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Texture Feature Based Analysis of Segmenting Soft Tissues from Brain CT Images using BAM type Artificial Neural Network

A.PADMA[1*], R.SUKANESH[2]

1. Research Scholar, Thiyagarajar College of Engineering , Madurai – 625 015, India .
2. Professor of ECE, Thiagarajar College of Engineering, , Madurai – 625 015, India.

* Email: giri_padma2000@yahoo.com

Abstract

Soft tissues segmentation from brain computed tomography image data is an important but time consuming task performed manually by medical experts. Automating this process is challenging due to the high diversity in appearance of tumor tissue among different patients and in many cases, similarity between tumor and normal tissue. A computer software system is designed for the automatic segmentation of brain CT images. Image analysis methods were applied to the images of 30 normal and 25 benign ,25 malignant images. Textural features extracted from the gray level co-occurrence matrix of the brain CT images and bidirectional associative memory were employed for the design of the system. Best classification accuracy was achieved by four textural features and BAM type ANN classifier. The proposed system provides new textural information and segmenting normal and benign, malignant tumor images, especially in small tumor regions of CT images efficiently and accurately with lesser computational time.

Keywords: Bidirectional Associative Memory classifier(BAM), Computed Tomography (CT), Gray Level Co-occurrence Matrix (GLCM), Artificial Neural Network (ANN).

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. CT 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 (Duncan, et al 2000). Pathologies are clearly identified using automated computer aided diagnostic system (Tourassi et al 1999). 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 and Ultra sound B scan. The CT 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 the 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 the methods for classifying and segmenting soft tissues in brain CT images. Image segmentation is the process of partitioning a digital image into set of pixels. Accurate, fast and reproducible image segmentation techniques are required in various applications. The results of the segmentation are significant for classification and analysis purposes. The limitations for CT scanning of head images are due to partial volume effects which affect the edges produce low brain tissue contrast and yield different objects within the same range of intensity. All these limitations have made the segmentation more difficult. Therefore, the challenges for automatic segmentation of the CT brain images have many different approaches. The segmentation techniques proposed by (Nathali Richarda et al 2007) and (Zhang et al 2001) include statistical pattern recognition techniques. (Kaiping et al 2007) introduced the effective particle swarm optimization algorithm to segment the brain images into Cerebro spinal fluid (CSF) and suspicious abnormal regions but without the annotation of the abnormal regions. (Dubravko et al 1997) and (Matesin et al 2001) proposed the rule based approach to label the abnormal regions such as calcification, hemorrhage and stroke lesion. (Ruthmann.et al 1993) proposed to segment cerebro spinal fluid from computed tomography images using local thresholding technique based on the maximum entropy principle. (Luncaric et al 1993) proposed to segment CT images into background, skull, brain, ICH, calcifications by using a combination of k means clustering and neural networks. (Tong et al 2009) proposed to segment CT images into CSF, brain matter and detection of abnormal regions using unsupervised clustering of two stages. (Clark et al 1998) proposed to segment the brain tumor automatically using knowledge based techniques. From the above literature survey shows that intensity based statistical features are the most straight forward and have been widely used, but due to the complexity of the pathology in human brain and the high quality required by clinical diagnosis, only intensity features cannot achieve acceptable result. In such applications, segmentation based on textural feature methods gives more reliable results. Therefore texture based analysis have been presented for segmentation of soft tissues gray level co-occurrence matrix feature extraction method is used and achieve the promising results.

2. Materials and methods

The study comprised 80 non contrast enhanced CT examinations with normal and 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 thichness,120 Kv,150 mA and 2.9s scan time. In each examination the CT section through the maximum cross sectional diameter of the brain image was selected; the CT density matrix of the sub image size 32*32 or 64*64 pixels depending on the size of the image was transferred to the computer for further processing.

2.1 Feature extraction

From each CT density matrix, 13 features were calculated. The 13 features were extracted from gray level co-occurrence matrix (Mohd et al 2009) 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,θ) for $\theta = 0^o, 45^o, 90^o$ and 135^o. The function P(i,j / d, θ) is the probability matrix of two pixels, which are located with an inter sample distance d and direction θ have a gray level i and gray level j. The gray level co-occurrence matrix ¢(d, θ) as follows

$$\phi(d,\theta) = [P(i, j/d,\theta)], \qquad 0 \le i, \qquad i \le N_g \tag{1}$$

Where, N_g is the maximum gray level. In this method, four gray level co-occurrence matrixes for four different directions ($\theta = 0^o, 45^o, 90^o, 135^o$) are obtained for a given distance d (=1, 2, 3, 4) and the following 13 textural based Haralick features (Haralick at al 1973) 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 13 features was tested by student t-test. Only the best segmenting features ($\rho<0.001$) were selected and were further employed in the design of computer software for segmenting soft tissues from normal, benign, malignant tumor images.

2.3 Classifier

Classification is the process where a given test sample is assigned a class on the basis of knowledge gained by the classifier during training.

2.3.1 BAM classifier

The extracted features are presented to a bidirectional associative memory (BAM) type artificial neural network (Rajasekharan et al 1998) for segmentation of the brain CT images. BAM network classifier has guaranteed convergence and good error correction capability with less connection complexity compared with other neural networks. The koskoo introduced (Koskoo,1988) two level non linear neural networks.

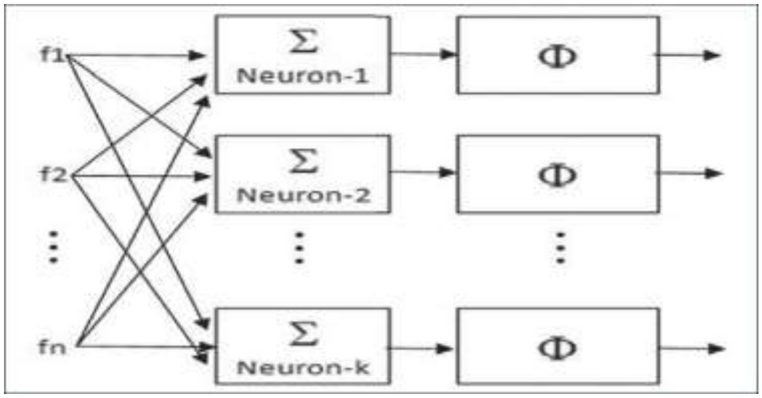


Figure 1. Architecture of BAM Network

But the BAM network designed in this algorithm is single level network and it also capable of recognizing the features even in the presence of noise .The network of this study was composed of two layers: input layer, and output layer. Input vector, output vector, and target vector were needed to execute the training algorithm of the BAM type ANN network. BAM type ANN Architecture is as shown in Figure 1. The number of output neurons used is equal to the number of objects (ROI) to be segmented , and hence for each ROI, there is one neuron. The number of inputs to each neuron is equal to the number of features in the input data. The feature vector of each ROI act as a weight vectors of respective neurons. The threshold function can be used as a transfer function (φ).

Algorithm for BAM type ANN as follows:

BAM (N, X,Y)

N is number of pattern sets : X,Y are the pattern pair sets where $X=X_1,X_2....X_N$; $Y=Y_1,Y_2...Y_N$

Step 1 : Normalize (X,Y)

For i ← 1 to N

$X_i(norm) = X_i / ||X_i||$; $Y_i(norm) = Y_i / ||Y_i||$

End

Step 2: Input A the pattern pair sets to be segmented and classified obtained its normalized equivalent.

$A_i(norm) = A_i / ||A_i||$

Step 3: Compute the inner product of A(norm) with X(norm) where i = 1 2 ... N

For i ← 1 to N

$Z_i(norm) = A_i(norm)*Xi(norm$

End

Step 4 : Apply threshold function φ on Z to obtain correlation vector M

$$M = \varphi (Z) = (M_1, M_2 \ldots M_n)$$

Where φ is equal to 1 for Max(Z) and zero elsewhere.

Step 5 : Output Y_k where k is such that

$$K = \max (M_i) \text{ where } i = 1\ 2 \ldots\ldots N$$

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. Thus the final system includes the computation of the optimum combination of textural features from the CT tumor's density matrix and for the segmentation of soft tissues by the BAM type ANN classifier.

3. Results and discussions

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 in DICOM format. The proposed algorithm is implemented in Mat lab 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 segmentation for two types of images which are the brain image with normal and abnormal. Best textural features ,determined in the feature reduction stage ($\rho<0.001$) were : variance, angular second moment, contrast, correlation, entropy, sum entropy, difference variance, and difference entropy. These eight features used in combinations of 2,3,4….8 as inputs to the classifier and the highest classification accuracy was achieved by the energy, entropy ,variance, inverse difference moment feature combination. This system classified correctly 28/30(93.33%) normal mages and 47/50 (94.5%) benign, malignant tumor images. The same system 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 2 shows the variation of system classification performance in relation to the number of textural features. The optimal design parameters of the system were : entropy, energy, variance, inverse difference moment input features and one input and output layer. Classification accuracy of a new image by the system, after input of its CT density matrix, requires < 1seconds of computer processing time. The BAM structure designed has 4 neurons in the input units of input layer for giving 4 extracted features as inputs, and 4 neurons in the output unit for the 4 classes of cerebrospinal fluid (CSF), gray matter(GM), white matter(WM), tumor region of CT brain images.

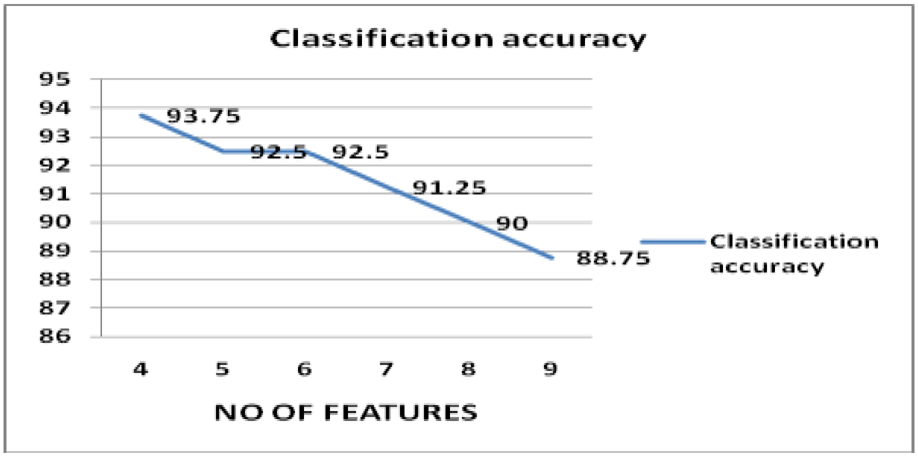
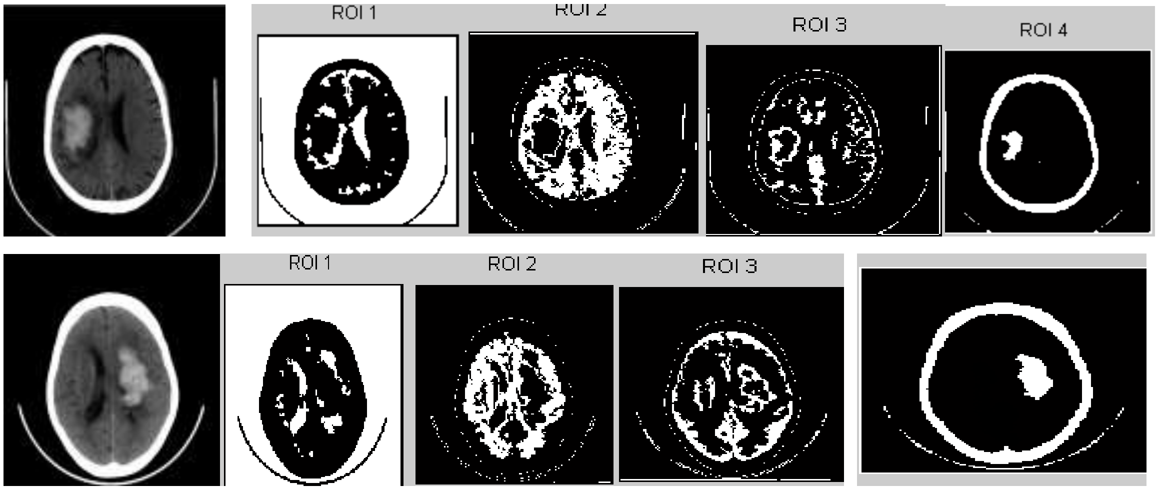


Figure 2. Classification accuracy based on No of texture features

We have tested our system on segmentation for two types of images which are the brain image with tumor regions and without tumor regions. However, for the images without tumor regions , only three clusters exist which are CSF, white matter, gray matter cluster . The results of all the clusters are shown in Figure 3. For the images without tumor regions the image display i.e., ROI4 under tumor region column will be left block as in the fourth example in Figure 3. We have tested segmentation accuracy of our system using BAM classifier with gray level co-occurrence texture features. The output of the segmented tumor image is compared with the ground truth (target). Ground truth was obtained from the boundary drawings of the radiologist. The segmentation results of two benign tumor images and two malignant tumor images and one normal image are as shown in Figure 3.



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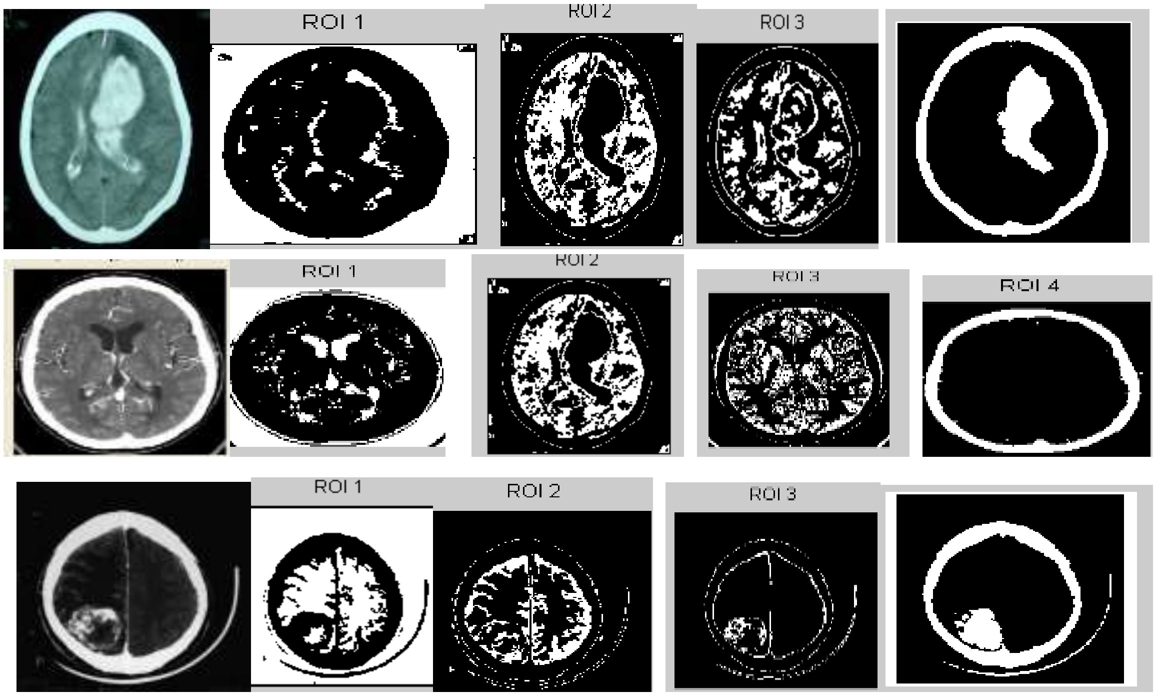

Figure 3. Segmented results for sample images

The quantitative results in terms of the performance measure such as segmentation accuracy is obtained using Eq. (2) for sample 4 slices of 4 patients with benign tumor images and 4 slices of 4 sample patients with malignant tumor images and 2 slices of 2 patients with normal images is tabulated in Table 1.

Segmentation accuracy = (no of pixels matched / total no. of tumor pixels in ground truth)*100 **(2)**

The segmentation accuracy is calculated as the direct ratio of the number of tumor pixels common for ground truth and the proposed method output to the total ground truth tumor pixels.

Table 1 .Segmentation accuracy of different slices

Slices	BAM with four features	Bam with above four features
1.	99.7163	94.658
2.	97.1298	95.342
3.	99.62701	97.865
4.	99.8289	96.765
5.	97.9301	93.678
6.	98.7618	94.7685
7.	99.68	95.987
8.	99.89	95.658
9.	98.764	93.4568
10.	96.764	92.289

A comparative study is made between BAM with four features and above 4 features using the performance criteria as the segmentation accuracy of segmented soft tissues. The results of the comparison is represented using a bar graph and is shown in Figure 4. From the results, it is observed that the performance of the BAM with four co-occurrence texture features have better classification and segmentation accuracy than above 4 features both quantitatively and qualitatively.

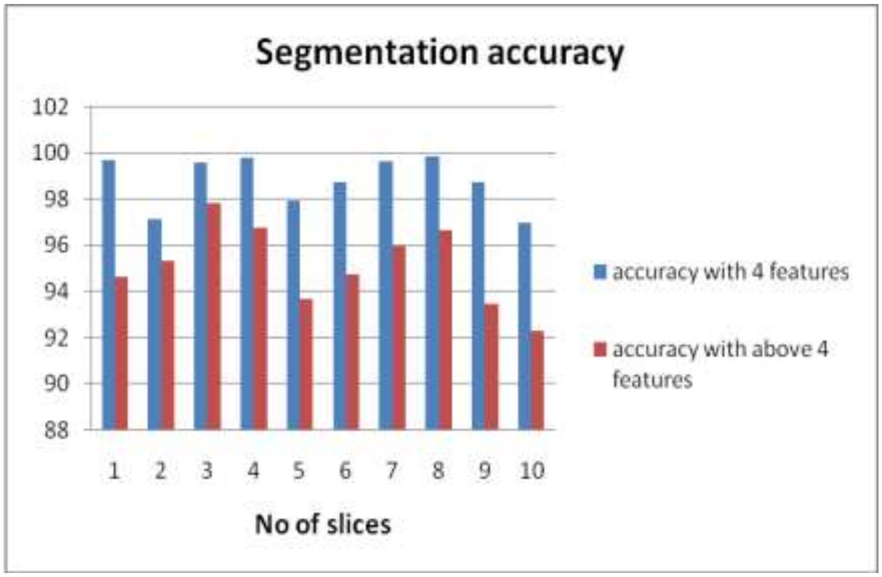

Figure 4.Segmentation accuracy of different slices

4. Conclusion

In this work a BAM type ANN classifier is proposed for the segmentation of soft tissues in the brain CT images using co-occurrence texture features. The algorithm has been designed based on the concept of different types of brain soft tissues (CSF, WM, GM, tumor region) have different textural features and also performing well for soft tissue characterization and segmentation. The results show that the new BAM type ANN classifier yields better results using minimum number of co-occurrence texture features. It is found that this method gives favorable result with segmentation accuracy percentage of above 97% for the CT images that are being considered. This would be highly useful as a diagnostic tool for radiologists in the automated segmentation of brain CT images. The automation procedure proposed in this work using a BAM type ANN enables proper abnormal tumor region detection and segmentation thereby saving time and reducing the complexity involved. The proposed system may be particularly useful in small tumor regions, where segmentation between these two types of brain normal and abnormal images is radio logically difficult .The work can be extended to other types of images such as MRI imaging and ultrasonic imaging as a future work.

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Authors

A.Padma received her B.E in Computer science and Engineering from Madurai Kamaraj University ,Tamilnadu ,India in 1990. She received her M.E in Computer science and Engineering from Madurai Kamaraj University, Tamilnadu, India in 1997 She is currently pursuing P.hd under the guidance of . Dr.(Mrs).R.Sukanesh in Medical Imaging at Anna university, Trichy. She is working as Asst Professor in Department of information Technology, Velammal college of Engineering and Technology, Tamilnadu, India.. Her area of interest includes image processing, Neural Networks, Genetic algorithm. She is a Life member of ISTE, CSI.

Dr.(Mrs).R.Sukanesh ,Professor in Bio medical Engineering has received her B.E from Government college of Engineering and Technology, Coimbatore in 1982. She obtained her M.E from PSG college of Engineering and Technology, Coimbatore in 1985 and Doctoral degree in Bio medical Engineering from Madurai Kamaraj university, Madurai in 1999. Since 1985, She is working as a faculty in the Department of Electronics and Communication Engineering, Madurai and presently she is the Professor of ECE, and heads the Medical Electronics division in the same college. Her main research areas include Neural Networks, Bio signal processing and Mobile communication. She is guiding twelve P.hd candidates in these areas. She has published several papers in National, International journals and also published around eighty papers in National and International conferences both in India and Abroad. She is a reviewer of international Journal of Biomedical Sciences and International Journal of signal Processing. She is a life member of Biomedical Society of India.