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Optimization and evaluation of a mobile IMU-based ballistocardiography system

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Abstract: In recent decades ballistocardiography (BCG) has regained popularity as a way to measure the mechanical activity of the heart. In this paper we present and evaluate a new iteration of our mobile BCG measurement system. The proposed system uses an inertial measurement unit (IMU) placed on the carotid artery to derive the BCG. We conducted a measurement series to evaluate the system and to do an initial investigation into whether more complex heart parameters can be derived from BCG data. The evaluation shows that heart rate (HR) and heart rate variability (HRV) calculated using BCG data, agrees well with the reference measurement and amplitudes calculated are mostly comparable in range to other papers. In conclusion, the system can reliably derive features from BCG data that can be used in further research.

Keywords: Ballistocardiography, BCG, IMU, heart rate

1 Introduction

Electrocardiography (ECG) has proven to be a reliable method for deriving cardiac function [1] and is the current gold standard. BCG has come back into use as an alternate method for gauging heart activity in recent years. In the late 1800s, it was first discovered that the ballistic forces caused by ejection of blood from the heart into the blood vessels, provoke a measurable reaction from the body [2]. Then, modern BCG was developed in the 1950s by Isaac Starr among others. Back then BCG measurements were taken by putting the subject in bed suspended from the ceiling and attaching a pen to one end of the bed to record its movements [3]. The method was abandoned in favor of the much simpler and more reliable ECG, as the data recorded by the BCG was susceptible to interference. However, the substantial progress made in sensor technology since BCGs birth in the 50s have greatly expanded the ways it can be measured. As a result, many different types of BCG systems have been developed like some being built into nursing beds [4] or into wheelchairs [5]. Alternatively, a BCG can also be performed with non-contact sensor technology, like radar [6] or optical measurement using LEDs [7]. One can derive multiple parameters from a BCG like heart rate or HRV. In addition to these two, it is feasible to derive additional complicated factors, such as valve activity, heart abnormalities or disorders, rhythm disturbances, stroke volume, heart ejection force, and pulse wave velocity [8, 9].

In this paper we present a new version of our system [10]. In addition, the data collected with this system will be evaluated and an initial investigation of the possibility of using these data to derive more complex cardiac parameters will be performed.

2 System Overview

As presented in [10], the system consists of a micro controller unit (MCU; Fig.1,(1)), an IMU (Fig.1,(2)) and a photoplethysmogram sensor (PPG;Fig.1,(5)). The used microcontroller is a ESP32-DevKit-LiPo from Olimex, which obtains the sensor data via I2C.

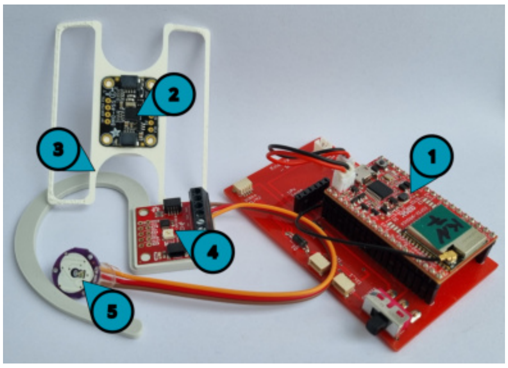

Fig. 1: This figure shows the prototype of the BCG system: (1) ESP32 micro controller, (2) IMU sensor, (3) carrier, (4) ADC Module, (5) PPG Sensor

A PPG sensor (PulseSensorPlayground, with the Sensorchip APDS-9008)(Fig.1,(5)) is used as a reference measurement. It measures the amount of blood flowing through the artery by measuring the amount light reflected by the blood. For this purpose, it is attached to the earlobe via a clip (Fig. 2, (5)).

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Unlike an ECG, this keeps the system more mobile and makes it easier to attach. An analog-to-digital converter (SparkFun Qwiic 12 Bit ADC)(ADC; Fig.1,(4)) is used to read out the PPG sensor, which is attached to the ear via an ear mount.

Using the IMU (Bosch BNO055 on an Adafruit Breakout PCB), the actual BCG will be derived. For this purpose, only the acceleration data from the sensor will be extracted, as it provided promising results. To obtain the data at the carotid artery, a carrier (Fig.1(3)) was created for easy attachment to the body using an elastic strap. Currently, the system is connected to a computer via serial interface to facilitate data analysis. To fully exploit the mobility aspect of the system, the serial connection would have to be replaced by a wireless solution (i.e. bluetooth or WiFi).

An advantage to placing the IMU sensor on the carotid artery as opposed to measuring on the chest, is that there is less distortion due to clothing for example. Also, measuring at the carotid directly allows for a clearer measurement as the blood flow is more pronounced. Unlike other BCG systems, such as those integrated into beds [4] or wheelchairs [5], in this way, the presented system is mobile and comparatively compact. Additionally, placing the on the ear PPG, close to IMU the wave propagation speed is minimized.

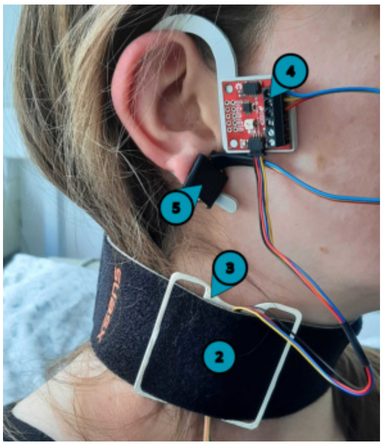

Fig. 2: This figure shows the position of the sensors on the subjects neck and ear. (2) IMU sensor, (3) carrier, (4) ADC Module, (5) PPG Sensor

3 Evaluating the System

This section first explains the BCG-Waveform, followed by the procedure of how the measurements were taken. Finally the data processing and the features used to evaluate the system will be explained.

3.1 BCG-Waveform

BCG derives the ballistic forces of the heart, caused by the ejection of blood. Each period has a number of distinctive waves which can be split into three groups (pre-systolic, systolic and diastolic waves), corresponding to different points in time during the cardiac cycle. For example the highest peak (J-wave) is caused by the largest headward movement of blood in the systole, while the I-wave, which precedes it, is caused by footward deflection in the early systole. The I-J and K-waves are referred to as the IJK-complex [3]. In the following, local maxima will be called peaks (i.e. J-peak) and minima will be called valleys (i.e. I-valley). In figure 3, an ideal BCG wave is shown.

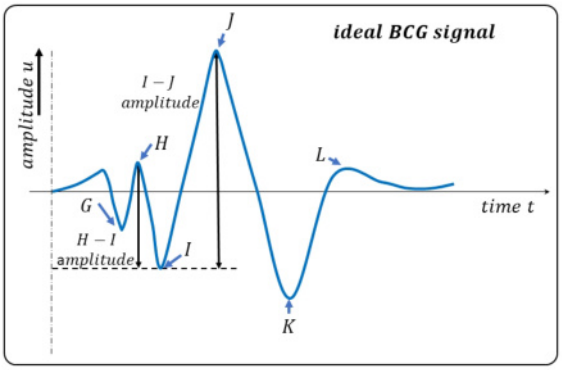

Fig. 3: This figure shows an ideal BCG-waveform. Peaks, valleys and amplitudes are labeled accordingly.

3.2 Measurement Series

An initial collection of test data was created to evaluate the system. A total of 10 measurements series were made, with six healthy subjects (1 female, 5 male, ages 26-35). Every subject took one series of measurements in the morning and one in the afternoon. For this purpose, a test procedure with three different body postures was selected. The subjects are measured first lying on the back, then lying on the side and finally sitting up. In each position the subjects were asked to breath calmly over three minutes and then to suppress their breath for 30 seconds.

All measurements were recorded with a sampling frequency of 100Hz (both IMU and PPG). This ensures that the IMU and PPG signals, which contain relatively low frequency components, can be captured completely.

The system was fastened to the subjects as shown in figure 2. The adjustment of the strap was done by the subjects themselves to minimize discomfort. To save the recorded data the micro controller is connected via a USB to the virtual serial port of a computer. Before each measurement, the BCG signals are manually checked for IJK-complexes and for the typical spike pattern in the PPG via visualization using the program *SerialPlot*[1]. If any irregularities or artifacts dominated the signal, the sensor position was adjusted to avoid recording too noisy data. Such artifacts might be caused by the sensors moving when the subject changed positions. The data is then saved it to a csv-file and further processed using *Matlab* [2].

3.3 Signal Pre-Processing

To extract the desired features, the recorded data first had to be pre-processed. To do this both the BCG and PPG signal were smoothed using a moving mean filter, to ensure the value range was similar for each signal. This was done to do an initial visual analysis of the signals. For the next step we extracted the locations K-waves to determine the locations of the I and J-waves as they form the basis for all our calculations. To achieve that, the positive parts of the BCG signal were removed and its energy was calculated. Then, the locations of the K-waves were extracted from the signals energy value. The K-waves were chosen as a starting point as they were easier to extract due to being much higher than neighboring peaks. The positions of J- and I-waves were calculated from the K-waves position. From the PPG signals, only the local maxima were extracted from the flattened signal. The thresholds to extract the peaks were determined empirically for each data set.

3.4 Extracted Features

In this section the extracted features used to verify the correctness and reliability of the system are described. To validate the measurements HR is calculated in beats per minute (BPM) and HRV is calculated in milliseconds (ms) with both the BCG data recorded by the IMU and the PPG data. HRV is calculated using root mean square of successive differences over the J-peaks [11]. The results are then compared and ideally will not differ greatly. Additionally, as more complex parameters the slope between I-valley and J-peak [12], the ratio of the amplitudes of I-valley and J-peak [13] are calculated as well. For a better comparison of the data, the mean as well as the standard deviation (STD) are calculated for the IJ-slope and the IJ-and JK-amplitude ratios respectively. The slopes and amplitudes are calculated to investigate the possibility of deriving more complex heart parameters. So far BCGs have shown to reliably measure simple parameters like HR [14].

1 SerialPlot: https://github.com/hyOzd/serialplot

2 Matlab: https://de.mathworks.com/products/matlab.html

Measurement	HR Diff.	HRV Diff.
1_1	2.5	2.68
1_2	1.06	1.30
2_1	0.34	0.11
2_2	2.53	0.09
3_1	0.5	0.28
3_2	0.76	0.57
4_1	0.54	0.91
6_1	2.13	0.20
7_1	0.85	0.05
7_2	0.62	0.20

Measurement	IJ-slope Mean	IJ-slope STD
1_1	4.89	1.95
1_2	5.05	2.08
2_1	4.36	1.43
2_2	3.92	1.48
3_1	8.26	3.78
3_2	6.35	3.71
4_1	3.63	1.78
6_1	7.66	3.79
7_1	6.53	1.87
7_2	7.06	1.67

Tab. 1: The left table shows the differences between calculations of HR and HRV. The right table shows the mean of the IJ-slope and its STD across all positions per measurement.

4 Results and Discussion

As each position was recorded separately, the features were calculated for each position. Then the mean and STD were calculated, respectively. As can be seen in table 1, the difference between HR and HRV values was calculated and is smaller than one in most cases. Also, the HR and HRV values are within typical ranges for healthy humans (average of our subjects for HRBCG: 73.89 BPM, HRPPG: 74.15 BPM, HRVBCG: 68.86 ms, HRVPPG: 69.12 ms) [15, 16]. The small difference between values computed with the BCG and PPG data indicate that the system can record reliable and accurate data for further analysis.

Shown in table 2 are the amplitude ratios between the I- and J-waves as well as the J and K-waves. While many BCG measurements are taken with subjects lying on their back [4, 13] some like [5] have taken measurements with the subjects sitting. As can be seen the numbers for the IJ-amplitude are comparable to the results shown by Jones and Goulder in [13], whereas the JK-amplitude values are overall smaller than in their paper. This is likely due to the measurement device used. Jones used sensors below a mattress while our sensor was strapped to the carotid artery. Comparing the amplitude ratios with regard to measuring position, it can bee seen that for most measurements the change in position had only a minimal effect on the IJ-amplitude values while it is more noticeable for the JK-values, likely due to gravity having a stronger effect on the footward movement of blood that causes the K-wave.

While other research lacks concrete data for IJ-slopes it has been used as input to generate features for a regressor model [12]. As such further analysis of the numbers in table 1, will be done in the future.

Measurement	IJ-Amp Lying	IJ-Amp Sitting	JK-Amp Lying	JK-Amp Sitting
1_1	28.02	24.25	76.04	97.52
1_2	23.63	21.42	92.9	105.09
2_1	21.06	22.54	123.34	166.42
2_2	43.19	79.53	116.31	133.93
3_1	17.43	15.44	84.36	64.04
3_2	73.27	51.64	149.41	137.24
4_1	47.29	36.94	119.87	97.73
6_1	35.35	26.21	104.29	101.29
7_1	14.18	28.09	134.04	69.75
7_2	15.91	20.2	128.4	72.96
Mean	31.93	32.63	112.9	104.6
STD	18.46	19.4	23.18	32.86

Tab. 2: This table shows the IJ- and JK-amplitude ratios, calculated from data recorded in dorsal and sitting positions.

5 Conclusion and Future Work

The presented system mobile BCG system can be used to detect various cardiac parameters. The investigations have shown that it reliably collects data and can keep up with the results of a PPG signal. Furthermore it was shown that the measurement at the carotid artery can yield data from which features can be extracted to derive more complex heart parameters. In addition, because of the mobile nature of the system, it could be used to analyze and evaluate noise and artifacts caused by movement for example. To extend the system, the next steps would be to develop an algorithm to detect features and to calculate more complex parameters and to do measurements with an ECG as reference. For that, further test measurements will be performed to obtain more data for analysis with signal processing methods or even neural networks. Additionally, the system will be given to a cardiologist to evaluate a possible application of the system in practice.

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Author Statement

Informed consent: Informed consent has been obtained from all individuals included in this study.

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