# Adaptive Suppression of Random and Physiological Noise in Event-Related fMRI data using Nonparametric Spectrum Subtraction

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# <u>Syno</u>psis

We present a new technique for suppressing both random and physiological noise in event-related fMRI data. The new technique has the advantage of being model-free and having no assumptions about the statistical relationship between signal and noise. It is therefore more robust than previous techniques given its fewer assumptions. Introduction

Many approaches were developed for noise suppression in event-related fMRI signal. Most of these methods assume a particular noise model that is uncorrelated with the activation signal, which can be a limitation in many cases especially when we consider both physiological and random components of noise. In this work, we propose a new non-parametric technique for noise suppression of both components of noise. The new technique is based on generalized spectral subtraction that allows correlated noise components to be treated robustly. Moreover, it adaptively estimates a nonparametric model for random and physiological components of noise from the acquired data in a simple and computationally efficient manner. This allows the new method to overcome the limitations of previous methods while maintaining a robust performance given its fewer assumptions.

#### Theory

Let the corrupted fMRI signal y(n) be represented as the sum of two components: a deterministic yet unknown part s(n) representing the true activation signal and another signal d(n) representing the sum of physiological and random noise parts. The power spectrum of y(n) can be computed as follows (1):

$$|Y(k)|^{2} = |S(k)|^{2} + |D(k)|^{2} + S(k) \cdot D^{*}(k) + S^{*}(k) \cdot D(k),$$
<sup>[1]</sup>

where Y(k), S(k) and D(k) are the Fourier transforms of y(n), s(n) and d(n) respectively. Note that the last two terms arise as a result of a nonzero cross-correlation between the deterministic signal and noise. Typically, if d(n) is zero mean and uncorrelated with s(n) then the last two terms are reduced to zero. But if the noise and the signal are correlated, we can no longer neglect these terms. To compute these terms, we compute the cross correlation between y(n) and d(n),  $r_{vd}(m)$  as the sum of the

desired cross correlation  $r_{sd}(m)$  as well as the autocorrelation of the noise  $r_{dd}(m)$  which in the frequency domain is given by  $|D(k)|^2$  and can be lumped with the same term in [1]. So, the estimate of the power spectrum of the denoised signal can be given by:

$$\left|S(k)\right|^{2} = \begin{cases} \left|Y(k)\right|^{2} - \alpha \left|D(k)\right|^{2} - \delta \left|Y(k)\right| \cdot \left|D(k)\right| & \text{if } \left|Y(k)\right|^{2} > \alpha \left|D(k)\right|^{2} \\ \beta \alpha \left|D(k)\right|^{2} & \text{otherwise} \end{cases}$$
[2]

Here  $\alpha$  is a subtraction factor,  $\beta$  is the spectral floor parameter, and  $\delta$  is the cross-correlation subtraction coefficient defined in (1).

### Methods

In order to implement the proposed technique, the power spectrum of the noise term and the cross-correlation of the original signal and the noise term must be computed in an adaptive manner. Here, we use a non-parametric technique to compute both terms (as opposed to the parametric method used in (2)). In our method, the time course signals from background pixels are used to perform averaged periodogram estimates of the noise power spectrum and its cross-correlation with the original signal. This allows an accurate estimate of these functions to be computed in an adaptive manner. The power spectrum of the denoised signal is computed using [2] and taking the parameters  $\alpha, \beta$  and  $\delta$  as unity. The denoised signal can be derived from its power spectrum using one of several phase recovery methods. Here, the method outlined in (2) was used whereby the phase of the original signal is used with the square root of the power spectrum to estimate the Fourier transform of the denoised signal.

To verify the new technique, event-related fMRI data from an activation study performed on a volunteer using a Siemens 1.5T clinical scanner were used. In this study, an oblique slice through the motor and the visual cortices was imaged using a T2\*-weighted EPI sequence (TE/TR= 60/300 ms, Flip angle=55°, FOV=22cmx22cm, slice thickness=5 mm). The subject performed rapid finger movement cued by flashing LED goggles. The study consisted of 31 epochs, with 64 images per epoch (3). Temporal data from a single pixel in each of the motor and visual cortices are processed using the new method. The nonparametric estimation method was conducted using the time courses of 256 background pixels outside the brain area selected by the user.

### Results

The results of the proposed technique are shown in Figs. 1-4. As can be seen, the results of the proposed method appear much improved from the original. Moreover, if we compared the results of the new technique to that of the classical parametric spectrum subtraction in (2), we observe the absence of baseline variations as well as further random noise suppression. This is evident from the difference signal in Fig. 4.

### Conclusions

A new nonparametric technique for suppressing both random and physiological components of noise has been developed. The new method showed further improvement in the ER-fMRI data as compared to previous techniques while maintaining a robust performance as a result of its fewer assumptions. This indicates that it is important to take into account the correlation between activation signal and noise and the importance of noise model selection. \*This work was supported in part by NIH (grants RO1MH55346 and RO1EB00321), Georgia Research Alliance, and

The Whitaker Foundation.

#### References

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Fig. 3: Denoised signal using new method





Fig. 4: Difference signal between Figs. 1 and 3