Spectral analysis of photoplethysmographic signals: The importance of preprocessing

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A B S T R A C T

Heart rate variability (HRV) is an important and useful index to assess the responses of the autonomic nervous system (ANS). HRV analysis is performed using electrocardiography (ECG) or photoplethysmography (PPG) signals which are typically subject to noise and trends. Therefore, the elimination of these undesired conditions is very important to achieve reliable ANS activation results. The purpose of this study was to analyze and compare the effects of preprocessing on the spectral analysis of HRV signals obtained from PPG waveform. Preprocessing consists of two stages: filtering and detrending. The performance of linear Butterworth filter is compared with nonlinear weighted Myriad filter. After filtering, two different approaches, one based on least squares fitting and another on smoothness priors, were used to remove trends from the HRV signal. The results of two filtering and detrending methods were compared for spectral analysis accomplished using periodogram, Welch’s periodogram and Burg’s method. The performance of these methods is presented graphically and the importance of preprocessing clarified by comparing the results. Although both filters have almost the same performance in the results, the smoothness prior detrending approach was found more successful in removing trends that usually appear in the low frequency bands of PPG signals. In conclusion, the results showed that trends in PPG signals are altered during spectral analysis and must be removed prior to HRV analysis.

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1. Introduction

Photoplethysmography (PPG) is a simple, noninvasive and useful technique that detects blood volume changes in the blood vessels by optical methods. The PPG sensor consists of an infrared emitter, which passes light through the blood vessels, and a detector, which detects light reflected from the vessels. Typically the emitter and detector are located in a transducer placed on the finger or earlobe [1]. The PPG waveform reflects fluctuations in blood volume and is synchronized with the beating of the heart [2,3].

Because the PPG signal contains information about heart rate and heart rate variability (HRV), it can be used instead of the ECG signal in analysis. HRV is defined as the variation of ECG R-wave intervals (RR) with respect to time and is an important index used in autonomic nervous system (ANS) analysis [3–5]. For the PPG signal, peak-to-peak (PP) intervals could replace the RR intervals detected from ECG signal [6,7] in HRV analysis. Many studies [2,8–10] verify the high correlation between the RR intervals obtained from ECG signals and PP intervals obtained from PPG signals.

Although PPG signals are more simple and useful than ECG signals, difficulties in analysis arise due to noise usually caused by motion artifacts and a quasi DC signal component that corresponds to the changes in the venous pressure [7]. Therefore, HRV waveforms obtained from PPG signals include both noise and slowly changing trends from this DC component [4,7]. These undesired components must be removed due to their detrimental effect on the spectral analysis results of HRV.

Spectral analysis of HRV gives information about ANS activity. While the low frequency band reflects sympathetic and parasympathetic activity, the high frequency band is related to parasympathetic activity [11]. The power spectral density (PSD) is a spectral analysis method to find the power distribution over a frequency band contained in a signal. In several studies [6,7], non-parametric and parametric PSD estimation methods are applied to HRV data obtained from PPG signals to interpret variations of ANS.

Because the PPG signal includes various sources of noise, such as the patient’s motion or respiration, both linear and adaptive filters have been used by researchers for removing these artifacts from PPG signals [12–14]. To remove slow non-stationary trends in the signal, various methods have been proposed [15–18]. While
some methods analyze only non-stationary segments in HRV data [15], other methods, typically based on polynomial models, remove these trends from the signal before HRV analysis [16–18] by subtracting from the instantaneous RR interval a linear polynomial fit to data. One method based on smoothness priors is an advanced detrending method for HRV analysis and performs like a time-varying FIR high pass filter [19].

The main purpose of the present study is to determine the effects of preprocessing on HRV signals obtained from PPG waveform. To this end, a linear Butterworth filter and a nonlinear weighted Myriad filter, as well as two different detrending methods were used and compared as preprocessing. The effects of denoising and detrending were evaluated using periodogram, Welch’s periodogram and Burg’s method, respectively. The PSD results were compared for data with and without trends after Butterworth or weighted Myriad filtering.

To our knowledge, no study has yet analyzed and compared the effects of linear (Butterworth), nonlinear (weighted Myriad) filtering, and two different detrending methods on artifact reduction in PPG signals. Thus, this research represents one of the first studies that investigate the effect of combining filtering and detrending on PPG signals to achieve reliable ANS activation results.

2. Methodology

The PPG signals used in this study were recorded at the Bakırköy Mental and Nervous Diseases Training and Research Hospital using the BIOPAC MP150WSW data acquisition system and Acknowledge software. Fifteen healthy adults (8 female, mean age 34 ± 9.7 years; 7 male, mean age 37.8 ± 12.3 years) volunteered to participate in the study. The study was approved by both the university and hospital ethics committee, and written informed consent was obtained from all subjects. The PPG transducer (TS200), which consists of an infrared transmitter/emitter of 860 ± 60 nm wavelength, was strapped to the non-dominant hand middle finger of the subject and connected to the PPG amplifier (PPG100C) through a shielded cable to record the blood volume pulse waveform of gain 100 and cut-off frequencies at 0.05 Hz and 10 Hz. Data were recorded for a duration of two minutes with a sampling rate of 250 Hz.

3. Preprocessing

3.1. Butterworth filtering

The Butterworth filter is a simple, linear frequency domain filter. Due to the monotonically decreasing magnitude response and a highly flat magnitude response in the pass-band, the Butterworth method is commonly used in signal processing applications [20]. The magnitude squared response of an N-th order analog low-pass Butterworth filter $H_0(s)$ is [21]

$$|H_0(j\Omega)|^2 = \frac{1}{1 + (\Omega / \Omega_c)^{2N}}$$

(1)

where $\Omega_c$ is the 3 dB cut-off frequency.

3.2. Weighted Myriad filtering

The weighted Myriad filter is a nonlinear filter. In linear filtering approaches, it is assumed that signal noise is normally distributed [22]. However, noise in biomedical signals is usually impulsive and therefore not well described by the Gaussian model. A filter proposed as being better equipped to eliminate this sort of impulsive noise is the weighted Myriad filters, which is based on $\alpha$-stable distributions [23]. Given a set of $N$ weights $(w_1, w_2, \ldots, w_N)$ the output of a weighted Myriad filter is [23]

$$\hat{y}_{k,w} = \text{myriad}(k; w_1 \circ x_1, \ldots, w_N \circ x_N)$$

(2)

$$\hat{y}_{k,w} = \text{argmin}_\beta \prod_{i=1}^{N} \left| k^2 + w_i (x_i - \beta)^2 \right|$$

(3)

where $\beta$ is the real-valued location parameter, $k$ is the dispersion of the distribution, and $x = [x_1, x_2, \ldots, x_N]^T$ is the observation vector. Here, $w_i \circ x_i$ represents the weighting operation.

3.3. Detrending with linear least-squares fitting

To solve the equations of the overdetrended or inexact/ly

specified systems in an approximate sense, the least-squares are

frequently used. A very common source of least squares problems

is curve fitting. Minimizing the sum of the squares of the resid-

uals, which are defined as the difference between observed and

predicted modal values, fit parameters are calculated. The linear

least-squares fitting technique, is the simplest and most commonly

applied form of linear regression, yields a line that best fits to

the data [24]. On the other hand, the least-squares polynomial fit

method computes the coefficients of the n-th order polynomial that

best fits the input data in the least-squares sense. The equation for a

polynomial line is

$$\hat{y} = a_0 x^n + a_1 x^{n-1} + \cdots + a_{n-1} x + a_n$$

(4)

where $a_0, a_1, \ldots$ are the coefficients. Here, straight line is polyno-

mials of one order and is given as

$$\hat{y} = a_0 x + a_1$$

(5)

is the line with $a_0$ and $a_1$ parameters which minimizes the quantity

$$\sum_{i=1}^{M} (y_i - \hat{y}_i)^2$$

(6)

where $y_i$ is the ith element in the input vector. A distinct set of n + 1 coefficients is computed for each column of the M-by-N input, $u$.

The MATLAB detrend function generally operates to remove linear trend. It computes the least-squares fit of a straight line to the data and subtracts the resulting function from the data [24].

3.4. Detrending with smoothness priors

To remove slow non-stationary trends from the HRV signal, smoothness priors, an approach that performs like a time-varying FIR high-pass filter, was used [19]. According to this method, the RR interval time series is given as

$$z = (R_2 - R_1, R_3 - R_2, \ldots, R_N - R_{N-1})^T \in \mathbb{R}^{N-1}$$

(7)

where $N$ is the number of R peaks of ECG signal. The RR time series contains two components

$$z = z_{\text{stat}} + z_{\text{trend}}$$

(8)

where $z_{\text{stat}}$ is the nearly stationary RR series component and $z_{\text{trend}}$ is the low frequency, aperiodic trend component. $z_{\text{trend}}$ can be modelled as

$$z_{\text{trend}} = H\theta + \nu$$

(9)

where $H \in \mathbb{R}^{(N-1) \times M}$ is the observation matrix, $\theta \in \mathbb{R}^M$ are the regression parameters and $\nu$ is the observation error. A regularized least squares solution can be used to estimate $\hat{\theta}$ as

$$\hat{\theta} = \text{argmin}_\theta \left\{ ||H\theta - z||^2 + \lambda^2 \left\| D_{\theta}(H\theta) \right\|^2 \right\}$$

(10)
where $\lambda$ is the regularization parameter and $D_d$ shows the discrete approximation of $d$th derivative operator. The solution of Eq. (10) can be obtained in the form

$$\tilde{\theta}_k = (H^T H + \lambda^2 H^T D_d H)^{-1} H^T z$$

(11)

$$\hat{z}_{\text{trend}} = H\tilde{\theta}_k$$

(12)

where $\hat{z}_{\text{trend}}$ is the estimated trend that must be removed. To select the observation matrix $H$, a trivial choice of identity matrix $H = I \in \mathbb{R}^{(N-1) \times (N-1)}$ can be used. To solve the regularization part of Eq. (10), an optimal $D_d$ regularization matrix can be selected. The second order difference matrix $D_2 \in \mathbb{R}^{(N-3) \times (N-1)}$ is proposed as a good choice for estimating the aperiodic trend of the RR series. According to the method of smoothness priors, the detrended nearly stationary RR series can be written as

$$\hat{z}_{\text{stat}} = z - H\tilde{\theta}_k = (I - (I + \lambda^2 D_1 D_2)^{-1}) z.$$  

(13)

4. Spectral methods

Spectral methods are used to describe how the power of a time series is distributed with frequency.

4.1. Nonparametric methods

4.1.1. Periodograms

The periodogram is the Fourier transform of the autocorrelation sequence and can be determined as [22]

$$P_s(e^{jw}) = \sum_{k=-\infty}^{\infty} r_s(k)e^{-jkw}$$

(14)

where $r_s(k)$ is the autocorrelation sequence, which may be written as the time average

$$r_s(k) = \lim_{N \to \infty} \frac{1}{2N+1} \sum_{n=-N}^{N} x(n+k)x^*(n)$$

(15)

where * (for Rev. 1) represents the complex conjugate. When $x(n)$ in Eq. (15) is only measured over a finite interval, the autocorrelation sequence can be estimated with a finite sum

$$f_s(k) = \frac{1}{N} \sum_{n=0}^{N-1} x(n+k)x^*(n)$$

(16)

where $n = 0, 1, ..., N - 1$ is the discrete time index. Then, the periodogram is calculated by taking the discrete time Fourier transform of $f_s(k)$.

$$P_{\text{per}}(e^{jw}) = \sum_{k=-N+1}^{N-1} f_s(k)e^{-jkw}$$

(17)

Eq. (17) may be more convenient to use when written in terms of the $x(n)$. Consider the signal $x_N(n)$ of finite length $N$:

$$x_N(n) = \begin{cases} x(n) & 0 \leq n < N \\ 0 & \text{otherwise} \end{cases}$$

(18)

The estimated autocorrelation sequence may be written as

$$f_s(k) = \frac{1}{N} \sum_{n=-\infty}^{\infty} x_N(n+k)x_N^*(-k) = \frac{1}{N} x_N(k)x_N^*(-k)$$

(19)

Finally, the periodogram, an estimate of the power spectrum, may be calculated by taking the Fourier transform and applying the convolution theorem as

$$P_{\text{per}}(e^{jw}) = \frac{1}{N} X_N(e^{jw})X_N^*(e^{jw}) = \frac{1}{N} |X_N(e^{jw})|^2$$

(20)

where $X_N(e^{jw})$ is the discrete time Fourier transform of the $N$ point data sequence $x_N(n)$

$$X_N(e^{jw}) = \sum_{n=-\infty}^{\infty} x(n)e^{-jnw} = \sum_{n=0}^{N-1} x(n)e^{-jnw}$$

(21)

4.1.2. Welch’s periodogram

Welch’s method is an averaging modified periodogram to estimate the power spectrum [25]. This method splits the time series into overlapping segments, and window, and calculates the periodogram for each window separately. Averaging the resulting periodograms, the Welch periodogram is calculated. Data segments are given as

$$x_i(n) = x(n + i\delta) \quad n = 0, 1, \ldots, M - 1 \quad i = 0, 1, \ldots, L - 1$$

(22)

where $\delta$ is the starting point for the $i$th sequence, $M$ is the length of the segments and $n$ is the index of the segments. The windowed data segments are

$$P_{\text{w}}(e^{jw}) = \frac{1}{M} \sum_{n=0}^{M-1} x_i(n)w(n)e^{-j2\pi fn}$$

(23)

where $U$ is a normalization factor for the power of the window function $w$ and may be found

$$U = \frac{1}{M} \sum_{n=0}^{M-1} w^2(n)$$

(24)

The Welch’s power spectrum is formulated from the average of these modified periodograms as [26]

$$P_{\text{w}}(e^{jw}) = \frac{1}{L} \sum_{i=0}^{L-1} P_{\text{w}}(e^{jw})$$

(25)

4.2. Parametric methods

Fourier transform based non-parametric spectral analysis methods have some limitations such as poor frequency resolution and spectral leakage due to windowing [27]. Parametric analysis methods manage to overcome these limitations of the Fourier transform, by estimating the parameters of a chosen signal model. Autoregressive (AR) methods are the most widely used parametric methods for power spectral estimation.

4.2.1. Burg method

Burg’s method [28] estimates the AR model coefficients to obtain the power spectrum. The Burg method finds model parameters that minimize the forward and backward prediction errors. These prediction errors for a $p$-th (for Rev. 2) order model are defined as

$$\hat{\epsilon}_{b,p}(n) = x(n) - \sum_{i=1}^{p} \hat{\alpha}_p^* x(n-p+i)$$

(26)

$$\hat{\epsilon}_{f,p}(n) = x(n) - \sum_{i=1}^{p} \hat{\alpha}_p x(n-i)$$

(27)

The AR parameters $\hat{\alpha}_p$ can be written by reflection coefficient $\hat{k}_p$.

$$\hat{\alpha}_{p,i} = \begin{cases} \hat{\alpha}_{p-1,i} + \hat{k}_p \hat{\alpha}^*_{p-1,i} & i = 1, \ldots, p - 1 \\ \hat{k}_p, & i = p \end{cases}$$

(28)

The estimation of reflection coefficient is given by

$$\hat{k}_p = \frac{-2 \sum_{i=1}^{p} \hat{\epsilon}_{f,p-1}(n)\hat{\epsilon}_{b,p-1}(n-i)}{\sum_{i=1}^{p} |\hat{\epsilon}_{f,p-1}(n)|^2 + |\hat{\epsilon}_{b,p-1}(n-1)|^2}$$

(29)
The prediction errors meet the following recursive expressions

\[ \hat{\epsilon}_{f,p}(n) = \hat{\epsilon}_{f,p-1}(n) + \hat{\lambda}_p \hat{\epsilon}_{b,p-1}(n-1), \]  
\[ \hat{\epsilon}_{b,p}(n) = \hat{\epsilon}_{b,p-1}(n-1) + \hat{\lambda}_p \hat{\epsilon}_{f,p-1}(n) \]  

These prediction expressions are used to generate a recursive-in-order algorithm for estimating the AR coefficients. The PSD estimate can thus be found as [26]

\[ p_{xx}(f) = \frac{\hat{\epsilon}_p}{|1 + \sum_{k=1}^{p} \hat{\lambda}_p(k)e^{-j2\pi fk}|^2} \]  

where \( \hat{\epsilon}_p \) is the total least-squares error, \( p \) is the model order and \( \hat{\lambda}_p(k) \) are estimates of the AR parameters.

5. Results

The goal of this study is to assess the effects of preprocessing of HRV in spectral estimations. Therefore, the effects of filtering and detrending in spectral estimation of PPG signals are investigated. PPG data are analyzed using MATLAB 7.6® software. The PPG signal was first filtered using Butterworth and Myriad filters, separately. The effects of a linear Butterworth low-pass filter of the 8th order (cutoff – 8 Hz) and a weighted Myriad filter on a sample PPG signal are shown in Fig. 1. The 8th order Butterworth filter is generally recommended in the literature [7,13].

A min–max detection algorithm developed by the authors was implemented in MATLAB to identify the peaks and determine the intervals between them. Thus, systolic peaks of the PPG signal were detected (Fig. 2). Fig. 2 shows the peaks of the Butterworth low-pass filtered PPG signal. Using this min–max detection algorithm, peak intervals obtained from the PPG signal were used to obtain tachograms in which the beat intervals are plotted against beat number. For spectral analysis, the x-axis indicating beat number must be converted to time using

\[ t(k) = PP(k) + t(k-1) \]  

where \( t \) is time, \( PP \) is the peak-to-peak interval and \( k \) is the number of beats. Then, the obtained data were interpolated to obtain a regularly sampled series with sampling rate of 4 Hz. To remove the quasi DC signal that corresponds to changes in venous pressure [7] in the waveform, a detrending approach based on smoothness prior method (SPM) was applied to the resampled data. The regularization parameter was chosen as \( \lambda = 200 \) based on the results of a previous study [4]. To deduce the effects of this method for detrending, a second method based on the MATLAB detrend function was applied to the resampled data. The effects of the two detrending methods on the PPG signal tachogram are shown in Fig. 3.

To compare the effects of these two detrending methods on a variety of spectral analysis methods, the periodogram, Welch’s periodogram and Burg’s method were used in this study. Each spectrum is limited to 2 Hz to enable the comparison of the spectra before and after detrending with the detrend function and SPM. The default rectangular window function was used for PPG signal in periodogram analysis. Spectral analysis results using periodograms of the Butterworth low-pass filtered PPG signal and the weighted Myriad filtered PPG signal are given in Figs. 4 and 5. No significant differences for each frequency were found in both figures. Results showed that the periodogram-based PSD decreases at all frequencies of both detrended PPG signals. However, there are more ripples in detrended and spectral analyzed PPG signals because of spectral leakage in periodogram technique.

The Welch’s periodogram of the low-pass Butterworth filtered PPG signal is calculated using a Hamming window length of 32 and 50% overlap (Fig. 6). The Welch PSD of both detrended sig-

![Fig. 1. The raw, Butterworth filtered and weighted Myriad filtered PPG signal.](image1)

![Fig. 2. Detected peaks represented by circles from the Butterworth filtered PPG signal.](image2)

![Fig. 3. PPG tachogram, and detrended PPG tachogram with detrend function and smoothness prior method.](image3)
Fig. 4. Periodogram PSD analysis of PPG signals with and without trends (using the detrend function and SPM) after Butterworth filtering.

Fig. 5. Periodogram PSD analysis of PPG signals with and without trends (using the detrend function and SPM) after Myriad filtering.

Fig. 6. Welch PSD analysis of PPG signals with and without trends (using the detrend function and SPM) after Butterworth filtering.

Fig. 7. Welch PSD analysis of PPG signals with and without trends (using the detrend function and SPM) after Myriad filtering.
nals decreases nearly 40 dB between 0 and 0.5 Hz and the ripples between 0.5 and 2 Hz disappear. The Welch’s periodogram spectral analysis results of the weighted Myriad filtered PPG signal are shown in Fig. 7. While the Welch PSD of very low frequency components (0.01–0.04 Hz) decreased nearly 45 dB after detrending the Butterworth filtered PPG signal using the detrend function, the PSD over the same frequency range of the Myriad filtered PPG signal after detrending decreased even more.

The PSD results of Burg’s method are shown in Fig. 8 for the low-pass Butterworth filtered PPG signal and in Fig. 9 for the weighted Myriad filtered PPG signal. The order of the AR model in the Burg method was selected as \( p = 16 \) based on [4,29], using the Akaike information criteria [30]. Although the PSD of signal detrended with the `detrend` function decreased nearly 80 dB between 0 and 0.05 Hz, over the same frequency range, the PSD of the signal detrended with SPM decreased 90 dB, as shown in Fig. 8. At other frequencies, no difference was obtained. Fig. 9 shows the Burg PSD of the weighted Myriad filtered PPG signal. The Burg PSD of very low frequency components (0.01–0.04 Hz) decreased nearly 80 dB after both detrending with the `detrend` function and with SPM.

The average power of the Butterworth low-pass filtered and weighted Myriad filtered PPG signal without detrending, detrending via the `detrend` function, and detrending via smoothness priors for the varying periodogram approaches applied to 15 subjects are compared in Tables 1 and 2.

### Table 1
Average Butterworth filtered PPG signal powers for differing periodogram methods.

<table>
<thead>
<tr>
<th>Periodogram</th>
<th>With trend</th>
<th>Without trend via <code>detrend</code> function</th>
<th>Without trend via SPM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Periodogram</td>
<td>0.2207</td>
<td>0.0188</td>
<td>0.0007</td>
</tr>
<tr>
<td>Welch’s periodogram</td>
<td>2.53e−4</td>
<td>1.35e−4</td>
<td>1.28e−5</td>
</tr>
<tr>
<td>Burg’s periodogram</td>
<td>3.0e−4</td>
<td>1.28e−4</td>
<td>1.21e−5</td>
</tr>
</tbody>
</table>

### Table 2
Average weighted Myriad filtered PPG signal powers for differing periodogram methods.

<table>
<thead>
<tr>
<th>Periodogram</th>
<th>With trend</th>
<th>Without trend via <code>detrend</code> function</th>
<th>Without trend via SPM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Periodogram</td>
<td>0.3406</td>
<td>0.0073</td>
<td>0.0011</td>
</tr>
<tr>
<td>Welch’s periodogram</td>
<td>2.47e−4</td>
<td>1.42e−4</td>
<td>1.39e−5</td>
</tr>
<tr>
<td>Burg’s periodogram</td>
<td>2.57e−4</td>
<td>1.05e−4</td>
<td>1.02e−5</td>
</tr>
</tbody>
</table>

### 6. Conclusion

The purpose of this study is to investigate the effects of pre-processing (filtering and detrending) of PPG signals on different spectral estimation methods. To remove noise, a linear low-pass Butterworth filter and adaptively weighted Myriad filter were first separately applied to PPG data, then two different detrending methods (the MATLAB `detrend` function and smoothness prior method) were used to remove trends in the signal. The `detrend` function removes the linear component of a signal. It computes the least-squares fit of a straight line (or composite line for piecewise linear trends) to the data and subtracts the resulting function from the data [24]. The smoothness prior approach is also a simple method for detrending and operates like a time-varying FIR high-pass filter.

The effect of the two detrending methods on the PSD of the Butterworth filtered PPG signal calculated with a periodogram, Welch’s periodogram and Burg’s method is presented in Figs. 4, 6 and 8. According to the differences between detrended and original PPG data, the periodogram does not provide effective solution for each frequency band because of spectral leakage. The results of Welch periodogram are more successful than periodogram technique. For Welch’s periodogram, the PSD of the low frequency components decreases while the value at higher frequencies is not significantly
affected by detrending. For Burg’s method, the PSD of very low frequency components decreased more for both detrended signals.

Similarly, the periodogram-based PSD values of the Myriad filtered PPG signal decreased at all frequencies of both detrended signals, just as for the Butterworth filtered signal. The results of Welch’s and Burg’s periodogram of the Myriad filtered PPG signal also show a similar change with the Butterworth filtered signal pattern, such as the PSD of low frequency components decreasing after detrending.

The power reduction in very low frequency and low frequency bands after spectral analysis of detrended PPG signal can be evaluated as an important indicator of the dominant effects of trends in these frequency bands. This confirms the results of a previous study that examined the effects of trends on ECG based HRV data [4]. Moreover, the obtained power reduction values vary depending on applied spectral analysis technique and investigated frequency band, similarly to this previous study.

We found that the PSD of data detrended with the smoothness prior method decreased more in comparison to that of data detrended with the detrend function over the 0.01–0.15 Hz frequency band for both Welch’s and Burg’s periodogram applied to Butterworth and Myriad filtered signals. This frequency band consists of very low frequency and low frequency components of heart rate variability analysis. In comparing the results over the frequency range of 0.2–2 Hz in Tables 1 and 2, smoothness prior method detrending showed a greater decrease in average power for all periodogram approaches. This may be due to its success to removing trends, which is shown in Fig. 3. So, in our study, the smoothness prior detrending approach was found to be more successful at removing trends at low frequencies. No significant differences at each frequency were found between the PSD results of the linear Butterworth filtered and adaptively weighted Myriad filtered PPG signals. One possible explanation is that the parameters of the Myriad filters were selected without any optimization.

For future research in this subject, it may be useful to use an optimization algorithm for weight selection. In conclusion, the results showed that the spectral analysis of HRV signals are affected by the trends and thus the trends must be removed prior to HRV analysis.

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