Anomaly Detection with Smartwatches as an Opportunity for Implicit Interaction

Marian Haescher

Fraunhofer IGD

Joachim-Jungius-Str. 11

18059, Rostock, Germany

marian.haescher@igd-r.fraunhofer.de

Denys J.C. Matthies

Fraunhofer IGD

Joachim-Jungius-Str. 11

18059, Rostock, Germany

denys.matthies@igd-r.fraunhofer.de

Bodo Urban

Fraunhofer IGD

Joachim-Jungius-Str. 11

18059, Rostock, Germany

bodo.urban@igd-r.fraunhofer.de

Abstract

In this paper we introduce application scenarios for implicit interaction with Smartwatches for the purpose of user assistance, to create awareness, and to enhance as well as simplify the interaction with Wearables. We envision three scenarios (1) the detection of sleep apnea, (2) the detection of epileptic seizures, and (3) a detection of accidents such as falling, car crashes etc., which are presented and discussed. Therefore, the recognition of all incidents described will be discussed under the meta-topic of anomaly detection.

Author Keywords

Smartwatch, Anomaly Detection, Implicit Interaction, Scenarios, Activity Recognition, Vital Data

ACM Classification Keywords

H.5.m. Information interfaces and presentation (e.g., HCI): Miscellaneous.

Introduction

With the ongoing proliferation of smart devices in general a development branch, which specifically addresses wearable smart devices, has evolved. In this branch, devices such as smartwatches enable for an easy integration in our daily life as well as high degree of user acceptance with regard to obtrusiveness and

Figure 1. Sleep recognition to detect apnea or epileptic seizures. (Implemented on MetaWatch Strata)

fashion. The constantly high availability of Wearables such as Smartwatches enables for a potentially gapless monitoring of several data emitted by the wearer. Various wearable sensors allow for monitoring activity and vital data, which enable to draw conclusions and enable for an intervention if necessary. Especially research topics such as the Anomaly Detection already apply a broad variety of mobile and wearable systems [7][13]. Due to compliance issues in interacting with current monitoring tools (such as activity loggers or food diaries) - which often require explicit input - new and unobtrusive interaction methods are inevitable. Because of the fact, that the human body constantly emits data (e.g. heart rate, respiration rate etc.) without the individual consciously taken part in it, we already obtain input data, which can be utilized in the process of implicit interaction [10]. Therefore, a reduction in cognitive load is potentially accomplished to decrease the workload of the user.

In this paper three examples are introduced to motivate the application of smartwatches in an implicit interaction scenario. We believe that an implicit interaction with smartwatches incorporates these important benefits:

- Creation of user-awareness
- Providing recommendations to the user
- Intervention in critical conditions
- Emergency notification for third parties

Use Case 1: Sleep Apnea

Sleep apnea describe a serious and common health risk. The term describes sudden pauses in respiration during sleep. As a result, patients suffering this condition feel unrested and often complain about headaches. Furthermore, the undersupply in oxygen can lead to serious brain damages in the long term [6]. By using diagnostic methods such as the polysomnography, which marks the gold standard in sleep science, pathologic sleep conditions can be recognized. Thereby, the observation of vital parameters such as respiratory movements or heart rate can give an insight in when and how these conditions occur. By applying wearable devices such as smartphones [11] or smartwatches [2] during the night the recognition of sleep quality or pathological conditions is made possible in a non-laboratory environment. Typical smartwatch sensors, such as photoplethismography (PPG) sensors, inertial sensors (e.g. accelerometers and gyroscopes), as well as built-in microphones thereby enable for the detection of sleep related anomalies. This way a suddenly rising heart rate accompanied by changes in respiratory noise or even respiratory movements can indicate an anomalous situation during sleep. After detecting a sleep apnea the wrist worn device can actuate a vibro-tactile feedback to the user in order to initiate a change in position or wake up the wearer to avoid possible damage due to an oxygen deficiency. We already implemented a system that constantly monitors the respiration rate on a smart watch during sleep (*see Figure 1*).

Figure 2. Detection of muscle tremor and current activity state. (Implemented on Simvalley AW-420.RX)

Figure 3. Radial visualization of standard activities over the day (Implemented on an LG G Watch R)

Use Case 2: Epilepsy Detection

The pathologic condition of epilepsy comprises a broad variety of different seizures. The patterns thereby vary from total absence of clinical symptoms (seizure only measurable via electroencephalography; EEG) to a variety of clinical symptoms such as flapping extremities, pain, vertigo and others. Currently, most epileptic seizures are detected in clinical diagnosis environments, such as by applying a polysomnography in a sleep laboratory. With the use of smartwatches characteristic movement patterns (e.g. rhythmic flapping extremities) can be detected in sleep situations [9]. As proposed in the aforementioned example, the monitoring can be done in a familiar home environment. For the purpose of detection, sensors such as the watches' built-in accelerometer can be applied to recognize the specific seizure pattern. After detecting a seizure, relatives or caregivers receive a notification, to watch out for the patient and avoid or react to conditions such as a sudden unexpected death in epilepsy (SUDEP). Moreover, the system could log seizures to identify patterns that indicate coherences between lifestyle and health condition. This way, the device could advice the user to avoid certain situations or habits to reduce the risk for an epileptic seizure. Our system monitors muscle tremors in resting situations and allows to set achievements, which can be collected through daily activities (see Figure 2). In a far future scenario we envision these classified events to provide the basis for an implicit interaction. For example: (1) Electro-shocks/impulses can be triggered by the smartwatch to wake up the user in order to prevent a (SUDEP) at night. (2) By detecting characteristic pre-epileptic markers, a third party system would adjust its behavior such as a car performing an autonomous emergency break.

Use Case 3: Fall- / Car-Crash Detection

The risks of serious injuries in consequence of falling to the ground or crashing with a car are common situations that often require help by third parties. In these scenarios, the application of a wearable device such as a smartwatch, which is worn constantly enables for an impact detection [8]. After detecting the impact, the device can send an automated emergency call to guarantee an in time treatment. With regard to the car crash scenario, the detection of an accident could be broadcasted to other drivers instantaneous. While car crash detections for smart devices have been lately explored on a smartphone [1], we envision such systems to be more complex in order to distinguish between different anomalies in more diverse situations (e.g. also when jogging or riding a bike). Our system (see Figure 3) so far incorporates a fall detection and activity recognition in order to gain information about the user's situation (e.g. if the user is riding a bike, driving a car, walking, jogging, sitting or sleeping). Knowing about the current activity is fundamental in order to improve classification of an anomaly. While such system could also utilize GPS, our system intentionally solely relies on the accelerometer in order to achieve alonger battery lifetime.

Conclusion & Future Work

The wearable design of smartwatches enables for a variable detection of anomalies. This allows for a constant, gapless, and unobtrusive recognition of apneas, seizures, or impact based accidents. The aforementioned scenarios do not require a laboratory environment and therefore can be performed in a familiar home environment. While this reduces influences such as adaption to a different sleep location or obtrusive sensor setups as provided by

polysomnography in sleep laboratories, it also enables a new kind of implicit interaction. We see high potential in smartwatches to measure accurate vital parameter at the user's wrist [5] constantly over the day, which will enable a continuous monitoring of patients in the future. Besides the measurement of common vital data, we rediscovered the microvibrations of muscles [3], but which still needs to be investigated more deeply. As well as blood pressure and heart rate, microvibrations will be an important parameter for future diagnostics, as we presume. Beyond focusing on smartwatches, we already evaluated the head position for smartglasses to be a promising position for activity recognition [4]. We expect smartglasses to have a high potential for being equipped with implicit interaction as well, since it has a much higher availability and presence (meaning the PHMD resting in the user's FOV) [10].

Acknowledgements

References

[1]   Aloul, F., Zualkernan, I., Abu-Salma, R., Al-Ali, H., & Al-Merri, M. (2014). iBump: Smartphone application to detect car accidents. In *Proc of IAICT 2015*. IEEE.

[2]   Borazio, M., & Van Laerhoven, K. (2012). Combining wearable and environmental sensing into an unobtrusive tool for long-term sleep studies. In *Proc of SIGHIT 2012*. ACM.

[3]   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 HealthyIoT* 2014.

[4]   Haescher, M., Trimpop, J., Matthies, D. J. C., Bieber, G., Urban, B., & Kirste, T. (2015). aHead: Considering the Head Position in a Multi-Sensory Setup of Wearables to Recognize Everyday Activities with Intelligent Sensor Fusions. In *Proc of HCII 2015*.

[5]   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 *Proc of iWOAR 2015*. ACM.

[6]   Halbower, A. C., Degaonkar, M., Barker, P. B., Earley, C. J., Marcus, C. L., Smith, P. L., ... & Mahone, E. M. (2006). Childhood obstructive sleep apnea associates with neuropsychological deficits and neuronal brain injury. In *Proc of PLoS,* 3(8), e301.

[7]   Hamid, R., Johnson, A., Batta, S., Bobick, A., Isbell, C., & Coleman, G. (2005). Detection and explanation of anomalous activities: Representing activities as bags of event n-grams. In *Proc CVPR 2005.*

[8]   Hsieh, S. L., Chen, C. C., Wu, S. H., & Yue, T. W. (2014). A wrist-worn fall detection system using accelerometers and gyroscopes. In *Proc ICNSC 2014*.

[9]   Lockman, J., Fisher, R. S., & Olson, D. M. (2011). Detection of seizure-like movements using a wrist accelerometer. In *Epilepsy & Behavior*, 20(4), 638-641.

[10] Matthies, D. J.C., Haescher, M., Alm, R., & Urban, B. (2015). Properties Of A Peripheral Head-Mounted Display (PHMD). In *Proc of HCII 2015*. Springer.

[11] Min, J. K., Doryab, A., Wiese, J., Amini, S., Zimmerman, J., & Hong, J. I. (2014). Toss'n'turn: smartphone as sleep and sleep quality detector. In *Proc of CHI 2014,* 477-486. ACM.

[12] Schmidt, A. (2000). Implicit human computer interaction through context. *In Proc of Personal technologies,* 4(2-3), 191-199.

[13] Schmidt, A. D., Peters, F., Lamour, F., Scheel, C., Çamtepe, S. A., & Albayrak, Ş. (2009). Monitoring smartphones for anomaly detection. In *Proc of Mobile Networks and Applications*, *14*(1), 92-106.