A Study on Measuring Heart- and Respiration-Rate via Wrist-Worn Accelerometer-based Seismocardiography (SCG) in Comparison to Commonly Applied Technologies

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ABSTRACT

Since the human body is a living organism, it emits various life signs which can be traced with an action potential sensitive electromyography, but also with motion sensitive sensors such as typical inertial sensors. In this paper, we present a possibility to recognize the heart rate (HR), respiration rate (RR), and the muscular microvibrations (MV) by an accelerometer worn on the wrist. We compare our seismocardiography (SCG) / ballistocardiography (BCG) approach to commonly used measuring methods. In conclusion, our study confirmed that SCG/BCD with a wrist-worn accelerometer also provides accurate vital parameters. While the recognized RR deviated slightly from the ground truth (*SD*=16.61%), the detection of HR is non-significantly different (*SD*=1.63%) to the gold standard.

Author Keywords

Accelerometer; Sensors; Heart Rate; Respiration Rate; Smartwatch.

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 vital signs, which reflect the current mental and physical state of a person. These vital parameters such as respiration rate, heart rate, or microvibrations of muscles contain crucial information that allow to draw conclusions on one's body processes and states, such as stress level, arousal state, the quality of sleep, well-being and anomalous situations. Such emitted vital signs are controlled by the autonomic nervous system and therefore can only be influenced indirectly by the human itself. In this paper, we utilize a simple motion sensor for detecting the aforementioned vital signs (HR, RR, MV) at the user's wrist while being in rest and while only making use of a single accelerometer, which is denoted as seismocardiography (SCG) / ballistocardiography (BCG). When only using a single inertial sensor, we do not face the problem of a high power consuming and complex sensor setup, which is usually the case for commonly used technologies, such as photoplethysmography (PPG) or electrocardiography (ECG). We envision our method to be applied at smartwatches in order to track the user's vital parameters in a state of rest, such as when lying on a sofa, which is required for the algorithm to provide precise data.

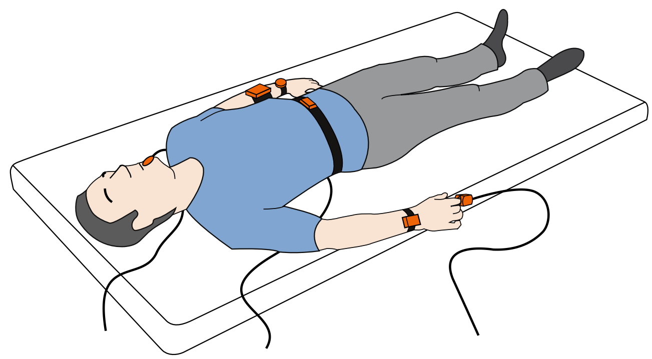

Figure 1. Sensing respiration and heart rate in the state of rest. This setup includes 6 sensors: microphone (head), Medisana blood pressure monitor (left wrist), PPG of LG G Watch Round (left wrist), accelerometer of Shimmer3 IMU (right wrist) and the Pulox pulse-oximeter (right index finger).

In this paper, we contribute the following:

- An energy efficient, unobtrusive method and straightforward design of measuring vital parameters based on SCG / BCG at the user's wrist.
- An algorithm that is capable of measuring three vital parameters: heart rate (HR), respiration rate (RR), and microvibrations (MV) by merely using a simple accelerometer.
- A comparative study that proves our design to provide valid vital parameters. We evaluated that our heart rate recognition algorithm is as reliable as the current gold standard (*SD*=1.63%) and the respiration rate only slightly differs to the ground truth (*SD*=16.61%).

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RELATED WORK

Wearable devices are widely used in the area of activity recognition. The use-cases include medical or rehabilitation scenarios as well as general sports or health topics. In this section, we provide an overview of related research and technologies in the given context.

Heart Rate Detection

The most common wearable devices make use of optical sensors in order to detect the heart rate and the saturation of peripheral oxygen. Thereby, the pulse-oximetry sensor is either implemented into a finger-clip [13,14,15,18], or into a wrist-worn device, such as a watch. Anliker et al. [1] presents AMON, a wrist-worn device capable of measuring heart rate, blood pressure, ECG-activity, peripheral oxygen saturation, temperature, and physical activity. The authors measure the heart rate by utilizing a pulse-oximeter at the back of the wrist-worn sensor device. Other related works make use of the electrocardiography (ECG) and calculate the heart rate based on the ECG signals [10,11]. In these publications, the authors attach smart shirts with ECG electrodes. In contrast, Garverick et al. [8] use a continuous-wave Doppler ultrasound device for measuring the heart rate of a fetus. Apart from measuring heart activity in a myographic or optical way, we can also determine heart activity based on small body movements caused by the contraction of the heart. This method is known as ballistocardiography (BCG) or seismocardiography (SCG) [2,19]. Thereby, sensors such as accelerometers or pressure sensors are applied to the human body to measure the exiguous movements induced by heartbeats. For that reason, the sensors are usually being placed nearby the heart (e.g. sternum or clavicle). Bieber et al. [5] recently utilized an accelerometer in a smartwatch – which had to be placed on the chest - to measure the user's heart rate.

Respiration Rate Detection

There are several ways to detect the respiration rate in a wearable setup. The most common and simple setup consists of strain gauges, which are worn as a belt around the torso [12]. Another approach is to make use of accelerometers, which are placed directly on the chest or torso [7,16]. Mundt et al. [13] utilize the impedance plethysmography, which measures the change in tissue volume as a change in impedance on the body surface. Apart from the respiration rate, the authors provided the monitoring of heart rate, blood pressure, ECG-activity, and peripheral oxygen saturation [13]. Di Rienzo et al. [6] apply a textile-based transducer for measuring the respiratory movements as changes in thorax volume. Kundu et al. [9] apply a capacitor to a shirt and measure the respiration rate by analyzing the changes in permittivity as a result of tissue movement between the electrodes. Bello et al. [3] also use capacitive sensing to detect the expansion of the thorax. The authors use a shirt with three capacitive sensors, which detect changes in capacitance after a textile expansion that leads to an increase in electrode distance. Other works make use of microphones or nasal airflow sensors [4].

Microvibrations / Muscle Tonus Detection

The most common wearable systems for detecting muscle activity are based on accelerometry. Thereby, the use cases are very widespread and contain topics such as sleep detection, the detection of pathological tremor, the detection of epileptic seizures, or general activity recognition. In 1962, Hubert Rohracher [17] initially investigated the occurrence of low amplitude muscle vibrations that he referred to as microvibrations. In this work, Rohracher used piezoelectric phono player pickups to measure the continuously detectable vibration of the muscle tissue. He also mentioned processes that are connected to and influenced by the muscle vibration, respectively (medication, level of stress, temperature etc.). In contrast to microvibrations, which are also measureable in sleep or states of unconsciousness, most research is conducted in the area of pathological tremors, which tend to disappear in these situations [17].

VITAL SIGN EXTRACTION WITH ACCELEROMETERS

The algorithm proposed in this paper works in three filtering stages, which provide the extraction of heart rate, respiration rate as well as microvibration from a single acceleration signal. As a peculiarity of the accelerometer, the measured motion is split into three axes, containing the valuable information. To cope with the dimensionality, a combination of all three axes in a single signal was enabled via building the magnitude of the acceleration vectors (1).

$$|\vec{a}| = \sqrt{{a_x}^2 + {a_y}^2 + {a_z}^2} \tag{1}$$

$$v[i] := v[i-1] + \alpha \cdot (w[i] - v[i-1]) \tag{2}$$

$$v[i] := \alpha \cdot (v[i-1] + w[i] - w[i-1]) \tag{3}$$

$$v[i] := v[i]^2 \tag{4}$$

Now, the resulting combined raw signal includes all oscillations and is further processed in the subsequent steps. Figure 2 shows the three stages of signal recognition in the time domain and frequency domain. In the first stage, the raw signal is low-passed (2) to capture the breathing frequency. Hereinafter, the raw signal is high-pass filtered (3) to capture the high frequent microvibrations. In the last step, the high-passed signal is further processed by applying a squaring algorithm (4) to reduce noise and capture the heart rate. Since the filters were applied to a time-discrete signal, $\boldsymbol{v}$ describes the input value at the time $\boldsymbol{i}$. The value $\boldsymbol{w}$ describes the current mean value at the time $\boldsymbol{i}$, while $\boldsymbol{\alpha}$ is a weighting coefficient. By performing a FFT (Fast Fourier Transform) after each filtering step, the resulting frequencies can be extracted. Note: to ensure an accurate measurement, a resting state such as sleeping or a low amplitude activity (e.g. watching TV, sitting resting) is required.

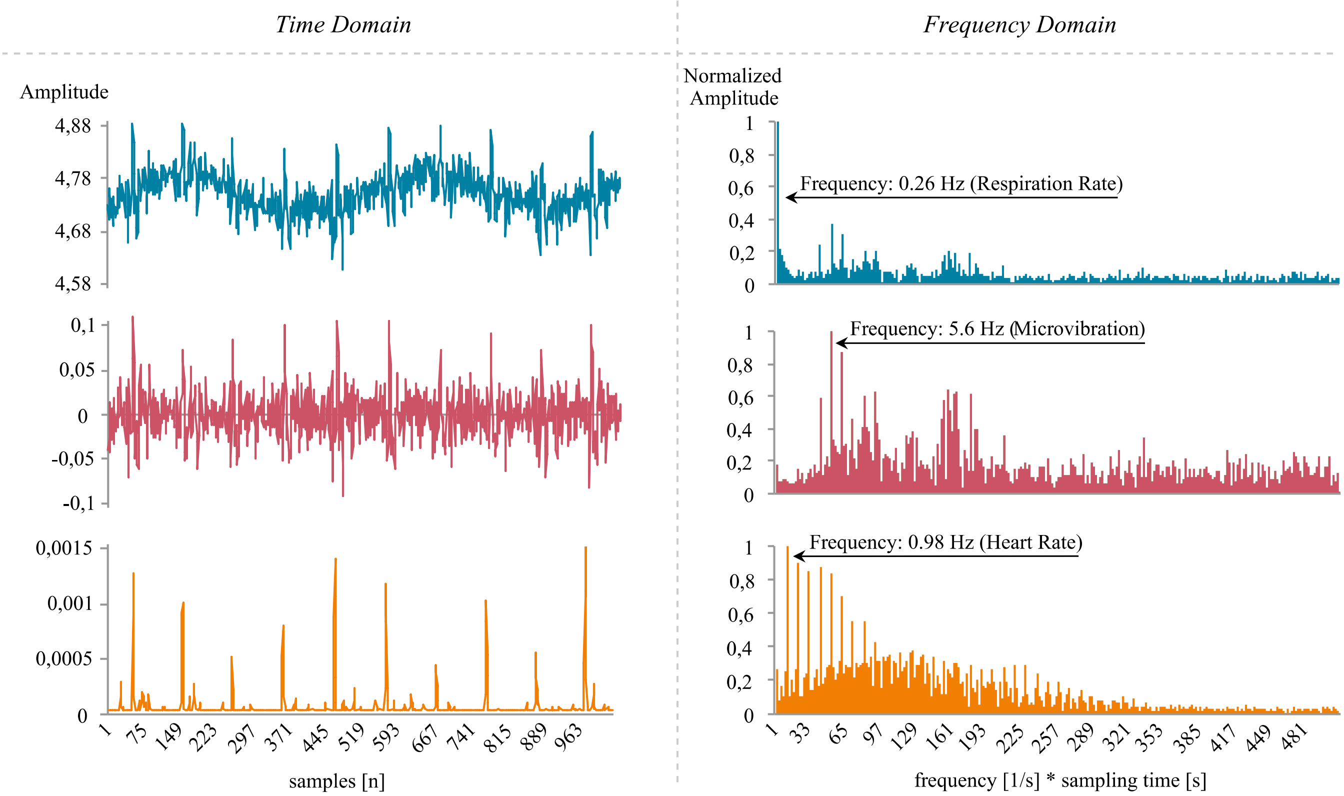

Figure 2. Filtering process for detecting respiration, microvibration, and heart rate. The blue color shows the combined raw signal in time domain (left side) and frequency domain (right side). When applying a high pass filter, we can easily recognize the microvibrations in the frequency domain (red color). Reducing the noise and squaring the signal makes the heart rate visible (orange color).

EVALUATION

To evaluate our sensing approach, we conducted a study with 15 participants and compared our measured vital parameters with state of the art sensing devices. This way, a comparison of the heart rate as well as respiration rate values between all devices is enabled. By applying a statistical significance test, we determined the actual difference in comparison to the other tested devices.

Study design

To evaluate the different approaches and devices, we designed a study that compared our presented approach to state of the art hardware in the area of heart rate and respiration rate detection. We recorded data of 15 subjects (14 male, 1 female) aged 22 to 50 years (*M*=31.4 years). All subjects where in their optimal BMI and therefore had no problems with obesity. To capture the vital parameters, the subjects had to wear a pulse-oximeter at the index finger of the right arm, as well as the Shimmer3 IMU to log the occurring accelerations induced by blood flow and respiratory movements. Furthermore, a blood pressure monitor (Medisana BW 300 connect) was worn at the left arm, as well as a LG Watch R that captured the heart rate via an internal photoplethysmography (PPG) sensor. A chest worn belt recorded respiratory movements with a capacitive electrode, which is sensitive to deformation due to respiratory movements. At the head position, a microphone was placed to record respiratory noise. The devices where applied by a technician to ensure a correct individual fixation. While recording the data, the subjects were lying on a blanket on the ground and were instructed to lie as calm as possible.

Gathered Signals

Figure 3 shows the different signals provided by the tested devices. Each signal shows a window with the length of 30 seconds. The signals shown were extracted by the data set of subject P09. All signals are aligned in time. The pulse-oximeter signal (Pulox) shows a clean heart rate signal as well as the respiration influence as a change in amplitude on the aforementioned. The chestband shows a clean respiration signal with a small drift due to environmental and electrode displacement effects. The respiration signal provided by the head worn microphone shows a small change in amplitude for inspiration cycles and increased amplitudes for the following expiration cycles. The last signal was provided by the Shimmer3 IMU, which incorporates the heart rate and respiration rate. Besides this, we can perceive an additional signal which is accumulating movements in the higher frequency range (microvibrations) and some white noise.

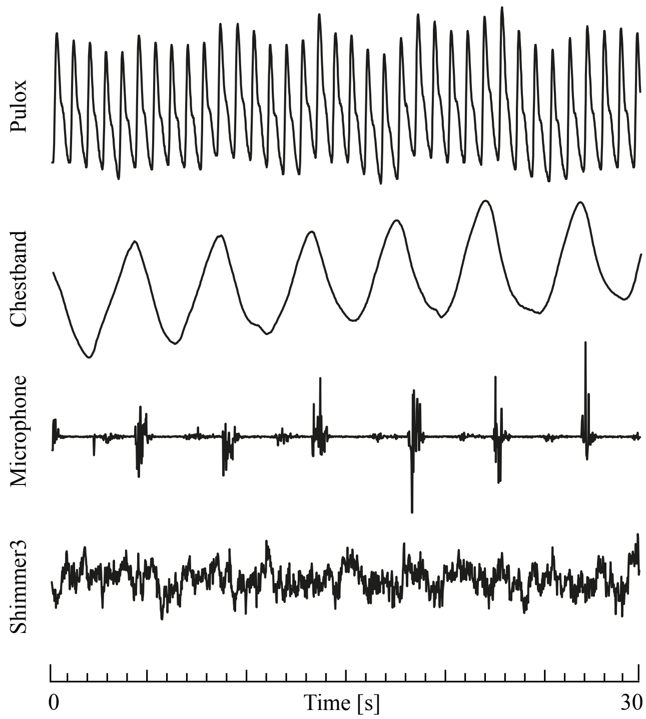

Figure 3. The different signals provided by the tested devices.

Heart rate

To compare the quality of the heart rate measurement, the Shimmer3 IMU, Medisana BW 300 connect blood pressure monitor, and LG Watch results were compared to the Pulox pulse-oximeter sensing device, which is referred to as the gold standard. Table 1 shows the results in comparison.

Table 1. Comparison of heart rate results of all three tested devices and the gold standard (Pulox).

	Pulox	Shimmer3		Medisana		LG Watch	
	Gold St.	HR	Dev.	HR	Dev.	HR	Dev.
P01	70	69	1,43%	69	1,43%	73	4,29%
P02	67	67	0,00%	66	1,49%	66	1,49%
P03	66	67	1,52%	65	1,52%	69	4,55%
P04	68	69	1,47%	70	2,94%	67	1,47%
P05	64	62	3,13%	62	3,13%	62	3,13%
P06	71	70	1,41%	70	1,41%	77	8,45%
P07	67	67	0,00%	72	7,46%	73	8,96%
P08	68	67	1,47%	69	1,47%	66	2,94%
P09	73	72	1,37%	72	1,37%	79	8,22%
P10	63	60	4,76%	61	3,17%	59	6,35%
P11	70	70	0,00%	72	2,86%	68	2,86%
P12	81	82	1,23%	80	1,23%	78	3,70%
P13	82	78	4,88%	79	3,66%	78	4,88%
P14	58	57	1,72%	57	1,72%	70	20,69%
P15	56	56	0,00%	56	0,00%	57	1,79%
		1,63%		2,32%		5,58%	

Comparing all four devices (Pulox, Shimmer3, Medisana, and the LG watch) yielded significant differences by a one-way ANOVA ($F_{3,42}$=11.99; p<.0001). A Tukey HSD Test determines that the Shimmer3 (M=1.63%; SD=1.55%) and the Medisana (M=2.32%; SD=1.72%) does not show any statistically significant differences towards the Pulox, which is the gold standard. There are no differences between the Shimmer3 and Medisana. The test confirms that the Shimmer3 and the Medisana are both capable of determining the correct heart rate. Furthermore, the Tukey HSD Test found the LG watch (M=5.58%; SD=4.86%; p<.01) to perform significantly worse than all the other devices. Even though the LG watch cannot compete to the gold standard, it still provides "good-enough" results.

Respiration Rate

For determining the respiration, the capacitive chestband, Shimmer3 IMU, and Pulox pulse-oximeter where compared to the results measured by the head worn microphone. As expected, the pulse-oximeter could also be used for determining the respiration rate due to respiratory influences (change in amplitude) on the captured heart rate signal. Table 2 shows the results of the comparison.

Table 2. Comparison of the respiration rate results of all tested devices and the microphone as the gold standard.

	Micro.	Chestband		Shimmer3		Pulox	
	Gold St.	RR	Dev.	RR	Dev.	RR	Dev.
P01	13	13	0,00%	13	1,41%	12	7,69%
P02	11	11	0,00%	10	9,09%	10	9,09%
P03	13	13	0,00%	13	1,41%	10	23,08%
P04	14	14	0,00%	15	7,14%	13	7,14%
P05	10	10	0,00%	10	2,54%	11	10,00%
P06	14	14	0,00%	13	5,83%	13	7,14%
P07	16	16	0,00%	19	18,75%	16	0,00%
P08	16	16	0,00%	23	43,75%	12	25,00%
P09	13	13	0,00%	16	23,08%	13	0,00%
P10	15	15	0,00%	15	2,34%	12	20,00%
P11	15	15	0,00%	16	7,42%	15	0,00%
P12	13	13	0,00%	16	23,08%	17	30,77%
P13	15	15	0,00%	16	7,42%	15	0,00%
P14	9	9	0,00%	12	33,33%	11	22,22%
P15	8	8	0,00%	13	62,50%	10	25,00%
		0,00%		16,61%		12,48%	

The data analysis of the respiration rate from all devices (microphone, chestband, Shimmer3, and the Pulox) provided statistically significant differences by a one-way ANOVA ($F_{3,42}$=11.67; p<.0001). While the chestband provided exactly the same results as the microphone, the Shimmer3 (M=16.6%; SD=17.94%; p<.01) and the Pulox (M=12.47%; SD=10.8%; p<.01) performed significantly worse than the gold standard and the chestband, following the results of a Tukey HSD Test. Significant differences between the Shimmer3 and the Pulox could not be determined. In conclusion, we can see that the Shimmer3 and the Pulox are both capable of sensing the respiration rate, but suffer of a slight inaccuracy.

CONCLUSION

In this paper we show that wrist-worn devices are capable of detecting vital signs such as heart rate, respiration rate and microvibration. The study results indicate that by using standard consumer products, such as smartwatches, human vital signs can be captured by reading accelerometer data and applying our algorithms to it. This way, vital parameters can be logged in any resting states or periods of low amplitude movements via devices that are using built-in accelerometers. Now, this enables all smart devices (with a built-in accelerometer) to capture vital parameters that were not detectable before because of a missing photoplethysmography (PPG) sensor. Moreover, making use of an accelerometer instead of a PPG lowers energy consumption drastically. (Typical power consumptions: PPG, 1 – 50mW; Acc., 0.5 – 2mW). Even though the detected respiration has slight inaccuracies, the heart rate recognition could be proven to match the state-of-the-art standards, as it is even more accurate than the PPG. Several post-studies indicate that elastic underground surfaces (e.g. a mattress) can even raise the accuracy level, since such surfaces act as a resonator. As an effect, this increases the recognition of respiratory movements up to a flawless detection.

FUTURE WORK

By applying further algorithms, additional vital parameters such as heart rate variability or respiration rate variability could be determined. This could provide more complex insights into the topic of stress detection. Furthermore, the detection and monitoring of microvibrations and vital signs such as heart rate variability etc. could possibly contribute to a more detailed sleep analysis.

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