TEXTURE FEATURE BASED ANALYSIS OF BRAIN CT IMAGES FOR DISCRIMINATING BENIGN, MALIGNANT TUMORS

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Abstract: A computer software system is designed for the automatic discrimination of benign tumor from malignant tumor in brain CT examinations. Image analysis methods were applied to the images of 40 benign images and 40 malignant images. Textural features extracted from the gray level co-occurrence matrix of the tumor images and back propagation neural network classifier were employed for the design of the system. Best classification accuracy was achieved by four textural features and two hidden layers and 6 hidden nodes of the classifier. The proposed system provides new textural information and differentiating benign tumor from malignant tumor, especially in small tumor regions of CT images efficiently and accurately with lesser computational time.

Keywords: Back Propagation Neural Network classifier (BPN), Computed Tomography (CT), Computer analysis(CA), Gray Level Co-occurrence Matrix(GLCM).

1. INTRODUCTION

In recent years, medical CT Images have been applied in clinical diagnosis widely. That can assist physicians to detect and locate pathological changes with more accuracy. Computed Tomography images can be distinguished for different tissues according to their different gray levels. The images, if processed appropriately can offer a wealth of information which is significant to assist doctors in medical diagnosis. A lot of research efforts have been directed towards the field of medical image analysis with the aim to assist in diagnosis and clinical studies [1]. Pathologies are clearly identified using automated CAD system [2]. It also helps the radiologist in analyzing the digital images to bring out the possible outcomes of the diseases. The medical images are obtained from different imaging systems such as MRI scan, CT scan, Ultrasound B scan. The computerized tomography has been found to be the most reliable method for early detection of tumors because this modality is the mostly used in radio therapy planning for two main reasons. The first reason is that scanner images contain anatomical information which offers the possibility to plan the direction and the entry points of radio therapy rays which have to target only the tumor region and to avoid other organs. The second reason is that CT scan images are obtained using rays, which is same principle as radio therapy. This is very important because the intensity of radio therapy rays have been computed from the scanned image. Advantages of using CT include good detection of calcification, hemorrhage and bony detail plus lower cost, short imaging times and widespread availability. The situations include patient who are too large for MRI scanner, claustrophobic patients, patients with metallic or electrical implant and patients unable to remain motionless for the duration of the examination due to age, pain or medical condition. For these reasons, this study aims to explore methods for classify the abnormal brain tissues into benign, malignant tumors in CT images. Image classification is the process of assigning a set of pixels with similar properties. Accurate, fast and reproducible classification techniques are required in various applications. Brain tumor is any mass that results from abnormal growths of cells in the brain. It may affect any person in almost any stage. Brain tumors can have a variety of shapes and sizes; it can appear at any location and in different image intensities. Brain tumors can be benign, Malignant. Low grade Gilomas and Meningiomas which are benign tumors represent the most common type of tumor. Glioblastoma multiforme is a malignant tumor and represents the most common brain...
neoplasm. Benign brain tumor have a homogeneous structure and do not contain cancer cells. They can be either simply be monitored radiologically or surgically eradicated and they seldom grow back. Malignant brain tumors have a heterogeneous structure and contain cancer cells. They can be treated by radiotherapy, chemotherapy or a combination of both. Many diagnostic imaging techniques can be performed for the early detection of any abnormal changes in tissues and organs such as Computed Tomography (CT) imaging and Magnetic resonance Imaging (MRI).

Many techniques have been reported for classification of brain tumors in MR images most notably, Support Vector Machine classifier (SVM) [3], Neural Network classifiers [4], Knowledge based techniques [5]. Chang et al [6][7] proposed the SVM classifier for the diagnosis of breast cancer in ultrasonic images. Luiza Antonie et al [8] proposed a method for Automated segmentation and classification of Brain MR images in which an SVM classifier was used to classify normal and abnormal images with statistical features. Chaplot et al [9] proposed the SVM classifier was used for the classification of MRI image and also show that classification rate of SVM was higher while compared to Neural Networks self organizing maps. Gering et al [10] proposed the EM algorithm to detect the abnormalities but this method requires high computational effort. The knowledge based techniques are also proposed to make more efficient segmentation and classification results but these techniques required more intensive training.

In medical image analysis, the determination of tissue type (normal or pathological) and classification of tissue pathology are performed by using texture analysis. To solve the texture classification problem, many approaches have been developed such as Multi channels methods [11], Multi resolution analysis [12]. Dunn et al proposed optimal Gabor filters [13] for texture segmentation. Chang et al [14] proposed the Tree structured Wavelet transform for texture classification. Gabor filters are poor due to their lack of orthogonality that results in redundant features at different. Here, brain CT images with benign, malignant tumor were processed employing image analysis methods. Only small tumor regions were considered since there are not easily differentiated by visual inspection. The aim was to analyze the internal structure of the tumor region in order to obtain the information concerning its nature. This textural information, together with neural network classifier, was used in the design of a software system for the automatic discrimination between benign and malignant tumors.

2. MATERIALS AND METHODS

The study comprised 70 non contrast enhanced CT examinations with benign ,malignant tumor images. Diagnosis was confirmed on the basis of patient's history, clinical data, and CT followed up examinations. All examinations were performed on 512*512 reconstruction matrix, 10 mm slice thickness, 120 Kv, 150 mA and 2.9s scan time. In each examination the CT section through the maximum cross sectional diameter of the brain damage was selected; the CT density matrix of the tumor central region-32*32 or 64*64 pixels depending on the size of the damage was transferred to the computer for further processing.

2.1. Feature Generation

From each CT density matrix, 18 features were calculated. Five were extracted from the tumor's density histogram, which gives the frequency of density values in the tumor’s image matrix: mean, variance, kurtosis, uniformity and skewness. The remaining were extracted from gray level co-occurrence matrix [15], which is a two dimensional histogram describing the frequency with two adjacent CT density values occur in the tumor’s image matrix. The gray level co-occurrence matrix is based on the estimation of second order joint conditional probability density functions ($P(i, j)/d, \theta)$ for $\theta = 0^\circ$, $45^\circ$, $90^\circ$ and $135^\circ$. The function $P(i, j/d, \theta)$ is the probability matrix of two pixels, which are located with an inter sample distance $d$ and direction $\theta$ have a gray level $i$ and gray level $j$. The gray level co-occurrence matrix $\phi(d, \theta)$ as follows

$$\phi(d, \theta) = [P(i, j/d\theta)], \quad 0 \leq i, i \leq N_g$$

Where, $N_g$ is the maximum gray level. In this method, four gray level co-occurrence matrixes for four different directions ($\theta = 0^\circ$, $45^\circ$, $90^\circ$ and $135^\circ$) are obtained for a given distance $d$ (=1, 2, 3, 4) and the following 13 textural based Haralick features [16] are calculated for each gray level co-occurrence matrix and take the average of all four gray level co-occurrence matrices.
2.2. Feature Reduction
The discriminatory ability of each of the 18 features was tested by student t-test. Only the best discriminating features (p < 0.001) were selected and were further employed in the design of computer software for discriminating benign from malignant tumor.

2.3. Classification
Classification was performed by means of the back propagation neural network classifier [17]. The network of this study was composed of three layers: input layer, hidden layer, and output layer. There were 4 neurons in the input layer, 6 neurons in the hidden layer, and 2 neurons in the output layer. Input vector, output vector, and target vector were needed to execute the learning algorithm of the BPN. More than one hidden layer may be beneficial for some applications, but one hidden layer is sufficient if enough hidden neurons are used. The BPN will have better categorization capability if the training samples are sufficient and representative. The strength of the BPN lies in its ability to generalize the training sample; namely, the network learning would focus on both benign and malignant training sample. A non linear sigmoid function is used as the activation function for each neuron and is defined by

\[
O_j = \frac{1}{1 + \exp\left(\sum_i W_{ji}O_i + V_j\right)}
\]  

(2)

Where \(O_j\) is the \(j_{th}\) element of the actual output pattern produced by an input pattern, \(W_{ji}\) is the weight from \(i_{th}\) neuron to \(j_{th}\) neuron and \(V_j\) is the threshold of the \(j_{th}\) neuron. In the training process, the weights between neurons are adjusted iteratively so that the differences between the output values and the target values are minimized.

The iteration can be described by

\[
W_{ji}(\text{new}) = W_{ji}(\text{old}) + \eta \delta O_j\]
\[\mu + [W_{ji}(\text{old}) - W_{ji}(\text{old} - 1)]\]

(3)

Where \(\eta\) is learning rate 1 is the number of epochs, \(\delta\) the error signal, \(\mu\) is the momentum parameter, \(\delta\) is the difference between \(j_{th}\) output of neural network and the \(j_{th}\) target output to evaluate the network performance during the training process. The global error measure is given as

\[
\sum_{g=1}^{G} \left[ O_g - t_g \right]^2
\]

(4)

Where \(O_g\) and \(t_g\) are the output value and target value for the \(g_{th}\) input pattern and \(G\) is the total number of training patterns. The training process is repeated until global error measure becomes small than a given constant \(\varepsilon_0\).

![Figure 1: Block Diagram of BPN Architecture](image)

Classification performance was tested by the leave one out cross validation method, and for all possible combinations of the textural features selected in the feature reduction stage. The aim was to determine the optimum combination that achieves the highest classification accuracy with the minimum number of features. Classification performance was also tested by the number of hidden nodes and hidden layers, in order to determine the best structural parameters of the BPN classifier. Thus the final system includes the computation of the optimum combination of textural features from the CT tumor’s density matrix and for the classification of tumors by the BPN classifier into benign, malignant.

2.4. Statistical Analysis
The accuracy of the classifier was evaluated based on the error rate. This error rate can be described by the terms true and false positive and true and false negative as follows.

True Positive (TP): Abnormal cases correctly classified, True Negative (TN): Normal cases correctly classified, False Positive (FP): Normal
cases classified abnormal, False Negative (FN): Abnormal cases classified normal. The above terms are used to describe the clinical efficiency of the classification and segmentation algorithm.

\[
\text{Sensitivity} = \frac{TP}{TP + FN} \times 100
\]
\[
\text{Specificity} = \frac{TN}{TN + FP} \times 100
\]
\[
\text{Accuracy} = \frac{(TP + TN)}{(TP + TN + FP + FN)} \times 100.
\]

Accuracy is the proportion of correctly diagnosed cases from the total number of cases. Sensitivity measures the ability of the method to identify abnormal cases. Specificity measures the ability of the method to identify normal cases. To make the classification results comparable and for exhaustive data analysis, the classification performance was first evaluated by the following two methods (i) Jack knife method (ii) Round robin method (leave one out cross validation method) This method can be used to estimate the classifier performance in unbiased manner.

In jack knife method, one half of the sample patterns were selected randomly for training the classifier. Subsequently, the other half of the sample patterns was used for testing the trained classifier. In round robin method, in each step one data set is left out and the classifier is trained using the rest and the classifier is applied to the left out data set. This procedure is repeated such that each data set is left out once. In our application for evaluating the classification accuracy, 10 fold cross validation method is done on the data set collected from 80 images. (40 benign images and 40 malignant images). The images are divided into 10 sets each consisting of 4 benign images and 4 malignant images. Then 9 sets are used for training and remaining set is used for testing. In next iteration (2-10), 9 sets are used for training and remaining set is used for testing. This process is repeated for 10 times. The classification accuracy was calculated by taking the average of all the correct classifications of 10 iterations.

2.5. ROC Analysis

The another statistical method known as Receiver Operating Characteristics (ROC)[18] analysis is also used to analyze the performance of the classifiers. In this method, the data set is divided randomly into 5 groups of 80 images with 45 benign and 45 malignant images. Sensitivity and specificity values are recorded for each group and ROC curve is drawn and analyzed. Depending on the training set, each group will have a different threshold value for determining true positive and true negative cases. ROC curve is a graphical representation of sensitivity versus specificity as a threshold parameter is varied. By calculating the Area under ROC Curve (AUC), we can measure the class discrimination capability of a specific classifier. An area of above 0.5 represents a perfect test while an area of less than or equal to 0.5 represents worthless test. The larger the area (the higher AUC value) means higher the classification performance.

3. RESULTS AND DISCUSSION

An experiment has been conducted on a real CT scan brain images and the 80 images were partitioned arbitrarily into training set, testing set with equal number of images. The proposed methodology is applied to real datasets representing brain CT images with the dimension of 512*512 and all images are inDICOM format. The proposed algorithm is implemented in Matlab 7.2 platform and run on 3.0GHz, 512MB RAM Pentium IV system in Microsoft Windows operating systems. The proposed algorithm is implemented in Matlab 7.2 platform and run on 3.0GHz, 512MB RAM Pentium IV system in Microsoft Windows operating systems. The brain CT images were collected from M/s Devaki MRI and CT scans Madurai, INDIA are used. We have tested our system on classification for two types of images which are the brain image with benign tumor and malignant tumor.

Best textural features, determined in the feature reduction stage (p<0.001) were: variance, skewness, angular second moment, contrast, correlation, entropy, sum entropy, difference variance, and difference entropy. These nine features used in combinations of 2, 3, 4,...9 as inputs to the classifier, and classification accuracy was evaluated by means of leave one out cross validation method (round robin method) and jack knife methods. Highest accuracy (93.75% in round robin method and 92.5 % (in jack knife method) was achieved by the energy, entropy, variance, inverse difference moment feature combination. This system discriminated correctly 38/40 (95%) benign tumor images and 37/40 (92.5%) malignant tumor images. The same classification accuracy (93.75%) was also found for combinations of four, five, six features;
these were combinations of the entropy, variance, inverse difference moment, contrast textural features with either four, five, six, seven of the following: difference variance, sum entropy, angular second moment, correlation. Employing more than five features the classification accuracy of the system was decreased. Figure 3(a) shows the variation of system performance in relation to the number of textural features. System accuracy in relation the number of nodes or hidden layers of the BPN classifier is represented in Figure 3(b) and Figure 3(c), respectively. System performance in relation to the number of passes over the BPN classifier's training set including all tumor images is shown in Figure 3(d). The optimal design parameters of the system were: entropy, energy, variance, inverse difference moment input features and two hidden layers-and six hidden nodes for the classifier. Using learning rate for input and hidden layer as 0.4, moment = 0.2 and the error allowed as 0.001, maximum accuracy was achieved after 450 epochs over the training set of the BPN classifier. Classification accuracy of a new tumor image by the system, after input of its CT density matrix, requires < 1 seconds of computer processing time.

We evaluated the classification accuracy of the BPN classifier for the classification of brain CT images into benign, malignant tumors using gray level co-occurrence texture features. The results from the classifier is evaluated using both statistical analysis and ROC analysis. The BPN structure
designed has 4 neurons in the input units of input layer for giving 4 extracted features as inputs, and 2 neurons in the output unit for the 2 classes of benign, malignant tumor of CT brain images.

Table 1 shows the classification results of the BPN classifier with jack knife and round robin methods in terms of gray level statistical texture features. The classification accuracy of the BPN classifier is 92.5% in jack knife method and 93.75% in round robin method respectively. Figure 2 shows the ROC analysis curve of the BPN classifier using both round robin and jack knife methods. From the ROC analysis, the AUC values of the BPN classifier using round robin method and jack knife methods are 0.937 and 0.923% respectively.

Table 1
Classification Performances of the BPN Classifier for 80 Images

<table>
<thead>
<tr>
<th>Classification parameter</th>
<th>Round robin method</th>
<th>Jack knife method</th>
</tr>
</thead>
<tbody>
<tr>
<td>TP</td>
<td>38</td>
<td>37</td>
</tr>
<tr>
<td>TN</td>
<td>37</td>
<td>37</td>
</tr>
<tr>
<td>FP</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>FN</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Sensitivity in %</td>
<td>95%</td>
<td>92.5%</td>
</tr>
<tr>
<td>Specificity in %</td>
<td>92.5%</td>
<td>92.5%</td>
</tr>
<tr>
<td>Classification accuracy in %</td>
<td>93.75%</td>
<td>92.5%</td>
</tr>
</tbody>
</table>

The results show that, if the representative samples increased, it gives good classification accuracy for both the round robin and jack knife methods.

In the initial stage of the system design, nine features with high ability in discriminating benign tumor from malignant tumor images were selected. This reduction in feature space dimensionality was important, since it is computationally to test system performance with all possible combinations the 18 initially calculated features. Highest classification accuracy was achieved by a four-feature combination, while system performance did not improve by increasing the number of combined features, because of feature inter correlation. Energy, entropy, variance, inverse difference moment was the optimum combination giving the highest discriminating power with the minimum number of features. Energy corresponds to the disorder of an image in the CT density matrix of the tumor image, entropy corresponds to the textural uniformity of an image, variance corresponds to the heterogeneity of an image, inverse difference moment corresponds to the homogeneity of an image. Highest classification accuracy was achieved by two hidden layer and 6 hidden nodes in the BPN classifier. Using the number of nodes and layers, the classification accuracy did not improve, while system design complexity increased. The advantage of incorporating more nodes in a neural network classifier is to give a higher degree of system fault tolerance, in case some hidden nodes fail to function. The proposed system which may be valuable especially in cases of small region of brain tumor images.

4. CONCLUSION
In this work, an automatic classification of benign, malignant brain tumor CT images using an efficient neural network classifier is proposed. The algorithm has been designed based on the concept of different types of brain soft tissues have different textural features. It is found that this method gives favorable result with accuracy percentage of above 93% for the brain CT images that are being considered. This would be highly useful as a diagnostic tool for radiologists in the automated classification of benign, malignant brain tumor CT images. The automation procedure proposed in this work using a BPN enables proper tumor classification thereby saving time and reducing the complexity involved. The proposed system may be particularly useful in small tumor regions, where distinction between these two types of brain tumors is radio logically difficult. The work can be extended to get 100% segmentation accuracy by using other feature extraction techniques such as wavelet based gray level co-occurrence feature extraction method with genetic algorithm feature selection as a future work.

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REFERENCES
Texture Feature Based Analysis of Brain CT Images for Discriminating Benign, Malignant Tumors


