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Medical Image Retrieval – Performance Comparison using Texture Features

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Abstract:- Image retrieval is a specialized search to find images of interest. User may give a keyword, sketch or image itself to image search engine to retrieve back relatively similar images from the already stored image database. The similarity used as the search criteria could be based on features such as text, tag, color distribution of images (histogram), texture, shape, etc. The limitation of the text based retrieval is subjected to human interpretation of the mages in the form of combination of few texts/ key words. This is a very cumbersome process and could be highly error prone also. However, when it comes to medical images low level features of the image are more important than the semantics of the images. The low level features generally include color, texture and shape. The extraction of these features needs to be done for every image and to be pre-stored in the database to retrieve the images quickly. The retrieval method based on the content is known as Content Based Image Retrieval (CBIR).

Keywords: - CBIR, GLCM, Contrast, Dissimilarity, Homogeneity, Angular Second Moment, Entropy, Precision, Recall, Retrieval time.

I. INTRODUCTION

Diagnostics will be the hardest and most important application of image retrieval. To be used as diagnostic aid, the algorithms need to prove their performance and they need to be accepted by clinicians as a useful tool. This also implies that integration of the systems into the daily clinical practice which will not be an easy task. It is often very hard to change the practices which people are accustomed with. Confidence need to be built. For domains such as evidence based medicine or case based reasoning it is essential to supply relevant, similar cases for comparison.Most of the image retrieval techniques omit the relevance feedback in the system even though it definitely improves the performance of the system. The argument being, medical doctors do not have enough time. But if the system is interactive and responsive (preferred time is less than 1 sec), then there should not be much problems in an expert making use of the system and marking the few images positive or negative.Also the prospect of long term learning from this marking of images motivates people to use it. As there are several solutions in image retrieval it is also interesting to study the effect of interfaces, ergonomics and usability issues on the acceptance and use of the technology in clinical practice.

II. PERFORMANCE MEASURES OF A CBIR SYSTEM

Researchers have developed variety of CBIR systems. However comparison of these developed systems is not being carried out. People have used various performance measures such as error rate, retrieval efficiency, Precision (P) and Recall (R) graphs. However the most common evaluation measures used in Content Based Image Retrieval (CBIR) are Retrieval Time (tr), Precision (P) and Recall (R). Retrieval time is defined as the time taken by the CBIR system to retrieve the similar images from the database to that of the query image.

$$\text{Precision} = \frac{\text{number of relevant items retrieved}}{\text{number of items retrieved}}$$

$$\text{Recall} = \frac{\text{number of relevant items retrieved}}{\text{number of relevant items}}$$

2.1 Defining relevant image set

Consider Figure 1, if image number 14 is the query image, then we define "**relevant image set"** as the collection of images from 5 to 23 (if these images are similar or nearly similar) excluding 14. This results in a set of totally 18 images.

Relevant Image set for the query image brain0014.jpg																		
5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23

Fig. 1. A Relevant Image set for the query image brain0014.jpg

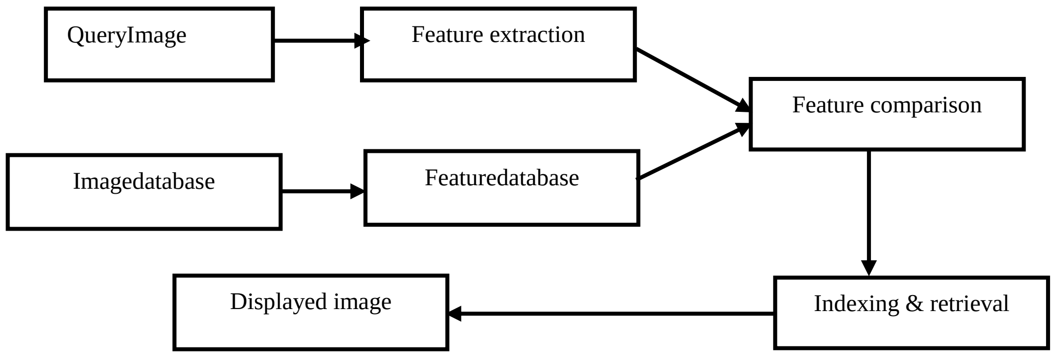

Fig. 2. A general block diagram of Image Retrieval System

The Figure 2. shows the block diagram of a typical Image retrieval system. The query image is selectable by the user and the feature extraction is done based on the method or algorithm being implemented. It is also possible to extract the features dynamically but it takes more time for the retrieval of the images. The retrieval time is reduced significantly by pre-storing the extracted features of all the images in the data base. In our system this is stored as the .mat file. The number of images to be displayed can be indexed depending on the user's interest and convenience.

III. IMAGE TEXTURE

In this article we discuss mainly two performance parameters namely Precision (P) and Recall (R) based on the Gray Level Co-occurrence Matrix (GLCM).

All present day medical images used for the diagnosis purpose are digital. Study of these digital images leads to identification of lesions to differentiation of healthy and non-healthy organs. The texture analysis is in principle is a technique for evaluating the position and intensity of pixels in an image and their gray level intensities. Texture features are in fact mathematical parameters computed from the distribution of pixels, which characterize the texture type and the structure of the medical image. It contains structural arrangement of surfaces and their relationship to the surrounding environment.

It is almost impossible to describe textures in words, although each human definition involves various informal qualitative structural features, such as fineness, coarseness, smoothness, granularity, lineation, directionality, roughness, regularity, randomness, and so on. These features, which define a spatial arrangement of texture constituents, help to single out the desired texture types. It is difficult to use human classifications as a basis for formal definitions of image textures, because, there is no obvious ways of associating these features, easily perceived by human vision. However, after several decades of research and development of texture analysis and synthesis, a variety of computational characteristics and properties for indexing and retrieving textures have been found. The textural features describe local arrangements of image signals in the spatial domain or the domain of Fourier or other spectral transforms. In many cases, the textural features follow from a particular random field model of textured images (Castelli and Bergman, 2002).

The common practice to obtain texture based descriptors is to implement standard transform domain analysis tools such as Fourier transform, Gabor filter, wavelet transforms or Stockwell filters on local image blocks [1, 2, 4-6]. In addition, one can also derive the Haralick's texture features such as energy, entropy, coarseness, homogeneity and contrast from the local image neighborhood [3, 4, 5, 7, 8] or utilize linear system approaches such as simultaneous autoregressive models [9]. In the medical domain, texture-based descriptors become particularly important as they can potentially reflect the fine details contained within an image structure. For example, cysts and solid nodules generally have uniform internal density and signal intensity characteristics, while more complex lesions and infiltrative disorders have heterogeneous characteristics. Some texture features may be below the threshold for humans to identify, and computers may be able to extract important texture and pattern information that is not readily visible.

Texture analysis can be carried out by techniques such as structural model based, Statistical and transform methods. Statistical based approach is based on the representation of the texture using properties governing the distribution and relationships of gray level values in the image. These methods normally achieve higher discrimination indexes than the structural or transform methods. We have implemented Co-occurrence method and extracted features such as Contrast, Dissimilarity, Homogeneity, Angular Second moment and Entropy.Contrast represents the amount of local gray level variations in an image. High values of this parameter may indicate the presence of edges, noise or wrinkled textures in an image.Homogeneity measures the smoothness of the gray level distribution of the image. It is inversely correlated with contrast. If contrast is small, homogeneity is large.Angular Second Moment is a measure of the uniformity of the gray level distribution of the image. Images with smaller number of gray levels have larger uniformity. Entropy is the degree of disorder among pixels in the image. Images with larger number of gray levels have larger entropy.

IV. FEATURE EXTRACTION USING GRAY LEVEL CO-OCCURRENCE MATRIX (GLCM)

Texture features can be extracted in several methods, using statistical, structural, model based and transformation based, in which the most common way is, using the Gray Level Co- occurrence Matrix (GLCM). GLCM contains the second-order statistical information of spatial relationship of pixels of an image.

From GLCM, many useful textural properties can be calculated to expose details about the image content. However, the calculation of GLCM is very computationally intensive and time consuming.
The calculation of GLCM features is done by the following equation:

Contrast [T1] = $$\sum_{i,j=0}^{N-1} P_{i,j}(i-j)^2 \qquad (4.1)$$

Dissimilarity [T2] = $$\sum_{i,j=0}^{N-1} P_{i,j}|i-j| \qquad (4.2)$$

Homogeneity [T3] = $$\sum_{i,j=0}^{N-1} \frac{P_{i,j}}{1+(i-j)^2} \qquad (4.3)$$

Angular Second Moment [T4] = $$\sum^{N-1} P_{i,j}^{\,2} \qquad (4.4)$$

Entropy [T5] = $$\sum_{i,j=0}^{N-1} P_{i,j}\left(-\ln P_{i,j}\right) \qquad (4.5)$$

Figure 3 displays texture based retrieval results for T. Where T = T1+T2+T3+T4+T5. It is observed from this result that, the combined value of the Precision is 1 (100%), which is more accurate than the individual feature Precision. However the total retrieval time (0.171087 seconds) in this case is little more than the individual feature comparison.

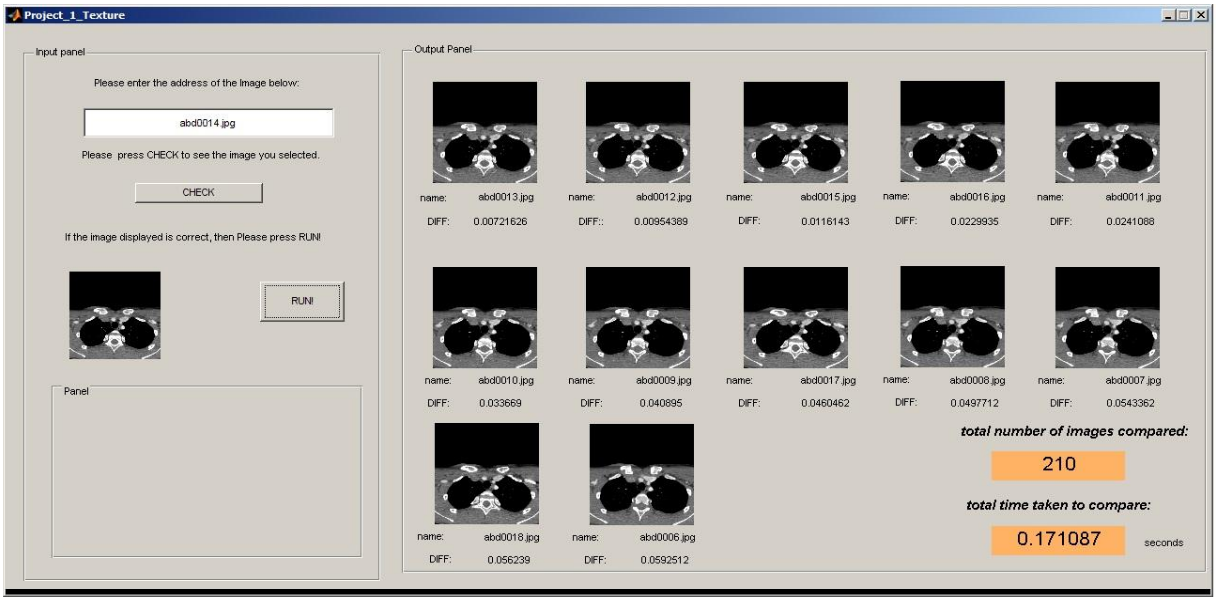

Fig.3. Screen shot of the retrieved images with T=T1+T2+T3+T4+T5

V. RESULTS

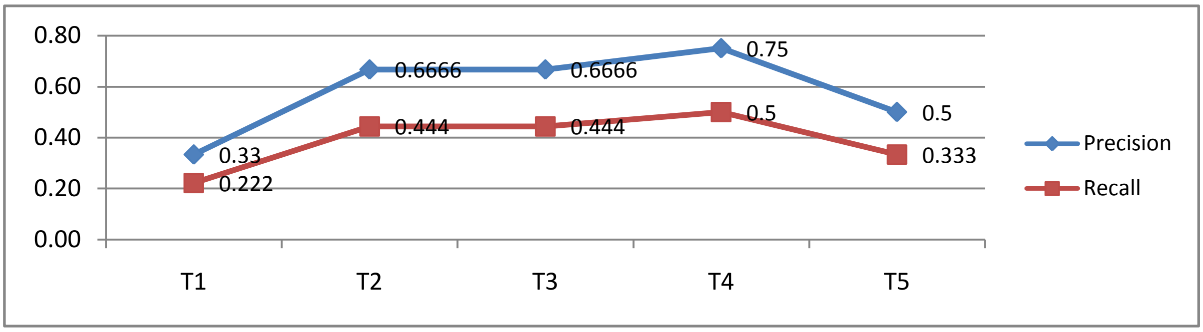

Fig 4. GLCM features for the Brain images of CT modality

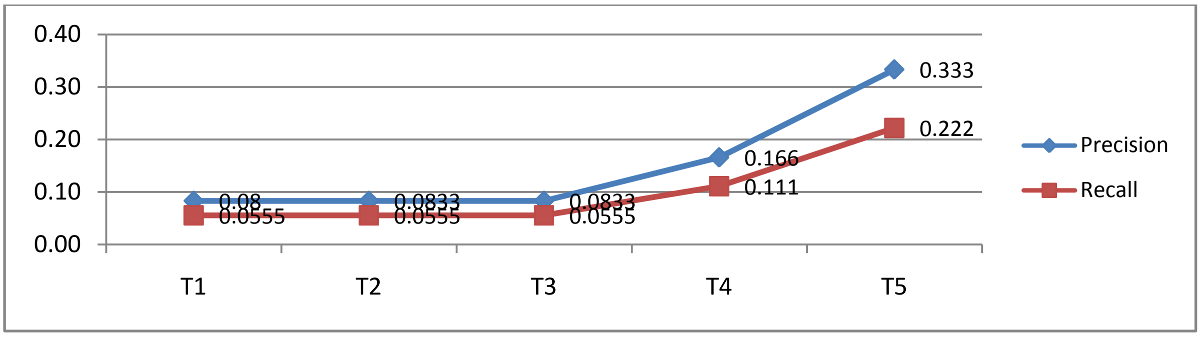

Fig. 5. GLCM features for the Brain images of MRI modality

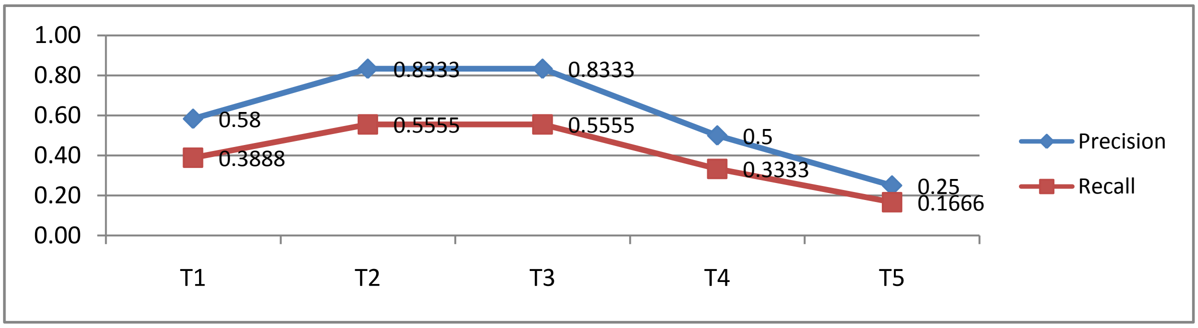

Fig. 6. GLCM features for the Chest images of CT modality

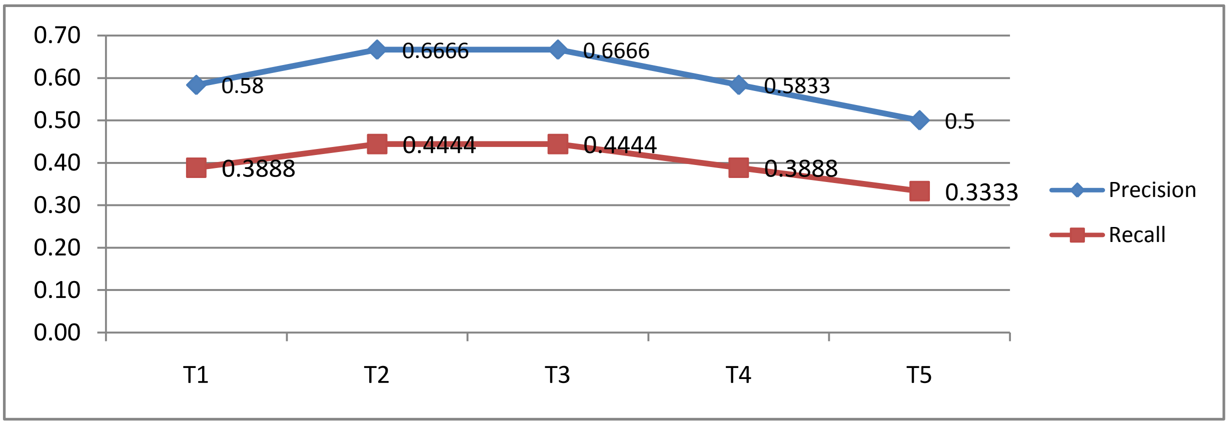

Fig. 7. GLCM features of Knee images of MRI modality

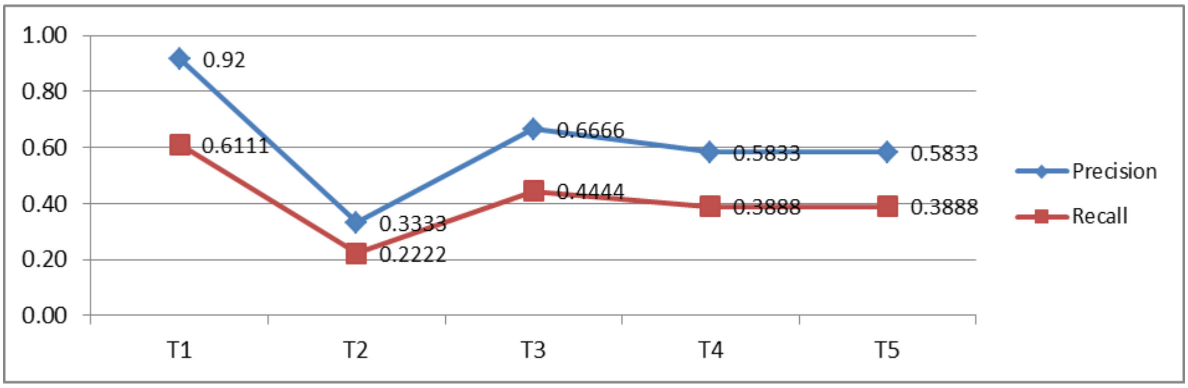

Fig. 8. GLCM features of Ultrasound images

VI. CONCLUSION

The results of the figure 4 to figure 8 are tabulated as shown below

Sl.No.	Modality	Dominant feature	Precision (P)	Recall (R)
1.	Brain_CT	Angular Second Moment (T4)	0.75	0.5
2.	Brain_MRI	Entropy (T5)	0.3333	0.2222
3.	Chest_CT	Homogeneity / Dissimilarity (T2/T3)	0.8333	0.5555
4.	Knee_MRI	Homogeneity / Dissimilarity (T2/T3)	0.6666	0.4444
5.	Ultrasound	Contrast (T1)	0.9166	0.6111

From the results in the table it is observed that, depending on the modality of the image only one or two features are dominant. In case of Brain_CT images, Angular Second Moment (T4) is the dominant feature compared to the other. Similarly Entropy is dominant in case of Brain_MRI images. Homogeneity / Dissimilarity are the dominant features in case of Chest_CT and Knee_MRI images. Contrast is the dominant feature in case of Ultrasound images. The experiments have been carried out with digital images acquired by the Radio diagnosis department of Kasturba Medical College, Manipal. A total of 210 images of dimension 512 x 512 with modality CT, MRI and Ultrasound have been stored in the database.

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