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Spectral Fusion of Heartbeat and Accelerometer Data for Estimation of Breathing Rate in Wearable Patches

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> **Abstract.** Despite developments in wearable devices for detecting various biosignals, continuous measurement of breathing rate (BR) remains a challenge. This work presents an early proof of concept that employs a wearable patch to estimate BR. We propose combining techniques for calculating BR from electrocardiogram (ECG) and accelerometer (ACC) signals, while applying decision rules based on signal-to-noise (SNR) to fuse the estimates for improved accuracy.

> Keywords. seizures, epilepsy, monitoring, outpatient, electrocardiography, accelerometry, respiratory rate, wearable electronic device

1. Introduction

Chest-worn medical sensors are equipped with both ACC and ECG sensors. The efficacy of both modalities has been previously demonstrated for computing BR [1,2]. Nonetheless, low SNR may lead to imprecise calculation of BR in both cases. Combining estimates from ACC and ECG has shown promising results [3]. Our adaptation of the approach in [3] incorporates an improved BR estimation method from ACC data as in [2], derives spectral information from ACC and ECG signals, and utilizes an SNR-based decision rule for final BR estimation.

2. Methods

The presented data were collected using a wearable device at the RWTH Aachen University Hospital. One-minute recordings were obtained from a patient with epilepsy, during periods of movement and non-movement. BR was determined using respiratory

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sinus arrhythmia (RSA), which corresponds to the modulation of the time intervals between R peaks on ECG during respiration. To derive RSA, R-peaks were detected, and the intervals between them were computed. As in [1], three RSA waveforms were produced by applying three finite impulse response (FIR) bandpass filters of 0.1-0.6 Hz, 0.2-0.6 Hz, and 0.1-0.5 Hz, followed by FFT (Fast Fourier transform). The RSA waveform with a BR (at peak frequency) within 3 bpm of the previous 60-second window was selected. To estimate BR from ACC data, an adaptive line enhancer (ALE) based on least-mean-square (LMS) was initially applied. Following ALE, singular spectrum analysis (SSA) was performed. For each ACC axis, a trajectory matrix was created, followed by singular value decomposition (SVD) to extract two narrow-band signals [2]. Finally, if the mean signal-to-noise ratio (SNRm) of all analyzed signals was > 2dB, majority voting was applied, and the final BR was estimated using the mean BR of all signals except those with a difference in BR > λ (defined by the frequency resolution of FFT) to 40% of the other signals. For SNRm < 2dB, power voting was applied. Here, signals with low magnitude at the frequency of interest were filtered out based on whether the difference between themselves and the signal with the highest magnitude was greater than λ , and the final BR was computed using the mean BR of the remaining signals.

3. Results

The selection of the voting method for estimating BR was based on the SNRm values, which were 3 dB for non-movement segment and -15 dB for movement segment. Thus, majority voting was employed for the former, while power voting was employed for the latter. The resulting BR were 23.74 BPM and 16.5 BPM for the non-movement and movement segments, respectively.

4. Discussion

In this work we present a proof of concept for BR monitoring that builds on state-of-theart algorithms [1,2,3] but is also adapted to work with data from a specific wearable used for seizure detection in patients with epilepsy. By deriving BR from ACC and ECG data with differences not greater than a conservative threshold of 0.02 Hz, we provided a preliminary clue for the potential functionality of our method. To confirm this, our next step is to test and validate our approach on a larger cohort of patients.

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1026