Denoising of Event-Related fMRI Data Based on a Rician Noise Model For Robust Analysis Using ICA

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Abstract
Given the fundamental constraints in ICA of having the number of sources less than that of signals, the number of independent noise signals must be lowered to enable this technique to work. To this end, the new scheme uses spectrum subtraction denoising assuming a Rician noise model. We derive the model characteristics and present the method for its implementation. We demonstrate the potential of this method as a preprocessing step to enable the ICA algorithm to converge and to provide efficient separation of signal components.

Introduction
The poor signal-to-noise ratio (SNR) of event-related fMRI data triggered some work that addressed the denoising of such data (1-2). Denoising is essential for subsequent analysis steps to work. In particular, in ICA, the main assumption is that the number of signals available is higher than the number of underlying independent sources. Given that each signal must contain an independent noise component in addition to the possible other physiological fluctuations and true activation components, denoising must be employed to reduce the number of effective noise components to satisfy the fundamental condition of ICA. In this work, we propose a strategy that estimates in the noise from the acquired data for denoising and demonstrate its effectiveness as a preprocessing step to ICA.

Theory
The technique is based on spectrum subtraction (3). In this technique, a denoised power spectrum is obtained by subtracting the noise power spectrum model from the power spectrum of the original signal. Then, the denoised signal is computed using magnitude reconstruction from the square root of this power spectrum. Simpler reconstruction can be obtained by using a phase estimated from phase of the Fourier transform of the original signal. Unlike a technique described earlier (3), we rely on the more realistic Rician noise model rather than the generic Gaussian noise model that does not apply to fMRI data in general. The use of such denoising makes the subsequent use of ICA more robust computationally and enables the separation of different signal sources more efficiently.

Methods
The magnitude in MR image obeys the Rician distribution. This distribution depends on the value of the means of the component distributions (4). Given that these mean values are unknown (in fact their values represent the solution for the denoising problem), the actual distribution of each time point is also unknown. Nevertheless, the computation of the power spectrum can be shown to provide a simple expression of a constant component plus an impulse at the DC frequency. When the magnitude of the mean is above five times the standard deviation of the noise, the distribution depends only on the variance of the noise. Given that this is the case in fMRI, the level of this power spectrum was obtained from simulations that relate the calculated variance of Rician distributed points to the constant level of their power spectrum. Finally, the denoised time courses were analyzed using ICA (5) and the results are compared with those of the original.

Experimental Verification
The technique was implemented to process data obtained from an event-related fMRI study on a normal human using a Siemens 1.5T Magnetom Vision scanner. An oblique slice through the motor and the visual cortices was imaged using a T2*-weighted EPI sequence. The study consists of 32 epochs with 64 images per epoch. Temporal data from only 8 epochs of pixels in both the motor and visual cortices were processed using the new method and compared to the average of all epochs.

Results and Discussion
The results showed a marked improvement in the numerical stability of ICA after denoising. ICA components obtained before (top) and after (bottom) denoising are shown in the figure below. The ability of ICA to separate components was also clearly enhanced.

References
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