# Measuring Heart Rate with Mobile Devices for Personal Health Monitoring


Toon De Pessemier and Luc Martens

imec - WAVES - Ghent University
Technologiepark-Zwijnaarde 15
9052 Ghent, Belgium
Email: toon.depessemier@ugent.be luc1.martens@ugent.be



***Abstract*—The growing availability of mobile devices, such as smartphones, fitness trackers, and smart watches, induce an increased interest in personal health monitoring. These devices are equipped with the necessary sensor hardware, such as accelerometer and heart rate sensor, for measuring physical activities and heartbeat. However, the accuracy of these measurements is still unclear. In this paper, we evaluate heart rate monitoring with four different device types: a specialized device with a chest strap, a fitness tracker, a smart watch, and a smartphone using plethysmography. The results show similar measurements for the four devices in a state of rest. In contrast, during physical activities the fitness tracker, smart watch, and smartphone may register sudden variations in heart rate with a delay, due to physical movements of the wrist or hand. The specialized device with chest strap shows the most accurate heart rate, highly correlated with measurements obtained with a blood pressure monitor that is approved for medical purposes. These results are important for developers who use data of heart rate for mobile applications and services.**



***Keywords*–Wearable computers; Health information management.**


## I. INTRODUCTION

Obesity and insufficient physical activity are an ever growing problem in modern society. Obesity can induce amongst others, heart diseases and stroke, diabetes, gallbladder disease, and gallstones. Research has shown that the majority of health care costs [1] are due to physical inactivity [2]. Recent research in health care supports the theory that regular physical activity and a healthy diet are much more effective than traditional medication to cure diabetes [3]. Nutrition and training schedules can be downloaded from the Internet, but are often inadequate for users' personal needs or physical capacities and static without taking into account users' progress.

Therefore, new efforts are made to decrease national obesity levels [4], thereby using technology, such as multi-modal sensors, web frameworks, and data mining. Multi-modal sensors enable real-time monitoring of physical activities, such as exercises performed by the user. In the domain of public health monitoring, most applications of these sensors keep track of energy expenditure while performing daily activity [5][6]. The resulting data can be used in a lifestyle recommender that encourages users to adopt a more healthy way of life. With the evolution of Web 2.0 [7], more formal and informal health information has become available, with the perspective of a new generation of well-informed, healthy individuals. This phenomenon is often referred to as *eHealth 2.0*. eHealth 2.0 turns users into health information producers and consumers by offering a multitude of health information data [8][9].

To cope with the problem of information overload incurred by Web 2.0 and its eHealth 2.0 counterpart, recommender systems are used as an effective information filter and at the same time as a tool for providing personal advice through suggestions [10][11]. Recommender systems can e.g. suggest a specific fitness activity or a running trail out of the many available physical activities. Suggestions for physical activities should be tailored to the physical capabilities of each individual. Measuring the physical activity of a person through sensors, such as accelerometers, is insufficient to estimate that person's physical capabilities. Heart rate measurements combined with motion sensors can be used to assess the intensity of physical activities for a person and his/her physical limits [12].

Although specialized devices exist for measuring heart rate, most people do not have these at their disposal. Nowadays, popular mobile devices and wearables are equipped with sensors that promise to measure heart rate as well. However, the accuracy of these heart rate measurements is still unclear. Manufacturers choose not to assert claims regarding the accuracy of the detection of (abnormal) beating patterns; otherwise their gadget would get classified as a medical device and would have to undergo FDA (Food and Drug Administration) regulatory scrutiny [13]. Therefore, the research question of this paper is: how accurate are heart rate measurements of these devices for physical activities with different intensity? This is investigated by an application (developed on Android for this research) for monitoring heart rate of test subjects simultaneously with different devices, during various physical activities. These results are important for all (mobile) applications and services that rely on heart rate data from these devices.

The remainder of this paper is structured as follows. Section II gives an overview of related work in the domain of eHealth and mobile health apps. Section III discusses existing methods for heart rate measuring. The various types of mobile devices for heart rate measuring are listed in Section IV. In Section V, details about our measuring method and our experiences with the various devices are discussed. The results of the measurement experiments are provided in Section VI. In Section VII, conclusions are drawn and future work is mentioned.

## II. RELATED WORK

The domain of eHealth has been evolved by two major influences: on the one hand by the increasing availability of sensors for tracking physical activities, not only in smartphones but also in other devices, such as smart wearables; on the other hand by the easy accessibility of health information, stimulating the users' interest for monitoring their physical condition. This evolution has brought the problem of information overload [14] to the healthcare sector. For example, too many diet plans and sport schedules are available, but only a minority are tailored to the specific needs of a person. This emphasizes the need to personalize the health information, which is ongoing since the mid-90s [15] and is demonstrated in Computer-Tailoring Health Education Systems [14].

Personalization can be achieved by a recommender system. Personalized recommendations, customized information, and tailored messages have shown to be far more effective than the non-personalized alternative [11][16]. Health promotion and wellness driven applications often use collaborative filtering techniques to cope with the overload of health info and identify the most relevant data [17]. The selection is not made by a central agency or individual, but based on actions of the community. As a result, the quality of the selection is depending on the size and engagement of the community.

Various Health Information Systems (HIS) have been proposed in recent years. These HIS may have three primary goals: inform, assist in the decision making, or convince the end-user. In the HOMEY project, technology for innovative tele-medicine services is developed [18]. The goal of these services is to effectively manage an incremental dialogue between a tele-medicine system and a patient, taking into account user needs, preferences, and the time course of her/his disease. More specifically, the focus was on an automated, telephone-based home monitoring service for chronic hypertensive patients [19]. Patients are regularly asked to specify their blood pressure values and heart rate. Based on these data, suggestions for physical activities are provided e.g., "Are you still swimming two times a week?" or health advice is offered, such as "You should stop smoking". The personalized dialog with the patient is based on goals and rules specified by medical staff. A clinical trial involving 300 hypertensive patients showed a blood pressure decrease in the group of patients exploiting the Homey service. This study emphasizes the importance of the usability of the HIS to stimulate an intensive use. In contrast to our Android application, the Homey service is not able to automatically measure heart rate.

On the mobile platform, tens of thousands health apps are available [20], often called mHealth (Mobile Health) apps [21]. Sometimes, the offer of health apps is even considered as an overload for medical professionals and consumers [22]. Both continue to express concerns about the quality of many apps [20]. Moreover, the importance of personalization strengthens the need to automatically acquire personal data, such as performed physical activities or heart rate.

However, tracking physical activities or measuring heart rate is complex and maybe insufficiently accurate with general-purpose wearables. For commercially available breast belt measuring devices, evaluations in terms of accuracy have been performed [23]. However for newer wearable devices, the actual accuracy is still unclear. A limited number of studies investigated the accuracy of heart rate monitoring using wearable devices. Heart rate monitoring using a wrist-worn personal fitness tracker has been investigated in non-moving conditions (with patients in the intensive care unit) [24]. The heart rate values obtained using the personal fitness tracker were slightly lower than those derived from continuous electrocardiographic monitoring. The authors argued that further evaluation is required to see if personal fitness trackers can be used in hospitals, e.g. as early warning systems. Another study has investigated the accuracy of step counts and heart rate monitoring with wearables [25]. Test subjects were asked to walk a number of steps during the measurements. The accuracy of the heart rate measurements with the tested wearable devices showed to be very high. In contrast, our paper investigates the accuracy of heart rate monitoring during intense physical activities and with various types of wearable devices.

## III. Measuring Heart Rate

Various methods to measure heart rate exist. Two important methods will be discussed in more detail: electrocardiography and photoplethysmography. Others are echocardiography, and measurements based on carotid pulse or radial pulse.

### A. *Electrocardiography (ECG)*

Electrocardiography is the process of recording the electrical activity of the heart using electrodes placed on the skin [26]. These electrodes detect the tiny electrical changes on the skin that arise from the heart muscle's electrophysiologic pattern of depolarizing during each heartbeat. In professional environments, such as hospitals, this technique is applied with 10 electrodes, placed on the patient's limbs and on the surface of the chest. The signals of the various electrodes are combined into an electrocardiogram [27], a record of the electrical activity of the heart over a period of time.

### B. *Photoplethysmography (PPG)*

Photoplethysmography is the scientific name of Optical Heart rate Sensing (OHS). It is a technique to monitor heart rate based on the combination of photo diodes and LEDs [28]. Blood absorbs green light (hence its red color). As a result, the photo diode detects a reduction in green light intensity during a pulse of the heart. A low intensity of the green light corresponds to a pulse; a high intensity is measured during periods between two pulses. A green LED provides the most accurate results. However, an infrared LED is often used since this consumes less energy. A disadvantage of this method is that motion artifacts have been shown to be a limiting factor. This hinders accurate readings during exercise and free living conditions. In addition, person-dependent variations may also cause distorted readings. For example, a different blood perfusion induces a different absorption of light, thereby registering a deviated reading.

Since the hardware of a smartphone camera is very similar to a pulse-oximeter, it can be used for measuring heart rate by PPG. This works as follows. The index finger is covering the camera lens and the LED. The light from the LED is reflected by the skin of the finger through diffusion; then this light is captured by the camera lens. Contrary to traditional OHS, the red spectrum is often used on smartphones, because the device-specific distribution of red pixels varies less than the distribution of green pixels. Still, this technique relies on hardware-dependent parameters, such as the number of pixels, the LED, etc.

## IV. Measuring Devices

Four types of devices for measuring heart rate can be distinguished.

### A. *Specialized devices*

The main purpose of this type of devices is measuring. Therefore, these devices often have only a limited number of sensors and a limited number of features. Examples are heart rate chest straps, pulse-oximeters, and blood pressure monitors. These devices are often approved for medical use and can therefore be used as reference devices.

In this study, the Polar H7 was used. This is a popular heart rate chest strap, which produces very accurate readings (correlation of $0.97$ with true heart rate [29]). To test its accuracy, we compared the measurements of the Polar H7 to the ones of the Omrom M6 Comfort [30]. The Omrom M6 is a blood pressure monitor that is approved for medical purposes, and can therefore be considered as the correct heart rate.

The measurements with two users, at two different times, showed that the Polar device produces heart rate measurements with a precision similar to the Omrom. This justifies the use of the Polar H7 as specialized device for heart rate monitoring. Since a blood pressure monitor is rather expensive and less suitable for sports activities, we chose the Polar H7 as reference device during our experiments.

### B. *Fitness trackers / fitness wearables*

These devices, typically worn around the wrist, measure motion, such as counting up steps, monitoring sleep, and calculating the difference between a light jog and a mad sprint. These devices are packed with multiple sensors, such as a 3-axis accelerometer to track movement in every direction, and an altimeter that can measure your altitude, handy for tracking the height of the mountains you have climbed. Some come with a gyroscope too, to measure orientation and rotation. These devices are often not approved for medical purposes, but are cheaper than the specialized devices. The Microsoft Band 2 was chosen for this study because of two reasons. It allows the real time analysis of sensor data and Microsoft provides a comprehensive API. This API allows for example to aggregate the results of a query thereby shifting the computational load to the Microsoft servers.

### C. *Smart wearables / watches*

Similar to fitness trackers, smart wearables and smart watches are equipped with various sensors and are not medically approved. In contrast, fitness trackers their main focus is on tracking physical activities, whereas the goal of smart wearables is more general including tracking physical activities, context recognition, and informing users. The target group of these devices contains not only sports people but also a broader group of people who like the design, or the extra features of a smart watch. Compared to fitness trackers, smart wearables often have more hardware capabilities (e.g., color screen, more processing power), allowing to extend their functionality with additional apps. In this study, the Huawei Watch is used because of its popularity and typical smart watch functionality. To capture heart rate data in real time from the Huawei Watch, a special Wear app was developed. The Wear app communicates with our Android app running on a smartphone through the Wearable Data Layer API.

### D. *Secondary device feature*

This category covers hardware components of devices that allow measuring heart rate. By using (hardware-specific) apps, smartphones are able to measure heart rate using the built-in camera and LED flash based on PPG techniques. In this study, the camera and LED of the Google Nexus 6P are used.

## V. Measurement Method

Heart rate measurements are collected and stored on a smartphone (Google Nexus 6P) by a self-developed Android app, since most wearables have a direct bluetooth communication channel. For every device, a service was running on the smartphone to transfer the raw sensor data to the smartphone.

Since different sensors are differently calibrated, differences in the measurements can be witnessed for the same person in the same conditions. Therefore, the heart rate data is normalized based on three levels: resting, walking at low ($\leq$ 4m/s) speed, and walking at high speed. This normalization method has shown its usefulness for physical activities of different intensities [31][32]. This normalization is performed as follows. For each of the activity levels, the heart rate is measured using the different devices simultaneously and over a long period of time ($>$ 10 minutes). For each of the devices, the difference in average heart rate with the reference device (Omrom M6) is calculated. This difference is compensated in the measurements during physical activities (Figure 1, 2, 3, and 4). First, we discuss our practical experiences with the four devices used for measurements.

### A. *Specialized device: sensor with chest strap*

This device is comfortable during sports, while holding its position on the chest. After all, this kind of devices is designed for measuring heart rate during sports.

### B. *Fitness tracker*

Although the Microsoft Band 2 is a fitness tracker designed for sports, we do not experience it as ideal for heart rate measurements from a practical viewpoint. The device hinders when the wrist moves during exercises.

### C. *Smart watch*

During the experiment, we witnessed that motions of the wrist disturb the measurements, even if the strap is tightened excessively. The sensor in the smart watch loses the reference point and measuring the heart rate is interrupted. To cope with this problem, our developed app starts to recalibrate as soon as the measuring process is interrupted. Also variations in light intensity showed to disturb the measurement process. If the wrist is moved to a position where it absorbs more light, measurements turned out to be invalid.

### D. *Secondary device feature: PPG on smartphone*

Using the PPG technique on a smartphone to measure heart rate also has some practical difficulties. The PPG technique is influenced by personal characteristics of the (blood / finger of the) test user. In addition, PPG is very sensitive to motion; so the user has to keep his/her finger still on the flash LED. This complicates heart rate measurements during physical activities. Moreover, the prolonged use of the flash LED and camera heats up the phone excessively. The device becomes so hot, making it impossible to put your finger in the correct position on the LED for a long time. The heating of the device is associated with a drain of the battery. In our experiments, we witnessed a 4% decrease of the battery level during each measurement of 5 minutes.

## VI. Measurement Results

Table I shows the resulting heart rate measurements for two test subjects in rest condition (home environment) without normalization. PPG using a camera is not included, since this method is highly influenced by the type of smartphone that is used. The first user (TS1 - female) has a high heart rate, whereas the other test subject (TS2 - male) has a low heart rate in rest condition. Measurements are repeated at two different times for the two persons. For each device, the average, standard deviation, and median are listed in Table I. The results show that all devices provide consistent results. So in rest conditions, heart rate measurements of these devices can be considered as reliable. The measurements of the Polar H7 are the most similar to the measurements of the Omrom M6, which can be considered as the correct heart rate.

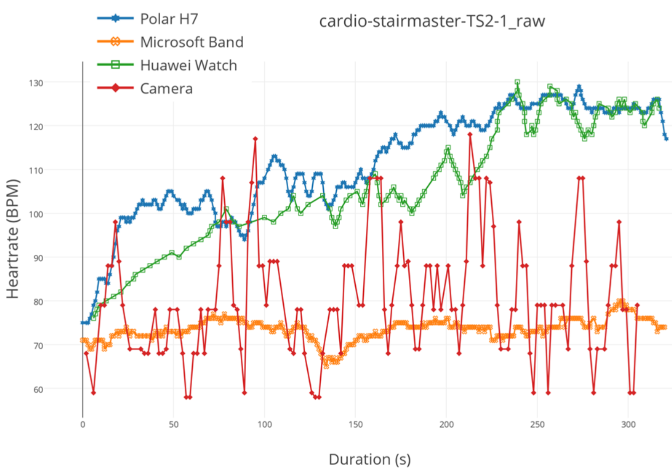


Figure 1. Heart rate measured during stair master.

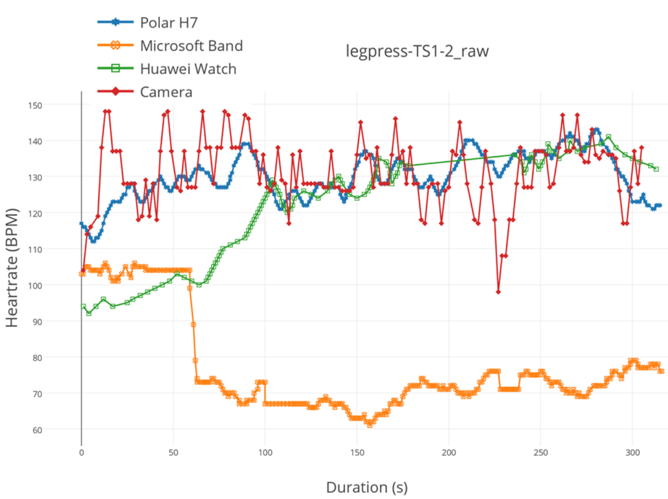


Figure 2. Heart rate measured during leg press.

Figure 1, 2, 3, and 4 show the heart rate measurements obtained with the four devices for four different exercises, respectively Stair Master, Leg Press, Dumbbell Curl, and Long Walking. All exercises are performed in a fitness room by two persons with similar results. The results of one person

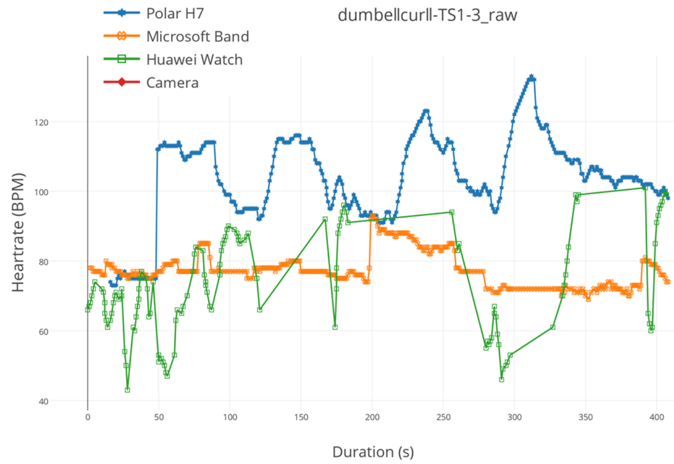


Figure 3. Heart rate measured during dumbbell curl.

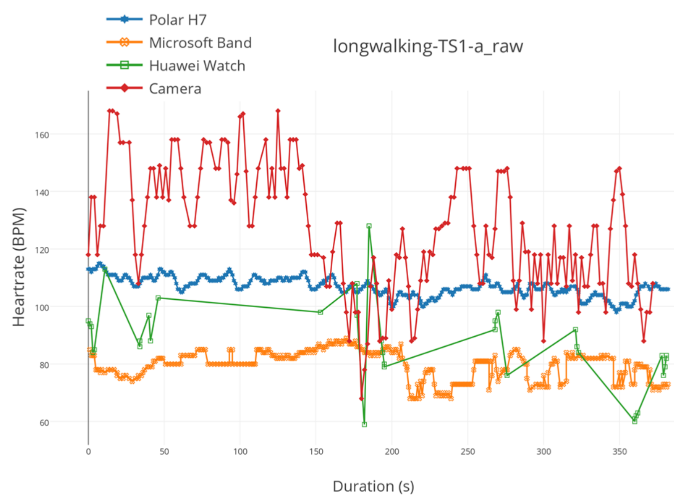


Figure 4. Heart rate measured during long walking.

are shown in these Figures. Because of practical reasons, it was not possible to measure heart rate with the Omrom M6 during physical activities in the fitness room.

For each device, we investigated trend and reactivity. Trend only judges a scoped-out-view of the heart rate signal based on the statistics average and correlation. Reactive is more strict and judges short periods of time. If an intense physical activity causes a sudden increase in heart rate, it is important that the sensor registers this increase. If a sensor is able to detect these sudden changes quickly, then it can be considered as highly reactive.

### A. *Specialized device: sensor with chest strap*

The Polar H7 is considered as a reference. The output of the other devices is compared to the heart rate registered with the Polar.

### B. *Fitness tracker*

The Microsoft Band 2 registers a heart rate that is consistently lower than the reference value of the Polar. This

TABLE I. HEART RATE MEASUREMENTS WITH TWO USERS (TS1 AND TS2) IN REST CONDITION AT TWO DIFFERENT TIMES

| | TS1-1 | | TS1-2 | | TS2-1 | | TS2-2 | |
|---|---|---|---|---|---|---|---|---|
| Device | $\bar{x} \pm \sigma$ | median | $\bar{x} \pm \sigma$ | median | $\bar{x} \pm \sigma$ | median | $\bar{x} \pm \sigma$ | median |
| Omrom M6 | 76±2.5 | - | 84±4.2 | - | 55±2.8 | - | 58±2.9 | - |
| Polar H7 | 77±3.0 | 76 | 80±3.7 | 79 | 56±1.7 | 56 | 59±1.4 | 59 |
| Huawei Watch | 73±3.3 | 73 | 72±3.2 | 71 | 55±2.0 | 55 | 55±2.0 | 56 |
| Microsoft Band | 75±3.3 | 75 | 76±1.7 | 76 | 50±2.9 | 60 | 64±6.0 | 64 |

discrepancy varies for different heart rates, which makes it hard to correct. Moreover, measures of the Microsoft Band deviate substantially from the reference during intense activities. Figure 3 shows that the sensor has a low reactivity. Rapidly varying heart rates are not detected during the Dumbbell Curl exercise.

### C. Smart watch

Because of interruptions in the measurement process due to movements, the number of measurement results obtained with the Huawei Watch is smaller than obtained with the Polar H7. Time periods without measurements correspond to periods of sensor (re)calibration due to movements of the wrist. As a result, this device shows to be less suitable for measuring heart rate during activities with a lot of movement (of the wrist).

In terms of accuracy, the results show a trend that corresponds to the reference of the Polar. The mean value is 5 beats per minute below the mean value of the Polar reference. But this difference is consistent for different heart rates which allows a correction by adding the fixed difference to the measurements. Figure 3 shows this smart watch has some difficulties in detecting physical activities with varying intensities. Intensive periods are noticeable in the measurement data; but a delay in the peaks of the data is visible if the Polar and Huawei are compared.

### D. Secondary device feature: PPG on smartphone

Because of the physical movements, PPG on the smartphone is not possible during Dumbbell Curl exercises. Because of the algorithm's dependency on the hardware, fluctuations in the measurements can be witnessed, even for a stable heart rate. The trend of the PPG method matches with the measurements of the Polar device. The trend of PPG is even better than the trend of the smart watch and fitness tracker for an exercise with low variation in intensity, as shown in Figure 2. In other cases, the heart rate measurements obtained with PGG may significantly differ from the Polar reference, as visible in Figure 4.

## VII. CONCLUSION AND FUTURE WORK

This paper investigated the accuracy of heart rate measurements with sensors in wearables and smartphones. Experiments showed that specialized devices, using a sensor with chest strap, produce very accurate results, similar to devices that are approved for medical purposes. Measurements with the fitness tracker and smart watch that were tested, showed very accurate results in conditions with little physical movement, e.g., in resting state. However, a discrepancy in measured heart rate is witnessed during periods with a highly variable heart rate, e.g., during high intensity interval training. This low reactivity is often due to physical movements of the wrist. Devices around the wrist may lose their reference during movement, and subsequently require a recalibration of the sensor for a few seconds. Measuring heart rate by using PPG on a smartphone showed fluctuating measurements, even in case of little physical movements. This might be due to changes in light intensity in the environment or movements of the finger. Aggregating multiple measurements showed that statistics, such as average and median, are a good representation of the real heart rate. Because of hardware dependent characteristics, algorithms using the PPG technique are often too general. The general applicability of the algorithms for PPG allows heart rate monitoring on different smartphone devices, but reduces the accuracy of the results. Although fitness trackers, smart watches, or PPG on smartphones are useful tools to get information about the heart rate, we experienced some inaccuracies in the measurements during physical movements or sudden variations in heart rate. For medical purposes or professional athletes, specialized devices with a chest strap might be a better choice because of their higher accuracy. In future work, we will investigate how to automatically detect physical exercises, such as squats, and couple these exercises to the heart rate for further analysis. For the detection of exercises, sensors of mobile devices, such as the accelerometer, will be used. Next, we plan to develop an eHealth recommender system offering personal suggestions for physical activities based on the measured heart rate and performed exercises.

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