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Content Based Medical Image Retrieval – Performance Comparison of Various Methods

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ABSTRACT

Present healthcare system calls for standardization and interoperability of images acquired by various equipment manufacturers. The healthcare system is also not limited to a single super-specialty hospital where state of the art machines and excellent physicians are available but should also these services need to be available in remote places too. Nowadays, number of images acquired by the hospitals is increasing due to the various modalities available to identify accurately the cause of the deceases. This results in more number of medical images being stored in the database in hospitals. The interpretation of these medical images becomes even more critical, as it may contain the information which cannot be perceived by human eye. Therefore the images need to be annotated appropriately while it is stored so that, retrieval of the images of interest can be done quickly. The manual annotation is very cumbersome process when large number of images is involved in the retrieval process. Hence it is necessary to have an efficient Content Based Image Retrieval System which is user friendly and user definable in terms of speed and Precision.

Keywords: *CBIR, Histogram, Retrieval time, Precision, Recall, CDF, GLCM, DICOM, RSNA,*

I. INTRODUCTION

All human beings have the inherent nature of organizing the objects based on their perception. When we have very few items to arrange or organize, we can do so manually with ease. When the number increases, we need the help of an intelligent machine to do the same. In case of non-medical images variation in perception can be acceptable, since it may not have major impact even if there is some error. However in case of medical images a small error may have serious implications, which should not be overlooked. Hence it is important to compare medical images "based on the content" rather than only on perception. Looking for the contents which are not visible to the human eye calls for extracting features of the image, storing it in the database and retrieving based on the query.

Figure 1 describes the general block diagram of Image Retrieval System where, features extracted from query image are compared with the features in the image database. Pre calculating the features of the images in

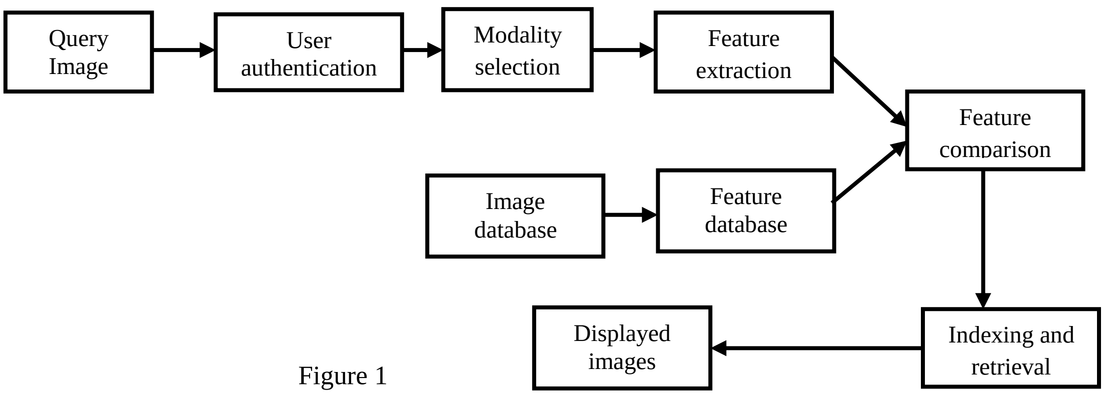


Figure 1

the image database reduces the time required for comparison and retrieval. However the challenge lies in finding the right features of the image so that, retrieved image is accurate and the retrieval time is also less. User authentication is needed to restrict only the authorized user to use the system. The modality selection helps to categorize correct modality images to be compared for retrieval. Most of the times, it may not be sufficient to have one feature comparison to retrieve the image accurately. It may be necessary to refine the query process by extracting more than one feature (for example intensity, shape, edge, texture) so that, retrieved image is more precise.

As the medical images in the PACS system at present need to conform to the DICOM (Digital Imaging and Communication in Medicine) standard, the size of any medical image is well defined by National Electrical Manufacturer's Association (NEMA) specification. The medical equipment used in the imaging process in hospitals or diagnostic centers need to confirm to standards defined by NEMA.

In order to provide efficient patient care many hospitals are implementing Picture Archival and Communication Systems (PACS). In a practical scenario mid-sized hospitals cannot afford to have the PACS due to the initial investment which is quite huge. These hospitals can have the services of PACS through a Wide Area Network (WAN). Size of the medical image being very large, transmission of these images to a distant healthcare setup will be limited by the bandwidth of the Wide Area Network or Internet. The image viewing at a remote station will be a very slow process and likely to cause severe delay which is a great concern for a physicians if he/she wants to view these images before treatment. Hence it is necessary to have an efficient Content Based Image Retrieval System which is user friendly and user definable in terms of speed and Precision.

II. SIGNIFICANCE OF CBIR IN HEALTHCARE

Images in medical domain are being captured only when the exact diagnosis need to be carried out. The images are very rich in their content and the information may not be clearly visible to physicians for visual inspection. These images are being large in size and require accurate interpretation a good Content Based Image Retrieval system will definitely help physicians in their decision by comparing it with similar cases in the image database.

Many Image Retrieval systems that have been developed are independently accessed and are usually text based. These systems have been developed mainly to categorize pictures which are generally non – medical. Here image perception is of higher priority than the content and thus text based retrieval is appropriate.

Apart from the rich information contained in the medical images, medical images also contain meta data information such as image modality, image slice number, patient age, gender, family status. Use of meta data along with the content of the image will prove to be more accurate in medical image retrieval, than using content alone.

Much of the radiological practice is currently not based on the quantitative image analysis, but on heuristics. Such heuristics may fail some time in variety of circumstances such as poor quality of imaging equipment, associated noise during the imaging procedure, lack of experienced technician, poor quality imaging station. Computer assisted image interpretation and retrieval will assist radiologists in correct interpretation. Image retrieval system combined with decision support system will be a real advantage in proper diagnosis.

There is a need to address the challenge of a specialized internet based Content Based Medical Image Retrieval (CBMIR) system that can help the doctors or medical practitioners across the globe in referring the existing medical records before taking a final decision over the diagnosis. If the system is distributed and accessible to the physicians, there will be definitely improvement in the quality of healthcare.

III. CBIR SYSTEM EVALUATION

In the general image retrieval domain, it is difficult to compare any two retrieval systems. Still, there are several articles on the evaluation of imaging systems in medicine or on general evaluation of clinical systems.

Henning Muller [1] provides an overall view of the various CBIR systems being developed. It would be hard to name or compare them all but some well-known examples include Candid, Photobook and Netra that all use simple color and texture characteristics to describe the image content. Using higher level information, such as segmented parts of the image for queries, was introduced by the Blobworld system. PicHunter on the other hand is an image browser that helps the user to find an exact image in the database by showing to the user images on screen that maximizes the information gain in each feedback step. A system that is available free of charge is the GNU Image Finding Tool (GIFT). Some systems are available as demonstration versions on the web such as

Viper, WIPE or Compass.
A single example result does not reveal a great deal about the real performance of the system and is not objective as the best possible query result can be chosen arbitrarily by the authors.

The commonly used measurement parameters in CBIR are:

1. Retrieval Time (tr): The time taken by the system to display relevant images to the given query image

$$2. \text{Precision (P)} = \frac{\text{number of relevant items retrieved}}{\text{number of items retrieved}}$$

$$3. \text{Recall (R)} = \frac{\text{number of relevant items retrieved}}{\text{number of relevant items}}$$

Defining the relevant image set can be done in various ways. This paper defines a set of "n" images which are varying by some factor as defined by the user. A total of 1720 images procured from Radio diagnosis department of K.M.C Manipal hospital is maintained in the database. The images are of different modality like CT, MR, US & CR and of dimension (256 x 256, 2500x2048, etc..)

Figure 2 shows the relevant set for the query image 14.

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

Figure 2

Query image

IV. RETRIEVAL METHODS IMPLEMENTED

Retrieval time (tr) comparison of eight different methods is provided in section 4.6 in the form of a graph.

4.1 Histogram Based Retrieval

One of the most commonly used parameters for image comparison is the color or intensity of the image. In our research we have emphasized on the gray level medical images. An experienced physician can interpret the images better than a lay man due to his experience in identifying similar images in the past. However subtle changes in the image cannot be easily observed. A histogram is the count of the number of pixels at each intensity level over the entire image. It is given by,

$$hist(r_k) = n_k$$

Where, k=0 …L-1,
L is the number of intensity levels.
nk = number of pixels at gray level rk

It plots the number of pixels for each intensity value. By looking at the histogram for a specific image, a viewer will be able to judge the entire intensity distribution at a glance.

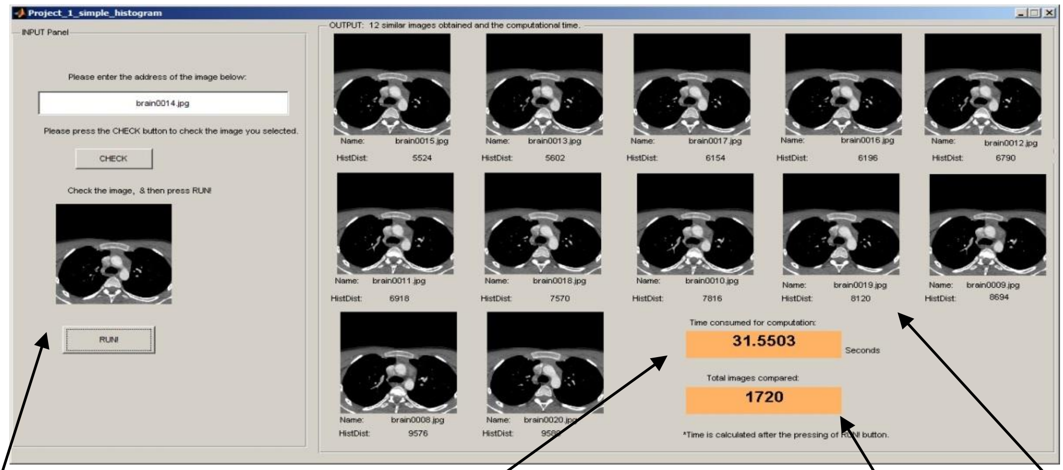
In histogram matching technique, the histogram of all the images in the database are computed and stored in a file. When a query image is given, the histogram of the query is computed and compared with the stored histograms. For each and every image in the database, the distance metric is calculated as,

$$histdist[dataset] = \sum_{j=0}^{255} | hist\_dataset[j] - hist\_query[j] |$$

Where,

- j denotes the various gray levels ranging from 0 to 255.
- hist_query is the histogram of query image, hist_dataset is histogram of the image in the database.

The images in the database nearly matching with the query image, have the least distance metric. The exact match is the one with the zero distance metric.



Query image

Screen shot of the Histogram based retrieval

12 retrieved images

Retrieval time

Figure 3

Images in the database

The result of the Histogram based retrieval is shown in Fig.3. Twelve closest images are displayed from a total 1720 images in the database. The total time for retrieval is 31.5503 seconds.

4.2 Bit Plane Based Retrieval

In this method, the image is composed of eight one bit planes, ranging from bit plane 0 for the Least Significant Bit (LSB), to the bit plane 7 for Most Significant Bit (MSB) as shown in Fig.4. Usually most of the visually significant information is contributed by higher order bits and less by the least significant bits. An 8 bit image can have 256 different shades of gray, where 0 represents black and 255 represent white, and Integers between 0 and 255 represent various shades of gray. So out of the 8 bits, when 7th bit is set, it represents the intensities ranging from gray level 128 to 255, and, when 6th bit is set, it represents totally 128 gray levels in the range 64 to 127 and 192 to 255, and when 5th bit is set, represents totally 128 gray levels in the range 32 to 63; 96 to 127; 160 to 191 and 224 to 255 and so on.

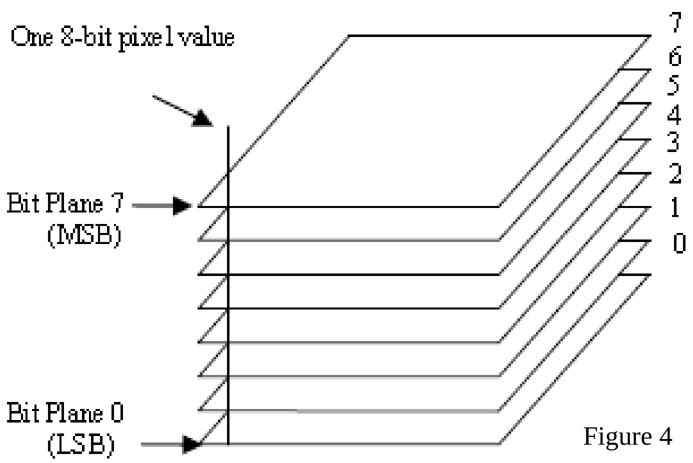


Figure 4

In this method, the number of occurrences of set bits in each bit plane is computed. The bit plane histogram is represented mathematically as,

$$hist\_database[i] = \sum \sum_{x,y}^{m,n} f(x,y)_i \qquad (2.5)$$

Where, $f(x, y)_i$ is the pixel value at (x, y) having i^{th} bit set to 1, i = 7,6..0.

4.3 Hierarchical Bit Plane based retrieval

To make the bit plane histogram matching more efficient, a method is proposed to discard the dissimilar images in the database by a method called Hierarchical bit plane histogram matching.

4.3.1 Histogram percentage as threshold

This method begins with the most significant bit (MSB), and is based on the distance metric equation. The distance metric at the MSB for each image in the database is compared with the threshold specified by the user in terms percentage of histogram. Those images in the database with the distance metric less than the specified threshold are retained for subsequent search at lower bit planes. This is continued till the least significant bit i.e. till the 0th bit is reached. This bit plane technique allows one to compare the query and database images with only one arithmetic operation per bit plane and hence needs less computational time and power compared to the traditional grayscale histogram matching.

4.3.2 Image size as the threshold

It is common that, the major object in an image is located at the center part of the image. In this method query image as well as the images in the database are re-sized according the percentage of the threshold specified by the user in terms of dimension. If image dimension is [m x n] and the percentage of the threshold is 90%, then image dimension is re-sized to 90% * [m x n]. it has been observed that smaller dimension of the image takes less time for retrieval.

Result of Histogram and Bit plane

Table 1, shows comparison of four retrieval methods in terms of retrieval time, Precision and Recall parameters.

Table 1

Total number of images in the database= 1720

Sl.No	Retrieval Method	Retrieval time (Tr) in secs	Precision (P)	Recall (R)
1.	Histogram comparison	31.6323	1	0.667
2.	Bit plane histogram	4.27613	0.583	0.389
3.	Hierarchical bit plane 2% histogram as the threshold)	4.64211	1	0.667
4.	Hierarchical bit plane 98% size of the image as the threshold)	5.31345	1	0.667

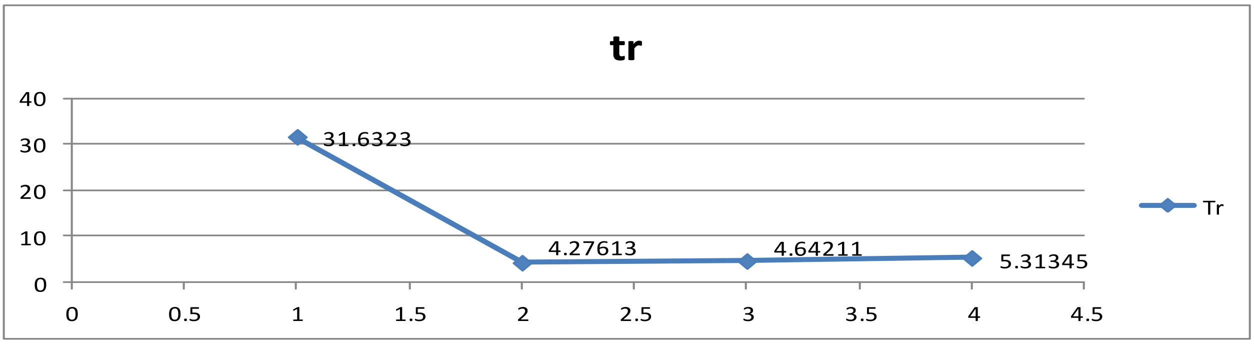


Fig. 5, Retrieval of four different methods

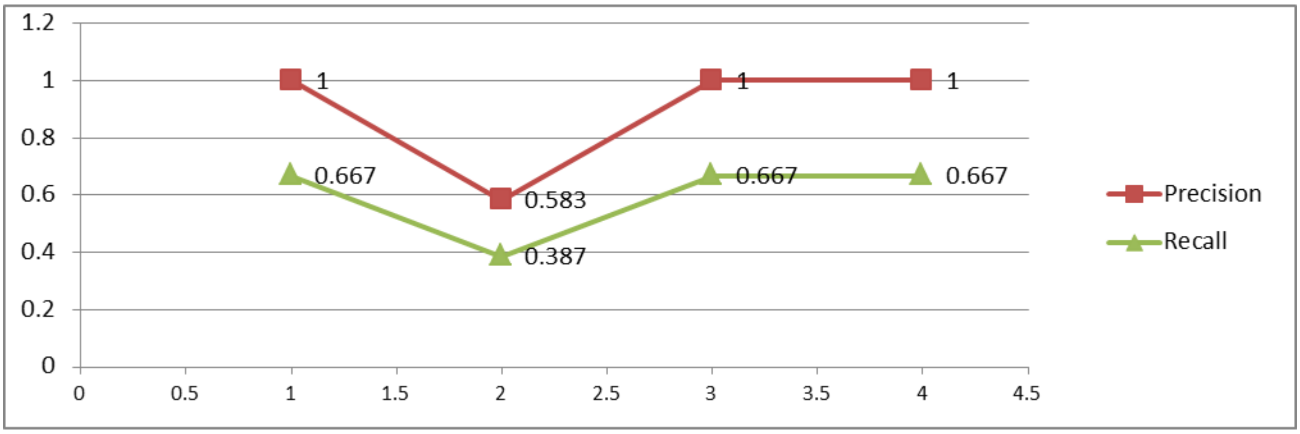


Fig. 6, Precision, Recall graph of four methods

From the graph in the Fig.5, it can be observed that, there is a considerable improvement in retrieval time in case of Bit plane histogram compared to that Simple histogram method. Fig.6 shows the Precision and Recall parameters of the four different methods implemented. From the above two graphs it can be observed that the least retrieval time (Tr) amongst the four method is the Bit plane histogram (4.27613 sec). While retrieval time being the lowest in Bit plane method, the Precision and Recall values are 0.583 and 0.387 respectively, which is lower than the other 3 methods namely Histogram comparison, Hierarchical bit plane with Histogram as threshold and Hierarchical bit plane with size as the threshold. From the user's perspective the Precision and Recall being the most important parameters, Hierarchical bit plane with 2% histogram as the threshold is the best method amongst the four being described here. It is also observed that the Precision and Recall parameters remain same irrespective of the image dimension in the database.

The retrieval time will also depend on the speed and type of the processor on which the algorithm has been implemented. Results are obtained on a computer with Processor type: Intel i3-2370M CPU @ 2.4 GHz processor with 4 GB RAM.

4.4 Cumulative Distribution Function (CDF) based retrieval

Medical images are of different dimension depending on the modality of the image as defined by Radiological Society of North America (RSNA). The pixel depth and image dimension vary depending on the size of the image. The comparison of images of different dimension will be difficult and needs sophisticated algorithms to match the two images in terms of intensity or histogram value. This puts extra computation time as well as complexity to the CBIR system. Another problem being the registration of the two images. In the pixel matching method where pixel intensity of the query and database images is compared, the rotation of the image leads to comparison of two dissimilar pixels. This requires image registration to be carried out before the comparison. This problem is overcome by CDF where The CDF of the query image and the images in the database are approximated by piecewise linear models with two parameters, slope and intercept at various grayscale intervals. The contiguous set of lines approximating the CDFs enables us to compare the query image and the images in the database with corresponding estimated slopes and intercepts. As the dynamic range of CDF is from 0 to 1, images of different sizes can be compared. Approximation of CDFs with lines further reduces the dimension of the image features and thus improves the speed of matching. Also, the monotonically increasing CDF is well suited for approximations with lines. Resolving the CDF with lines of different lengths recasts the matching to a hierarchical methodology.

Cumulative Distribution Function (CDF) for retrieving the medical images from the database provides a considerable reduction in the retrieval time and also flexibility to the user in terms of selecting suitable number of line segments (p) and the percentage of CDF threshold depending on the situation providing control over precision and time of retrieval.

The Cumulative Distribution Function cdf (i) upto the gray level 'i' is given by:

$$cdf(i) = \sum_{j=0}^{i} h(j) = \sum_{j=0}^{i} \frac{nj}{M.N} \quad 0 \leq i \leq 255 \qquad (3.2)$$

Where, h (j) is the normalized histogram at gray level j

nj is the number of pixels with gray level j

M.N is the size / dimension of the image

The CDF contains the same information as that of the histogram, but in another form. However, it has two interesting properties (a) It is a monotonically increasing quantity which allows fairly well approximation of the CDF with just a first order curve (b) It has a dynamic range between 0 and 1 which allows one to fit piecewise linear models on CDFs of images of any size.

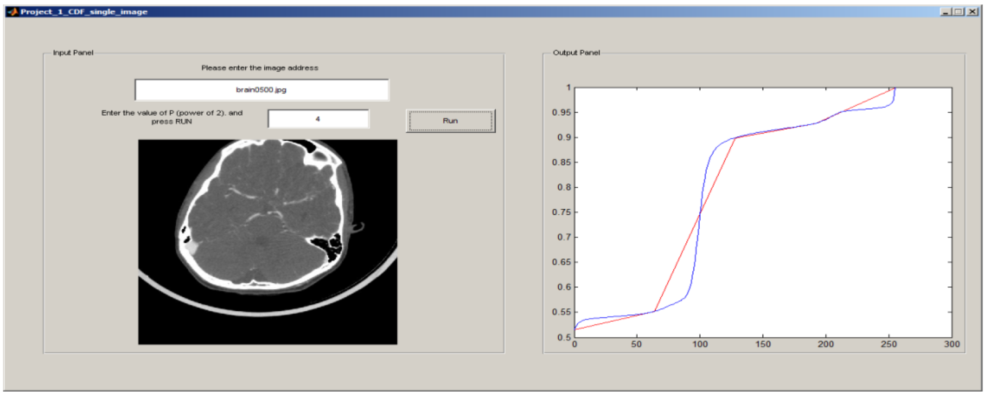


Fig 7. CDF of image brain0500.jpg with p=4 and continuous cdf overlapped

4.5 Edge and Texture based retrieval

It is also equally important to consider the edge / shape of the medical images for comparison especially in case of bone / skull images. As the edges give idea about the shape of the objects present in the image, they are useful for segmentation, registration and identification of objects. We have implemented edge detection using Sobel Operator. The Sobel operator consists of a pair of 3×3 convolution kernels as shown in Fig.8. One kernel is simply the other rotated by 90°. Sobel operator is very simple and effective way for finding the edges in image.

-1	0	+1
-2	0	+2
-1	0	+1

Gx

+1	+2	+1
0	0	0
-1	-2	-1

Gy

Fig 8

These kernels are designed to respond maximally to edges running vertically and horizontally relative to the pixel grid, one kernel for each of the two perpendicular orientations. The kernels can be applied separately to the input image, to produce separate measurements of the gradient component in each orientation (call these Gx and Gy). These can then be combined together to find the absolute magnitude of the gradient at each point and the orientation of that gradient. An approximate gradient magnitude is computed using

$$|G| = |Gx| + |Gy|$$

The Edge = |Gd – Gq|

Where Gd is the gradient of the database image

Gq is the gradient of the query image

Texture is a very general notion that can be attributed to almost everything in nature. For a human, the texture relates mostly to a specific, spatially repetitive (micro) structure of surfaces formed by repeating a particular element or several elements in different relative spatial positions. Generally, the repetition involves local variations of scale, orientation, or other geometric and optical features of the elements. 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. After calculating GLCM, normalization is being carried out by dividing each element by the sum of all elements as shown in the equation below:

$$P_{i,j} = \frac{V_{i,j}}{\sum_{i,j=0}^{N-1} V_{i,j}}$$

Where,

- $V_{i,j}$ is the (i , j) element of the GLCM
- $P_{i,j}$ is the (i , j) element of the Normalized GLCM

From the normalized GLCM the following features have been extracted

- Contrast [T1]
- Dissimilarity [T2]
- Homogeneity [T3]
- Angular Second Moment [T4]
- Entropy [T5]
-

The calculation of GLCM features is done by the following equation:

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

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

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

Angular Second Moment [T4] = $\sum_{i,j=0}^{N-1} P_{i,j}^{\ 2}$

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

From the above equations the feature vector F is calculated as shown below.

F = [T1, T2, T3, T4, T5]

The magnitude of the feature vector F = T1+T2+T3+T4+T5

The Similarity metric of the texture can be calculated as Etexture = | Fd – Fq |

Where,

- Fd = Magnitude of Feature Vector of Database Image
- Fq = Magnitude of Feature Vector of Query Image

The results of our research work where we have implemented eight different methods are shown in are shown in Table 2.

4.6 Retrieval time comparisons of various methods implemented

Sl.No	Method			Retrieval Time (Tr) in seconds
1.	Histogram			31.6323
2.	Bit plane	Simple		4.09868
3.	Hierarchical bit plane -1	20% histogram as threshold		4.51706
4.	Hierarchical bit plane -2	98% size as threshold		5.69741
5.	CDF	P = 3 [8 lines]		0.61504
6.	Hierarchical CDF	P = 3	1% of cdf diff as threshold	0.351143
7.	Edge based - 1	Sobel method		12.6268
8.	Texture based	GLCM method		0.401352

Table 2

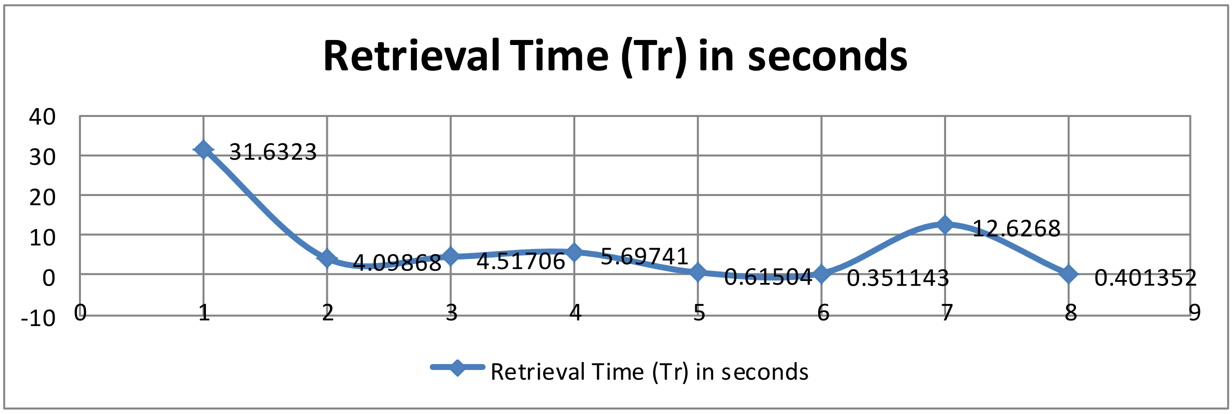


Fig. 9

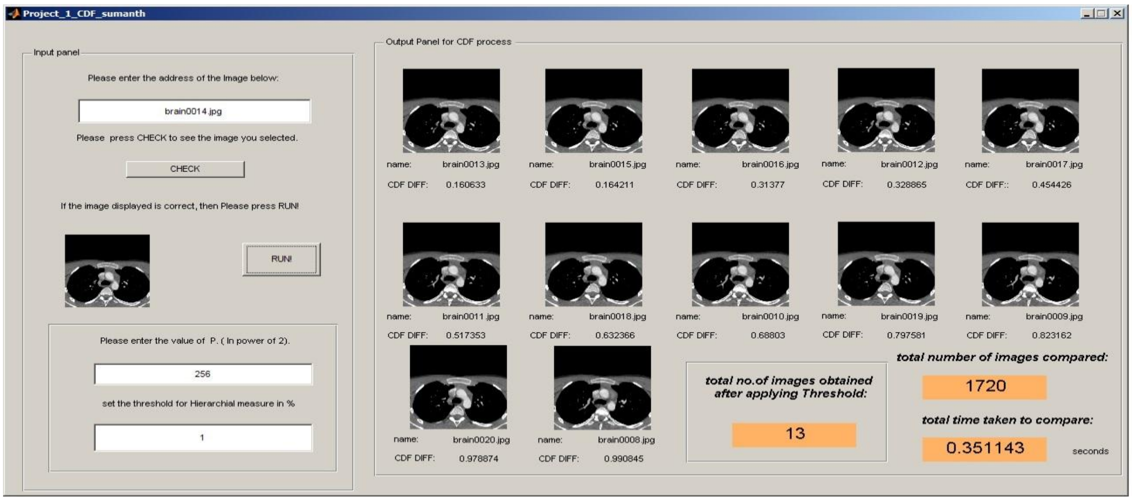


Fig. 10. Retrieved images for query image brain0014.jpg with p=8, with 1% as CDF threshold

Figure 9 shows the retrieval time (tr) comparison of various methods implemented in our research work. Y- axis indicates the retrieval time (tr) in seconds. Figure 10 shows the screen shot for CDF based retrieval with p=8 with 1% as CDF as the threshold.

X – axis indicates 8 different methods implemented. The details of the 8 different methods are given below:

1. Histogram based retrieval (without pre-stored features)
2. Simple Bit plane (pre-stored features)
3. Hierarchical Bit plane – 20% histogram as the threshold (pre-stored features)
4. Hierarchical Bit plane – 98% size as the threshold (pre-stored features)
5. CDF based retrieval (p=3) (pre-stored features)
6. Hierarchical CDF based retrieval (p=3) (pre-stored features)
7. Edge based retrieval (Sobel method) (pre-stored features)
8. Texture based retrieval (GLCM method) (pre-stored features)

V. CONCLUSION AND FUTURE SCOPE FOR THE RESEARCH

Content-Based Image Retrieval (CBIR) is a very important research area with its innumerable applications especially in the medical and healthcare domain. Presently there is a substantial gap between CBIR, and its focus on raw image information and decision support systems, which typically enter the workflow beyond the point of image analysis itself. This gap represents what we believe is a major opportunity to develop decision support systems that integrate image features exploited in CBIR systems. With such integration, CBIR may be a starting point for finding similar images based on pixel analysis, but the process would be augmented by inclusion of image and non-image metadata as well as knowledge models, broadening the system from "image based search" to "case-based" search.

The present research work focuses on retrieval of images quickly based on three parameters namely Intensity, Texture and Shape. However including physician in the image retrieval loop (relevance feedback) will be better for accurate diagnosis. It would be better, if the physician is given a choice to select a specific area in the image and image is re-sized according to the selected area for better precision. However this will need extra time in terms of re-building the feature database.

The proposed system addresses global feature extraction of the images. However implementing local feature extraction based on automatic segmentation of the images may improve the accuracy of the system.

In our systems we have maintained single CDF feature database irrespective of line segments (2p) being selected by the user. Maintaining different feature databases as per the number of line segment should improve the retrieval time. This method could be explored in the future implementations.

In the texture comparison using GLCM we have taken into account the added values of the features (i.e. T1 + T2 +T3 + T4 + T5). Retrieval performance based on the individual GLCM features may give us more insight into the content of the medical images.

Extending the above features into the video images such as endoscopy may also help physicians in the diagnosis.

From the research perspective it is better to develop a standard CBIR frame work where various algorithms can be implemented on standard image database hosted at a central location. Giving options to students / researches to develop new algorithms and adding it to the existing methods will make the CBIR system usable by everyone.

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