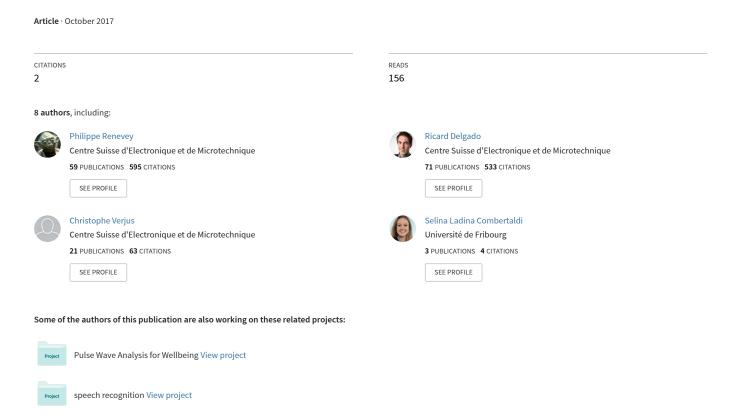
# Respiratory and cardiac function monitoring during night using a wrist-worn optical system



# Respiratory and cardiac function monitoring during night using a wrist-worn optical system

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Abstract—Sleep monitoring permits valuable insights into the general health of a person and allows to identify specific sleep-related problems. Unfortunately the gold standard for sleep studies, polysomnography, is very unwieldy and therefore not suitable for long-term measurements. Here, we present a fully wearable system that allows to extract the beat-to-beat intervals using photoplethysmography, resulting in a reliable estimation of heart rate and breathing rate during the night. The performance of the proposed approach was evaluated empirically in the Department of Psychology at the University of Fribourg. Each participant was wearing two Ava bracelets as well as a complete polysomnographic setup to obtain reference signals. The resulting mean absolute errors are less than one breath-per-minute for the breathing rate, less than one beat-perminute for the heart rate, and around 17 ms for the beat-to-beat intervals.

#### I. Introduction

Sleep is a natural mechanism that allows the restoration of cognitive and physical abilities in humans and most mammals. The alteration of the normal sleep pattern is an indication of an underlying medical condition, or of a degradation of sleep itself, and is therefore a significant indicator of health status [1]. Additionally, sleep is a privileged period during which short or long oscillations of physiological regulation (*e.g.*, circadian rhythms [2], menstrual cycles [3]) can be analyzed. At night, exogenous perturbations are limited and thus most of the measured physiological signals are less affected by the environment, allowing analysis of the underlying regulation rhythms.

The gold standard for sleep analysis is the polysomnograph (PSG). The typical setup for polysomnographic measurements involves a plurality of sensors, such as an electrocardiograph (ECG), an electromyograph (EMG), and an electrooculograph (EOG), among others. However, its obtrusiveness makes it unsuitable for long-term sleep studies. Recently it has been shown that using an optical wrist-worn sensor allows to obtain reliable estimates of cardiac activity (e.g., beat-to-beat intervals) with minimal obtrusiveness [4], [5]. The detection of beat-to-beat intervals allows for the subsequent estimation of several key features such as heart

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rate, heart rate variability (HRV), sleep phases [6], and respiration rate during sleep.

The current paper presents the performance of the wrist-worn device at performing multiple tasks: (1) detecting beat-to-beat intervals, (2) estimating heart rate, and (3) estimating respiration rate. The quality of the heart rate and respiratory rate estimates from the device will strongly depend on the capability of the system to detect every single beat, identify and reject outliers, and ignore ectopic beats.



Fig. 1. Ava bracelet with a multi-wavelength PPG sensor to record beat-to-beat intervals.

#### II. MATERIALS

### A. Sensor

The data collected for the performance evaluation has been obtained using the commercial system developed by Ava<sup>1</sup>. The recording system is depicted in Figure 1. This system acquires simultaneous data from a three-axis accelerometer and a PPG sensor. The sampling frequency for all signals is 25 Hz. The raw signals are processed within the device to extract beat-to-beat intervals and the average power of

<sup>&</sup>lt;sup>1</sup>https://www.avawomen.com

the norm of the high-pass filtered acceleration signal. The resulting features are stored on the bracelet and transmitted to a server at the end of the night for further analysis.

The reference polysomnographic system recorded 6 EEG signals (F3, F4, C3, C4, O1, O2), left and right EOG signals, a 1-lead ECG signal, respiration signal and EMG signal, all sampled at 200 Hz.

During data collection two Ava bracelets were worn by each participant, one on each wrist, as well as a full PSG setup to use as reference data. Reference beat-to-beat intervals were extracted from ECG measurements and the reference breathing rate was recorded using a chest strap.

#### B. Data acquisition

The data was collected at the sleep lab of the Department of Psychology of the University of Fribourg. Seven participants, all female, spent four nights each in the lab. The average interval between consecutive recordings of a participant was about one week. Thirty-one full night signals were available after discarding recordings that exhibited acquisition problems, either on the wrist sensor or on the PSG reference signals.

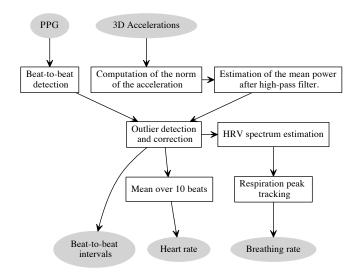


Fig. 2. Schematic representation of the proposed algorithm.

#### C. Data processing

The proposed algorithm focuses on the estimation of beatto-beat intervals, heart rate, and breathing rate, by combining the PPG measurements and the acceleration signals. This algorithm can be divided into two main parts: the first part is performed directly on the device, and the second part is run on a server. The motivation behind this decoupling is to balance the amount of computation that is performed on the bracelet, optimizing for battery life and fast data transfer between bracelet and server. The general outline of the algorithm is shown in Figure 2.

The acceleration signals are used to detect time periods where the optical measurements are corrupted by motion artifacts. In order to find a motion indicator, the norm of the 3D acceleration is first computed, and after the constant gravity component is removed from the norm, the power of the resulting signal is estimated.

The beat-to-beat intervals are calculated by computing the interval of time between consecutive maxima of the first-order derivative of the PPG signal. Physiological constraints, such as the refractory period of the heart, are used to reject false detections that would result in erroneously short intervals. The sampling frequency of the PPG is 25 Hz, corresponding to a temporal resolution of 40 ms. However, the analysis of HRV requires a temporal resolution on the order of one millisecond. In order to overcome this limitation the accuracy of the position of the maxima is improved by fitting a second order polynomial spline, using the values of the maxima sample and the two surrounding samples as interpolation values. The resulting spline is then used to obtained the position of the maxima with a resolution higher than the sampling period.

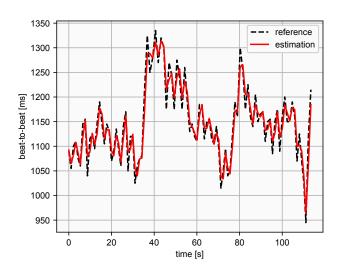


Fig. 3. Typical result for the estimation of the beat-to-beat intervals. PSG reference in black and described approach in red.

The beat-to-beat intervals that are corrupted by movement or that are not physiologically plausible are corrected using a linear interpolation to replace the corrupted values.

The heart rate is obtained by averaging the inverse of ten consecutive corrected beat-to-beat intervals.

The resulting corrected series of beat-to-beat intervals is then uniformly resampled at a frequency of 2 Hz and band-pass filtered between 0.04 and 0.5 Hz. This frequency band corresponds to the control of the autonomic nervous system (ANS) over the heart [7]. The HRV spectrum is obtained by applying an auto-regressive (AR) model [8] of  $20^{th}$  order. The parameters of the AR model are iteratively estimated using a normalized a least mean square algorithm (NLMS) [8]. The resulting HRV spectrum is used to track the peaks in the respiratory frequency band (0.1 to 0.5 Hz). This band corresponds to respiratory rates between six and thirty breaths per minute, which is the normal range for respiratory rates during the night [9]. The breathing rate is then directly

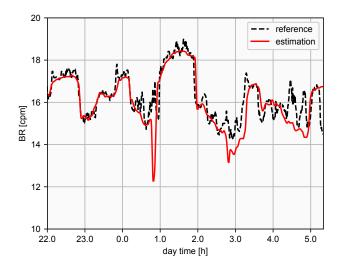


Fig. 4. Typical result for the estimation of the breathing rate. PSG reference in solid black and estimates of the proposed approach in dashed red.

estimated from this peaks frequency. The breathing rate is estimated recursively from the current estimation using the ratio of the power of the respiration peak over the total power in the band as a learning gain. Figure 4 gives an example of the resulting estimation of the breathing rate (solid red line) compared to the reference value obtained from the PSG's respiration sensor (dashed black line).

#### D. Performance evaluation

To determine the accuracy of beat-to-beat intervals, heart rate, and breathing rate estimates from the wrist-worn device, we selected two different performance measures: the mean absolute error (MAE) and the mean absolute percentage error (MAPE).

As the performance evaluation requires a perfect alignment of the test and reference time series, we use a dynamic time warping algorithm (DTW) [10] to align the respiratory peaks in both datasets. The MAE and MAPE are estimated on the aligned series after the removal of the segments where the reference was corrupted or missing.

The heart rate reference signal is obtained by averaging the inverse of the beat-to-beat aligned intervals over ten beats and the MAE and MAPE is then computed.

To estimate breathing rate accuracy, we interpolated the estimated breathing rate at the times of the reference respiration signal obtained from the PSG setup. The MAE and MAPE are then directly computed from the two series.

#### III. RESULTS AND DISCUSSION

The results obtained by the proposed approach are presented in Table I. For each evaluation of the performances the minimal (Min), the 25% quantile ( $Q_{25}$ ), the median, the 75% quantile ( $Q_{75}$ ), the maximal (Max) and the mean scores are are presented. The different estimations are abbreviated by RR for beat-to-beat interval (in reference to the distance

	Min	$Q_{25}$	Median	Q <sub>75</sub>	Max	Mean
RR MAE [ms]	8.1	16.5	18.1	19.8	24. 5	17.4
RR MAPE [%]	0.7	1.5	1.8	2.0	2.4	1.8
HR MAE [min <sup>-1</sup> ]	0.06	0.10	0.12	0.14	0.23	0.13
HR MAPE [%]	0.10	0.16	0.19	0.22	0.41	0.20
BR MAE [min <sup>-1</sup> ]	0.3	0.5	0.8	1.2	2.5	0.9
BR MAPE [%]	2.1	3.8	5.5	8.7	18.2	6.7

TABLE I

PERFORMANCE EVALUATION FOR BEAT-TO-BEAT INTERVAL (RR), HEART RATE (HR), AND BREATHING RATE (BR).

between R peaks within the ECG), HR for heart rate, and BR for breathing rate.

The results obtained for the estimation of the heart rate exhibit a small error (typ. MAE is less than one beat-per-minute) for all the signals. It has to be accounted that the segments where the reference is not reliable have been discarded.

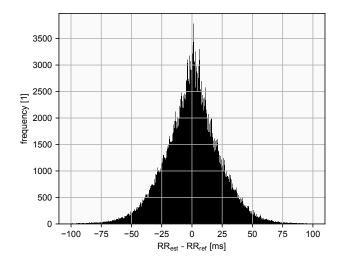


Fig. 5. Histogram of the error of the beat-to-beat detection.

The beat-to-beat intervals exhibit a MAE between 8 to 24 ms. Such error is acceptable for some applications, such as breathing rate estimates, but can be a limiting factor for other features (e.g., accurate estimation of the power in the HF, LF and VLF spectral bands of HRV spectrum). This error is dependent on different factors. First, the beat-tobeat intervals measured on the wrist are not the exactly identical to the beat-to-beat intervals extracted from the ECG. Indeed the pressure pulse, initiated by the heart contraction, is propagated through the arterial system and undergoes modifications of its shape that affects the accuracy of the arrival time detection. Such distortions are unavoidable and represent a limitation of HRV estimation using a wrist-based sensor. The second factor is the detection algorithm that is embedded in the device. It has to fulfill some constraints about memory and computational complexity, which results in suboptimal detection of the pressure pulses. Improving pulse detection is possible but was out of the scope of this study. Finally, the measured optical signal is strongly sensitive to motion artifacts that can, even for very small movements, affect the accuracy of the pulse wave detection.

The results obtained for heart rate estimates exhibit a small error (typ. MAE is less than one beat-per-minute) for all the signals. It should be noted that segments with unreliable reference signals have been discarded, which are generally segments with large estimation errors.

The results for the breathing rate show that around 75% of the signals have a MAE of less than one breath-per-minute. The mean error for the whole dataset is also less than one breath-per-minute. It has to be highlighted that the breathing rate estimates, based on indirect estimation through HRV, require that the participant is in resting condition and that the beat-to-beat series is not strongly corrupted. At the beginning and at the end of the night the person was awake and these two conditions were no longer satisfied, resulting in a much larger error during these time intervals.

#### IV. CONCLUSION

This study has shown that the measurement of beat-to-beat intervals during sleep permit obtaining a reliable estimation of breathing rate. This measurement is made possible because the participant is at rest, allowing a reliable breathing rate detection due to the quasi-absence of motion, and is not applicable to everyday life. For the same reason the heart rate estimation is also accurate. The extraction of beat-to-beat intervals is satisfactory for some applications, but wrist measurements are only an approximation of beat-to-beat intervals obtained from ECG measurements, currently the gold standard for cardiac variability analysis.

It should also be noted that the indirect estimation of the respiration rate from the cardiac variability requires that the ANS driven modulation of the beat-to-beat intervals is normal. For unhealthy or elderly people, whose cardiac function or nervous control of the heart is affected, the proposed approach should be investigated further in a dedicated clinical study.

The algorithms presented in this paper are under development, and in future versions we plan to add supplementary features extracted from the PPG, such as the modulation of amplitude of the observed pulses in the optical signal and the modulation of the baseline. These signal contain relevant information about the breathing rate and the control of the autonomic nervous system, which can then be used to extract relevant information about sleep.

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