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Spine MRI Image Retrieval using Texture Features

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ABSTRACT
The main intention of content based medical image retrieval (CBMIR) is to efficiently retrieve medical images that are visually similar to a query image. Medical images are usually retrieved on the basis of low level and high level features. This work deals with the concept of texture based spine MRI image retrieval in the wavelet compressed domain. We use two statistical methods such as Haralick features and texture spectrum features for spine MRI image feature extraction and project the features to a set of signatures. The obtained statistical features are classifying, according to various types of spine MRI images using k-means clustering algorithm. Then the image retrieval is carried out by calculating the distance between the signatures in the database images and the query image. This method is applied around 500 spine MRI images and improvements of retrieval efficiency are found with standard precision and recall analysis.

General Terms
Medical Imaging, Content based image retrieval

Keywords
Haralick features, Texture spectrum features, Haar DWT, K-means clustering

1. INTRODUCTION
Content – Based Image Retrieval (CBIR) system is a type of framework which retrieves images based on features such as colors, texture and shape of the image [1]-[2]. The commonly designed CBIR systems have focused on generic retrieval system. But Content – Based Medical Image Retrieval (CBMIR) system [3]-[5] has focused on domain – specific retrieval system. Nowadays, there are enormous numbers of medical images being generated in hospitals around the world. It is expected that the amount of such images will further increase exponentially in the future. The importance of new technologies such as X-Ray radiography, Ultrasound, Computed Tomography (CT), Magnetic Resonance Imagining (MRI) and Picture Archiving and Communication Systems (PACS) have resulted in an explosive growth in the number of images stored in the database. This will lead various new frameworks for storage, organization, indexing and retrieval of the medical images in various fields like medical diagnosis, research and teaching.

Generally, the medical image database contains a lot of texture [6] based information for competent retrieval purpose. This paper, proposed the concept of spine MRI image retrieval using two different statistical features such as Haralick and texture spectrum features [7]-[8] in the wavelet compressed domain [9]-[10].

2. RELATED WORKS
There are different existing systems that provide different techniques and algorithms for content based medical image retrieval. The main purpose of all these systems is to show the improvement of results so as to aid the doctors and radiologists in diagnosis of treatments.

IBM introduced ILive (Interactive Life sciences Imaging Visualization and Exploration) system [11]. To allow content based queries in diverse collections of medical images, the retrieval system must be memorable with the current image class prior to the query processing. So ILive was developed for the automatic categorization of medical images according to their modalities. The key emphasis of IBM ILive was with diverse imaging modalities.

The IRMA (Image Retrieval in Medical Applications) database used for content based image retrieval in medical applications [12] contains different semantic layers of information modeling, a hierarchical concept of feature representation and utilized distributed system architecture for proficient implementation. In this system the classification of images were achieved by sustaining texture analysis.

In [13], the authors presented a concept by combining low level content features and high level semantic features to carry out retrieval on medical image databases. The semantic information was extracted from DICOM header which was used to perform the initial search and images were retrieved. Gabor wavelet [14] was one of the methods for texture feature extraction and description in content based medical image retrieval. In this approach texture feature vector was computed according to the multi-scale and multi-direction fuzzy set which is calculated based on all energy co-efficient.

The GMM-KL framework [15] was comprised of a continuous and probabilistic image representation scheme using Gaussian Mixture Modeling (GMM) along with information theoretic image matching via the Kullback-Leibler (KL) measure. The GMM-KL framework was used for matching and categorizing X-ray images by body region.

In a recent paper [16], the authors described a novel method for retrieving vertebra pairs that demonstrate a specific disc space narrowing (DSN) and inter-vertebral disc shape. DSN was characterized using spatial and geometrical features between two adjacent vertebrae. In order to obtain the paramount retrieval result, all selected features were ranked and assigned a weight to indicate their importance in the computation of the final similarity measure. Using a two phase algorithm, initial retrieval results were clustered and used to construct a voting committee to retrieve vertebra pairs with the highest DSN similarity. There were several other CBIR researches in the medical field [17]-[18]. They used a variety of different image features, including co-occurrence statistics, shape descriptors, Fourier transforms and global gray level statistics.

This paper is organized such that brief discussion on proposed work and discrete wavelet transform in section 3 and 4. In sections 5 and 6, we explain about Haralick and texture spectrum based texture feature extraction. In section 7, we deal with texture classification. Section 8 shows experiments and results. In section 9, we conclude our work with feature prospects.

3. PROPOSED WORK

The block diagram of the proposed wavelet and low level statistical features based image retrieval system is shown in Fig 1.

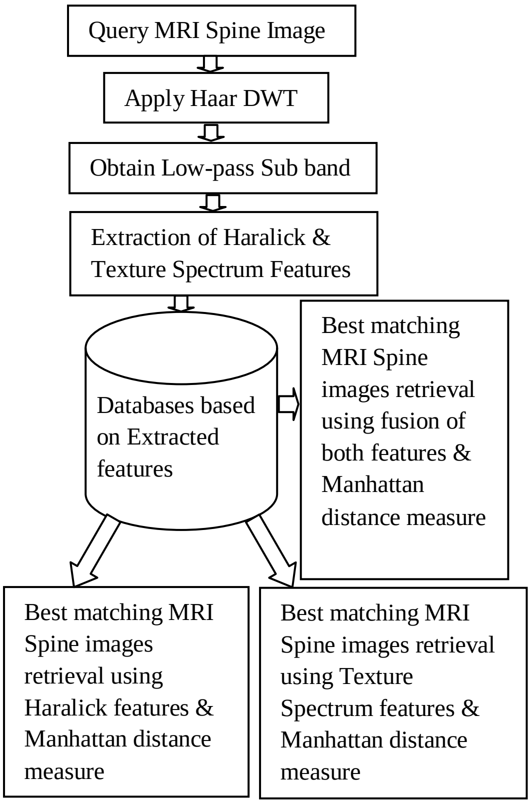


Fig 1: The configuration of the proposed retrieval system

In our work, after Haar discrete wavelet transform (DWT) [19], Haralick features such as contrast, angular second moment, coarseness, entropy and texture spectrum features such as black-white symmetry, geometric symmetry, degree of direction, orientation features and central symmetry are extracted from the low-pass sub band of the image and the database are created. Then according to k-means clustering [20] and Manhattan (city-block) distance function [21]-[22], N-best matches for the query image are retrieved using Haralick features, Texture spectrum features and combination of both features.

4. DISCRETE WAVELET TRANSFORM

While extracting the Haralick features and texture spectrum features instead of taking the whole image, the Haar discrete wavelet transform of the image can be considered and only the first sub band of the image after applying Haar DWT is taken for feature extraction.

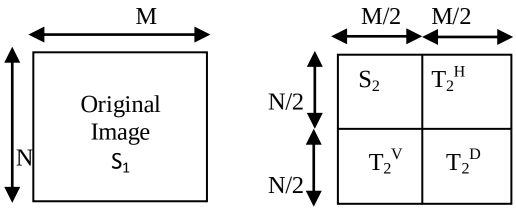


Fig 2: 1-Level Wavelet Transform

The process for Haar DWT is simpler than that of any other wavelets. The wavelet coefficients can be obtained from the gray-level image using addition and subtraction. In the first level of decomposition using Haar DWT, one low-pass sub band S_2 and three directional high-pass sub bands, T_2^H, T_2^V, T_2^D are created. The low-pass sub band is the most important among all wavelet sub bands, because it is the thumbnail version of an original image. Fig 2 shows the 1-level decomposes of Wavelet Transform.

2-D DWT is achieved by two ordered 1-D DWT operations (row and column). First of all, we perform the row operation for the image pixel representation shown in Fig 3(a) to obtain the result shown in Fig 3(b).Then it is transformed by the column operation and the final resulted 2-D Haar DWT is shown in Fig 3(c). This reduced the size of the image. Then the features are extracted and stored in the database for classification and retrieval.

$$\begin{pmatrix} A & B & C & D \\ E & F & G & H \\ I & J & K & L \\ M & N & O & P \end{pmatrix} \qquad \begin{pmatrix} (A+B) & (C+D) & (A-B) & (C-D) \\ (E+F) & (G+H) & (E-F) & (G-H) \\ (I+J) & (K+L) & (I-J) & (K-L) \\ (M+N) & (O+P) & (M-N) & (O-P) \end{pmatrix}$$

(a) (b)

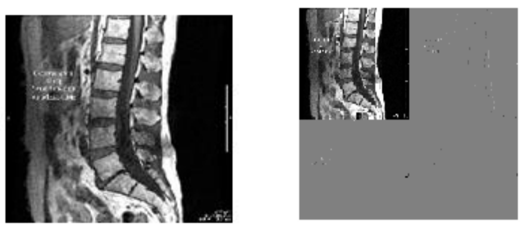
$$\begin{pmatrix} (A+B)+(E+F) & (C+D)+(G+H) & (A-B)+(E-F) & (C-D)+(G-H) \\ (I+J)+(M+N) & (K+L)+(O+P) & (I-J)+(M-N) & (K-L)+(O-P) \\ (A+B)-(E+F) & (C+D)-(G+H) & (A-B)-(E-F) & (C-D)-(G-H) \\ (I+J)-(M+N) & (K+L)-(O+P) & (I-J)-(M-N) & (K-L)-(O-P) \end{pmatrix}$$

(c)

(a)Original image (b) Row operation of 2-D Haar DWT
(c) Column operation of 2-D Haar DWT

Fig 3: Haar DWT

Two-dimensional discrete wavelet transform (2-D DWT) decomposes an input image into four sub-bands which is shown in Fig 4.



(a) Original Image (b) Decomposed 4 Sub bands

Fig 4: 2-D DWT

This reduces the image size and hence the image retrieval speed increases. The operation for Haar DWT is simpler than that of any other wavelets. It has been applied to image processing especially in multi-resolution representation. The wavelet coefficients can be obtained in gray-level image using addition and subtraction. In the first level of decomposition using Haar DWT, one low-pass sub band S_2 and three directional high-pass sub bands, T_2^H, T_2^V, T_2^D are created. The low-pass sub band is the most important among all wavelet sub bands, because it is the thumbnail version of an original image. After wavelet transform, Haralick Features and texture spectrum features were extracted from the low-pass sub band with spatial information.

5. HARALICK FEATURES

5.1 Feature selection

Since we are interested in the statistical approach, first we make use of the most suitable Haralick features [23]. The most common features used in practice are the measures derived from spatial gray tone co-occurrence matrix i.e., Haralick features such as contrast, angular second moment, entropy etc. These features have been widely used in the analysis, classification and interpretation of medical images.

5.2 Contrast

Local contrast is commonly defined for each pixel as an estimate of the local variation in a neighborhood. More precisely, given a pixel p= (i, j) and neighbor mask WxW of the pixel, local contrast is computed as,

$$\text{local contrast}(i,j) = \frac{\text{Max}_{p\in WXW}(p) - \text{Min}_{p\in WXW}(p)}{\text{Max}_{p\in WXW}(p) + \text{Min}_{p\in WXW}(p)}$$

We proposed to measure the global contrast as the global arithmetic mean of all the local contrast values over the image:

$$\text{contrast} = \frac{1}{m*n} * \sum_{i=1}^{n}\sum_{j=1}^{m} \text{local contrast}(i,j)$$

Where, n and m are the dimensions of the image.

5.3 Coarseness

Coarseness is “the quality of being composed of relatively large particles [syn: graininess, granularity]”. Coarseness is defined as,

$$C = 1 - \frac{1}{1 + S_D}$$

Where, S_D is the dispersion of the image.

$$S_D = \sum_{i=0}^{L-1} (i - S_M)^2\ h[i]$$

Where, S_M is the mean of histogram h[i] and L is the number of levels.

5.4 Angular Second Moment

ASM is a measure of homogeneity of the image. It is defined by,

$$\text{ASM} = \sum_{i=1}^{N_g}\sum_{j=1}^{N_g} [P(i,j)]^2$$

Where P(i,j) is the (i,j) th element in co-occurrence matrix, which represents the probability of going from the gray level i to j, given the displacement vector. N_g represents the number of gray levels in the image.

5.5 Entropy

Entropy is the measure of randomness. It is defined by,

$$\text{Entropy} = -\sum_{i=1}^{N_g}\sum_{j=1}^{N_g} P_{ij} \log P_{ij}$$

Where, P(i,j) is the (i,j) th element in co-occurrence matrix, which represents the probability of going from the gray level i to j, given the displacement vector. N_g represents the number of gray levels in the image. Table 1 shows the sample values of the Haralick features.

Table 1: Extracted sample values of Haralick features

IMAGE id	CONTRAST	COARSENESS	ASM	ENT
1	-0.15	0.9999999473792	27004632.70	-49371
2	-5.	0.999999865297589	56964368.01	-75086
3	-5.44	0.999999831195012	26385312.64	-54735
4	-0.15	0.999999945826585	27495324.81	-49833
5	-0.26	0.999999972949448	1346307.13	-11257
6	-0.26	0.999999974677931	1080737.69	-10303
7	-0.23	0.999999973025063	924809.65	-10049
8	-9.07	0.999999895532065	14673602.92	-39643
9	-7.78	0.999999874242684	15702853.89	-41601
10	-6.40	0.999999855389911	26855701.24	-50840
1	-5.44	0.999999831195012	26385312.64	-54735

6. TEXTURE FEATURES BASED ON TEXTURE SPECTRUM

The texture features based on texture spectrum extract textural information of an image with a more complete respect of texture characteristics in all the eight directions instead of only one displacement vector used in co-occurrence matrix approach. He and Wang [24] have proposed the texture spectrum approach. In this new statistical method, the corresponding texture unit represents the local information for a given pixel and its neighborhood, and the global texture of the image is characterized by its texture spectrum. An image can be considered as a set of essential small units termed ‘texture units’, which characterize the local texture information for a given pixel and its neighborhood. The statistics of all the texture units over the whole image reveal the global texture aspects.

In a square raster digital image, each pixel is surrounded by eight neighboring pixels. The local texture information for a pixel can be extracted from a neighborhood of 3x3 pixels, which represents the smallest complete unit. Given a neighborhood of 3x3 pixels, which will be denoted by a set containing nine elements:

$$V_i = \{V_0, V_1, V_2, V_3, V_4, V_5, V_6, V_7, V_8\}$$

Where V_0 represents the intensity value of the central pixel and V_i {i=1,2,3,…,8}, is the intensity value of the neighborhood pixel i. The corresponding texture unit (TU) is defined by a set containing eight elements.

$$TU = \{E_1, E_2, E_3, E_4, E_5, E_6, E_7, E_8\}$$

Where E_i (i=1, 2…8) is determined by the formula:

$$E_i = \begin{cases} 0 & \text{if } V_i < V_0 \\ 1 & \text{if } V_i = V_0 \quad \text{for:} i = 1,2 \ldots 8 \\ 2 & \text{if } V_i > V_0 \end{cases}$$

and the element E_i occupies the same position as the pixel i.

As each element of TU has one of three possible values, the combination of all the eight element results in 3^8=6561 possible texture units in detail. There is no unique way to label and order the 6561 texture units. The 6561 texture units are labeled by using the following formula:

$$N_{TU} = \sum_{i=1}^{8} E_i \times 3^{i-1}$$

Where N_{TU} represents the texture unit number and E_i is the i^{th} element of texture unit set.

Texture Spectrum is termed as the frequency distribution of all the texture units, with the abscissa indicating the texture unit number N_{TU} and the ordinate representing its occurrence frequency. Based on the concept of texture units and texture spectrum, the features are extracted.

6.1 Black-white symmetry

The Geometric Symmetry (GS) for a given image is defined as,

$$BWS = \left(1 - \frac{\sum_{i=0}^{3279} |S(i) - S(3281 + i)|}{\sum_{i=0}^{6560} S(i)} \times 100\right)$$

Where S(i) denotes the occurrence frequency of the texture unit number i. BWS values are normalized from 0 to 100 and measure the symmetry between the left part (0-3279) and right part (3281-6560) in the texture spectrum with the axis of symmetry at position 3280.

6.2 Geometric symmetry

The Geometric Symmetry (GS) for a given image is defined as,

$$GS = \left(1 - \left(\frac{1}{4}\right) \sum_{j=1}^{4} \frac{\sum_{i=0}^{6560} |S_j(i) - S_{j+4}(i)|}{2 \times \sum_{i=0}^{6560} S_j(i)} \times 100\right)$$

Where, $S_j(i)$ is the occurrence frequency of the texture unit numbered i in the texture spectrum under the ordering way j, where i=0,1,..,6560, and j=1,2,…,8. (Ordering ways a, b... h are respectively represented by j=1,2...8). GS values are normalized from 0 to 100 and measure the symmetry between the spectra under the ordering way, a and e, b and f, c and g, d and h for a given image.

6.3 Degree of direction

The Degree of Direction (DD) for a given image is defined as,

$$DD = \left(1 - \left(\frac{1}{6}\right) \sum_{m=1}^{3} \sum_{n=m+1}^{4} \frac{\sum_{i=0}^{6560} |S_m(i) - S_n(i)|}{2 \times \sum_{i=0}^{6560} S_m(i)} \times 100\right)$$

Where, $S_m(i)$ and $S_n(i)$ are the occurrence frequency of the texture unit. DD values are normalized from 0 to 100 and measure the degree with in an image.

6.4 Orientational features

For the eight elements of a texture unit, if E_a=E_b=E_c and E_g=E_f=E_e, then the original image has a micro-structure that is aligned to the horizontal axis. Let S(i) denotes the occurrence frequency of the texture unit number i, in the texture spectrum, P(i,j,k) represents the number of elements having the same value in E_i, E_j and E_k, HM(i) denotes the horizontal measure of the texture unit numbered i, VM(i) denotes the vertical measure of the texture unit numbered i, DM1(i) denotes the diagonal-1 measure of the texture unit numbered i and DM2(i) denotes the diagonal-2 measure of the texture unit numbered i, then the image features can be defined as follows:

6.4.1 Micro-Horizontal Structures (MHS)

If HM(i) is defined as,

$$HM(i) = P(a, b, c) \times P(e, f, g)$$

Then MHS is given by,

$$HMS = \sum_{i=0}^{6560} S(i) \times HM(i)$$

6.4.2 Micro-Vertical Structure (MVS)

If VM(i) is defined as,

$$VM(i) = P(a, h, g) \times P(c, d, e)$$

Then MVS is given by,

$$MVS = \sum_{i=0}^{6560} S(i) \times VM(i)$$

6.4.3 Micro-Diagonal Structure-1 (MDS-1)

If DM1(i) is defined as,

$$DM1(i) = P(a, b, h) \times P(d, e, f)$$

Then MDS1 is given by,

$$MDS1 = \sum_{i=0}^{6560} S(i) \times DM1(i)$$

6.4.4 Micro-Diagonal Structure-2(MDS-2)

If DM2(i) is defined as,

$$DM2(i) = P(b, c, d) \times P(f, g, h)$$

Then MDS2 is given by,

$$MDS2 = \sum_{i=0}^{6560} S(i) \times DM2(i)$$

6.5 Central symmetry

Central-symmetry is defined as,

$$CS = \sum_{i=0}^{6560} S(i) \times [K(i)]^2$$

Where K(i) denotes the number of pairs having the same value in elements (E_a, E_e), (E_b, E_f), (E_c, E_g),and (E_d, E_h). Table 2 shows the sample values of the texture spectrum based texture features.

Table 2: Extracted sample values of Texture spectrum features

IMAGE id	BSW	GS	DEG	MHS	MVS	MDS1	MDS2	CS
1	49	99	100	39344	36206	37596	37866	54461
2	64	99	100	41132	39449	40408	40222	62045
3	61	99	100	40408	38564	39557	39466	60794
4	50	99	100	39258	36072	37590	37803	54371
5	12	99	99	33457	29207	31365	31288	36510
6	12	99	99	33125	28560	30999	30760	35840
7	10	99	99	32816	28214	30693	30333	34254
8	36	99	100	36497	32781	34690	34631	46858
9	37	98	100	36208	33280	34752	34637	47482
10	47	99	100	36783	35355	36056	36141	55761

In the next section, we discussed about how these extracted features are classified.

7. TEXTURE CLASSIFICATION

Texture Classification is the process of assigning the texture to one of the already defined templates. Cluster analysis is the process of grouping objects into subsets that have meaning in the context of a particular problem. Unlike classification, clustering does not rely on predefined classes. Clustering is referred to as an unsupervised learning method because no information is provided about the "right answer" for any of the objects.

The *k*-means clustering algorithm is one of a group of algorithms called partitioning methods. The problem of partition clustering can be formally stated as follows: Given *n* objects in a *d*-dimensional metric space, determine a partition of the objects into *k* groups, or clusters, such that the objects in a cluster are more similar to each other than to objects in different clusters. A partition divides a set into disjoint parts that together include all members of the set. The value of *k* may or may not be specified and a clustering criterion, typically the squared-error criterion, must be adopted.

The solution to this problem is straightforward. The *k*-means algorithm initializes *k* clusters by arbitrarily selecting one object to represent each cluster. Each of the remaining objects is assigned to a cluster and the clustering criterion is used to calculate the cluster mean. These means are used as the new cluster points and each object is reassigned to the cluster that it is most similar to. This continues until there is no longer a change when the clusters are recalculated. The following screen shot shows the clustering of database using cluster number as four.

Fig 5: Image clustering

8. EXPERIMENTAL RESULTS

The domain of medical imaging as a specific part of medicine is very convenient environment for using variety of CBIR systems. The main reason is the necessity of effective content based analysis, extracting clinically relevant features out of the image and successful retrieval. This CBMIR (content based medical image retrieval) system consists of two major parts. The first one is feature extraction, where a set of features is generated to represent the content of each image in the database. The second task is similarity measurement, where a distance between the query image and each class in the database is computed using their image feature values so that the N most similar images which are belonging to one class can be retrieved.

Retrieval results are evaluated for three categories of database, consisting of the haralick features, the texture spectrum based texture features and the fusion of both features of the images by splitting the original images using Haar DWT. The retrieval results for the three categories of database are obtained by using Manhattan distance function between the feature vector of the query image and other feature vectors in the database. The Manhattan distance function would be a suitable method to compute the distance between two points and it is impossible to move straightforward from one point to another. The Manhattan distance is defined as,

$$D(x,y) = \sum_{i=1}^{m} |X_i - Y_i|$$

Where X and Y are the two input vectors, m is the number of input attributes, and X_i and Y_i are the input values for input attribute i for the two instances under comparison. The performance of the co-occurrence matrices, texture spectrum and fusion of both are compared. To evaluate the retrieval efficiency of the proposed system, we use the performance measure, *Recall* and *Precision*.

$$\text{Recall} = R_r/T$$

$$\text{Precision} = R_r/T_r$$

Where R_r is the number of relevant retrieved images, T is the total number of relevant items in an image database, and T_r is the number of all retrieved items. The results are given in the following Fig 6 and 7.

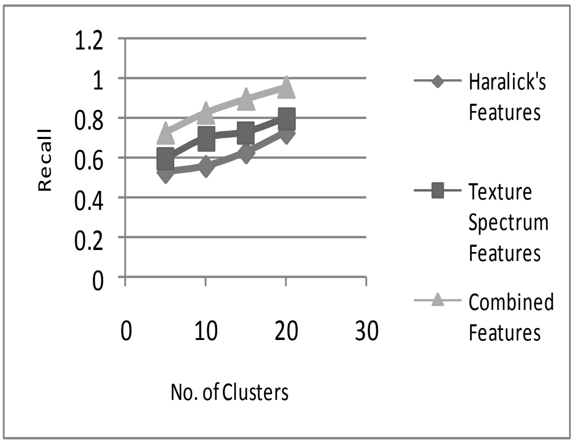


Fig 6: Performance measures based on Recall

The performance measures prove that texture Spectrum based texture features of image retrieval was somewhat good compare to Haralick features of image retrieval and the combination of both features of image retrieval is the best compare to other techniques. In case of Haralick features, considering entropy alone or considering ASM alone gives

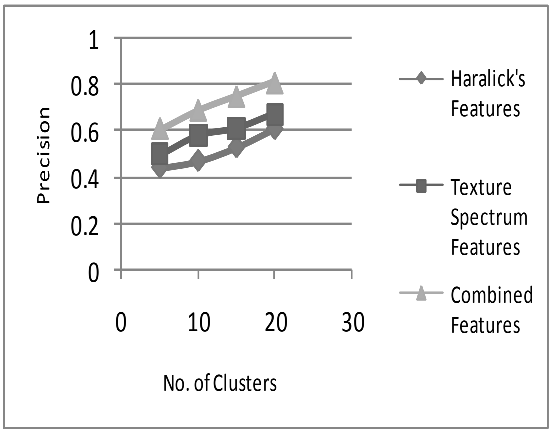


Fig 7: Performance measures based on Precision

better results than considering the features like contrast, coarseness or the combination of four features. In case of Texture Spectrum features, considering BWS, DD and GS alone gives better results than considering the combination of all other features. This method is implemented on a computer system using JAVA as the programming language and MS-Access as the back end. In this work we use around 500 spine MRI scan images as a database with different categories of diseases such as metastatic epidural spinal cord compression and expansion, degerative disc disease and spinal stenosis. The sample output screens are shown in Fig 8 and 9.

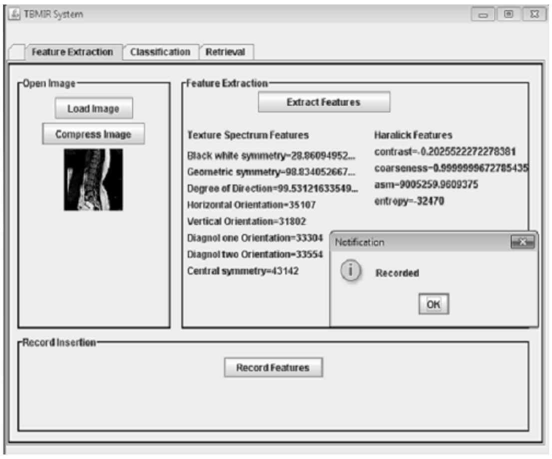


Fig 8: Extracted Features

Fig 9: Best retrieved images

9. CONCLUSION

Content based medical image classification and retrieval based on wavelet and statistical methods are a field of diversity and have an enormous scope of application in various fields. This method is applied around 500 spine MRI images and retrieval efficiency is found with usual precision and recall analysis. We have planned to extend our work to all parts of human body MRI images with different types of texture features and test its performance for large number of images in future.

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