Wrist Sensors – An Application to Acquire Sensory Data from Android Wear® Smartwatches for Connected Health

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***Abstract*— In our days where P4 (predictive, preventive, personalized, and participatory) medicine is recognized as a promising sustainable solution to the problems of healthcare systems, there is an evident demand for individual-level biological, physical, behavioral or environmental data to support the development of efficient P4 medicine interventions. The self-acquisition of such data with the help of wearable sensor technology is the primary objective of the trending Quantified Self (QS) movement. Smart devices (smartphones, smartwatches, wrist sensors, etc.), with dozens of built-sensors and great adoption by the public, emerge as the perfect technology tools for satisfying the data acquisition pursuits of QS. In this effort, smartwatches demonstrate certain sensory advantages when compared to portable smart devices (e.g., smartphones). In this work we introduce Wrist Sensors, a novel Android Wear app for presenting the available sensors of compatible smartwatches and recording measurements from any user-specified subset of them. The recordings are persistently stored and made available in the communicating Android smartphone. The app, which has been made freely available via the Google Play distribution service, can serve as a valuable data acquisition tool to facilitate the development of efficient P4 medicine interventions. In fact, the app has already been used by a published study for acquiring the input dataset for developing a novel real-time bite detection algorithm.**

I. INTRODUCTION

Modern medicine is rapidly moving from conventional practices towards alternative paradigms, such as the **P4** (predictive, preventive, personalized, and participatory) **medicine scheme.** P4 medicine has emerged as a sustainable solution to the pathogenies of conventional healthcare provision systems – ever increasing costs, worsening outcomes and new epidemics [1]. Investing in (i) disease prevention instead of cure, (ii) precision approaches instead of generic ones, and (iii) participation of the patient in disease management, P4 medicine has the potential to transform healthcare [2].

However, the development of the interventions that P4 medicine envisions necessitates the **prior availability** of relevant, health-related information that is acquired from health subjects at individual level. Especially the design of successful P4 medicine interventions can be an intensively data-driven process that concerns, depending on its application, biological, physical, behavioral or environmental data [3]. Based on the above statements, the need for **collecting/acquiring** the aforementioned data becomes evident. The trending **Quantified Self** (QS) movement envisions the use of technology for the acquisition of such data by the individuals themselves [3]. QS has been identified as a powerful instrument in the realization of personalized preventive medicine [1] with several successful applications in the pursuit of health goal (e.g., weight loss). The self-monitoring assumed by QS relies heavily on **wearable sensors**, which maintain a close proximity to the individuals and are able to provide large volumes of objective information.

The various portable and wearable **smart devices** (smartphones, smartwatches, wrist bands, etc.) form the perfect candidate for realizing the data acquisition objectives of QS in order to support the development of P4 medicine interventions, owing to (i) their numerous built-in sensors, (ii) their extensive usage by the subjects, and (iii) their impressive computation power and data storage capabilities. Although more recent and, as a consequence, less common than other smart devices, **smartwatches** demonstrate certain advantages over the portable smart devices (such as smartphones): (i) they can support the acquisition of vital signs (such as continuous heart rate) not supported by portable devices, and (ii) they are able to provide more accurate information concerning certain behaviors (e.g., physical activity).

This work has addressed the demand for acquisition of sensory data from smartwatches to support the development of P4 medicine interventions. Smartwatches supporting the popular Android Wear platform[1] have been targeted. An Android Wear app called *Wrist Sensors* has been developed and made freely available via the Google Play distribution service[2]. Through the simple, easy-to-use interface of the app, the users are notified about the available sensors on their smartwatch and they can, subsequently, record timeseries of measurements from a user-selected list of sensors for a user-controlled period of time.

II. BACKGROUND

The scientific literature already includes a number of studies that exploit smartwatch sensors in order to predict/detect (i) behavioral patterns that are potentially harmful or unhealthy [4-11], or (ii) incidents related to specific diseases [12-13].

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The research leading to these results has been partially funded from the H2020 Programmes INLIFE, PATHWAY and BIGO under Grant Agreements no 643442, 643491 and 727688 respectively.

[1] https://www.android.com/wear/

[2] https://play.google.com

These studies either make exclusive use of the smartwatch sensory data or combine them with other sensory data, while the built-in 3-axis accelerometers and gyroscopes turn out to be the most commonly-used smartwatch sensors.

Regarding the exclusive exploitation of smartwatch sensors, a recent study proposes a smartwatch software architecture for health hazard handling for elderly people [4]. Another study exploits smartwatch sensors to evaluate medication adherence via the recognition of specific gestures (e.g., bottle cap opening or palm facing up) [12]. Smartwatch sensors have also been applied in the estimation of blood alcohol content [5] and driver alertness [6]. Additionally, a couple of publications rely on smartwatch sensors to detect eating related events, such as eating episodes [7-9] or eating mode [8].

When it comes to the fusion of smartwatch sensors with the sensors of other devices, the most common complementary device is the smartphone. A recent study attempts the detection of bad habits (e.g., smoking and drinking alcohol) by fusing smartwatch and smartphone sensors [9]. In the personalized Parkinson Disease intervention that is introduced in [13], smartwatch sensors are used for the detection of disease outbreak symptoms such as limb dyskinesia and gait abnormality. Another study evaluates the impact of adding smartwatch sensors in an activity recognition task initially based on smartphone sensors [10]. Finally, a far more complex hardware setup that combines a smartwatch with Google glass and an earbud is proposed in [11] for food type and amount estimation.

III. The Wrist Sensors App

The Wrist Sensors App is an Android Wear 5.0 API 21+ application that presents the sensors embedded on the host wearable device and enables the simultaneous recording of the measurements performed by one or multiple of those sensors. The graphical user interface (GUI) of the app is simple and intuitive. Moreover, the settings menu is hosted on the smartwatch enabling the initiation/termination and the on-demand configuration of the recording from the smartwatch without requirement for proximity with the smartphone. The GUI screens of the app are presented in Fig. 1, while sample photograph of the app running on two smartwatches with different screen types is given in Fig. 2.

A. App Usage

Once the application starts, the app discovers and presents the list of all available sensors on the smartwatch (`List of Sensors Screen`). This list may contain hardware-based sensors (e.g., accelerometer, gyroscope, light sensor) but also software-based sensors (i.e., sensors that report values after sensor fusion, such as the step counter). The user may scroll up and down the list by swiping up and down respectively. In order to view details about the specific sensor a short press (tap) on the sensor name is needed. The later leads to the `Sensor Info Screen` where the current measurement and its reported accuracy is displayed along with the sensor's (i) description, (ii) max possible reported value, (iii) power consumption, (iv) sensor vendor information. This screen is updated each time the sensor reports a new measurement.

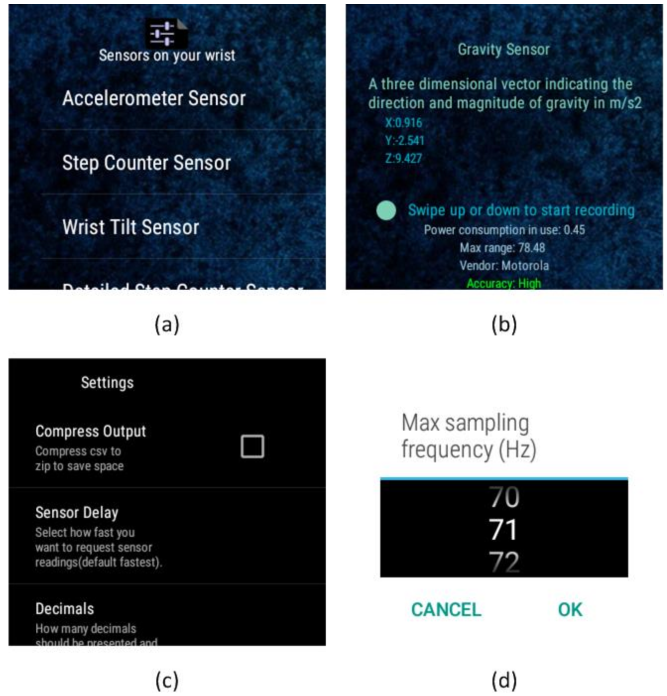

Figure 1. GUI Screens of the Wrist Sensors App: (a) `List of Sensors Screen`, the main screen of the app; (b) `Sensor Info Screen`, providing details about a selected sensor; when the selected sensor is recording, the green circle turns red; (c) `Settings Screen`, providing on-demand configuration of the recording process; (d) a number picker for setting the `Max sampling frequency` option.

In order to start recording the measurements of the sensor, the user just has to swipe up or down as instructed also by the GUI. Using the same gestures the user finalizes the current recording session. The acquired measurements are then persistently stored in a CSV. In order to exit the `Sensor Info Screen` and return to the `List of Sensors Screen` the user has to swipe right.

Apart from the *single-sensor recording* use case, the app supports the simultaneous recording of multiple sensors (*multi-sensor recording* use case). In the latter use case, the user selects one sensor by long pressing on the sensor entry in `List of Sensors Screen`. The sensor name is highlighted without proceeding to `Sensor Info Screen`. The user may repeat this procedure for any number of sensors and enter the `Sensor Info Screen` of the last selected sensor – short pressing is needed this time. The persistent storage of the sensors' measurements in this use case is as well in a single, yet now multiplexed file.

Figure 2. Example photographs of the Wrist Sensors App running on two different smartwatches with rectangular and circular screen.

B. Synchronization

Once a recording is completed the corresponding CSV file is stored in the smartwatch internal storage. In order to make it easier to retrieve the file for analysis, when the wearable connects to the accompanying smartphone the file is automatically transferred to that device's external storage which is easily accessible by the user. When this operation is completed successfully the original file is deleted from the smartwatch's storage.

C. Recording File Format

The recording file is a comma delimited text file, whose schema is fixed independently of the selected sensors. More specifically, the file includes one row for each measurement acquired from one sensor. The file starts with a header that specifies the content of each one of the 6 columns describing each measurement/row. These columns are placed in the following order: (1) TIMESTAMP: the measurement time in UNIX epoch milliseconds. (2) VALUE[1]: the measurement value in the x axis – this assumes 3-dimensional measurement type; in case of scale measurement type, this column is the actual measurement value. (3) VALUE[2]: the measurement value in the y axis – if applicable. (4) VALUE[3]: the measurement value in the z axis – if applicable. (5)ACCURACY: the sensor-reported measuring accuracy – this applies to each particular measurement. (6) SENSORTYPE: the index of the employed sensor.

After the measurement section of the file, a legend is appended to link the aforementioned SENSORTYPE indices to the corresponding sensor names. An excerpt from a real recording file is presented in Listing 1.

```
TIMESTAMP,VALUE[1],VALUE[2],VALUE[3],ACCURACY,SENSORTYPE
1436527384625,229.50264,-18.73434,3.675108,3,3
1436527384625,0.096841484,0.13448608,0.89774853,3,11
1436527384625,0.33444005,-2.1377227,0.063895255,3,10
1436527384627,229.50264,-18.73434,3.675108,3,3
...
1436527855858,225.99216,-30.157047,-4.916269,3,3
1436527855858,0.06341421,0.25542778,0.8836612,3,11
1436527855858,0.048482586,-0.25184008,-0.27742812,3,10
LEGEND for SENSORTYPE:
3 : MPL Orientation
10 : MPL Linear Acceleration
11 : MPL Rotation Vector
```

Listing 1. Excerpt from a real recording file using multiple sensors.

D. Recording Settings

In order to optimize the recording output, the user may alter the recording settings directly on the smartwatch using the settings screen. This screen includes a list of 6 configuration options outlined below:

- `Measurement truncation` (radio button list). This option determines the number of decimals that are retained for each measurement. The supported choices are 0 to 4 decimals.
- `Compress output` (checkbox). When this option is checked the output file of the recording is compressed in order to save storage space on the smartwatch.
- `Split output file` (number picker). This option aims to split a long recording into chunks of user specified duration (in minutes). When selected, a number picker is displayed where the user may specify the chunk duration.
- `Sensor delay` (radio button list). The Android Wear platform delivers the measurements to the app at a frequency (measurement delivery frequency) that is controlled by the platform itself. This option instructs the platform to deliver the measurements at a specific frequency level. Three frequency levels are supported, namely Fastest, Normal and UI (slow).
- `Max sampling frequency` (number picker). This option applies, if possible, an upper limit on the measurement delivery frequency resulting to a constant sampling frequency at which the measurements are presented in the UI of the app and recorded in the CSV file (measurement recording frequency). When selected, a number picker appears allowing the user to specify the measurement recording frequency in Hz.
- `Smooth results` (checkbox). In the case where the samples that are delivered by the Android Wear platform (`Sensor delay` option) have higher frequency than the one selected by the user (`Max sampling frequency` option), the final option determines how to exploit the redundant samples. If checked, the redundant samples are employed to smooth the presented and recorded measurements via averaging. In the opposite case, the redundant samples are discarded.

This rationale behind the `Compress output` and `Split output file` options has been to optimally manage the limited storage and memory resources of the smartwatch (e.g., in the case of lengthy recordings from multiple sensors). On the other hand, a number of options (`Sensor delay`, `Max sampling frequency` and `Smooth result`) has been included to deal with the sampling frequency. While it is not possible for the app to determine the measurement delivery frequency, it can still request for a desirable delivery frequency level (fast, normal or slow). This selection has an impact not only on the eventual recording frequency but also on the battery life of the smartwatch. Since the delivery frequency cannot be known, the app allows the user to set an upper limit for the measurement recording frequency via the `Max sampling frequency` option. In addition, the redundant samples can be exploited to smooth the presented/recorded measurement timeseries. Finally, the `Measurement truncation` option serves the purpose of discarding the non-informative part of the measurements (i.e., measurement noise).

IV. DISTRIBUTION INFORMATION

The Wrist Sensors App has become freely available on Google Play[3] on October 2015. Since then, the app has been installed almost 230 times, and no *application not responding* (ANR) reports were filed. Overall, the app was

[3] play.google.com/store/apps/details?id=gr.auth.med.lomi.wristsensors

very well received (mean rating: 4.75/5 in 5 reviews). Additionally, requests for new features were made by the user. For instance, one user commented *"But I would like to have a setting for the frequency of the writes to the file in ms or summing up several polls. I had big files after only 5mins of recording of one sensor..."*. Based on the analysis of those requests, the app was updated with new features. In particular, the aforementioned comment led to the inclusion of the `Max sampling frequency` and `Split output file` settings.

V. A SUCCESS STORY

To demonstrate the capacity of this application, we present the case of a study introducing a novel algorithm for real-time bite detection from smartwatch orientation data [14].

All the smartwatch sensory data that were needed for the design and evaluation of the bite detection algorithm in [14] were acquired via the Wrist Sensors app. Data used were recorded from: (i) short-term measurements from all smartwatch sensors (LG G watch[4]) by one subject for the conceptualization of the approach, (ii) long-term measurements from the smartwatch orientation sensor (LG G watch) by one subject for the initial design of the bite detection algorithm, and (iii) several real-life, long-term measurements from the smartwatch orientation sensor (LG G watch and Motorola Moto 360 watch[5]) by many subjects for testing the accuracy of the developed algorithm. The Wrist Sensor app was able to successfully and efficiently carry out all the data acquisition requests (data retention rate: 100%).

The main characteristics of the app was the simplified acquisition of the sensory data needed to design and evaluate the introduced bite detection algorithm, allowing the researchers to concentrate on the efficiency of the algorithm (accuracy and speed) instead of waist time in getting the required data. This successful application shows the capacity of the Wrist Sensor app can to serve as a P4 medicine interventions enabler.

VI. CONCLUSION

Given the dependence of P4 medicine interventions during their development phase on the availability of high-quality biological, physical, behavioral, and/or environmental data, the efficient acquisition of such data emerges as a vital prerequisite for P4 medicine. The QS movement promotes the self-acquisition of these data with the help of wearable sensory devices and the smart devices, with dozens of built-in sensors, can perfectly embody the principles of QS.

This work introduces a valuable tool for the acquisition of a wide variety of sensory data from Android Wear enabled smartwatches, i.e., the freely available Wrist Sensors App. With the help of the app, the users can see all the available sensors in their smartwatch and take recordings of arbitrary duration from any subset of the available sensors. The app has great potential in supporting the development of P4 medicine interventions, as indicated by the previously discussed published study that developed a novel bite detection algorithm from smartwatch sensor data.

[4] http://www.gsmarena.com/lg_g_watch_w100-7718.php

[5] http://www.gsmarena.com/motorola_moto_360_(1st_gen)-7682.php

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