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Nonparametric suppression of random and physiological noise components in functional magnetic resonance imaging using cross-correlation spectrum subtraction

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ABSTRACT

The advent of event-related functional magnetic resonance imaging (fMRI) has resulted in many exciting studies that have exploited its unique capability. However, the utility of event-related fMRI is still limited by several technical difficulties. One significant limitation in event-related fMRI is the low signal-to-noise ratio (SNR). In this work, a new non-parametric technique for noise suppression in event related fMRI data is proposed based on spectrum subtraction. 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 and suggests its value as a useful preprocessing step for fMRI data analysis.

Keywords: Functional magnetic resonance imaging, denoising, spectrum subtraction, adaptive filters

1. INTRODUCTION

The functionality of the human brain is still relatively unknown, in spite of the fact that much effort has been put into its understanding. A relatively new and promising tool for this purpose is functional magnetic resonance imaging (fMRI). This technique provides a valuable noninvasive tool for investigating brain function. In particular, the different magnetic properties of oxyhemoglobin and deoxyhemoglobin are used to visualize localized changes in blood flow, blood volume and blood oxygenation in the brain[1]. These in turn become indicators for local changes in neural activity. To observe these homodynamic changes, the subject is exposed to controlled stimuli that are carefully designed to affect only certain brain functions while 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, which represents sensory, motor, and cognitive functions in the brain[2].

Classically, most fMRI studies are conducted using the so-called block design approach, whereby two sets of data are acquired. First, a number of frames are acquired while the subject is at rest or under some baseline condition, then another set is acquired during the stimulus[2]. This pattern is repeated for a number of cycles in order to improve the signal-to-noise ratio (SNR), which would otherwise be rather low. Recent advances in both data acquisition and analysis have improved the temporal resolution of fMRI and made it possible to observe transient homodynamic changes with reasonable accuracy. A good example for that is a new experimental design, similar to that of evoked-response potential (ERP) protocol, 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[3]. 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. One significant limitation in ER-fMRI is the degradation in signal-to-noise ratio (SNR) due to the transient nature of the response. Several methods of data analysis have been used to process the ER-fMRI raw data. The ultimate goal of such analysis is to try to separate

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signal components due to true activation, physiological fluctuations and random noise. The latter two components are considered as nuisance and must be removed for correct results[4]. Several methods have been proposed to suppress physiological noise including the use of a harmonic model[5] and noise subspace characterization[6]. 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[3], and Wiener filtering[9]. These techniques suffer from at least one of the following limitations: the assumption of a certain signal characteristic to enable building the denoising filter, the assumption of limited epoch-to-epoch variability to enable the averaging (which ignores the information associated with each execution of the task and as a result assumes that subject behavior and brain function do not vary during repeated trials) and the assumption of a particular noise model that is uncorrelated with the activation signal to enable the removal of this type of noise. All these assumption are not always valid especially when we consider both physiological and random components of noise. In fact, the noise behavior is very hard to model in fMRI due to the large number of noise sources and their complex nature. Besides, the noise is often found to be correlated with the activation signal. Moreover, it does not always show white Gaussian noise behavior (i.e., it does not affect the activation response uniformly over the entire spectrum). Therefore, a denoising strategy that would overcome the above limitations would be rather useful in the clinical practice.

In the present work, which focuses on denoising, an extension to the well-known spectrum subtraction technique[10] along with a nonparametric estimation for the noise behavior have been adapted for processing ER-fMRI data. The proposed method considers a generalized model for the denoising process that takes into account random noise, physiological noise, in addition to relaxing the assumption of uncorrelatedness of true activation signal and noise. Being nonparametric, it adapts well to individual data sets and works well in the clinical practice. This technique mainly aims at improving the SNR in the activated time courses, which can be considered an important preprocessing step before characterizing the signal for aspects such as onset, duration, and amplitude of the activation response. The proposed method is verified using real ER-fMRI data acquired from a healthy volunteer and the results supports the theory and shows the potential of the new technique for clinical use.

2. THEORY

Generally speaking, the fMRI temporal signal can be modeled as the summation 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. That is:

$$y(n) = s(n) + d(n) \quad . \tag{1}$$

In the frequency domain, we have:

$$Y(k) = S(k) + D(k) \, . \tag{2}$$

The power spectrum of Y(k) can be computed as follows:

$$|Y(k)|^2 = |S(k)|^2 + |D(k)|^2 + S(k)\cdot D^*(k) + S^*(k)\cdot D(k) \tag{3}$$

or,

$$P_{yy}(k) = P_{ss}(k) + P_{dd}(k) + r_{sd}(k) + r_{ds}(k) \tag{4}$$

The last two terms represent the cross correlation between the signal and the noise. Typically, if d(n) is zero mean and uncorrelated with s(n) then the terms $E\{S^*(k).D(k)\}$ and $E\{S(k).D^*(k)\}$ can be reduced to zero and the signal power can be estimated by:

$$P_{ss}(k) = P_{yy}(k) - P_{dd}(k) \tag{5}$$

However, if the noise and the signal are correlated, then we can no longer neglect those cross terms, which represent the cross correlations ($r_{sd}(k)$ and $r_{ds}(k)$) between d(n) and s(n). Unfortunately, we cannot estimate these cross-correlation terms as we have no access to s(n). But, since we have access to the corrupted signal y(n), we can get an estimate of the cross correlation $r_{ds}(k)$ (or $r_{sd}(k)$) by computing the cross correlation the corrupted signal y(n) and d(n), i.e. $r_{yd}(k)$:

$$r_{yd}(k) = r_{sd}(k) - r_{dd}(k) \tag{6}$$

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Note that $r_{yd}(k)$ contain the desired cross correlation terms $r_{sd}(k)$ plus the autocorrelation of the noise component, which in the frequency domain is given by $|D(k)|^2$ and can be lumped with the same term in Eq.(3).

Now, the estimate of the power of the activation signal can be given by,

$$|S(k)|^2 = |Y(k)|^2 - \alpha |D(k)|^2 - \delta |Y(k)| \cdot |D(k)| \; . \tag{7}$$

Here, α is a subtraction factor (to account for the two lumped terms containing $|D(k)|^2$) and δ is the cross-correlation subtraction coefficient, which provide an estimate of the correlation between the corrupted signal and the noise component. δ can be calculated as,

$$\delta = \frac{\chi_{yd} - \mu_y \cdot \mu_d}{\sigma_y \cdot \sigma_d} \; , \tag{8}$$

where μ_y and μ_d are the mean values of the corrupted signal and the estimated noise signal respectively, σ_y and σ_d are their variance and χ_{yd} can be computed as:

$$\chi_{yd} = \frac{1}{N} \sum |Y(k)| \cdot |D(k)| , \tag{9}$$

where N is the number of points in the signal.

If we assume that the noise affects the whole spectrum in a uniform way (i.e. white noise), then α will be constant. Unfortunately, this is not always the case. So, to take into account this color behavior of the noise, we divide the power spectrum into N non-overlapping bands, each band will have its own subtraction factor, which will depend upon SNR in this band. So, Eq. (7) can be rewritten as:

$$|S(k)|^2 = |Y(k)|^2 - \alpha_i |D_i(k)|^2 - \delta |Y_i(k)| \cdot |D_i(k)| \qquad for \quad b_h \le k \le e_i \tag{10}$$

Where b_i and e_i are the beginning and ending frequency of the i^{th} frequency band, α_i is a band specific subtraction factor and is a function of the SNR of this band which can be calculated as:

$$SNR_i(dB) = 10 \log_{10} \left(\frac{\sum_{k=b_i}^{e_i} |Y(k)|^2}{\sum_{k=b_i}^{e_i} |D(k)|^2} \right) \tag{11}$$

3. METHODS

3.1. Adaptive nonparametric estimation of the noise

According to the above derivation, we need to compute the power spectrum of the noise and the cross-correlation of the original signal and the noise. The simplest way to do that is to use the background areas within the available data set. Here, we use a non-parametric technique to compute both terms (as opposed to the parametric method used in[11]). 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.

3.2. Signal power spectrum estimation

Since the proposed technique is applied to a single time course at a time, the periodogram estimate of signal power spectrum is expected to have a rather large variance[12]. As a result, the subtraction of power spectra in Eq. (10) may contain negative values in practical implementations. This causes a problem in trying to compute the square root to recover the processed signal. In our implementation, we introduce a new parameter β (which called the spectral floor parameter[13]) to overcome this problem by replacing all negative values in the subtraction results by a small fraction of the corrupted signal as in Eq. (12). Since in most cases β is equal to zero, this approach is justified because all values lower than the estimated power spectrum are more likely to be noise components within the variance limits of the periodogram estimate.

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$$|S(k)|^2 = \begin{cases} |Y_i(k)|^2 - \alpha_i |D_i(k)|^2 - \delta |Y_i(k)| \cdot |D_i(k)|, & if\, |Y_i(k)|^2 > \alpha |D_i(k)|^2 \\ \beta \alpha_i |Yi(k)|^2, & otherwise \end{cases} \quad (for \;\; b_h \le k \le e_i) \qquad (12)$$

3.3. Retrieving the denoised signal from its power spectrum

As shown, the signal power spectrum is obtained by spectrum subtraction of the noisy signal and noise power spectra. In order to compute the deterministic signal component from its power spectrum, the magnitude of the Fourier transform can be obtained as the square root of the power spectrum. The problem now becomes that of reconstructing the signal using magnitude only information about its Fourier transform. Several phase recovery techniques can be used to do that. The one used for this work relies on an estimate obtained from the phase of the Fourier transform of the original signal Y(k). Hence, the Fourier transform of the processed signal S(k) can be expressed as,

$$S(k) = \sqrt{P_{ss}(k)} \cdot e^{j \cdot phase(Y(k))}. \qquad (13)$$

The enhanced deterministic signal s(n) is then computed as the real part of the inverse Fourier transformation of this expression. A block diagram for the proposed strategy is shown in Figure 1.

4. RESULTS

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[9]. 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. The values of subtraction factor (α) and the spectral floor parameter (β) were chosen in their simplest form which are α=1 and β=0 to allow the comparison with the different implementations of spectral subtraction algorithm.

The results of the proposed technique are shown in Figs. 2-9. As can be shown in Figs. 2-5, 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[11-13], we observe an improved noise suppression that is evident in the shown difference signal. The same algorithms were applied to the same pixel time course but for a large number of time frames to clarify the effect of every algorithm on the physiological noise. As shown in Figs. 6-9, the proposed algorithm was able to effectively suppress the base line variations results from the physiological noise. Moreover, when the two results were subtracted, the trend of the physiological noise was very clear as in Fig. 9.

5. CONCLUSIONS

The new technique is based on generalized spectral subtraction that allows correlated and colored 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.

ACKNOWLEDGEMENTS

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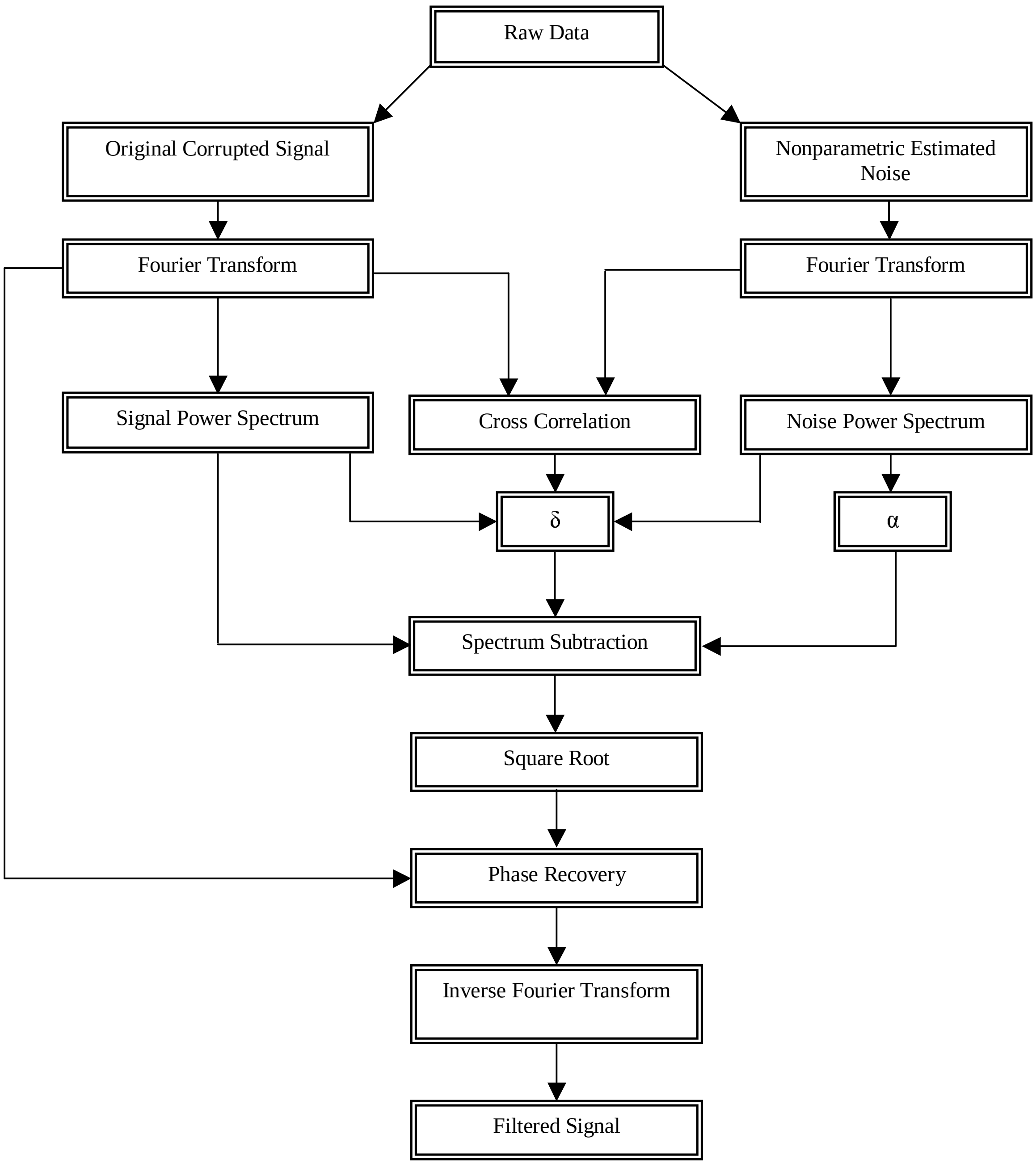

Figure 1. Block diagram of the proposed Algorithm.

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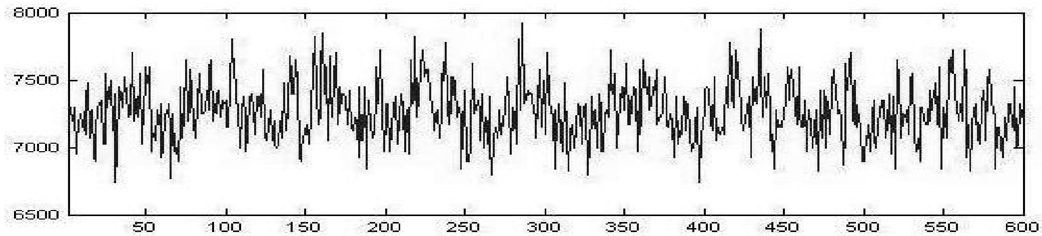

Figure 2. Original Signal.

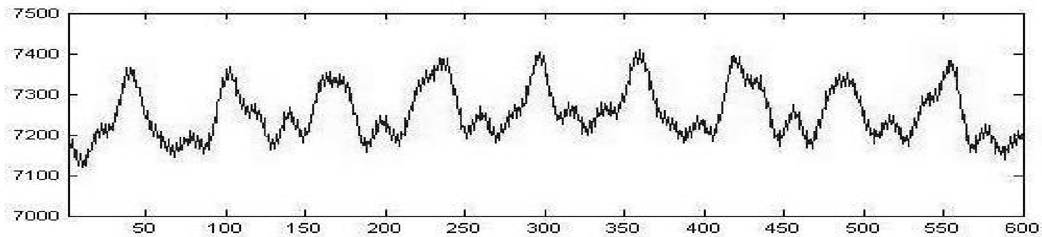

Figure 3. Denoised Data using classical spectrum subtraction. Note the presence of baseline variations due to physiological noise as a result of the parametric model of the noise.

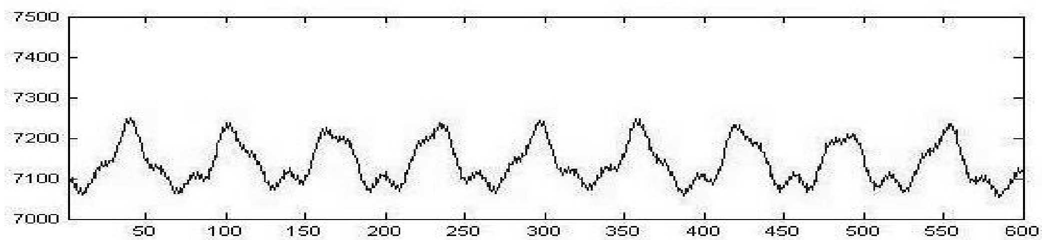

Figure 4. Denoised Data using the new method. Note the removal of baseline variations.

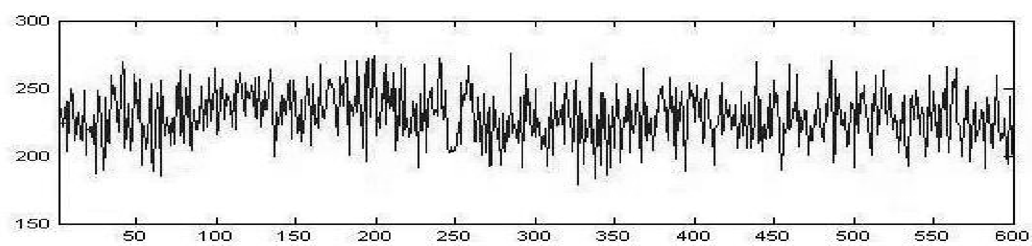

Figure 5. Difference between the raw signal in Fig. 2 and the denoised signal in Fig. 4.

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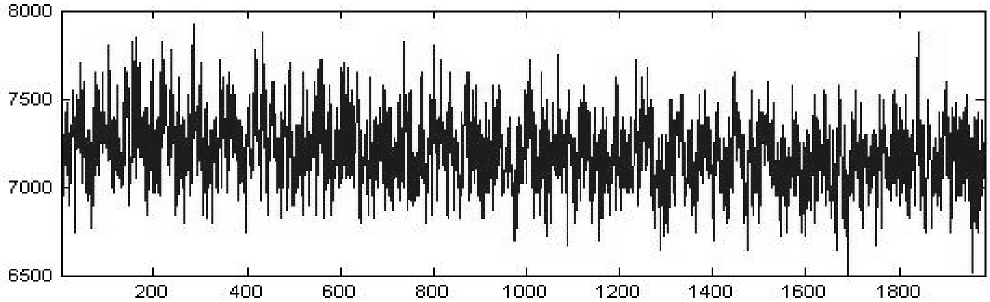

Figure 6.. Original Signal

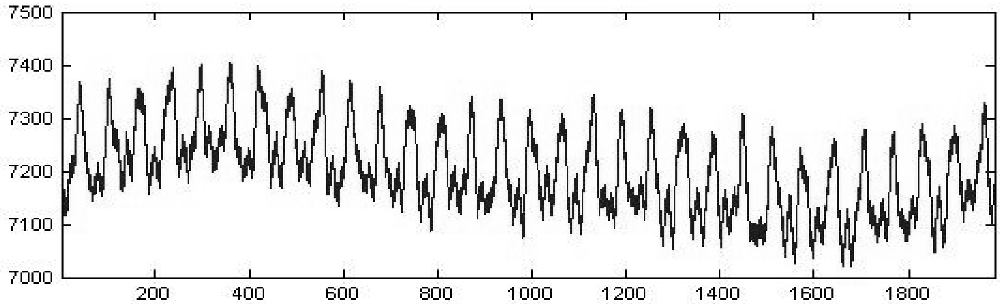

Figure 7. Denoised Data using classical spectrum subtraction. Note the baseline variation (physiological noise) due to the parametric model of the noise.

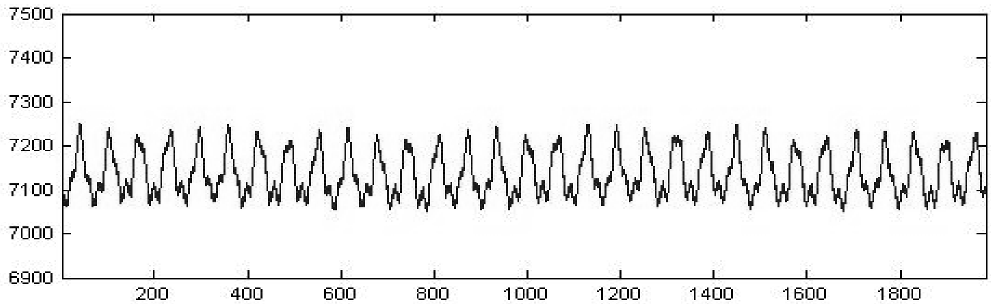

Figure 8. Denoised Data using the new method. Note the removal of the correlated noise plus the physiological noise.

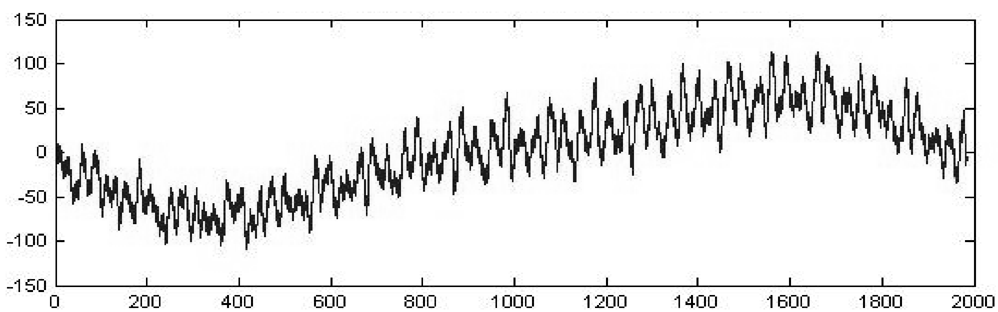

Figure 9. Difference between the parametric solution and the proposed nonparametric solution. Note the baseline variation between the two solutions.

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