A New Approach for Heart Rate Monitoring using Photoplethysmography Signals Contaminated by Motion Artifacts

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Introduction

We considered the problem of accurately estimating the heart rate (HR) using photoplethysmography (PPG) signals that are contaminated by motion artifacts (MA). A novel HR estimation approach based on GRid-less spectral Estimation and SVM-based peak Selection, denoted by GRESS, was proposed. It first obtained the sparse spectrum of PPG using a continuous dictionary, then a simple spectral subtraction step was adopted to remove MA, finally an SVM-based method was developed to select the spectral peak corresponding to HR. Experimental results on the PPG datasets used in 2015 IEEE Signal Processing Cup showed that the proposed approach had excellent performance.

Method

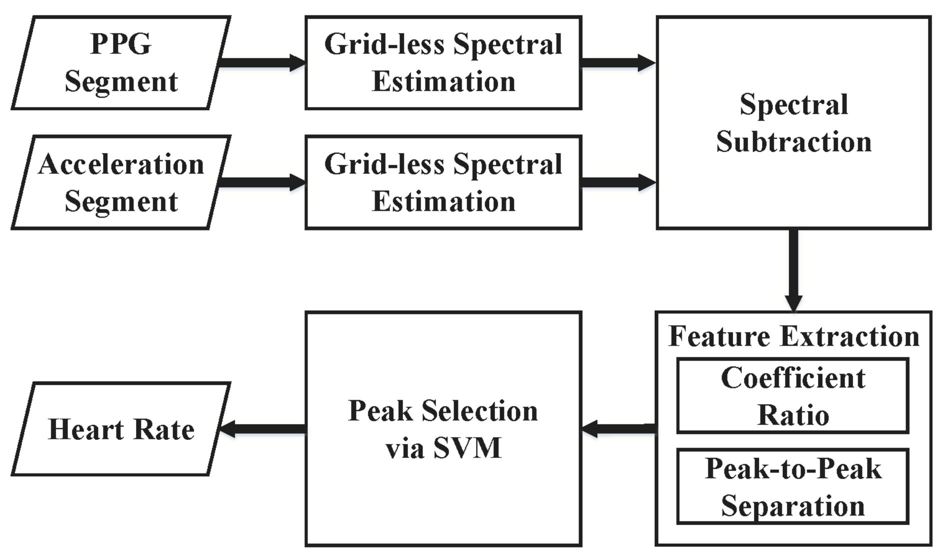

Figure 1: Flowchart of GRESS

Grid-less Spectral Estimation. The spectrum of PPG signal was assumed to be sparse, i.e., a segment of raw PPG signal $\boldsymbol{x} \in \mathbb{C}^{N\times 1}$ can be expressed as

$$\boldsymbol{x} = \sum_{k=1}^{K} c_k a(f_k) + \boldsymbol{e} = \boldsymbol{A}(\boldsymbol{f})\boldsymbol{c} + \boldsymbol{e}, \qquad (1)$$

then the noiseless PPG signal $\boldsymbol{z} = \boldsymbol{A}(\boldsymbol{f})\boldsymbol{c}$ can be estimated using the atomic norm soft thresholding (AST) method, which tried to solve the following optimization problem

$$\operatorname*{argmin}_{\boldsymbol{z}} \frac{1}{2}\|\boldsymbol{x}-\boldsymbol{z}\|_2^2 + \tau\|\boldsymbol{z}\|_{\mathcal{A}}, \qquad (2)$$

The above problem can be computed via semidefinite programming (SDP):

$$\operatorname*{argmin}_{t,\boldsymbol{u},\boldsymbol{z}} \frac{1}{2}\|\boldsymbol{x}-\boldsymbol{z}\|_2^2 + \frac{\tau}{2}(t+u_1), \text{ s.t. } \begin{bmatrix} t & \boldsymbol{z}^H \\ \boldsymbol{z} & T(\boldsymbol{u}) \end{bmatrix} \geq 0, \qquad (3)$$

where $\boldsymbol{u} \in \mathbb{C}^N$ and $T(\boldsymbol{u}) \in \mathbb{C}^{N\times N}$ denotes a (Hermitian) Toeplitz matrix. Given the optimal solution $(t^*, \boldsymbol{u}^*, \boldsymbol{z}^*)$, the frequency and coefficient estimates $\hat{\boldsymbol{f}}$ and $\hat{\boldsymbol{c}}$ can be obtained via Vandermonde decomposition of $T(\boldsymbol{u}^*)$,

$$T(\boldsymbol{u}^*) = \boldsymbol{A}\left(\hat{\boldsymbol{f}}, \hat{\boldsymbol{\phi}}\right) \cdot \operatorname{diag}\left(|\hat{\boldsymbol{c}}|\right) \cdot A^{\mathrm{H}}\left(\hat{\boldsymbol{f}}, \hat{\boldsymbol{\phi}}\right). \qquad (4)$$

SVM-based Spectral Peak Selection. We adopted Support Vector Machine (SVM) to build a decision boundary classifying true spectral peaks from false ones using the following 2 features:

- *coefficient ratio* of the i^{th} peak, defined as

$$R_i = \left|\frac{c_i}{c_{\max}^{\Omega}}\right|, \quad i = 1, \ldots, p, \quad R_i \in (0, 1], \qquad (5)$$

- *peak-to-peak separation* of the i^{th} peak, defined as

$$S_i = |f_i - f_{\text{pre}}|. \qquad (6)$$

Results

The PPG database was used for the 2015 IEEE Signal Processing Cup. It includes 12 training datasets and 10 test datasets. Each dataset consists of two channels of PPG signals, three channels of simultaneous acceleration signals, and one channel of simultaneous ECG signal. The PPG signals were recorded from subjects' wrist (dorsal locations) using PPG sensors built in a wristband. The acceleration signals were recorded using a tri-axis accelerometer also built in the wristband. All signals were sampled at 125 Hz.

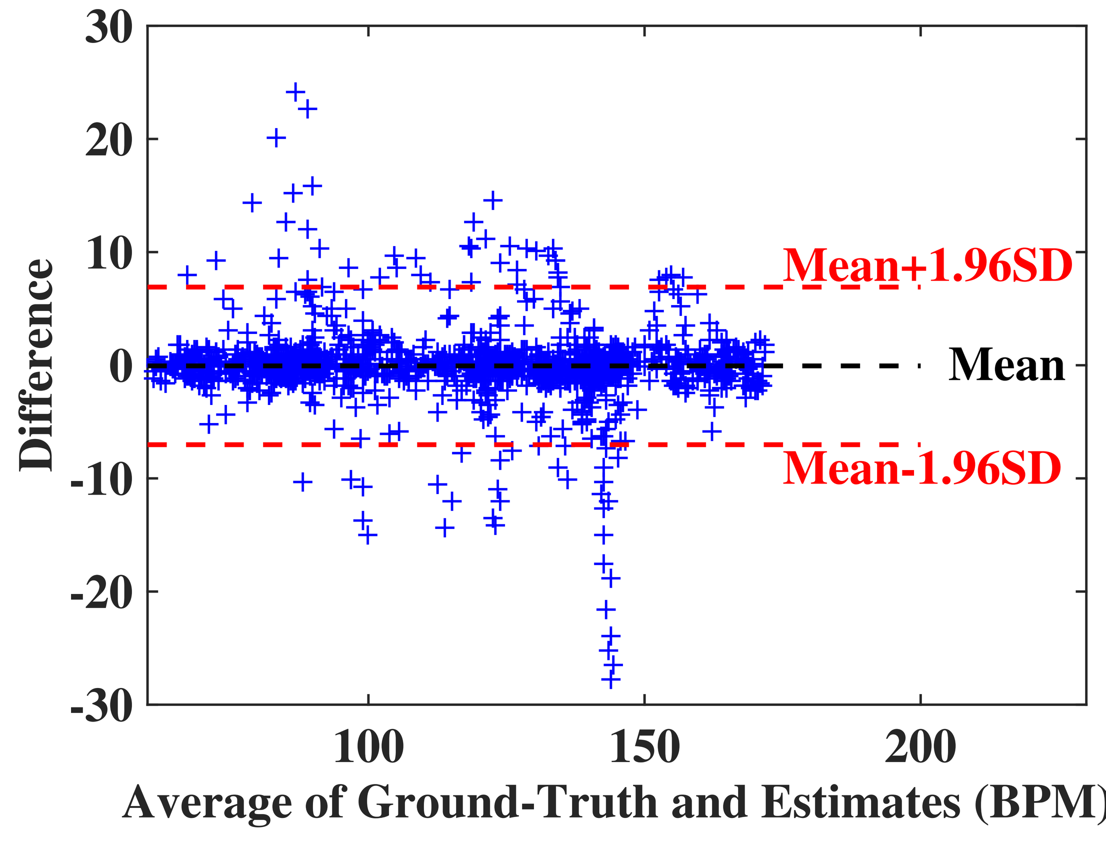

Figure 2: Bland-Altman plot of the estimation results

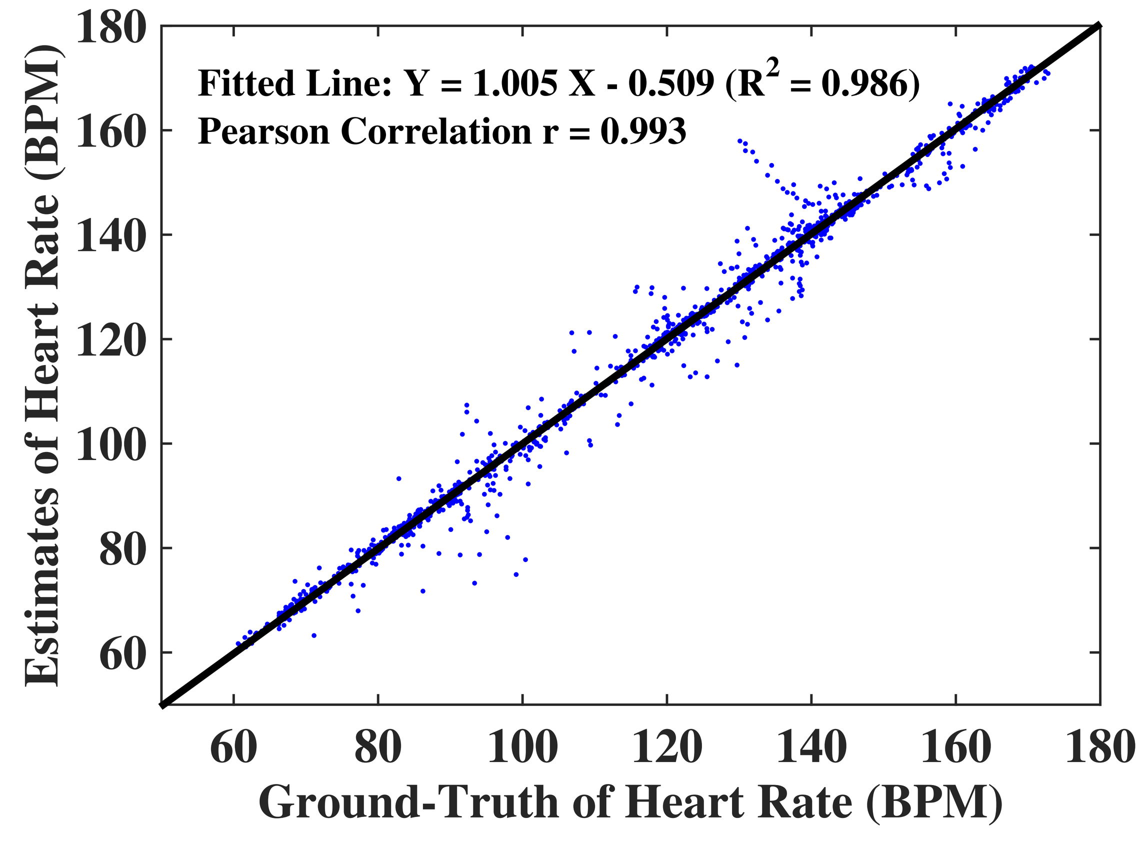

Figure 3: Scatter plot between the ground-truth heart rate values and the associated estimates

The Bland-Altman plot over all 22 datasets showed that the LOA was [-7.02, 6.90] BPM. The Scatter Plot between the ground-truth HR values and the associated estimates shows the fitted line was $Y = 1.005X - 0.509$, where X indicates the ground-truth heart rate value, and Y indicates the associated estimate. The Pearson coefficient was 0.993. The goodness of fit characterized by R^2 value was 0.986.

Averaged across the 10 test datasets, the average absolute error of GRESS was 1.78 ± 3.07 BPM, and the average absolute error percentage was $1.57\% \pm 2.71\%$. Note that these results were much better than that of the first place in the 2015 IEEE Signal Processing Cup, where the average absolute error (over the testing datasets) of the first three places in the Cup were 2.27 BPM, 3.26 BPM, and 3.44 BPM, respectively.

Conclusion

we have presented a new method termed GRESS for HR estimation using a wrist-type PPG during physical exercise which is based on the grid-less spectrum estimation and SVM-based peak selection. Experimental results proved the efficacy of GRESS for reliable and accurate estimation of heart rate.

References

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