Signal Processing in Functional MRI: Robust Suppression of Random and Physiological Noise Components using Threshold Spectrum Estimation and Harmonics analysis

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Abstract- **Denoising procedure for functional Magnetic Resonance Imaging (fMRI) is introduced in this paper. The noises are classified into random noise components and physiological baseline fluctuation components. The proposed technique based on threshold the Fourier spectrum of the output response to remove any frequencies less than the fundamental frequency and harmonics of the true activation, which it is periodic. The new technique is tested using computer simulations (block design) as well, real data from event-related fMRI experiments. The results show that, the new technique is suppressing both random and physiological noise components while preserving the true activation in the signal from the acquired data in a simple and efficient way. This allows the new method to overcome the limitation of previous techniques while maintaining a robust performance and suggests its value as a useful preprocessing step for fMRI data analysis.**

Keywords - **functional Magnetic Resonance Imaging (fMRI), signal denoising, parametric spectral subtraction denoising.**

I. Introduction

Functional Magnetic Resonance Imaging (fMRI) is a non-invasive brain imaging technique, which developed in the early 1990's [1] for determining which parts of the brain are activated by different types of physical sensation or activity, such as sight, sound, or the movement of subject's fingers, and detecting the corresponding increase in blood flow. To observe these hemodynamic changes, rapid acquisition of a series of brain images is performed. The sequence of images is analyzed to detect such changes and the result is expressed in the form of a map of the activated regions in the brain [2].

In the majority of reported functional human brain mapping studies using fMRI, blocks of baseline and activation images are scanned periodically. Typically, a number of frames are acquired while the subject is at rest or under some baseline condition, this is followed by a number of activation frames during which the subject is receiving a sensory stimulus or performing a specified motor or cognitive task [3]. This pattern is repeated in order to improve the Signal-to-noise ration (SNR). New advances that improve the temporal resolution of fMRI called single trial or event-related fMRI (ER-fMRI). In this new design, the subject receives a short stimulus or performs a single instance task while the resultant transient response is measured [4]. Event-related fMRI offers many advantages over block design that include versatility, investigation of trial-to-trial variations, and extraction of epoch-dependent information and direct adaptation of the methods used for ERP to fMRI [5]. One significant limitation in ER-fMRI is the degradation in signal-to-noise ratio (SNR) due to the transient nature of the response [5].

Several methods of data analysis have been used to process the fMRI raw data. The ultimate goal of such analysis is to try to separate signal components due to true activation, physiological fluctuations and random noise [5]. The latter two components are considered as nuisance and must be removed for correct results [6]. Several methods have been proposed to suppress physiological noise including the use of harmonic model [7], and noise subspace characterization [3]. Others attempted to use different strategies to suppress the effect of random noise in the analysis using finite impulse response (FIR) filter modeling [8], smart spatial averaging [9], inter-epoch averaging [4], and Wiener filtering [10]. These techniques suffer from at least one of the following limitations: the assumption of a certain signal characteristic to enable building the denoising filter and the assumption of limited epoch-to-epoch variability to enable the averaging.

In this paper, that concentrates on denoising. The proposed method technique based on threshold the Fourier spectrum of the output response take into account physiological and random components noise while preserving the true activation in the signal. The new technique is tested using computer simulations (block design) as well, real data (ER-fMRI experiments).

II. Methodology

A. Theory

When examining the BOLD response we often look at a system as a linear system composed of several subsystems (Fig 1). It implies response from short stimuli should predict responses to longer stimuli.

A "linear system" satisfies the following: Scaling- Increasing stimulation by some ratio will increase the output by the same ratio, Superposition- Combining (adding) any two stimuli will lead to an output that is the sum of the two responses, Time-invariance-a response is the same irrespective of when it comes or what precedes or follows it.

Generally, the fMRI temporal signal can be modeled as the Linear combination system , which are the summation of the true activation signal s(t), a physiological baseline fluctuation component, and a random noise d(t) component (Linear combination system)

$$y(t) = s(t) + d(t) ,$$

In frequency domain, we have:

$$Y(k) = S(k) + D(k),$$

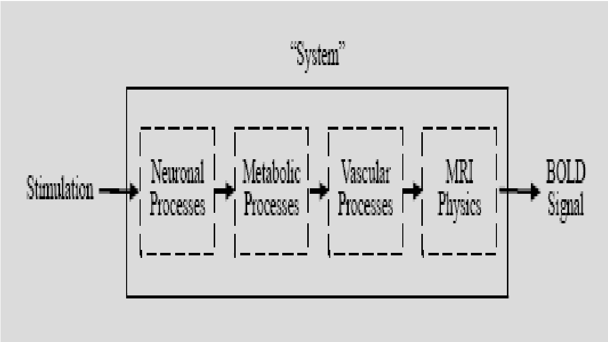

Fig.1. BOLD response system

We proposed this linear combination system, since the true activation is periodic; we assume the output response signal also periodic

$$Y(t) = y(t + T) \qquad \text{for all t, T(period Time)}$$

$$y(t) = \sum_{k=-\infty}^{+\infty} a_k e^{jk\omega_0 t} \qquad k = 0, \pm 1, \pm 2, \pm 3$$

Each signal in the linear combination has a fundamental frequency that is a multiple of w. From the linear combination we select $k = 0, \pm 1, \pm 2, \pm 3$ -DC, first, second and third harmonics. The selected components refer to the true activation and other threshold to zero refer to physiological and random components noise.

After that, we reconstruct the resulting signal using real part of inverse Fourier transformation.

B. Signal Fourier transform estimation:

According to the above theorem, we need to compute the Fourier transform of the signal and visualizing the Fourier transform with zero frequency components in the middle of the spectrum. The spectral of the physiological and random noise centralized in low frequency overlapped with that of the true activation.

C. Denoising the signal:

We chose then threshold or amplitude (less than the smallest harmonic amplitude chose) from the visualizing Fourier transform to remove random and physiological noise components The remaining is the fundamental frequency and harmonics of the true activation signal. The technique strategy is shown in Fig. 2

III. RESULTS

This technique is tested using computer simulation as well, real data from human volunteer. The computer simulation by computer generated block design activation signal was added to an actual baseline set. The baseline data were collected on a healthy human volunteer using an EPI sequence (TE/TR=25/500ms, Matrix=64x64, field of view (FOV=20cmx20cm, slice thickness=5mm, 640 images) on a Siemens MagnetomVision 1.5 T clinical scanner. The number of epochs was 10.

The actual data were obtained from an ER-fMRI study performed on a normal human volunteer using a Siemens 1.5 T Magnetom Vision clinical scanner [10]. In this study, an oblique slice through the motor and the visual cortices was imaged using a $T2^*$- weighted EPI sequence (TE/TR=60/300ms, flip angle= 55°,Matrix=64x64,FOV=22cmx22cm, slice theckness=5mm). The subject performed rapid finger movement cued by flashing LED goggles. The study consists of 32 epochs with 64 images per epoch [5]. Temporal data from a single pixel in each motor and visual cortices were processed using the new method and compared to the case when the remainder of the acquired epochs are used for classical spectral subtraction denoising[5].

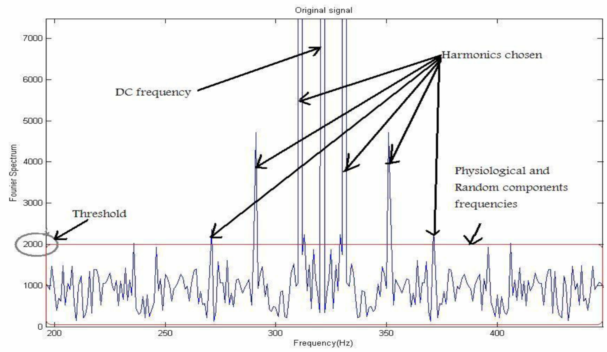

Fig.2. The technique strategy

In Fig. 3, the result of applying the new technique to process computer simulated fMRI data. As can be observed the noise in the data was eliminated clearly in the output, compared to the classical parametric spectrum subtraction denoising [5].

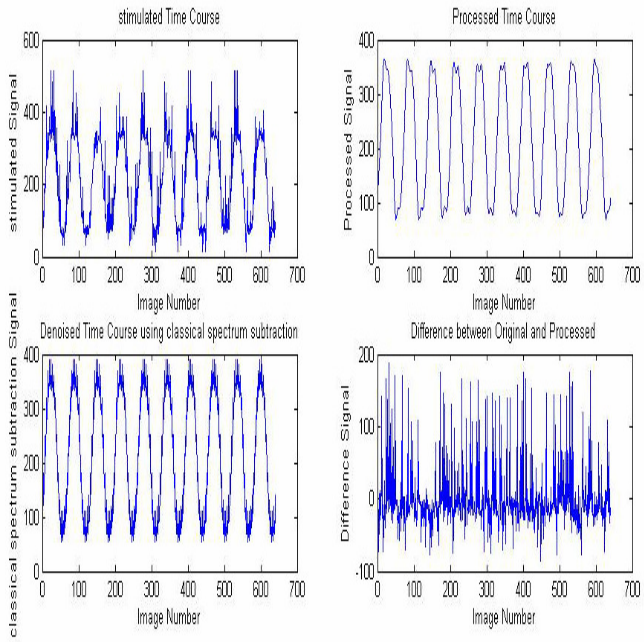

Fig. 3.Result from computer simulation data time course.

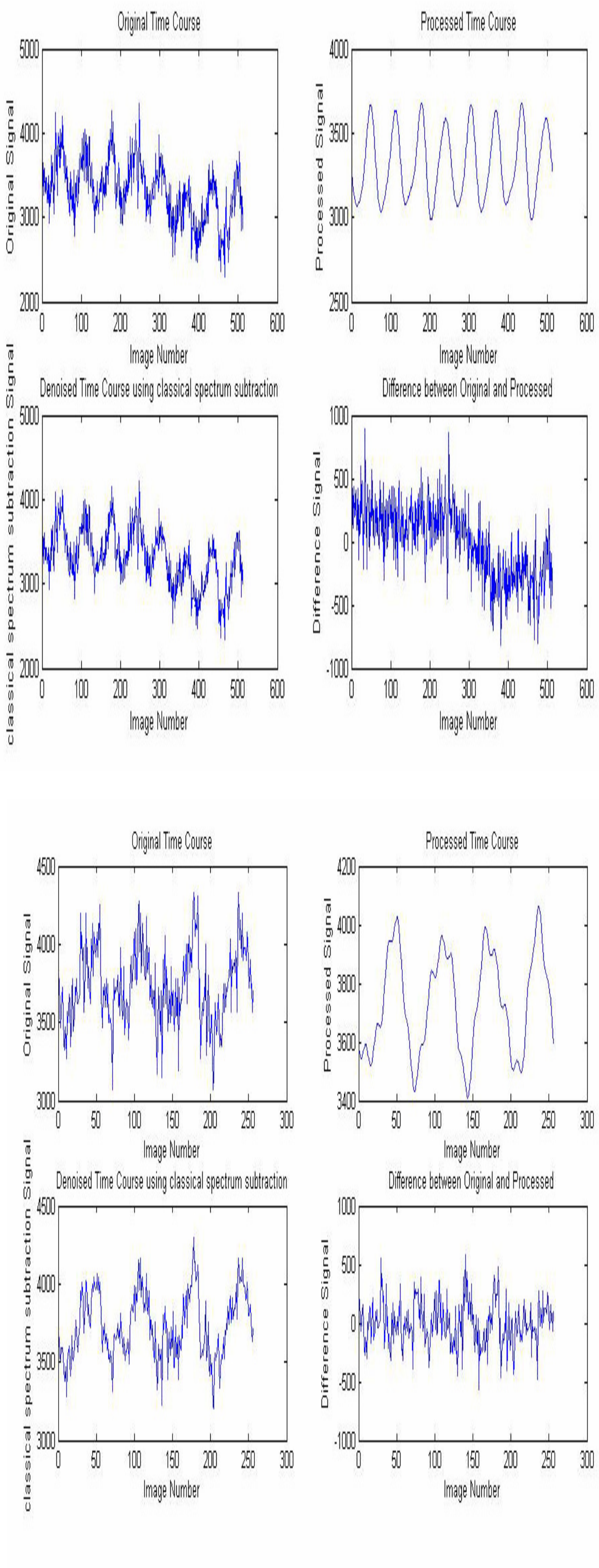

Fig. 4.Result from real data time course.

Also, the difference between original and processed signal appear to have no signal components

In Fig. 4, the result of applying the new technique to process real fMRI data from activated pixel with in time course length 512 and 256 points (i.e., correspond to 8 or 4 epochs). As can be observed, the process removed the random noise and baseline variation, this achieve one's aim that this processing technique suppressing both random and physiological components noise while preserving the true activation in the signal from the acquired data in a simple and efficient way, we emphasized that by the difference between original and processed signal. Compared to the classical parametric spectrum subtraction denoising which remove amount of the random noise, while keeping the baseline variation.

In Fig.5, shown the Fourier spectrum of the signals in Fig, 3 and Fig. 4. As can be shown the peaks corresponding to the fundamental frequency and harmonics of the activation signal are still present in the Fourier spectrum, certain that by the difference between original and denoising Fourier spectrum compared to classical parametric spectrum subtraction denoising, which contained noisy peaks corresponding to the physiological noise peaks.

IV. Discussion

The results show that, the new technique is suppressing both random and physiological noise components while preserving the true activation in the signal from the acquired data in a simple and efficient way. This allows the new method to overcome the limitation of previous techniques.

The technique is virtually transparent to conventional statistical analysis methods, which assume statistical independence of samples. This is important for further analysis of the fMRI data (c.f., activation detection [10] and motion correction of fMRI time series [11]. This means that no constraints are imposed on the data analysis when the new method is used as a preprocessing step.

This technique provide control over noise removal using a threshold. This allows the user to customize its use to specific data analysis too his/her choice.

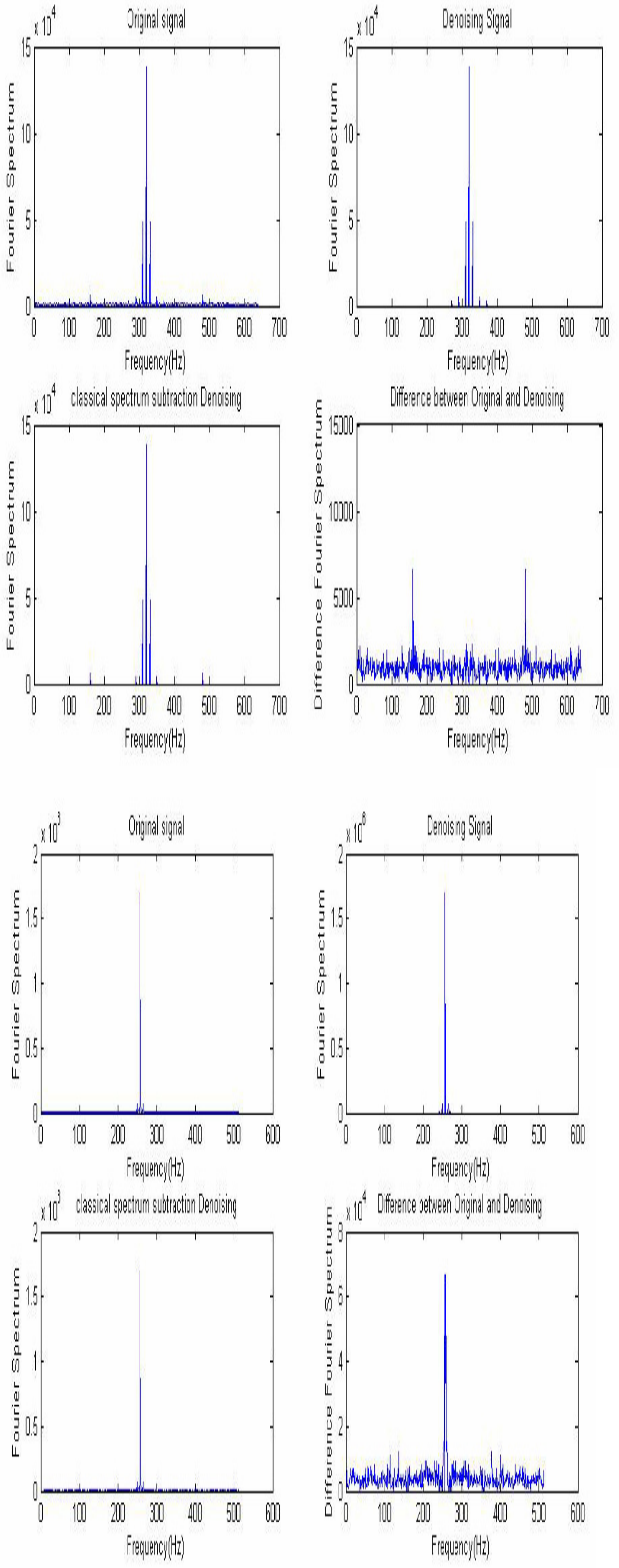

Fig. 5.illustration of the Fourier spectrum of the original signal, the denoised signal, classical parametric spectrum subtraction denoising signal and the difference between original and denoising signal for time course shown in Fig.2 and fig. 3.

V. CONCLUSION

A new signal denoising technique was proposed for fMRI signals. The proposed technique based on threshold the Fourier spectrum of the output response suppressing both random and physiological components noise while preserving the true activation in the signal from the acquired data in a simple and efficient way. The new technique is tested using computer simulations as well, real data, the implementation was described and its performance was demonstrated.

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