Proceedings of the 11th International Conference on Applied Informatics
Eger, Hungary, January 29–31, 2020, published at http://ceur-ws.org

Extracting Physiological Signals From Smartphone Sensors*

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Abstract

Two of the primary vital signs are breathing and pulse rate. There are various solutions to monitor them, however, all require additional equipment and expertise to use. Smartphones are nowadays at almost every person's arm length, therefore, it could be cost-effective for crowd and personal health screening. Diaphragmatic breathing can be measured with Inertial Measurement Units (IMU). To optimize the breathing detection the smartphone has to be placed in the middle of the epigastric region. The tissue in the region vibrates because of the presence of the abdominal aorta which is also picked up by the IMU. Breathing, which is usually under 1 Hz during sleep can be filtered out with a Bandpass filter. The heartbeat is present as vibrations which can be seen between 1–30 Hz. After filtering, breathing is detectable by a peak detector algorithm and can be differentiated from noises.

Keywords: Sensors, IMU, Filters, Peak detection, Vital signs, Physiological signals, Screening

1. Introduction

Right now it is a growing need and supply for personal health devices and applications. Companies are emerging in the telemedicine market and established

*The research has been supported by the European Union, co-financed by the European Social Fund (EFOP-3.6.2-16-2017-00013, Thematic Fundamental Research Collaborations Grounding Innovation in Informatics and Infocommunications).

companies are creating divisions for both telemedicine and to develop commercial devices [3]. Phone manufacturers, for example, Samsung is putting pulse-oximeter in its phones. Apple developed the Apple Watch, which is unbelievably powerful especially compared to its size and has enormous potential. The development of monitoring applications is also funded by governments and EU initiatives mainly. In-home short- or long-term monitoring could be generally important especially to screen for disease, assess well-being and to provide history of data. It is not a solved problem yet for heterogeneous reasons. The most important question is as always how reliable and precise could be the devices and techniques. It is important to keep in mind that even clinical devices have reliability issues. Companies are developing less and less intrusive and better target devices, however many of these are not widespread. Usually for short term monitoring and general well-being, like sleep monitoring people are not willing to buy an expensive target device [4, 2, 14]. A significant portion of people uses smartphones already for communication, photography, fitness, healthcare, smart home, and diary purposes, etc. In many cases right now, a smartphone is just not enough for the task. However, in a few cases may be useful.

1.1. Reviews

Extensive review was done by [11] on contact-methods for measuring respiratory rate. Smartphone's camera for Photoplethysmography has been investigated many times by multiple authors [9] and it is said to be enough at least acquiring pulse rate at rest. IMUs in smartwatches are used for Human Activity Recognition (HAR) including sleep analysis, fall detection [6]. Evaluating Inertial Measurement Units for Physiological Signal monitoring is still ongoing and relatively new. Till now, mainly used for simple step detection, complex gait analysis for exercise monitoring and rehabilitation. A few authors started to measure breathing and pulsation at different parts of the body, mainly they work with often just the accelerometer [7, 10, 11].

A review was done by [8] on the topics of smartphone accelerometers for the detection of heart rate.

2. Materials and Methods

2.1. Data Acquisition

As a data recorder, we used an iPhone6. According to iFixit's teardown an InvenSense MP67B 6-axis Gyroscope and Accelerometer Combo was found.(we did not receive any funding from Apple or iFixit) It is important to mention that the phone's weight, morphology and the place where the IMU is to be found also matters. The weight matters particularly because the pulse vibrations have to vibrate the phone.

To acquire the data from the phone we were using Bernd Thomas's iPhone application called SensorLog. Here we can partially choose which type of data we want to record, few of them are mandatory. We chose: "Accelerometer", "Gyro" and "Altimeter". Every sample is a row, which gets a timestamp. The sampling rate is configurable between 1-100 sample/second, we set it to 100. The high sampling rate is needed because of the fast vibration from which the pulse wave is calculated. In the application, data can be saved into a comma-separated values file (CSV) or JavaScript Object Notation (JSON) format. After recording, the file (measured values) was transmitted to the computer (server) by AirDrop.

Figure 1: (Illustration) It has to be placed directly to the skin and stabilized to make sure no displacement can happen

We looked for the breathing signal on the accelerometer and gyroscope on the accelerometer during ideal supine position and near-perfect placement (Figure 1). It is crucial that in this position the phone measures abdominal breathing movement, rather than thorax breathing movements. During Rapid Eye Movement sleep(REM) one relies on abdominal breathing[12]. In this placement and body posture, the z-axis is pointing downwards and has a value close to -1, the x-axis is perpendicular to the body and y-axis parallel to the body, both of them are close to the 0 value. Y-axis is the most sensitive to angular changes because the gravitational force is not linearly dependent on the change of angle. It is very important that the breathing can be seen from angle changes and not linear acceleration. The problem is that, in not ideal placement the rotation won't happen around one base axis. This limits the breathing signal quality then the breathing can be hard to detect. The accelerometer has a best position to use near the angle where force changes on both axes are maximal and there is nearly no gravitational force on the x-axis. Because of these reasons accelerometers are mainly useful for approximating breathing rate and should be used rather in a sensor fusion with the gyroscope. In this article, we are not dealing with sensor fusion. Any body posture which deviates from the ideal supine changes the forces present on the axes of the accelerometer which also decreases breathing signal quality and also it could abolish it if the person sleeps perfectly on his/her side.

In comparison, the gyroscope is only affected by body morphology which can vary based on posture. Yaw angles can not be calculated from just the accelerometer, only roll and pitch angles [15], however, magnetometer could be used for this purpose, but magnetometers have a big downside. It is a different kind of measurement therefore hard to match with the accelerometer readings. They pick up electromagnetic noises and introduces additional room variability. In this article, we will stay with the ideal orientation. It is important that we are using the angular velocity acquired from the gyroscope and not the calculated roll, pitch, yaw angles because the correcting algorithm is not known and also we are not evaluating the IMU.

2.2. Raw Data

We show the presence of respiration on the accelerometer, however we extract it only from the gyroscope. We also show the pulse waveform on the gyroscope. The figures have been created with matplotlib [5].

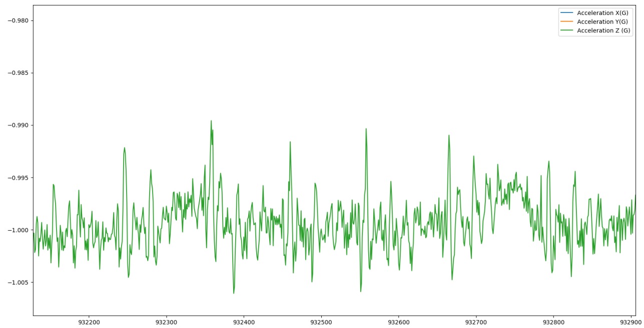

Figure 2: Pulse's vibration on the accelerometer's z-axis

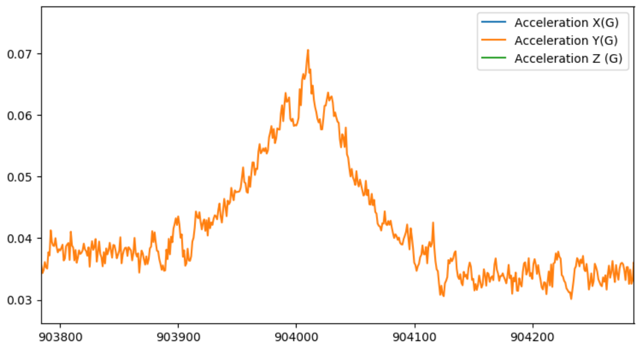

Figure 3: Abdominal breathing movement on the accelerometer's y-axis, the pulse's vibration also can be seen

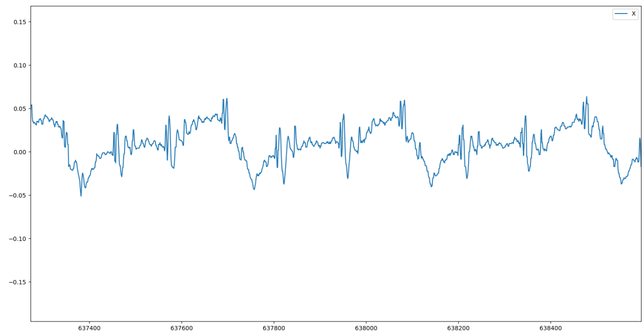

Figure 4: Abdominal breathing movement and the pulse's vibrations on the gyroscope rotation rate around x-axis

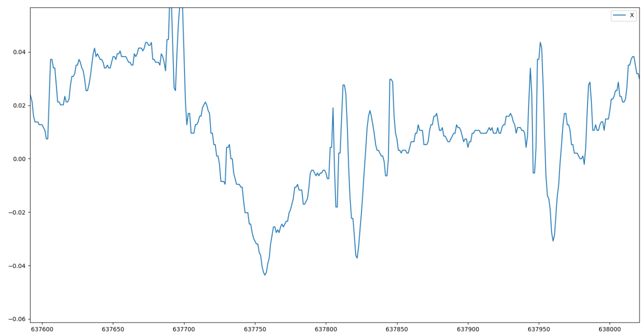

Figure 5: A zoom in of the previous figure. The bigger slow frequency wave is respiratory movement and the pulse wave sits on top of it. After it 2 pulse vibration can be seen.

2.3. Transformation

We extract offline the pulse and abdominal breathing movement from the gyroscope's angular velocities due to inherent problems with the accelerometer.

We are free to use Finite Impulse Response (FIR) and Infinite Impulse Response (IIR) filters because we process the data offline and also in this scenario signal distortion is acceptable. For the former integer arithmetic is enough, but latter requires floating-point arithmetic. Generally, a lower order IIR can achieve similar results to a higher-order FIR filter, therefore we chose IIR Butterworth bandpass filters. [16, 13]. We extract the respiratory movement signal with IIR Butterworth bandpass filter, The low-pass cut-off frequency is 0.1 Hz and high-pass cut-off frequency is 1 Hz. The filter order is 4 (the higher the filter's order the higher the steepness is in the transition band). We applied the filter forward then backward to minimize phase shift.

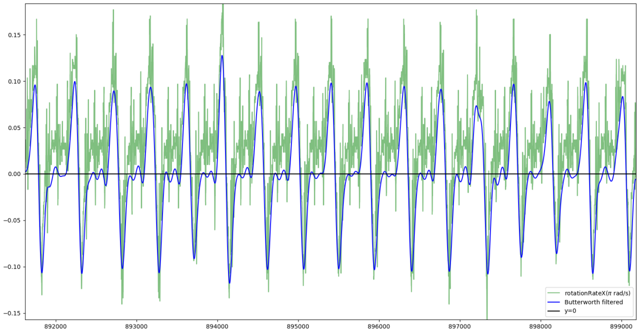

Figure 6: IIR Butterworth filtered against raw. Low amplitude oscillation can be seen caused by the pulse.

To produce a wave for heartbeat detection we are using an IIR Butterworth bandpass filter with a low-pass cut-off frequency of 10 Hz and high-pass cut-off frequency of 22 Hz with an order of 15. Again we applied the filter forward then backward. Some post-processing is needed to produce a wave which could be suitable to detect heartbeats. Both filters were created with Scipy using Matlab-style design[17]. Because the pulse wave is present as oscillation and also has negative values, we take the absolute of the signal after filtering, then we smooth the curve with moving average filter using a 0.2s rectangle window.

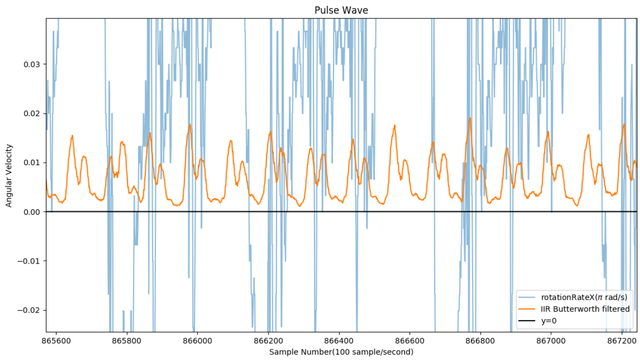

Figure 7: Calculated signal for heartbeat detection

2.4. Peak Detection

During a regulated state like sleep, the detection of normal breathing becomes much simpler. Usually, after an inspiration soon comes an expiration. We could find the inspiration and expiration peaks if they were significantly bigger than the interference caused by the pulse. The condition that the inspiration and expiration peak(which is negative) have to be close to each other easily handles noises however it misses breaths without expiration and doesn't handle most of the abnormal breathing patterns [1]. This simple peak detection algorithm is capable of providing data for the detection of central sleep apnea. Which often can indicate an underlying disease or present as an idiopathic condition.

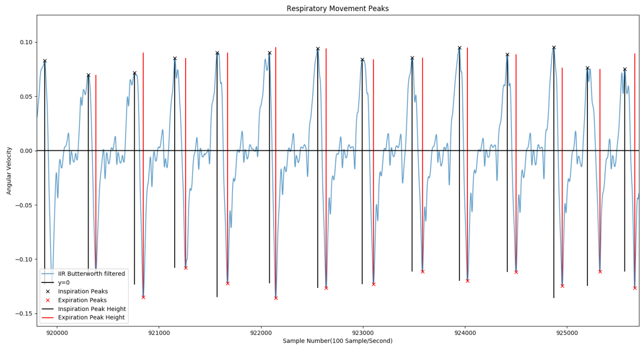

Figure 8: IIR Butterworth filtered against raw(Gyroscope's angular velocity). Low amplitude oscillation can be seen caused by the pulsed

3. Results

In this paper, we showed that a smartphone, in this particular case an iPhone6 can be used to obtain a signal which approximates abdominal breathing movement and for detecting heartbeats. Measuring physiological signals just with a phone could provide data about people's health and sleep at a scale and level which is unprecedented. We are confident that the following metrics can be calculated:

1. Inspiratory time
2. Expiratory time
3. Respiratory Rate.
4. Pulse Rate

We suspect that many more features can be calculated, however that is less clear how robust would they be. At least for short time windows respiratory effort approximation could be highly useful to detect obstructive apnea. It is very important that IMU's gyroscope gives more reliable, stable and robust data. Accelerometers output is dependant on the absolute orientation they are in.

3.1. Limitations

1. We are not evaluating IMUs. We plan to create a simulation which points to the required IMU properties, with the appropriate simulation intra- and

inter-user variability can be assessed.

2. We are focusing only on sleep because there is little movement to be found. It gives the opportunity to extract more precise data about breathing and pulse rate than in any other scenario.

3. We did not validate against a reference device.

4. We measured our abdominal breathing movement and pulse rate.

3.2. Suggested and future work

1. Validating should be done against a reference device.

2. A further developed technique could estimate respiratory effort.

3. Frequency components and amplitudes of breathing and the pulse wave can highly overlap and change, therefore adaptive filtering is needed.

4. For the same reason and also for respiration effort estimation a more sophisticated adaptive peak detection is needed.

5. Calibration would be mandatory in an application which can have clinical significance.

6. Aces fusion should be developed for handling orientation deviations caused by displacement and body morphology.

7. Review and investigate sensor fusion options to provide robust and better data.

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