Heart Rate Monitoring and Activity Recognition using Wearables

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***Abstract*—Wearables enable measuring physical activities and heart rate using accelerometer and heart rate sensor. However, the output of these sensors is often aggregated into a general activity status without detailed analysis and the link between activity recognition and heart rate measurement is often missing in health apps. This paper compares heart rate measurements during physical activity of three wearable devices: a specialized sports device with chest strap, a fitness tracker, and a smart watch. Due to unintended shifts of the device with respect to the wrist, the fitness tracker and smart watch have difficulties to measure sudden variations in heart rate. During the physical activity, movements of the user's wrist were measured using the accelerometer of the wearable. Correlations in the data patterns of the heart rate sensor and accelerometer are identified. Both sensors are used as input for personal recommendations for physical activities with a rule based filter. These recommendations are tailored to the user's physical capabilities and preferences by matching them to a user profile that is learned from the user's data. Combining the insights from heart rate sensor and accelerometer may allow to improve the accuracy of detecting physical activities, estimate the intensity of an activity, and generate more accurate recommendations.**

Keywords–Activity Recognition; Health Information; Recommendation; Personalization.

I. Introduction

The last decade, more formal and informal health information has become available, with the perspective of a new generation of well-informed, healthy individuals. This phenomenon turns users into health information producers and consumers by offering a multitude of health information services and data [1][2].

To cope with the problem of information overload incurred by this growing availability of data, recommender systems are used as an effective information filter and at the same time as a tool for providing personal suggestions [3][4]. These recommenders may suggest a specific fitness activity or a running trail out of the many available physical activities. But good recommendations should match the physical capabilities of each individual.

To assess the physical load of an activity for a user, measuring the user's physical movements (e.g., using a pedometer) is insufficient, since this neglects the user's effort with respect to his/her physical capacities. The user's physical limits and the intensity of an activity for a user can be estimated by the combination of heart rate measurements and motion sensors [5]. Recent wearable devices are often equipped with accelerometers for measuring movements and heart rate sensors. However, the accuracy of heart rate measurements using these devices is still unclear.

For heart rate monitoring, various methods exist. For this study with wearables, the two most important methods are electrocardiography and photoplethysmography. Electrocardiography (ECG) is the process of recording the electrical activity of the heart using electrodes placed on the skin [6]. These electrodes detect the small electrical changes on the skin that arise from the heart muscle's electrophysiologic pattern of depolarizing during each heartbeat. For medical purposes, e.g., in hospitals, this technique is applied with 10 electrodes, placed on the patient's limbs and on the surface of the chest.

Photoplethysmography (PPG), also known as optical heart rate sensing, is monitoring heart rate using photo diodes and LEDs [7]. Green light is absorbed by blood, hence its red color. When a light source is covered by a body part (e.g., the wrist in case of a wearable), the light is partially absorbed by the blood and partially reflected. The photo diode captures the reflected light. During a heart beat, more light is absorbed and the photo diode detects a reduction in green light intensity. Although a green LED provides the most accurate results, an infrared LED is often used since this consumes less energy. PPG is a cheap method for measuring heart rate, often used in wearables, but has some disadvantages. Motion artifacts can reduce the accuracy during exercises and free living conditions. Person-dependent variations may also influence the measurements, e.g., a different blood perfusion induces a different absorption of light. This paper discusses the use of PPG in wearables for heart rate measuring (Section IV).

Besides heart rate measurements, wearables can perform activity recognition based on the motion detected by the accelerometer. This typically results in a few statistics about the user's physical activity, such as the number of steps taken or the average speed of a running session; but the recognition of specific physical exercises is often still missing. More advanced solutions for activity recognition are often relying on multiple sensors placed on different parts of the body, e.g., on the chest and on the hip, composing a body sensor network [8]. However, this is often considered too intrusive for daily activities. Therefore, this study investigates activity recognition using popular wearable devices (Section V).

The goal of this study is to investigate the accuracy of heart rate measurements obtained with different wearables, and to analyze if measurements of heart rate sensor and accelerometer can be combined for an accurate activity recognition. According to our knowledge, this is one of the first studies that compares wearables worn around the wrist and a sports device with a chest strap for heart rate measurements during a physical activity with a lot of movement of the wrist. These measurement data are the input of recommender systems, which can improve human-web interaction by personalizing interfaces of web applications with tailored suggestions for physical activities. This study presents a rule based filter as recommender system.

The remainder of this paper is organized as follows. Section II refers to interesting related work. An overview of the wearable devices used in this study is provided in Section III. The next sections discuss the measurements of the wearables: the heart rate measurements are discussed in Section IV, activity recognition is the topic of Section V, and the usage of the combination of both is covered in Section VI. Section VII is about the rule based filter to generate personalized recommendations. Section VIII draws conclusions and points to future work.

II. Related Work

The rising interest in health-related data and applications strengthens the need to monitor heart rate and automatically recognize physical activities on a daily basis. Although the commercial sports devices and wearables are equipped with the necessary hardware to accomplish this challenging task, their accuracy is still unclear.

For commercially available breast belt measuring devices, detailed evaluations of the accuracy have been performed [9]. But for recent wearable devices, only a limited number of studies investigated the accuracy of heart rate data, often in specific conditions. In non-moving conditions, heart rate monitoring using a wrist-worn personal fitness tracker has been evaluated with patients in an intensive care unit [10]. The measured values were slightly lower than those derived from continuous electrocardiographic monitoring, i.e., the medical method for heart rate monitoring. The authors concluded that further evaluation is required to investigate if personal fitness trackers can be used in hospitals, e.g., as early warning systems. Another very related study has investigated the accuracy of step counts and heart rate monitoring with wearables [11]. Test subjects were asked to walk a specific number of steps during the measurements. The accuracy of the heart rate measurements with the tested wearable devices showed to be very high. Our paper contributes to the domain of health monitoring with wearables by studying the accuracy of heart rate measurements during intensive physical activities, and with various types of wearable devices.

In the domain of activity recognition with wearables, the focus is often on the classification of movement or transportation types. Hidden Markov models have been proposed [12] to recognize different physical activities, such as driving a car, riding a bicycle, walking, or standing still. In recent Android versions, similar activity recognition functionality is available through Google's activity recognition API [13]. In contrast, our research targets activities that cannot be classified based on the movement speed, but are characterized by specific hand or arm movements, such as Dumbbell Biceps Curl exercises. Our focus is on recognizing the number of repetitions in view of tracking the physical load, rather than on classifying the activities.

The growing availability of these health data on the World Wide Web has brought the problem of information overload [14] to the ehealth domain. For instance, too many sports schedules are available in online databases, but only a minority is matching the physical capabilities and preferences of an individual. This emphasizes the need to personalize health information and services, i.e., "adapting the content, with the aid of computers, to the specific characteristics of a particular person" [15]. Personalized recommendations, tailored messages, and customized information have shown to be far more effective than the non-personalized alternative [3][4]. Unfortunately, many of these recommender systems rely on the manual input of users reporting their performed exercises. Our solution combines automatic activity recognition and heart rate measurements, which are used as input for a rule-based recommender system.

III. Wearable Devices

For measuring heart rate, three types of wearables were used: a smart watch, a fitness tracker, and a specialized device.

A. *Smart Watch*

Smart watches are equipped with various sensors but are not medically approved. The smart watch is a general purpose, fashionable device with features such as tracking physical activities and informing users. From a commercial viewpoint, the target group of customers is not limited to sports people, but includes also a broader group of people who like the design or the extra features of the gadget. Smart watches often have hardware capabilities allowing to extend their functionality with additional apps. In this study, the Huawei Watch was used as smart watch for the measurements because of its popularity and typical smart watch characteristics (e.g., Android Wear). Heart rate measurements are based on photoplethysmography. To capture heart rate data in real time, a special Android Wear app was developed for the Huawei Watch. This app communicates with our developed Android app running on a smartphone through the Wearable Data Layer API.

B. *Fitness Tracker*

These devices, typically worn around the wrist, measure movements and behavior, such as the number of steps taken, sleeping patterns, and sports activities, e.g., a light jog or a mad sprint. As with smart watches, fitness trackers are seldom approved for medical purposes. They are equipped with multiple sensors, such as a 3-axis accelerometer to monitor movement in every direction, an altimeter to measure altitude and keep track of the traveled height, and sometimes a gyroscope to measure orientation and rotation. Compared to smart watches, fitness trackers are more focused on tracking physical activities. In this study, the Microsoft Band 2 was chosen as fitness tracker because of two reasons. It allows real time analysis of sensor data (heart rate data using photoplethysmography and movement data through the accelerometer) and Microsoft provides a comprehensive API. The API offers functionality, such as aggregating the results of a query, thereby shifting the computational load to the Microsoft servers.

C. *Specialized Device*

The main purpose of this type of devices is measuring heart rate. Typical examples are pulse-oximeters, blood pressure monitors, and heart rate chest straps. These often have only a limited number of sensors and a limited number of features.

In this study, the Polar H7 was used as specialized sports device. This is a popular heart rate chest strap, which produces very accurate measurements (correlation of 0.97 with true heart rate [16]). Heart rate is measured using electrodes in the chest strap that detect heart pulse via an electronic signal.

IV. Heart Rate Measurements

To gather, store, and analyze heart rate measurements of these three device types, an Android app was developed and deployed on a Google Nexus 6P smartphone. Figure 1 shows a screenshot of this app. The wearable devices have a Bluetooth communication link with this smartphone and the app has a separate service running for each device to transfer the raw data to the smartphone.

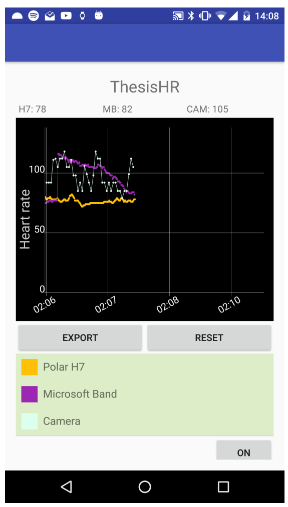

Figure 1. Screenshot of the Android app for gathering heart rate data.

A. In Rest Condition

To evaluate the accuracy of heart rate measurements of the three device types, these heart rate measurements were compared with the measurements of a specialized device that is approved for medical purposes, i.e., the Omrom M6 Comfort [17]. The Omrom M6 is a blood pressure monitor, which has to be attached around the upper arm for measuring the heart rate. Heart rate was measured for two persons, in a rest condition, in a home environment, at two different times. The first test subject (male) had a low natural heart rate, whereas the second test subject (female) had a rather high heart rate in rest condition. Table I shows for each device the mean, standard deviation, and median, indicating that all devices provide consistent results. The mean values and small standard deviation show that in rest condition, heart rate measurements obtained with these devices can be considered as reliable. The measurements of the Omrom M6, which is medically approved, are considered as the correct heart rate. The measurements of the Polar H7 are the most similar to the measurements of the Omrom M6. Since a blood pressure monitor is rather expensive and not practical during sports activities, the Omrom was not suitable to measure heart rate during physical activities. Therefore, the Polar H7 was considered as the reference device during physical activities.

B. During Physical Activity

Figure 2 shows the heart rate measurements obtained with the different devices during physical activity, more specifically Dumbbell Biceps Curl. These exercises for bicep muscles were performed in a fitness room by two people. Similar results are obtained for both persons (results are shown for only one person). During physical activities, such as Dumbbell Biceps Curl, measuring heart rate cannot be performed with the blood pressure monitor due to body movements and the non-wearable characteristic of the Omrom M6. For the three wearable devices, a significantly different signal of the heart rate measurements can be witnessed during this physical activity.

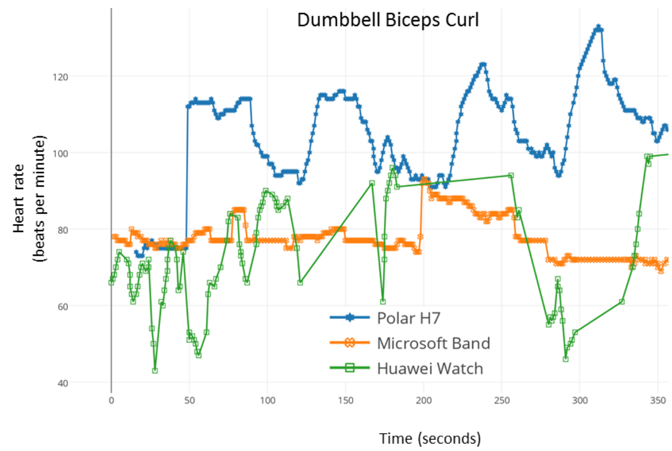

Figure 2. Heart rate measurements during Dumbbell Biceps Curl.

The heart rate signal produced by the *Polar H7* clearly shows a repetitive pattern that corresponds to the repetitions of the Dumbbell Biceps Curl exercise. The accurate measurements can be explained by the use of the chest strap, which is less influenced by movements than the devices worn around the wrist.

The heart rate registered by the *Microsoft Band 2* is consistently lower than the values measured by the Polar device. Moreover, rapidly varying heart rates due to periods of intensive physical activity are difficult to detect. As a result, the subsequent repetitions of the physical exercise are not clearly visible in the graph of the Microsoft Band in Figure 2.

With the *Huawei Watch*, less measurement samples are obtained compared to the Polar H7 and the Microsoft Band. Movements of this device, which is worn around the wrist, cause interruptions in the measurement process. Changes in the device's position relative to the wrist induce a sensor recalibration and can be noticed in Figure 2 as the time periods without measurement data from the Huawei Watch. Periods of intensive physical activities are noticeable by the variations in the data of the heart rate measurements. But the interruptions in the measurement data might be a problem for detailed heart rate monitoring during physical activities.

V. Activity Recognition

In order to monitor the proper execution of physical exercises by users, wearables can be used to register specific physical movements. The Dumbbell Biceps Curl exercise is a typical activity that allows detection of repetitions of this

TABLE I. MEAN $\bar{x}$, STANDARD DEVIATION σ, AND MEDIAN $\tilde{x}$ OF THE HEART RATE IN REST CONDITION WITH TWO USERS AT TWO TIMES

	User 1 - Test 1		User 1 - Test 2		User 2 - Test 1		User 2 - Test 2	
Device	$\bar{x} \pm \sigma$	$\tilde{x}$	$\bar{x} \pm \sigma$	$\tilde{x}$	$\bar{x} \pm \sigma$	$\tilde{x}$	$\bar{x} \pm \sigma$	$\tilde{x}$
Smart Watch (Huawei Watch)	55±2.0	55	55±2.0	56	73±3.3	73	72±3.2	71
Fitness Tracker (Microsoft Band)	50±2.9	50	64±6.0	64	75±3.3	75	76±1.7	76
Specialized Sports Device (Polar H7)	56±1.7	56	59±1.4	59	77±3.0	76	80±3.7	79
Specialized Blood Pressure Monitor (Omrom M6)	55±2.8	55	58±2.9	58	76±2.5	76	84±4.2	84

exercise by using data of the accelerometer of the wearable worn around the wrist. Figure 3 shows the pattern of the accelerometer data, gathered with the fitness tracker around the wrist, during the execution of this exercise. Although the execution speed of the activity and the body characteristics of the user may have an influence on the absolute values of the data of the accelerometer, the typical pattern consisting of local minima and maxima can be witnessed for every repetition.

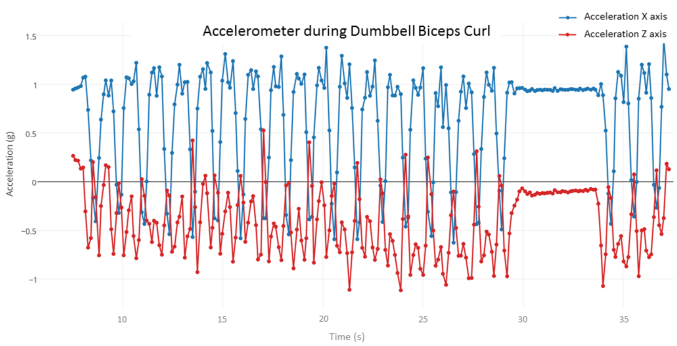

Figure 3. Measurements of the accelerometer of a wearable during Dumbbell Biceps Curl.

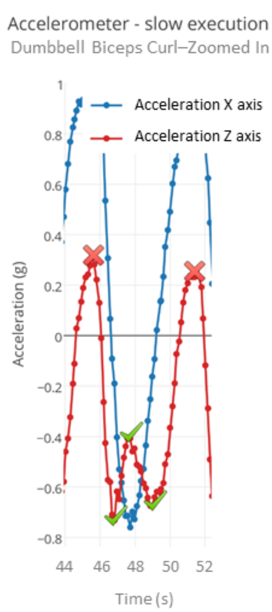

Figure 4. Detailed view on the local optima in the accelerometer data during Dumbbell Biceps Curl.

For each repetition of the Dumbbell Curl activity, 5 local optima on the Z-axis and 3 on the X-axis can be witnessed as visible in Figure 4: 1) a maximum on the Z-axis co-occuring with a maximum on the X-axis, 2) a minimum on the Z-axis, 3) a maximum on the Z-axis co-occuring with a minimum on the X-axis, 4) a minimum on the Z-axis, and 5) a maximum on the Z-axis co-occuring with a maximum on the X-axis. The red cross marks in Figure 4 denote the beginning and end of a repetition of the exercise, the green check marks indicate the intermediate optima. Recognizing the Dumbbell Biceps Curl execution based on the identification of a sequence of these 5 events has some benefits. The recognition process requires limited processing power, allowing real-time recognition (e.g., for e-coaching purposes) and making it usable on devices with limited processing power, such as wearables. Moreover, the detection of local optima makes the recognition method directly usable for different variations of the Dumbbell Curl, such as Concentration Curl, Hammer Curl, and Barbell Curl.

VI. HEART RATE AND ACTIVITY RECOGNITION COMBINED

Monitoring heart rate and simultaneously recognizing repetitions of an activity with the accelerometer allow a better health monitoring and e-coaching during workouts. Since raw data streams of both sources (heart rate sensor and accelerometer) are suffering from inaccuracies, the combination of both can improve health monitoring. For example, the intensity of a physical activity for an individual can be estimated based on the heart rate data. But in case of measurement interruptions in the heart rate data, accelerometer data can be used to estimate the performed physical activities.

For e-coaching purposes, our Android app uses both data sources to instruct the user during physical exercises thereby maintaining a healthy heart rate. Repetitions of an exercise are recognized and through text-to-speech techniques the repetitions are counted aloud or shown on the screen of the wearable. Each physical activity has a target range of the heart rate that can be expected during the performance. If the measured heart rate is out of this range, the user is warned by a clear indication on the screen of the wearable. After performing an activity, the app evaluates the intensity of the physical exercise as "too intensive", "to easy", or "just good".

VII. USER PROFILING AND RECOMMENDATIONS

The physical exercises measured with the accelerometer, the heart rate, and the characteristics of the exercises are stored online in a user profile. Users can access their profile using a web application to analyze their history of physical activities. Moreover, this user profile is used for personalization of suggestions for new activities in our Android app, such as a set of Dumbell Biceps Curl exercises, a running track, a cycling track, etc.

To match the user's preferences and physical capabilities to the physical activities and select the most suitable ones as recommendations, the activities of each type are processed by a specialized rule based filter. This rule based filter makes a selection of the activities based on characteristics of that type of activity, e.g., the distance for a running activity or the weight and number of repetitions for Dumbbell Biceps Curl. For each type of activity, a separate rule based filter is used in order to take into account the user's experience level for each activity individually. For example, suppose a user is an excellent runner. Recommendations for intensive running activities will be the most suitable, given the user's physical capabilities and history. Now, suppose that this user visits the gym for the first time with the goal of training the arm muscles. The user's body is not used to intensive Dumbell Biceps Curl activities. Recommendations at the level of starting users might be appropriate here. Therefore, a separate rule based filter is assigned to each activity type to handle these differences in training level for users. In future work, explanations about the recommendations can be added in order to further convince the user to adopt one of the offered recommendations [18]. These explanations can be expressed in terms of (the progress of) the physical capabilities of the user.

The rule based functionality is implemented based on Drools [19]. Drools is a business rules management system with business rules engine that is scalable and extendible through the use of drl files containing the rules. The goal of these rules is to filter the available activities in order to come up with the most suitable activity for the user taking into account the conditions/context at the moment of the recommendation.

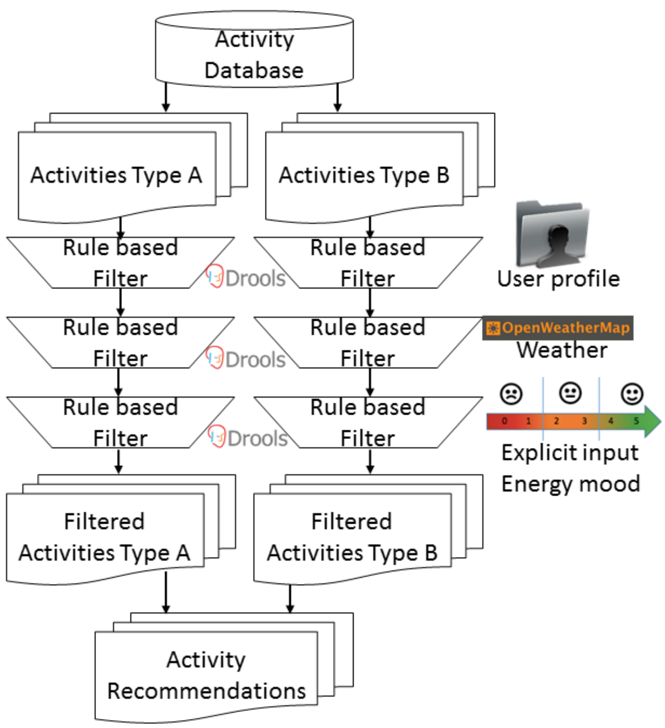

Figure 5. Graphical overview of the rule based filtering of the activities.

Figure 5 gives a graphical overview of the rule based filtering that is applied to the activities. The rules check the following conditions: 1) *User profile*: Do the length and intensity of the cycling or running track match the user's physical capabilities and habits? The target length of a track is similar to the length of the tracks in the user's history, but a small difference is tolerated. The intensity of the track is estimated based on the difference in altitude meters. For gym exercises, the intensity is estimated based on the weight or resistance of the fitness equipment and the number of repetitions. 2) *Weather*: Does the activity match the current weather conditions? For example, outdoor running activities are not recommended when it rains. To retrieve weather data at the user's location, the OpenWeatherMap.org REST API [20] is used. 3) *Energy Mood*: Does the activity match the user's energy level of the moment? The energy mood is a value, ranging from 0 to 5, that users can specify in the Android app to express their current feeling, e.g., energetic, tired, or something in between.

VIII. CONCLUSION

This study discussed the usage of wearables for heart rate measurements and the automatic recognition of physical activities. Measurements with a fitness tracker and a smart watch showed to be very accurate in case of limited physical movement, e.g., in a state of rest. In contrast, a discrepancy in the measurements of the wearables is witnessed during intensive physical activities (Dumbbell Biceps Curl). Shifts of the wearable with respect to the position of the wrist induce inaccuracies or even interruptions in the measurement process thereby hindering the monitoring of heart rate variations. Specialized sports devices, using a sensor with chest strap, produce more accurate heart rate measurements, even during intensive physical activities, and enable recognizing subsequent repetitions of a physical activity based on the periodic peaks in the heart rate. Therefore, our advise is to use a device with a chest strap for heart rate measurements in case of physical activities that involve a lot of movement of the wrist.

Besides, raw data produced by the accelerometer of wearables can be used to recognize repetitions of physical exercises with characteristic movements of wrist/hand/arm. E.g., the Dumbbell Biceps Curl exercise can be recognized based on a specific pattern with 5 local optima on the X and Z-axis of accelerometer data. Both raw data streams (heart rate and accelerometer data) can be combined for further analysis, but also to assist the user in coaching tasks, such as counting the number of times an exercise is performed, or instructing to decrease or increase the intensity of the exercise. Automatic activity recognition can help the user by reducing the burden of providing input about the performed activities in digital health services or fitness apps. Moreover, recognized activities can be stored in a user profile, which can be used as an indicator for the user's physical capabilities and habits. Based on this profile, the current weather, and the user's mood, personalized recommendations are generated using a set of rule based filters. In future research, we will investigate the recognition of other physical exercises and relate the resulting accelerometer data to heart rate data more in depth.

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