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MRI Image Retrieval Using Gabor Wavelet Based Texture Features

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ABSTRACT

Due to vast number of medical technologies and equipments the medical images are growing in rapid rate. This directs to retrieve efficient medical images based on visual contents. This paper proposed the content based medical image retrieval system by means of Gabor Wavelet to extract texture features of MRI images. Then the K-means clustering and Euclidean distance measure are used to retrieve related images for the query image in medical diagnosis. The experimental results demonstrate the efficiency of this system in clustering and MRI image retrieval against Haralick's and Texture Spectrum based texture features.

Introduction

The Content Based Medical Image Retrieval (CBMIR) systems are search engines for medical image databases, which indexing and retrieving medical images according to their visual contents like colour, texture and shape information. [1-3]

Today, there are huge numbers of medical images being created in hospitals around the world. It is estimated that the amount of such images will further increase exponentially in the future. The significance 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 systems for storage, organization, indexing and retrieval of the medical images in different fields like medical diagnosis, research and teaching.

Generally, the medical image database contains a lot of texture based information capable for retrieval purpose. This paper, proposed the concept of spine, brain, knee and abdomen MRI image retrieval using Gabor Wavelet [GW] [4] based texture features and the performance of this system is compared with Haralick's [5] and Texture Spectrum [6] based texture features.

Related Works:

There are many existing systems that provide different methods and algorithms for CBMIR. The most important intention of all these systems is to prove the improvement of results so as to give support to the doctors and radiologists in diagnosis of treatments.

In [7], the authors presented an idea by combining low level content features and high level semantic features to retrieve medical images. Gabor wavelet [8] was one of the methods for texture feature extraction 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.

In [9], the authors described a new system 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. The GMM-KL structure [10] was consisting of a continuous and probabilistic image representation process using Gaussian Mixture Modelling (GMM) for image matching via the Kullback-Leibler (KL) measure. For matching and categorizing X-ray images, the GMM-KL framework was used.

Horsthemke et. al. [11] explained two different texture features based CBMIR systems. The first system can be used to provide context-sensitive tools for computer-aided diagnosis with pixel-level co-occurrence matrices. The second system can be used directly as a computer-aided diagnosis system for case-based and evidence-based medicine with pixel level and global level co-occurrence matrices. Muller et. al. [12] compared several texture analysis methods, colour (grey level) quantization and other useful features to extract include image intensity, region size, shape and statistical moments.

Sanghavi et. al. [13] focused on recent advances in CBIR system in medical domain. It also focused on various feature extraction techniques and algorithms implemented for CBIR systems in different cases of medical domain. B. G. Prasad et. al. [14] evaluated the performance of two statistical methods of texture features proposed by Haralick's and Tamura for retrieving similar cases for CT scan brain images. In [15] the author demonstrated CBMIR system using canny edge based shape detection and k-means clustering algorithms.

S. Nagendram et. al. [16] gave an overview in the field of content based access to medical image data and on the tools used in the field. They also gave about generic content based image retrieval for medical images and described various methods of CBIR implementing. In [17] the importance of medical visual information search and the major challenges were detailed and proposed a flexible framework for indexing medical visual information of any dimension and any modality based on texture information.

Xiang Sean Zhou et. al. [18] took a critical look at the semantic medical CBIR problem and provided their perspective regarding the gaps and opportunities present in this domain. They listed today's medical imaging modalities, along with an almost exhaustive list of existing medical CBIR systems. Katarina Trojacanec et. al. [19] applied the edge histogram and region-based shape descriptors standardized by MPEG-7 standard to MRIs. The analysis showed that the edge histogram descriptor achieves higher precision.

In our previous work [20-21] the performance measures for spine MRI image retrieval proved that Texture Spectrum based texture features (black-white symmetry, geometric symmetry, degree of direction, orientation features and central symmetry) were somewhat good compared to Haralick's texture features (contrast, angular second moment, coarseness, entropy) and the combination of both features of image retrieval was the best.

This paper is organized such that brief discussion on proposed work and Gabor Wavelet Transform in section 3 and 4. In sections 5 and 6, we explain about Gabor Wavelet based texture features and K-means clustering. In section 7, we deal with image retrieval. Section 8 shows experiments and results. In section 9, we conclude our work with feature prospects.

Proposed Work:

The block diagram of the proposed Gabor Wavelet and texture features based MRI medical image retrieval system is shown in Fig 1.

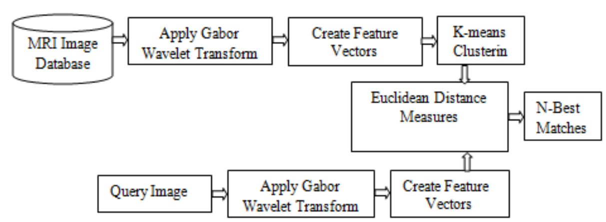


Fig. 1 The configuration of the proposed retrieval system

In our work, applying Gabor Wavelet Transform (GWT) to the collection of MRI image database and feature vector is constructed using mean, standard deviation, skew and kurtosis as feature components and the database are created. Then with K-means clustering [22] the database images are clustered. After that Euclidean distance measure [23] is using to retrieve N-best matches for the query image.

Gabor Wavelet Transform:

In the spatial domain, a GW is a complex exponential modulated by a Gaussian function. In the most general the Gabor Wavelet is defined as follows:

$$\varphi_{\omega,\theta}(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{(x\cos\theta + y\sin\theta)^2 + (-x\sin\theta + y\cos\theta)^2}{2\sigma^2}} \left[e^{i(\omega x\cos\theta + \omega y\sin\theta)} - e^{-\frac{\omega\sigma^2}{2}} \right] \quad (1)$$

Where, x, y denote the pixel position in the spatial domain, ω is the radial centre frequency of the complex exponential, θ is the orientation of the GW, and σ is the standard deviation of the Gaussian function. By selecting different centre frequencies and orientations, we can obtain a family of Gabor kernels, which can be used to extract features from an image.

The GW $\varphi_{\omega,\theta}(x,y)$ forms complex valued function like real and imaginary parts. Other wavelets are shifted, rotated and dilated versions of these two. Given an image f(x, y), GW features are extracted by convolving f(x, y) with $\varphi_{\omega,\theta}(x,y)$ as follows:

$$Y_{\omega,\theta}(x,y) = f(x,y) * \varphi_{\omega,\theta}(x,y) \quad (2)$$

Where, $*$ denotes the convolution operator. For a neighbourhood window of size W × W for W = 2t + 1, the discrete convolutions operation of the image f(x, y) with GW we get

$$W(x,y) = f(x,y) * \varphi_{\omega,\theta}(x,y) = \frac{1}{2\pi\sigma^2} \sum_{l=-t}^{t} \sum_{m=-t}^{t} f(x+l, y+m)\, \varphi_{\omega,\theta}(x,y) \quad (3)$$

We can write down,

$$W(x,y) = M(x,y)\exp(j\theta) \quad (4)$$

With,

$$M(x,y) = \sqrt{W(x,y) \times \overline{W(x,y)}} \quad (5)$$

$$\theta = \arctan\left[\frac{W(x,y) - \overline{W(x,y)}}{j(W(x,y) + \overline{W(x,y)})}\right] \quad (6)$$

Where, $\overline{W(x,y)}$ is a complex conjugate of $W(x,y)$.

Gabor Wavelet Based Texture Features:

The feature vectors μ(x, y), STD(x, y), Skewness and Kurtosis are constructed as feature components using equation (7) to (10).

$$\mu(x,y) = \frac{1}{XY} \sum_{x=1}^{X} \sum_{y=1}^{Y} Y_{\omega,\theta}(x,y) \quad (7)$$

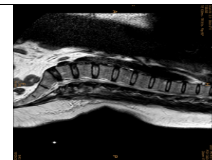
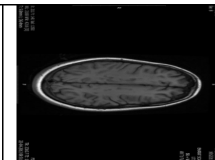
$$STD(x,y) = \sqrt{\sum_{x=1}^{X} \sum_{y=1}^{Y} \left| |Y_{\omega,\theta}(x,y)| - \mu(x,y) \right|^2} \quad (8)$$

$$Skewness = \frac{1}{XY} \sum_{x=1}^{X} \sum_{y=1}^{Y} \frac{(Y_{\omega,\theta}(x,y) - \mu(x,y))^3}{(std(x,y))^2} \quad (9)$$

$$Kurtosis = \frac{1}{XY} \sum_{x=1}^{X} \sum_{y=1}^{Y} \frac{(Y_{\omega,\theta}(x,y) - \mu(x,y))^4}{(std(x,y))^4} - 3 \quad (10)$$

Where, (X, Y) is the image dimension. Table 1 shows the sample values of the feature vectors for a MRI spine and brain images.

Table. 1 Extracted sample values of feature vectors

MRI Images	□	0	45	90	135
	μ(x, y)	40.221	13.120	41.010	26.031
	STD(x,y)	37,203	16,336	38,251	19,162
	Skew	2.062	3.060	1.303	1.431
	Kurtosis	3.554	12.602	2.422	4.023
	μ(x, y)	35.132	12.501	33.435	14.201
	STD(x,y)	32.262	10.451	31.547	12.534
	Skew	1.221	3.011	2.004	2.220
	Kurtosis	2.455	16.830	3.508	11.031

K-means Clustering:

In our problem, the K-means clustering algorithm can be formally stated as follows: Given 1850 MRI images in a 16-dimensional metric space, determine a partition of the images into maximum 10 clusters and 20 iterations, such that the images in a cluster are more similar to each other than to images in different clusters.

We initialize 10 clusters by arbitrarily selecting one image to represent each cluster. Each of the remaining images 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 image 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 Fig.2 shows the sample output of fifth cluster out of ten clusters.

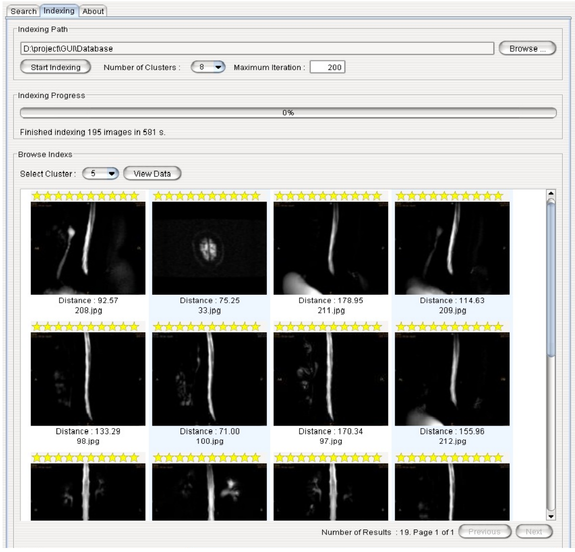


Fig. 2 Sample Output of fifth cluster

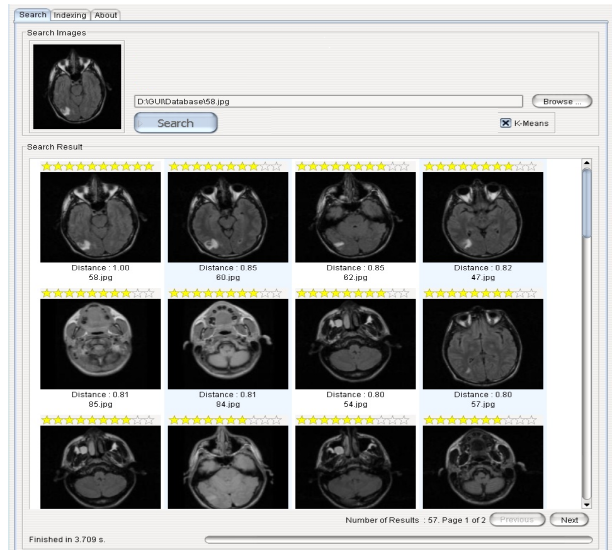


Fig. 4 Best retrieved brain MRI images

Image Retrieval:

We use Euclidean distance measure in order to balance between computational complexity and retrieval accuracy. The Euclidean distance is calculated between the query image and the selected precise images. If xi and yi are 2D feature vectors of selected precise images and query image respectively then the distance measure is defined as, $d_{E(X,Y)} = \sqrt{\sum_{i=1}^{d}(x_i - y_i)^2}$. The calculated distances are sorted in increasing order and display the first N images as the best matching images. The sample output screens are shown in Fig. 3 and 4.

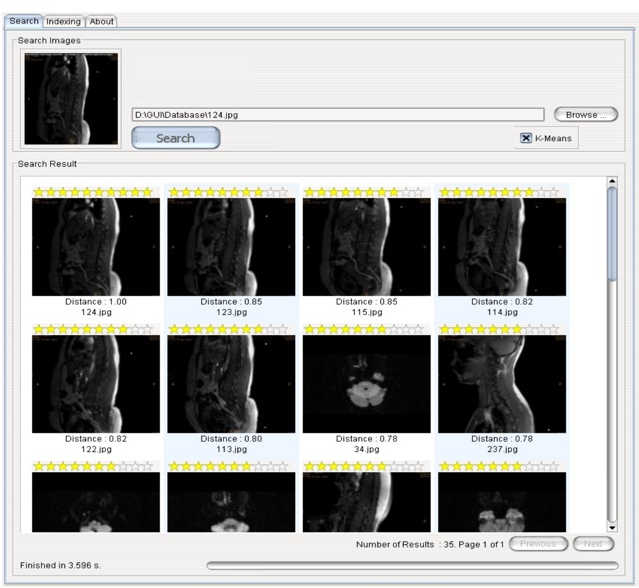


Fig. 3 Best retrieved spine MRI images

Experiments and Results:

This method is implemented on a computer system using JAVA as the programming language and MySQL as the backend. In this work, we used around 1850 MRI scan images in BMP format with the size of 256 x 256 as a database. Different parts of human body MRI scan images such as 850 spine, 400 brain, 300 abdomen and 300 knee images are used.

The effectiveness of the proposed K-means clustering algorithm can be measured by accuracy. Accuracy is defined as, the ratio between the sum of true positive and true negative images with the sum of full negative, full positive, true negative and true positive images. (i.e) (TP+TN) / (FN+FP+TN+TP). Where, TP – Correctly clustered images, TN – Wrongly clustered images, FN – Radiologists consider correctly clustered images but actually wrong, FP - Radiologists consider wrongly clustered images but actually correct. The K-means clustering algorithm gave a test accuracy of 74.8% while using Haralick's texture features alone and gave a test accuracy of 77.5% while using Texture Spectrum based texture features alone. Furthermore, when the both features are combined then the K-means clustering algorithm's accuracy increases to 88.2%. But in our Gabor Wavelet based texture features, the K-means clustering algorithm gave an accuracy of 98.8%. The accuracy of the reporting radiologist's diagnosis was also analyzed. The proposed method yielded best recognition rate and help radiologists for best medical diagnosis.

We did many experiments and recorded the feature extraction time and response time for a query image on different capacity of database. After a large number of experiments the Table 2 showed the feature extraction time and the response time when retrieval of 140 MRI images. Along with growth of the database, the extraction time and response time increases proportionally. These results compared to Haralick's and Texture Spectrum based texture features.

Table. 2 Comparison of feature extraction time and the response time

Methods	Number of Features	Feature Extraction Time (in Seconds)	Response Time (in Seconds)
Gabor Wavelet	16	581	3.742
Texture Spectrum	8	321	4.85
Haralick's Features	14 used only 4	258	5.23
Texture Spectrum + Haralick's Features	8 + 4 =12	433	4.205

Our proposed Gabor Wavelet based texture features like mean, standared diviation, Skewness and Kurtosis are extracted for four different orientations with the extraction time of 581 seconds which is higher compare to other techniques. But it's response time is 3.742 seconds which is lesser compare to other techniques.

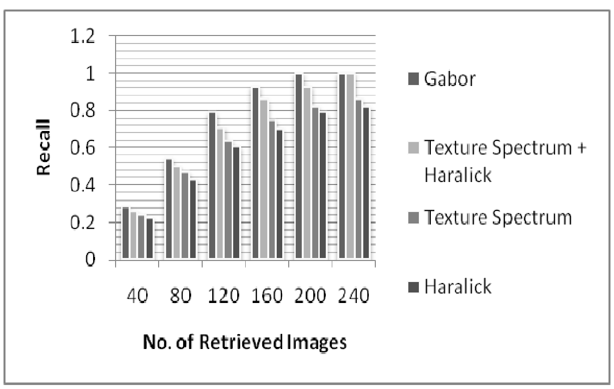


Fig. 5 Performance measures based on Recall

The effectiveness of the proposed method can be measured by Recall and Precision, which are often referred to together since they measure the different aspects of the system performance. Recall measures the system's ability to retrieve relevant images from the database. It is defined as the ratio between the number of retrieved relevant images and the total number of relevant images in the database. Thus, the recall rate demonstrates the power of a learning system by revealing its level of false negatives. The performance measures of recall are given in Fig. 5 which proved that our proposed method has highest recall rate than methods.

Precision measures the retrieval accuracy and is defined as the ratio between the number of retrieved relevant images and the number of total retrieved images. This measure demonstrates the efficiency of a learning system and is closely related to its level of false positives. The performance measures of precision are given in Fig. 6 which proved that our proposed method has highest precision rate than other methods.

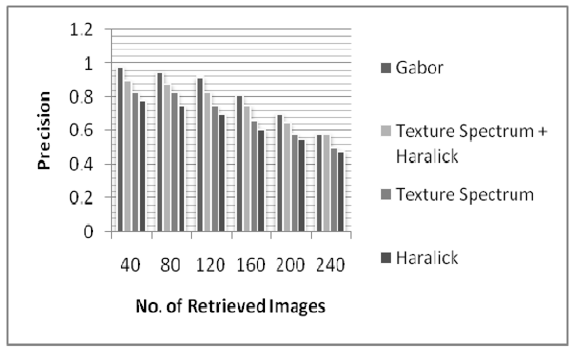


Fig. 6 Performance measures based on Precision

Conclusion:

In this paper, we have proposed an efficient MRI image retrieval method using Gabor Wavelet based texture features. Our Experimental results demonstrate that the proposed method has best clustering accuracy and retrieval efficiency than other conventional methods such as Haralick's and Texture Spectrum based MRI image retrieval methods. Further, Euclidean distance measure to reduce the execution time whereas maintaining a reasonable level of retrieval performance. We have planned to extend our work via Curvelet Transform based texture features with all types of human body scan images.

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