Content Based Medical Image Retrieval using Artificial Neural Network

Preetika D’Silva
PG Student
Department of Electronics and Communication
Rajarajeswari College of Engineering, Bangalore

P. Bhuvaneswari
Associate Professor
Department of Electronics and Communication
Rajarajeswari College of Engineering, Bangalore

Abstract
Large database of images in the field of medicine requires proper systems that will help in accurate diagnostics and their efficient management. Content based medical image retrieval is a system that helps to browse, explore, find, and retrieve images similar to the query image with minimal user input. In this paper we propose a system that will retrieve all medical images that matches the query image. Shape and texture features are extracted from the pre-processed medical images for creating the medical database. Once the medical database is created, the features of the query image are extracted and are used by the neural network to train it. Euclidean distance between the database features and the query features are computed, ranked and we label the relevant images from the initial retrieved images. Then the feed forward back propagation neural network is used finally to retrieve the similar medical images. We have taken X-ray images of hand, foot, chest, head and ankle. The precision and recall values for the retrieval system using only texture features, using only shape features and using combined texture and shape features are calculated and compared.

Keywords: Content based Medical Image Retrieval, Euclidean Distance GLCM, Neural network, Zernike

I. INTRODUCTION
People can create, then process and store images on the internet using many available resources. This has produced the requirement for a way to manage and search these images. Hence, finding efficient image retrieval mechanisms from large resources has become an extensive area of interest to researchers [2] [11]. Searching and retrieving images from a huge database of images is performed by a method called as image retrieval. In today’s modern age, virtually all spheres of human life including hospitals, surveillance, crime prevention, commerce, architecture engineering, fashion and graphic design, journalism, academics, government, and historical research utilize images for efficient services. Image data are integrated and stored in a system called an image database. Image data consists of the raw images and information extracted from images by automated or computer assisted image analysis. [2]

Content based medical image retrieval (CBMIR) [3] [6] [7] [8] is the digital image searching problem in huge database that utilizes the contents of image themselves rather than depending on the textual information. Hospitals generate many medical images like X-ray, CT, and MRI of different parts of the human body contain semantic information. We can use this information to retrieve images. Under such situation, medical image retrieval has changed from earlier text based method to the content based method or a combination of the two methods. [3]

This paper is organized as follows: The proposed system is described in Section II, Shape feature extraction is described in Section III, Texture feature extraction is described in Section IV, Euclidean distance is described in Section V, Artificial neural network is described in Section VI. In Section VII we describe the implementation results, in Section VIII we describe the performance evaluation and in Section IX we draw the respective conclusion.

II. PROPOSED SYSTEM
The fig.1 shows the block diagram of the proposed system. Firstly, the medical images are pre-processed. Then features are extracted from them and stored in a database. In the testing phase, a query image is pre-processed and different features are extracted. Then Euclidean distance between the query features and the database features are calculated and the images are sorted and labelled.

These labelled features along with the database features are then used by the feed forward neural network to retrieve the medical images.
**III. SHAPE FEATURE EXTRACTION**

There are many methods for extraction of shape features. Out of which we are using Zernike moments which is a very efficient shape descriptor that can be used for shape extraction in medical images. The block diagram for computing Zernike moments is shown in fig. 2.[4]

Zernike moments let independent moment invariants to be constructed to an arbitrarily high order. Zernike polynomials are used to get the complex Zernike moments. The Zernike polynomials are given as [9]:

\[ V_{nm}(x, y) = V_{nm}(x, y) = e^{j m \theta} \]

\[ R_{nm}(\rho) = \sum_{s=0}^{(n+|m|)/2} (-1)^s \frac{(n+|m|)!}{s! (n+|m|/2-s)! (n+|m|/2+s)!} \rho^{n-2s} \]  

where \( \rho \) is the radius from \((x, y)\) to the shape centroid, \( \theta \) is the angle between \( \rho \) and \( x \) axis, \( n \) and \( m \) are integers and subject to \( n-|m| = \text{even}, |m| \leq n \). Zernike polynomials are a total set of complex-valued function orthogonal over the unit disk, i.e., \( \chi^2 + y^2 = 1 \). Then the complex Zernike moments of order \( n \) with repetition \( m \) are defined:

\[ A_{nm} = \frac{1}{\pi} \sum_{x} \sum_{y} f(x, y) V_{nm}(x, y), \quad \chi^2 + y^2 \leq 1 \]  

Since Zernike basis functions take the unit disk as their domain, this disk must be specified before moments can be computed. Only using magnitudes of the moments gives us the rotational invariance. The magnitudes are then normalized into \([0, 1]\) by dividing them by the mass of the shape.[1][9]

The theory of Zernike moments is similar to that of Fourier transform, to expand a signal into series of orthogonal basis. Though, the computation of Zernike moments descriptors does not require to know boundary information, making it suitable for more complex shape representation [3] such as X-ray images.

**IV. TEXTURE FEATURE EXTRACTION**

Texture is one of the most vital defining characteristic of an image. Texture of an image is characterized by the spatial distribution of gray levels in a neighbourhood. There are numerous types of texture feature extraction methods like geometrical, statistical, and model-based and signal processing features. We have used the Gray Level Co-occurrence Matrix (GLCM) for extracting the texture features. [10]

The extracted texture features are [14]:
A. Contrast:

\[ Contrast = \sum_{i=1}^{m} \sum_{j=1}^{n} (i-j)^2 GLCM(i,j) \]  

(4)

B. Correlation:

\[ Correlation = \sum_{i=1}^{m} \sum_{j=1}^{n} \frac{\mu_x \mu_y}{\sigma_x \sigma_y} GLCM(i,j) \]  

(5)

C. Energy:

\[ Energy = \sum_{i=1}^{m} \sum_{j=1}^{n} (GLCM(i,j))^2 \]  

(6)

D. Homogeneity:

\[ Homogeneity = \sum_{i=1}^{m} \sum_{j=1}^{n} \frac{GLCM(i,j)}{1+|i-j|} \]  

(7)

V. EUCLIDEAN DISTANCE

Euclidean distance is defined as [13]

\[ d(Q, R) = \sum_{i=1}^{N} (Q_i - R_i)^2 \]  

(8)

Where, \( d(Q, R) \) is distance between features of the query \( Q \), features of the database \( R \) and \( N \) is number of features. In our work we have used Euclidean distance for the first retrieval on the basis of which we label the relevant images which will be hence used by the neural network for the final retrieval.

VI. ARTIFICIAL NEURAL NETWORK

A feed forward back propagation neural network is created that consists of the first (input) layer, the hidden layer, and the output layer. Since the nodes in the input layer could take in values from a large range, a transfer function is used to transform data first, before sending it to the hidden layer, and then was transformed with another transfer function before sending it to the output layer. The training data is firstly given to the hidden layer.

Fig. 3: Block Diagram of Feed Forward Back Propagation Neural Network

The hidden layer performs the actual processing on the input data. Then it transforms the result to the output layer. The final output is compared with the desired output and the difference gives us the error [5]. The error is then used to adjust the weights in order to minimize the error hence making the final results optimum. The back propagation algorithm used utilizes Levenberg-Marquardt optimization. The block diagram of feed forward back propagation neural network is shown in fig.3 [5].

VII. IMPLEMENTATION RESULTS

The complete work is performed in MATLAB 2012b. The image database is created by first pre-processing the images. A total of 50 X-ray images of ankle, chest, foot, hand and head are resized to 512 X 512. Then texture features namely contrast, correlation, energy and homogeneity are extracted using GLCM.
We also extract shape features using Zernike moments. Here we have considered Zernike moments from order \( n=2 \) to \( n=8 \) and a total of 23 Zernike moments are extracted.

These features are stored in a database. Now a query image is selected. We extract the texture and shape features from the resized query image. Then the Euclidean distance between the features of the query image and the features stored in the database are calculated and the images are sorted in ascending order and ranked. Now, the user selects few relevant images from the ranked retrieved images and these images are labelled. Then the labelled features and the feature database are used by the feed forward neural network to retrieve the most relevant images. The retrieved images are shown in fig.9, fig.10 and fig.10.
Fig. 8: User Selected Relevant Images

Fig. 9: Retrieved Images by Neural Network using Only Texture Features

Fig. 10: Retrieved Images by Neural Network using Only Zernike Moments (Shape Features)

Fig. 11: Retrieved Images by Neural Network using Texture Features and Shape Features
VIII. PERFORMANCE EVALUATION

The parameters like Precision, Recall and Accuracy are used to evaluate the performance of the retrieval system. We calculate the average precision and recall values. Precision (P) can be defined as the ratio of the number of retrieved relevant images to the total number of retrieved images. The accuracy of the retrieval is measured by precision [12].

\[
\text{Precision} \; P = \frac{\text{Number of relevant images retrieved}}{\text{Number of images retrieved}}
\]

Recall (R) can be defined as the ratio of the number of retrieved relevant images to the total number of relevant images in the whole database.

\[
\text{Recall} \; R = \frac{\text{Number of relevant images retrieved}}{\text{Total Number of relevant images in database}}
\]

The Accuracy rate has been calculated using the standard formula.

\[
\text{Accuracy Rate} = \frac{\text{Precision} + \text{Recall}}{2}
\]

A graph showing the performance of the retrieval system is shown in fig.12. The performance of the retrieval system is better when combinations of texture and shape features are used compared to only texture and only shape.

IX. CONCLUSION

In this paper we have proposed content based medical image retrieval system for efficient retrieval of images. The accuracy rate for the retrieval system is higher when combinations of texture and shape features are used compared to when only texture and only shape features are used. The accuracy of the system can be increased by increasing the medical image database and also combining different other features for training the system.

REFERENCES