FMRI Signal Modeling Using System Identification Techniques

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In this study we derived a mathematical model for the fMRI signal using system identification techniques. Most of the statistical fMRI data analysis techniques depend on calculating the correlation between each voxel's temporal intensity change and an expected waveform, such as a "box car" or a Gaussian curve. Although a delayed box car may represent a low temporal resolution fMRI signal quite well, it is critical to know the exact delay and signal shape for a reliable statistical analysis when the temporal resolution is high. It has been suggested by several studies that the measured fMRI signal is linearly dependent, at least within certain limits, to the applied stimulus [1]. Therefore, we can find a better estimate for the fMRI signal using the system identification techniques. We used ARARX [2] model for our calculations. We applied this model to a fMRI signal with 500ms sampling time. The noise in the signal, defined as an autoregressive (AR) process in ARARX model, is very effectively removed from the signal model. Then, we used this signal model for the statistical analysis. We observed that the statistical map scores obtained with our signal model are higher compared to the analysis done with sinusoidal basis functions.

Materials and Methods:

The ARARX model is defined as:

$$A(q)\cdot y(t) = B(q)\cdot u(t-nk) + \frac{1}{D(q)}e(t)$$

$$A(q)y(t) = \sum_{k=1}^{\infty} a(k)y(t-k)\ ;A(q) = \sum_{k=1}^{\infty} a(k)q^{-k}\ ;q^{-1}y(t) = y(t-1)$$

B(q) and *D(q)* are defined similarly. Here, *y(t)* is the output of the system, *u(t)* is the input and *e(t)* is Gaussian white noise.

We acquired three fMRI data sets on a 1.5T whole body magnet interfaced with a SMIS console. Medical Advances head insert gradient coil and a homemade birdcage coil was used for all experiments. For all data acquisitions, we used a modified 3D EPI acquisition method to achieve high temporal resolution and better SNR [3]. For activation, a flashing checkerboard visual stimulus was projected onto the screen in the scanner room. Two healthy volunteers were scanned. A written consent was obtained from the subjects prior to the experiments. For subject 1, the visual stimulus cycle lasts 64s with 10s blank screen at the beginning, followed by two 6s ON periods separated by 20s and another 22s blank screen period at the end. Two separate data were collected from subject 2. In the first run, stimulus was on for 4s, with 10s and 50s blank screen before and after the stimulus, respectively. In the second run, a 10s blank screen was followed by an 8s stimulus, which is followed by another 46s of blank screen.

The data were analyzed by means of General Linear Model that is implemented by the SPM96 software [4] and the activation maps were generated for voxels that survive a statistical threshold of p=0.001. First, the data from subject 1 was analyzed using the sinusoidal basis functions. A cluster of 38 voxels was mapped as activated in the primary visual cortex and the voxel intensity signal from that cluster was recorded. The average of these 38 voxels were used for modeling.

Results:

Prior to calculating the model, we removed the linear trends and lowpass (LP) filtered the voxel signal with a 0.4s Gaussian filter. Then, we evaluated the ARARX model with different orders and delays using both the filtered and unfiltered signal. With the unfiltered signal, we observed that the model gives a good estimate with much better SNR compared to the original signal and a good fit to the actual measurement with [na nb nd nk] = [14 18 8 4] (Fig.1.). Here, na, nb and nd are the orders of the polynomials *A(q), B(q)* and *D(q)*, respectively and nk is the delay of input term. The LP filtered signal can be modeled with a much smaller order and the convergence is more stable with respect to the changes in order and delay. Remaining noise is also removed more effectively. For further analysis, we used the model obtained from the filtered signal with [na nb nd nk] = [8 8 4 0] (Fig.1.). The predicted fMRI signal is used for the analysis of subject 1's data. Table 1 summarizes the z scores of randomly selected voxels in V1, obtained from the analysis using sinusoidal basis functions and our model. We also used the model obtained from subject 1 to predict the response of subject 2. We applied the 4s and 8s single pulse stimulus input to that model for prediction. Then, we used these predicted signals in the analysis of data from subject 2. Subject 2's data were also analyzed by sinusoidal basis functions for comparison. The results are also given in Table 1.

Conclusion:

As seen from the figures and the tables, the ARARX is an efficient mathematical model to define the fMRI signal. We also tried models that treat the noise *v(t)* as an autoregressive-moving average (ARMA) process. However, we could not get a stable convergence. Hence we conclude that the noise in fMRI signal can be modeled best with an AR process and can be removed from the predicted signal effectively. This predicted noise free signal could be used for statistical analysis of the data for more reliable results. Currently, most of the analysis programs use a delayed boxcar model, a sine or a Poisson response function. We show that the model obtained directly from the measured fMRI signal will yield better statistical significance compared to the existing models. Although we have not shown all voxel scores, we got consistently higher scores with the predicted signals. The fMRI signal has approximately 8s FWHM, so the smoothness of the low pass filter is small compared to the smoothness of the fMRI signal. Therefore, the biasing of our model towards a Gaussian shape will be minimum.

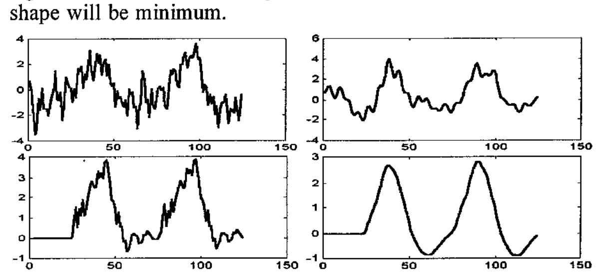

Figure.1. Original fMRI signal (upper left) and predicted response (lower left). LP Filtered fMRI signal (upper right) and its predicted response (lower right). Horizontal scale is image number, vertical scale is percent signal change.

	z-score, ARARX	z-score, sine wave
Subj.1	Z_{ROI1}=5.87, Z_{ROI2}=5.43	Z_{ROI1}=5.40, Z_{ROI2}=4.46
Subj.2 (4s)	Z_{ROI1}=5.36 , Z_{ROI2}=4.57	Z_{ROI1}=4.38 , Z_{ROI2}=4.09
Subj.2 (8s)	Z_{ROI1}= 4.95, Z_{ROI2}=4.88	Z_{ROI1}= 4.16, Z_{ROI2}=4.42

Table 1. Comparison of z scores obtained from different ROI in V1 with linear prediction and with a sine basis function.

References

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