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fMRI Segmentation Using Echo State Neural Network

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Abstract: This research work proposes a new intelligent segmentation technique for functional Magnetic Resonance Imaging (fMRI). It has been implemented using an Echostate Neural Network (ESNN). Segmentation is an important imaging process that helps in identifying objects of the image. Existing segmentation methods are not able to exactly segment the complicated profile of the fMRI accurately. Segmentation of every pixel in the fMRI correctly helps in proper location of tumor. The presence of noise and artifacts poses a challenging problem in proper segmentation. The proposed ESNN is an estimation method with energy minimization. The estimation property helps in better segmentation of the complicated profile of the fMRI. The performance of the new segmentation method is found to be better with higher Peak Signal to Noise Ratio (PSNR) of 61 when compared to the PSNR of the existing Back-Propagation Algorithm (BPA) segmentation method, which is 57.

Key words: Echo State Neural Network (ESNN), Intelligent segmentation, functional Magnetic Resonance Imaging (fMRI), Back-Propagation Algorithm (BPA), Feature Extraction, Peak Signal to Noise Ratio (PSNR)

INTRODUCTION

Medical imaging plays a vital role in the field of bio-medical engineering. Some of the organs of the human body require non-invasive approach to understand the defects such as tumor, cancer in different parts of the body. Study and analysis of brain are done through the images acquired by various modalities like X-ray, Computer Tomography (CT), Positron Emission Tomography (PET), Ultrasound (US) and Single Photon Emission Computed Tomography (SPET) etc. The present day-to-day study of brain is much preferred through functional Magnetic Resonance Imaging (fMRI). The acquired fMRI image need to be preprocessed, registered and segmented for understanding the defects in the brain by physician. Current tomographic technologies in medical imaging enable studies of brain function by measuring hemodynamic changes related to changes in neuronal activity. The signal changes observed in functional Magnetic Resonance Imaging (fMRI) are mostly based on Blood Oxygenation Level Dependent (BOLD) contrast and are usually close to the noise level. Consequently, statistical methods and signal averaging are frequently used to distinguish signals from noise in the data. In most fMRI setup, images are acquired during alternating task (stimulus) and control (rest) conditions.

Automatic tissue segmentation approaches for 3D magnetic resonance images for brain have been developed under three broad algorithms, namely classification-based, region-based and contour-based approaches. Anatomical knowledge, used appropriately, boost the accuracy and robustness of the segmentation algorithm. MRI segmentation strive toward improving the accuracy, precision and computation speed of the segmentation algorithms (Liew and Yan, 2006).

The complex dependence structure of fMRI noise precludes parametric statistical methods for finding appropriate thresholds. The non-parametric thresholds are potentially more accurate than those found by parametric methods. Three different transforms have been proposed for the resampling: Whitening, Fourier and wavelet transforms. Resampling methods based on Fourier and wavelet transforms, which employ weak models of the temporal noise characteristic, may produce erroneous thresholds. In contrast, resampling based on a pre-whitening transform, which is driven by an explicit noise model, is robust to the presence of a BOLD response (Friman and Westin, 2005).

A commonly used method based on the maximum of the background mode of the histogram, is Maximum Likelihood (ML) estimation This method is evaluated in terms of accuracy and precision using simulated MR data

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But this method outperforms in terms of mean-squared-error (Poot *et al.*, 2006). A fully automated, parametric, unsupervised algorithm for tissue classification of noisy MRI images of the brain has been done under varying noise conditions (Hayit *et al.*, 2006). Parametric and non-parametric statistical methods are powerful tools in the analysis of fMRI data (Pajevica and Basser, 2003). Probabilistic approaches to voxel based MR image segmentation identify partial volumetric estimations. Maximum Posterior Marginal (MPM) minimization and Markov Field (Moussaoui *et al.*, 2006) were used for contextual segmentation. Functional MRI segmentation using fuzzy clustering technique is proposed for objective determination of tumor volumes as required for treatment monitoring. Knowledge based technique is essential both in time and accuracy to expand single slice processing into a volume of slices (Heller *et al.*, 2006). A method for semiautomatic segmentation of brain structures such as thalamus from MRI images based on the concept of geometric surface flow has been done. The model evolves by incorporating both boundary and region information following the principle of variational analysis. The deformation will stop when an equilibrium state is achieved (Heckenberg *et al.*, 2006). Energy minimization algorithm provides a high quality segmentation due to region homogeneity and compactness. The graph algorithm for multiscale segmentation of three dimensional medical data sets has been presented (Parker, 2002).

Problem definition: The proposed method focuses on a new segmentation approach using energy minimizing echo state neural network. Due to the complicated profiles of the brain, the new method helps in segmenting the profiles by learning the different states of the profile of fMRI. Statistical features are calculated form the fMRI. These features are learnt by the training phase of the ESNN. The learnt weights are further used for segmentation of the fMRI during the testing phase.

ECHO STATE NEURAL NETWORK (ESNN)

Artificial neural networks are computing elements which are based on the structure and function of the biological neurons (Lippmann, 1987). 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 (Rumelhart *et al.*, 1986). The inner product is called the activation value.

Dynamic computational models require the ability to store and access the time history of their inputs and outputs. The most common dynamic neural architecture is the Time-Delay Neural Network (TDNN) that couples delay lines with a nonlinear static architecture where all the parameters (weights) are adapted with the Backpropagation Algorithm (BPA). Recurrent Neural Networks (RNNs) implement a different type of embedding that is largely unexplored. RNNs are perhaps the most biologically plausible of the Artificial Neural Network (ANN) models. One of the main practical problems with RNNs is the difficulty to adapt the system weights. Various algorithms, such as backpropagation through time and real-time recurrent learning, have been proposed to train RNNs. These algorithms suffer from computational complexity, resulting in slow training, complex performance surfaces, the possibility of instability and the decay of gradients through the topology and time. The problem of decaying gradients has been addressed with special Processing Elements (PEs).

The Echo State Network (ESN), Fig. 1, with a concept new topology has been found by Jaeger (2001). ESNs possess a highly interconnected and recurrent topology of nonlinear PEs that constitutes a "reservoir of rich dynamics" and contain information about the history of input and output patterns. The outputs of these internal PEs (echo states) are fed to a memory less but adaptive readout network (generally linear) that produces the network output. The interesting property of ESN is that only the memory less readout is trained, whereas the recurrent topology has fixed connection weights. This reduces the complexity of RNN training to simple linear regression while preserving a recurrent topology, but obviously places important constraints in the overall architecture that have not yet been fully studied.

The echo state condition is defined in terms of the spectral radius (the largest among the absolute values of the eigenvalues of a matrix, denoted by (|| ||) of the

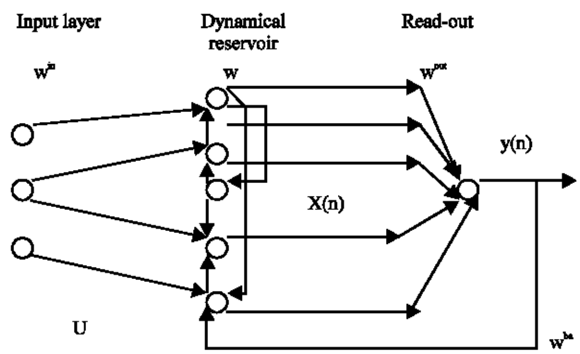

Fig. 1: An echo state neural network

reservoir's weight matrix (|| W || < 1)). This condition states that the dynamics of the ESN is uniquely controlled by the input and the effect of the initial states vanishes. The current design of ESN parameters relies on the selection of spectral radius. There are many possible weight matrices with the same spectral radius and unfortunately they do not all perform at the same level of Mean Square Error (MSE) for functional approximation.

ESN is composed of two parts (Jaeger, 2002b): A fixed weight (|| W || < 1) recurrent network and a linear readout. The recurrent network is a reservoir of highly interconnected dynamical components, states of which are called echo states. The memory less linear readout is trained to produce the output (Jaeger, 2002b). Consider the recurrent discrete-time neural network given in Fig. 1 with M input units, N internal PEs and L output units. The value of the input unit at time n is $u(n) = [u_1(n), u_2(n), \ldots, u_M(n)]^T$,

The internal units are $x(n) = [x_1(n), x_2(n), \ldots, x_N(n)]^T$ and output units are $y(n) = [y_1(n), y_2(n), \ldots, y_L(n)]^T$. The connection weights are given:

- In an (N×M) weight matrix $W^{back} = W^{back}_{ij}$ for connections between the input and the internal PEs,
- In an N×N matrix $W^{in} = W^{in}_{ij}$ for connections between the internal PEs
- In an L×N matrix $W^{out} = W^{out}_{ij}$ for connections from PEs to the output units and
- In an N×L matrix $W^{back} = W^{back}_{ij}$ for the connections that project back from the output to the internal PEs.

The activation of the internal PEs (echo state) is updated according to

$$x(n+1) = f(W^{in} u(n+1) + Wx(n) + W^{back} y(n)) \quad (1)$$

Where,
$f = (f_1, f_2, \ldots, f_N)$ are the internal PEs' activation functions.
All f_i's are hyperbolic tangent functions

$$\frac{e^x - e^{-x}}{e^x + e^{-x}}$$

The output from the readout network is computed according to

$$y(n+1) = f^{out}(W^{out} x(n+1)) \quad (2)$$

Where,
$f^{out} = (f_1^{out}, f_2^{out}, \ldots, f_L^{out})$ are the output unit's nonlinear functions. The training and testing procedures are given in the study.

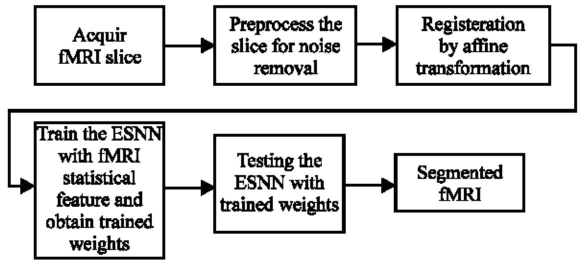

Fig. 2: Schematic diagram of the intelligent segmentation

PROPOSED METHOD FOR INTELLIGENT SEGMENTATION

In this research, much concentration is done for improving segmentation of fMRI by implementing the ESNN. Figure 2 illustrates the sequence of steps involved in fMRI intelligent segmentation Acquiring the image is done through standard fMRI equipment. The image is preprocessed to make sure that the noise is removed. Removal of noise is mostly preferred by using adaptive filtering methods. Depending on the severity of noise, the internal parameters of the filtering method can be fine tuned. Contrast enhancement of the image is done to have better clarity of the image. Since image slices of the brain are considered, registration of the slices have to be done effectively. This is done with affine transformation. Once the registration process is completed, segmentation of the slices have to be done. This process is very important for further study of the fMRI slices. The ESNN is initialized with random weights. The statistical features obtained from the FMRI are used to train the ESNN. The process of training is used to obtain set of trained weights. Testing of ESNN is done for fMRI segmentation using the trained weights.

IMPLEMENTATION OF SEGMENTATION USING ESNN

Training of ESNN to obtain trained weights

Step 1: Find the statistical features of the registered image

Step 2: Fix the target values(labeling)

Step 3: Set the no. of inputs, no. of reservoirs , no. of outputs

Step 4: Initialize weight matrices- no. of reservoirs versus no. of inputs, no.of outputs versus no. of reservoirs, no. of reservoirs versus no. of reservoirs

Step 5: Initialize temporary matrices.

Step 6: Find values of matrices less than a threshold

Step 7: Apply heuristics by finding eigenvector of updated weight matrices.

Step 8: Create network training dynamics and store the final weights.

Implementation of ESNN for segmentation of fMRI using the trained weights of ESNN

Step 1: Read the trained weights

Step 2: Input the statistical features of fMRI.

Step 3: Process the inputs and fMRI

Step 4: Apply transfer function

Step 5: Find the next state of the ESNN.

Step 6: Apply threshold and segment the image

MATERIALS AND METHODS

The fMRI was obtained with standard setup conditions. The magnetic resonance imaging of a subject was performed with a 1.5-T Siemens Magnetom Vision system using a gradient-echo echoplanar (EPI) sequence (TE 76 ms, TR 2.4 s, flip angle 90, field of view 256-256 mm, matrix size 64 * 64, 16 slices, slice thickness 3 mm, gap 1 mm) and a standard head coil. A checkerboard visual stimulus flashing at 8 Hz rate (task condition, 24 s) was alternated with a visual fixation marker on a gray background (control condition, 24 s). In total, 110 samples (3-D volumes) were acquired. The brain was segmented from the EPI slices to enable identification of voxels belonging to the brain volume. The brain was assumed to remain at a fixed location during the scanning, so it was considered sufficient to segment only one volume. The sample number 60 was selected.

RESULTS AND DISCUSSION

In Fig. 3, some of the fMRI sequences have been displayed for clarity. The image numbered (2) and (3) are considered for analyzing the performance of segmentation by ESNN algorithm. As the initial image is affected with electronic noise, it has been adaptively filtered to remove the noise and subsequently registered.

Figure 4(e) shows the registered image of noise filtered images of Fig. 4(c and d). The registration process helps in aligning the contents of the images to enable segmentation. During the process of registration, the registered image is contrasted and enhanced. For

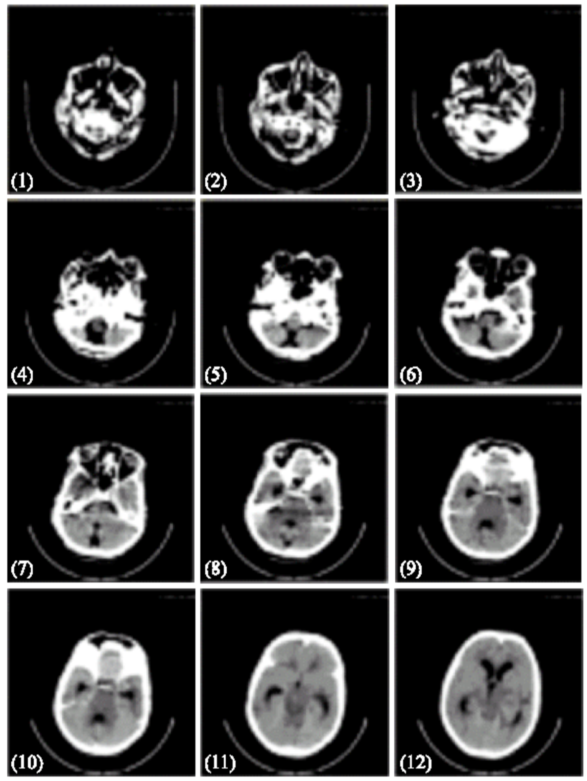

Fig. 3: fMRI sequences

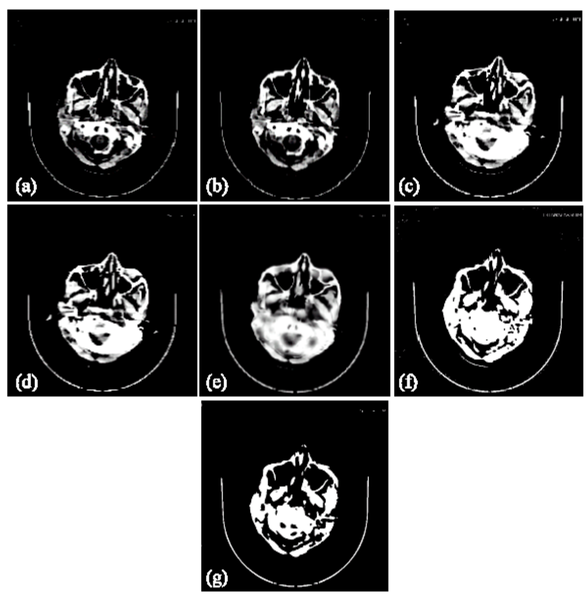

Fig. 4: Segmentation of fMRI-sequence of outputs, (a) Source-1, (b) Source-2, (c) Source-1 filtered, (d) Source -2 filtered (e) Source 2 registered with source-1, (f) BPA segmentation, (g) ESNN segmentation

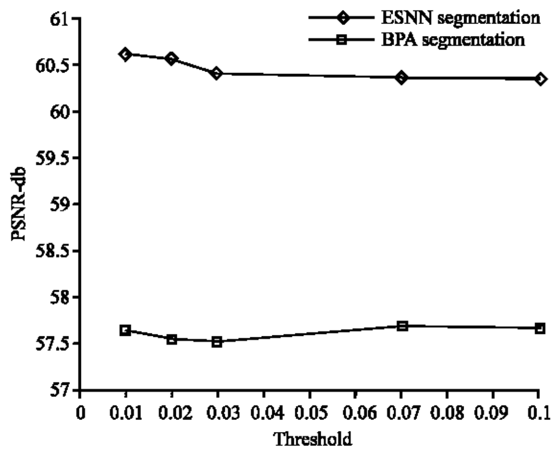

Fig. 5: Comparison performance of ESNN and BPA

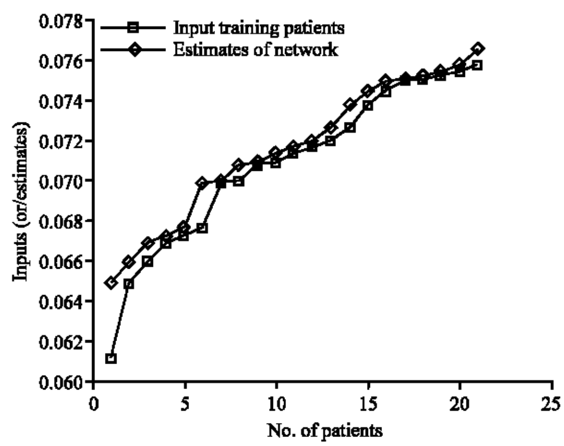

Fig. 6: Training performance of the ESNN

the comparison of the segmentation performances of the ESNN, BPA segmentation is taken as the reference, since BPA is the oldest neural network method used earlier for image segmentation. The segmented image through BPA is shown in Fig. 4(f). Similarly the segmented image using ESNN is shown in Fig. 4(g).

One of the important segmentation performance comparison is PSNR. The PSNR is expressed as

$$\text{PSNR} = 10*\log10\,(255*255/\text{MSE}) \quad (3)$$

$\text{MSE} = \sum (\text{Original image-segmented image})^2$
Where, MSE is the mean squared error

Figure 5 shows peak signal to noise ratio for different threshold used in both the BPA and ESNN algorithms. The PSNR values starts with minimum 57 and goes upto approximately 61. The range of PSNR for the segmented image using BPA is 57-58. The PSNR value for the segmented image by ESNN ranges from 60 to 61. The maximum PSNR value is obtained in case of ESNN segmentation is for threshold of 0.01 with 60.58. In case of segmentation by BPA, the maximum PSNR is only 57.9 for the threshold of 0.07. By comparison, the maximum PSNR is obtained at lower threshold for the ESNN algorithm. The PSNR can be further improved by further modifying the ESNN algorithm in terms of number of nodes I the hidden layer. Figure 6 shows the ESNN estimation and the corresponding input patterns. The estimate is based on the number of reservoirs used during the training process.

CONCLUSION

The fMRI segmentation has been done with a recurrent ESNN that stores the different states of fMRI. The PSNR value for this method is 60.6867. Where as, the PSNR value for the segmentation done by back-propagation algorithm is 55.67. The work can be further extended by incorporating modifications of internal states in ESNN and fine tuning the noise filtering methods.

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