The matrix is classified as *A* the approximation area, *H* is the horizontal area, *V* is the vertical area and *D* is the diagonal area.

$$M = \begin{pmatrix} x_{11} & x_{12} & x_{13} & x_{14} \\ x_{21} & x_{22} & x_{23} & x_{24} \\ x_{31} & x_{32} & x_{33} & x_{34} \\ x_{41} & x_{42} & x_{43} & x_{44} \end{pmatrix} \quad ...(8)$$

$$A = \begin{pmatrix} x_{11} & x_{12} \\ x_{21} & x_{22} \end{pmatrix} \quad ...(9)$$

The classification is performed by using the mean as a measure and Euclidean as a distance metrics.

Rotated Complex Wavelet Transform

RCWFs that are obtained by rotating nonseparable wavelet filters obtained using (11)-(14) by 45° so that the decomposition is performed along the new direction, 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 with 2-D RCWFs followed by 2-D down sampling operations as illustrated in Figure 2. 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. The set of RCWFs retains the orthogonality property. These rotated complex wavelets are strongly oriented in six direction and when image is decomposed using RCWF, which captures image information in those directions. If, then the same derivation can be used to implement an oriented nonseparable 2-D wavelet transform by combining the subbands of two separable 2-D DWTs. The scaling and directional complex wavelets are obtained by defining a 2-D separable wavelet basis via the following equations. Where $\Phi_h(x)$ and $\Phi_g(x)$ are both real-valued wavelets. The real valued scaling function $\Phi_h(x)$ and the real valued wavelet $\Phi_h(x)$ associated with the pair are defined implicitly by the following pair of equations:

$$\psi_g(x) = H\{\psi_h(x)\psi_h(y)\} \quad ...(10)$$

$$\phi_1(x, y) = \phi_h(x)\ \phi_h(y)$$

$$\phi_2(x, y) = \phi_g(x)\ \phi_g(y) \quad ...(11)$$

$$\psi_{1,1}(x, y) = \psi^{+15°}(x, y) = \phi_h(x)\ \phi_h(y)$$

$$\psi_{2,1}(x, y) = \psi^{-15°}(x, y) = \phi_g(x)\ \phi_g(y) \quad ...(12)$$

$$\psi_{2,2}(x, y) = \psi^{+75°}(x, y) = \phi_h(x)\ \phi_h(y)$$

$$\psi_{2,2}(x, y) = \psi^{-75°}(x, y) = \phi_g(x)\ \phi_g(y) \quad ...(13)$$

$$\psi_{1,3}(x, y) = \psi^{+45°}(x, y) = \phi_h(x)\ \phi_h(y)$$

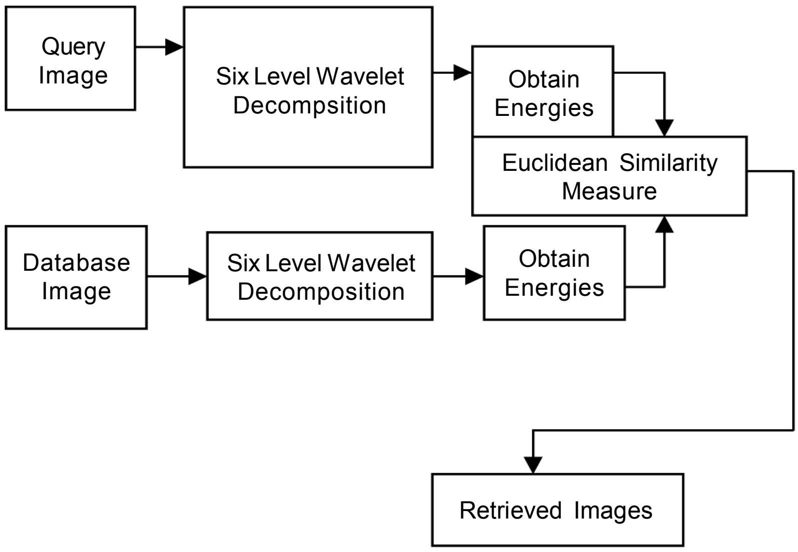
$$\psi_{2,3}(x, y) = \psi^{-45°}(x, y) = \phi_g(x)\ \phi_g(y) \quad ...(14)$$

These rotated complex wavelets are strongly oriented in {–30°, 0°, 30°, 60°, 90°,120°}. The classification is performed by using the mean and standard deviation on. Complex sub images.

METHODOLOGY

The first approach for medical image retrieval using texture features by discrete wavelet transform. The first approach using Haar

Figure 1: Haar Wavelet Based Image Retrieval



wavelet based medical image retrieval. The steps followed by taking Discrete Wavelet Transform (DWT) and then applying Haar wavelet, then proceeded by computing total energy at sub bands and finding the energy level differences for dissimilarity computation. Figure 1. Shows the block of Haar wavelet based image retrieval (Manesh *et al.*, 2005).

Algorithm for Haar wavelet based retrieval:

- Read the query image.
- Decompose the image for six level decomposition.
- Obtain energies.
- Repeat the above steps for databases.
- Find the Euclidean distance between database and query image and energy as a measure.
- Sort the results in descending order.

Finally the relevant images similar to the query image were obtained in descending order.

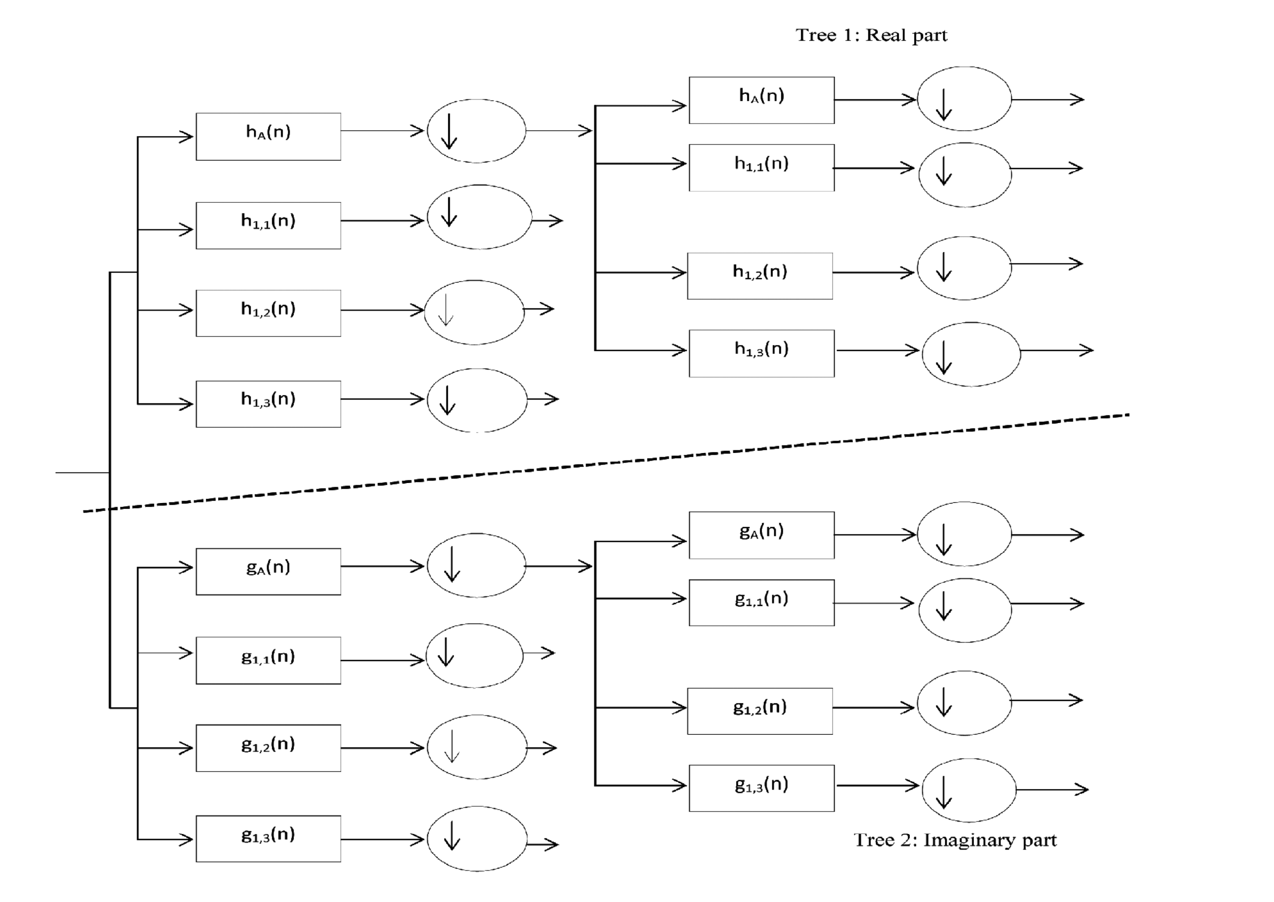
$$\text{Energy } E = \Sigma_X \Sigma_Y P(x, y)^2 \qquad ...(15)$$

Energy is a gray-scale image texture measure of homogeneity changing, reflecting the distribution of image gray-scale uniformity of weight and texture. $P(x, y)$ is the gray-level value at the coordinate (x, y) .

The second approach for medical image retrieval using texture features by rotated complex wavelet transform. The classification algorithm is as follows. Figure 2 shows the one level decomposition of input image with dual-tree 2-DRCWFs.

- Find the first, L sub images of the decomposed texture pattern with largest averaged energy values.
- Find the means and standard deviations of these sub images and form the feature vector including $2L$ complex feature element.
- For another texture pattern in the database, form its feature vector computing energy of its sub images corresponding to the same

Figure 2: Two Level Decomposition of Input Image with 2-D RCWFs



channels with the first pattern. If the corresponding sub image is not found in the decomposition that texture pattern is not included in the list.

- Compute the normalized Euclidian distance between the feature vectors.
- 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.

Algorithm for RCWF based retrieval:

- Read the query image.
- Decompose the image
- Obtain energies.
- Repeat the above steps for databases.
- Find the Euclidean distance between database and query image and energy as a measure.
- Sort the results in descending order.

IMPLEMENTATION

This technique can be implemented using MATLAB software. Similarity measure is to retrieve images. Here Euclidean similarity measure is implemented. CBIR system ranks similarity in descending order and then returns relevant images that are most similar to the query images. The direct Euclidean distance between an image *p* and query image *q* can be given as follows,

$$\sqrt{\sum \left(V_{pi} - V_{qi}\right)^2} \quad ...(16)$$

The direct Euclidean distance between a database image *p* and query image *q* is given in Mallat (1989),

Experimental Results and Performance Measure

In the above, different distance measurements with measures for retrieval of medical images have been described and discussed. In order to determine which distance measurement is most suitable for medical image retrieval, the retrieval accuracy and precision of different distance measurements are tested.

Retrieval Performance

The evaluation of the retrieval performance is carried out subjectively by selecting only the image containing straight forward obvious content. In other words, if there is any subjective ambiguity on what the retrieval result should be for a particular image, that sample is simply discarded from the database. Therefore the experimental results described in the section depend only on the decisive subjective evaluation. For the analytical notion of performance along with the subjective evaluation, We used the traditional precision(*p*) – recall(*R*) value performance.

Table 1: Comparison of Precision and Recall Values for DWT and RCWF

Images in the Database	Discrete Wavelet Transform	Rotated Transform	Complex	Wavelet
	Precision (%)	Recall (%)	Precision (%)	Recall (%)
Image 1	60	30	80	70
Image 2	60	30	80	70
Image 3	58	29	65	55
Image 4	57	29	80	70
Image 5	60	30	80	70

Table 2: Comparison of Relevant and Irrelevant Images for DWT and RCWF

Images in the Database	Discrete Wavelet Transform	Rotated Transform	Complex	Wavelet
	Number of Relevant Images	Number of Irrelevant Images	Number of Relevant Images	Number of Irrelevant Images
Image 1	6	4	9	1
Image 2	7	3	9	1
Image 3	7	3	8	2
Image 4	8	2	9	1
Image 5	6	4	9	1

Figure 3: Retrieved Medical Images Using RCWF for MRI, CT Images

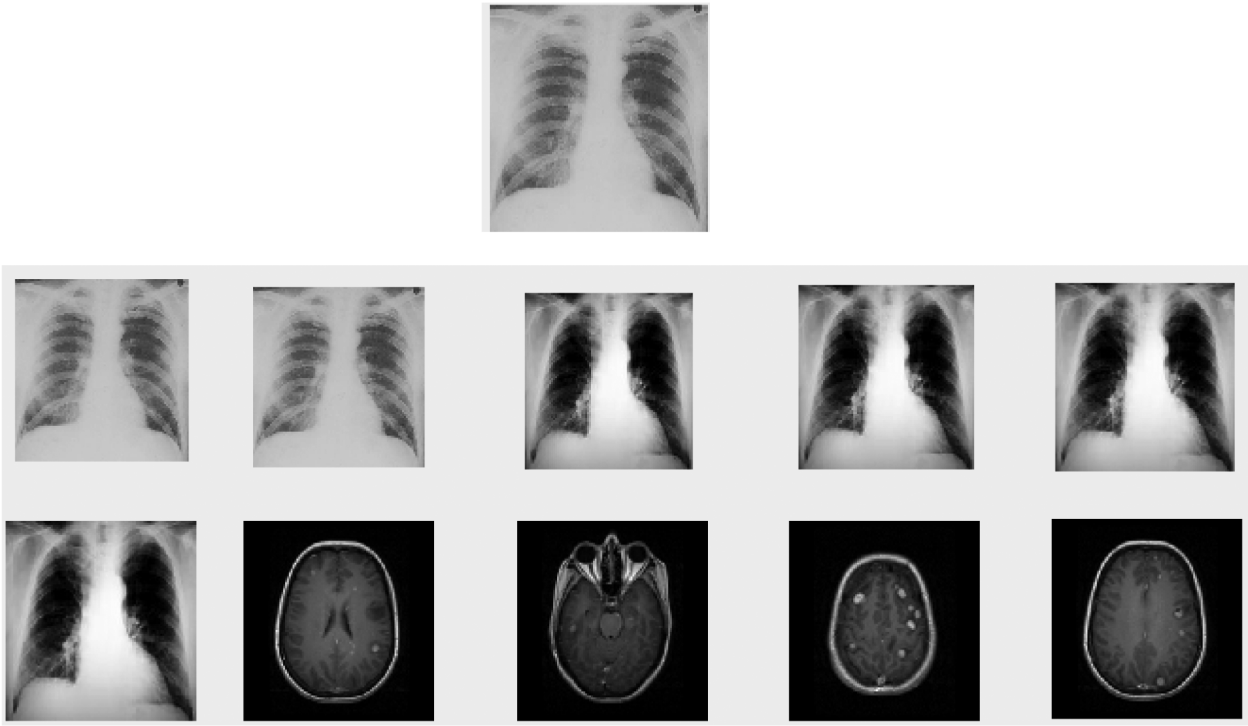


Figure 4: Retrieved Medical Images Using RCWF for Ultrasound Images

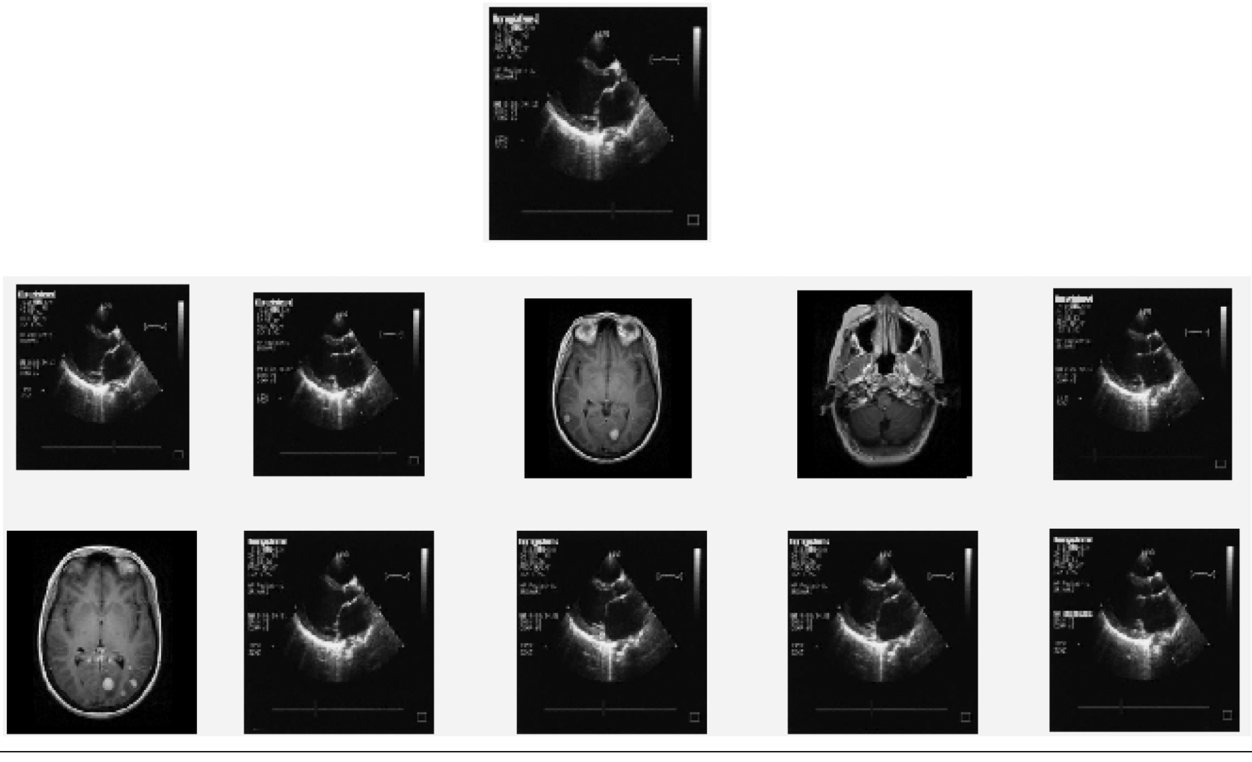


Figure 5: Retrieved Medical Images Using DWT for MRI, CT Images

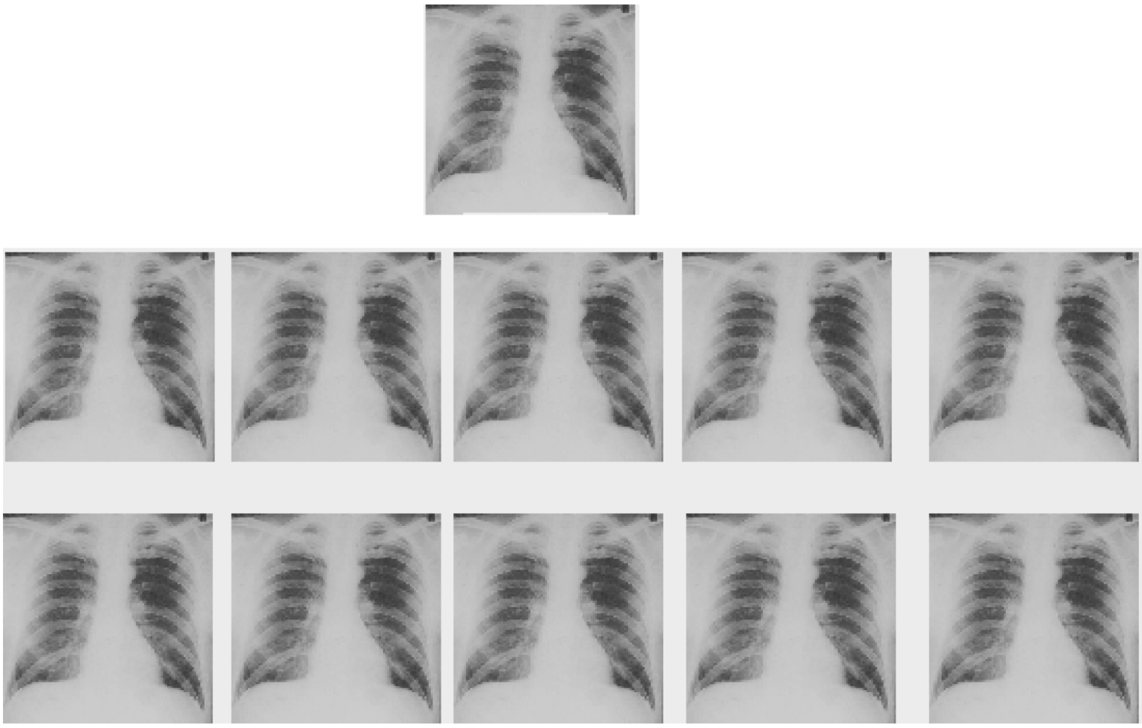


Figure 6: Retrieved Medical Images Using DWT for Ultrasound Images

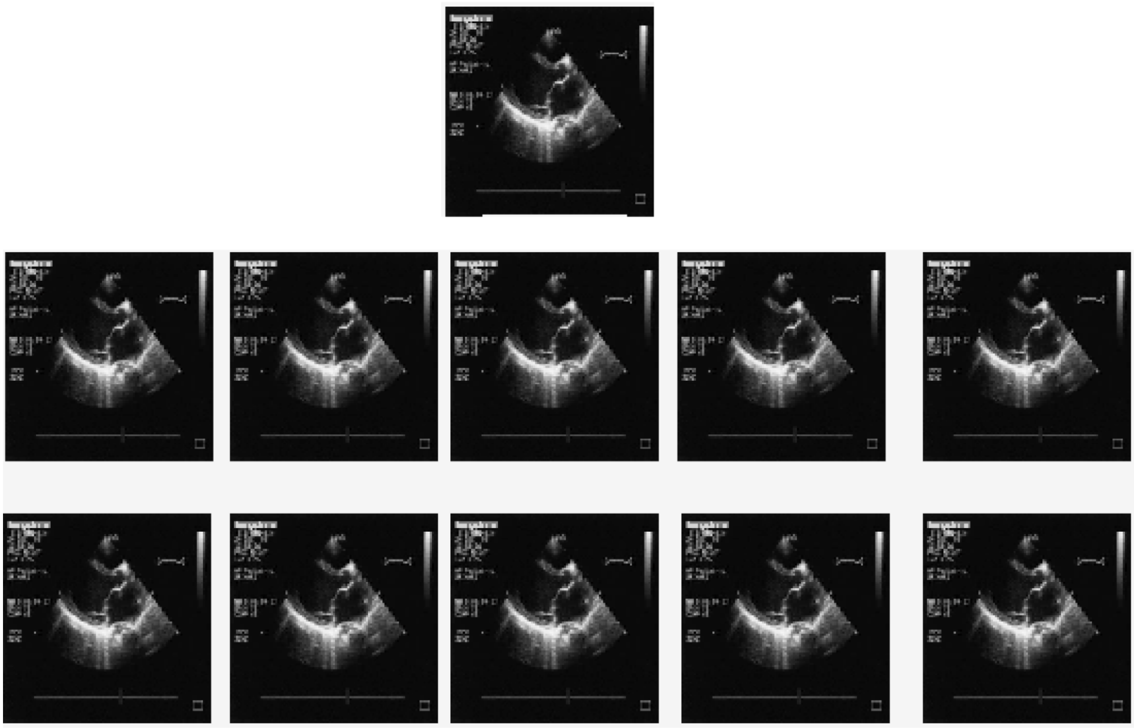


Table 1 shows the Comparison of Precision and Recall values for DWT and RCWF. Table 2 shows Comparison of relevant and irrelevant images for DWT and RCWF.

$$P = \frac{Number\ of\ relevant\ items\ retrieved\ (i.e.,\ correct\ matches)}{Total\ number\ of\ relevant\ items} \quad ...(17)$$

And

$$R = \frac{Number\ of\ relevant\ items\ retrieved\ (i.e.,\ correct\ matches)\ in\ the\ database}{Total\ number\ of\ items\ (relevant + irrelevant)} \quad ...(18)$$

Figure 3 shows Retrieved medical images using RCWF for MRI, CT images. Figure 4 shows Retrieved medical images using RCWF for ultrasound images. Figure 5 shows Retrieved medical images using DWT for MRI, CT images. Figure 6 shows Retrieved medical images using DWT for Ultrasound images. From the calculation of retrieval performance it is clear that, DWT outperforms RCWF. But usually other than for medical images, RCWF outperforms others. Here it is practically proved that DWT s percentage of retrieved images is accurate with high precision and Recall values. The images in the database considered are CT, MRI and ultrasound. MRI and CT retrieval rate is similar both for DWT and RCWF. But, for ultrasound images, there is slight deviation in the retrieval rate. Overall performance, it is concluded that DWT outperforms RCWF in medical image retrieval.

CONCLUSION

In this paper, an image representation method that enables efficient texture feature extraction from the encoded data is introduced. Since the amount of image data that is stored in image databases is increasing rapidly, the data should be represented so that both effective compression and easy retrieval can be performed. The 2-D RCWFs are nonseparable 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 2-D dual-tree rotated complex wavelet filters and dual-tree complex wavelet transform jointly. Experimental results on database. indicates that the retrieval rate of DWT outperforms RCWF. RCWF shows less retrieval rate in precision and recall values as 60% and 30% comparing with traditional discrete wavelet transform based approach with 80% and 70% while retrieving the medical image. It is very well concluded that DWT outperforms RCWF in retrieval of medical images with precision rate of 80% and recall value of 70%.

The results of our proposed method were also compared with previous reported methods on corresponding databases. Our proposed method was found to perform better than those existing methods. Further research could be carried out on extending the proposed method to other pattern recognition applications, lesion detection. 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 application, lesion and tumor detections.

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