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RESPIRATION RATE ESTIMATION FROM NOISY ELECTROCARDIOGRAMS BASED ON MODULATION SPECTRAL ANALYSIS

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ABSTRACT

This paper presents a novel method to estimate the respiration rate (RR) from a noisy electrocardiogram (ECG) signal. The method exploits the second order periodicity of the ECG signal, caused by the influence of respiration, and relies on the so-called modulation spectral signal representation to quantify RR from the noisy ECG. The methodology is validated on two datasets, one collected at rest using medical-grade sensors and another with users wearing an off-the-shelf smartshirt throughout their workday. The paper also explores the impact of ECG recording duration on RR estimation. Results show that ECG signal recordings of 120 seconds, or longer, lead to an adequate RR estimate with an error percentage ≤12.5%.

INTRODUCTION

Breathing or respiration rate (RR) is a valuable feature that assists in the evaluation of a person's health or even help diagnose certain diseases. Other representative examples include stress level monitoring and affective state recognition, to name a few [1] [2]. Despite its usability, RR measurement is not common for ambulatory recordings, as the methods often bring discomfort and disturbance to the user, as tools such as nasal sensors, microphones near the respiratory airways or, thorax-placed strain gauges need to be used [3]. Notwithstanding, other more practical ways to obtain RR exist and can be implemented via the analysis of other physiological signals, such as the electrocardiogram (ECG) and the photoplethysmogram (PPG). Such methods exploit the influence of the respiration process on the cardiac activity.

In the case of the ECG signal, the three major effects of respiratory influence are: (i) amplitude modulation (AM), where the amplitude of the ECG signal changes synchronously with respiration; this is most notorious in the QRS complex, (ii) baseline wander (BM), where respiration changes the baseline or isoelectric line in the ECG signal, and (iii) frequency modulation (FM), where the beat-to-beat interval decreases on inspiration and increases on expiration; this phenomenon is known as respiratory sinus arrhythmia (RSA) [4]. The AM and BW effects have their origin in the relative movement between the heart and the electrodes, at every breathing, which causes a displacement of the projection of the cardiac electrical vector and changes in the thoracic impedance [1]. From the analysis of these effects, many respiration estimation methods have been proposed. These methods range from the utilization of one-lead to multiple-lead ECG signal, with the latter not suitable for wearable applications. A review on ECG- and PPG-derived-respiration methods can be found in [5]. The analysis of the AM effect is commonly carried out by measuring the pulse peak-to-trough amplitude or by filtering out non-respiration components from the raw ECG signal [1].

In the last few years, the so-called modulation spectrogram has shown to be a relevant tool in the study of signals which present second-order periodicity as the result of an AM process [6]. Indeed, it has been argued that the presence of AM biological signals is a direct consequence of the processes of control, synchronization, regulation and inter-system interaction found in biological systems [7]. Representative examples of its utilization in biomedical signals include Alzheimer's disease diagnosis, heart and lung sound separation and ECG quality measurement and enhancement [8], [9], [10], [11].

In this paper, we explore the use of the modulation spectrogram as a tool for the estimation of the RR from potentially noisy ECG signals and test the proposed method across two datasets where the ground-of-truth respiration signal is recorded using traditional techniques. In addition, we analyze the impact of the duration of the ECG signal recordings om the RR estimate. The obtained results are encouraging and warrant further investigation.

METHODS AND MATERIALS

In this section we present the modulation spectrogram, describe the signal processing for the estimation of the RR from the raw ECG signal and, describe the datasets that were utilized for evaluation.

Modulation spectrogram

The spectrogram, $X(t,f)$, of a time signal $x(t)$ is a complex-valued spectro-temporal representation that provides amplitude and phase of a certain frequency component at a specific time instance. Such a representation is commonly obtained with methods such as short-time Fourier transform (STFT) or continuous wavelet transform (CWT). By applying an additional transform across time of this spectrogram, one obtains the so-called modulation spectrogram, $X(f,f_{mod})$, i.e.:

$$X(f,f_{mod}) = \Phi_t\{|X(t,f)|\}, \quad (1)$$

where $\Phi_t\{\}$ is the Fourier transform operator over the time dimension. As such, (1) can be regarded as the frequency representation of the amplitude time-series of each frequency component in the spectrogram, i.e. analyzing the second-order periodicity of $x(t)$. The block diagram of the signal processing steps involved in the computation of the modulation spectrogram can be seen in Fig 1. In this work we make use of the CWT to compute the spectrogram $X(t,f)$. The interested reader is referred to [6] and [12] for more details on the modulation spectrogram.

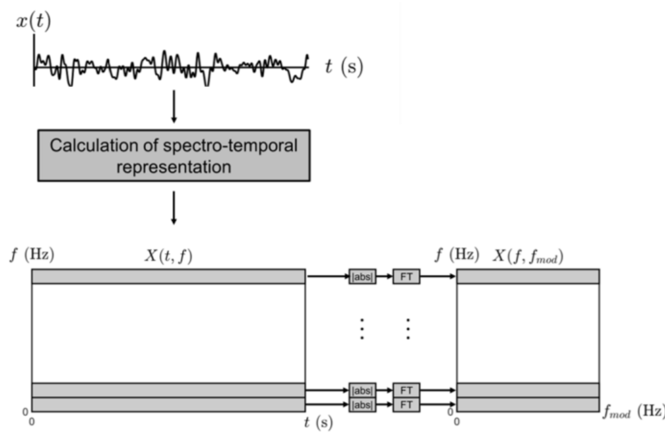

Figure 1: Signal processing steps for the modulation spectrogram calculation.

RR estimation signal processing pipeline

First, the ECG signal is bandpass filtered with zero-phase FIR filter with a bandwidth from 4 to 30 Hz to remove baseline wandering and preserve most spectral content of the QRS complex [13], [14] (see Fig. 2a). The corresponding modulation spectrogram is then obtained, as previously described, but now constrained to a range of feasible respiration rates i.e. 4 to 40 breaths per minute (i.e., 0.067 to 0.667 Hz, as per Fig. 2c). Next, the power modulation spectrogram is averaged across the conventional frequency axis to obtain the mean power spectrum density (PSD) of the effect of the respiration AM over the complex QRS. Finally, the estimated RR is obtained from the major spectral component in the resulting PSD, as shown in Fig 2d.

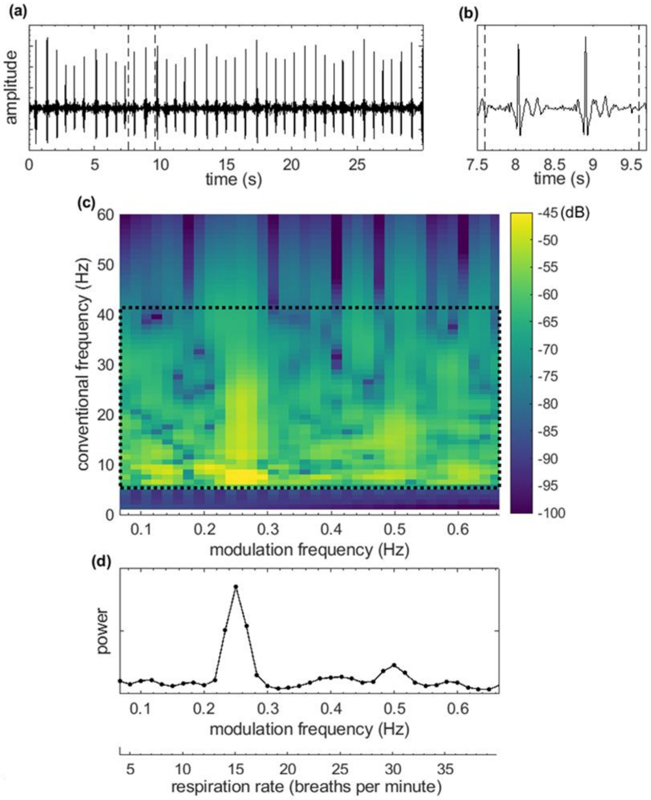

Figure 2: (a) Filtered ECG signal, (b) 2-second segment of filtered ECG, (c) corresponding power modulation spectrogram and, (d) average modulation PSD.

Experiment Setup

The proposed method for the RR estimation was evaluated on different 2 datasets.

Dataset A

With this database, lead-I ECG and respiration signals were simultaneously acquired during three scenarios, each lasting six minutes, for 7 participants in a resting sitting position. Two controlled breathing scenarios were used, namely, 15 and 36 breaths per minute, as well as one non-controlled normal respiration scenario. The RR ground-of-truth was obtained from the respiratory signal by measuring the air pressure changes in a balloon harnessed to the participant thorax. Participants consented to participate in the study and comprised students at ESIME Culhuacan, IPN. [15].

Dataset B

The second dataset is comprised of data collected from 11 participants as they wore a smartshirt (OMSignal, Montreal, Canada) equipped with textile ECG and a chest strain gauge to measure breathing parameters, such as RR, as well as a processing module equipped with a 3-axis accelerometer. The garment was set up to record several 15-second excerpts of raw ECG throughout the day as participants went about their daily work routine. Participants consented to participate in the study and comprised students, faculty, and staff at the University of Southern California (USC). The segments used herein are those deemed to be of usable quality based on the MS-QI quality index [9].

EXPERIMENTAL RESULTS AND DISCUSSION

Here, the experimental results are reported and discussed.

Dataset A

Estimates of RR were derived from 60 s ECG segments with an overlap of 30 s between consecutive windows, thus totaling 11 RR values per recording. Table 1 presents the error percentage between the proposed RR estimation method and the ground-of-truth measure, for each scenario

Table 1: RR estimation error

Scenario	***RR error (%)***
Non-controlled RR	14.8 %
Controlled RR (15 breaths per minute)	3.6 %
Controlled RR (36 breaths per minute)	14.9 %

The obtained low error percentage in the 15-breaths-per-minute scenario has its origin in the easy-to-maintain RR, which is reflected as a unique modulation spectral component (see Fig. 3b). In contrast, in the hard-to-maintain high RR (36-breaths-per-minute) scenario and the non-controlled RR scenario often multiple modulation spectral components of similar power are present leading to an inaccurate RR estimate (Fig. 3a).

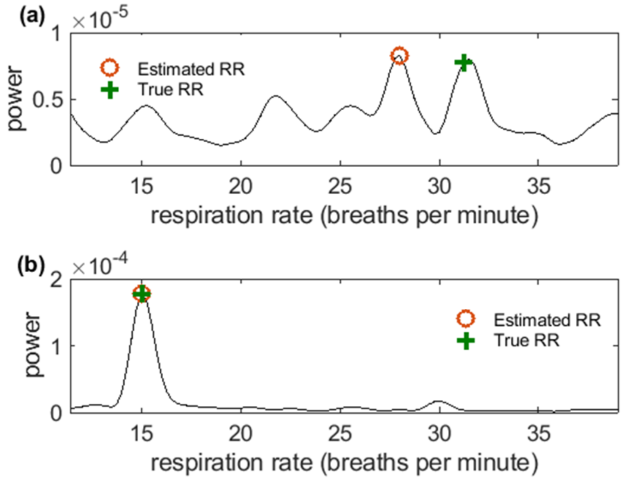

Figure 3: PSD of the AM effect of the respiration, estimated and true RR for (a) non-controlled and (b) 15-breaths-per-minute scenario.

Figure 4, in turn, presents a scatterplot of the estimated versus true RR values, as well as the obtained correlation for the no-controlled scenario.

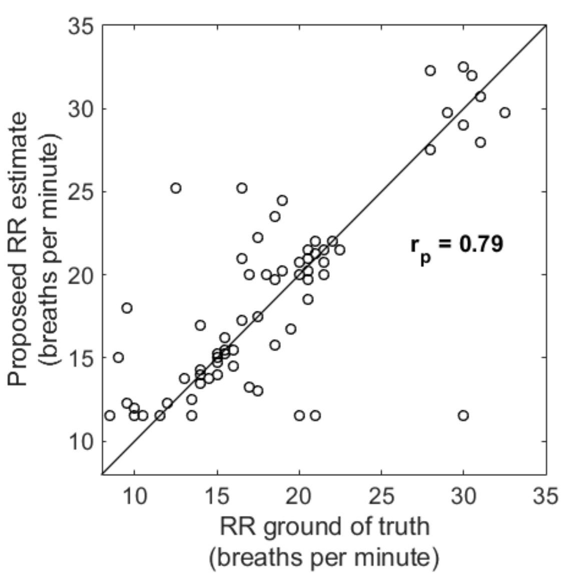

Figure 4: Scatterplot of estimated versus true RR for Dataset A, non-controlled RR scenario.

Dataset B

Here, a total of twelve 15-second ECG segments were analyzed per participant. As stated previously, these were randomly selected segments that met the "usable" criteria stipulated by the MS-QI ECG quality metric; segments were randomly sampled throughout the day's recordings. On this dataset, the overall estimation error percentage was 20.2%. Since the average ground truth RR was 20.05 breaths per minute, the obtained findings are inline with those obtained with Database A, thus suggesting that reliable estimates can be obtained with noisy data collected via portable devices and ambulant users.

Impact of ECG segment length

Motivated by the discrepancies in the error percentage values reported above, we explored the effect of the ECG window length and RR estimation accuracy. For this purpose, Table 2 presents error percentage and Pearson's correlation coefficients between estimated and true RR values for the non-controlled RR scenarios in Dataset A and different ECG signal durations; in the analysis, window overlap of 50% was used.

As can be seen, lower error and higher correlation values are attained for larger segments; the lower performance accuracy for shorter duration signals is due to the uncertainty principle, where shorter segments result in poorer modulation frequency resolution, thus causing errors in the proposed method. From these findings, it is suggested that portable devices measure ECG segments of at least 120 seconds, thus allowing for accurate RR estimation, thus potentially allowing for data imputation methods in case of very noisy recordings.

Table 2: RR estimation error percentage as function of ECG segment length

ECG Segment length (s)	***RR estimation error (%)***	***Pearson's correlation***
10	33.73	0.344
15	26.90	0.417
30	16.90	0.702
45	17.29	0.718
60	14.82	0.788
75	16.01	0.755
90	16.99	0.752
120	12.52	0.910
150	9.25	0.946
180	14.95	0.893
210	12.47	0.923
240	7.85	0.967
300	10.49	0.962
360	9.49	0.969

CONCLUSION

In this work we presented a method for respiration rate estimation from a single-lead ECG signal. The proposed method makes use of the so-called modulation spectrogram signal representation to exploit the second-order periodicity in the ECG signal caused by the amplitude modulation effect of respiration. The method was tested and validated on two datasets, one controlled with users sitting at rest and another with signals collected by a smartshirt with users in an everyday work environment. It was also found that ECG signal recordings with a duration of at least 120 seconds are adequate for RR estimation.

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