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# Bioelectric signal detrending using smoothness prior approach

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ABSTRACT

Bioelectric signals such as electromyogram (EMG) and electrocardiogram (ECG) are often affected by various low-frequency trending interferences. It is critical to remove these interferences from the recordings so that the critical features of the bioelectric signals could be clearly observed. In this study, an advanced method based on smoothness prior approach (SPA) was proposed to solve this problem. EMG and ECG signals from both the MIT-BIH database and the experiments were employed to evaluate the detrending performance of the proposed method. For comparison purposes, a conventional high-pass Butterworth filter was also used for the detrending of the EMG and ECG signals. Two numerical measures, the correlation coefficient (CC) and root mean square error (RMSE) between the clean data and the detrended data, were calculated to evaluate the detrending performance. The results showed that the proposed SPA method outperformed the high-pass filtering method in reducing various kinds of trending interferences and preserving the desired frequency contents of the EMG and ECG signals. The study suggested that the SPA method might be a promising approach in detrending bioelectric signals.



## 1. Introduction

Bioelectric signals played an important role in the diagnoses and treatments of various diseases in clinical applications and practices. The surface electromyogram (EMG) is measured on mobile limbs and could provide information about the physiological and biomechanical states of the muscles [1]. EMG signals have been utilized in many fields such as clinical diagnosis and therapy, evaluation of neuromuscular disorders [2] and myoelectric control of artificial limbs [3]. Meanwhile, electrocardiogram (ECG) recorded on the chest is a clinical routine for the diagnosis of various cardiovascular diseases and the evaluation of heart working states. However, these bioelectric signal recordings are often contaminated by low-frequency interferences that would cause the baseline trending of the recorded signals. The surface EMG signals are often affected by the baseline wanders introduced by the undesired movements of limbs and contact alteration of the electrodes. In ECG recordings, the signals may also be contaminated by various low frequency noises such as breathing, sweating, and electrode motion and even the slow activities of the muscles. These low-frequency interferences (or trending) in EMG or ECG recordings can often have significant impacts on the signal interpretations [4,5]. Therefore, the detrendings of the EMG or ECG recordings are always desirable so that the features of these bioelectric signals could be clearly determined to improve the reliability of the diagnoses in clinical applications.

Although some trending noises may be reduced by careful skin preparation and common-mode amplification [6], it is impossible to remove all the trending interferences in real-time applications. Therefore, appropriate signal processing algorithms are necessary for a clean bioelectric signal. Several filtering methods have been used to reduce the trending effects on EMG and ECG signal recordings [7–13]. The most common approach may be high-pass filtering in which the low-frequency trendings are prevented from passing through the filter [7,8]. However, the spectral features of the trendings should be precisely known in advance for a proper cutoff frequency. Another detrending approach is called empirical mode decomposition (EMD) that is a logical choice algorithm for extracting trends from a data set [9]. However, the EMD method lacks a sound mathematical theory, and the selection of modes is highly data-dependent [10]. Moreover, the wavelet transform (WT) method has been proposed for ECG signal detrending and showed some comparatively encouraging results in reducing

*Abbreviations:* BW, baseline wander; EM, electrode motion; CC, correlation coefficient; RMS, root mean square.

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the heart rate variability [11]. However, the computational complexity of WT method may limit its application in most clinical practices.

Recently, a method based on smoothness prior approach (SPA) was proposed to detrend the heart-rate variability [14]. The key feature of the SPA method is that it acts like a time-varying high-pass filter and only one parameter is required, making it easier to use in clinical applications. However, whether the SPA method is appropriate for detrendings of bioelectric recordings remains unclear.

In this paper, we used the SPA method to detrend bioelectric signals including EMG and ECG. The feasibility and performance of the SPA method in removing the low-frequency trending interferences were systemically evaluated by using data from both the MIT-BIH database and the hand-motion experiments. A conventional Butterworth high-pass filter was also employed to examine whether the performance of the SPA method is superior to conventional methods in bioelectric signal detrendings.

## 2. Materials and methods

### 2.1. Signal preparation

#### 2.1.1. EMG data with trendings

In order to perform EMG signal detrending, three healthy subjects were recruited in the study to participate the experiments of EMG signal acquisition. One self-adhesive bipolar EMG electrode was placed on the forearm over flexor digitorum superficialis and flexor digitorum profundus for EMG recordings. In the experiment, each subject was asked to perform closing hand for three seconds and then to relax for another three seconds. This procedure was repeated ten times with five times of maximal voluntary contraction (MVC) level and five times of constant force isometric contractions at 50% MVC level [15], resulting in one-minute EMG recordings per subject. The EMG signals were acquired with a sampling rate of 4 kHz using a commercial EMG recording system (*Delsys, EMGworks Signal Acquisition and Analysis Software*) [16]. The protocol of this study was approved by the Shenzhen Institutes of Advanced Technology Institutional Review Board, Chinese Academy of Sciences, China. All subjects gave the written informed consent and provided permission for the publication of photographs with a scientific and educational purpose.

The EMG recordings from three subjects were used as the original EMG recordings that were considered as trend-free signals or clean signals. For further validation, the EMG data of a 44-year-old man without history of neuromuscular disease from MIT-BIH database [17] were also included as clean signals in the study. Various possible trending interferences were added into these clean EMG data to mimic the trended EMG recordings. In the study, a ratio that reflects the energy between the trending interference and the clean EMG signals was used as a measure of how much trending interference was added into the clean EMG recordings. Statistically, the power of trending interference over the power of the clean EMG signals was defined as their standard deviation ratio. Three kinds of common trending interferences were considered as follows:

- **Baseline wander (BW)**. The baseline wander due to the respiration may be the most commonly met trend interference in surface EMG acquisition [4,5], especially acquiring EMG from chest muscles. This interference might be simulated by adding a low frequency sinusoid into the EMG recordings. With a maximum breathing rate usually ranging from 18 breaths per minute for adults to 30 breaths per minute for children, a 0.4-Hz (corresponding to 24 breaths per minute) sinusoid with a peak value of 1.0 mV was chosen as the BW signals. Since the power of the BW is usually less than that of the EMG signal in both the experimental data and MIT database, the simulated BW power was set at 100% of EMG power in this study.
- **Electrode motion (EM)**. In practical applications of EMG signals such as myoelectric prostheses, electrode shift on body surface due to mobile body and/or limb movements is a common issue that could cause an artifact trend in EMG recordings [4,5]. In the study, electrode motion was mimicked by moving the electrode along the target muscle within a short distance. To get pure electrode motion trending signals, the targeted muscle was relaxed without any voluntary contractions during signal recordings. The power of EM was set at 10% of active EMG power.
- **The combination of BW and EM**. A composite trending interference was the combination of the BW and EM trends as described previously. The power of composite interference was chosen as 50% of the EMG power.

#### 2.1.2. ECG data with trendings

The ECG data from the MIT-BIH Arrhythmia Database (*PhysioBank*) were adopted as clean signals to evaluate the detrending performance of the proposed SPA algorithm. The sampling frequency of the ECG data was 360 Hz. Three types of trending interferences typically observed in ECG recordings (the baseline wander, electrode motion, and EMG) were obtained from MIT-BIH Noise Stress Test Database (*PhysioBank*) [18]. These interferences were added into clean ECG data to simulate their effects on ECG recordings. The trending interferences considered in the study were as follows:

- **Baseline wander (BW)**. BW is mainly consisted of low-frequency signals caused by body motion and leads. The power of the simulated BW was set at 100% of the ECG power in this study.
- **Electrode motion (EM)**. The electrode motion was generally considered as the most troublesome, since it can mimic the pattern of ectopic beats and cannot be removed easily by simple filters. The power of EM was set at 50% of ECG power.
- **EMG**. In ECG recordings, the EMG signals produced by muscles would be in turn considered as the interference. The power of EMG was set at 50% of ECG power.
- **Composite of BW, EM, and EMG**. The composite noise was composed of the three types of trends mentioned above and its power was set at 100% of the ECG power.

### 2.2. Smoothness prior approach (SPA)

Bioelectrical signals could be presented with two general components: the stationary part (or quasi-stationary) $Z_{stationary}$ and the nonstationary part $Z_{trend}$:

$$Z = Z_{stationary} + Z_{trend} \tag{1}$$

The detrended signal, an estimate of $Z_{stationary}$, can be represented as [14]:

$$\hat{Z}_{stationary} = Z - H\hat{\theta}_{\lambda} = (I - (I + \lambda^2 D_2^T D_2)^{-1})Z \tag{2}$$

where $H$ is the observation matrix, $\hat{\theta}_{\lambda}$ is the estimate of the regression parameters by the regularized least squares method, $\lambda$ is the regularization parameter, and $D_2$ is the second order difference matrix which indicates the discrete approximation of the 2nd derivative operator in the form of

$$\begin{bmatrix} 1 & -2 & 1 & 0 & \cdots & 0 \\ 0 & 1 & -2 & 1 & \ddots & \vdots \\ \vdots & \ddots & \ddots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & 1 & -2 & 1 \end{bmatrix} \tag{3}$$