Applied Medical Informatics
Original Research Vol. 32, No. 2 /2013, pp: 54-66

Medical Image Retrieval using Transforms

Swarnambiga AYYACHAMY [1,*], Mannivannan VASUKI [2]

[1] SACS MAVMM Engineering College, Madurai, Tamilnadu, India.
[2] Velammal College Of Engineering &Technology, Viraganoor, Madurai-09, Tamilnadu, India.
E-mails: aswarnambiga@gmail.com (*); hello_vasuki@yahoo.co.in

* Author to whom correspondence should be addressed; Tel.: 0452-4522522098;

Received: 30 March 2013 / Accepted: 6 June 2013 / Published online: 6 June 2013

Abstract
The purpose of this study is to access the stability of transformation methods for medical image analysis. The reason for image retrieval is due to the increase in acquisition of images. Imaging has occupied a huge role in the management of patients, whether hospitalized or not. Depending upon the patient's clinical problem, a variety of imaging modalities were available for use. In this article various distance methods were used and then they are compared for effective medical image retrieval. A transform based approach is followed for effective retrieval. This paper describes discrete Fourier transforms (DFT), discrete cosine transforms (DCT), discrete wavelet transforms (DWT), complex wavelet transforms (CWT) and rotated complex wavelet transform filter (RCWF) for medical image retrieval. From the final results it is very clear that each transforms performance defers and shows different results in retrieval of medical images. DWT shows the best results in terms of average retrieval results with 95% precision and 83% recall value, average searching time with 8 seconds, and less number of irrelevant images. These results indicate that these easily computable similarity distance measures have a wide variety of medical image retrieval applications.

Keywords: Distance metrics; CBMIR; Measures; Imaging modality; Retrieval performance.

Introduction

Up to our knowledge transforms based retrieval is widely applied for medical images. Content based image retrieval, is a technique that uses visual content to search images from large scale image databases. CBIR uses the visual content of an image and this visual content of the images in the database are extracted and described by multidimensional feature vectors.They are color, texture, shape and spatial layout to represent and index the image. Then, the system changes these samples into its internal representation of feature vectors. Then the similarities/distance between the feature vectors of the query example or sketch of the images in the database are calculated and retrieval is performed.Content based medical image retrieval (CBMIR) is for medical image interpretation. It consists of three key tasks the first task is perception of image findings and the second task is interpreting the findings for the diagnosis and the third task is recommendation for clinical management, clinical diagnosis, clinical treatment and biopsy.

With traditional radiology screening techniques, visually analyzing medical images is time consuming, expensive, and each individual scan is prone to interpretation error. The visual analysis of radiographic images is subjective; for some physicians and radiologists may choose a particular lesion as a important, while another radiologists may find this lesion is insignificant. Consequently some lesions are being missed or misinterpreted. To reduce the error rates, a secondary opinion may be obtained with a CAD system (automatically reanalyze the images after the physician). These 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 reproducible manner. To this end, this work concerns the development of a generalized computer-aided diagnosis system thatis based on the transforms.

In this paper, transform based medical image retrieval is experimented. This paper is based on the research in CAD system design for specific modalities or applications.To improve the retrieval performance both in terms of retrieval accuracy and retrieval time, a set of transforms were experimented. A detailed comparison with the performance of transforms using texture features is provided. Earlier methods for transform based image retrieval focus on anyone of the transforms up to our knowledge. In this article, we concentrate on discrete Fourier transforms (DFT), discrete cosine transforms (DCT), discrete wavelet transforms (DWT), complex wavelet transforms (CWT), rotated complex wavelet transform filter (RCWF), for efficient retrieval both in terms of accuracy and computational complexity. The main contribution and novelty of this paper are summarized as follows,

1) Design of 2-D transforms to handle medical images efficiently.

2) Formulation of results for transforms based medical image result concluding with best search result.

The purpose of this article is twofold. First, we experiment some of the most promising retrieval strategies currently used in medical imaging. We show that all these techniques may be phrased in terms of a variation problem and allow for a unified treatment. Second, we introduce, with the new framework, retrieval of medical images using transforms.

In this paper a brief overview of the system is presented. Section 2 explains the rationale for using specific transforms and details how they are computed. The results of our run are presented in section 4, followed by a detailed analysis of images in the database. Some of our ideas for our future work are presented with a conclusion.

General System For Transform Based Medical Image Retrieval And Multi-Step Approaches In Image Retrieval For Medical Applications

Before performing retrieval, one has to choose these categories. The database created should also follow these criteria. For different categorization, categories oriented database can be created. Here the database is created by considering the above categories, anatomical regions with 2-D images were considered with monomodal magnetic resonance images .The head, thorax , abdomen, pelvis, perineum , limbs and spine and vertebrae falls under the object category.

The point has to be cleared here is though, the transforms based image retrieval is not new but the way presented here for the medical images and the way how the approach is done is new. The medical images were broadly classified into three main categories. They are based on the imaging modality, anatomical region and based on the body orientation [2]. These categories were considered mainly during scanning. The patient's anatomy, orientation and angle were considered during scanning. These categories play a vital role in CBMIR. Though the database created on specific categories performs well, techniques have to be developed for all categories.

- **Categorization (using global features)**

(I) Image modality (physical)
(II) Anatomic region (anatomical)
(III) Body orientation (technical)

- **Registration (in geometry and contrast)**

A. Dimensionality

Spatial Dimensions only

- 2D/2D
- 2D/3D
- 3D/3D

Time Series

- 2D/2D

- 2D/3D

B. Subject

Intrasubject
Intersubject
Atlas

C. Object

1. Head
    - Brain/Skull
    - Eye
    - Dental
2. Thorax
    - Entire
    - Cardiac
    - Breast
3. Abdomen
    - General
    - Kidney
    - Liver
4. Pelvis and perineum
5. Limbs
    - General
    - Femur
    - Humerus
    - Hand
6. Spine and vertebrae.

- **Feature extraction (using local features)- feature selection (category and query dependent)**
    - Color
    - Texture
    - shape
- **- Identification**
- **- Retrieval**

Refer [9] [10] for the above multistep approaches. In this way categorization is performed using global features , registration by spatial dimension and by using monomodality images, feature extraction using local features and majorly considered here is texture features, feature selection by and identification by subjective and quantitative evaluation [2].In this paper, described a statically optimal and subjectively efficient technique for retrieval of medical image. The results show improved resolution beyond the resolution of the detector offering system designers new tradeoffs in system design.

Cost effective medical image retrieval is proposed. The database needed for retrieval of medical images is created. The method for performing medical image retrieval can be chosen from above classification.

Discrete Fourier Transform

The DFT allows you to efficiently estimate component frequencies in data from a discrete set of value sampled at fixed rate. The sequence of N spatial complex coefficients $x_0,x_1,\ldots\ldots,x_{N-1}$ is transformed in to sequence of N frequency complex coefficients x(0) ,x(1) ,……,x(N-1) by the DFT and is given in the equation (1) given below

$$X(K) = \sum_{N=0}^{N-1} x(n) \exp\frac{(-j2\pi nk)}{N} \qquad (1)$$

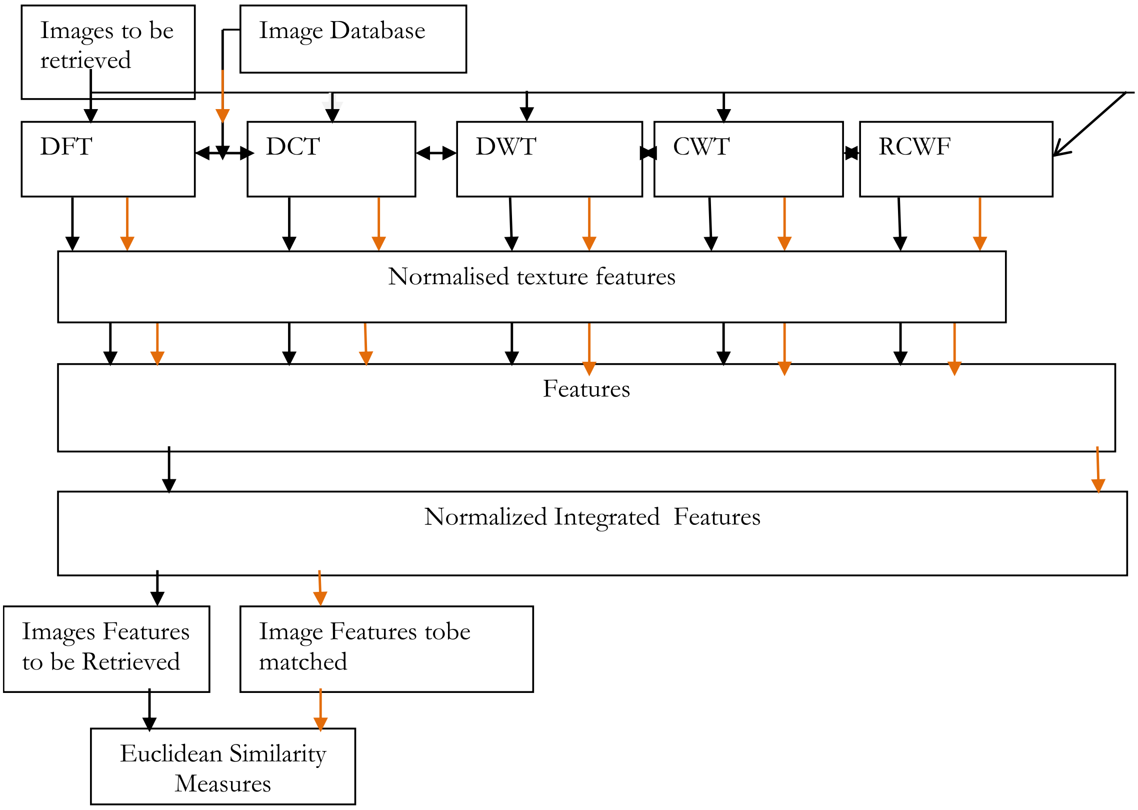


Figure 1. The proposed framework

Discrete Cosine Transform

A Discrete Cosine Transform (DCT) expresses a sequence of finite number of data points in terms of a sum of cosine functions oscillating at different frequencies. The DCT is conceptually similar to DFT. The below equation is the more commonly used form, and is often simply referred as DCT. This transform is exactly equivalent (up to an overall scale factor of 2) to a DFT of 4N real inputs of even symmetry where the even – indexed elements are zero. That is, it is half of the DFT of the 4N inputs $y_{in}=0, y_{2N+1}=x_n$for $0<=n< N$, and $y_{4N+1}=y_n$, for $0<n<2N$. Equation (2) defines DCT.

$$X_k = \sum_{n=0}^{N-1} X_n \cos[{}^{\pi}/_{N} (n + {}^{1}/_{2})k] \qquad k = 0 \ldots . N-1 \qquad (2)$$

Discrete Wavelet Transform

The discrete wavelet considered here is Haarwavelet. The Discrete Wavelet Transform (DWT) is used as a feature extraction and/or classification tool. The results achieved using them are unique and edge details are quantified efficiently by few coefficients. These coefficients may be used as feature themselves, or features can be computed from wavelet domain that describes the anomalies in the data.

It offers a multiresolution representation (decompose the image using various scale- frequency resolution), which is achieved by dyadically changing the size of the window. The texture features events could be efficiently represented using a set of multiresolution basis function. The DWT utilizes the critical sub sampling along rows and columns and uses these sub sampled sub bands as the input to the next decomposition level. For a 2D image, this reduces the number of input samples by a factor of four at each level of decomposition. 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 ϕ_r and scaling ϕk 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. 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. The flow of Haarwavelet based medical image retrieval is revealed in Fig. 3.

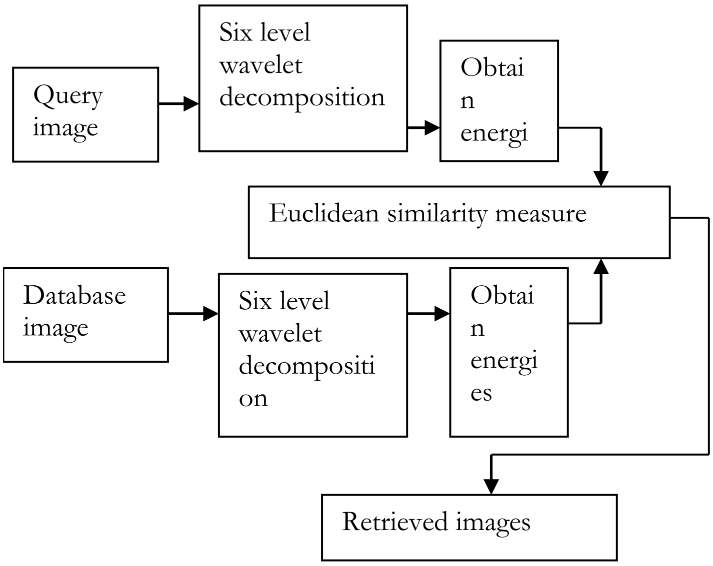


Figure 2. Haar wavelet based image retrieval

For a Haar wavelet, the equation (3)-(7) gives the detail for calculating the scaling function and wavelet function. The equation (8)-(9) gives the detail for calculating sub signal and their details. Then,

$$h_\emptyset \quad = [h_\emptyset(0), h_\emptyset(1-0) = \ h_\emptyset(1) = [\frac{1}{\sqrt{2}} \ , \ \frac{1}{\sqrt{2}} \ ] \tag{3}$$

$$h_\emptyset\,(0) = (-1)^{\circ} \quad [h_\emptyset(1-0)] \ = \ h_\emptyset(1) = \frac{1}{\sqrt{2}} \tag{4}$$

$$h_\emptyset\,(1) = (-1)^1 \quad [h_\emptyset(1-1)] \ = -h_\emptyset(1) = \frac{1}{\sqrt{2}} \tag{5}$$

Wavelet function ϕ (x) can be described as

$$\psi(x) \ = \ \begin{cases} 1 & 0 \le x \le {}^{1}/_{2} \\ -1 & {}^{1}/_{2} < x < 1 \\ 0 & elsewhere \end{cases} \tag{6}$$

Scaling function ϕ (x) can be described as

$$\emptyset(x) \ = \ \begin{cases} 1 & 0 \le x \le 1 \\ 0 & elsewhere \end{cases} \tag{7}$$

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 $(a_1, a_2, \ldots, a_{n/2})$ for a signal length of N is given as follows

$$a = \frac{y_{2n-1} - y_{2n}}{\sqrt{2}} \qquad n = 1,2 \ldots. \tag{8}$$

and the first detail sub signal

$d = (d_1 d_2 d_3 \ldots\ldots\ldots\ldots\ldots\ldots.. \ d_{\frac{N}{2}})$ is given as

$$d_n = \frac{y_{2n-1} - y_{2n}}{\sqrt{2}} \qquad n = 1,2 \ldots \tag{9}$$

Complex Wavelet Transform

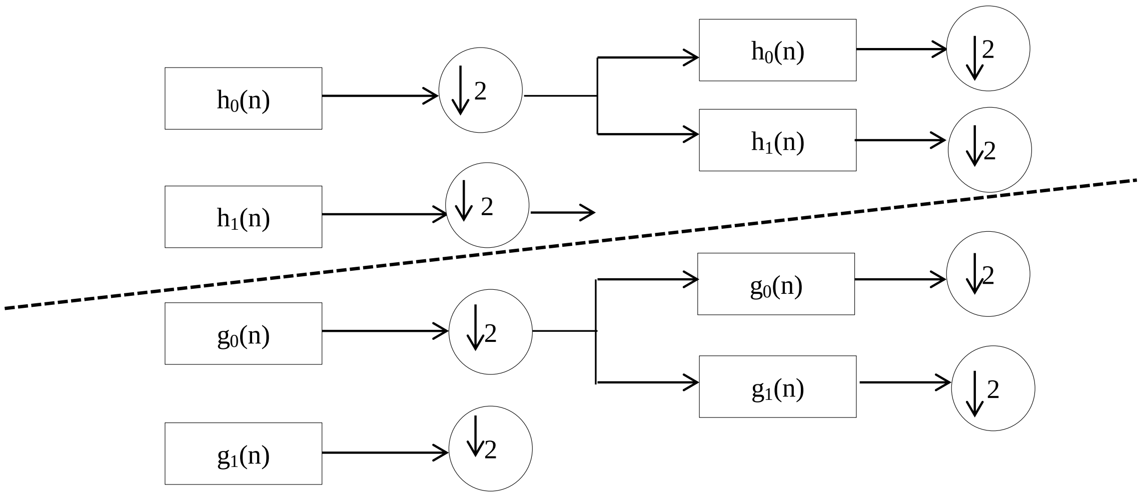
Real DWT has poor directional selectivity and it lack with shift invariance. It is found that both the above problems can be solved effectively using complex wavelet transform (CWT). They provide true directional selectivity with six band pass sub images of complex coefficients which are strongly oriented at 15 °, 45°, 75°. The image texture is represented using the quantized DT- CWT coefficients. The way for calculating DT-CWT by using signal f(x) is shown in equation (10) and scaling function is shown in equation (11). In DT-CWT, to achieve perfect reconstruction and good frequency characteristics, two parallel fully decimated trees with real filter coefficients were used [1]. The 1-D DT-CWT decomposes a signal f(x) in terms of a complex shifted and dilated mother wavelet ψ(x) and scaling function ∅(x).

$$f(x) = \sum_{l \in z} s_{j0,l} \emptyset_{j0,l}(x) + \sum_{j \geq j0} \sum_{l \in z} c_{j,l} \psi_{j,l}(x) \tag{10}$$

where $s_{j0,l}$ is scaling coefficients and $c_{j,l}$ are complex wavelet coefficients with $\emptyset_{j0}$ and $\psi_{j,l}$ complex.

$$\emptyset_{j0} = \emptyset^r_{jo,l} + \sqrt{-1\, \emptyset^i_{j0,l}} \quad , \emptyset_{j0} = \psi^r_{jo,l} + \sqrt{-1\, \psi^i_{j0,l}} \tag{11}$$

Tree 1: Real part



Tree 2: Imaginary part

Figure 3. The 1-D dual tree complex wavelet transforms

The real and imaginary parts of the DT - CWT are computed using separate filter bank structures with wavelet filters $h_0 h_1$ and $g_0 g_1$ for the imaginary part. Fig. 4 . shows the flow of 1-D dual tree complex wavelet transforms. The retrieval of medical iamges using CWT is performed and is depicted in th figure.

The DT-CWT is implemented using separable transforms and by combining sub band signals appropriately. There are six sub bands capturing features along lines at angles of$2\mathrm{D}-\mathrm{DTCWT}$. They are strongly oriented at$\theta = \{+15°, +45°, +75°, -15°, -45°, -75°\}$.

2-D Rotated Complex Wavelet Filters

Characterization of specific directional information of an image is important in the texture based retrieval application.2-D-RCWFs are nonseparable and give complementary information to the DT-CWT by making use of its orientation selectivity [1]. For designing directional 2-D RCWF, first we obtain the directional 2-D complex wavelet filters and then those filters are obtained by using equations (13)- (20) rotated by $45°$.

If$\psi_g \ (x) = H\{\psi_h \ \ (x) \ \ \psi_h \ (y)\}$ (12)

$\emptyset_1(x, y) = \ \emptyset_h(x)\emptyset_h \ \ (y)$ (13)

$\emptyset_2(x, y) = \ \emptyset_g(x)\emptyset_g \ \ (y)$ (14)

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

$\psi_{2,1}(x, y) \ \ = \psi^{-15°}(x, y) = \ \emptyset_g(x)\emptyset_g \ \ (y)$ (16)

$\psi_{1,2}(x, y) \ \ = \psi^{+75°}(x, y) = \ \emptyset_h(x)\emptyset_h \ \ (y)$ (17)

$\psi_{2,2}(x, y) \ \ = \psi^{-75°}(x, y) = \ \emptyset_g(x)\emptyset_g \ \ (y)$ (18)

$\psi_{1,3}(x, y) \ \ = \psi^{+45°}(x, y) = \ \emptyset_h(x)\emptyset_h \ \ (y)$ (19)

$\psi_{2,3}(x, y) \ \ = \psi^{-45°}(x, y) = \ \emptyset_g(x)\emptyset_g \ \ (y)$ (20)

Then the six wavelets defined by

$$\psi_i \ (x, y) = \frac{1}{\sqrt{2}} \ \ (\ \psi_{1,i}(x, y) \ + \ \ \ \psi_{2,i} \ \ (x, y) \tag{21}$$

$$\psi_{i+3} \ (x, y) = \frac{1}{\sqrt{2}} \ \ (\ \psi_{1,i}(x, y) \ - \ \ \psi_{2,i} \ \ (x, y) \tag{22}$$

Wavelet transform based on these six wavelets is implemented by taking sum and difference. This is preceded by two separable 2-D DWTs. The resulting directional wavelet transform is two – times redundant. The six sub bands of the 2-D DT-CWT give information strongly oriented at$\{\pm 15°, \pm 45° , \pm 75° \}$. The wavelet functions were calculated by using equation (21)-(22).Hence the decomposition is performed along the new direction of CWT. The size of the filter is (2N-1)×(2N-1) , where N is the length of 1-D filter. The decomposition of input image with 2-D RCWF can be performed by filtering an given image f(x, y) with 2-D RCWFs followed by 2-D down sampling operations. $h_A h_{1,1} h_{1,2} h_{1,3} g_A g_{1,1} g_{1,2} g_{1,3}$were rotated $45°$ and obtained by using above equations. They correspond to$\emptyset_1 \psi_{1,1} \psi_{1,2} \psi_{1,3} \emptyset_2 \psi_{2,1} \psi_{2,2} \psi_{2,3}$respectively. The rotated complex wavelets are strongly oriented in $\{ -30°, 0°, \ 30°, 60°, 90°, 120°\}$diections. Two level frequency-domain partitions resulting from RCWF decomposition. This characteristic of RCWF provides complementary information to the CWT filter set in extracting texture features in 12 different directions.

Experimental Analysis and Results

Here, we consider a specific medical imaging application. We assume that there exists a huge database containing images acquired via Computed Tomography (CT), Magnetic Resonance Imaging (MRI), Ultrasound (US), Positron Emission Tomography (PET), Computed Radiography (CR), etc. We consider the scenario where a physician diagnosing a patient and observing a new result of an imaging exam wishes to fetch from the database visually similar images that have been already pre-diagnosed by him/her or others. The important section in this work is this experimental setup. The database (DB) consists of 1500 images. The point to be cleared here is, this is small scale level carried work carried for retrieval of medical images. The ethical clearance is the major drawback while collecting the medical image. Another issue in creating the largest database is time taken for retrieval. The application focused in this work is to help patients by retrieving relevant query images from past and recent records found in the database. There may be a question how this helps the patients and physicians. But this classification using levels of databases and more precise search of images reduces unnecessary searching by reducing the computational time. Our database (DB) consist of all these 6 categories of images in limited number this helps in wide search when not focused on precise search of images for retrieval. The database considered here is created by our own. Most researches have not focused on this clearly or else they have been created under acknowledgement from hospitals with ethical clearance from the patients which is complicated process and varies for countries. Hence in our work limited database has been created, but can be applied at various database levels which are focused by other researches. Some of the issues has been briefly discussed. Some are beyond the scope of this work.

Retrieval Efficiency

For retrieval efficiency, traditional measures namely Precision and Recall were computed with 500 medical images as test samples. Standard formulas have been computed for determining the Precision and Recall measures. For the analytical notion of performance along with the subjective evaluation, we used the traditional precision-recall value (PR) performance metrics measured under relevant (and unbiased) conditions. The precision and recall values are given as

$$R = \frac{RR}{TR} \tag{24}$$

and

$$P = \frac{RR}{N} \tag{25}$$

where RR is the number of relevant items retrieved (i.e., correct matches) among the total number of relevant items, TR. N is the total number of items (relevant + irrelevant) retrieved. By randomly selecting some sample query images from the MATLAB – image processing tool box- Workspace database, the system was tested and the results are shown.

The query processing and feature extraction with distance classification is given below,

The Euclidean Distance

The direct Euclidean distance calculation between a database image p and query image q is given below. By using equation (26) euclidean distance metric is made possible.

$$\text{Euclidean distance} = \sqrt{\sum (v_{pi}-v_{qi})^2} \tag{26}$$

where i=1 to n.

Energy

It is a grayscale image texture measure of homogeneity changing, reflecting the distribution of image gray-scale uniformity of weight and texture. Here p(x, y) is the gray-level value at the coordinate (x, y). Energy measure can be calculated from equation (13)

$$\text{Energy } E = \sum_X \sum_Y P(x,y)^2 \tag{27}$$

The Euclidean distance metrics and energy as the measure is followed as the second step in the retrieval of medical images.

Average Retrieval Accuracy, Time and Effectiveness

Table 1. Average results of transforms based retrieval

Transforms	Actual image	Relevant Image	Irrelevant Image	Total number of images retrieved
DFT	1	11	1	12
DCT	0	7	5	12
DWT	1	12	0	12
RCWF	1	8	4	12
CWT	1	11	1	12
CURVELET	1	11	1	12

Table 2. Average searching time taken for retrieval

Transform	Elapsed Time (in seconds)
DFT	10
DCT	30
DWT	8
RCWF	35
CWT	8
CURVELET	8

Table 3. Average retrieval accuracy for retrieval of medical images

Transform	Precision (%)	Recall (%)
DFT	91.6	83
DCT	58	14
DWT	95	83
RCWF	66	83
CWT	91.6	83
CURVELET	91.6	83

From the experimental results it is found that DWT shows best results with 95%precision and 83% of Recall value, which is followed by DFT, CWT transforms. DFT, RCWF performs similar during the retrieval. The overall experimental details were listed in the table (1).

The Euclidean distance metrics and energy as the measure is followed as second step in the retrieval of medical images. The average results from the retrieved images depict the performance of transforms. This is given in descending order according to their performance as DWT, CWT, DFT, RCWF, and DCT. Table II shows the elapsed time taken for retrieval of medical images. DWT takes lesser time for retrieval followed by CWT, DFT, DCT,and RCWF. From the classification it is found that even though RCWF performs well in retrieval with 11 relevant images due to its increase in searching time with 35 seconds this found to be less suitable for faster retrieval. Table III shows average retrieval accuracy for retrieval of medical images. This clearly shows the average performance of our system. This is given in descending order according to their performance as DWT, CWT, DFT, RCWF, and DCT. From the above all classification of the experimental setup DWT performs well in terms of average results for transforms based retrieval, on average searching time taken for retrieval and on the average retrieval accuracy calculated in terms of precision and recall values for retrieval of medical images.

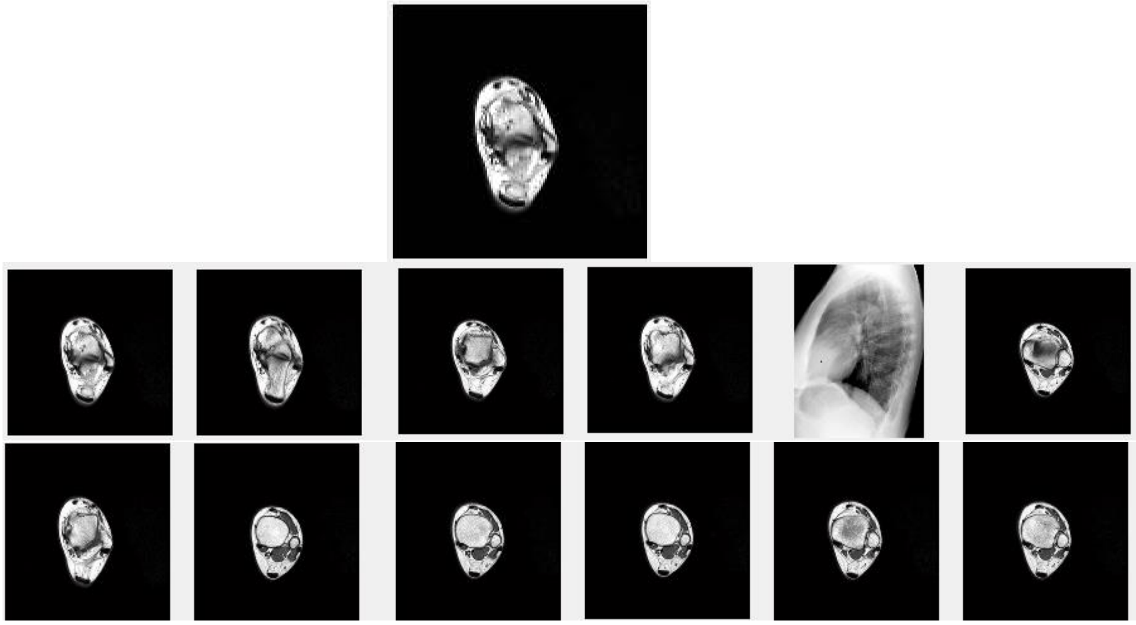


Figure 4. Retrieved medical images using DFT transform

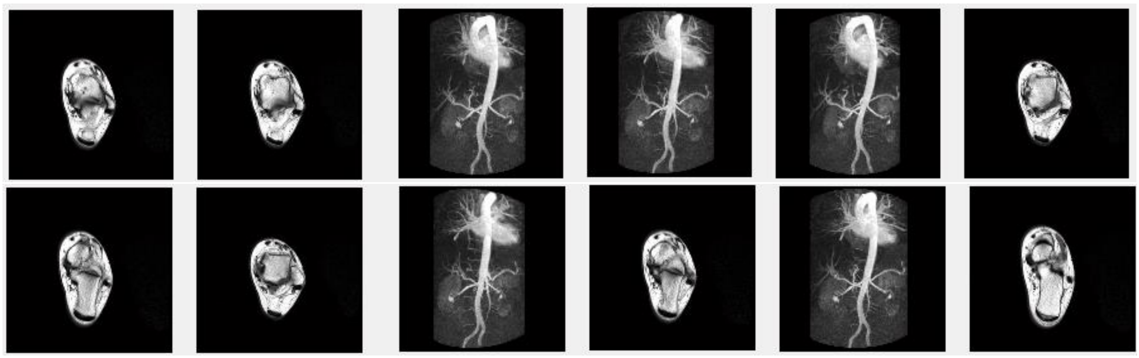


Figure 5. Retrieved medical images using DCT transform

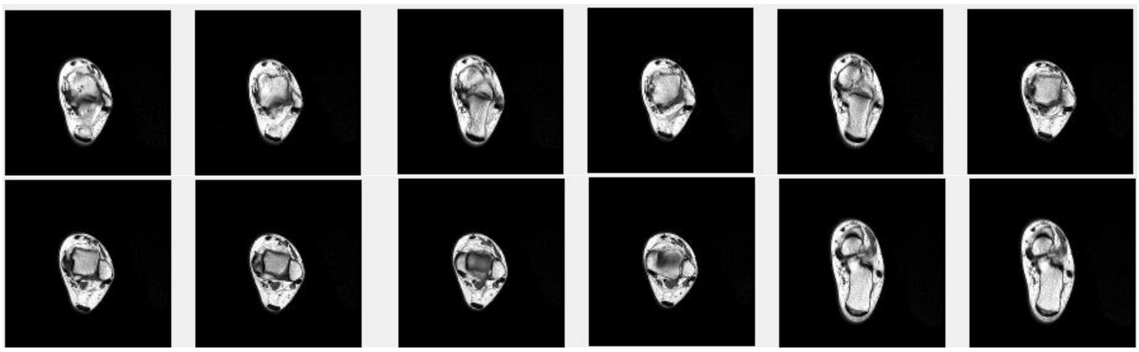


Figure 6. Retrieved medical images. using DWT transform

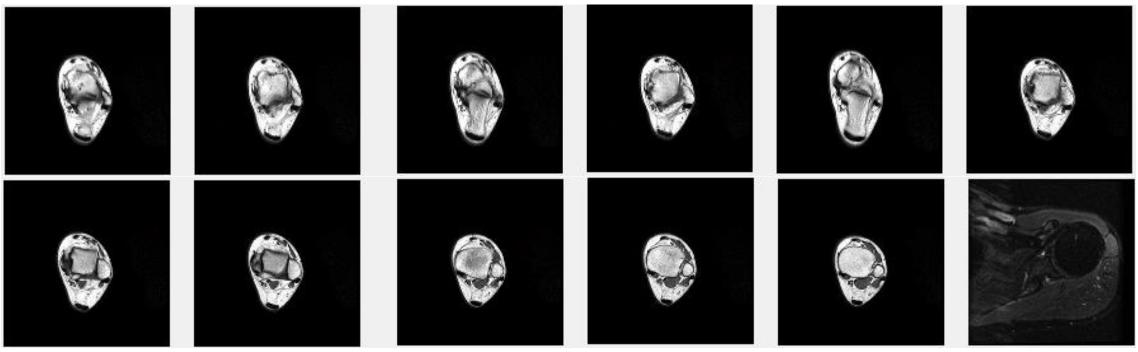


Figure 7. Retrieved medical images using RCWF transform

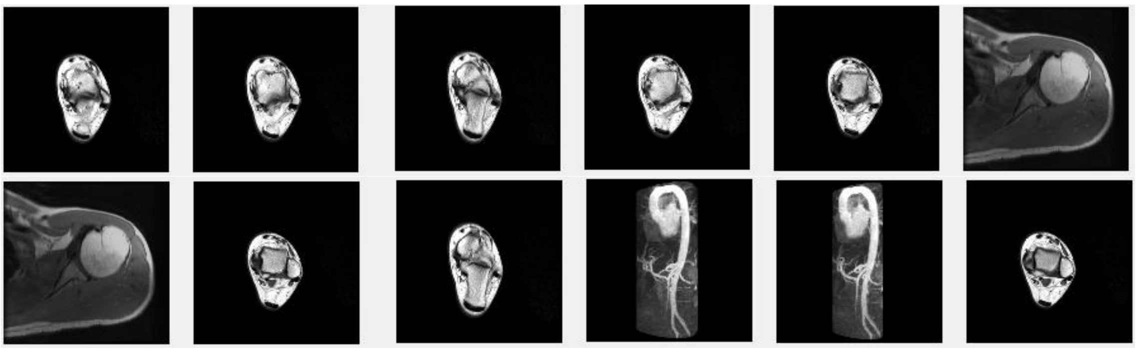


Figure 8. Retrieved medical images using CWT transform

Figure 4. Shows retrieved medical images using DFT transform, Figure 5. Shows retrieved medical images using DCT transform, Figure 6. Shows retrieved medical images using DWT transform, Figure 7. Shows retrieved medical images using RCWF transform. Figure 8. shows retrieved medical images using CWT transform. These retrieved images help in the detailed evaluation of retrieval.

Conclusion

In this paper, transforms which were commonly used in medical image retrieval have been described and evaluated. The transforms processed are the most desirable transform than the other for medical imageretrieval .This retrieval flow performs well in medical image retrieval showing high performance results in medical image retrieval. Experimental results confirm that the results of DWT performs well in retrievals precision, accuracy and in terms of elapsed time, also reducing the searching time and enhancing the retrieval for effective diagnosis and clinical evaluation. This reduces the searching time and higher retrieval rate for searching from the past and relevant database.

The point to be noted from this work is this helps in choosing the best transform for effective retrieval of medical images. Because medical imaging based retrieval is a vast area and with many more complexities as previously described, this helps in choosing the combination for distance metrics with measures.

List of abbreviations

Discrete Fourier transforms (DFT)

Discrete cosine transforms (DCT)
Discrete wavelet transforms (DWT)
Complex wavelet transforms (CWT)
Rotated complex wavelet transform filter (RCWF)
Computed Tomography (CT)
Magnetic Resonance Imaging (MRI)
Ultrasound (US)
Positron Emission Tomography (PET)
Computed Radiography (CR)

Conflict of Interest

The authors declare that they have no conflict of interest.

Acknowledgements

The authors like to thank the editors and reviewers for their useful comments in improving the quality of the paper.

References

1. Manesh K et.al. Texture image retrieval using new rotated complex wavelet filters. IEEE Transaction on system, management and cybernetics-Part B: Cybernetics 2005;35(6).
2. AntaneMaintz JB, Max A, Viergever. A Survey of Medical Image Registration. Medical Image Analysis, 1998.
3. Manjunath BS, Ma WY, Texture feature for browsing and retrieval of image data, IEEE Transaction on PAMI, 1996;18(8):837-842.
4. Rui Y, Alfred C, Huang TS. Modified descriptor for shape representation, a practical approach, In: Proc of First Int's workshop on Image Database and Multimedia Search, 1996.
5. LiHua C, Wei L, GuoHui L. Research and Implementation of an Image Retrieval Algorithm Based on Multiple Dominant Colors. Journal of Computer Research & Development 1999;36(1):96-100.
6. Braveen M, Dhavachelvan P. Evaluation of content based image retrieval systems based on color feature. International Journal of Recent Trends in Engineering 2009;1(2):57-62.
7. Kalyanasundaram K, Sanoj CS. Content based Image retrieval using wavelet based multiresolution analysis. Int. J. Comput Appl 2012;40(4):14-18.
8. Yang Y, Shifu C, Hui L. A Novel Image Retrieval Method Using Texture Features Based on Color-Connected Regions. Acta Electronica Sinica 2005;33(1):57-62.
9. Carballido-Gamio J, Belongie S, Majumdar S. Normalized Cuts in 3-D for Spinal MRI Segmentation. IEEE Trans. Medical Imaging 2004;23(1):36-44.

10. Muller H. User interaction and performance evaluation in content based visual information retrieval, Ph.D. thesis, Computer Vision and Multimedia Laboratory, June 2002, University of Geneva, Geneva, Switzerland.