SeismoTracker: Upgrade any Smart Wearable to enable a Sensing of Heart Rate, Respiration Rate, and Microvibrations

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CHI'16 Extended Abstracts, May 07-12, 2016, San Jose, CA, USA
ACM 978-1-4503-4082-3/16/05.
http://dx.doi.org/10.1145/2851581.2892279

Abstract

In this paper we present a method to enable any smart Wearable to sense vital data in resting states. These resting states (e.g. sleeping, sitting calmly, etc.) imply the presence of low-amplitude body-motions. Our approach relies on seismocardiography (SCG), which only requires a built-in accelerometer. Compared to commonly applied technologies, such as photoplethysmography (PPG), our approach is not only tracking heart rate (HR), but also respiration rate (RR), and microvibrations (MV) of the muscles, while being also computational inexpensive. In addition, we can calculate several other parameters, such as HR variability and RR variability. Our extracted vital parameters match with the vital data gathered from clinical state-of-the art technology. These data allow us to gain an impression on the user’s activity, quality of sleep, arousal and stress level over the whole day, week, month, or year. Moreover, we can detect whether a device is actually worn or doffed, which is crucial when connecting such data with health services. We implemented our method on two current smartwatches: a Simvalley AW420 RX as well as on a LG G Watch R and recorded user data for several months. A web platform enables to keep track of one’s data.

Contribution

By porting our algorithm to any standard consumer Wearable, we can enable these devices for:

- Vital data extraction (heart rate +variability, respiration rate +variability, and microvibrations)
- Vital data translation (user's activity, quality of sleep, arousal, and stress level)
- Longer battery life (due to accelerometer-based vital data sensing compared to PPG)
- Doffed detection (to avoid ghost heart rates)

In addition, we introduce a pilot study to determine the signal quality in dependence on sensor placements at different body positions.

Figure 1: SeismoTracker enables any smart Wearable with an accelerometer to sense vital data, such as: heart rate (HR), respiration rate (RR) and microvibrations (MV) of the muscles. Our approach relies on seismocardiography (SCG), which basically senses low-amplitude movements caused by the users' body functions. This method works flawlessly in resting states, which are for example: a) sleeping b) sitting calmly c) shoring up the body part (e.g. laying down the hand).

Author Keywords

Activity Monitoring; Activity Recognition; Wearables; Smartwatch; Smartglass; Microvibration; Seismocardiography.

ACM Classification Keywords

H.5.2 [User Interfaces]: Information Interfaces and Presentation; I.5.2 [Design Methodology]: Pattern Recognition; J.3 [Life and Medical Sciences].

Introduction

The human body is constantly emitting bio-signals, which reflect the current mental and physical state of a person. These vital data, such as respiration rate, heart rate or microvibrations of muscles contain crucial information that allows to draw conclusions on one's body processes and states, such as stress level, arousal, quality of sleep, well-being, and anomalous situations. These emitted bio-signals are controlled by the autonomic nervous system and therefore can only be influenced indirectly by the human. In this paper, we demonstrate how to software-upgrade a simple smartwatch to detect the aforementioned bio-signals while only making use of the built-in accelerometer. Since this software upgrade is in theory possible for any wearable, such as a leg band or chest band, we also investigated which positions of the human body are suitable. Provided the user is in a low-amplitude movement, such as resting, we are able to accurately recognize respiration rate, heart rate, and microvibration with a single sensor instead of a complex sensor setup, which usually incorporates pulse-oximetry, strain gauges or electrocardiography. In contrast to other consumer wearables that already incorporate optical heart rate sensors, we can avoid measurement artifacts (ghost heart rates), which occur when the device is not worn.

Related Work

Nowadays, wearable devices have the unique property to be always available, worn at the human body. Since wearables already incorporate a great variety of sensors, we can utilize them for activity recognition [5] in medical or rehabilitation scenarios or in general sports and health domains based on their capabilities to sense vital signals [13].

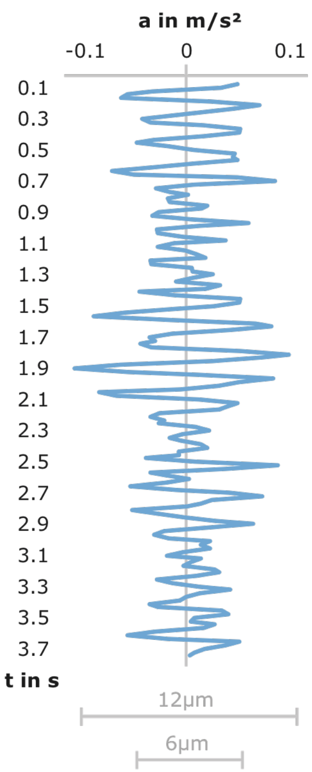

Figure 2. A low-amplitude motion describes motions with deflection amplitudes below 20µm. This includes tiniest motions, such as heart rate or microvibration.

Heart Rate

Many wearable devices make use of optical sensors in order to detect the user's heart rate and saturation of peripheral oxygen. For this purpose, pulse-oximetry sensors are being widely used. These sensors are often implemented into a finger-clip [18,19,20,26], or a wrist worn device, such as a watch [1]. Following Anliker et al. [1], even the wrist as a sensor position can provide heart rate, blood pressure, ECG-activity, peripheral oxygen saturation, temperature, and physical activity, such as presented in AMON [1]. Other works not only make use of a pulse-oximeter, but also utilize electrocardiography (ECG) to calculate the heart rate [15,16]. This is demonstrated in literature with various wearables, such as shirts with ECG electrodes. Other approaches, such as the one from Garverick et al. [8] use a continuous-wave Doppler ultrasound device for measuring the heart rate of a fetus. The heart rate can also be detected while using an accelerometer from a smartwatch as demonstrated in 2013 by Bieber et al. [4] or shown in 2015 by Hernandez et al. [10].

Respiration Rate

The detection of respiratory movements can be performed in various ways. Most common setups are belts with strain gauges mounted around the torso [17]. Alternative approaches make use of accelerometers, which are also placed directly onto the chest/torso [7,21], worn at the head [11], or wrist-worn [10]. Another technique is presented by Mundt et al. [18], who utilize impedance plethysmography in order to measure the change in tissue volume as a change in impedance on the body surface. Apart from the respiration rate, the authors provide the monitoring of heart rate, blood pressure, ECG-activity, and peripheral oxygen saturation [18]. The work of Di Rienzo et al. [6], who applied a textile-based transducer for measuring the respiratory movements through changes in thorax volume, also focused on wearable technologies. The same applies to the research of Kundu et al. [14], who attached a capacitor to a shirt and measured the respiration rate due to the changes in permittivity as a result of tissue movement between the electrodes. Further techniques have been introduced by Bello et al. [2], who measured changes in capacitance based on textile electrode expansion as a result of thorax movements. Older approaches demonstrate microphones or nasal airflow sensors, which are, however, rather obtrusive [3].

Microvibrations

Even though Hubert Rohracher [22] already investigated the occurrence of low-amplitude muscle vibrations (see Figure 2) in the early sixties with a piezoelectric phono player, nowadays, the phenomenon of microvibrations still remains mostly unused for medical applications. Following Rohrachers initial investigations, the change of the continuously detectable muscle vibration stands in connection to body processes (medication, level of stress, temperature etc.). In contrast to microvibrations, which are also measureable in sleep or states of unconsciousness, most research has been done in the area of pathological tremors [12,23], which tend to disappear in certain situations [22]. While muscle activity to date is being sensed with electromyography (EMG), one can also use accelerometry in order to keep track of muscular movements [24]. Based on the application of accelerometry, one can sense a widespread spectrum of body functions and diseases, such as sleep [25], pathological tremor, epileptic seizures [27], or general activity measurements.

Vital Data Extraction
To extract the vital information from the accelerometer, a stepwise preprocessing and filtering was applied to the raw data. Figure 2 shows the complete extraction process. The first stage of the process (marked in blue color) shows the unfiltered raw data in time and frequency domain. In this stage, the prevalent signal amplitude can be extracted from the frequency spectrum. This frequency represents the respiration (0.26 Hz for the subject in Figure 2). In the next stage, the signal is high-pass filtered and as a result of this process, the microvibrations in higher frequency ranges can be extracted (≥ 5.6 Hz for the subject in Figure 2). In the last stage, an additional low-pass filtering was performed (the combination results in a bandpass filter) plus a squaring of the signal. Now, the heart rate can be clearly seen in the signal (0.98 Hz for the subject in Figure 2).

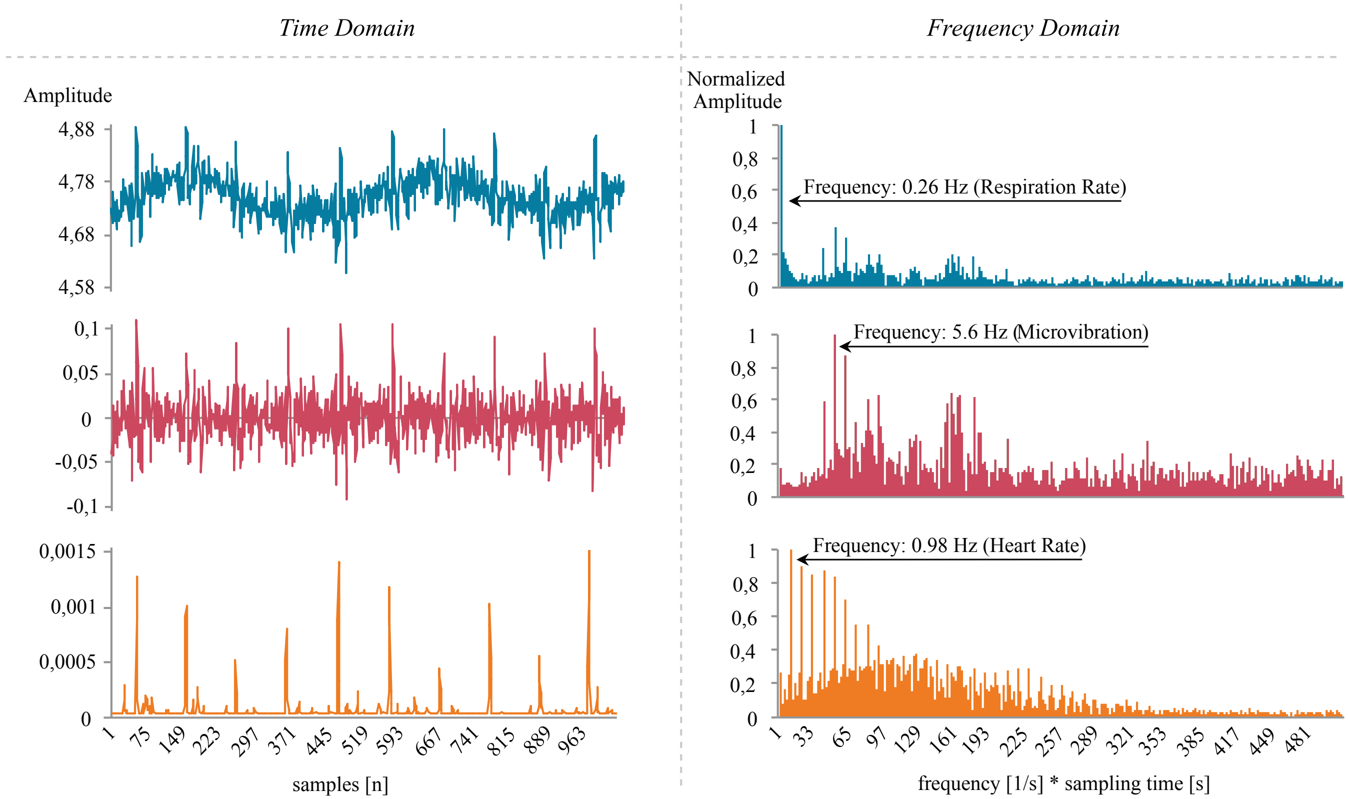

Figure 3: Filtering process for detecting respiration, microvibration, and heart rate. The blue color shows the original raw data signal in time domain (left side) and frequency domain (right side). After the fist filtering process, we can perceive the microvibrations (pink color). Further filtering brings out the heart rate signal very clearly (orange color)

Seismotracker

In this work we provide a method to detect heart rate (HR), respiration rate (RR), and microvibrations (MV) in resting states with a wrist worn accelerometer from a smartwatch. Our method also opens up the possibility to enable the system for many other features, such as sleep detection, doffed detection etc. Since we envision our technique to be deployed to any other smart wearable at any body position, we investigated the signal quality at different areas.

Background and Theory

To date, the detection of vital parameters, such as HR, RR, MV is realized in various techniques as presented before. Our detection of vital parameters is based on characteristic body movements, which are created by the phenomena of interest. The thorax movement in respiration cycles (inspiration and expiration) is measurable at different body positions. Apart from common measuring points, such as the chest, the respiration movement is also transferred to directly physically connected body parts, such as arms and legs. In addition to respiratory movements, tiniest vibrations of muscle tissue in the area of the placed sensor can be detected. In case of a wrist placed sensor setup, the heart rate can also be detected as a pulsation of veins in close proximity to the sensor device. As a result of this, these characteristic body movements can be measured physically, which is also known as seismocardiography (SCG) or ballistocardiography (BCG) when it comes to measure heart functionality.

Signal Quality

In a previous study [9], we have already proven accelerometer-extracted vital data gathered at the wrist to be valid and non-significantly different to vital data sensed by clinical devices.

However, depending on anatomical structures, the signal quality for each vital parameter is individual for each body part. To gain an idea, we here present some first insights based on series of measurements at one test subject with the accelerometer of a *Shimmer3 IMU*. To enable an evaluation of the signal quality at different body parts, we determined the *Peak Signal to Noise Ratio* (PSNR) of the filtered acceleration signals (HR, RR, MV). Therefore, 12 body positions: 1) throat, 2) shoulder, 3) upper arm, 4) biceps, 5) forearm, 6) wrist, 7) back of hand, 8) index finger, 9) belly, 10) thigh, 11) calf, and 12) foot were recorded for three separate measurements. For each measurement, the vital parameter specific filter was applied and a *Fast Fourier Transform* (FFT) was conducted. The frequency with the highest amplitude was extracted as the peak signal of the spectrum, whereas the remaining frequencies were considered as noise. By using the formula for PSNR as follows:

$$PSNR = 10 \cdot log_{10} \frac{{P_{MAX}}^2}{P_{Noise}}$$

This way, a normalized ratio was computed for all of the aforementioned body positions. The results of the position dependent measurements are visualized in the following graph (Figure 4).

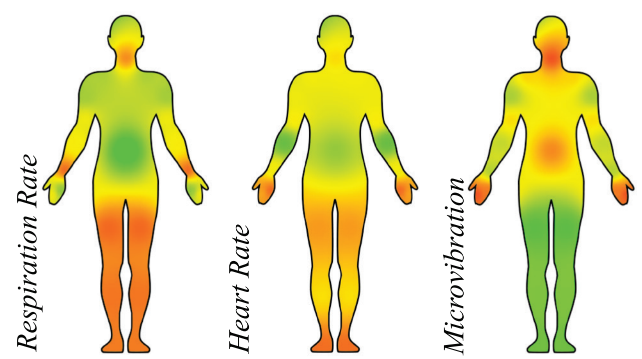

Figure 4. PSNR of the acceleration signal after the associated filtering stages for respiration (RR), heart rate (HR), and microvibration (MV) measurement, depending on the body position. Green areas indicate a high signal quality whereas red areas indicate inferiority.

Technological Advantages and Limitations

As every technology, our approach underlies certain limitations as well. For example, a flawless measurement is only enabled when the body part with the sensor attached is in rest. Nevertheless, a combination with an optical sensing in movement is conceivable. However, other sensing approaches including optical sensing may also fail during high-amplitude movements. In terms of power consumption, acceleration-based sensing approaches are less battery draining (typical power consumptions: PPG, 1 – 50mW; Acc., 0.5 – 2mW). Also in contrast to PPG, our approach is not affected by the skin structure (e.g. inked, sweaty, dirty, or hairy skin). In addition, we can extract several vital parameters including respiration rate and microvibrations. Another feature is our doffed detection, which overcomes an encountered phenomenon we call ghost heart rates.

Vital Data Translation (Scenarios)

For the purpose of visualization and awareness creation, we developed a web platform which collects and computes the data and displays the translated information. Some of the following scenarios have been already implemented or are in focus of our current research.

- *Sleep Detection* (while low heart and respiration rates or low microvibration amplitudes are being detected in relaxation, we can use these features for improving sleep detection)
- *On-Body Detection* (current sleep or activity trackers often provide erroneous data due to the fact that the device provides data even though it is not worn. Microvibrations can be used to recognize whether the device is worn or doffed)
- *Anomaly Detection* (in sleep-like situations we can detect: epileptic seizures, sleep apnea, and unconsciousness)
- *Stress Level Detection* (the user's personal stress level is often indicated by higher heart rate and lower heart rate variability)
- *Exertion, Hypothermia or* Relaxation (breathing can indicate many different states of our body)
- *Individual Medication* (certain drugs influence the microvibrations, as found out by Rohracher [22]. This effect can be utilized to detect false dosage of medication)
- *Weight Abatement* (physical activity is a major aspect in a successful therapy for patients with adiposity. By sensing heart rate and respiration rate after exertion, a more precise determination of calories burnt can be achieved)
- *Health Monitoring* (respiration rate, heart rate or microvibrations of muscles provide a sufficient basis for detecting resting and active states of a user. It might be interesting for occupational safety to help following a suggestion by the health office.)
- *Individual Identification* (which is based on wearer's habitus and constitution over past days)

Conclusion and Future Work

In this paper we presented a method for extracting several vital parameters out of a simple accelerometer signal. According to a previous study, the extracted vital data can be considered as valid, since it is non-significantly different to state-of-the-art medical devices [9]. The algorithm can be deployed to any smart wearable device in order to capture vital signs at different body positions. This is interesting, since we found out that the recognition of vital signs is position-dependent in terms of signal quality. The demonstrated approach is superior in terms of energy consumption when compared to an optical sensing. Also, current devices showed false detections (ghost heart rates – *see video figure*) while lying on a table, which can be fixed with our proposed doffed detection.

For future work, we envision the captured vital data to be processed for the purpose of an implicit interaction. Furthermore, we try to enable the recognition of vital data in movement by subtracting global motion patterns from the raw data. One approach could rely on the use of an additional high-g accelerometer.

Acknowledgements

This research is supported by the Federal Republic of Germany and the European Social Fund under the grants: *BMWi/ESF* 03EFFMV017; *BMWi* 16KN049121.

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