Implementation of FMRI Segmentation using ESNN

Mrs. D. Suganthi
Department of Computer Applications
Shri Shankarlal Shasun Sundarbai Jain College for Women,
3, Madley Road, T.Nagar, Chennai – 600017.
Tamilnadu, India.

Abstract—*Image segmentation plays a crucial role in image analysis and computer vision which is also regarded as the bottleneck of the development of image processing technology applications. Medical Resonance Image (MRI) plays an important role in medical diagnostics and different acquisition modalities are used. Major goal of fMRI data analysis is to recognize activated brain areas and one of the major steps has segmentation. ANN is a computational simulation of a biological neural network, has classified into many networks. Recurrent neural network specifically in ESNN have implemented fMRI segmentation. The performance of ESNN for different number of reservoirs, different range of initial weights in reservoir matrix and different range of initial weights are discussed. In Brain MRI images, the features extracted with ESNN with CC gives 97% accuracy. MATLAB R2011a software was used. The texture features of each class gives high efficiency rate. The evaluation of result demonstrates the effectiveness of the proposed method.*

Keywords—*Segmentation, Echo State Neural Network (ESNN), Contextual Clustering (CC), Brain tumor, MATLAB.*

I. INTRODUCTION

Image segmentation plays an important role in many imaging applications. Medical Resonance Image (MRI) plays an important role in the field of medical diagnostics.In medical imaging for analyzing anatomical structures such as blood vessels, bones,tissue types, muscles, pathological regions such as multiple sclerosis, cancer, lesions and for dividing an entire image into sub regions such as the grey matter (GM), white matter (WM) and cerebrospinal fluid (CSF) spaces of the brain automated delineation of different image components are used. Study and analysis of brain through the images acquired by various single and multimodalities.

The medical images are captured by different acquisition modalities like Ultrasounds (US), X-rays, Computed tomography (CT), magnetic resonance imaging (MRI), Single Photon Emission Tomography (SPECT), Positron Emission Tomography (PET). MRI can provide plentiful information about human soft tissues anatomy as well as helps diagnosis of brain tumor.

Brain MR images are used to analyze and study behavior of the brain. Diseases are shown using MRI signal between neural activity and the local blood flow that results in BOLD signal. But are looking at how blood oxygen levels change and assuming that this is connected to nerves.

Functional magnetic resonance imaging (fMRI) has become an important method for the investigation of human brain function, both for research and for clinical purposes. Functional areas identified by motor, sensory and language tasks have been shown to correspond well with intra-operative mapping and also with classically defined anatomical regions responsible for these functions.

Segmentation of an object in an image is performed either by locating all pixels or voxels that form its boundary or by identifying them that belongs to the object. In an Medical imaging, segmentation is an important analysis function for which lots of algorithms and methods have been built up. Segmentation techniques provide flexibility.

The developing platform for the detection is **MATLAB**. Introduce to acquire high-resolution brain images with ultrahigh field (7T) MR scanner and identify voxels responding to the task using our approach.

II. PRE-PROCESSING

The need for pre-processing arises from the fact that the raw fMRI data is contaminated with artifacts primarily due to body movement, Physiological noise and scanner artifacts during the course of data acquisition. Pre-processing attempts to increase BOLD contrast and signal to- noise (SNR) in general by removing the amount of noise as much as possible. Pre-processing tools are SPM, Brain Voyager, AFNI and etc. The conventional fMRI pre-processing pipeline includes motion correction, slice-timing correction, co-registration, Region of interest identification, Bias field correction, filtering and etc.

The motion correction ensures the motion-related artifacts in the data is removed by choosing the reference image volume and realigning all the remaining image volumes to the reference to minimize the variance caused by motion. A new image volumesare acquired in every repetition time (TR) in fMRI. During this time period, individual slices in the volume are acquired either sequentially or in an interleaved manner (where all odd slices are acquired before even slices). The slices within the same volume are therefore acquired at different times.

Realignment

Movement-related variance induced by gross head motion in fMRI time-series represents one of the most serious confounds of analysis. Before analysis, head motion detection should be made to evaluate the quality of data. The adjustment may be furthered by correction based on an estimate from a moving average auto-regression model of spin-excitation history effects.

Spatial Smoothing

There are several advantages of spatial smoothing. First, it generally increases SNR. The neuropsychological effects of interest are produced by homodynamic changes that are expressed over spatial scales of several millimeters, whereas noise usually has higher spatial frequencies. In fMRI the noise can be regarded as independent for each voxel and has therefore very high spatial frequency components. Second, it enhances statistical inference.

Segmentation

Image segmentation is very useful in separating grey matter, white matter, cerebrospinal fluid, blood vessels, and other brain structures. Segmentation methods usually utilize the differences in intensity distribution of different tissues. In fMRI study, segmenting structures are help usto differentiate the functional responses in gray matter from large vessels. Thus provides better spatial localization and quantification accuracy.

III. PROPOSED SYSTEM ARCHITECTURE

Segmentation is an important process that helps to identifying objects in the given image. Existing segmentation methods are not able to correctly segment the complicated profile of the fMRI accurately. The Segmentation of every pixel in the fMRI correctly helps in proper location of tumor. The presence of artifacts and noise poses a challenging problem in proper segmentation.

This research work proposes a new intelligent segmentation technique for functional Magnetic Resonance Imaging (fMRI) using artificial neural network.It is mainly used for better segmentation of the complicated profile of fMRI. In this segmentation process, the fMRI image can be segmented with contextual clustering method and Echo state neural networks.

Analysis Methods

First, data are analyzed to find the regions with MR signal changes temporally correlate with the experiment paradigm. Second, a threshold is used to discriminate the "inactive" brain regions (i.e., those with signal changes that are more consistent with noise) from the "active" regions.

Finally, the results of the activation analysis are registered to high-resolution structural images, which are used to more accurately determine the brain structures involved in the activation task.

This approach provides reliable analysis of the known functional responses. Methods belonging to this category include: correlation analysis, t-test, general linear model.

The functional activities are performed, detection and identification of tumor in the brain. Preprocessing and Segmentation is an important role in order to distinguish between normal patients and their abnormalities or tumor patients.

The proposed method consists of three stages:

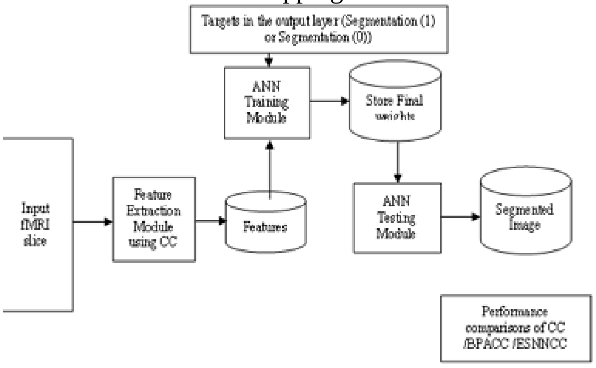
1. Feature Extraction module
2. Selection pattern using BPA
3. ANN Training module
4. ANN Testing module

FMRI DATABASE

A number of online neuroscience databases are available which provide information regarding gene expression, macroscopic brain structure, neurons and psychiatric or neurological disorders. The Internet Brain Segmentation Repository (IBSR) provides a manual guidance to shown the expert segmentation results along with magnetic resonance brain image data. fMRI slice images have been obtained from IBSR for use in this research work.

1. FEATURE EXTRACTION MODULE

Feature extraction is essential for segmentation process. Since the performance of a segmentation algorithm is based on the type of features used to train the algorithm. In this research work, statistical features are used to train the proposed segmentation algorithms. This is achieved by using the contextual clustering (CC) algorithm for feature extraction and segmentation of fMRI. The 3x3 overlapping windows are used.



These 9 features are used as inputs for the BPA / ESNN algorithms. The values of the features will be different for windows of different pixels. These changes in the values of the features are responsible for proper segmentation of the fMRI from the background of the fMRI.

2. SELECTION PATTERN USING BPA

In a selection pattern method, the overall 9 features are collected from the Feature Extraction module using contextual clustering methods. These features are taken as input values for the BPA and ESNN algorithms. The values of the features are different pixels of windows. These changes in the values of the features are implemented for proper segmentation of the fMRI from the background of the fMRI.

2.1 Pattern generation for training BPA with CC

A pattern is a vector containing many features. The features are the representation of a window of 3 x 3 pixels uniquely. An average number of total blocks are obtained from a cropped 136 x 136 fMRI slice. Each block is considered as a pattern of features. From each block, mean of intensity values, summation of intensity values and the V_{cc} obtained as outputs of CC algorithm. Target value as 0.1(black) or 0.9(white) is allotted for each pattern. The patterns obtained are further used for training BPA with CC

The patterns are normalized so that the values of the features are in the range of 0 to 1 and the computational complexity is reduced. The normalization of the patterns is done by equation (1.1).

$$x_i = x_i / x_{max} \qquad (1.1)$$

wherex_i is the value of a feature, andx_{max} is the maximum value of the feature

2.1.1 Selection of patterns for training

The numbers of classes, which are based on the classification range of the outputs, are decided. If only one output is considered the range of classification is simple. If more than one output is considered a combination criterion has to be considered. The total number of patterns is decided for each class.

Out of these patterns, the number of patterns to be used for training the network is decided. The remaining patterns are used for testing the classification performance of the network. The patterns selected for training the network should be, such that they represent the entire population of the data.

The selection of patterns is done using equation 1.2.

$$E_i^2 = \frac{\sum_{j=1}^{nf}(x_{ij} - \bar{x}_j)^2}{\sigma_i^2} \qquad \textbf{(1.2)}$$

WhereE_i^2 is the maximum variance of a pattern,

nf is the number of features.

2.1.2 Training strategies for the network

For the network to learn the patterns different weight updating algorithms have been developed. They are called supervised methods and unsupervised methods. Since both the inputs and outputs are considered for segmentation supervised learning technique has been used. The present work involves modification of existing weight updation, method of training the network for more number of patterns, and training the network properly for correct segmentation and estimation.

The network functions on a supervised learning strategy. The inputs of a pattern are presented. The output of the network obtained in the output layer is compared with the desired output of the pattern. The difference between the calculated output of the network and the desired output is called Mean squared error (MSE) of the network for the pattern presented. This error is propagated backwards such that the weights connecting the different layers are updated.

By this process the MSE of the network for the pattern presented is minimized. This procedure is summed up. After presenting the last training pattern, the network is considered to have learnt all the training patterns through iterations, but the MSE is large. To minimize MSE the network has to be presented with all the training patterns many times.

There is no guarantee that the network will reach the global minimum. Instead it will reach one of the local minima. The MSE may increase which means divergence rather than convergence. Sometimes there may be oscillations between convergence and divergence.

The training of the network can be stopped, either by considering MSE or by considering classification performance as the criterion. When classification performance is considered as the criterion, test patterns are presented at the end of each iteration. Once the desired performance is obtained, training of the network is stopped.

When MSE is considered as the criterion, one may not know the exact MSE to which the network has to be trained. If the network is trained till it reaches a very low MSE over fitting of the network occurs. Over fitting represents the loss of generality of the network. That is the network classifies only the patterns which are used during training and not the test patterns.

The BPA uses the steepest-descent method to reach a global minimum. The number of layers and number of nodes in the hidden layers are decided. The connections between nodes are initialized with random weights. A pattern from the training set is presented in the input layer of the network and the error at the output layer is calculated.

The error is propagated backwards towards the input layer and the weights are updated. This procedure is repeated for all the training patterns. At the end of each iteration, test patterns are presented to ANN and the classification performance of ANN is evaluated. Further training of ANN is continued till the desired classification performance is reached.

3. ANN TRAINING MODULE

Artificial neural networks are computing elements which are based on the structure and function of the biological neurons. These networks have nodes or neurons, which are described by difference or differential equations. The nodes are interconnected layer wise or intra-connected among themselves. Each node in the successive layer receives the inner product of synaptic weights with the outputs of the nodes in the previous layer. The inner product is called the activation value. The activation value is passed through a non-linear function.

A network is feed forward, if there is no closed chain of dependence among neural states. The same network is feed backward, if there is such a closed chain. When the output of the network depends upon the current input the network is static.The inputs are statistical parameters and the outputs are segmentation values. The combination of input and output constitutes a pattern. Many patterns will be called data.

The ANN training module trains the supervised algorithms namely back propagation algorithm (BPA) and echo state neural network (ESNN) to learn the segmentation of fMRI. The features obtained from the feature extraction module are presented to the input layer of the ANN topology. The number of nodes in the hidden layer varies depending on the training data used, the initial weights used for assigning the connection strengths between input-hidden layer, hidden-hidden layer, hidden-output layers. At the end of the training process in both BPA and ESNN, a set of matrices called final weights is stored.

3.1 Training ESNN with CC

The ANN algorithms used are BPA and ESNN. These two algorithms undergo two phases before segmenting the fMRI images. Phase-1 is the training and Phase-2 is the testing of BPA /ESNN which gives segmented fMRI. In both the Phase-1 and Phase-2, features such as mean of the 9 intensity values, summation of 9 intensity values and the V_{cc} obtained from CC algorithm for a moving overlapping window are given as input to the input layer of the ANN topology.

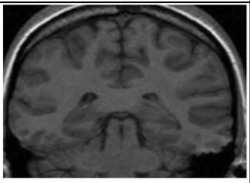
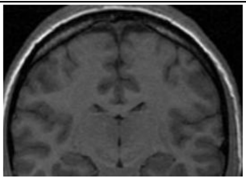
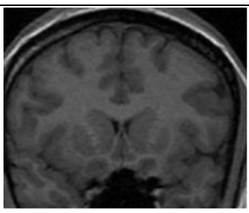
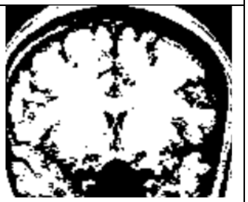
The training patterns obtained in the contextual clustering are used to train the ANN topology with ESNN algorithm. In order to segment the image, the three features of the windows are presented in the input layer and the corresponding target outputs (0.1 or 0.9) are presented in the output layer of the ESNN. The summation of (input pattern multiplied with initial weights between input and hidden layers, multiplication of initial state vector with the initial weights of the reservoir and multiplication of target value with the initial weights between hidden layer and output layer) is obtained.

4. ANN TESTING MODULE

The implementation of the neural network in a training process is shown in the schematic flow. The schematic flow shows training of ANN and implementation of ANN for segmentation. During training of ANN, the network learns the training patterns by a weight updating algorithm. The training of ANN is stopped when a desired performance index of the network is reached. Statistical features are further processed with the final weights to obtain a value in the output layer of the ANN. Based on the output obtained further segmentation is done by allotting either 0 or 1.

4.1 Testing ESNN with CC

A pattern with three features obtained in the contextual clustering is presented to the input layer of the ESNN. The summation of (input pattern multiplied with final weights between input and hidden layers + multiplication of final state vector with the final weights of the reservoir + the final weights between hidden layer and output layer) is obtained.

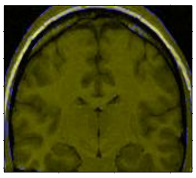
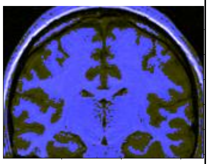
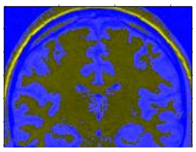
Segmentation Results for Different Images using ESNN		
Image No.	**Original image**	**Segmented result**
Image 25		
Image 30		
Image 40		

This method of evaluating segmentation accuracy helps as follows:

1. The various objects present in the segmented fMRI can be chosen as a whole and the accuracy of segmentation for each object inside the fMRI can be evaluated.
2. As the intensity values are likely to overlap in the adjacent regions of the objects inside the fMRI, the region properties will show how accurately the objects are segmented.

The output of ESNN is obtained from {tanh (summation) + (pseudo inverse (state matrix) x target of all the patterns during training}. It presents the segmented outputs for different number of reservoirs in the hidden layer of ESNN.

The best segmented output is obtained with reservoir as 22. It can be observed that the optimum number of reservoir is 22 for a block size 3x3 window.

SEGMENTATION OVERLAPS FOR IMAGE-25		
Segmentation methods	**Segmentation output by each method**	**Overlapped with fMRI slice**
CC		
BPA		
ESNN		

Segmentation Accuracy Evaluation based on Correct Number of Pixels Segmented in the fMRI Slice

The segmentation accuracy based on the correct number of pixels segmented (A_p) is obtained using Equation

$$A_{pixel}(\%) = \frac{N_C}{T_P} * 100$$

where, A_{pixel}= segmentation accuracy
N_c = number of correctly segmented pixels in the fMRI
T_p= total number of pixels corresponding to the fMRI in the unsegmented image (Ground Truth).

Segmentation Accuracy based on Number of Pixels			
Image	**N_C**	**T_P (Ground truth)**	**A_{pixel} (%)**
Image 25	344	362	95.01
Image 30	1009	1062	94.99
Image 40	760	792	96.01

The performance remains closely consistent which indicates the value of the variables of ESNN with CC algorithm are optimal. This can be visualized in terms of pixel-based segmentation and object based segmentation accuracy.

IV. CONCLUSION AND FUTURE ENHANCEMENT

The performance analysis of the implemented segmentation method is carried out as follows. For this process, fMRI slices are considered. All the slices are segmented by CC and ESNN with CC methods. This segmentation is applied for all the fMRI images.

A three layer BPA Neural Network is proposed with CC features. These features are given as the input layer for proper learning by BPA network and it shows the good experimental results. The experimental results obtained from the proposed BPA with CC segmentation algorithm helps in reducing the false positive rate.

Future Enhancement:

Many future works are possible to make this segmentation more effective. The number of features can be increased to represent the different properties like density, change in greyscale and change in contrast in the successive slices. For the purpose of enhanced segmentation the Gray Level Co-occurrence Matrix (GLCM) properties can be used combined with genetic algorithm for decreasing the false positive rate.

REFERENCES

[1] Afshin S., and Fatemeh J., 2012, Automated technique for medical images using neural network, International journal of Multidisciplinary sciences and Engineering, Vol.3, No.3, pp.38-41.

[2] Anamika Ahirwar, 2013, Study of techniques used for medical image segmentation and computation of statistical test for region classification of brain MRI, International Journal of Information Technology and Computer Science, Vol.5, No.5, pp.44-53.

[3] Beaulieu J.M. and M. Goldberg, 1989, Hierarchy in picture segmentation: a stepwise optimization approach, IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol.11, No.2, pp.150-163.

[4] Bezdek J.C., Hall L.O., and Clarke L.P., 1993, Review of MR image segmentation techniques using Pattern Recognition, Medical Physics, Vol.20, No.4, pp.1033–1048.

[5] Carlos A.P., Khan I., and Robert Kozma, 2003, Automated brain data segmentation and pattern recognition using ANN, International Conference on Computational Intelligence, Robotics and Autonomous systems, pp.27-31.

[6] Dzung L.P., Chenyang Xu and Jerry L.P., 2000, Current methods in medical image segmentation, Annual Review of Biomedical Engineering, Vol.2, pp.315-337.

[7] Fesharaki M.N, and Hellestrand G.R., 1994, A new edge detection algorithm based on a statistical approach, International symposium on Speech, Image Processing and Neural Networks, Vol.1, pp.21-24.

[8] Ghanshyam D. Parmar, Suman K. Mitra DA, 2011, Effectiveness Analysis of Fuzzy Unsupervised Clustering Algorithms for Brain Tissue Segmentation in Single Channel MR Image, International Journal of Bio-Science and Bio-Technology, Vol.3, No.2,pp.39-48.

[9] Hamed Shamsi and Hadi S., 2012, A Modified fuzzy c-means clustering with spatial information for image segmentation, International Journal of Computer Theory and Engineering, Vol.14, No.5, pp.762-766.

[10] Javad A., Jernigan M.E., and Nahmias C., 1997, Neural network based segmentation of magnetic resonance images of the brain, IEEE Transactions on Nuclear Science, Vol.44, No.2, pp.194-198.

[11] Kannan S.R., 2008, A new segmentation system for MR images based on fuzzy techniques, Applied Soft Computing, Vol.8, Issue 4, pp.1599-1606.

[12] Logeswari T and Karnan M, 2010, An improved implementation of brain tumor detection using segmentation based on soft computing, Journal of Cancer Research and Experimental Oncology, Vol.2, No.1, pp.6-14.

[13] Manoj kumar V., and Sumithra M.G., 2012, Performance comparison of different medical image segmentation algorithms for normal and abnormal brain MRI, International Journal of Latest Research in Science and Technology, Vol.1, Issue 4, pp.369-372.

[14] Murugavalli S., and Rajamani V., 2007, An improved implementation of brain tumor detection using segmentation based on neuro fuzzy technique, Journal of Computer Science, Vol.3, No.11, pp.841-846.

[15]. Priyanka and Balwinder Singh, 2013, A review on brain tumor detection using segmentation, International Journal of Computer Science and Mobile Computing, Vol.2, No.7, pp.48-54.