Modelling of X-Ray Image Retrieval System using Zone Based Transform Techniques

P. Nalini, B. L. Malleswari

Abstract*: Medical image retrieval based on its visual attributes is one of the prime aspects for the clinical decision making process. It can be beneficial and important to find other images of the same modality, the same anatomic region in disease identification. This results in improved healthcare system with increased efficiency. In this paper we proposed a model of medical image retrieval system that works on the features extracted from transformed coefficients by applying four different transformations viz. Discrete Fourier Transform (DFT), Discrete Sine Transform (DST), Discrete Cosine Transform (DCT) and Discrete Wavelet Transform (DWT). Visual content of X-Ray images better expressed with textural features. The texture attributes computed from transformed domain shown superior performance over spatial domain computed GLCM matrix based features. So in this paper we presented the comparison analysis of the four transformation techniques, DFT, DST, DCT and DWT in analyzing the performance of medical image retrieval system. IRMA 2009 X-Ray image database was used for experimentation. X-Ray image retrieval worked well with regionally computed attributes over global features, transform coefficients computed by partitioning the images into 64 regular regions of 16 x 16 in size. Images retrieved by finding the similarity between the region wise feature vectors. Among the four transformations, DWT and DCT result with more than 75% Mean Average Precision (MAP) at 100% recall rate.

***Index Terms*: CBMIR, RBIR, Transform techniques, Zoning.**

I. INTRODUCTION

Without burdening a physician unduly, what can be accomplished by a computer is the primary goal of Content Based Medical Image Retrieval (CBMIR). This helps the doctor and radiologist in understanding and analysing the case and leads to an automatic medical image annotation. In medical image retrieval process, image attributes play crucial role. Integration into Picture Achieving Communication Systems (PACS) is an essential process for the clinical use of a retrieval system. Annotation process may be considered as a concept detection in which images pertaining to the same concept can be described linguistically in different ways based on the specific instance of the concept.

In medical applications, images scanned from imaging modalities such as the Magnetic Resonance Imaging (MRI), ultrasound and tomography databases for clinical analysis and diagnosis become more time consuming with increased number of images, and this in turn increases the retrieval time of the search algorithm while extracting similar looking images from database [1].Therefore retrieval algorithm should compute optimal and minimal attributes that better represent the images. This speeds up the retrieval process and results in faster extraction of similar images from database.

X-Ray medical images are rich in textural representation, compared to intensity and shape attributes, texture attributes represent these images in a better way. According to the survey of [5] and the work done in [2] textural features computed in transformed domain shown superior retrieval performance over spatially extracted attributes. Based on that in this work features extracted by transforming the image with Discrete Sine Transform (DST), Discrete Cosine Transform (DCT), Discrete Fourier Transform (DFT) and Discrete Haar Wavelet Transform (DWT).

In this work we did the experimentation on IRMA 2009 dataset. Image Retrieval in Medical Applications (IRMA) database consists of fully annotated radiography X-Ray images arbitrarily taken from Department of Diagnostic Radiology, Aachen University of Technology, RWTH Aachen, Germany. All IRMA images fit in 512 x 512 pixel size. This database is created every year and is used in CLEFMED medical image retrieval task challenges [3]. These image databases can be downloaded from the link given in [4] with special permissions.

Joseph Fourier has proposed a new signal analysis tool called Fourier Transform in 1882, with this transform any signal can be represented on frequency basis functions. This transform extracts frequency information very efficiently but greatly limited in extracting the timing information of the signal [6].

Discrete Sine Transform (DST) is similar to DFT but is equivalent to the DFT imaginary parts and operates on real data with odd symmetry. DST expresses any signal in terms of a sum of sine functions with different frequencies and amplitudes.

The DCT tends to concentrate information, making it useful for image compression applications. Discrete Cosine Transform (DCT) is equivalent to DFT of real and even functions. DCT transform any signal in terms of sum of cosine functions at various frequencies with different amplitudes. DCT got its most usage in feature selection in pattern recognition and image processing. It is a popular transformation in JPEG image compression. The DCT can be used in the area of digital processing for the purposes of pattern recognition and Wiener filtering. Its performance is compared with that of a class of orthogonal transforms and is found to compare closely to that of the Karhunen Lo'eve transform, which is known to be optimal.

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P. Nalini, Department of Electronics and Communication Engineering, Mahatma Gandhi Institute of Technology, Hyderabad, India. E-mail: pasumarthinalini@gamil.com

Dr. B. L. Malleswari, Department of Electronics and Communication Engineering, Sridevi Woman's Engineering College, Hyderabad, India. E-mail: blmalleswari@rediffmail.com

The performances of the Karhunen-Lo'eve and discrete cosine transforms are also found to compare closely with respect to the rate-distortion criterion [7].

To overcome the drawback of Fourier Transform researchers come up with a new signal analyzing tool based o wavelet functions. The transformed signal better represent frequency as well temporal information of the original signal. The wavelet transform represents a mother wavelet function with scaling and translation coefficients. The wavelet transform of a two dimensional image results in one approximated wavelet subband called LL band and three detail wavelet subbands LH,HL and HH.

II. RELATED WORK

IRMA image data sets and retrieval of similar modality images based on prior learning of classifier presented by RWTH Aachen university developers, Mono hierarchical multi axial classification code is presented in [3]. DICOM header provides tags to decode the body part examined and the patient position.

A fast computational algorithm for discrete sine transform by using a sparse matrix factorization is discussed in [6]. Discrete Cosine Transform (DCT) and its computation using FFT presented and performance of KLT and DCT compared in [7]. In [8] DCT coefficients representing dominant directions and gray level variations are used as features with hierarchical similarity measure used for efficient retrieval. JPEG image retrieval performed in frequency domain based on the DCT coefficients as features. Energy histograms of the low frequency DCT coefficients as features proposed in [9]. To increase the stipulated time of retrieval DCT compression technique of low level image features presented in [10].

Texture classification based on the energies computed from wavelet subband, DCT, uniform subband and spatial partitioning of image subbands proposed in [11]. An extensive survey has done on Weyl-Heisenberg coherent states and affine coherent states (wavelets) and analyzed the way of expressing any function in terms of integral of these states in [12]. [13] described about wavelets and their applications in various fields also analyzed various other transformation techniques and compared Fast Fourier Transforms with Discrete Wavelet Transforms.

A new approach to region based image retrieval using shape adaptive discrete wavelet transform discussed in [14]. By computing SADWT coefficients independently for individual regions features are independent of region translation, rotation and scaling. Performance analysis of CBIR with cosine and sine transforms with other transformations discussed in [15]. Medical image retrieval using Discrete Sine Transform discussed in [16].

According to [17] Haar transform is a symmetric separable transform that uses Haar function as basis. The Haar function, which is an odd rectangular pulse pair, is the simplest and oldest orthonormal wavelet, whereas the Fourier transform basis functions differ only in frequency, the Haar functions vary in the both scales of width and position. All N^2 elements of DCT, DST and Walsh-Hadamard transforms are nonzero except the Haar transform, which has only 2N nonzero entries. These features are very important in image processing because in many cases spectral coefficients have zero entries before next retrieval operations. This case occurs in black and white images very often.

III. METHODOLOGY

According to our previous works [2] and [5], we learnt that region based feature extraction result in good retrieval performance when compared with global feature extraction. In this work first the query and database images of 128 x 128 in size divided into 64 square blocks of 16 x 16 in size. The four transformation coefficients computed for every zone and used as feature vectors. The implementation of proposed retrieval system is shown in fig 1. We compared the performance of the retrieval in two ways. In first approach, we chosen all transformed coefficients as feature vector and in second case, only few dominating coefficients of every region were chosen as feature vectors. Based on [18], [19] Manhattan distance shown improved retrieval compared to Euclidean distance. In both cases query image feature vector and database image feature set checked with Manhattan distance metric for similarity measurement.

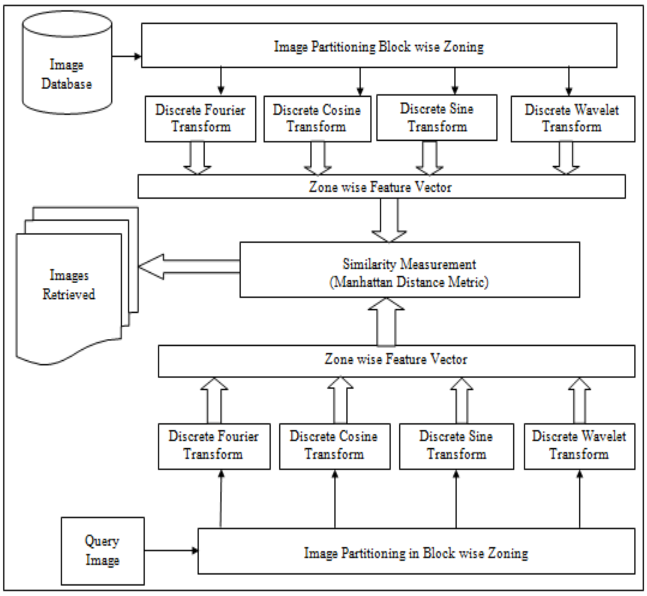

Fig 1: Implementation of Proposed Image Retrieval System

Computation of four transformed coefficients to obtain feature attributes is as follows. The DFT for every symmetrical region of query and database image computed with equation 1. 2D-DFT, though a self-consistent transform, can be considered as a mean of calculating the transform of a 2D sampled signal defined over a discrete grid. The signal is periodized along both dimensions.

$$F[k,l] \quad = \frac{1}{MN}\sum_{m=0}^{M-1}\sum_{n=0}^{N-1} f[m,n]e^{-j2\pi\left(\frac{k}{M}m+\frac{l}{N}n\right)} \qquad (1)$$

Computation of Inverse DFT is given in equation 2.

$$f[m,n] = \sum_{k=0}^{M-1}\sum_{l=0}^{N-1} F[k,l]e^{-j2\pi\left(\frac{k}{M}m+\frac{l}{N}n\right)} \qquad (2)$$

Where k, m ∈ {0, 1, ..., M − 1} and l, n ∈ {0,1, . . . , N − 1}

M and N indicate the size of every region in image in terms of rows of columns. F [k, l] represent the DFT transformed coefficients for the given image region f [m, n].

The Discrete Sine Transform coefficients for every zone of query and database image is obtained by applying equation 3and the inverse DST is given in equation 4.

$$F[k,l] = \sum_{m=1}^{M}\sum_{n=1}^{N} f[m,n]\sin\left(\pi\frac{km}{M+1}\right)\sin\left(\pi\frac{ln}{N+1}\right) \quad (3)$$

$$f[m,n] = \frac{2}{MN}\sum_{m=0}^{M}\sum_{n=0}^{N} F[k,l]\sin\left(\pi\frac{km}{M+1}\right)\sin\left(\pi\frac{ln}{N+1}\right) \quad (4)$$

Where k, m ∈ {1, . . . , M} and l, n ∈ {1, . . . , N}.

M and N indicate the size of every region in image in terms of rows of columns. F [k, l] represent the DST transformed coefficients for the given image region f [m, n].

The DCT is closely related to the DFT. It is a separable linear transformation; that is, the two-dimensional transform is equivalent to a one-dimensional DCT performed along a single dimension followed by a one-dimensional DCT in the other dimension. The two-dimensional DCT and IDCT for an input image region f [m, n] and output coefficients of that region F [k, l] is given in equation 5 and 6 respectively.

$$F[k,l] = \alpha_p\alpha_q\sum_{m=0}^{M-1}\sum_{n=0}^{N-1} f[m,n]\cos\frac{\pi(2m+1)k}{2M}\cos\frac{\pi(2n+1)l}{2N} \quad (5)$$

$$f[m,n] = \sum_{m=0}^{M-1}\sum_{n=0}^{N-1} \alpha_k\alpha_l F[k,l]\cos\frac{\pi(2m+1)k}{2M}\cos\frac{\pi(2n+1)l}{2N} \quad (6)$$

Where $0 \le k \le M-1$ and $0 \le l \le N-1$

$$\alpha_k = \begin{cases} \frac{1}{\sqrt{M}}, & p = 0 \\ \sqrt{\frac{2}{M}}, & 1 \le p \le M-1 \end{cases}$$

and

$$\alpha_l = \begin{cases} \frac{1}{\sqrt{N}}, & q = 0 \\ \sqrt{\frac{2}{N}}, & 1 \le q \le N-1 \end{cases}$$

M and *N* are the row and column size for region of image, respectively.

Two–dimensional N × N = 2n × 2n forward Discrete Haar Wavelet Transform (DWT) and IDWT are defined in matrix notation as shown in equation 7 and 8. Regular notation is shown in equation 9 and 10 respectively.

$$F = a.H(n).f.a.H(n)^t \quad (7)$$

$$f = b.H(n)^t.F.b.H(n) \quad (8)$$

Where f is the image in matrix form, the matrix is of dimension N × N pixels, F is the spectrum matrix and a and b = 1/N, hence parameters a or b may be defined as values 1/N, 1/√N or 1, n = log2 N.

$$F(k,l) = \sum_{x=0}^{N-1}\sum_{y=0}^{N-1} f(m,n)\times haar(k,m)\times haar(l,n) \quad (9)$$

$$f(m,n) = \sum_{k=0}^{N-1}\sum_{m=0}^{N-1} F(k,l)\times haar(k,m)\times haar(l,n) \quad 10$$

Where, k, m ∈ {0, 1, . . . , M − 1} and l, n ∈ {0, 1, . . . , N − 1}

M and N indicate the size of every region in image in terms of rows of columns. F [k, l] represent the Haar DWT transformed coefficients for the given image region f [m, n].

For similarity measurement, Manhattan distance metric as shown in equation 11 was used. The images that pose least dissimilarity value were chosen as outputs by the system.

$$d_{Manhattan}(x,y) = \sum_{i=1}^{n}|x_i - y_i| \quad (11)$$

The retrieval performance analyzed with two metrics Average Precision (AP) and Mean Average Precision (MAP) as given in equation 12 and 13. Class wise AP is determined for all the coefficients and dominated coefficients based retrieval for all the queries of that class. These values are shown in Table 1. Mean Average Precision (MAP) is obtained by finding the arithmetic mean of average precision of all the classes.

$$AP = \frac{Number\_of\_relevant\_images\_retrieved\_of\_that\_class}{total\_number\_of\_images\_retrieved} \quad (12)$$

$$MAP = \frac{Relevant\_images\_retrieved\_for\_all\_the\_classes}{total\_images\_retrieved\_for\_all\_the\_classes} \quad (13)$$

IV. EXPERIMENTS AND RESULTS

In this paper we presented the comparison of X-Ray image retrieval performance using four transformation techniques viz. Discrete Fourier Transform (DFT), Discrete Sine Transform (DST), Discrete Cosine Transform (DCT) and Discrete Wavelet Transform (DWT). We used IRMA 2008 and 2009 X-Ray image databases for experimentation. Sample query images are shown in fig 2.

Fig 2: Sample Query Images of IRMA dataset

As part of this work, we first resized the IRMA data set to 128 x 128 images. Experimentation is done on 2000 X-Ray images of ten different classes with each class representing an anatomical region of the human body.

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50 % of dataset that is 100 images of each class chosen as query images to analyze the retrieval system performance. For feature extraction, query and database image partitioned into 64 symmetrical blocks with 16 rows and 16 columns with 256 pixels in each block. Block wise transformation coefficients were computed and those coefficients are used as feature vector for similarity check. In case of Haar wavelet coefficients only the approximated band that is LL band coefficients were used as feature vector. We also tested the retrieval system by obtaining the feature vectors by choosing only dominant coefficients of every block for similarity measurement.

Comparison analysis of the region wise transformed coefficients (all and important features) based X- Ray image retrieval in terms of Average Precision (AP) for every class and Mean Average Precision for the entire dataset is shown in table 1. From the table it can be clearly understood that the retrieval performance improved in all the four transformations with dominant features rather using all coefficients as feature vectors. This also results in reduced the time of retrieval.

Table I: Comparison Analysis of Region Wise Transformed Coefficients for X-Ray Image Retrieval

Class / AP	DST		DCT		DFT		DWT	
	ALL	IMP	ALL	IMP	ALL	IMP	ALL	IMP
Abdomen	85.6	90	87.2	92.8	94.4	93.6	92.8	**96**
Spine	68.8	78.4	81.6	**84.4**	81.2	81.2	76.4	75.2
Lungs	94	**94.4**	92	94	92	92.8	88	**94.4**
Skull	61.6	70.8	63.2	80	68.4	76.8	67.6	**88.8**
Breast	**76**	74.8	70	75.6	63.6	72	69.2	70.4
Knee	74.8	75.6	**76.8**	72.8	75.6	69.6	65.6	75.2
Feet	60.8	64	57.6	63.6	58.4	63.2	60.8	**67.6**
Hand	38.4	48.8	39.2	58	48	57.2	57.6	**64.8**
Elbow	53.6	57.2	56.4	**59.2**	54.4	59.2	52.4	50.4
Shoulder	65.2	66.8	62.4	65.6	66.4	66.4	52	**68.8**
%MAP	67.88	**72.1**	68.64	**74.6**	70.2	**73**	68.2	**75**

It is also observed from the table that for classes 1, 3, 4, 7, 8 and 10 that is abdomen, lungs, skull, feet, hand and shoulder images dominant coefficients of DWT result in high Average Precision (AP) and for class 2, 6 and 9 (spine, knee and elbow) images DCT coefficients result in higher AP score and for breast images DST coefficients shown significant performance. According to retrieval performance (MAP) scores dominant coefficients of DWT and DCT coefficients shown superior performance among all the transformed features.

V. CONCLUSIONS

A. Figures and Tables

In this paper we presented a comparison analysis of X-Ray image retrieval system with region based transformed coefficients as visual attributes. We applied four different transformations viz. Discrete Fourier Transform (DFT), Discrete Sine Transform (DST), Discrete Cosine Transform (DCT) and Discrete Wavelet Transform (DWT) in determining features. we also tested the retrieval performance by choosing only the dominated coefficients from every region of the image as the features. The texture attributes computed from approximated subband of Haar DWT and DCT shown superior performance with more than 75% Mean Average Precision (MAP) at 100% recall rate. It is also worth noting that different transform coefficients shown different retrieval efficiencies depending on the anatomical region chosen as query. Such as DST coefficients results in better average precision for breast images. DWT coefficients worked well while identifying and retrieving abdomen, lungs, skull, feet, hand and shoulder images. DCT coefficients efficiently retrieved spine, knee and elbow images. Therefore it can be considered that based on the type of query being searched choosing appropriate attributes play crucial role in efficient retrieval of similar images from the database. Based on this experimental work it can be concluded that the transformation coefficients that better represent one type of query image may not represent the other in same way. As part of extension to this work a classifier can be included in the front end of the retrieval system. This classifier understands the query image and decides the attributes to be computed for efficiently retrieving the visually similar looking images.

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AUTHORS PROFILE

Mrs. P. Nalini currently working as Assistant Professor in Department of ECE at Mahatma Gandhi Institute of Technology since 2008 and doing research in medical image retrieval and classification as part of Ph.D work at JNTU Hyderabad. She published 10 papers in international journals and conferences.

Dr. B. L. Malleswari currently working as Principal at Sridevi Woman's Engineering College, Hyderabad since June 2014. She awarded with doctorate in 2008 from JNTU Hyderabad. Her area of interests includes image processing, Kalman filtering and OFDM communication. She published more than 100 papers in various international journals and conferences.