Reducing Systematic Spatially Correlated Noise in fMRI

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Introduction
"Physiological noise", including respiratory, cardiac, and vasomotor components, corrupts fMRI data. Attempts to remove such noise have not been completely successful as most methods require either intense computations or additional data such as pulse oximeter or EEG data [1-3]. We propose an alternative method based on the simple assumption that physiological noise and other signal fluctuations in the pixel of interest (an active pixel) are correlated with signal fluctuations in inactive comparison pixels nearby. The time series of these inactive pixels are combined to create a composite time series best matching the active pixel signal during an initial dark (control) period. This composite time series is then subtracted from the time series of the active pixel to reduce physiological and other systematic noise.

Methods
Data were collected at 4.1 T with a double echo snapshot spiral sequence [4] (TR/TE=250/6-30 ms), 50x50 interpolated to 128x128, FOV=15 cm, and a slice thickness of 5 mm. The functional paradigm incorporated a reversing checkerboard at 8 Hz. The entire sequence lasted 125 seconds (500 frames) and repeated the following pattern: A 20 second (80 frame) dark period followed by a 5 second (20 frame) visual stimulation. Data were then regridded and reconstructed separately to produce first echo and second echo data sets. Pixels of interest were chosen for which both: 1) The correlation coefficient of the first echo time series with the reference boxcar time series was less than 0.2 and 2) The second echo time series correlated with a boxcar time series (cc=0.38). Comparison pixels within a 12x12 grid around each active pixel were chosen for which the second echo time series was 1) not correlated with the stimulus boxcar time series (cc<0.1) and 2) correlated over the first 80 frames (20 seconds) with the first 80 frames of the pixel of interest. These top ten dark-correlation coefficient values were combined to create a composite time signal. A least squares fit to the dark period of the pixel of interest was used to find the coefficients for the pixels in this composite time series. This composite signal was subtracted from the active pixel of interest.

Results and Discussion
Figure 1 is the second echo time from a typical active pixel, with boxcar cross correlation of 0.41. The first echo data from this pixel were not significantly correlated with the boxcar reference (cc=0.096). Figure 2 shows the composite signal created from inactive pixels near the active pixel of figure 1. Each pixel used for this composite was highly correlated with the active pixel over the first 80 frames of the time series, but was not highly correlated over its entire time course. Figure 3 is the time series of the same active pixel after subtracting the time series in figure 2 from the original signal in figure 1. The correlation coefficient value for the time series in figure 3 as compared to the boxcar time series is 0.56.

Figures 1-3 demonstrate that much of the systematic fluctuation can be removed from pixels of interest by using a combination of nearby pixels as a model for the physiological noise. This technique incorporates several parameters that may be optimized in the future, including the number of initial "control" frames in the original activation paradigm, the number of comparison pixels included in the composite noise signal, and the correlation coefficient thresholds for each step of the analysis. Advantages of this technique include the simplicity of the computations and that all needed information is included in the image data. This technique has potential advantages over frequency domain filtering techniques because it can reproduce quasi-periodic and nonstationary physiological fluctuations more accurately. A future extension of the technique will use prior time points as well as simultaneous values in determining the "noise signal", permitting detection of "noise" components with spatiotemporal lags.

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References