# MODEL-FREE FMRI DETECTION OF NEURAL ACTIVATION IN THE TEMPORAL FREQUENCY DOMAIN

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**Introduction**

Most brain activation detection methods, such as Cross Correlation (CC) [1] and General Linear Model (GLM) [2], depend on an assumed model response. In these methods, a voxel is detected as activated if its timecourse signal is similar to the model response. However, if the model is not an accurate representation of the true response, activation detection result will be adversely affected. Detection performance could be further compromised given that different voxels may have different hemodynamic response delay [3], but in these methods a universal hemodynamic response delay is assumed. Independent Component Analysis (ICA) [4-5] is able to decompose the timeseries into independent components without an assumed model response. ICA, however, is computationally complex, and interpretation of the results still involves using certain prior knowledge of the brain function . Levin et. al. [6] presented an approach to detect activated voxels without prior knowledge of the brain activation spatiotemporal characteristics. Their approach involved pairwise scans that used the same stimulation/tast paradigm. Cross correlation coefficients between the two scans were calculated, and activation maps were determined by these coefficients. Their approach is model free, but if a temporal delay is present between the timeseries in the two scans, the detection performance will be compromised. In the current study, a model-free (MF-FFT) solution has been proposed to cope with these problems using a new timeseries analysis approach in the temporal Fourier Transform domain.

**Materials and Methods**

Finger tapping activation studies were carried out to assess the characteristics and performance of the MF-FFT method. Five MRI experiment data were acquired on a whole body 1.5-T MRI system (Siemens Medical Systems). Functional scans were acquired with a single-shot gradient echo EPI sequence (matrix size 64*64, voxel size 4*4*6 $mm^3$, TR/TE/FA = 800ms/40ms/$90^0$), with an activation paradigm consisting of four cycles of "30 seconds OFF, 30 seconds ON" bilateral finger tapping, and ending with 30 seconds of resting state. With each subject, the scan was repeated immediately using the same paradigm. The Fourier transform decomposes timeseries into amplitudes and phases of different temporal frequencies, and the phases include the hemodynamic response and other scan temporal delays. When frequency is considered and phase is ignored in the calculation of activation detection neither the hemodynamic response delay nor the temporal delay of the scan will be a factor in the determination of the activation map. This new process of activation detection, which eliminates the dependence of the activation map on the hemodynamic response and scan delays, includes the following four steps applied to each of two scans obtained using the same experimental paradigm: 1. Image post-processing, such as image alignment, as well as timeseries de-noising and low temporal frequency de-trending. 2. Transformation of each timeseries data into the amplitudes and phases of each temporal frequency using FFT. 3. Calculation of cross-correlation coefficients between the amplitudes obtained in the two scans, while ignoring the phase information. 4. Determination of activation maps by setting a lower limit of coefficients.

**Results**

Brain activation was reliably detected using the FFT-MF method in five subjects. Figure 1 shows a representative activation map obtained using Maximization Cross Correlation (MCC) [3] method with an assumed model as reference function. Figure 2 shows a distribution of the hemodynamic response temporal delay of the activated voxels identified in Figure 1. As can be seen, the temporal delays of these different voxels have a wide range, indicating different hemodynamic response delays. Figure 3 shows the activation map using the MF-FFT method. In comparison with Figure 1, Figure 3 shows activation voxels focus in the cortical regions expected to be activated in a finger tapping experiment. Also, the map shown in Fig. 3 is consistent with that shown in Fig. 1, but the map shown in Fig.3 is believed to be more accurate because it is not based on an assumed model response. Results comparison on all the subjects are similar to that on this representative subject.

**Conclusion and Discussion**

In this study, the MF-FFT activation detection method was introduced. Finger tapping experiments were carried out to assess the characteristics and performance of this method. Results showed that this method can reliably detect voxel activation. The primary advantage of the MF-FFT method is that it is model free, i.e., no model response (reference signal) is assumed. Specifically, the method detects activated voxels without requiring a model for the hemodynamic response function and without assuming a univeral hemodynamic response delay in different voxels. Another advantage of the new method is that it also works well if the two scans have a scan time delay. The experiment results suggest the new MF-FFT method performed better than the conventional CC method, and improved upon Levin's original approach.

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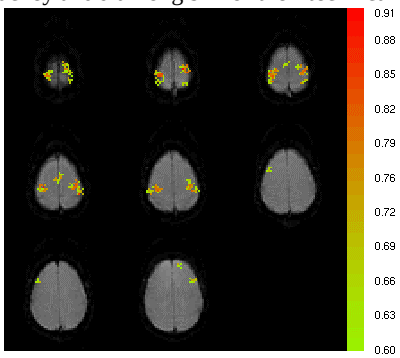


Fig 1 Activation map from MCC method, the threshold is 0.65 and the cluster is 3.

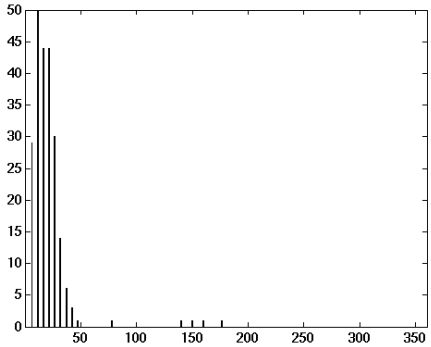


Fig. 2 the distribution of hemodynamic response delay, x-axis is temporal delay in degree, y-axis is its number.

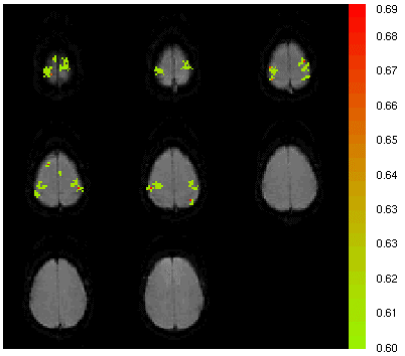


Fig.3 Activation map from MF-FFT method

**References:**

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