COMPARISON OF LINEAR PARAMETRIC MODELS FOR PREDICTING fMRI RESPONSE

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Introduction

The purpose of this study was to compare different parametric models and in particular their ability to predict the fMRI response. The transfer function for each voxel depends upon the complex interactions among neurons, underlying hemodynamic function and the task. However, the linear transform model may vary on a voxel by voxel basis. The noise also plays an important role in predicting the stimulated response. This helps in understanding the underlying neuronal activity of the brain. Investigators have tried to predict the fMRI response using linear-time invariant (LTI) techniques. In a LTI system, an output can be determined by convolving the input with the transfer function. Boynton and colleagues [1] characterized LTI relationship between fMRI and neural activity. In a similar study, Glover [2] measured the temporal characteristics of the BOLD response in sensorimotor and auditory cortices while stimuli were presented that varied between durations of 167 msec to 16 seconds. Cohen [3] used a gamma-variate model to fit the impulse response function with the behavioral conditions to obtain a better prediction of the fMRI response.

Theory

A parametric model can be defined as a system which has an input, an output and some noise. The linear parametric models that have been used included the Autoregressive (ARX) Model, Autoregressive Moving Average (ARMAX) Model, Box-Jenkins (BJ) model, Prediction Error Model (PEM) and Instrumental Variable (IV) Model. The figure below shows the general parametric linear model for fMRI and the schematic for the ARX, ARMAX and BJ model. For the fMRI data, the system was assumed as a single input multiple output system, where every voxel response was treated as different output. Thus, u, y, and n represent the input stimulus, the output fMRI signal, and the number of time points in every voxel respectively. The noise parameter present in the voxel time series was represented as e(t). The A(q) polynomial was the auto regressive part of the output which means how the previous instances of the output affects the input and B(q) shapes the input. The C(q) parameter makes the model a moving average auto regressive model, D(q) parameter makes the model more general to noise properties and F(q) makes the model error free. Here, q was the model order required to adequately represent the input and output regressors. Prediction Error Model (PEM) is the state space model. This model gives maximum likelihood estimate for a Gaussian distribution that minimizes prediction errors. The Instrument Variable model is method which makes the system independent of noise.

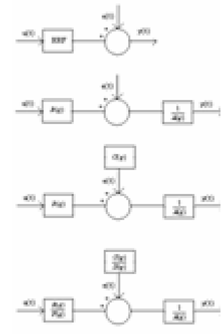

figure1

Method

All the data were collected using a 3T Siemens Allegra system. For each subject, echo-planar images were obtained in the axial plane in six slices covering the motor cortex using the following parameters: 64×64 matrix, TR/TE=1000/27 ms, FOV=22 cm, and slice thickness=5 mm. Six healthy volunteers (2 females, 22–38 years) were scanned. Two scans were performed on all subjects. During the first scan, subjects performed bilateral finger tapping for 20 sec followed by 20 sec of rest for three cycles resulting in 90 images. The second scan had a rest of 1024 sec and random on and off. All voxels from the whole brain including the sensorimotor cortex were used for comparing and building input-output models using each of the five parametric models described earlier. An estimated response was generated using the corresponding parameters and Cross correlation was then calculated between every voxel time-series measured response and the corresponding predicted response obtained using the model parameter. To test the reliability of the prediction of all the methods, a statistical t-test was done whereby 100 voxel time series data sets were randomly chosen. Each of the voxel time courses obtained from one of the models was fitted with each of the remaining four models and the correlation of the fit was obtained for all the methods. A significance value $P<0.01$ was used to identify differences To check the consistency of the transfer function of the models, the transfer function of the high correlated voxels was used to predict the response of other high correlated voxels.

Results and Discussion

A representative voxel time course along with the idealized “ON/OFF” reference waveform is shown in Figure 2. A second order model was determined to be optimal for all the data sets using Akaike’s information criterion. However, delay values of 1, 0, 1, 2 and 0 were selected for PEM model, ARX model, IV model, ARMAX model and BJ model respectively to get the optimal fit between the measured and the predicted output of the fMRI response. In the present study, the PEM model had the best fit with the measured fMRI data. The reliability of the prediction of PEM model was checked by the method described above. The result of t-test showed that the average p-value $P < 0.0001$, which shows that there was a significant difference between PEM and the other models. To test the predictability of the transfer function, the output response was predicted by using the transfer function of one voxel to get the response for another voxel. Correlation was then obtained between the predicted response and the actual data to quantify the match. A significant correlation of 0.7745 ± 0.1741 was obtained using the PEM method. Using the other four methods like ARX, ARMAX IV4 and BJ resulted in correlation values of 0.7513 ± 0.1741, 0.7488 ± 0.1821, 0.7587 ± 0.576 and 0.76892 ± 0.1157 respectively. Qualitative comparison between the five methods were calculated by performing a pair wise correlation between predicted response obtained from each of the method with every other method shown in fig 3.. As can be seen, all the five methods had significant correlation with the other methods. The mean correlation value was found to be 0.43 with a minimum and maximum value of 0.13 and 0.76 respectively. Across all the subjects the mean correlation value was found to be 0.49.

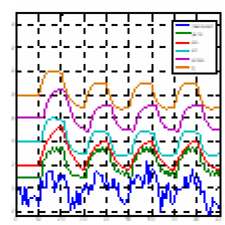

figure2

The temporal characteristics of fMRI noise have been typically assumed to be a white Gaussian noise by most statistical methods. The noise has also been assumed as temporally independent. It is thus possible that the various system identification methods here other than PEM have not accounted this property of the noise and have tried to model it along with the signal resulting in a prediction less than that obtained using PEM. PEM estimates the maximum likelihood of Gaussian distribution while minimizing the prediction error. Using PEM, the estimated transfer function is similar to a Gaussian distribution and the influence of noise on the estimation of impulse response function is minimized. Since fMRI response of a bilateral finger is similar to Gaussian distribution PEM predicts the response more accurately than other models. The order selection is dependent on a number of factors including the underlying neurovasculature, the sampling rate, region of interest, pulse sequence used. Five different models were used such that the model giving the best fit could be determined. The primary advantage of using multiple approaches is that it can be used as a validation method. In several clinical cases abnormal pattern of detection could be due to a variety of reasons, including subjects’ inability to perform the task, or changes to patients’ vascular or neuronal effects that would consequently affect the estimated transfer function. Using the proposed method, it is possible that detection of abnormal transfer function can be estimated and differentiated from the subjects being unable to perform the task.

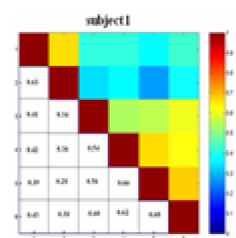

figure3

References

[1].Boynton GM et al. J Neurosci. 1996 Jul 1;16(13):4207-21.[2] Glover GH et al Neuroimage. 1999 Apr;9(4):416-29.[3] Cohen MS et al. Neuroimage.1997 Aug;6(2):93-103.