Health Monitoring and User Profiling for Sports Activities: Evaluating Heart Rate Measurements and Activity Recognition

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***Abstract*—Wearables are often equipped with an accelerometer and heart rate sensor. However, the accuracy of the generated heart rate measurements is still unclear. This paper evaluates heart rate measurements during various physical activities performed by test users and compares three types of wearable devices: the specialized sports device with chest strap, the fitness tracker, and the smart watch. Consistent heart rate measurements are obtained with all wearables during activities that require no or very little wrist movements, such as sitting in a chair, cycling, walking, or even squat exercises. In contrast, wearables worn around the wrist (smart watches and fitness trackers) and sport devices worn around the chest measure significantly different heart rates during activities that require a lot of movement of the wrist, such as dumbbell biceps curl and push up exercises. These movements of the user's wrist were measured using the accelerometer of the wearable, and allow the detection of repetitions of a physical activity with a typical movement pattern, such as a dumbbell biceps curl. Based on accelerometer and heart rate data, a user profile is created for a rule-based filter to generate personal recommendations for physical activities. A mobile app demonstrates that heart rate measurements and activity recognition can be used to assist and guide users during workouts.**

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

I. Introduction

Obesity due to insufficient physical activity is an ever growing problem in modern society [1]. Obesity can induce amongst others, heart diseases and stroke, diabetes, gallbladder disease, and gallstones. Research has shown that the majority of health care costs [2] are directly or indirectly due to physical inactivity [3]. Recent studies in health care support the theory that a healthy diet and regular physical activity are much more effective than traditional medication to cure diabetes [4]. Nutrition and training schedules are online available, but are often not personalized to the user's training goals or physical capacities and are static without taking into account the user's progress.

To tackle this problem, new efforts are made to decrease national obesity levels [5], thereby using technology such as data mining, web frameworks, and multi-modal sensors. Multi-modal sensors enable real-time monitoring of physical activities performed by the user. In the domain of public health monitoring, most of these sensor applications keep track of energy expenditure while performing daily activities [6][7].

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. Manufacturers choose not to assert claims regarding the accuracy of the detection of heart rate patterns; otherwise their gadget would get classified as a medical device and would have to undergo FDA (Food and Drug Administration) regulatory scrutiny [8].

Therefore, this study investigates the accuracy of heart rate measurements performed with different types of wearable devices. The heart rate measurements are evaluated in rest condition, as well as during different physical activities. This paper presents an extension of our previous research on wearables [1]. Compared to this previous study, one additional wearable device, the Polar M600, was evaluated. Moreover, this paper provides a more extensive comparison of the heart rates. The following additional activities are considered: interval training (cycling), rest (sitting in a chair), walking, squats, and push ups. The results of this study are important for (mobile) applications and services that rely on heart rate data generated by these wearables.

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 [9]. However, this is often considered too intrusive for daily activities. Therefore, this study investigates activity recognition using popular wearable devices (Section VI). More specifically, the number of repetitions of an exercise is counted through activity recognition. Compared to our previous research [1], this papers provides more in depth results by making a distinction between fast execution and slow execution of the exercise.

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. Section III discusses the different methods to measure heart rate. An overview of the wearable devices used in this study is provided in Section IV. The next sections discuss the measurements of the wearables: the heart rate measurements are discussed in Section V, activity recognition is the topic of Section VI, and the usage of the combination of both is covered in Section VII. Section VIII is about the rule-based filter to generate personalized recommendations. Section IX discusses the results and Section X draws conclusions and points to future work.

II. Related Work

The last decade, many digital healthcare services have emerged, also on the mobile platform, to deliver services such as health monitoring, medical consultations, diagnosis, and prescriptions [10][11]. Despite the security and privacy risks [12], 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 [13][14].

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 [15][16]. 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 [17].

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 [18]. 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 [19]. 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 [20]. 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 [21] 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 [22].

To classify activities such as walking, race walking, and running based on unlabeled data, an unsupervised method for recognizing physical activities using accelerometers of smart phones has been proposed [23]. Two additional smart phones were attached to the upper arms of the user to recognize specific actions while playing basketball, such as passing or bouncing the ball, or a free throw. Although the accelerometer hardware in smart phones might be very similar for wearables, the specific position of a wearable around the wrist can provide very different data reflecting movements of the hand and wrist, additional to the arm movements.

Other studies investigated how simple actions can be used to recognize more complex activities, which are semantically more representative for a human's real life [24]. The algorithm is based on temporal patterns (such as actions occurring after other actions, or actions that overlap) and a multi-task learning approach [25].

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 [26] 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, which is ongoing since the mid-90s [27] and is demonstrated for example in Computer-Tailoring Health Education Systems [26]. Personalization in the health domain is described as "adapting the content of the materials, with the aid of computers, to the specific characteristics of a particular person" [28].

Personalization can be achieved by using a recommender system. Personalized recommendations, tailored messages, and customized information have shown to be far more effective than the non-personalized alternative [15][16].

Health promotion and wellness driven applications often use collaborative filtering techniques to cope with the overload of health data and identify the most relevant information [29].

Collaborative filtering makes a selection of the available information for the user based on actions of the community, and does not rely on a central agency or individual expert. As a result, the quality of the selection is depending on the size and engagement of the community using the service. Alternative content-based solutions do not rely on community activity, but require specific metadata to assess the suitability of information items. Our proposed recommender is a combination of a rule-based and content-based system to filter the content for the users based on their preferences and physical capabilities. Unfortunately, many of the existing recommender systems rely on the manual input of users reporting their performed exercises. In contrast, our solution combines automatic activity recognition and heart rate measurements, which are used as input for the rule-based recommender system.

III. Heart Rate Monitoring

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 [30]. 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 [31]. 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.

Many wearables are equipped with one or more LEDs to measure heart rate using PPG. The LEDs (light emmitor) and photo diodes (light detector) are typically located on the back of the smart watch or fitness tracker and in direct contact with the skin. The popularity of this technique for wearables is largely due to the convenience and low cost of the hardware. But manufacturers often label their devices as "not a medical device" or "not intended to match medical devices or scientific measurement devices" [32]. This paper discusses the use of PPG in wearables for heart rate measuring in different situations (Section V).

IV. 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. Smart watches are typically equipped with a light sensor to enable heart rate measurements based on photoplethysmography.

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). This is a smart watch with a classic design that is not focused on sports activities.

In addition, the *Polar M600* smart watch was used as an alternative wearable device that has a clear focus on tracking sports activities. It is equipped with the typical hardware sensors such as an accelerometer and gyroscope. In contrast to the Huawai watch, the Polar M600 also has a built-in GPS. It is water resistance and can capture swimming metrics. An important characteristic for this research is that optical heart rate measurements are performed with 6 LEDs. These multiple LEDs should improve the accuracy of the heart rate measurements of the Polar M600.

To capture heart rate data in real time, a special Android Wear app was developed for the smart watches. 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 device 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 [33]). Heart rate is measured using electrodes in the chest strap that detect heart pulse via an electronic signal.

V. 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 and store the data in a Realm IO database. Realm is an alternative solution for SQLite and delivers real time performance [34]. The evaluations of the heart rate measurements have been performed in a controlled environment.

Figure 2 shows the data flow through the different components of the system. The data of accelerometers are processed and repetitions of specific movements are detected by activity recognition (Section VI) . The types of activities, the number of repetitions, and the intensity (speed of execution) are used for creating a user profile. Subsequently, a filtering with a rule-based system (Section VIII) is performed to match the intensity of an activity to the physical capabilities of the user (as estimated by the measured heart rate). The best matching activities are offered to the user as personal suggestions.

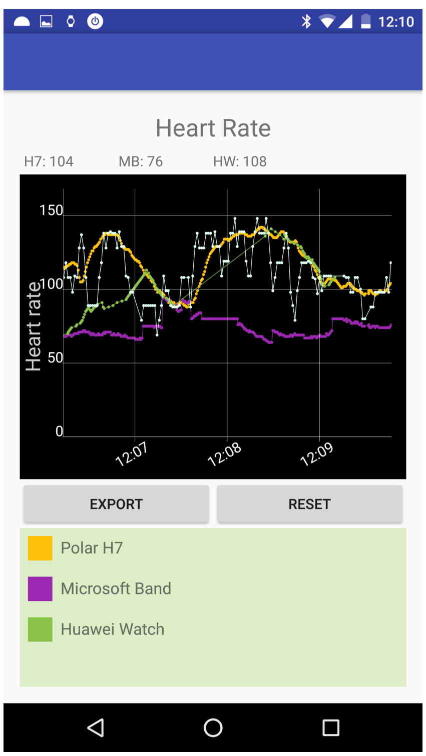

Figure 1. Screenshot of the Android app for gathering heart rate data.

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 [35]. The Omrom M6 is a blood pressure monitor, which has to be attached around the upper arm for measuring the heart rate.

Figure 2. Flow chart showing the data through the different components of the system.

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. Demographic and physical characteristics have an influence on the absolute value of the heart rate, but this research focuses on comparing measurements of different devices and variations in the heart rate, rather than on the absolute value of the heart rate.

The measurements of the heart rate during rest condition (Table I) were performed in a home, indoor environment. These test users were wearing the four devices simultaneously during the measurements. The Huawei Watch and Microsoft Band were worn around the wrist (one device per wrist), the Polar H7 around the chest, and the Omrom M6 around the upper arm. For optimal measurement results, test users wore only one smart watch per wrist; so the Polar M600 was not used in this experiment. Test users were asked to sit in a chair, doing nothing, while the devices measure their heart rate.

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 Dumbbell Biceps Curl

Figure 3 shows the heart rate measurements obtained with the different devices during physical activity, more specifically during the dumbbell biceps curl exercise. This exercise for bicep muscles was performed in a fitness room by two people. Similar results are obtained for both persons (results are shown for only one person). Before each experiment, a rest period of 10 minutes was imposed to avoid influence of previous activities and the coupled heart rate.

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

Device	User 1 - Test 1		User 1 - Test 2		User 2 - Test 1		User 2 - Test 2	
	$\bar{x} \pm \sigma$	$\tilde{x}$	$\bar{x} \pm \sigma$	$\tilde{x}$	$\bar{x} \pm \sigma$	$\tilde{x}$	$\bar{x} \pm \sigma$	$\tilde{x}$
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

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. Since the user was wearing the Microsoft Band 2 on one wrist and the Huawai Watch on the other, the Polar M600 smart watch was not evaluated in this experiment. For the three wearable devices that were used (Polar H7, Microsoft Band 2, and Huawai Watch), a significantly different measurement signal of the heart rate can be witnessed during this physical activity.

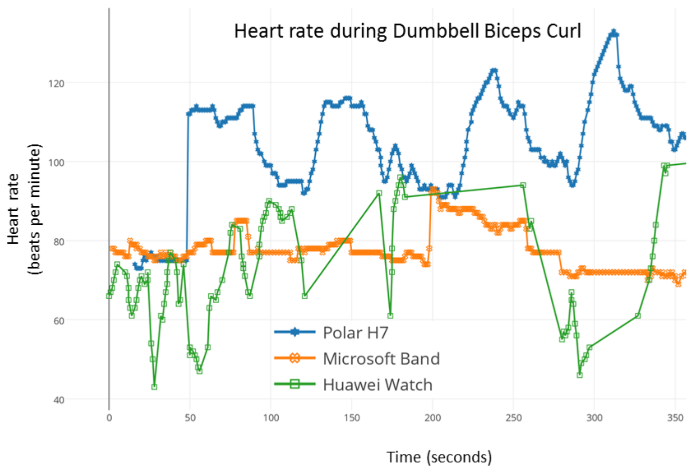

Figure 3. Heart rate measurements during dumbbell biceps curl.

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 3.

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 3 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.

C. *During various Physical Activities*

Based on the results of our previous study [1], this section further investigates the differences in the heart rate measurements between the smart watch and a specialized device, such as the Polar H7, as witnessed in Section V-B. For this experiment, heart rate measurements obtained with the Polar H7 were compared to the measurements of the Polar M600. Since, the Polar M600 smart watch is designed for sports activities, the measurements are performed during different physical activities. Special attention is paid to the activities that involve a lot of movement of the wrist in contrast to activities with limited movement of hands and arms.

Although both devices are connected to the same smartphone, as illustrated in Figure 2, a comparison of the raw data shows that the measurements are not synchronous. This can be illustrated by Figure 4, which shows the heart rate measurements during interval training. In this test setup, periods of intensive physical activity and rest periods alternate, which is reflected in a rising and falling heart rate. Figure 4 indicates a lower responsiveness of the Polar M600, which measures heart rate at the wrist, compared to the Polar H7, which measures heart rate at the chest. Sudden increases or decreases in heart rate are only visible a few seconds later with the Polar M600. This is important to take into account for users or application developers that intent to use these data for monitoring activities with rapidly varying heart rate.

By shifting the measurements of the Polar M600 with 9 seconds in time (by subtracting 9 seconds from the timestamp), the measurements appear to be synchronous with the measurements of the H7 chest strap. Figure 5 shows the measurements of both devices after this time shift. To compare the values of the heart rate measurements of both devices during various physical activities, this time shift is applied to all subsequent graphs visualizing heart rate (Figures 5 - 9).

Figure 6 shows the heart rate measurements during rest. The test users are sitting in a chair doing nothing, while wearing both devices to measure the heart rate for a period of 5 minutes. During this period, the measured heart rate varies between around 55 and 70 beats per minute (bpm). The measurements of both devices are very similar, except around second 120 and 195, differences up to 12 bpm are witnessed. This discrepancy was not due to movement of the wrist or body of the user, but might be due to inaccuracies of the measurement process. However, for most of the measurement period, the differences between both devices are small.

Table II lists the mean difference (Mean diff), the mean absolute difference (Mean abs diff), the median absolute difference (Median abs diff) and the maximum absolute difference (Max abs diff) between the measurements with the two devices.

The low values of the mean difference might be an indication that both devices report a reliable heart rate. The measurements of one of the devices are not consistently higher than the ones of the other device. The mean absolute difference is a measure for the average error between both. The low value in rest condition shows that measurements are very accurate. The maximum absolute difference stands for the largest error between both measurements. In rest condition, this error is obtained around second 195. The median absolute error is less influences by these extreme values. In rest condition, the typical difference between both devices is only 1 bpm.

Figure 7 shows the heart rate measurements while doing a light activity. In this test setup, the users were asked to walk while measuring heart rate. Users were is rest condition (sitting) before the test and during the first 30 seconds, so that an increase in heart rate could be detected during the first minutes. At timestamp 30, users started walking for 7 minutes. Subsequently, the users returned to their seat (rest condition), which can be seen by the decreasing heart rate during the last 3 minutes. Compared to rest condition, the differences in Table II are slightly higher for walking, but still small.

Figure 5 shows the heart rate during interval training. In this test setup, the accuracy is evaluated in case of peaks in the heart rate. The users were first in rest condition for 30 seconds. Next, the users were cycling on a home trainer during 1 minute, followed by 1 minute of rest. Subsequently, this pattern of 1 minute cycling and 1 minute resting was done 2 times more (so, 3 times in total). Again, Table II shows small differences between the measurements of both devices.

In the last two test setups, test users were performing muscle strengthening activities. This way, the accuracy of the heart rate can be evaluated during intensive physical activities, which are characterized by many body movements and a rapid variation of the heart rate.

Figure 8 shows the measurements obtained while performing squats. The squat is a compound, full body exercise that trains multiple types of muscles. For this, users have to bend the knees and move their arms, but wrist movements are limited. A similar test setup is used here. During the first 30 seconds, the users were doing nothing in order to measure their heart rate in rest. Next, the users were executing squat exercises during 30 seconds, followed by 30 seconds of rest. Subsequently, the users were asked to do a new set of squats during 30 seconds, rest 30 seconds, doing a last set of squats during 30 seconds, and rest 30 seconds. Although this exercise involves a lot of movement with arms and legs, thereby increasing the heart rate rapidly, the measurement differences remain small, as shown in Table II.

Figure 9 shows the heart rate measurements while doing push ups. The push up exercise is performed in a prone position by raising and lowering the body using the arms. It involves a lot of pressure on the wrists and subsequent repetitions implicate some movement of the wrists. Again, the test started with a period of 30 seconds in rest condition. Subsequently, the user performs push ups during 30 seconds, followed by 30 seconds of rest. This pattern (30 seconds push ups, 30 seconds rest) is executed 3 times.

For this activity, Table II and Figure 9 show large differences between the two different devices. These differences can be explained by the movements of the wrist, which are characteristic for this activity and much more prominent compared to the other activities, such as squats or interval training (cycling). The range of the heart rate is similar for interval training, squats, and push ups, starting at approximately 70 bpm and increasing until 120 - 140 bpm. For interval training and squats, the differences between the Polar H7 and M600 are typically only 1 bpm (median value), whereas for push ups the median difference is 18 bpm with maximum differences up to 58 bpm. Figure 9 shows that the two devices provide consistent measurement values during rest periods: during the first and last 30 seconds of the test, the heart rates of both devices are very similar. In contrast, during periods of push up activities, the two devices output very different measurement results. The Polar H7 shows a heart rate increase with peaks up to 130 bpm and active periods can be clearly detected, whereas the M600 measures only a slight heart rate increase up to 100 bpm and active periods can hardly be distinguished. This confirms the hypothesis that heart rate measurements with smart watches are less accurate during physical activities that involve a lot of movement of the wrist, such as push ups or dumbbell biceps curl exercises.

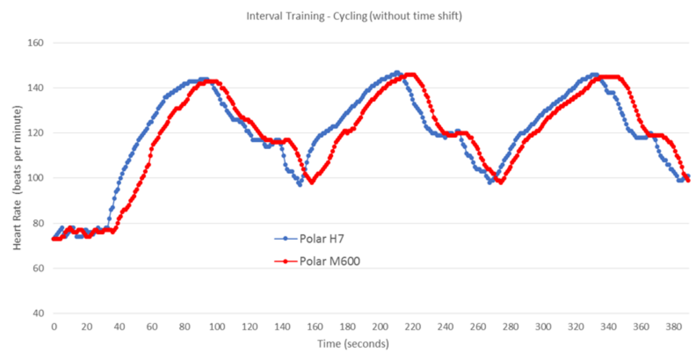

Figure 4. Heart rate measurements during interval training without a time shift.

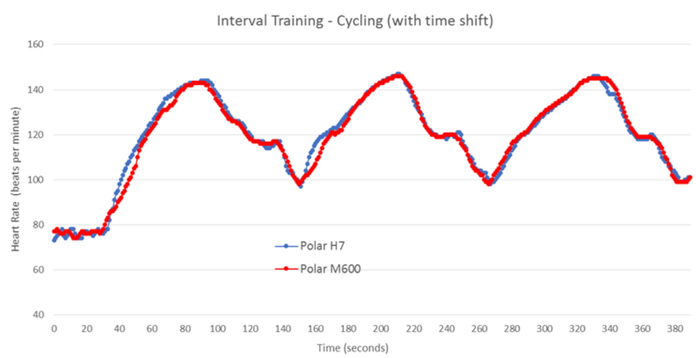

Figure 5. Heart rate measurements during interval training with a time shift.

TABLE II. COMPARATIVE STATISTICS FOR THE HEART RATE MEASUREMENTS OF THE POLAR H7 AND POLAR M600.

Activity	*Mean diff*	*Mean abs diff*	*Median abs diff*	*Max abs diff*
Rest	0.36	1.40	1	12
Walking	0.75	1.48	1	18
Interval	0.61	1.88	1	9
Squats	1.32	2.11	1	15
Push Ups	19.39	19.56	18	58

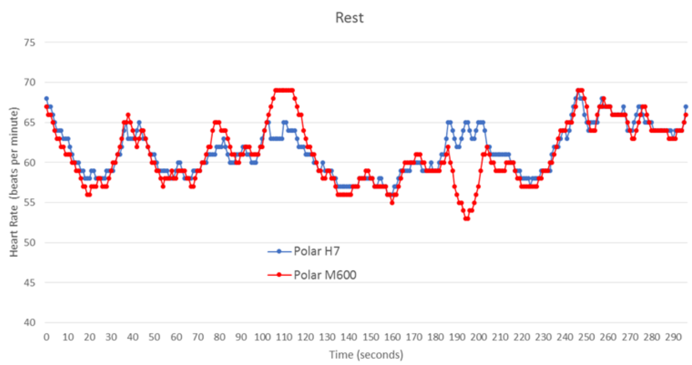

Figure 6. Heart rate measurements during rest.

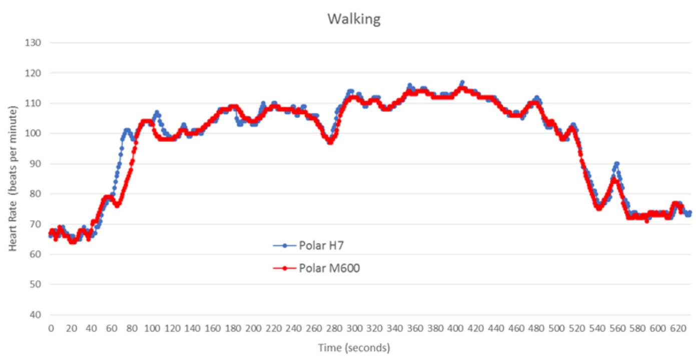

Figure 7. Heart rate measurements during walking.

Figure 8. Heart rate measurements during squats.

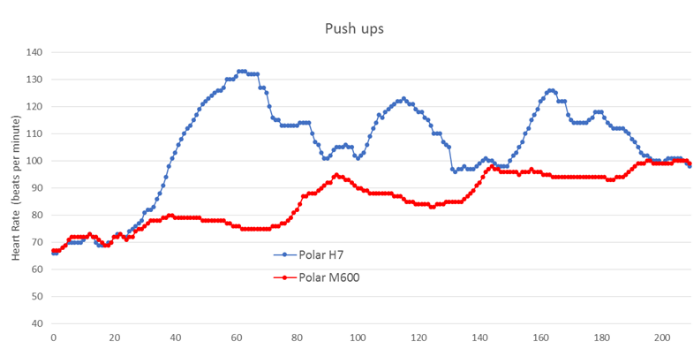

Figure 9. Heart rate measurements during push ups.

VI. Activity Recognition

Many studies have tackled the challenge of activity recognition by using multiple sensors placed on different parts of the body, e.g., on the hip and the chest [9]. But, the placement of these sensors can be considered too expensive and invasive for daily sports activities. In contrast, this study performs activity recognition using wearables.

The aim is to assist users in coaching tasks such as checking the proper execution of physical exercises or counting the number of repetitions of an exercise, rather than classifying the physical activities by type. Repetitions of an exercise are detected by real-time processing of the raw data of the accelerometer of the wearable worn around the wrist. The dumbbell biceps curl exercise is a typical activity that allows detection of repetitions of this exercise by using data of the accelerometer. This exercise is characterized by specific movements of the arm and wrist, which enable the detection.

Figures 10 and 11 show the pattern of the accelerometer data, gathered with the fitness tracker around the wrist, during the execution of this exercise. As an extension to our previous research [1], the accelerometer data was gathered during fast execution as well as slow execution. Figure 10 visualizes the accelerometer data gathered during a fast execution of the exercise. A slow execution, with a clearer pattern, is visible in Figure 11. The comparison of Figures 10 and 11 demonstrates that higher maximum and lower minimum values are reached with a fast execution. 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 minimums and maximums can be witnessed for every repetition.

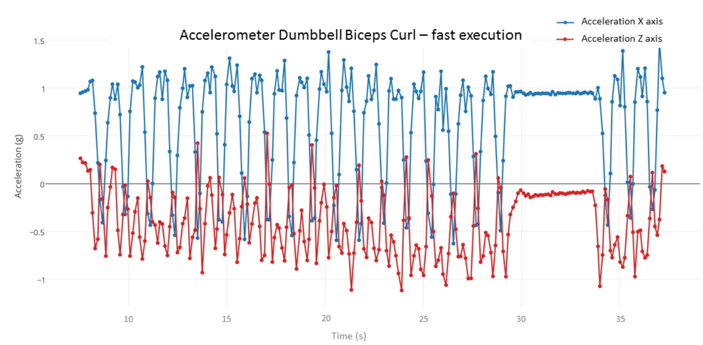

Figure 10. Measurements of the accelerometer of a wearable during fast execution of a dumbbell biceps curl exercise.

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 12: 1) a maximum on the Z-axis co-occurring with a maximum on the X-axis, 2) a minimum on the Z-axis, 3) a maximum on the Z-axis co-occurring with a minimum on the X-axis, 4) a minimum on the Z-axis, and 5) a maximum on the Z-axis co-occurring with a maximum on the X-axis. The red cross marks in Figure 12 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

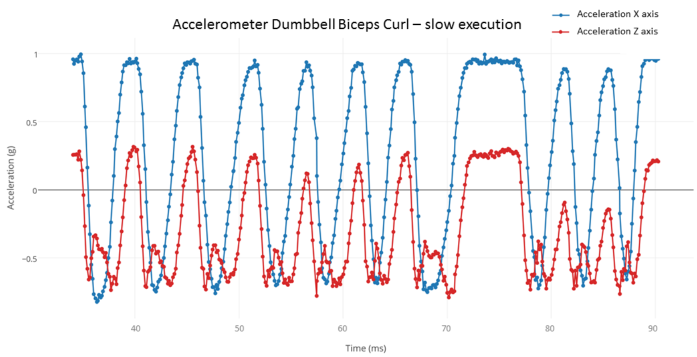

Figure 11. Measurements of the accelerometer of a wearable during slow execution of a dumbbell biceps curl exercise.

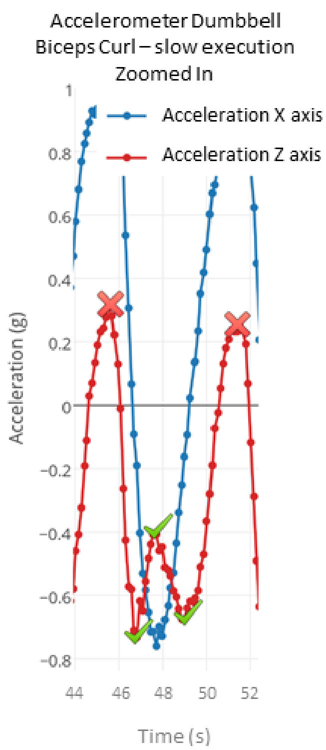

Figure 12. Detailed view on the local optima in the accelerometer data during slow execution of a dumbbell biceps curl exercise.

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.

VII. 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 execution. 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”.

VIII. 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 dumbbell biceps curl exercises, a running track, a cycling track, etc. Figure 13 shows a screenshot of the recommended activities for one of the users.

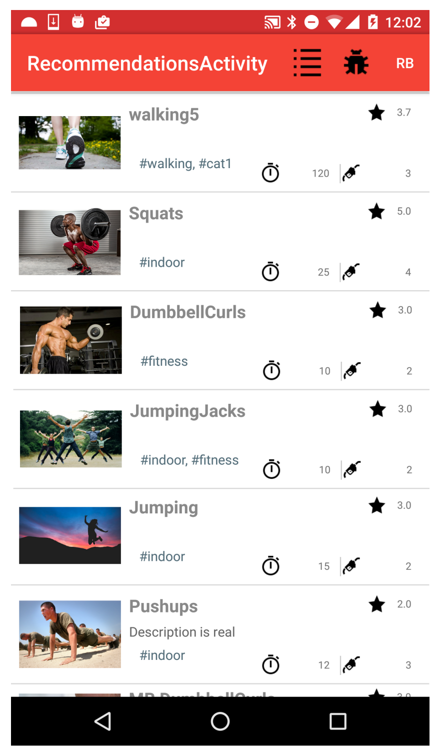

Figure 13. Screenshot of the Android app showing the recommended activities.

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 dumbbell 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 [36]. 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 [37]. 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.

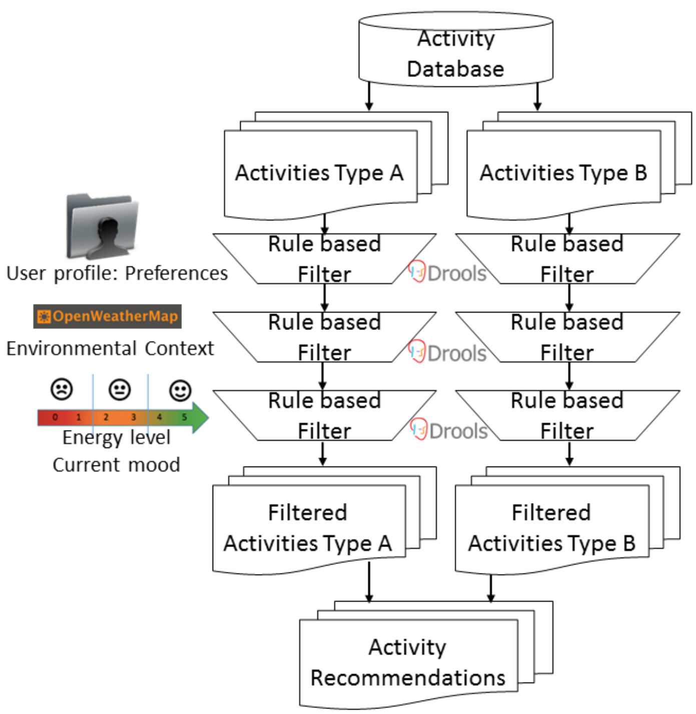

Figure 14. Graphical overview of the rule-based filtering of the activities.

Figure 14 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) *Environmental Context*: 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 [38] is used. 3) *Energy Level*: Does the activity match the user's energy level of the moment? The energy level is a value reflecting the user's current energy mood, 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.

IX. Discussion

During intensive physical activities with limited movement of the wrist, such as walking, cycling, or even squat exercises, the experiments showed accurate heart rate measurements (Section V-C). In contrast, a discrepancy in the measurements of the wearables is witnessed during intensive physical activities with a lot of wrist movements (dumbbell biceps curl and push ups). 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. The resulting measurements obtained with wearables around the wrist are often lower than the heart rate measured with a specialized sports device.

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 the 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, habits or preferences for sports activities. Based on this profile, the current weather, and the user's mood (energy level as specified by the user), personalized recommendations are generated using a set of rule-based filters.

X. 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. During intensive physical activities with a lot of wrist movements, measurements performed with wearables might be disturbed. Simultaneously measured accelerometer data showed to be useful for recognizing repetitions of physical exercises with characteristic movements of the arm, hand, or wrist. The combination of heart rate measurements and activity recognition allows to create a use profile that reflects the user's physical capabilities in view of generating personal recommendations. 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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