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Movement filtered heart rate variability (HRV) data from a chest-worn sensor

Abstract: Recording of heart rate variability (HRV) is a non-invasive and continuous measurement method that allows investigating the autonomic nervous system (ANS) and its reaction to environmental influences. For a precise measurement of HRV data, a carefully chosen study design and environment is required to minimize secondary influences. One major influence to be avoided is movement. However, in the daily routine and for some scientific questions, movement can often not be avoided. If so, a manual or automated method to differentiate between artifacts caused by body movement and the actual psychophysiological effect is needed to ensure the data quality.

In this approach, a chest-worn sensor was developed, that measures the heart rate using a single lead ECG and filters the measured change of the HRV caused by movement. Data from an integrated accelerometer is used to detect upper body movements that affect the resting heart rate. The movement-corresponding time stamps are then used to filter the Interbeat Intervals (IBI) accordingly. Functionality and effectiveness of the sensor system have been tested against state-of-the art sports- or clinical devices in varying scenarios.

As our test series showed, motion filtering has a decisive effect when motion occurs, two-thirds of all cases showed a significant effect of motion filtering, with small to medium effect sizes for the parameters SD2, SD2/SD1, and SDNN. Thereby, automatic filtering of motion artifacts can help to significantly reduce the need for costly post-processing of distorted data sets.

The results show a better data quality of HRV measurement, a method that is commonly used for the investigation of physiological processes in the field of chronic pain, psychology, psychiatry, or sports medicine.

Keywords: HRV, movement, filter, accelerometer, algorithm, psychophysiology, chest-worn, single-lead ECG, chronic pain, psychology, psychiatry, sleep

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1 Introduction

Due to more accessible technologies and standardization, analysis of heart rate variability (HRV) is becoming increasingly important for psychophysiological research. HRV is a good reference to the activity of the autonomic nervous system (ANS) [1]. The ANS reacts to environmental influences by self-regulatory mechanisms and constantly adapts the energy supply to the needs of the prevailing situation. Mental and physical sensation play a crucial role on these self-regulatory mechanisms, which is why insights into these processes are very important for psychophysiology [2]. In order to reliably detect these subtle changes in any research, a careful study design is required to minimize secondary influences [2]. Movement is one of the major influences to be avoided during HRV measurements [3]. When a person starts moving, it immediately affects HRV, as the ANS must cope with the demands of the physical load which distorts the information about psychophysiological processes. However, under certain circumstances, movement cannot be avoided, thereby necessitating a method to differentiate between movement artifacts and the psychophysiological effects. Approaches for automatic filtering of motion-specific HRV deviations are scarce. A promising approach is described by Verkuil et al. 2016 [4], which aims at long-term HRV analyses by measuring the mean acceleration over 30s periods and only slightly considers short-term movement phases. Additionally, the method requires an extensive calibration phase, and it contains only the evaluation of one HRV parameter (RMSSD), which makes it unsuitable for a broad adaption. Our work uses an universal approach, which was tested on a small scale.

2 Material and Methods

2.1 Data acquisition and signal processing

For the data acquisition, a system consisting of different microcontroller modules (see Figure 1) was developed to ensure maximum connectivity (BT & Wi-Fi), unrestricted data access and modulation as well as a waterproof housing to meet the requirements for future projects. Electrical activity of the

Figure 2: Hardware components: 1. Adafruit HUZZAH32, 2. MicroSD Module and 32 GB MicroSD, 3. AD8232 Heart Monitor, 4. BNO055 9DOF IMU, 5. Qi-Charging Receiver, 6. IP67 Housing with electrode snaps, 7. Polar Soft-Strap

heart is recorded with a sampling rate of 1000 Hz by an Analog Devices AD8232 analog digital converter with operation amplifier (sold by Sparkfun) clipped to an off-the-shelf "Polar Soft-Strap" chest strap with snap electrodes.

The signal processing and detection of the R-Peak is done according to the Pan-Tompkins algorithm [5] (see Figure 2).

Figure 1: Pan-Tompkins algorithm [5]

Motion data is collected by a Bosch BNO055 sensor combining accelerometer, gyroscope and magnetometer (sold by Adafruit) at a sampling rate of 100 Hz. The signal of the accelerometer first passes through a low-pass filter of 10 Hz to capture all motion-induced signals, then the total acceleration (Signal Vector Magnitude (SVM)) is formed and normalized by subtracting the gravitational influences according to V. T. van Hees et al. [6] (see eq. 1).

$$SVM = \sqrt{x^2 + y^2 + z^2} - g \quad (1)$$

To differentiate between larger and smaller movements. The factor $x_{mov} = 3$ was determined from previous tests. Thereby small movements still have absolute values smaller than 1, whereas larger movements reliably assume values larger than 1, which contributes to good differentiability when the signal is subsequently squared (see eq. 2).

$$sqSVM = (SVM * x_{mov})^2 \quad (2)$$

Due to squaring, steep spikes were caused by periodic movements (e.g. walking), necessitating signal smoothing by

a moving average window. A threshold value of 1.5 turned out to be reliable to classify large movements (see Figure 4).

To obtain data for HRV analysis, the time between two consecutive heartbeats (IBI) is measured. For the automatic acquisition of the rest data, there is a subdivision into 3 phases: 1. *movement phase*: movements with cardiovascular impact are detected. 2. *recovery phase*: no more movement is being detected but the heart rate still deviates from the previously measured resting heart rate. 3. *resting phase*: no movements are detected, and the heart rate has converged to the resting heart rate. The resting data is only saved in the *resting phase*. Resulting gaps are deleted and data points are seamlessly joined together. The 1-channel ECG raw data and the IBI data (all phases) are always saved for manual post-processing that may be necessary.

2.2 Evaluation Methods

To evaluate the quality of the IBI measurement, the developed system (*BioMed HRV*, sampling rate 1.000 Hz) was compared to three commercial systems: A clinical 3 channel ECG (*BioPack*, 1.000 Hz), a sports chest strap (*PolarH10*, 1.000 Hz) and a PPG-HRV system (*emWave2*, 370 Hz). The measurement was performed in a sitting position without major movement and synchronized in time.

For the evaluation of the movement detection, common movements such as standing up, sitting down, scratching the head, walking, lying down, turning back and forth (supine) and bending the legs (supine) were performed.

To test the reliability of removing of movement-related IBI deviations, the subject executed different movements such as standing up and sitting back down, walking for 30 seconds, and performing deep squads for 30 seconds while remaining seated for 1 minute in between.

We additionally evaluated whether data quality would benefit from motion filtering or not. Therefore, five individuals (3 female, 2 male, $\bar{x} = 28$ yrs, range: 25 - 32 yrs) executed four different movement patterns during 3-minute measurements: (1) turning over to one and to the other side while lying, (2) sitting up and lying back down once, (3) standing up and sitting back down, and (4) walking two times for 10 seconds. The following HRV parameters were used for comparison: Standard Deviation of IBI's (SDNN), mean IBI's (RR), Root Mean Square of Successive Differences (RMSSD), Standard Deviation of instantaneous IBI variability (SD1), the continuous long-term IBI variability (SD2), SD2 to SD1 ratio (SD2/SD1), and Baevsky's Stress Index (SI). All HRV parameter were calculated according to the Kubios HRV analysis methods [7] which are mainly based on the guidelines given in the task force for standards of HRV [3]. For significance testing, we analysed the differences between motion-filtered and randomly filtered data using an adapted bootstrapping technique. For this, we randomly picked an equal amount of data points from the raw dataset as the

motion-filtered dataset contains. After generating 10k randomly filtered datasets, we compared each calculated HRV parameter from the motion-filtered data to the full range of values of this very parameter from the randomly filtered datasets. If the motion filtered parameter is outside the range of 2.5% to 97.5% of the randomly filtered data, the motion filtering is considered to have a significant effect.

For effect size, we calculated Cohen's d based on the average HRV parameter difference between filtered and unfiltered raw data, and the standard deviation of parameters based on unfiltered raw data.

2.3 IBI measurement accuracy

In Figure 3, the measurement series of all four devices are plotted into one graph to show deviations to the other devices:

Figure 3: IBI measurement of four devices overlaying each other (*BioMed HRV* on top, outliers due to muscle artifacts)

As the *emWave2* deviates strongly from the other devices, it will not be considered further on. The measurement series of the *BioPack* shows some outliers, which can be explained by muscle artifacts caused by arm movements (verified by ECG curves). Apart from the outliers, the graphs are almost congruent. After removing the artifacts the measured values deviate in the single-digit millisecond range. These deviations are plotted in Table 1.

Table 1: Comparison of the deviation of the measured IBI's between all three devices

Parameter	BioMed HRV - BioPack	BioMed HRV - Polar H10	BioPack - Polar H10
SD	2,32 ms	1,88 ms	1,38 ms
Variance	5,40 ms ²	3,55 ms ²	1,91 ms ²
$SD/IBI_{BioPack}$	0,23 %	0,18 %	0,14 %

According to this measurement series, the *BioMed HRV* differs slightly from the other two devices. With a deviation effect of 0.23% to the *BioPack* and 0.18% to the *Polar H10*, the accuracy of the *BioMed HRV* is comparable to commercial devices at the same sampling rate.

2.4 Movement detection

The following graph shows the classification of different daily movements due to their cardiovascular impact (above/below threshold). Movements of larger magnitude such as standing up, sitting down, lying down, and turning back and forth are reliably above the threshold, whereas actions such as scratching the head or bending the legs remain below.

Figure 4: Classification of several different movements:
Below threshold = movements of little magnitude
Above threshold = movements of larger magnitude

2.5 IBI movement filtration

The movement filtering process of the IBI's is demonstrated graphically in figure 5. From the raw RR intervals in the first graph, the cardiovascular burden of the physical activities can easily be seen (rest: cyan, movement: red, recovery: orange).

Figure 5: Movement filtration process of Interbeat-Intervals

Each movement is accompanied by a decrease of the IBI's and heart rate variability. The second graph shows the smoothed raw (orange) and resting-only (cyan) curves as well as the realignment threshold (cyan dashed). Depending on the exercise intensity, after stopping the movement a more or less steep increase of the IBI's can be observed. When the smoothed value of the raw-IBI's has reapproached a value 100 ms below the value of the smoothed resting -IBI's, the recovery

phase is considered to be completed and the filtered resting-IBI's are recorded again, as can be seen in the 3rd graph.

2.6 Effects of movement filtration to HRV Parameters

80% of the total analysed parameters (7 parameters for each of 5 participants) showed a significant effect of filtering when turning over in a supine position. Sitting up showed a significant effect for 63% of cases, standing up from sitting on a chair 46%, and walking 77%. On average, two-thirds of all cases were significant. As Table 2 shows, motion filtering was most relevant for SD2, SD2/SD1, and SDNN. There is a modest effect for SI, and little to no effects on RMSSD, RR, and SD1. In general, walking and supine turning had the greatest effect on HRV-parameters, while standing up from a sitting position peculiarly had the least.

Table 2: Cohen's d effect size of filtered to raw HRV Parameters rounded to one significant value. Absolute values equal or greater to 0.2 (small effect) are marked green.

Parameter	turning over	sitting up	standing up	walking
SDNN	0.6	0.4	0.1	0.4
RMSSD	-0.1	0.0	-0.1	-0.2
RR	-0.2	-0.1	-0.1	-0.2
SD1	-0.1	0.0	-0.1	-0.2
SD2	0.7	0.5	0.2	0.4
SD2/SD1	0.7	0.4	0.3	2.8
SI	-0.2	-0.3	0.0	-0.2

3 Discussion and Conclusion

The main objective of this work was to develop a universal method for filtering movement-induced HRV distortions. This first required the development of a measurement system that would meet requirements for future work. The developed system was shown to have IBI measurement accuracy comparable to commercial and clinical devices with the same sampling rate. Likewise, based on the initial series of tests, robust motion detection was demonstrated. The analysis of results from the adapted bootstrapping method shows that motion filtering is sensible for the exclusion of times where motion significantly changes HRV parameters in most cases. The high percentage of significant changes to parameters when turning over in supine position highlights that filtering of motion artifacts should be considered in studies where motion is unavoidable, e.g.: sleep analysis. The importance of

motion filtering is underlined by the effect sizes across most movement patterns and parameters. SDNN, SD2, and SD2/SD1 turned out to be vulnerable to motion artifacts. While more robust in our analysis in terms of effect size, RR, SI, SD1, and RMSSD, should be viewed critically as well. They may warrant motion filtration as movement extends, as was shown with walking for short periods. This study serves as an entry point to the automated detection and removal of movement-related HRV distortion. We evaluated short HRV measurements and 4 movement patterns only. Further studies with different test scenarios, longer measurement durations, and with a larger test group of different ages and health status are needed to gain a clearer insight into motion induced alterations to HRV parameters.

Author Statement

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