Methods for Breathing Rate Measurement through Mobile Platform: a Review

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Abstract. *Breathing rate is a vital sign that can indicate someone's health status and even detect early diseases. Mobile health applications might become the main tool for estimating breathing rate out of the clinical environment. In this research, a review of the literature is conducted, aiming at finding out the most recent researches that have been proposed as solutions for respiratory measurement or monitoring using mobile devices. We discuss and compare their methods, highlighting pros and cons regarding ubiquity and feasibility. The results indicate that the combination of methods is a key aspect to improve measurements.*

1. Introduction

Continuous monitoring of vital signs is a common practice in clinical situations where the health stability of patients indicates if they are getting better or worse. People only use to care about vital signs when they feel symptoms of any health problem, but most of them do not know that continuous monitoring could prevent diseases and improve their quality of life. Nowadays, if someone out of clinical environment wants to check their basic vital signs, like heart rate (HR) or breathing rate (BR), this can be done by small equipment, sometimes commercially available [Milosevic et al. 2013].

Recently, mobile applications aiming at BR measurement have been developed or proposed in the literature. BR is expressed as the frequency of respiration cycle (inhalation and exhalation) per a certain range of time, usually minutes. It is usually obtained from body movement observation or obtaining via Peripheral Oxygen Saturation (SpO2) level, which can be converted to BR.

This research aims at conducting a literature review that brings methods or technologies regarding mobile BR measurement or BR monitoring and how they have been applied. The importance of this review is to understand what has been done until now to know what can be done in a short future, in accordance with the current constraints of the mobile platform. Then, in this paper, we first explain our review strategy (Section 2) and then we show the discussion, clustering the papers into different subgroups (Section 3). Section 4 concludes this paper with our main remarks and research directions.

2. The Review Strategy

Papers were searched in CAPES (Coordination for the Improvement of Higher Education Personnel) advanced search tool, which can link direct searches to the most famous digital libraries: *ACM Digital Library, IEEE Xplore Digital Library, ScienceDirect Digital Library,* and *PubMed*. Papers were taken from 2013 until now because 2013 was the year when multi-core smartphones became popular in the global market. The following key-words combination were applied to paper's title (any part of it): ("breathing" or "respiratory") and ("mobile" or "smartphone").

To guide the review discussion and restrict papers to what really matters, the following questions were made: *Which methods are currently being used to measure breathing rate through a mobile application? Could the application be implemented in actual smartphones? Can it be used in daily activities ubiquitously?* Papers that did not present a mobile application, or just integrated a BR commercial device to a phone, were not considered. Such decisions were obtained by means of a detailed analysis of the abstract and, sometimes, the full paper.

3. Results and Discussion

The review was restricted to a number of 16 papers from 128 that could answer the questions from the previous section. In this section, we focus our discussion on advantages and disadvantages of each method. Each paper will be discussed in a subsection, which also briefly presents the main method used for BR acquisition. The other 112 papers did not show methods that could even briefly answer the questions.

3.1. Pulse oximeter

The pulse oximeter is a small clinical optical device that can measure SpO2. Wanneburg and Malekian (2015) designed a system from the beginning in terms of software and hardware which can measure heart rate, saturation of oxygen, blood pressure, and skin temperature. BR is calculated directly from oxygen's saturation (even though it was not displayed to end user as BR in this work) and the data is acquired from a pulse oximeter made by the authors. The sensor passes the data to a board through a cable that sends the data to a smartphone via Bluetooth and then the user can see it. It is a really uncomfortable system and not ubiquitous, similar to ones currently used in hospitals.

Another type of sensor, the biometric sensor became popular among smartphones due to its commodity and safety. Looking through it [Hashizume et al. 2017] proposed an opportunistic way of measuring vital signs while a person authenticates with the fingerprint in the mobile device. In their application, photo-detectors and LED (Light Emitting Diode) were placed in the back of the phone surrounding the biometric sensor. Although PPG (Photopletismogram) was obtained, the research did not focus on obtaining and filtering respiratory rate. Using more sensors corroborates to more robust sensing however authors concerned at the end that the system needs improvement to achieve more accuracy, especially because the time required to sense PPG is much higher than the time required to check biometric.

3.2. Sound Recording

Mobile health applications are becoming more popular and regarding BR, several applications had already been built to record the sound of the breathing to calculate BR. Liu et al. (2018) proposed a new algorithm to improve BR estimation among other applications in view of their low accuracy and error rate. The algorithm is a deep learning filter that uses Bidirectional Recurrent Neural Network (RNN). Recording sounds from different positions were tested by the authors to validate the algorithm and the results show that an improvement can be done in future mobile applications.

The use of a mobile microphone to record sound opens many opportunities to build ubiquitous and non-contact applications. The microphone is more power-saving compared to a camera and it is supposed to satisfactorily perform in all devices. However, data storage seems to be a limitation of applications using the proposed algorithm by Liu et al. (2018), since it is deep learning based. Mobile cloud storage should be studied and considered in this case. In quiet places, the idea could work acceptably and it would also tolerate some noise due to its filter. However, no test regarding body movement was made so that the validation of the algorithm does not consider a person holding a phone and walking, for example.

Early, Nam et al. (2016) built a simple BR system placing a smartphone microphone or a headset microphone underneath the nose. Later, Gu et al. (2017) proposed a BR system while a person strides outdoor and, based on the breathing rate, it sends a message to a remote server on the internet that recommends music that will help to keep the running rhythm. A Bluetooth headset was used to play music and record the breathing sound. The data is stored in the smartphone that also estimates BR. A physiological model, Locomotor Respiratory Coupling (LCR), was necessary to deal with noise and to improve accuracy by indicating stride and breathe frequency.

Oletic and Bilas (2016) made a recording sound system for tracking of asthmatic respiratory symptoms. Similar to other approaches, a wearable belt, located in the wrist, was used with the same pros and cons than a wearable technology has. Their focus regards on sampling and quantization methods to deal with respiratory noise also saves energy through the compressed sensing. Narayan et al. (2018) had a focus on detecting a respiratory problem, but this time related to sleeping, like sleep apnea for example. Differently, their work did not focus on estimating BR, only finding sleep-disturbed breathing by means of mobile's microphone.

3.3. RSS (Received Signal Strength)

A completely different approach to BR monitoring was brought on [Patwari et al. 2014], which uses the wireless signal RSS to measure it. The strategy is to check the intensity of the RSS signal after it crosses the body of a person. The presence of breathing changes the frequency of the signal and its amplitude indicates BR. To do so and to warranty the accuracy, many wireless network devices are needed. The estimation is obtained from the overall devices. The solution itself can be very ubiquitous as it can easily be hidden from the user and it is completely non-contact. The result presented an accurate BR estimation because 20 wireless devices were used in a static environment.

3.4. Camera

Another method to estimate the breathing rate is presented in [Cho et al. 2017] and uses a thermal camera. The method consists in identifying the nostril in a thermal image and measuring its temperature variation. The paper proposes a thermal voxel-based technique that, after tests in different environments with considerable variation of light, showed itself to be more reliable than traditional average temperature methods. Furthermore, it is an algorithm based on quantization. There is also a contribution regarding tracking the nostril. In a short future, thermal cameras in smartphones might become more popular, as their price drops, making possible such ubiquitous application.

Regarding RGB camera, Lázaro et al. (2015) made a system that simulates a pulse oximeter with the common smartphone camera. The user must press the finger on the lens in order to the image recording to proceed. Actually, only the green band of images is necessary to be recorded because it varies depending on hemoglobin absorption. The pulse obtained is the same signal obtained by pulse oximeter so that algorithms for filtering and BR estimation are similar. Although this method is cheap, easy to implement, and could work in any type of smartphone camera, it is also susceptible to errors depending on environment illumination.

3.5. Manual Counting

The oldest method to measure BR, which even does not need a device, is the manual counting. The research of Black et al. (2015) implements 3 algorithms in a mobile device for manually counting breaths of infants and children: *60-Second count, Once-per-breath, Breath10Count*. The manual counting breathes method consists in counting how many times a person breathes in during a range of time and it results in breath cycles per minute. However, *Once-per-breath* and *Breath10Count* methods consist of counting a certain number of respiration cycles and then get the total time to calculate BR. Tests were made to compare the algorithms in a clinical environment observing illness children where nurses had to tap on the screen every time the child breaths in and the *Once-per-breath* was outstanding. Errors depend mostly on the person that is monitoring, hardly because of the application because the algorithm is very simple.

To infants, the application is completely ubiquitous, since they do not know they are being monitored. Also, the idea is safe and non-contact. In addition to the simplicity of the method, it is also reliable and low cost in terms of algorithm running and power saving. Counting breaths applications can be extremely useful to infants and children, especially because they need someone taking care of them most of the time and this person can monitor the BR. However, to adults, it might be inconvenient to spend time with someone else (take careers).

Similarly, Karlen et al. (2014) developed an application named *RRate* to measure BR in infants through taps on a smartphone screen. Nevertheless, they proposed a different method to increase accuracy and reduce the time required to estimate BR, removing inconsistent taps. Reliable values of BR were obtained in 9.9 seconds with a small error, what is much less than the standard 60 seconds. Later, they compared the *RRate* application with the timing aid *WHO ARI Timer* (World Health Organization Acute Respiratory Infections Timer) [Gan et al. 2015] regarding accuracy. Despite both had a similar and satisfactory measurement, RRate was much more biased than *WHO ARI Timer*. Furthermore, RRate can verify BR faster and with higher accuracy.

3.6. Accelerometer

In [Sun et al. 2017] the authors aim to monitor BR using an android smartwatch on the user's wrist while sleeping. The idea is to capture the oscillation of the wrist made by user's breathing along the time and Kalman filter is used after the frequencies are captured. Body position is also monitored with the device through an accelerometer. Movements during sleep are detected by the accelerometer so that it does not become a problem for the measuring.

Huang et al. (2018) were not aiming at BR, but they work with deep-breath for liveness detection. They made a wearable authentication system using an accelerometer and gyroscope integrated with a microphone. The accelerometer and the gyroscope detect deep-breath from chest movement while the microphone records heart sound. With some effort such system could be implemented only with a smartphone, what would bring more ubiquity.

3.7. ECG (Electrocardiographic)

The only ECG approach to obtain BR is described in [Sohn et al. 2017]. This work consists in monitoring ECG signals from the torso and then sending them to a smartphone via Bluetooth. Feasibility of BR is possible because of the thoracic impedance caused by respiration. However, the focus of this system is the BR on abnormal heart rate situations, not considering when the heart is at a normal rate. The authors also made a mobile user interface where information of BR could be checked in real time by users. Although ECG is affordable regarding mobile monitoring context, the ECG data acquisition requires body contact with sensors, bringing the same constraints about ubiquity discussed before regarding wearable devices.

4. Conclusion

Since the popularity of smartphone, several methods have been implemented in literature aiming at breathing rate estimation or monitoring. We discussed them elucidating their features and constraints and we concluded that measurement of vital signs through mobile technology is reliable and could support people's wellness.

Overall, some methods performed better from a ubiquitous point of view: accelerometer, camera, and sound recording. In the majority of the cases, the combination of methods is the most robust technique for measurement. RSS might be the most unusual method due to its cost and clinical constraints.

For the future of BR, we might expect more image processing methods that were not studied yet because of two major mobile trends: dedicated graphical processing in new smartphone's hardware and the need of convenient non-contact health applications. Furthermore, the integration of IoT devices was not deeply explored, so that the investigation of these devices seems to be a source of opportunities for the future.

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