A NEW METHODOLOGY FOR SEGMENTATION OF FUNCTIONAL MAGNETIC RESONANCE IMAGING USING FUNCTIONAL ECHO STATE NEURAL NETWORK

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Abstract: - In this paper a new intelligent segmentation of functional magnetic resonance imaging (fMRI) has been implemented using echo state neural network (ESNN). fMRI is a non-invasive method which can be used to indirectly localize neuronal activations in the human brain. The term segmentation includes not only the detection and localization, but also the delineation of activation region in the brain. Perfect segmentation is important especially for the detection and position of brain tumor. In spite of the existing segmentation methods, we have proposed a novel estimation method for accurate segmentation irrespective of noise level. The Recurrent ESNN is an estimation method able to produce an accurate segmentation when compared to the contextual clustering segmentation method. In order to show the accuracy of segmentation, the existing Contextual clustering (CC) segmentation method has been considered. Peak Signal to Noise Ratio (PSNR) of the segmented image of ESNN is 6 and found to be higher than PSNR of CC 57. The segmented images can be used in Medical Imaging application like 3D Reconstruction.

Keywords: - Echo state neural network (ESNN), intelligent segmentation, Functional magnetic resonance imaging (fMRI), Contextual clustering (CC)

1. 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 through the images acquired by various single and multimodalities They are x-ray, computer tomography(CT), positron emission tomography (PET), ultrasound (US), (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 setups, images are acquired during alternating task (stimulus) and control (rest) conditions.

Segmentation subdivides image into its constituent parts or objects. The level of subdivision depends on the requirement of depth of segmentation. Segmentation of images can be done by conventional and non-conventional (intelligent) methods. The conventional methods include standard mask operators, statistical methods, detection of discontinuities, edge linking and boundary detection, thresholding, region based segmentation, watershed segmentation etc. The intelligent methods include artificial neural networks, fuzzy logic and evolutionary algorithms. MRI images contain various noise artifacts, such as intra-tissue noise, inter-tissue intensity contrast reduction, partial-volume effects and others. The artifacts present due to voxel-wise based classification methods, such as Mixture of Gaussians modeling shall give unrealistic results, with tissue class regions appearing granular, fragmented, or violating anatomical constraints.

The analysis of the image series is frequently based on the computation of a statistical parametric map, and statistical inferences derived from it. For example, a voxel-by-voxel computation of the difference of means of intensities between control and task states normalized by the estimated standard error generates a statistical map that follows the distribution in the nonactive area, i.e., in the background. Correlation analysis, subspace modeling, Fourier, and wavelet transform methods; pseudo generalized least squares analysis using sinusoidal regression and nonparametric Kolmogorov–Smirnov test are examples of other approaches used to create statistical maps. The general linear model is a general framework that includes the simple statistic and most other parametric tests. Significant active areas are found by thresholding the maps. Methods that assess statistical significance levels based on the spatial extent of the activation cluster after intensity thresholding have been developed to improve sensitivity.

2. Literature Review

Maximum Posterior Marginal (MPM minimization) and Markov Field were used for segmentation [1]. The fuzzy-clustering method [2] was used very much for brain tissue segmentation. The MRI brain segmentation, noise removal were done [3] using Mixture of Gaussians and expectation maximization (EM) with constrained model. New graph algorithms for multiscale segmentation of three dimensional medical data sets have been presented [4]. It is a three dimensional generalization of an existing two-dimensional Mumford-Shah region-merging segmentation algorithm. Mumford-Shah functional formulation leads to improved segmentation results compared to alternative approaches; the graph theoretic approach yields improved performance and simplified data structures; and the automated stopping estimation allows a fully non-supervised algorithm with no tuning parameters required (except for an optional parameter to select the depth of segmentation) [4].

An unsharp mask sharpening algorithm [5] has been implemented to improve the clarity of the images prior to segmentation, based on a Monte Carlo simulation. A concept of geometric surface flow has been applied as a method for segmentation of brain structures such as thalamus from MRI images [6]. An interactive algorithm for image smoothing and segmentation [7] with a non-linear partial differential equation has been employed to smooth the image while preserving contours. The segmentation is a region growing and merging process initiated around image minima (seeds), which are automatically detected, labeled and eventually merged. A methodology that incorporates principles from cluster analysis and graph representation to achieve efficient image segmentation results have been applied [8]. A region grouping process is applied next to form the final segmentation results. The proposed approach was also compared to approaches that use feature-based or spatial information exclusively, to indicate its effectiveness.

An attempt to segment MRI images by correcting MRI signal in homogeneities and incorporating contextual information by means of Markov random filed has been achieved [9]. A Segmentation algorithm to provide brain surface-based analysis and automated anatomical labeling of cortical fields in magnetic resonance data sets based on oxygen metabolic state have been done [10]. An adaptive fuzzy c-means (FCM) clustering algorithm has been explored for segmentation of three-dimensional multi-spectral MR images. A segmentation method of MRI based on fuzzy Gaussian basis neural network (FGBNN), Gaussian basis function is used as fuzzy membership function and error backpropagation (BP) algorithm has been used to train the neural network.

3. Problem Definition

In order to overcome the drawbacks of segmentation, this work has focused on effective segmentation of fMRI using intelligent segmentation method. Echo state neural network is used which is an estimation method to segment the irregular profile. fMRI contains noise inherently due to varied reasons like electronic thermal effect and artifacts. Features of the fMRI are obtained using statistical method. These features are learnt by the FESNN during the training phase. By using the final weights obtained from the training, testing is done on fMRI which results in effective segmentation.

4. Proposed method for intelligent segmentation

In this work, much concentration is done for effective segmentation of fMRI using FESNN. Figure 1 illustrates the sequence of steps involved in fMRI intelligent segmentation

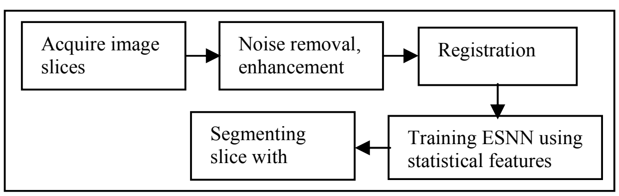


Fig.1 Schematic diagram of the Intelligent segmentation

Acquire fMRI: The fMRI slices are obtained from MRI equipment in DICOM format and convert into jpeg

Preprocess the image: Removal of noise and enhancing the image using discrete wavelet transform with db1.

Registration: The preprocessed slices are registered using pyramid algorithm and fluid flow method.

Segmentation: The registered slice is segmented using functional echo state neural network.

5. Functional Echo State Neural Network (FESNN)

Artificial neural networks are computing elements which are based on the structure and function of the biological neurons [11]. 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 [12]. 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 back propagation algorithm. 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 back propagation through time and real-time recurrent learning, have been proposed to train RNNs; however, 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), Figure 1, with a concept new topology has been found by [13]. 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 this 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 reservoir's weight matrix (|| W || < 1). This condition states that the dynamics of the FESN is uniquely controlled by the input, and the effect of the initial states vanishes. The current design of FESN 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. FESN is composed of two parts [14]: 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 [15]. Consider the recurrent discrete-time neural network given in Figure 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 x M) weight matrix $W^{back} = W_{ij}^{back}$ for connections between the input and the internal PEs
- in an $N \times N$ matrix $W^{in} = W_{ij}^{in}$ for connections between the internal PEs
- in an $L \times N$ matrix $W^{out} = W_{ij}^{out}$ for connections from PEs to the output units and
- in an $N \times L$ matrix $W^{back} = W_{ij}^{back}$ 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

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

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

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

where $f^{out} = (f_1^{out}, f_2^{out}, \ldots, f_L^{out})$ are the output unit's nonlinear functions.

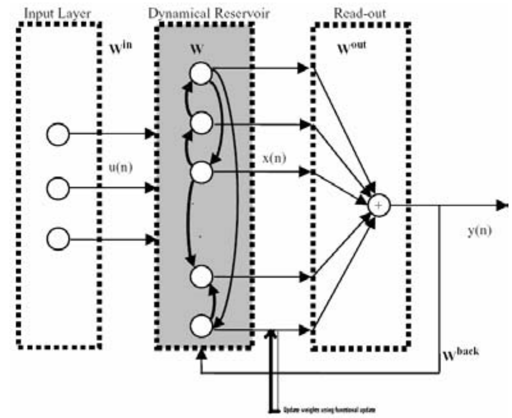


Fig. 2 Functional Echo state neural network

FESNNs resemble the RNN architecture. The critical difference is the dimensionality of the hidden recurrent PE layer and the adaptation of the recurrent weights. The ideas of approximation theory in functional spaces (bases and projections), so useful in adaptive signal processing should be utilized to understand the FESN architecture.

6. Flow Diagram

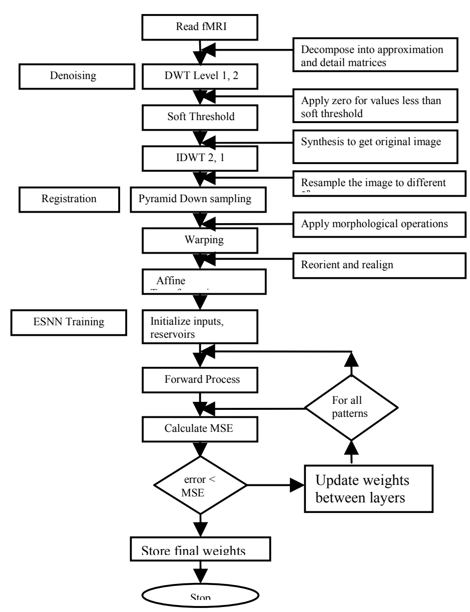


Fig. 3 Training of functional Echo state neural network

Figure 3 depicts detailed steps for training the FESNN followed by noise filtering, enhancement and registration of fMRI. The flow chart is self explanatory

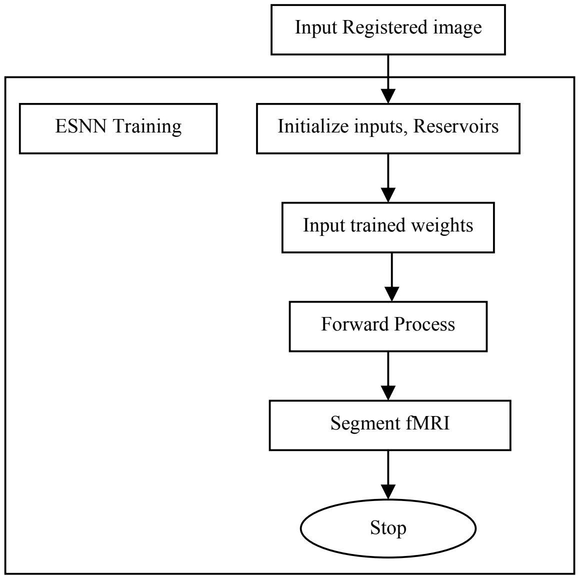


Fig. 4 Testing / Segmentation steps of Echo state neural network

Figure 4 indicates the use of trained FESNN weights for final fMRI segmentation. The flow chart is self explanatory

7. Experimental setup

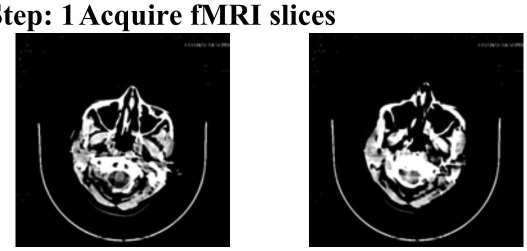
The fMRI *have been* obtained with standard setup conditions. The magnetic resonance imaging of a subject was performed with a 1.5-T Siemens Magnetom Vision system using a gradient-echo echo planar (EPI) sequence (TE 76 ms, TR 2.4 s, flip angle 90 , field of view 256 - 256 mm, matrix size 64 * 64, 16 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. The entire simulation was done using Matlab 7.0 software.

8. Results and discussion

The images Figure 4(a) and 4(b) are considered for analyzing the performance of ESNN algorithm segmentation compared to the performance of segmentation of contextual clustering. As the initial images are affected with electronic noise, they have been adaptively filtered to remove the noise. The filtered images are shown in Figure 4(c) and in Figure 4(d).

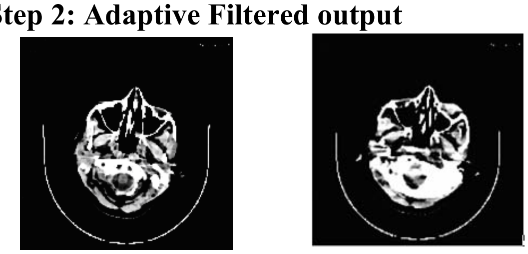
Figure 4(e) shows the source 2 registered with source 1 image. The registration process has been done with pyramid decomposition and affine flow transformation. The process will further help in volume reconstruction of the brain image. During the process of registration, the registered image is contrasted and enhanced. A comparison of the segmentation performance of the ESNN with contextual clustering, have been shown. Figure 4(f) show the segmented output of contextual clustering. Figure 4(g) shows the segmentation output of Echo state neural network. The contextual clustering uses hypothesis and with supervised clustering.

Step: 1 Acquire fMRI slices



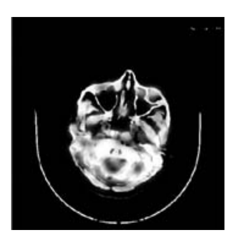
(a) Source 1 (b) Source 2

Step 2: Adaptive Filtered output



(c) Source 1 filtered (d) Source 2 filtered

Step 3: Registration of source with target

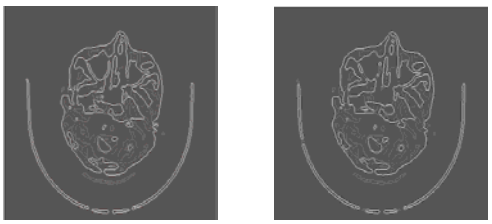


(e) Source 2 registered with Source 1

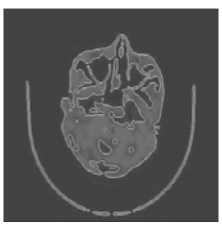
Step 4: Contextual clustering and Echo state neural network Segmentation

(f)Contextual Clustering (g) ESNN Segmentation

Fig.4 fMRI image segmentation



Segmentation accuracy
(a) (b)



(c)

Fig. 5 Visual Comparison of the segmented images

Figure 5 (a) shows overlapping of the segmented profile of Contextual clustering with registered image. In Figure 5(b), the FESNN segmented image is placed over the registered image. Figure 5(b) shows less deviation in the segmented profile than that of Figure 5(a). Figure 5(c) shows the placing of CC segmented image, FESNN segmented image over the registered image for better understanding. Close observation of Figure 5(c) shows large deviation in CC segmented image when compared to less deviation of FESNN segmented image.

Peak signal to noise ratio (PSNR)

PSNR depicts the quality of the segmented image comparing the amount of deviation of the segmented profile with the profile of the registered image. The PSNR is expressed as

PSNR = 10*log10(255*255/MSE)

MSE= $\sum$ (Registered image–segmented image)^2

where MSE is the mean squared error

Figure 6 depicts the PSNR obtained for contextual clustering and ESNN for different threshold values. There is a noticeable change in both ESNN and CC between the threshold values 0.01 to 0.03 and there is slight change between 0.03 to 0.1. The average increase in the PSNR for the ESNN segmentation when compared to the CC segmentation is 1.7658. This value is obtained by finding the difference between PSNR values of CC and FESNN at different threshold.

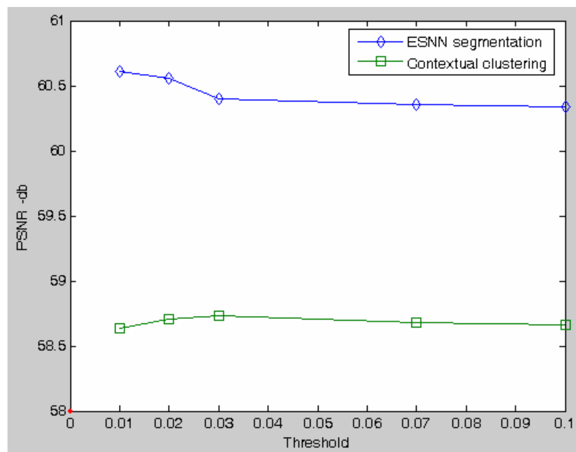


Fig. 6 Segmentation performance of CC and ESNN

Conclusion

This work has focused on implementation of a novel segmentation method for segmenting the fMRI slices. Due to the estimation property of FESNN, the accuracy of segmentation is better and provides detailed segmented profile which is a major challenging task in other segmented methods. Segmentation performance of FESNN has been compared to the segmentation performance of contextual clustering method in terms of PSNR. An improved PSNR is obtained by using ESNN method. Threshold values in the range of 0.01 to 0.03 are suggested for improved segmentation which is shown in the figure 6. The average increase in the PSNR for the FESNN segmentation when compared to the

CC segmentation is 1.7658. The work can further improved by modifying the topology of FESNN. The FESNN method can be applied for different image modalities. The work will be further extended for 3D reconstruction.

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