ICA COMPONENTS CLASSIFICATION OF fMRI DATA USING NEURAL NETWORKS

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Abstract-When ICA is applied to fMRI data, it results in components which are either a functional network or noise. Hence ICA helps to disintegrate the data and filter out the noise. This paper focuses on automatic classification of ICA components of fMRI data using neural networks. A total of 186 features were used tosuccessfully classify the components into noise or a valid network. A neural network with 186 input neurons and 2 output neurons was trained using the scaled conjugate back propagation algorithm. The neural networks performed exceptionally well in classifying the components with 10 fold cross validation performance of 99% on the two datasets.

***Keywords*— fMRI(functional Magnetic Resonance Imaging), BOLD(Blood Oxygen Level Dependence), ICA(Independent Component Analysis), Neural networks, Functional networks**

I. INTRODUCTION

fMRI(functional magnetic resonance imaging) measures the BOLD(Blood Oxygen Level Dependence) signals in the brain which helps to study the activated areas of the brain. The fMRI data is very noisy. So, it has to be made sure that the data is free of noise before analysis. ICA has emerged as a very important tool to denoise fMRI data. This is due to the fact that ICA results in components which are independent and since noise acts independent of the data, it separates noise from the data. Having established the fact that ICA separates noise, the problem is to identify the components that are noise. Various attempts have been made to identify noise. Some of the components are easily identifiable by visual inspection. However even a single run of fMRI data results in large number of components. Manually classifying the components is very tedious and time consuming job. Also, manual classification is error prone because the person might not be an expert. So, automatic classification can be really helpful and a great time and effort saver. Several attempts have been made to automate the process of ICA components classification. The earliest attempts were made in 2003. In 2008, J. Tohka et al., classified the components using six features and by using a GDT classifier. They obtained a misclassification rate between 0.2 and 0.3. The most popular software named FIX for ICA components classification came in 2007(G. Salimi-Khorshidi et al.). They used 186 features and used fusion of different classifiers such as kNN(k Nearest Neighbours),SVM(Support Vector Machines), Logistic regression, Random forests. FIX achieved an overall accuracy of 95%.

II. VISUAL INSPECTION OF ICA COMPONENTS

It is possible to distinguish between noise and functional networks by visually inspecting the components(R.E. Kelly Jr. et al.). This can be done by taking into account the spatial map, time course of the component, power spectrum and motion time series. Slabbing which is defined as large activation areas not respecting white matter and grey matter boundaries, Checker boarding are small random dots and represents head motion along z axis, ring pattern is also due to head motion, sinus is due to cardiac cycle and breathing are types of noise which are clearly visible in the spatial maps.

1. SPATIAL MAPS

The t-stat files obtained are the spatial maps of the components. The activations in white matter, ventricles, edges of brain and sinus indicate noise. Also, the activations should be inside anatomical boundaries.

2. TIME COURSE

Large drifts and spikes in the representative time series of the component implies noise. Sawtooth pattern occurs due to aliasing of cardiac and respiratory signals.

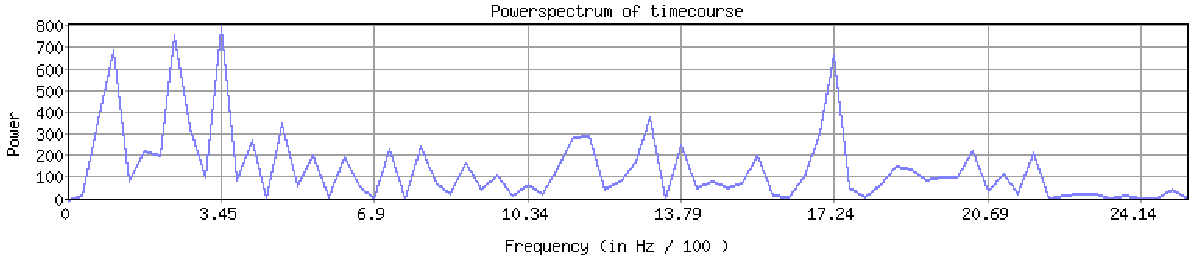

Figure 1:An example of power spectrum of a noisy ICA component

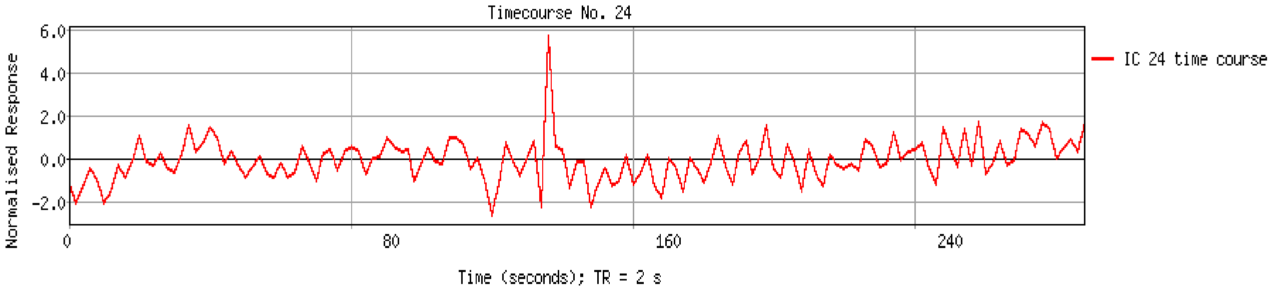

Figure 2:An example of time series of a noisy ICA component.

3. POWER SPECTRUM

The resting state gives low frequency fluctuations. If more than 50 % of power is present in frequencies above 0.1 Hz, gives an indication of the component being noise.

4. MOTION TIME SERIES

If the component time series is highly correlated with the head motion of thesubject then the component can be declared as noise.

III. FEATURES

A total of 186 features were used as given in G. Salimi-Khorshidi et al. The features are motivated from the parameters used in visual inspection such as spatial maps, time series and power spectrum.
feature 1 : Number of components.
feature 2-3 : Goodness of fit of AR(Autoregressive) model.
feature 4-5: AR(1) parameter and residual.
feature 6-8: AR(2) parameter and residual.
feature9-10: Kurtosis and skewness of Component’s time series.
feature 11: Difference in mean and median of time series
feature 12-13: entropy and negentropy
feature 14-19: jump characteristics of component’s time series
feature 20-23: Ratio of power above and below f Hz, f=0.1,0.15,0.2,0.25
feature 24-30: total % power in range 0:0.01, 0.01:0.025, 0.025:0.05,0.05:0.1, 0.1:0.15, 0.15:0.2 and 0.2:0.25 Hz
feature 31-38: Compare time series with noise convolved with HRF.
feature 39-44: Correlation of component’s time series with motion and its derivatives.
Feature45-46: Mean reversion features of time series.
feature 47-55: thresholded cluster size distribution characteristics feature
56-61: Balance of positive and negative voxels in maps
feature 62–65: Ratio of z stat to mean functional maps
feature 66–69: Slice characteristics
feature 70–73: Even and odd slices characteristics
feature 74–85: Correlation of component’s spatial map with White matter, Grey matter and CSF
feature 86–87: smoothness measures
feature88–90: TFCE features
feature91–105: Edge features

feature 106–177: Sagittal sinus and veins mask-based features
feature 178: Stripiness score/feature
feature179-186: Spatial resolution, temporal resolution, size of image in x,y,z and t dimension

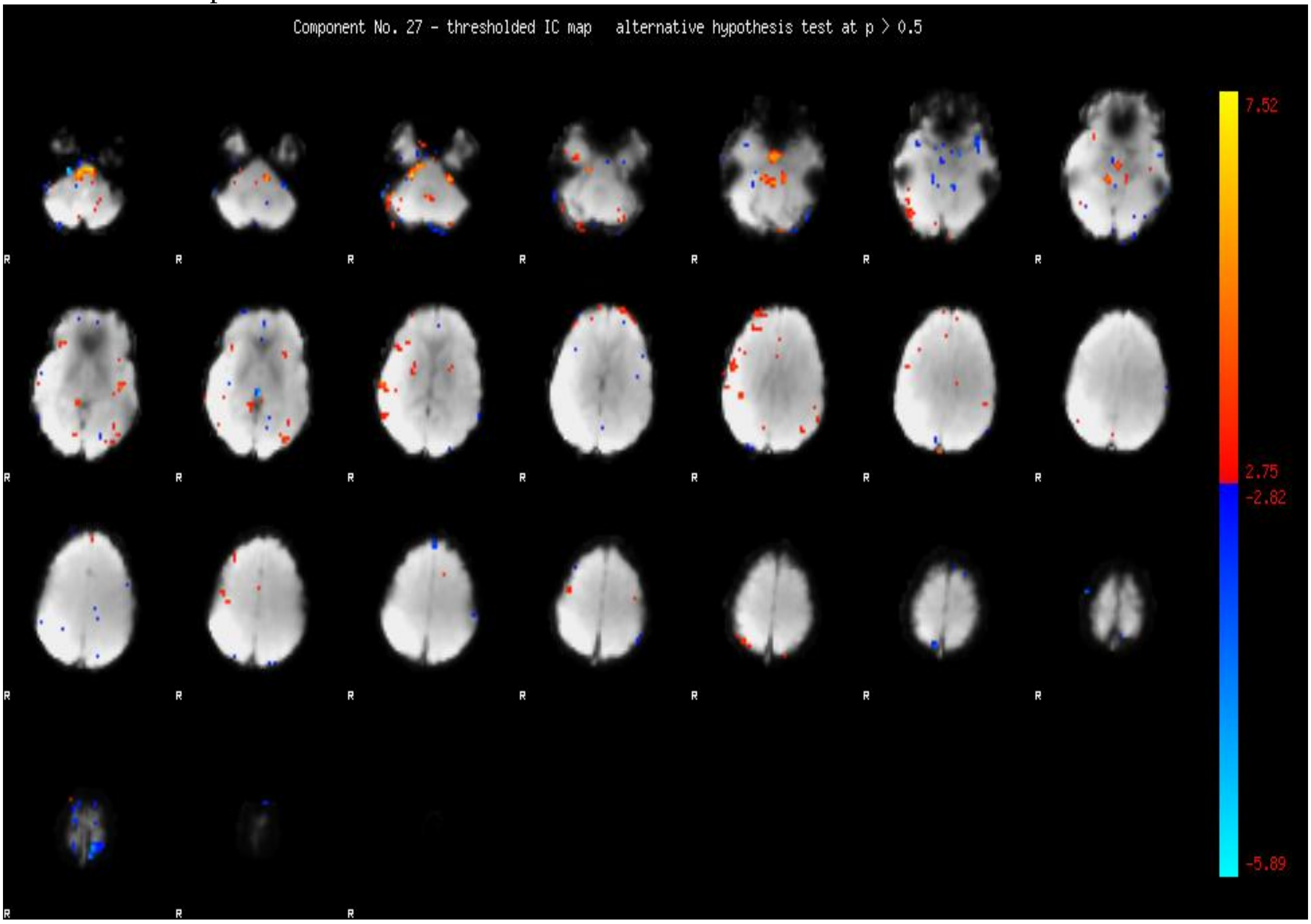

Figure 3:: An example of spatial map of a noisy ICA component.

IV. NEURAL NETWORKS

Neural networks are inspired from brain. The fundamental unit of neural network is the neurons which are analogous to neurons in the brain. These neurons fire based upon the input. Each neuron has an activation function associated with it.If the value of input is higher than a threshold, the neuron fires. There are different activation functions such as sigmoid, logtan etc. There are three layers in an ANN, namely

1. INPUT LAYER

Input is provided to this layer. There can be any number of neurons in input layer.

2. HIDDEN LAYER

Takes input from input layer. There can be many hidden layers and each layer can have any number of neurons. Number of neurons is generally less than the number of neurons in input layer.

3. OUTPUT LAYER

Input from Hidden layers. In case of classification, number of output neurons is equal to the number of classes. There are weights associated with edges of a neural network. These weights provide the capabilities of learning. Theweights are not fixed and can be learnt from the training data. A trained neural network can be used to classify new datasets.

V. BACK PROPAGATION ALGORITHM

The weights are learnt by this algorithm.
1. Initialize weights randomly.
2. while(error<0.01){

3. Calculate the output of the neural network, given the weights
4. error=1/n(true label - calculated label)
5. update the weights
6. }

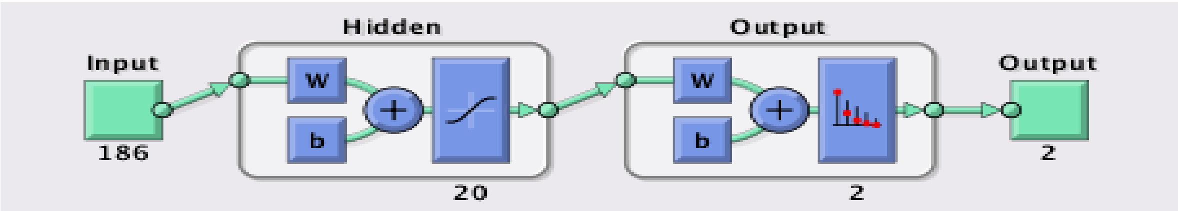

Figure 4:A trained neural network

VI. NEURAL NETWORK IN MATLAB

Patternet is a MATLAB function used to implement a classification neural network. The number of neurons in the input layer is 186 which is equal to the number of features and the number of neurons in the output layer is 2 as there are 2 output neural network.The number of hidden neurons is varied to optimize the performance of the neural network. The training algorithm used is trainscg (Scaled conjugate back propagation algorithm) and the error function used is cross entropy. 10 fold cross validation is used to evaluate the performance of classes.

VII. RESULTS

The figures show the Classification accuracy, sensitivity and specificity as a function of the number of hidden layers in the neural network. The performance of the 3 layer neural network is evaluated using 10 fold cross validation. As the number of layers increases, the time required to train the neural network increases drastically because of the number of parameters to be learned. Also as the number of layers increases, overfitting reduces the accuracy. 20 to 30 neurons in the hidden layer achieves an accuracy of 99% for the two different datasets each containing approximately 5000 ICA components. The time required to train a neural network with 20 to 30 neurons in the hidden layer is very less, close to 2 minutes

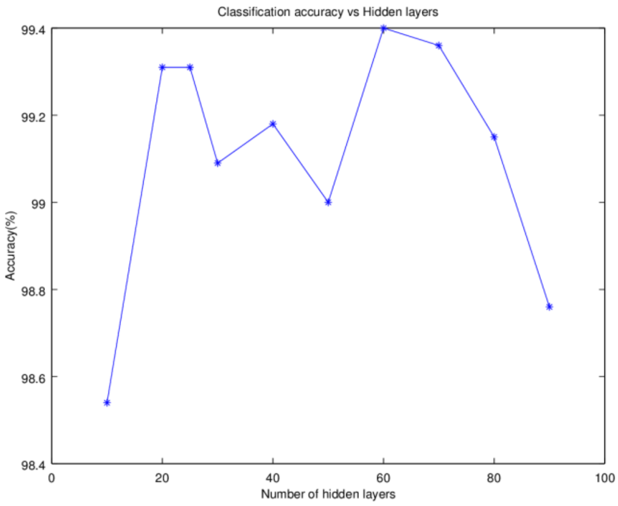

Figure 5: Classification accuracy for Dataset 1

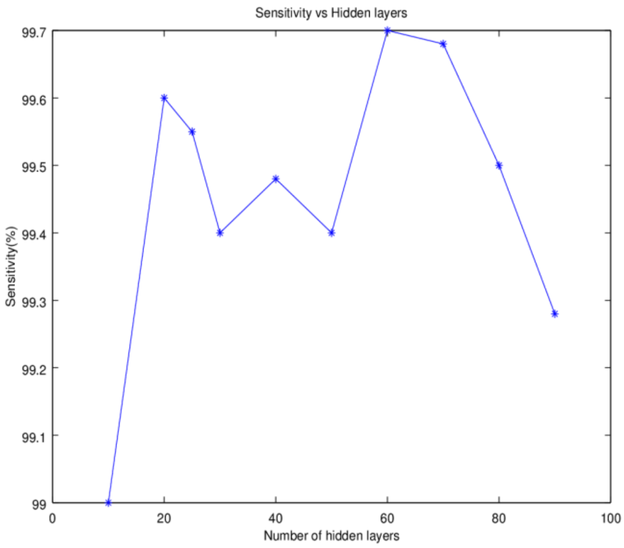

Figure 6: The sensitivity for dataset 1.

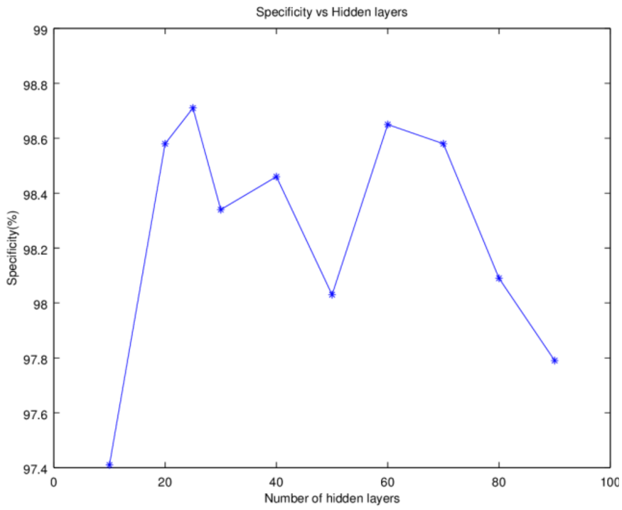

Figure 7: The specificity for dataset 1

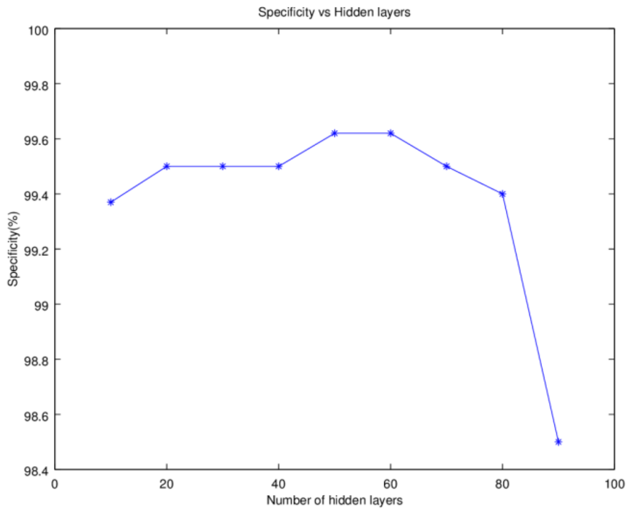

Figure 9: The specificity for dataset 2

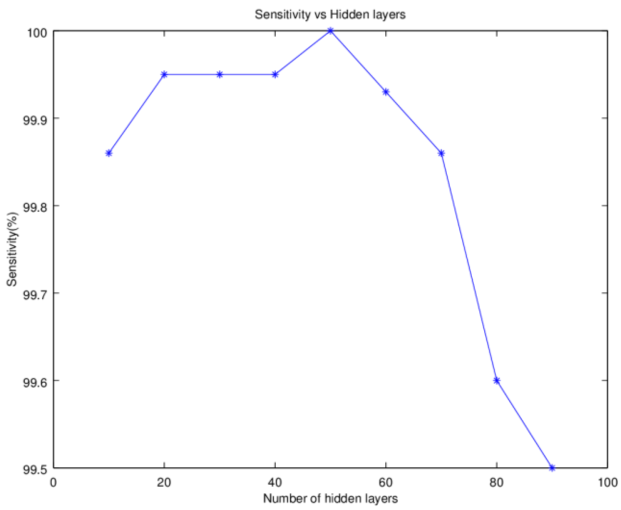

Figure 8:The sensitivity for dataset 2

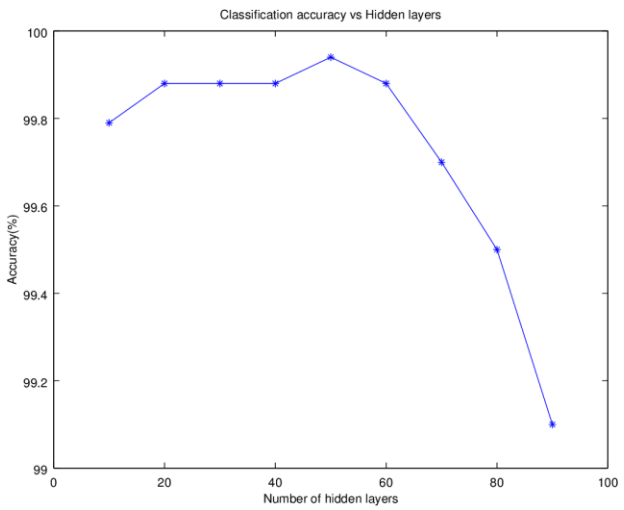

Figure 10:Classification accuracy for Dataset 2

VIII. CONCLUSION

A trained Neural network can be used to accurately classify the ICA components. It is fast and easy to train. Hence, the noisy fMRI data can be easily transformed into noise free data using ICA on the data followed by a trained neural network for classification so that error free analysis and conclusions can be made.

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