The Digital Health Companion: Personalized Health Support on Smartwatches via Recognition of Activity- and Vital-Data

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Abstract. It has been shown that in various fields of social life, people tend to seek opportunities to measure their daily activities, bodily behaviors, and health related parameters. These kinds of activity tracking should be accomplished comfortably, unobtrusively and implicitly. Tracking behavior can be important for certain user groups, such as the growing population of elderlies. These people have a substantially higher risk of falling down, as they often live alone and thus have a greater need for other supporting services, as emergencies quickly occur. We would like to support these people, while providing a comfortable emergency detection and a monitoring of physical activities. Moreover, we believe such tracking applications to be beneficial for any user group, since we can perceive the trend of quantified self: knowing about one's own body characteristics, which is expressed in body movement. Simultaneously, we also perceive that a strong desire for a comprehensive monitoring of vital and health data is emerging. In this paper we describe the concept and implementation of the Digital Health Companion, a smart health support system that combines research developments of activity, vital data, and anomaly recognition with the functionality of contemporary smartwatches. The system's health monitoring includes an emergency detection and allows for the prevention of health risks in the short and long term through the recognition of body movement patterns.

Keywords: Health Monitoring, Activity Recognition, Emergency Support, Smartwatch, Inertial Sensors, Quantified Self

1 Introduction

Latest customary smart devices are already capable to serve as a personal assistant while permanently collecting body parameters in an unobtrusive way. Moreover, a quantified-self-movement emerged during the last years; people desire to analyse and evaluate themselves, their movements, their sportive activities, and their sleeping behavior. To date, companies already provide extensive platforms to collect and save personal activity data [14].

While the process of collecting abstract activity data in everyday situations is continuously developing and improving, it is still a challenge to extract useful information in a format beneficial to end-users (e.g. doctors, patients, caretakers). Especially people in need of care such as elderlies, who live with a higher risk of requiring emergency support, could exceedingly profit from a system that is not just able to track activity data, but that is also able to interpret data and thus prevent emergencies and lower risks while automatically monitoring body functions and user activities.

In this paper we present a concept and a prototypical implementation of a smart health support system that is based on customary smartwatches, which we call the **Digital Health Companion (DHC)**. We combine activity, vital data, and anomaly recognition technologies with default functions of current smartwatches, such as location tracking, push messaging, or phone calls, to allow for the usage of a stigma-free automatic emergency assistant. We thus contribute improved activity recognition algorithms that can be implemented energy efficiently and user independently on customary smartwatches, while keeping the desired complexity and recognition accuracy. Furthermore, we address an important issue - permanent vital data extraction with smartwatches - that can be exploited as a feature and that allows for the detection of health risks. Moreover, we try to find new ways regarding interaction and usability with small screens that can be controlled by old and/or handicapped people. The DHC not only offers a smart health support to consumers, but also a solution for house emergency services and other aid organizations in order to efficiently support customers. Our prototypical implementation runs on customary smartwatch models (*see in Fig. 1*).

Fig. 1. Prototype of the DHC system implemented on a Samsung Gear S Smartwatch (left) and Activity watchface implemented on an Android Wear LG G Round (right)

2 Related Work

While physical activity recognition has become an attractive field of research over the past years [1, 6], different body positions and a variety of sensor types have been evaluated for many fields of applications, including mobile scenarios. To position our paper with respect to the mobile scenario, we here provide a brief overview of activity recognition approaches via wrist-mounted sensors and smartwatches as we present general smart health support systems.

2.1 Activity Recognition with Wrist-Mounted Sensors

While the hip can be seen as the classic body position for activity recognition with wearables, lately the wrist has increasingly been used in research works as well. Scientists developed watch-based prototypes while making use of built-in sensors (primarily accelerometers, or directly attached sensor units at the wrist) that are able to store or stream movement or activity data. Those prototypes are demonstrated to be used for activity recognition tasks or similar approaches as a single sensor setup or being embedded into a sensor networks – see also Bao and Intille [2] or Maurer et al. [17]. Surveys of different activity recognition systems are presented by Avci et al. [1] or Lara and Labrador [15].

Nowadays, especially smartwatches gain much more popularity since new consumer devices are being developed, which allow for a broad range of different applications, such as activity recognition, fall detection, sleep detection, or applications in industrial environments [4]. Besides smart bands, smartwatches can also provide a tracking of personal activity, which usually synchronize their data with another third party device or which directly broadcast the gathered data on the internet.

2.2 Smart Health Support Systems

The research area for smart health support is broad and diversified, due to many applications available for inter alia handicapped people or elderly care. In the scope of *Ambient Assisted Living* (AAL), many ideas, concepts, and also implementations have been presented [9, 10].

Various wearable health support systems can already provide an emergency detection, such as solutions for intelligent and automatic fall detection systems - Chen et al. [8] or Salomon et al. [20]. A review of different fall detection approaches has been published by Mubashir et al. [18]. Furthermore, Bieber et al. [3] describe a concept for an activity recognition-based anomaly detection system with smartwatches, which is intended to work for elderly users and their family members. Lutze and Waldhör [16] depict the possibility of a smartwatch-based house emergency service system and highlight the capability of current smartwatch models. Following their statements, smartwatches already incorporate all necessary functional units, such as communication services (e.g. microphone, 3G, GPS, WiFi) and enough relevant sensors (e.g. accelerometer, gyroscope, altitude sensor, and also vital sensors such as a PPG). All authors agree on the high potential of smartwatches in general, outline interesting concepts, and cite application experiences, but also current challenges.

In conclusion, the authors clearly demonstrate that smartwatches are capable of relieving classic house emergency services, while being unobtrusive, not stigmatizing and while providing a great variety of new functions [16].

Still, due to current hardware constrains, a reliable health support system for elderlies based on smartwatches is not yet available. In order to circumvent these issues and to still create a smartwatch-based health support system, we developed new improved activity recognition and anomaly detection algorithms with adaptive sampling rates.

3 Concept and Implementation

In this section we introduce the main concept of the DHC system and how the different technological parts are being implemented and how they interact with each other. Firstly, the single system components are being described, which mainly consist of the smartwatch (client side) and the server implementation. Subsequently, we outline the idea of our automatic emergency and long-term anomaly detection. To allow for a quick overview of the envisioned system architecture, the figure 2 illustrates the interaction between all system's components.

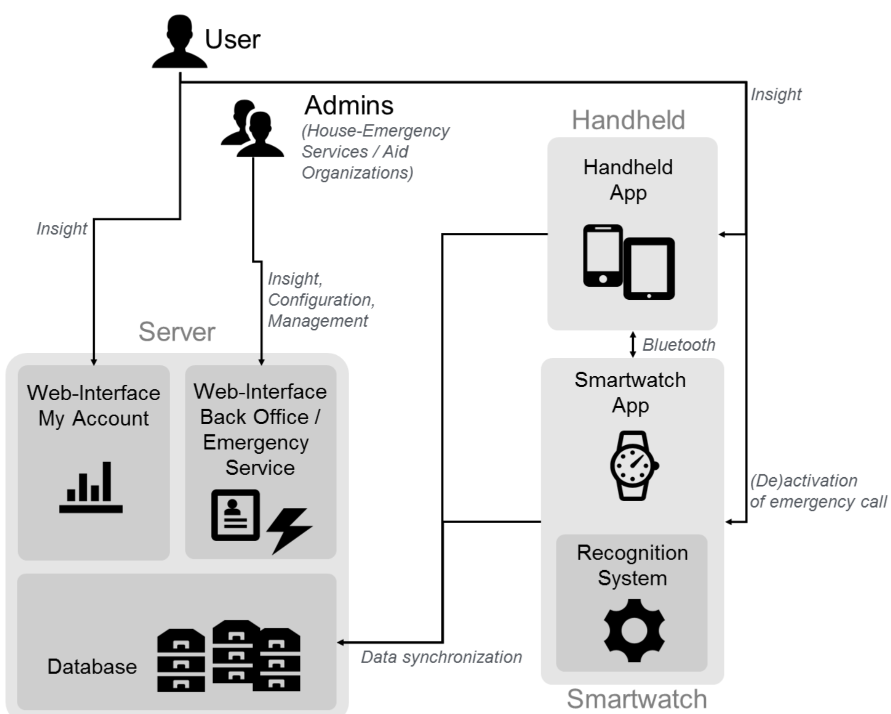

Fig. 2. Overview of the Digital Health Companion System

3.1 Smartwatch

The commercially available smartwatch can be considered as the key component of our system. All recognition technologies (*modules*) are implemented in a client app on the device, which also handles all incoming and outgoing connections and communication processes, respectively. All recognition algorithms were developed over the last years at Fraunhofer IGD Rostock and are now integrated into our system.

While there is a huge amount of customary smartwatches available, most watches dependent on a secondary hub device (e.g. *Android Wear* smartwatches or the *Apple Watch*) for communication services, but which are not as suitable for our autarkic solution. It has been shown that especially handicapped people have problems using an additional device at the same time. An autarkic smartwatch is usually independent from a secondary handheld (e.g. the *Simvalley AW-420.RX*, the *Samsung Gear S* or the upcoming *Samsung Gear S 2*) and can utilize all necessary communication possibilities, such as WiFi, GSM, and GPS without requiring a third party device to run.

In order to decrease energy consumption, we established algorithms that rely on adaptive sample rates, as well as on dedicated features and classifier models. We also implemented routines to disable and enable connection settings on demand. Instead of using new sensor units, such as the PPG heart rate sensor, we created a new approach to extract vital data from a conventional inertial sensor; the accelerometer [11, 12, 13]. This information can be obtained in resting situations of the user, for example during sleep periods. Furthermore, we created new visualization schemes, which for instance allow for an activity visualization as an integrated watchface to highlight activity and sleep patterns directly in the background. Moreover, our app provides a clear and intuitive user experience, which is especially designed for elderly or handicapped people.

All recognition modules are not visualized, but automatically running hidden in background. Moreover, we also developed single user screens with oversimplified one-button user input possibilities, to enable an easily accomplished emergency call that likewise can be cancelled comfortably (Fig. 1). In addition to that, we are planning to improve those user interfaces with the results of field studies involving many users. We believe this to provide a good basis for new design decisions to improve usability and user experience. Additionally, in the future, we also plan to perform field studies with sleep laboratories to evaluate our collected smartwatch vital data against vital data from validated laboratory devices.

The following table lists and categorizes all modules that are implemented in the app. Citations of the Fraunhofer technologies are also mentioned.

Table 1. Different modules of the smartwatch component of the DHC system

Recognition Modules	Communication Modules	Additional Modules
Accelerometer based activity recognition [6]	Manual emergency call	Text to speech
Sleep pattern recognition [4]	Push notifications	Energy efficient recognition routines [5]
Vital data recognition [12]	Remote phone calls	Big-Data analysis
Doffed detection [11]	Location services	
Microvibration recognition [11]		
Fall detection [20]		
Automatic emergency call		
Anomaly detection		

3.2 Server Implementation and Handheld

To provide a system with the desired functionality, a scalable and well-tested server side is being required. As seen in Fig. 2, the server consists of a database to store all relevant user data, which yields application interfaces to the smartwatch and handheld for upload and synchronizing purposes.

The server also incorporates two web interfaces. The *back office* serves as the main configuration, maintenance and insight service for administrators: the emergency services or aid organizations. The *back office* also has a connection to the emergency call service if needed. The second web interface, *My Account*, is intended to serve the user or his family members in order to provides insights in his personal user data and visualizations of activity patterns. This web interface is also accessible from a smartphone or tablet, while these devices of course can also server as a hub device for connection capabilities if required.

This server design allows specifically adapted options regarding user profile management and configuration, corresponding to the user groups' task profile. As the user's individual activity, vital, and health information constitute very sensitive data, best state of the art security standards are implemented on the server frontend and backend (e.g. OWASP).

3.3 Automatic Emergency and Anomaly Detection

The research domain of *Anomaly Detection (AD)* is widespread in multiple application domains. These domains include topics such as: credit card fraud detection, network intrusion detection, as well as the detection of health related anomalies. As a subcategory of pattern recognition, AD is closely related to data mining and machine learning approaches. The scarce occurrence of anomaly patterns in the data available is the biggest challenge researchers face in this area. As a result of this, initial anomaly patterns are hard to train or to learn. The anomaly detection, incorporated in the DHC system, is based on activity data, as well as vital parameters, which are gathered by a smartwatch, which allows for an easier, permanent and more extensive gathering of (anomaly) data. Due to the fact that sensor signals can differ in signal quality, an evaluation of the vital parameters captured is crucial in a medical or health context. Moreover, a possible loss of sensor data has to be taken into account. The AD concept of the DHC is based on a signal quality evaluation unit, that rates the quality of sensor inputs to weight the anomaly class detected based on the sensor input given. We envision detection scenarios such as: cardiac anomalies, falls, and unconsciousness, epileptic seizures, or sleep anomalies, such as sleep apnea.

4 Application and Distribution Potential

Fig. 3. Motorola Moto 360 smartwatch with DHC watchface

While the benefits of the DHC system as a whole are not limited to medical support or emergency services that supervise handicapped people, we also envision ways to directly commercialize it in the consumer market. In regard to this, we imagine DHC to have the potential to be used for several purposes such as:

- general health monitoring of body functions (for anyone at any age, who is interested)
- long term activity recognition and risk prevention (e.g. adults or active elderlies, who are interested in disease prevention and want to reveal risky physical and mental symptoms)
- special guardianship purposes (e.g. by basically healthy elderlies, who perform longer outside activities or young adults, who want to prevent severe injuries while conducting extreme sportive activities).

We already acquired potential customers and medical partners, with whom we are evaluating all ranges of functions of DHC and validate its capabilities. In contrast to contemporary activity tracking systems, we expect that our technologies have the ability to be efficiently used as a reliable support and medical tool by the wide public.

5 Conclusion and Future Work

Smartwatches are seen as the next big trend in relation to the development of mobile devices [16]. When using newly developed algorithms, they clearly offer the possibility to not only serve as rudimentary activity trackers, but also to reliable recognize activities and vital data to enable a trustworthy health data recognition systems. Interpreting and analysing this is the basis for offering proper health support and risk prevention based on smartwatches

Next to the big trend itself, a strong demand for new medical support technologies can be perceived. Europe experiences a demographic change; people simply live longer. Emergency service companies aim to prolong their average user subscription duration and lower the average user age by means of more comfortable and non-stigmatic solutions. Furthermore, researchers forecast the global market of mobile health services (which was at 6 billion US dollar in 2014) to rise to 26 billion US dollar in 2017 [19].

A prototype of the DHC system has already been implemented and will be further improved and rolled out as a product in the near future. In this respect, the core system is improved, existing functionality is validated for health care usage with renowned medical partners and additional features are added through profound research.

Building on that, the team dedicated to the deployment of the DHC system is about to launch a spin-off company; to ensure a continuous product improvement together with our initial partners and to realize the full commercialization potential of this next-generation health monitoring system

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References

1. Avci, A., Bosch, S., Marin-Perianu, M., Marin-Perianu, R., & Havinga, P. (2010, February). Activity recognition using inertial sensing for healthcare, wellbeing and sports applications: A survey. In *Architecture of computing systems (ARCS),* (pp. 1-10). VDE.
2. Bao, L., & Intille, S. S. (2004). Activity recognition from user-annotated acceleration data. In *Pervasive computing* (pp. 1-17). Springer Berlin Heidelberg.

3. Bieber, G., Fernholz, N., & Gaerber, M. (2013). Anomalienerkennung durch Analyse der körperlichen Aktivität. *Fachkongress Social Business*. Tagungsband, Rostock-Warnemünde.
4. Bieber, G., Haescher, M., and Vahl, M.(2013). Sensor requirements for activity recognition on smart watches. In *Proceedings of the 6th International Conference on PErvasive Technologies Related to Assistive Environments* (p. 67). ACM.
5. Bieber, G., Kirste, T., & Gaede, M. (2014). Low sampling rate for physical activity recognition. In *Proceedings of the 7th International Conference on PErvasive Technologies Related to Assistive Environments* (p. 15). ACM.
6. Bieber, G., Voskamp, J., & Urban, B. (2009). Activity recognition for everyday life on mobile phones. In *Universal Access in Human-Computer Interaction. Intelligent and Ubiquitous Interaction Environments* (pp. 289-296). Springer Berlin Heidelberg.
7. Bulling, A., Blanke, U., & Schiele, B. (2014). A tutorial on human activity recognition using body-worn inertial sensors. *ACM Computing Surveys* (CSUR), 46(3), 33.
8. Chen, J., Kwong, K., Chang, D., Luk, J., & Bajcsy, R. (2006, January). Wearable sensors for reliable fall detection. In *Engineering in Medicine and Biology* Society, 2005. IEEE-EMBS 2005. 27th Annual International Conference of the (pp. 3551-3554). IEEE.
9. Costa, R., Carneiro, D., Novais, P., Lima, L., Machado, J., Marques, A., & Neves, J. (2009, January). Ambient assisted living. In 3rd Symposium of Ubiquitous Computing and Ambient Intelligence 2008 (pp. 86-94). Springer Berlin Heidelberg. ISO 690
10. Georgieff, P. (2008). Ambient Assisted Living. Marktpotenziale IT-unterstützter Pflege für ein selbstbestimmtes Altern, *FAZIT Forschungsbericht*, 17, 9-10.
11. Haescher, M., Bieber, G., Trimpop, J., Urban, B., Kirste, T., & Salomon, R. (2014). Recognition of Low Amplitude Body Vibrations via Inertial Sensors for Wearable Computing. In *Proc. of Conference on IoT Technologies for HealthCare* (HealthyIoT).
12. Haescher, M., Matthies, D. J.C., Trimpop, J., & Urban, B. (2015). A study on measuring heart- and respiration-rate via wrist-worn accelerometer-based seismocardiography (SCG) in comparison to commonly applied technologies. In *Proceedings of the 2nd international Workshop on Sensor-based Activity Recognition and Interaction* (p. 2). ACM.
13. Haescher, M., Matthies, D. J.C., & Urban, B. (2015). Anomaly Detection with Smartwatches as an Opportunity for Implicit Interaction. In *Proceedings of the 17th International Conference on Human-Computer Interaction with Mobile Devices and Services Adjunct* (pp. 955-958). ACM.
14. Harvey, M. J., & Harvey, M. G. (2014). Privacy and security issues for mobile health platforms. *Journal of the Association for Information Science and Technology*, 65(7), 1305-1318.
15. Lara, O. D., & Labrador, M. A. (2013). A survey on human activity recognition using wearable sensors*. Communications Surveys & Tutorials*, IEEE, 15(3), 1192-1209.
16. Lutze, R., & Waldhör, K. (2015, January). SmartWatches als Hausnotrufsysteme der nächsten Generation. In *AAL-Kongress 2015*. VDE VERLAG GmbH.
17. Maurer, U., Rowe, A., Smailagic, A., & Siewiorek, D. P. (2006). eWatch: a wearable sensor and notification platform. In *Wearable and Implantable Body Sensor Networks*. BSN 2006. International Workshop on (pp. 113-116). IEEE.
18. Mubashir, M., Shao, L., & Seed, L. (2013). A survey on fall detection: Principles and approaches. *Neurocomputing*, 100, 144-152.
19. Research2Guidance (2014). mHealth App Developer Economics 2014. *mHealthEconomocs.com*, 05-06-2014.
20. Salomon, R., Luder, M., & Bieber, G. (2010). iFall-a new embedded system for the detection of unexpected falls. In *Pervasive Computing and Communications Workshops* (PERCOM Workshops), (pp. 286-291). IEEE.

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