An advanced detrending method with application to HRV analysis

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Abstract— **An advanced, simple to use, detrending method to be used before heart rate variability analysis (HRV) is presented. The method is based on smoothness priors approach and operates like a time-varying FIR high pass filter. The effect of the detrending on time and frequency domain analysis of HRV is studied.**

Keywords— **Heart rate variability, smoothness priors, signal detrending, spectral analysis.**

I. Introduction

Heart rate variability (HRV) is a widely used quantitative marker of autonomic nervous system activity. Various time and frequency domain methods have been applied to HRV analysis [1]. A traditional spectral method, power spectral density (PSD) estimation, provides information about power distribution as a function of frequency. Spectral estimation inherently assumes that the signal is at least weakly stationary. However real HRV is usually nonstationary. Nonstationarities like slow linear or more complex trends in the HRV signal, can cause distortion to time and frequency domain analysis. Origins for nonstationarities in HRV are discussed e.g. in [2].

Two kinds of methods have been used to get around the nonstationarity problem. Weber et al. [3] suggested that HRV data should be systematically tested for nonstationarities and that only stationary segments should be analyzed. Representativeness of these segments in some cases, in comparison with the whole HRV signal, was however questioned in [4]. Other methods try to remove the slow nonstationary trends from the HRV signal before analysis. The detrending is usually based on first order [5], [6] or higher order polynomial [7], [6] models.

In this paper we present an advanced detrending procedure based on smoothness priors approach. The presented method is simple to use, since the frequency response can be adjusted adequately to different situations by a single parameter. The properties of the method are tested by applying it to real RR interval data and the effect of the method on time and frequency domain analysis of HRV is considered.

II. Methods

A. Data acquisition

ECG was recorded continuously (NeuroScan$^{\mathrm{TM}}$ by NeuroSoft Inc.) during a passive event related potential paradigm, where subject sat in a chair while auditory pitch stimuli were delivered to right ear. Sampling rate of the ECG was 500 Hz. Discrete event series, $\mathrm{R}_i - \mathrm{R}_{i-1}$ intervals as a function of R_i occurrence times, was constructed by an adaptive QRS detector algorithm. The QRS detector was based on the one presented in [8]. As a result of the detection algorithm an unevenly sampled RR interval time series was obtained. In order to recover an evenly sampled signal from the irregularly sampled event series cubic interpolation was applied.

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B. Detrending with smoothness priors method

We denote the RR interval time series as

$$z = (\mathrm{R}_2 - \mathrm{R}_1, \mathrm{R}_3 - \mathrm{R}_2, \ldots, \mathrm{R}_N - \mathrm{R}_{N-1})^T \quad \in \mathbb{R}^{N-1} \quad (1)$$

where N is the number of R peaks detected. The RR series can be considered to consist of two components

$$z = z_{\mathrm{stat}} + z_{\mathrm{trend}} \quad (2)$$

where z_{stat} is the nearly stationary RR series of interest and z_{trend} is the low frequency aperiodic trend component. The trend component can be modeled with a linear observation model as

$$z_{\mathrm{trend}} = H\theta + v \quad (3)$$

where $H \in \mathbb{R}^{(N-1)\times M}$ is the observation matrix, $\theta \in \mathbb{R}^M$ are the regression parameters and v is the observation error. The task is then to estimate the parameters by some fitting procedure so that the prediction $\hat{z}_{\mathrm{trend}} = H\hat{\theta}$ can be used as the estimate of the trend. The properties of the estimate depend strongly on the properties of the basis vectors (columns of the matrix H) in the fitting. Widely used method for the solution of the estimate $\hat{\theta}$ is the least squares method. We use however a more general approach for the estimation of $\hat{\theta}$. We state the so called regularized least squares solution

$$\hat{\theta}_\lambda = \arg\min_\theta \left\{ \|H\theta - z\|^2 + \lambda^2 \|D_d(H\theta)\|^2 \right\} \quad (4)$$

where λ is the regularization parameter and D_d indicates the discrete approximation of the d'th derivative operator. This is clearly a modification of the ordinary least squares solution to the direction in which the side norm $\|D_d(H\theta)\|$ gets smaller. In this way we can implement prior information about the predicted trend $H\theta$ to the estimation. The solution of equation (4) can be written in the form

$$\hat{\theta}_\lambda = \left(H^T H + \lambda^2 H^T D_d^T D_d H\right)^{-1} H^T z \quad (5)$$

$$\hat{z}_{\mathrm{trend}} = H\hat{\theta}_\lambda \quad (6)$$

where $\hat{z}_{\mathrm{trend}}$ is the estimated trend which we want to remove. A detailed derivation of the result can be found in [10].

The selection of the observation matrix H can be implemented according to some known properties of the data z. For example a generic set of Gaussian shaped functions or sigmoids can be used. However, we want to avoid the problems arising from the basis selection and in this paper we

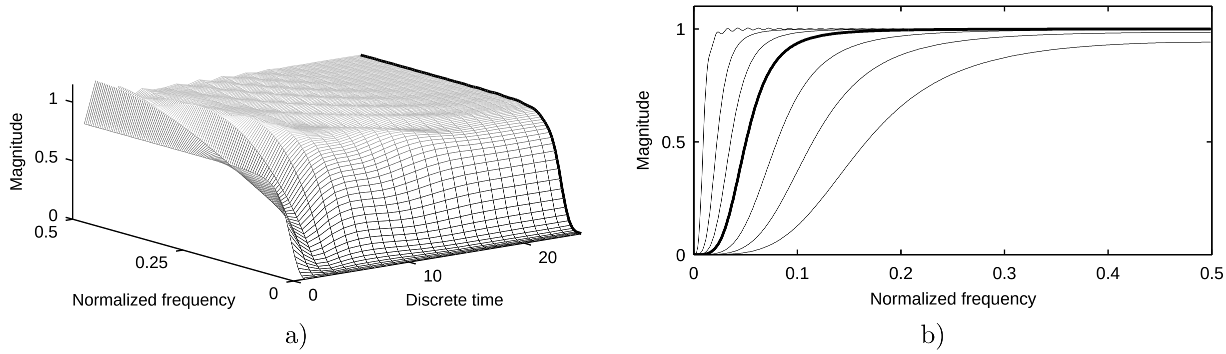


Fig. 1. a) Time-varying frequency response of $\mathcal{L}$ ($N-1=50$ and $\lambda=10$). Only the first half of the frequency response is presented, since the other half is identical. b) Frequency responses, obtained from the middle row of $\mathcal{L}$ (cf. bold lines), for $\lambda = 1$, 2, 4, 10, 20, 50 and 300. The corresponding cut-off frequencies are 0.189, 0.132, 0.093, 0.059, 0.041, 0.025 and 0.011 times the sampling frequency.

use the trivial choice of identity matrix for the observation matrix $H = I \in \mathbb{R}^{(N-1)\times(N-1)}$. The regularization part of (4) can be understood to draw the solution towards the null space of the regularization matrix D_d. The null space of the second order difference matrix contains all first order curves and thus D_2 is a good choice for estimating the aperiodic trend of RR series. The second order difference matrix $D_2 \in \mathbb{R}^{(N-3)\times(N-1)}$ is of the form

$$D_2 = \begin{pmatrix} 1 & -2 & 1 & 0 & \cdots & 0 \\ 0 & 1 & -2 & 1 & \ddots & \vdots \\ \vdots & \ddots & \ddots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & 1 & -2 & 1 \end{pmatrix} \tag{7}$$

With these specific choices the method is called the smoothness priors method [11] and the detrended nearly stationary RR series can be written as

$$\hat{z}_{\text{stat}} = z - H\hat{\theta}_\lambda = \left(I - (I + \lambda^2 D_2^T D_2)^{-1}\right) z \tag{8}$$

C. PSD estimation

Methods for PSD estimation can be classified as nonparametric (e.g. methods based on FFT) and parametric (methods based on e.g. autoregressive (AR) time series modeling). In the latter approach the RR time series is modeled as an AR(p) process

$$z_t = -\sum_{j=1}^{p} a_j z_{t-j} + e_t, \quad t = p+1, \ldots, N-1 \tag{9}$$

where p is the model order, a_j are the AR coefficients and e_t is the noise term. A modified covariance method is used to solve the AR model. The power spectrum estimate P_z is then calculated as

$$P_z(\omega) = \frac{\sigma^2}{|1 + \sum_{j=1}^{p} a_j e^{-i\omega j}|^2} \tag{10}$$

where σ^2 is the variance of the prediction error of the model. [12]

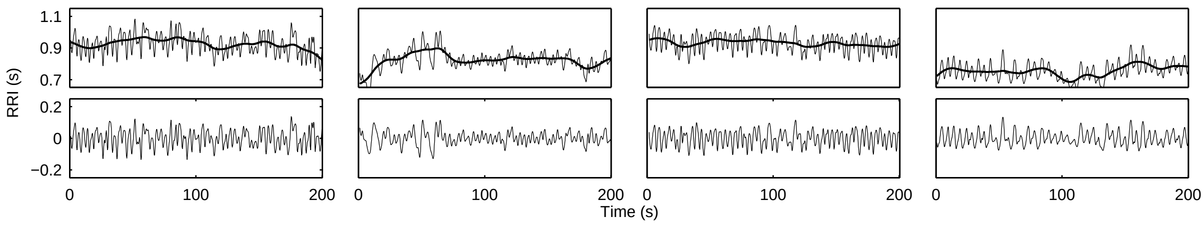
III. Results

In order to demonstrate the properties of the proposed detrending method, we first consider it's frequency response. Equation (8) can be written as $\hat{z}_{\text{stat}} = \mathcal{L}z$, where $\mathcal{L} = I - (I + \lambda^2 D_2^T D_2)^{-1}$ corresponds to a time-varying FIR high pass filter. The frequency response of $\mathcal{L}$ for each discrete time point, obtained as a Fourier transform of it's rows, is presented in Fig. 1 a). It can be seen that the filter is mostly constant, but the beginning and end of the signal are handled differently. The filtering effect is attenuated for the first and last elements of z, and thus the distortion of end points of data is avoided. The effect of the smoothing parameter λ on the frequency response of the filter is presented in Fig. 1 b). The cut-off frequency of the filter decreases when λ is increased. Besides the λ parameter the frequency response naturally depends on the sampling rate of signal z.

The performance of the presented method on real RR interval time series data is presented in Fig. 2, where it is applied to RR data of four different subjects. Each RR series was first interpolated to obtain a regularly sampled series with sampling rate of 4 Hz. The detrending was then performed using a smoothing parameter $\lambda = 300$, which equals a cut-off frequency of 0.043 Hz. The four RR series with the fitted trends and the corresponding detrended series are presented in Fig. 2 a). Three different time domain parameters, recommended in [1], were selected to demonstrate the effect of the used detrending method on time domain analysis (Fig. 2 b)). These were the standard deviation of all RR intervals (SDNN), the square root of the mean squared differences of successive RR intervals (RMSSD) and the relative amount of successive RR intervals differing more than 50 ms (pNN50).

The effect of the presented detrending method on the PSD estimates calculated with Welch's periodogram method and by AR modeling is presented in Fig. 2 c). AR model order $p = 16$ was selected according to [1], by using the corrected Akaike information criteria [13]. In each original PSD estimate the intensity of the very low frequency (VLF) component is clearly stronger than the intensity of low frequency (LF) or high frequency (HF) com-

a) **Original and detrended RR series**



b) **Time domain analysis**

	SDNN (ms)	RMSSD (ms)	pNN50 (%)	SDNN (ms)	RMSSD (ms)	pNN50 (%)	SDNN (ms)	RMSSD (ms)	pNN50 (%)	SDNN (ms)	RMSSD (ms)	pNN50 (%)
Original	63.62	72.40	53.00	60.96	37.34	16.80	53.01	62.72	53.95	52.93	37.48	17.29
Detrended	55.54	72.10	52.07	41.42	36.98	15.98	49.15	62.51	54.42	41.90	37.21	16.92

c) **Frequency domain analysis**

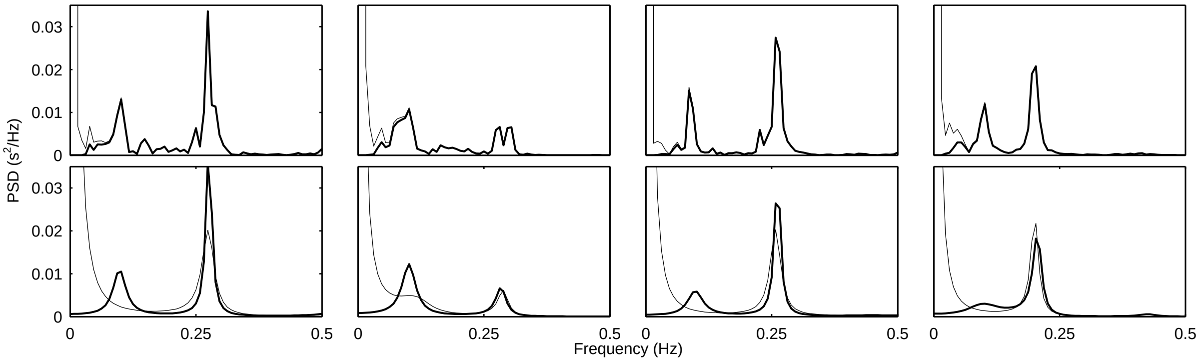


Fig. 2. The effect of the detrending method on time and frequency domain analysis. a) Original RR series and fitted trends (above) and detrended RR series (below) for four different data segments. The duration of each data segment is 200 seconds and they were obtained from different subjects. b) The effect of the detrending procedure on three time domain parameters (SDNN, RMSSD and pNN50). c) PSD estimates for original (thin line) and detrended (bold line) RR series with Welch's periodogram method (above) and by using a 16'th order AR model (below).

ponent. Each spectrum is however limited to 0.035 s^2/Hz to enable the comparison of the spectrums before and after detrending. For Welch's method the VLF components are properly removed while the higher frequencies are not significantly altered by the detrending. But when AR models of relatively low orders are used, which is usually desirable in HRV analysis in order to enable a distinct division of the spectrum into VLF, LF and HF components, the effect of detrending is remarkable. In each original AR spectrum the peak around 0.1 Hz is spuriously covered by the strong VLF component. However in the AR spectrums obtained after detrending the component near 0.1 Hz is more realistic when compared to the spectrums obtained by Welch's method.

IV. Discussion

We have presented an advanced detrending method with application to HRV analysis. The method is based on smoothness priors formulation. The main advantage of the method, compared to methods presented in [7], [5], is its simplicity. The frequency response of the method is adjusted with a single parameter. This smoothing parameter λ should be selected in such a way that the spectral components of interest are not significantly affected by the detrending. Another advantage of the presented method is that the filtering effect is attenuated in the beginning and the end of the data and thus the distortion of data end points is avoided.

The effect of detrending on time and frequency domain analysis of HRV was demonstrated. In time domain most effect is focused on SDNN, which describes the amount of overall variance of RR series. Instead only little effect is focused on RMSSD and pNN50 which both describe the differences in successive RR intervals. In frequency domain the low frequency trend components increase the power of VLF component. Thus, when using relatively low order AR models in spectrum estimation detrending is especially recommended, since the strong VLF component distorts other components, especially the LF component, of the spectrum.

The presented detrending method can be applied to e.g. respiratory sinus arrhythmia (RSA) quantification. RSA component is separated from other frequency components of HRV by adjusting the smoothing parameter λ properly. For other purposes of HRV analysis one should make sure that the detrending does not lose any useful information from the lower frequency components. Finally, it should be emphasized that the presented detrending method is not restricted to HRV analysis only, but can be applied as well to other biomedical signals e.g. for detrending of EEG signals in quantitative EEG analysis.

Appendix

All the computation of this paper are executed using MATLAB® 6 of The MathWorks Inc. The source code, in all its simplicity, for applying the presented detrending method to signal z is listed below.

```
T = length(z);
lambda = 10;
I = speye(T);
D2 = spdiags(ones(T-2,1)*[1 -2 1],[0:2],T-2,T);
z_stat = (I-inv(I+lambda^2*D2'*D2))*z;
```

For more information see

http://venda.uku.fi/research/biosignals

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