Optimal Feature Selection for Zone Based Medical Image Retrieval

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Abstract: The primary goal of Content Based Medical Image Retrieval (CBMIR) is not to burden a physician and to accomplish the same action by a computer. This helps the doctor and radiologist in understanding and analysing the case and leads to automatic medical image annotation. The choice of image attributes have crucial role in retrieving similar X-Ray images of various anatomic regions. In this paper we presented an empirical analysis of an X-Ray image retrieval system with spatial (intensity, statistical) and frequency domain (DFT, DWT) and Eigen value (SVD) attributes were computed for five different regular and irregular zones of the image. In our previous work we proved that analysing the image with local attributes result in better retrieval efficiency and hence in this paper we computed the attributes by dividing the image into 64 regular and irregular zones. For this experimentation IRMA 2008 and IRMA 2009 X-Ray data sets were used. With this work we come up with wonderful conclusions by stating that wavelet based textural attributes, intensity features and Eigen values extracted from different regular zones that worked well in excellent retrieval of different anatomy X-Ray images.

Keywords: Medical Image Retrieval, Region based retrieval, Regular zoning, Irregular zoning, intensity attributes, statistical attributes, DFT, DWT, SVD.

I. INTRODUCTION

The principle of Content Based Medical Image retrieval (CBMIR) is to organize digital medical image achieves by their visual content. The most common form of CBMIR is image search by its visual attributes. This mechanism deals with image classification, recognition and retrieval and these are the three important aspects of automatic image annotation. The annotation of medical image collections is an active research area. Annotation process is considered as concept detection where images pertaining to the same concept can be described linguistically in different ways based on the specific instance of the concept.

X -Ray image retrieval based on image content is very helpful in clinical decision making process. For the clinical decision making process it can be beneficial or even important to find other images of the same modality, the same anatomic region of the same disease. This process helps pathologists to authenticate decease and its stage by retrieving the similar looking images.

Integration into PACS is an essential step for the clinical use of a retrieval system. Medical images produced by various modalities are in DICOM format. Digital Imaging and Communication in Medicine (DICOM) is a complex standard. It covers a broad range of imaging modalities and deal with both communications and storage of images [1].

According to the literature survey of [2] considerable amount of work had already done in medical image retrieval but still it is a challenging task for researchers. X-Ray images are very rich in texture and it is the highly considerable attribute for retrieval. Researchers are trying to explore other optimal features for best retrieval of X - Ray images.

II. RELATED WORK

Image retrieval based on 2-D region based visual features is presented. Region features obtained with thresholding. Object regions are extracted and structural features of each region described [3]. Optimization of high resolution content in x ray images with morphological opening and closing operations along with convolution and subtraction discussed in [4]. Paper [5, 6] discussed about texture classification and discrimination based on the energies of image subbands using DCT, wavelet and spatial partitioning.

VisualSEEk is an image search engine that allows both color and spatial querying by using image regions and their colors, sizes, spatial location ships and relationships for retrieval. Able to perform automated extraction of localized regions and features, querying by both spatial and feature information, fast extraction from compressed data and developed fast indexing and retrieval techniques [7]. Images decomposed into blocks and wavelet coefficients are computed for each block and the query features compared with these features for fast retrieval of similar images from large databases [8].

ROI of the blood cell images is computed based on segmentation and shape, area, color and texture features computed in that region [9]. Global and semi local edge histograms generated from local histogram bins and compared for image matching [10]. Paper [11] developed a CBIR system in which user can select multiple regions of interest and can specify the relevance of their spatial layout in the retrieval process. Spectral graph theoretic frame work of normalized cuts is used in [12] to find the partitions of the image into regions of coherent texture and brightness. Translation invariant texture features provided by discrete wavelet coefficients in [13].

Statistical shape feature based image retrieval done in [14]. Image signature is calculated by finding gradient descriptor of texture features using a GLCM matrix by finding variance, energy, entropy, homogeneity, third order moment, inverse variance for image retrieval done in [15]. An efficient region based image retrieval presented in [16] by applying a multistep approach to use in region based retrieval techniques in large databases. This is done by using lower and upper bounds before applying a distance measure, with this retrieval processing time got significantly reduced. In [17] images are represented as signatures based on the distribution of wavelet transform and weighted signature distances computed between query and database images and an adapted wavelet base is proposed.

In paper [18] MRI brain image retrieval based on intensity histograms, texture features performed with and without adding spatial knowledge using LBP and proved texture along with spatial knowledge results in better retrieval efficiency. Medical image retrieval performed with energy efficient wavelet transforms such as Biorthogonal and Haar with Euclidean Distance as a similarity measure in [19]. [20] listed all low level features as color, texture and shape of images to use in CBIR. A figure of merit called retrieval efficiency defined in [21].

III. METHODOLOGY

We experiment our work on IRMA 2008 database by choosing ten different classes of images: Abdomen, Spine, Lung, Skull, Breast, Hand, Shoulder, Feet, Ankle and Knee. 20% of the database images are chosen as query set and the system is evaluated in terms of average precision for every image category and mean average precision (MAP) for all the 10 classes of images at 100% recall rate. Sample images of IRMA data set shown in fig 1.

Fig 1. Sample images from IRMA Dataset

The proposed retrieval system is shown in fig 2. An empirical evaluation of our previous work illustrates that local features significantly improve retrieval performance when compared with global feature based retrieval.

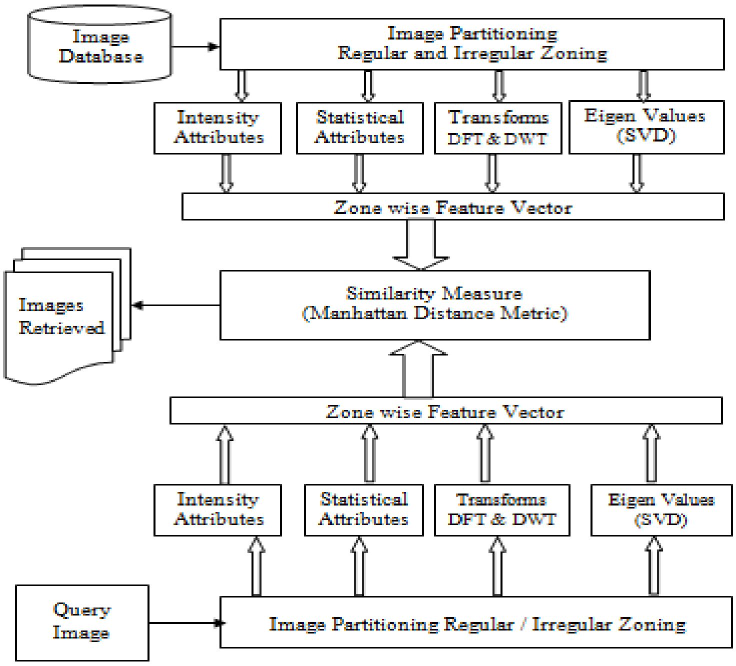

Fig.2. Proposed Medical Image Retrieval System

Based on this evaluation, in the present work we divided the query and database images of 128 x 128 in pixel size into non overlapped 64 regular regions in sizes as (16 x 16) as squared blocks, 128 x 2 and 2 x 128 sized rectangular blocks as squared zones, column zones and row zones respectively. We also analysed the system performance by partitioning the images into 64 non overlapped irregular sized regions as spiral zones and staircase zones. These five zone partitions shown in fig 3.a. to 3.e.

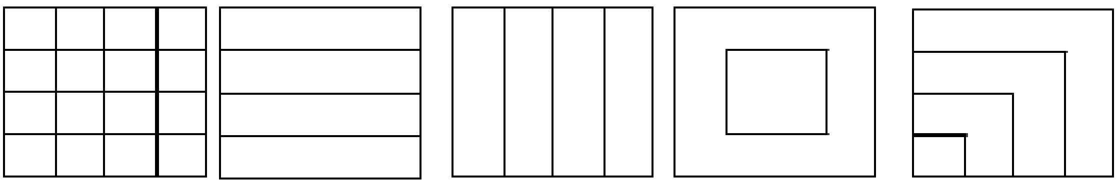

Fig 3.a. Squared, b. Row regions, c. Column regions d. Spiral regions e. Staircase regions

The query image is partitioned into regular and irregular regions as shown in fig 1. The data base images also divided into various non overlapping zones. Intensity attributes, texture attributes, statistical attributes transformed coefficients as DFT and DWT and Eigen values were determined for every zone of both images. The features extracted from all the zones of the image framed as a feature vector and the similarity between these feature vectors obtained by computing Manhattan distance metric. The data base images that got least difference values retrieved by the proposed system.

Intensity Attributes:

For every non overlapped zone of the image sum of pixel values within the zone is computed by Eq.1. Probability of intensity distribution is determined for every zone by using the histogram approach as given in Eq. 2. The values computed for all the zones were used as intensity based feature vectors and are used to retrieve the similar looking images from database.

$$Sum\ of\ Pixels\ in\ a\ Zone = \sum_i \sum_j f(i,j) \qquad (1)$$

$$Probability\ f(i,j) = \frac{N(i,j)}{M} \qquad (2)$$

Where $f(i,j)$ denote the pixel values within the zone. $N(i,j)$ denote number of pixels having same gray value and M represent total number of pixels within that zone.

Statistical Attributes:

Statistical features of mean, standard deviation, variance, smoothness, uniformity, entropy and third order moments were calculated for every zone of the image. All these seven attributes as shown in eq. 3 to eq. 9 respectively, used as a feature vector for every individual zone of the image. All feature vectors of 64 zones of query and database images are checked with Manhattan distance for retrieval of similar looking images.

$$Mean\ (\overline{g}) = \sum_{g=0}^{L-1} gP(g) = \sum_r \sum_r \frac{I(r,c)}{M} \qquad (3)$$

$$Standard\ Deviation(\sigma_g) = \sqrt{\sum_{g=0}^{L-1} (g-\bar{g})^2 P(g)} \qquad (4)$$

$$Variance\ = \sum_{g=0}^{L-1} (g-\bar{g})^2 P(g) \qquad (5)$$

$$Smoothness = \frac{1}{1-\sum_{g=0}^{L-1}(g-\bar{g})^2 P(g)} \qquad (6)$$

$$Entropy = -\sum_{g=0}^{L-1} P(g)\log_2[P(g)] \qquad (7)$$

$$Uniformity = \sum_{g=0}^{L-1} [P(g)]^2 \qquad (8)$$

$$Third\ order\ Moment = \frac{1}{\sigma_g^3} \sum_{g=0}^{L-1} (g-\bar{g})^3 P(g) \qquad (9)$$

where $P(g) = \frac{N(g)}{M}$

Transformed Coefficients:

Every zone of query and database images is translated to frequency domain from spatial domain using Discrete Fourier Transform (DFT) and first order Discrete Wavelet Transform (DWT). DFT coefficients are used as a feature vector for similar image retrieval. LL band of a transformed image consists of maximum information about it and hence energy of LL band coefficients for every transformed region are used as a feature vector in retrieval process.

Eigen Values (SVD)

By applying Singular Value Decomposition (SVD) for every zone of query and database images and principal diagonal values i.e. large Eigen values of the regions are used as feature sets for image retrieval.

Similarity Measures

The main issue in image retrieval systems is the number of dimensions of the feature vector which is normally huge. Manhattan distance metric measures the direct grid distance along the pixels and diagonal movements are not allowed. Manhattan distance metric given in Eq. 10 retrieve images at a faster rate when compared with Euclidean distance [22]. To speed up the retrieval process, we used this distance measure for all the five attributes computed from five zone partitions of the images.

$$Cityblock\ Distance = \sum_{i=1}^{n} |a_i - b_i| \qquad (10)$$

Performance Metrics:

The presented retrieval system performance analyzed by retrieval efficiency in terms of average precision (AP) and Mean Average Precision (MAP) at 100% recall rate as given in Eq.11, 12 and 13.

$$Average\ Precision\ (AP) = \frac{Number\ of relevant\ images\ retrieved\ for\ a\ class\ of\ images}{total\ number\ of\ images\ retrieved\ for\ a\ class\ of\ images} \quad (11)$$

$$Mean\ Average\ Precision\ (MAP) = \frac{Number\ of relevant\ images\ retrieved\ for\ all\ class\ of\ images}{total\ number\ of\ images\ retrieved\ for\ all\ class\ of\ images} \quad (12)$$

$$Recall\ Rate = \frac{No. of\ relevant\ images\ retrieved}{Total\ Number\ of\ relevant\ images\ in\ the\ database} \qquad (13)$$

IV RESULTS & DISCUSSIONS

As discussed in methodology section, we used 1000 images of IRMA 2008 and 1000 images of IRMA 2009 X - Ray image datasets. These are categorized into 10 different classes of 200 images for each class. Each class represents the images of various anatomical regions viz. abdomen, spine, lungs, breast, skull, hand, shoulder, leg, knee and ankle. From every class 20% of images are chosen as query images and the retrieval efficiency is computed in terms of Average Precision (AP) for every class and Mean Average Precision for the entire data set with a recall rate of 100%. i.e. the AP and MAP computed by retrieving the first 200 images (equal to the size of relevant images in the data set) that shown the least distance value with respect to query images.

The best retrieval efficiency with more than 75% of MAP obtained with features extracted from regular zones than features calculated from irregular zones. The comparison analysis of MAP for the features extracted from various zone partitions is shown in Table1. Graphical representation of comparison analysis is shown in fig 4.

Table I: % MAP for all queries

ZONE	Sum	HG	Stat	DFT	DWT	SVD
Square	76	69	71	70	68	76
Row	61	67	67	68	58	59
Column	52	59	56	58	49	55
Staircase	23	24	22	23	23	24
Spiral	23	23	21	17	19	17

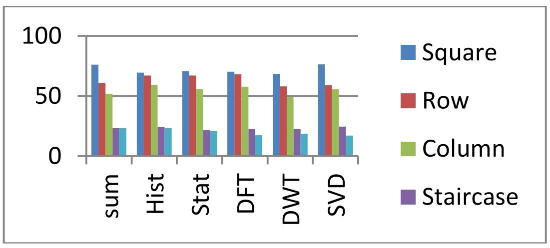

Fig.4. Zone wise % MAP comparison

From the comparison analysis we understood that squared and row wise regular regions out performed very well and hence we presented the class wise Average Precision (AP) for all the feature descriptors with square and row wise image partitioned zones in table 2. From the table it is clearly understood that for abdomen, spine lungs, skull, knee and feet image classes regular zoning with sum and SVD features shown good retrieval efficiency and for breast, palm and shoulder classes row wise zoning with histogram and statistical features shown better retrieval over square wise zoning. Optimal features with zoning methods for different anatomical X - Ray images shown in table 3.

Table II: Class wise % AP for squared and row wise regions

Zones	Features	abdomen	spine	lungs	skull	breast	knee	feet	palm	ankle	shoulder
square	**SUM**	93	**85**	**95**	78	72	74	**75**	**70**	54	65
	HG	90	82	88	**91**	54	64	72	62	37	54
	STAT	92	76	88	81	67	65	67	67	47	58
	DFT	**94**	81	92	68	64	**76**	58	48	54	66
	DWT	**94**	81	92	68	64	**76**	58	48	54	66
	SVD	**94**	**86**	**96**	73	72	74	**74**	**72**	**55**	65
row	**SUM**	46	46	87	59	68	65	69	58	45	66
	HG	72	73	84	**91**	57	66	66	**70**	40	56
	STAT	60	63	78	73	**90**	68	64	63	50	59
	DFT	89	74	81	64	67	67	58	53	53	**72**
	DWT	45	47	79	57	60	57	**73**	57	45	54
	SVD	46	52	86	61	56	61	69	58	48	56

Table III: Optimal feature set for various classes X-Ray images with Zoning Techniques

Zone	abdomen	spine	lungs	skull	breast	knee	feet	palm	ankle	shoulder
SQUARE	SVD, DWT, DFT	SVD, SUM	SVD, SUM	HG	-	DFT, DWT	SVD	SVD, SUM	SVD	DFT, DWT
% MAP	94	86	96	91	-	76	75	72	55	66
ROW	-	-	-	HG	STAT	-	-	HG	DFT	SUM
% MAP	-	-	-	91	90	-	-	70	53	66

V CONCLUSIONS

In this work we presented comparative analysis for retrieval of X - ray images of 10 different anatomical regions of 200 images each. The images used are of IRMA 2008 and IRMA 2009 datasets. The image attributes computed by partitioning the images into 64 zones of three regular sized and two irregular sized regions. These attributes include sum of pixel values, probability distributions, statistical features, transformed coefficients DFT and DWT and Eigen values zone wise. All these feature vectors were compared with Manhattan distance for similarity check between query and database images. Through the experimentation we learnt that Eigen values computed with SVD over square partitioned zones result in 75% to 95% Average Precision for abdomen, spine, lungs, knee, palm and ankle classes and histogram features of squared and row regions for skull images with 91%, statistical features computed over row regions result in 90% average precision for breast images and about 75% average precision by row region computed DWT and DFT for feet and shoulder images respectively. As extension to this we would like design an adaptive classifier that selects the optimal features for different classes of query images to improve retrieval efficiency further.

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