Willi Schüler, Nicolai Spicher*, and Thomas M. Deserno

Cardiopulmonary coupling analysis using smart wearables and mobile computing

Abstract: Cardiopulmonary coupling (CPC) analysis links heart and respiration rates to assess sleep-related parameters. Typically, the CPC is measured using multi-lead electrocardiography (ECG) and ECG-derived respiration (EDR). Novel textile shirts with embedded ECG sensors offer convenient and continuously monitored sleep at home. We investigate the feasibility of a shirt with textile sensors (Pro-Kit, Hexoskin, Quebec, Canada) for CPC analysis by mobile computing. ECG data is continuously transmitted from the shirt to a smartphone via Bluetooth Low Energy (BLE). We customize a CPC algorithm and use twelve whole-night recordings from four volunteers to perform qualitative and quantitative analysis. We compare EDR with respiratory inductive plethysmography (RIP). In average, EDR and RIP differ 17.22%. After one night, the batteries are reduced to approx. 70% (shirt) and 90% (smartphone). The run time for CPC processing is approx. 3 min. Hence, smart wearables in combination with mobile computing show technical feasibility for CPC analysis. Eventually, this could yield a useful solution for sleep analysis of non-expert users in a private environment.

Keywords: cardiopulmonary coupling, wearables, electrocardiography, respiratory inductive plethysmography

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1 Introduction

Sleep-related disorders, such as obstructive sleep apnea, are widely spread and lead to negative short- and long-term consequences [1]. Both, the cardiovascular as well as the respiratory system are informative for assessing sleep-relevant parameters [2].

***Corresponding author: Nicolai Spicher:** Peter L. Reichertz Institut für Medizinische Informatik der TU Braunschweig und der Medizinischen Hochschule Hannover, Mühlenpfordtstraße 23, 38106 Braunschweig, Germany, e-mail: nicolai.spicher@plri.de
Willi Schüler, Thomas M. Deserno: Peter L. Reichertz Institut für Medizinische Informatik der TU Braunschweig und der Medizinischen Hochschule Hannover, Braunschweig, Germany

Patients usually undergo polysomnography in a sleep laboratory but due to the high number of attached sensors and the unfamiliar sleeping environment, this is unpleasant. Due to the uprising of smart and wearables devices, home-based systems have been proposed [3].

CPC [4] detects sleep-related breathing disorders [5][6], sleep instability [7], and other effects. It yields a spectrogram with two important frequency bands: the lower (0.01 Hz – 0.1 Hz) and the higher (0.1 Hz – 0.4 Hz) which are associated with unstable and stable sleep, respectively.

RIP sensors measure the movement of the chest and abdominal wall. If no respiration sensor is available, the respiratory activity can be derived from the morphology of the ECG signal [8]. This EDR signal stems from the movement of the electrodes on the chest during respiration. There is a large number of EDR algorithms [9]; however, as the induced respiration effect in the ECG is rather subtle, measurements may be inaccurate.

In this work, we analyze a commercially-available ECG shirt with textile sensors for CPC in real-life conditions.

2 Material & Methods

We develop a custom mobile application that receives the ECG signal in real-time and computes EDR and CPC. We analyze the accuracy of EDR by comparison to a RIP sensor. Furthermore, we analyze aspects regarding usability, i.e. battery consumption and computation run-times.

2.1 ECG shirt

We use the Pro-Kit shirt (Hexoskin, Quebec, Canada) with single-channel ECG (256 Hz, 12 bits) and two RIP sensors (128 Hz, 16 bits) that measure breathing on the thorax and on the abdomen. The shirt is not a medical device.

The vendor provides a free mobile application, that allows to record and store data from all sensors on the shirt. It connects to a computer via the universal serial bus (USB). Data is uploaded to the cloud, and can be downloaded from a web-frontend. In addition, there is a software development kit

(SDK) allowing to continuously transmit ECG data via Bluetooth Low Energy (BLE) to an Android device. This makes it inevitable to use EDR for CPC analysis.

2.2 CPC application

We develop a mobile application with three components:

- *Recording* connects the shirt and stores the data;
- *Analysis* computes the CPC;
- *Plot* visualizes data in 2D and 3D.

Typically, the user connects the app to the shirt via BLE and starts the recording before going to bed. On the next morning, he/she stops the recording, waits for the analysis and views the spectrogram. This allows to monitor changes of sleep behavior over time.

We adopt the CPC method by Thomas et al. [3] for mobile computing. When calculating the coupling between the cardiovascular and the respiratory systems, we analyze two factors: (i) the cross-spectral power indicates common frequencies in both signals, and (ii) the coherence determines the synchronization of both signals. We use the product of cross-spectral power and coherence to determine the degree of CPC. We compute the EDR using the method by Schmidt et al. 2015 [10]. We filter the ECG signal (0.05 to 45 Hz band-pass) and then compute the 4th order central moment

$$m_4 = \frac{1}{n}\sum_{i=1}^{n}(x(i) - \bar{x})^4.$$

$x(i)$ denotes the ECG signal in a sliding window and $\overline{x}$ its arithmetic mean value. The sliding window has a length of 5 samples and a step length of 1 sample [10]. After interpolating the peaks using cubic splines, we filter the EDR signal again (0.05 to 1 Hz band-pass).

To detect the R-waves, we apply the Pan-Tompkins algorithm [11]. We linearly resample the EDR and the RR-intervals to 2 Hz. We calculate the product of coherence and cross-spectral power in fixed intervals. According to [3], we define 1024-sample (8.5 min) sliding windows with three overlapping 512-sample sub-windows. For each sub-window, we compute the product of coherence and cross-spectral density. We shift the 1024-sample sliding window over the recording of the whole night and repeat the process.

To account for the limited resources of a smartphone we make several adjustments to the algorithms. For example, due to the limited random access memory (RAM), we do not load signals completely but process them in smaller branches.

We use the SciChart library (SciChart Ltd, London, Great Britain) to visualize the CPC spectrograms. The app offers a 2D view and an interactive 3D visualization of the CPC spectrogram with zooming and rotation capabilities.

2.3 Experimental design

We evaluate the technical feasibility of the mobile app over five consecutive nights with a healthy volunteer (gender: male, age: 28 years, sleeping duration: 05:14 - 08:43 hours). The volunteer starts the app on an off-the-shelf mobile phone (Pixel 4a, Google, California, USA) before going to bed. The shirt transmit the ECG signal continuously to the smartphone and on the next morning, we read battery consumption and CPC run-time.

To evaluate EDR accuracy, we record data on full night sleeps of three healthy volunteers (gender: 1 female, 2 males, age: 20 - 33 years; sleeping duration: 07:15 - 08:18 hours) in their home environment. They use the vendor-provided mobile application for storing the ECG and the thorax RIP signals.

We use the `findpeaks()` function of MATLAB (R2021a, Mathworks, California, USA) to detect the peaks in EDR and RIP signals. As proposed in [10], a sliding window of length 30 s and a step width of 10 s is used to compute the error of respiration in units of breathes-per-minute (bpm). We compare EDR to RIP by the mean absolute error (MAE) and mean relative error (MRE).

3 Results

3.1 Technical feasibility

The longest sleep period was 8.8 hours with battery levels of 70% and 91% for shirt and phone, respectively. However, the phone was running our app exclusively.

We observed a linear trend for the computation times of the CPC spectrograms (Figure 1). Processing offline data (ECG + RIP) took between 3.5 min. and 4.5 min. and processing online (ECG + EDR) data between 1.5 min. and 2.5 min., respectively.

3.2 EDR / RIP analysis

We observed an average error of 17.22% (3.54 bpm) with individual values ranging from 13.23% (2.52 bpm) to 22.02% (5.12 bpm) (Table 1).

Table 1: EDR errors and average value (gray)

Night	MAE [bpm]	MRE [%]	Night	MAE [bpm]	MRE [%]
1	3.31	16.17%	**5**	3.01	16.83%
2	5.12	22.02%	**6**	2.52	13.23%
3	5.67	21.80%	**7**	2.58	14.68%
4	2.58	15.82%	**Ø**	3.54	17.22%

3.3 CPC analysis

As a representative example, we show the CPC spectrograms of a male subject using the RIP and the EDR signal (Figures 2 and 3, respectively). Throughout the whole night there were activities in the higher frequency band (0.1 Hz – 0.4 Hz) centered at approximately 0.25 Hz. Furthermore, there were motion artifacts resulting in vertical lines of high amplitudes. In EDR, similar structures are visible but amplitudes within the higher frequency band are reduced. For example, in the last hour the amplitudes around 0.25 Hz are barely visible.

The interactive 3D visualization view allows to identify peaks in the spectrogram (Figure 4).

4 Discussion

In this work, we analyzed the capability of a smart wearable in combination with mobile computing for CPC analysis.

The mean error comparing EDR to RIP is 17.22% and larger than that of Schmidt et al. [10] who reported 11.27% in a similar population in supine position. They used manually selected 10min ECG segments free of artifacts and their data was measured using conventional ECG. In contrast, we analyzed whole nights over several hours without removing any noisy sequences from the ECG or RIP signal. Therefore, our reported results must be taken with a grain of salt. In future work we will conduct a more in-depth analysis using manually selected segments similar to [10].

We qualitatively compared CPC spectrograms that were computed using EDR and the RIP signals. Using EDR, the high frequency structures are less prominent and blur with the background. Moreover, motion artefacts are more prominent. Currently, the wearable provides a single signal via BLE, which makes it inevitable to use EDR.

A limitation of our work and potential source of EDR error is using the Pan-Tompkins QRS detector [11] which is not state-of-the-art anymore. In future work, we will use a state-of-the-art QRS detector tuned for noisy ECG signals [12].

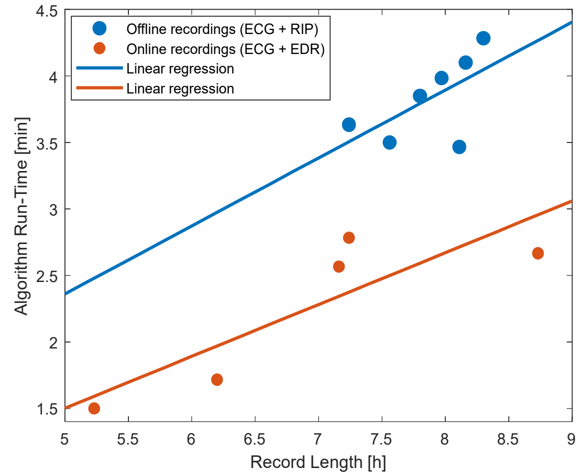

Figure 1: CPC analysis run-time on smartphone. Each dot represents a single analysis.

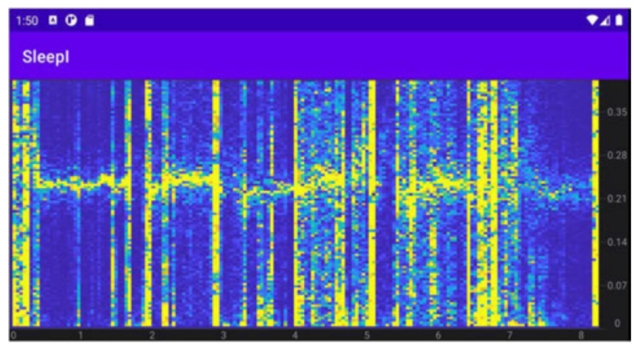

Figure 2: CPC spectrogram using RIP signal. X- and y-axis represent time (hours) and frequency (Hz), respectively. The colormap ranges from low (blue) to high (yellow) values and indicates CPC values.

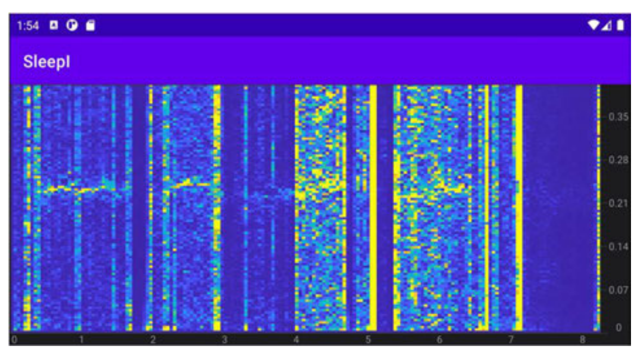

Figure 3: CPC spectrogram using EDR signal. X- and y-axis and colormap are identical to Figure 2.

The evaluation of the technical feasibility shows that the wearable in combination with mobile computing is well suited for in-home analysis. The runtime for computing a CPC spectrogram of a hole night is below three minutes and should be acceptable for a potential non-expert user. In future work, this duration could be significantly decreased. The CPC analysis could be performed continuously during the night or could be automatically started in the morning.

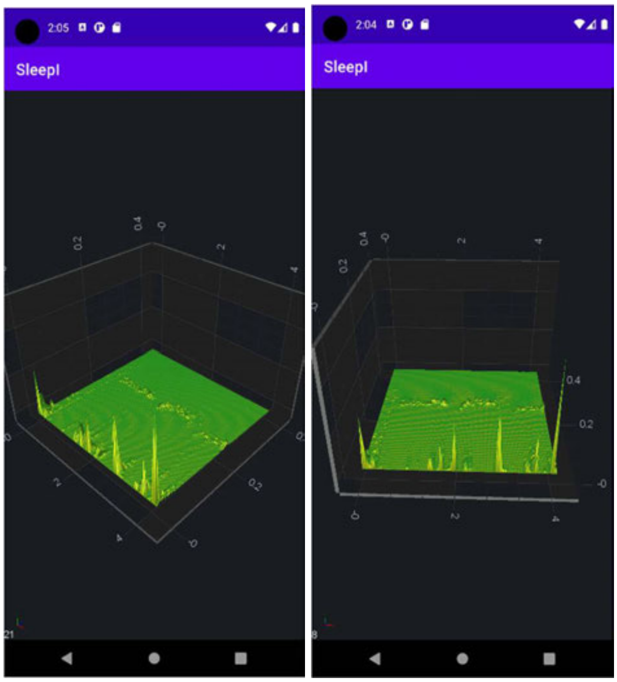

Figure 4: 3D visualization with two different perspectives. X- and y-axis represent time (hours) and frequency (Hz), respectively. Z-axis represents CPC values.

We observed that the limited RAM is an issue but issues could be solved by splitting computations. The battery capacities of the shirt and smartphone are hardly reduced, such that long-term (e.g. 24h) measurement are possible. This renders the possibility of developing other unobtrusive monitoring methods, such as ECG delineation for computing clinically relevant intervals [13] or arrhythmia detection [14].

Author Statement

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