Reducing Correlated Noise in fMRI Data

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Introduction: One limitation of BOLD fMRI is low sensitivity, generally requiring extensive temporal averaging (e.g. block paradigm) to detect the small BOLD effect in time-series data. Detection is compromised by thermal noise, instrumental instabilities, head motion, fluctuations in physiology (e.g. cardiac and respiratory cycles), and uncontrolled neuronal activity [1]. As a result, the temporal standard deviation (SD) increases. Often these noise sources coherently affect a large brain region or even the entire brain, yielding extensive spatial patterns of temporally correlated noise. Here we introduce a new noise suppression method that is model-free and simple to implement, which exploits the coherence of such noise sources. This noise suppression method aims at suppressing noise sources in active regions that exhibit substantial temporal correlation extending into inactive regions. The effect of the noise source on the fMRI signal is estimated from a region outside the area targeted with the stimulation paradigm.

Methods: In addition to functional data, the method requires the acquisition of a limited amount of (resting-state) reference data. The order of events in data processing is as follows: 1) An initial estimate of the active region, R_A, using conventional statistical analysis of the functional data, is obtained. 2) The average signal time-course in the reference data, $S_{A,R}$, for the voxels within R_A is then computed. 3) Voxels in the reference dataset which are not a member of R_A are correlated with $S_{A,R}$, those correlating more than a preset threshold (here 0.5) form reference region R_R. 5) The average signal time-course in the functional data in R_R is computed (referred to as $S_{R,F}$) and decorrelated from other regressors in the design matrix used in 1). 6) Functional analysis is then performed using an extended design matrix that includes $S_{R,F}$.

BOLD fMRI experiments were performed on a 3.0 T GE Signa MRI scanner using a 16-channel receive-only detector array. Six volunteers were scanned (IRB-approved protocol, 2 females, 4 males, average age 32.2 years). Scan parameters: single-shot gradient-echo EPI; 50% ramp-sampling; 44 ms TE; 2000 ms TR; 70° flip angle; 96×128 image matrix; 210×158 mm^2 field of view; ten oblique-axial 2.0 mm slices covering visual areas (0.5 mm gap); 2.3×2.3×2.0 mm^3 nominal voxel size. Each subject was exposed to a 5 min, 30 s off/30 s on, visual block paradigm, which was followed by a 5-min rest period. A 7.5 Hz contrast-reversing radial checkerboard was shown during on-periods, a uniform 50% grey disk during off- and rest-periods.

Data were corrected for slice timing and then for minor rigid body motion. The volumes 16 though 315 were used as functional data, analyzed using as regressors the paradigm convolved with a hemodynamic response function with a latency and full-width at half maximum of 3.5 s each, as well as 8 polynomials (≤8th order) and $S_{R,F}$. Part of the remainder of the data was used as reference for determining R_R. (A separate reference scan could also have been used.)

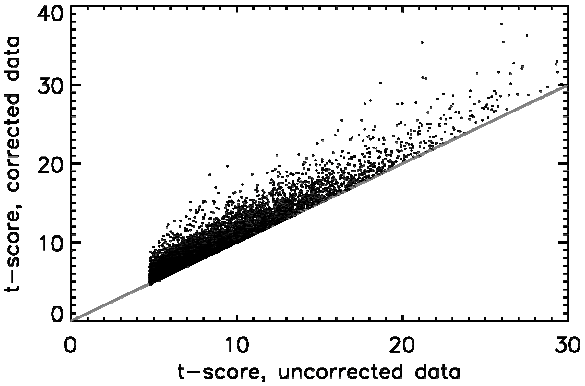

Figure 1: *Improvement in t-score in 6 volunteers (9040 voxels total) when using 120 s of reference data.*

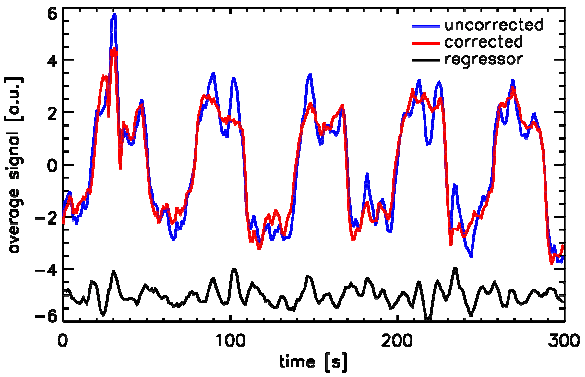

Figure 2: *Average corrected and uncorrected signal time-course for one of the volunteers, together with the correction regressor used (offset -5 a.u. for figure clarity).*

Results & Discussion: The proposed correction method significantly improved statistical performance of the fMRI experiment in virtually all voxels in all volunteers. Figure 1 shows the t-score after correction as a function of t-score before correction in voxels in which statistically significant activation was found in uncorrected data. Results show that on average the t-score improves by 15.0±1.6 % and the number of activated voxels by 29.1±9.5 % (both are standard errors over volunteers). The fitted activation amplitude did not change significantly (-0.5±0.6 %), t-score improvement was due to reduced SD. Figure 2 shows the average time course in one of the volunteers before and after correction. Data for Figures 1 and 2 were derived from the analysis using 120 s of reference data. Results from the other runs (30, 60, 180 or 270 s worth of reference data) were very similar. However, the use of less than 60 s of reference data significantly reduced performance. In conclusion, this method allows for substantial increases of detection sensitivity at the cost of the loss of a single degree of freedom (accounted for in our functional analysis) and the need for the acquisition of a small amount of additional data (on the order of one or a few minutes per volunteer per session).

References: [1] MD Fox et al., Nat Neurosci 9, 2006, p 23