Region Based X-Ray Image Retrieval using Transform Techniques

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Abstract - Region Based Medical Image Retrieval (RBMIR) became popular aspect in Content Based Medical Image Retrieval (CBMIR) domain. Locally computed visual attributes of a radiographic image has significant role in retrieving the similar images from databases when compared with globally computed features and this is one of the prime aspects in making clinical decisions. Better disease identification can be made by finding images of the same modality of an anatomic region. This obviously improves the healthcare system efficiency. X-Ray images are best described in textural distributions compared to shape and intensity. The texture attributes computed from transformed domains shown superior performance over spatially computed features. In this paper we proposed a novel approach for RBMIR by computing the region wise visual attributes from four transformed domains viz. Discrete Fourier Transform (DFT), Discrete Sine Transform (DST), Discrete Cosine Transform (DCT) and Discrete Wavelet Transform (DWT). We presented a comparative analysis stating which transformation worked well with what type of query image. We did the experimentation on IRMA 2008 and 2009 X-Ray image data sets. The efficiency of a retrieval process can be increased by selecting the optimal attributes depending on the given query image rather using the same attributes for all queries.

Keywords: *Region Based Medical Image Retrieval, Transform techniques, DWT, DCT, DFT, DST*

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, and 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. 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 features computed from an image. In this work first the query and database images of 128 x 128 in size divided into 64 equal sized regions of each in 16 x 16 sized. The DST, DCT, DFT and DWT transformation coefficients computed for every region. Dominant valued coefficients holding maximum energy used as feature vectors. The implementation of proposed retrieval system is shown in figure 1. 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. We presented the comparative analysis of the retrieval performance based on four different transformations.

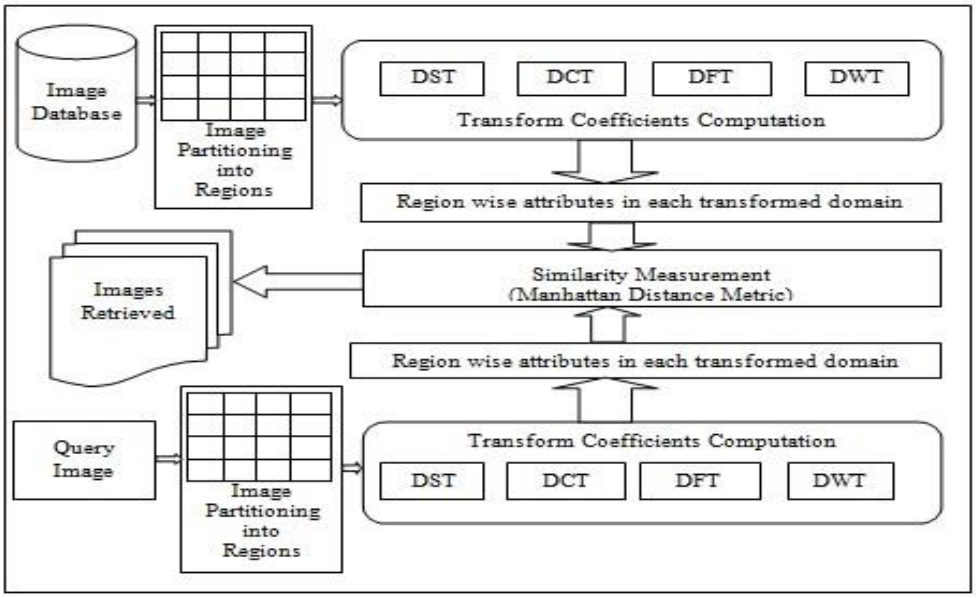

Fig 1: Implementation of Proposed Image Retrieval System

3.1. Feature Extraction

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.

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

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 were computed in every region of query and database image is obtained by applying equation 2.

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

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 Discrete Cosine Transform (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 3.

$$F[k,l] = \alpha_p\alpha_q\sum_{m=0}^{M-1}\sum_{n=0}^{N-1} f[m,n]cos\frac{\pi(2m+1)k}{2M}cos\frac{\pi(2n+1)l}{2N}, \quad {\scriptstyle 0\le k\le M-1 \atop 0\le l\le N-1} \tag{3}$$

Where

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

And

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

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 4. Regular notation is shown in equation 5.

$$F = a.H(n).f.a.H(n)^t \quad (4)$$

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.

$$F(k,l) = \sum_{x=0}^{N-1}\sum_{y=0}^{N-1} f(m,n) \times haar(k,m) \times haar(l,n) \quad (5)$$

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].

3.2. Performance Evaluation

For similarity measurement, Manhattan distance metric as shown in equation 6 was used. The images that pose least dissimilarity value were chosen as outputs and retrieved by the system.

$$d_{Manhattan}(x,y) = \sum_{i=1}^{n} |x_i - y_i| \quad (6)$$

The retrieval performance analyzed with two metrics Average Precision (AP) and Mean Average Precision (MAP) as given in equation 7 and 8. 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.

$$Average\ Precision = \frac{Number\_of\_relevant\_images\_retrieved\_of\_that\_class\_for\_all\_queries}{total\_number\_of\_images\_retrieved\_for\_all\_queries} \quad (7)$$

$$MAP = \frac{Number\_of\_relevant\_images\_retrieved\_for\_all\_the\_classes}{total\_number\_of\_images\_retrieved\_for\_all\_the\_classes} \quad (8)$$

IV. EXPERIMENTS AND RESULTS

In this paper we presented the comparison of X-Ray image retrieval performance by computing dominant coefficients in four transformed domains viz. Discrete Fourier Transform (DFT), Discrete Sine Transform (DST), Discrete Cosine Transform (DCT) and Discrete Wavelet Transform (DWT) to 64 equally partitioned regions of images. We used IRMA 2008 and 2009 X-Ray image databases for experimentation. Sample query images are shown in figure 2.

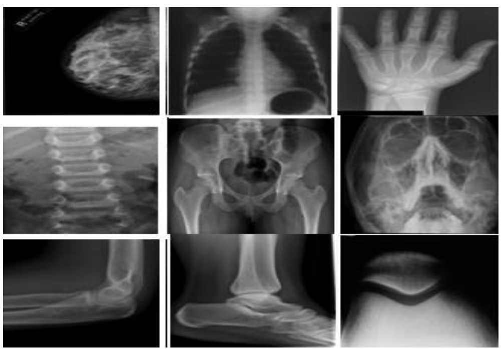

Figure 2: Sample Query Images of IRMA dataset

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. 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 the maximum valued coefficients are used as feature vector for similarity check. In case of Haar wavelet only the approximated (LL) band dominant coefficients were used as feature vectors.

Comparison analysis of the region wise dominant transformed coefficients for 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.1 it can be clearly understood that the retrieval performance is not entirely depending on one kind of transformed coefficients, viz. class wise average precision is varying. For few anatomical regions such as abdomen, lungs, skull, feet, hand and shoulder images DWT based features results in highest AP score, while for lungs and knee images DST results in higher AP value and DCT coefficients results in highest retrieval for spine, breast and elbow images. In overall MAP scores DWT and DCT coefficients shown superior performance.

Table 1: X-Ray image retrieval performance with Transformed coefficients

Class	Anatomical region	Discrete Sine Transform	Discrete Cosine Transform	Discrete Fourier Transform	Discrete Wavelet Transform
1	Abdomen	90	92.8	93.6	**96**
2	Spine	78.4	**84.4**	81.2	75.2
3	Lungs	**94.4**	94	92.8	**94.4**
4	Skull	70.8	80	76.8	**88.8**
5	Breast	74.8	**75.6**	72	70.4
6	Knee	**75.6**	72.8	69.6	75.2
7	Feet	64	63.6	63.2	**67.6**
8	Hand	48.8	58	57.2	**64.8**
9	Elbow	57.2	**59.2**	59.2	50.4
10	Shoulder	66.8	65.6	66.4	**68.8**
%MAP		72.1	**74.6**	73	**75**

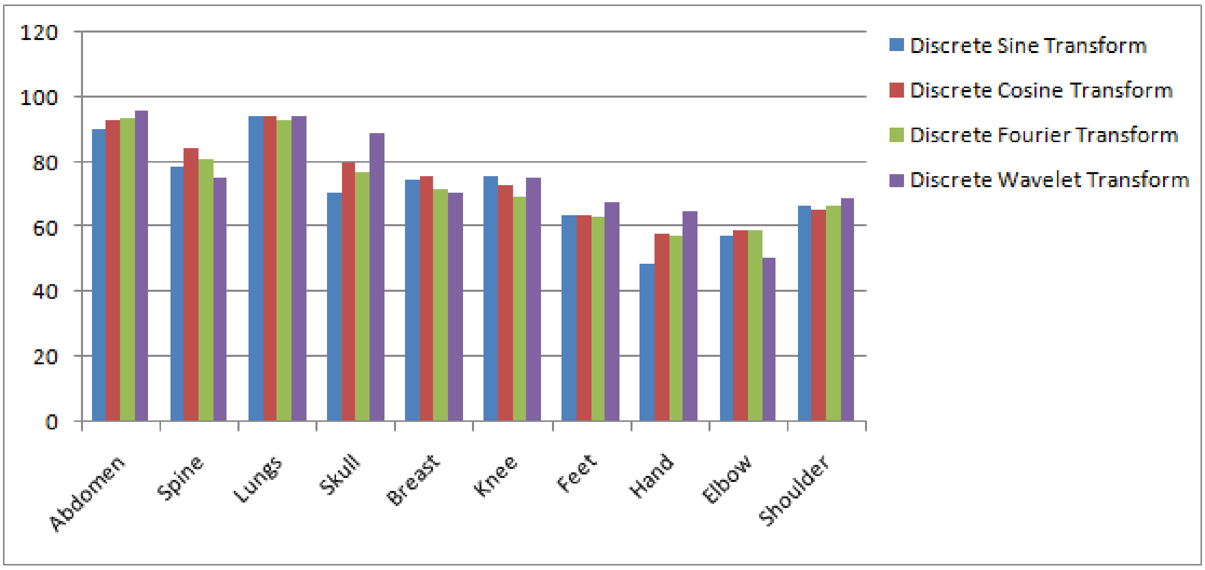

Fig 3: Graphical Representation of Retrieval Performance with transform coefficients

V. CONCLUSIONS

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.

With this work we come up with the conclusions stating the transform coefficients results in best precision in retrieving various anatomical region images. For abdomen, lungs, skull, feet, hand and shoulder images DWT based features results in highest AP score, while for lungs and knee images DST results in higher AP value and DCT coefficients results in highest retrieval for spine, breast and elbow images. According to overall MAP scores DWT coefficients shown superior performance with 75% MAP and DCT coefficients result in 74.6% MAP at 100% recall rate i.e. by retrieving 200 images (equal to its class size). Based on this experimental work we can conclude that choosing appropriate attributes based on the type of query being searched play crucial role in efficient retrieval of similar images from the database. The transformation coefficients can be optimally chosen for retrieval task. As part of extension to this work we try to include a classifier in the front end of the retrieval system. This classifier understands the query image and selects the optimal attributes that need to be computed for an efficient retrieval of visually similar images.

VI. REFERENCES

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