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Technique for Suppression Random and Physiological Noise Components in Functional Magnetic Resonance Imaging Data

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Abstract— ***Magnetic Resonance Imaging (MRI) uses Radio waves and strong magnetic field rather than X-ray to provide clear and detailed pictures of internal organs and tissues. Functional Magnetic Resonance Imaging (fMRI) is a non-invasive brain imaging technique, which developed in the early 1990's, 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. 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 proposed work was conducted using computer simulations data (block design), real baseline data with simulated activation patterns, as well as real data from event-related fMRI study on a normal human volunteer. 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— fMRI; Random noise; Physiological noise; Power spectrum.

I. INTRODUCTION

Functional Magnetic Resonance Imaging (fMRI) is a non-invasive brain imaging technique, which is 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 ratio (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 Evoked-response potential (ERP) to fMRI [5]. One significant limitation in Event-related functional Magnetic Resonance Imaging (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. Retrospective estimation and correction of physiological artifacts in fMRI by direct extraction of physiological activity from MR data [6]: A physiological artifact reduction method based on extracting respiratory motion and cardiac pulsation directly from functional MR data is described. Activation detection in functional MRI using subspace modeling and maximum likelihood estimation [3]: Statistical method for detecting activated pixels in functional MRI (fMRI) data. In this method, the fMRI time series measured at each pixel is modeled as the sum of a response signal which arises due to the experimentally controlled activation-baseline pattern, a nuisance component representing effects of no interest, and Gaussian white noise. Anisotropic 2-D and 3-D averaging of fMRI signals [8]: Method for denoising functional MRI temporal signals is presented in this note. The method is based on progressively enhancing the temporal signal by means of adaptive anisotropic spatial averaging. Detection of cortical activation during averaged single trials of a cognitive task using functional magnetic resonance imaging [9]: Here methods for acquiring fMRI data from single trials of a cognitive task. Wavelet transform-based Wiener filtering of event-related fMRI data [10]: The advent of event-related functional magnetic resonance imaging (fMRI) has resulted in many exciting studies that have exploited its unique capability. Adaptive Denoising of Event-Related Functional Magnetic Resonance Imaging Data Using Spectral Subtraction [5]: A signal-preserving technique for noise suppression in event-related functional magnetic resonance imaging (fMRI) data based on spectral subtraction. Combined with subsequent regression of physiological confounders is represented in [13]. Using a combination of high speed magnetic resonance inverse imaging (InI) and digital filtering is described in [14]. Data-driven noise correction, termed "APPLECOR" (for Affine Parameterization of Physiological Large-scale Error Correction) is modelled spatially-common physiological noise as the linear combination of an additive term and a mean-dependent multiplicative term, and then estimates and removes these components [15]. The above methods which proposed to suppress physiological noise including the use of harmonic model [6] 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 [7], smart spatial averaging [8], inter-epoch averaging [9], Wiener filtering [10] , and Canonical Correlation Analysis [11] [12]. These techniques suffer from at least one of the following limitations: the need for extended data acquisition for inter-epoch averaging that might not be practical, assumption of limited epoch-to-epoch variability, dependence on assumptions about the signal characteristics to build the denoising filter, and the inability to use conventional statistical detection approaches because of correlated noise among spatial and/or temporal points.

Adaptive Denoising of Event-Related Functional Magnetic Resonance Imaging Data Using Spectral Subtraction [5], the limitations of the technique include two parts, namely, the noise in phase component, and the effect of the clipping in the subtracted power spectrum. All these assumption are not always valid especially when we consider both physiological and random components of noise. Therefore, we propose a denoising strategy that does not have the above limitations and suggest it would be rather useful in the clinical practice.

The proposed technique is 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

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.

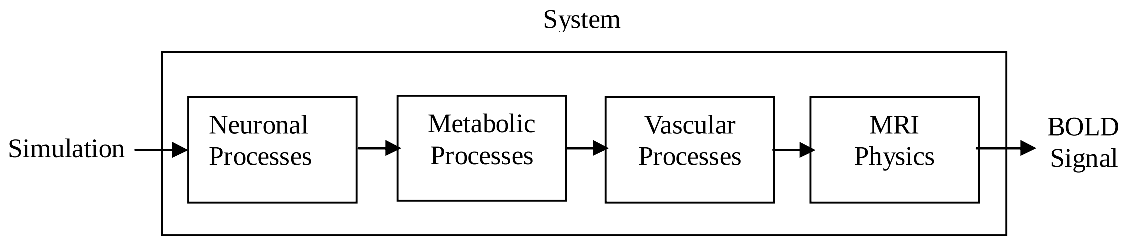


Fig 1 BOLD response system

The technique strategy steps are:

1. 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) as in equation 1:

$$y(t) = s(t) + d(t) \qquad 1$$

   Where y(t) is fMRI temporal signal, s(t) is true activation signal, and d(t) representing the sum of physiological and random noise parts.
2. Compute the Fourier transform of the linear combination system, In frequency domain, we have (equation 2):

$$Y(\omega) = S(\omega) + D(\omega) \qquad 2$$

   Here, Y($\boldsymbol{\omega}$) is fMRI temporal signal, S($\boldsymbol{\omega}$) is true activation signal, and D($\boldsymbol{\omega}$) representing the sum of physiological and random noise parts in the frequency domain.
3. Visualizing the Fourier transform with zero frequency components in the middle of the spectrum by multiply the input signal by $(-1)^t$.
4. The spectral of the physiological and random noise centralized in low frequency overlapped with that of the true activation.
5. We chose DC frequency and the first three harmonics less than DC frequency, implies the harmonics of true activation that is [16].as in equation 3 and 4.

$$Y(t) = y(t + T) \qquad 3$$

$$y(t) = \sum_{k=-\infty}^{+\infty} a_k\, e^{jkw_o t} \qquad 4$$

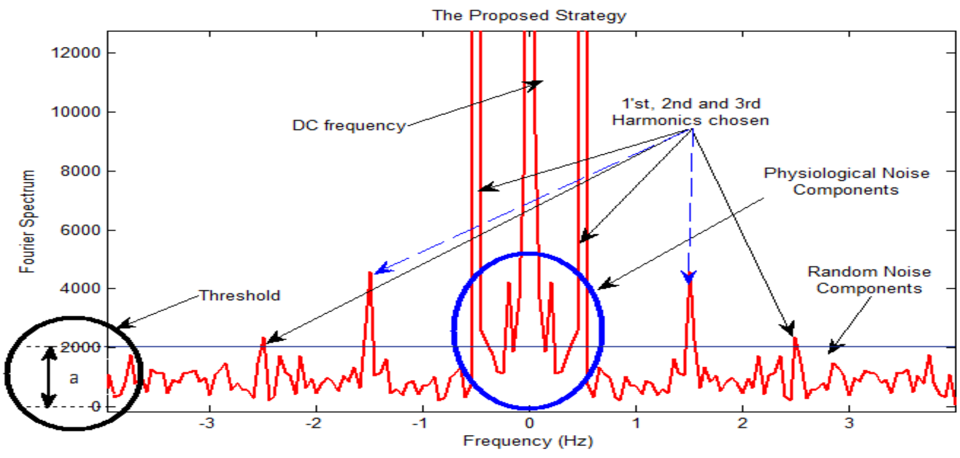
Where, T is time period, a_k is the Fourier series coefficients (, k=0, ±1, ±2, ±3,…) and w_o is fundamental frequency.

6. We chose then threshold or magnitude (a) less than the 3rd harmonic magnitude chose from the visualizing Fourier transform (ellipse in black the Fig.2 a) to remove random al noise components (equation 5).

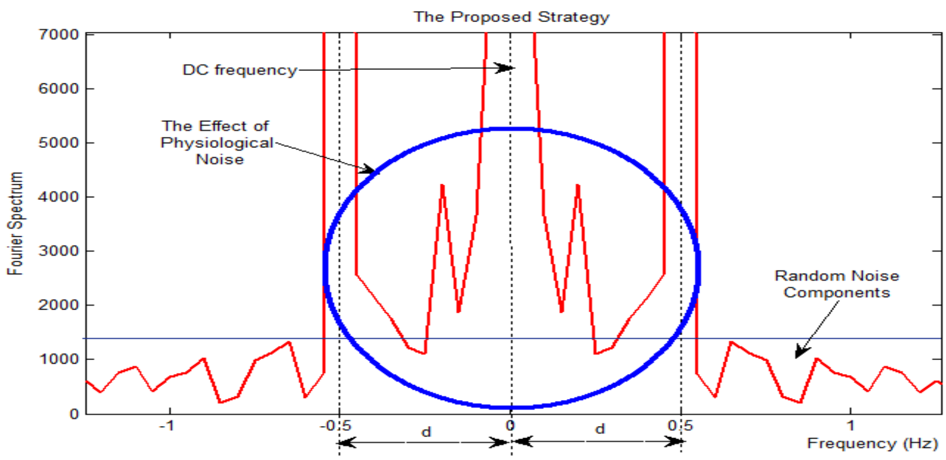
$$a = a_3 - \beta \qquad 5$$

Where, a_3 is the magnitude of the 3rd harmonic and $\beta \geq 0$.

7. To reduce the physiological noise we set the value of the magnitude of d to zero (the ellipse in blue in the Fig.2 b) where $0 < d <$ k-r (0 is the Dc frequency , k is the fundamental frequency and r ≥ 0)
8. The remaining is the fundamental frequency and harmonics of the true activation signal.
9. Then Reconstruct the resulting signal using real part of inverse Fourier transformation. Fig. 2.a and b is shown the proposed strategy.



(a)



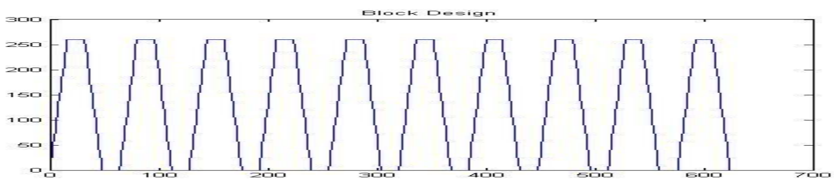
(b)

Fig 2 Noise reduction Technique. (a) Complete proposed strategy, (b) Magnification of physiological noise components in (a).

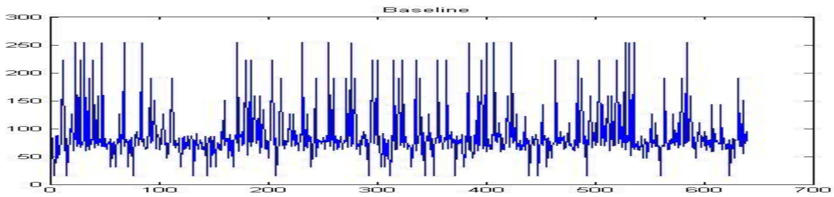
III. Results

A. The data

The proposed technique was verified using computer simulations as well as actual data from a human volunteer:



(a)



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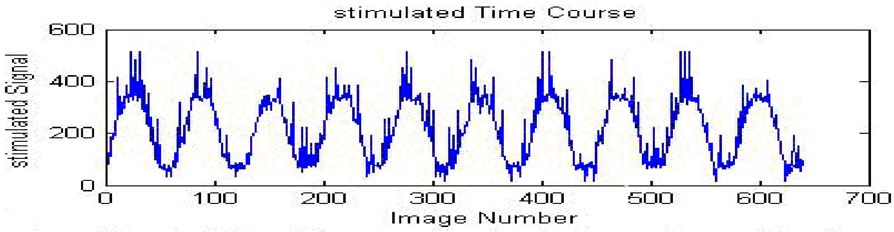

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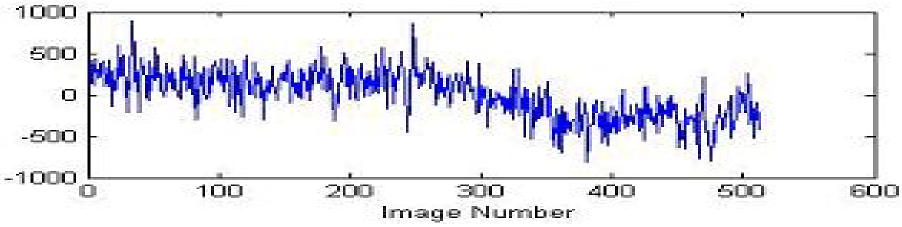

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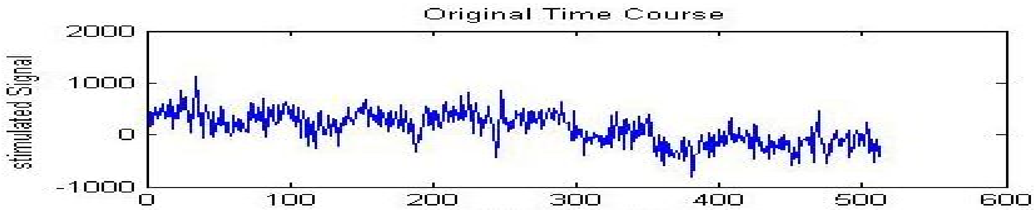
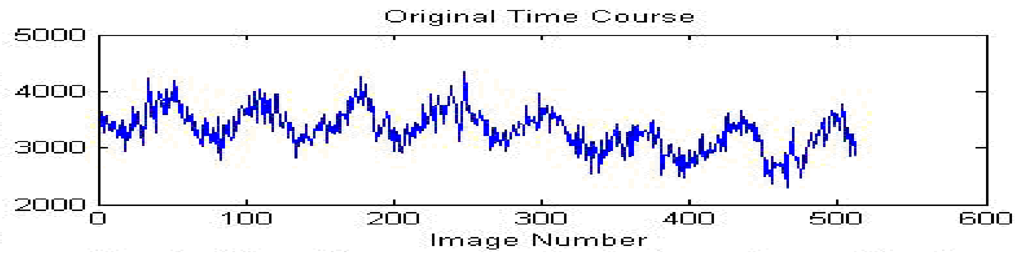


(e)

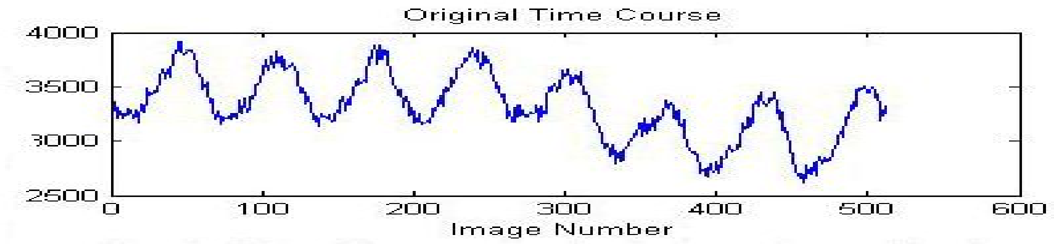
Fig 3 The computer simulations (block design): (a) block design activation signal; (b) The baseline data; (c) shifted computer simulations signal; (d) Variation baseline data; (e) Computer simulations signal with baseline variation.

B. The computer simulation

The computer simulations were performed by Computer generated block design activation signal was added to an actual baseline set (Fig 3).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 Magnetom Vision 1.5 T clinical scanner. The number of epochs was 8 or 10 and the length of each epoch was 64.



(a)



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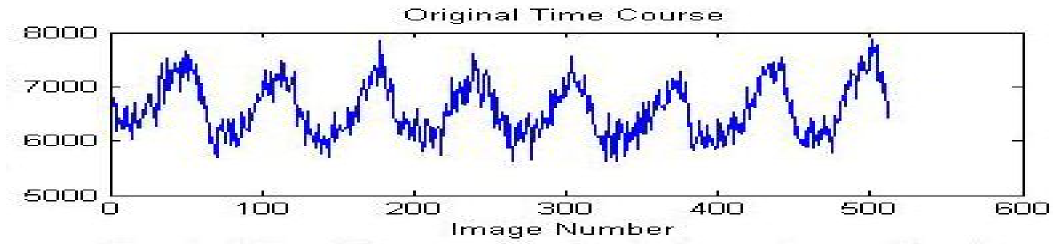
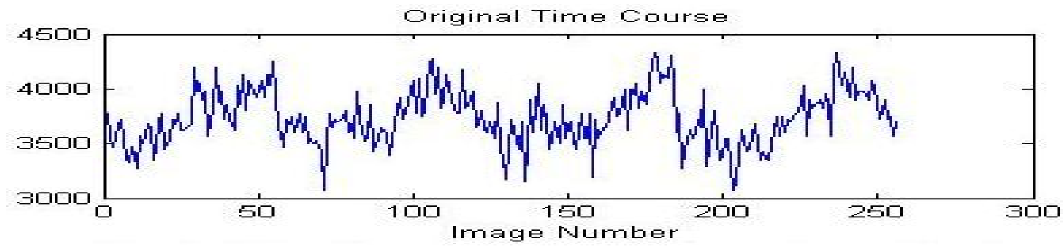


(c)



(d)

Fig 4 The actual data: (a) and (b) activated pixel with in time course length 512(8 epochs) with baseline variation; (c) activated pixel with in time course length 512(8 epochs) (d) activated pixel with in time course length 256(4 epochs).

C. *The actual data*

The actual data were obtained from an ER-fMRI study (Fig 4) 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 thickness=5mm). The subject performed rapid finger movement .The study consists of 32 epochs with 64 images per epoch. Temporal data from only 4 or 8 epochs of pixels in both the motor and visual cortices are used.

D. *Result from simulated data*

The result of applying the new technique to process computer simulated fMRI data, compared to classical spectral subtraction denoising [5].

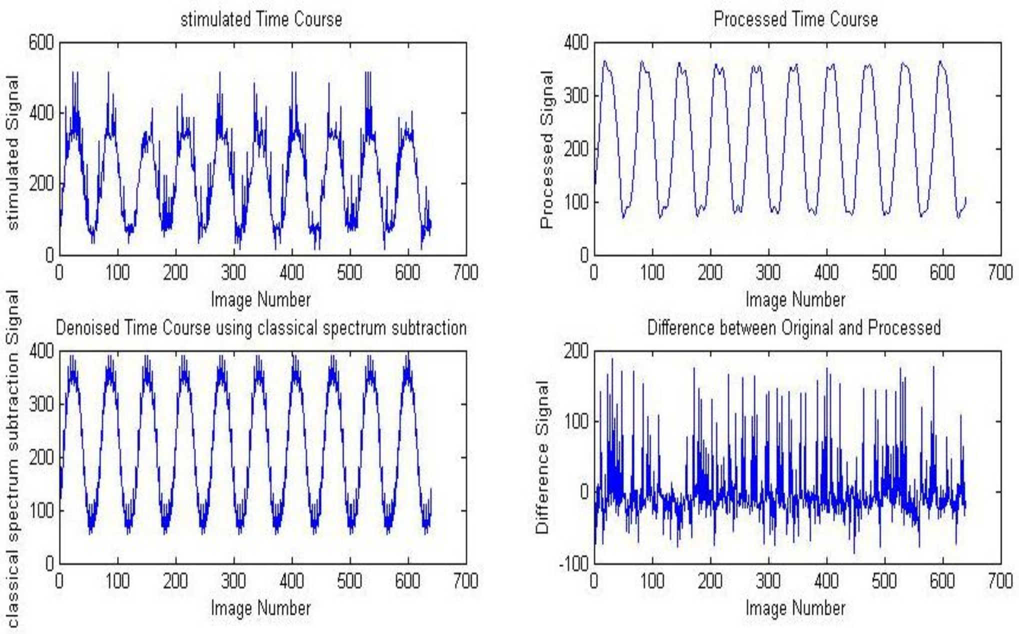


Fig 5 Result from simulation without baseline variation.

The result of applying the new technique to process computer simulated fMRI data are shown in Fig.5. As can be observed in Fig.5 when used simulation without baseline variation the noise in the data was eliminated clearly in the output, compared to the classical parametric spectrum subtraction denoising which eliminated amount of random noise. Also, the difference between simulated and processed signal appear to have no signal components.

E. Result from Real data

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). The results compared to the classical spectral subtraction denoising (Fig.6), (Fig.7), (Fig.8) and (Fig.9).In Fig.6 when used actual data for pixel time course containing neuronal activation (length = 512 points) with baseline variations the process eliminated the random and physiological baseline variations and we used in Fig.7 acud baseline variations the results look dramatically improved compared to the original. In fact, the process removed the random noise and baseline variation. 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. 8 when used actual data for pixel time course containing neuronal activation (length = 512 points) and Fig. 9 actual data for pixel time course containing neuronal activation (length = 256 points) without baseline variations , as can be shown, the results of 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, we observe an improved noise suppression that is evident in the shown difference signal.

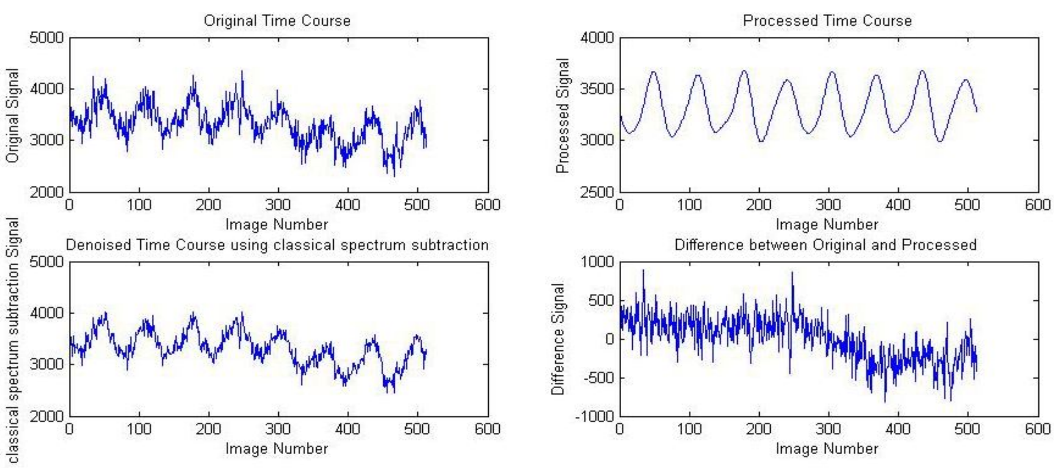


Fig 6 Results from actual data for pixel time course containing neuronal activation (length = 512 points) with baseline variations.

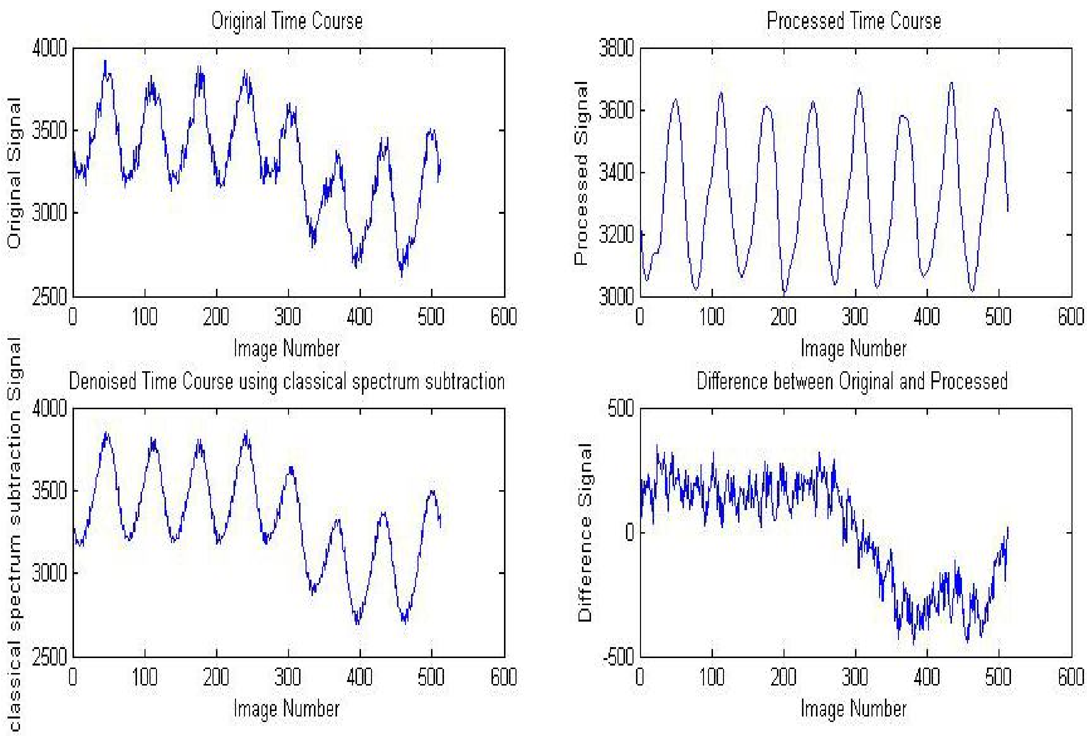


Fig 7: Results from actual data for pixel time course containing neuronal activation (length = 512 points) with a cud baseline variations.

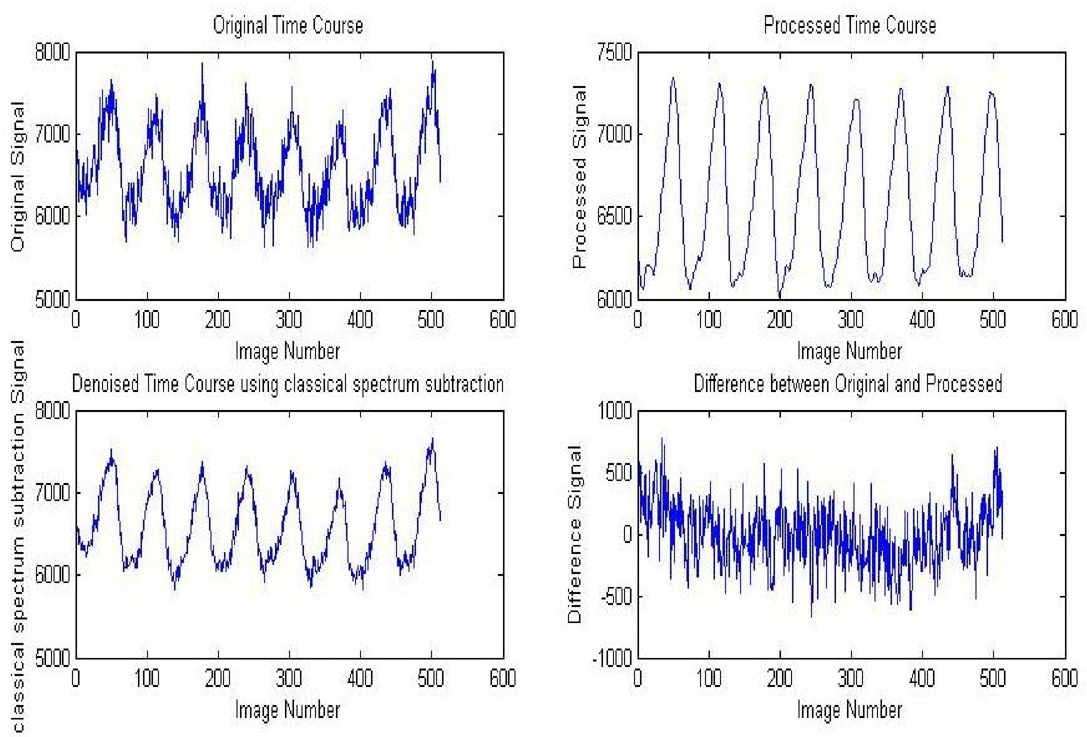


Fig 8 Results from actual data for pixel time course containing neuronal activation (length = 512 points) without baseline variations.

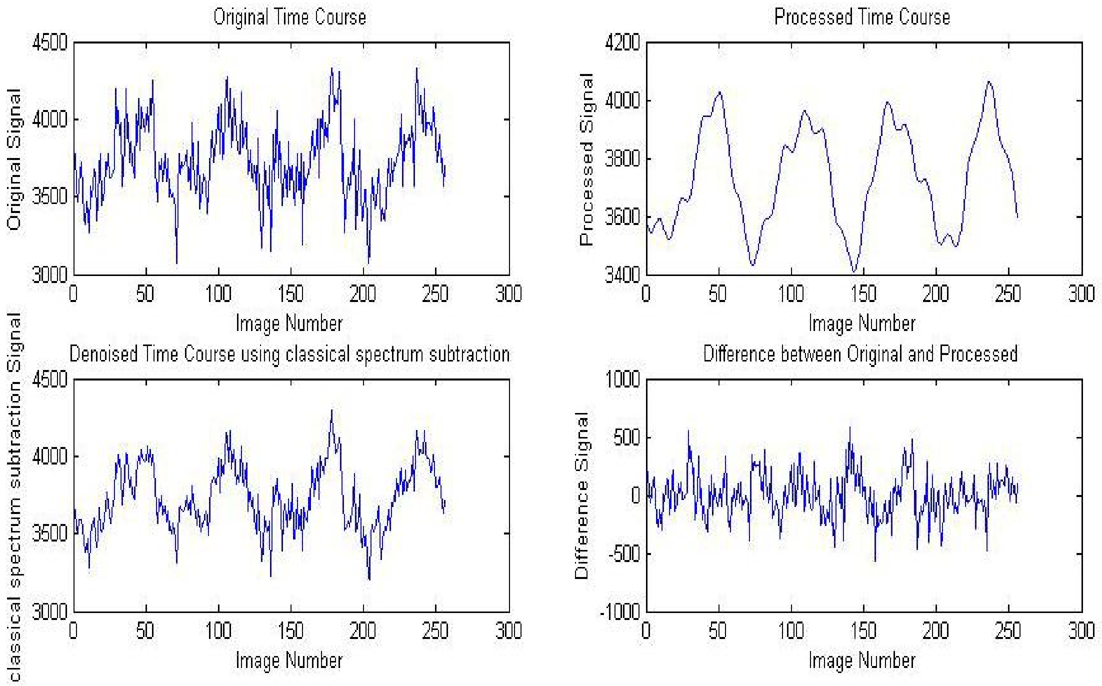


Fig 9 Results from actual data for pixel time course containing neuronal activation (length = 256 points) without baseline variations.

In Figs. 10 is shows the Fourier spectrum of original, denoising, and classical spectrum subtraction. As can be shown the peaks corresponding to the fundamental frequency and harmonics of the activation signal are still present in the Fourier spectrum.

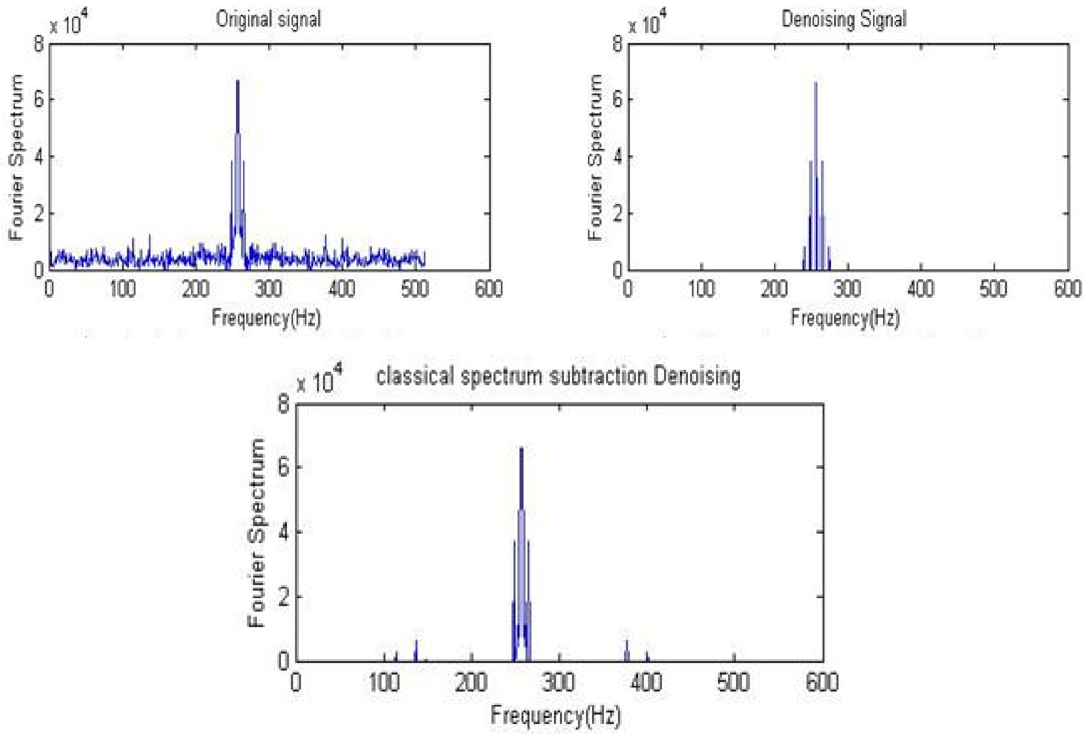


Fig 10: Fourier spectrum of signals in Fig. 5

I. DISCUSSIONS

The results show that, the new technique is appearing much improved from the original. Moreover, if we compared the results of the new technique to that of the classical parametric spectrum subtraction, we observe an improved noise suppression that is evident in the shown difference signal. The proposed algorithm was able to effectively suppress the baseline variations results from physiological noise. Moreover, when the two results were subtracted, the trend of the physiological noise was very clear. As can be shown the peaks corresponding to the fundamental frequency and harmonics of the activation signal are still present in the Fourier spectrum, emphasized that by the difference between original and denoising Fourier spectrum compared to classical parametric spectrum subtraction denoising, which contained noisy peaks .

I. CONCLUSIONS

The new technique was 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. This method avoids the shift in phase of the hemodynamic response, which is very valuable feature. This technique provides control over noise removal using a threshold. This allows the user to customize its use to specific data analysis his/her choice.

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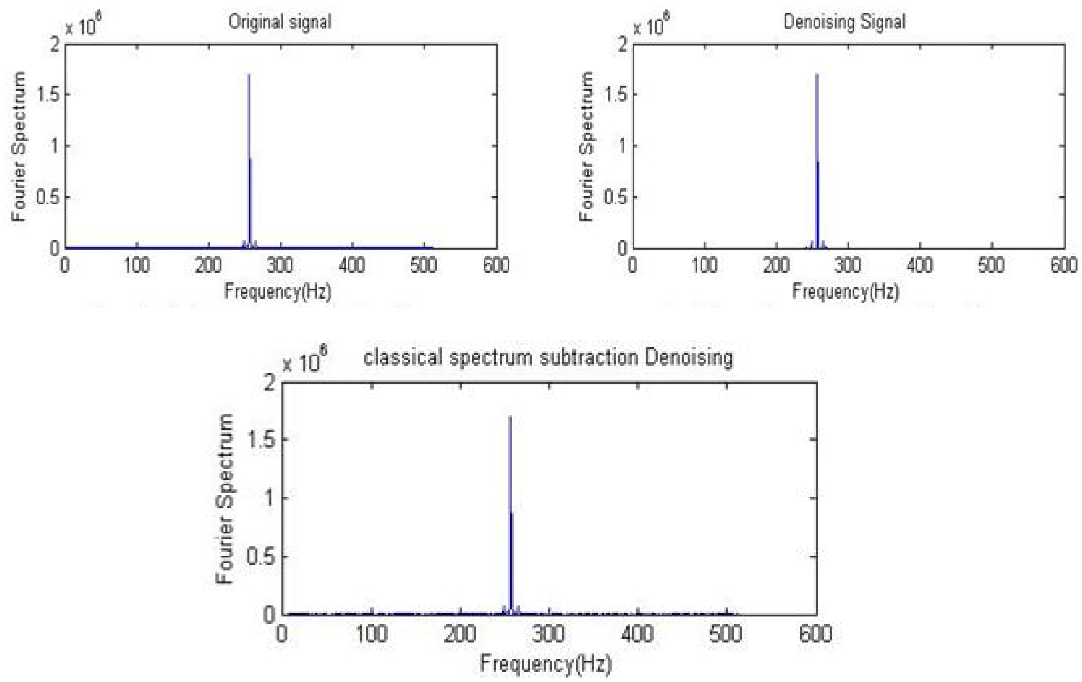

Fig.11 Fourier spectrum of signals in Fig.6

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