2dTCA For Detection of Irregular, Transient fMRI Activation

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Introduction

The Temporal Clustering Algorithm (TCA) [1-4] has been developed in order to detect irregular, transient fMRI BOLD activation signals when the timing of the stimulus is unknown. Unfortunately, these methods can be especially sensitive to signal changes caused by motion and physiological noise [5]. We have recently been developing a modified TCA technique, 2dTCA, that can detect more than one different activation timing pattern within one dataset so that motion or noise can be detected separately from BOLD activation. This technique utilizes a two-dimensional mapping of signal spikes instead of the one-dimensional histogram used in the original TCA methods.

Methods

The fMRI data set is prefiltered and each voxel time course in the brain is analyzed individually to look for times at which the signal is greater than a threshold. In the standard TCA technique, a histogram is created showing the number of voxels exceeding this threshold at each time point in the series. Peaks in the histogram are assumed to be BOLD responses to some stimulation. In the 2dTCA technique, histograms are grouped on a 2D grid by similarity as vertical columns so that voxels with similar time courses of signal increase are used to create one histogram (added in the same column), while other voxels with a different timing are used to create another histogram (added in other columns). In this case, the similarity measure is the time point of the first signal increase over threshold. Therefore, the time of the first signal increase over threshold is used as the x-coordinate in the 2d grid to indicate the column to which this voxel's peaks should be added. In this algorithm, the number of histograms is only limited by the number of time points. However, when implemented, the algorithm further combines similar histograms by adding together those with many matching peaks so that the number of resulting histograms is approximately one to five.

Using the simulated fMRI datasets we have developed previously including motion and noise [6] modified to incorporate irregular, transient BOLD activation peaks, the sensitivity of the TCA and 2dTCA methods in detecting true-positive activation at a false-positive activation level of 1% was determined. Activation levels were approximately 4% signal change in 10 regions of interest of 3x3x2 voxels. Differing levels of real subject random motion taken from six different subjects was used to create 6 different phantoms. Each phantom was analyzed with both the TCA and 2dTCA algorithm after motion correction. The histogram or histograms resulting from these analyses were incorporated in the general linear modeling function of SPM2 [http://www.fil.ion.ucl.ac.uk/spm/spm2.html] with the motion regressors to determine the *t*-maps. Programs written in IDL (Research Systems, Inc., Boulder, CO) were used to calculate the percent of true-positive activations at a false-positive rate of 1%. The procedure was repeated with phantoms containing two different BOLD activation time courses added in five regions of 3x3x2 voxels each.

Results

Table 1 shows that using one of the histograms resulting from the 2dTCA technique, 100% of the true positives were detected. The other histograms (if any) gave 0% of the true-positives and were probably due to motion or added noise. On the other hand, the original TCA technique detected less than 40% of the true-positive activations in two of the phantoms. When two activation time courses were present in the phantom, it can be seen that the 2dTCA technique created one histogram that detected greater than 90% of the true-positives for the first region of interest (ROI1) and a separate histogram that detected greater than 98% of the true-positives for the second region of interest (ROI2). Some datasets created a third histogram which detected less than 1% of either region of interest. This was probably due to motion or noise. In the original TCA analysis, the single histogram created was not able to detect 100% of both regions of interest.

Table 1. Percent of true-positive activations at 1% false-positive activation rate in phantoms with one BOLD activation time course added in 10 regions of interest (left) and two different BOLD activation time courses added in 5 regions each (right).

	One time course		Two time courses			
Phantom	TCA	2dTCA	TCA – ROI1	TCA – ROI2	2dTCA – ROI1	2dTCA – ROI2
1	100%	100%	100%	94%	100%, 0%	0%, 100%
2	37.2%	100%, 0%, 0%	0%	75%	0%, 100%, 0%	2.7%, 0%, 100%
3	100%	100%	0%	75%	100%, 0%	0%, 100%
4	100%	100%, 0%, 0%	1.8%	45.8%	0%, 100%, 0%	100%, 0%, 0%
5	0%	100%,0%	0%	0%	0%, 0%, 90.7%	0%, 98.6%, 0%
6	100%	100%, 0%	100%	2.7%	100%, 0%, 0.9%	0%, 100%, 0%

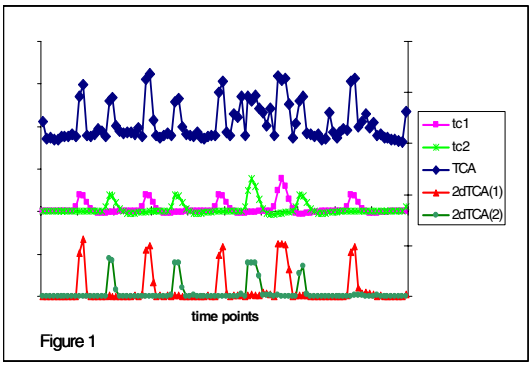

Figure 1

Figure 1 shows two BOLD activation time courses added to a phantom on the middle axis: pink (tc1) and light green (tc2). The top axis of the figure shows the histogram resulting from the original TCA algorithm: dark blue (TCA). The bottom axis shows the two histograms resulting from the 2dTCA algorithm: red (2dTCA(1)) and dark green (2dTCA(2)). Note that the TCA algorithm incorporates all of the peaks from each of the two time courses into one histogram, while the 2dTCA algorithm separates the two distinct time courses in order to detect separate regions of activation.

Conclusions

The 2dTCA algorithm showed higher sensitivity (true-positive) activation than the original TCA algorithm in the phantom datasets in the presence of various amounts of random noise and one activation time course. The 2dTCA was also able to successfully detect two distinct time courses of BOLD activation within a single dataset. Therefore, the 2dTCA algorithm has the potential to detect BOLD signal activation in the presence of other confounding signals such as motion or physiological noise.

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