Sensor requirements for activity recognition on smart watches

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Sensor Requirements for Activity Recognition on Smart Watches

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ABSTRACT
The new generation of watches is smart. Smart watches are connected to the internet and provide sensor functionality that allows an enhanced human-computer-interaction. Smart watches provide a gesture interaction and a permanent monitoring of physical activities. In comparison to other electronic home consumer devices with integrated sensors, Smart watches provide monitoring data for 24h per day, many watches are water resistant and can be worn constantly. The integrated sensors are varying in performance and are not intended to distinguish between different states of activity and inactivity. This paper reports on identified requirements on sensors of smart watches for detection of activity, inactivity as well as sleep detection. Hereby a new measurement quantity is introduced and applications of heart beat detection or wearing situation are presented.

Categories and Subject Descriptors
H.5.2 [**User Interfaces**]: Information Interfaces and Presentation
I.5.2 [**Design Methodology**]: Pattern Recognition
J.3 [**Life and Medical Sciences**]

General Terms
Mobile Computing, algorithms, smart watch, user interfaces, quantify self.

Keywords
Activity Monitoring, inactivity, acceleration, sensor, recognition, wrist, watch, smart, sleep.

1. INTRODUCTION
The ongoing trend of not wearing a watch because of an available phone with clock functionality seems to be stopped. The origin functionality of watches, just to display the time, is tremendously enhanced by the new generation of smart watches.

Smart watches are designed to display various messages such as SMS, RSS-feeds, Emails, or Facebook messages. For interaction purposes, smart watches provide additional sensor functionality that might be used for third party application providers. Hereby mainly sport or wellness applications are in focus of the manufactures. Because of the smart watch´s sensor functionality, the device enables new and innovative applications that expand the original application field. The smart watches allow a permanent monitoring of the activities of the user. The acquired information on the physical activity of a person can be used for various purposes, such as wellness, safety, various psychological identifier (degree of attention), or detection of micro-activities in an overall state of inactivity.

For activity and inactivity recognition by smart watches it is necessary to be aware of capabilities of the sensors. This paper introduces the current work of sensor technology and describes a generic identifier of the performance of the acceleration sensing functionality of the smart watches. The paper closes with a summary and an outlook of the future work in the area of activity recognition on smart watches.

2. RELATED WORK
2.1 Smart Watch
In the 90´s, some watches [1] were designed with an integrated light sensor that enabled a connection to a PC. Hereby data were transferred to optical information on the monitor of the PC and could be received by a light sensor of the watch (e.g. Timex data-link). Nowadays, the connectivity has been realized by wireless communication, e.g. Bluetooth or propriety protocols. The current models of smart watches are connected via Bluetooth to a smart phone. Because the watch is located at the wrist, a permanent look on the micro display of the watch is possible. The main application of smart watches is to display messages of services like Facebook, SMS, RSS or incoming calls. One of the most used sensors of a smart watch is an acceleration sensor to support fitness and wellness applications with pedometer functionality.

The smart watch idea provides two general concepts. The first concept of smart watches is the autarkical watch. The smart watch provides computational power. Hereby a wireless connection to the internet or phone is only needed for data synchronization purposes. This concept allows sensor data processing directly on the watch.

The second concept of smart watches is the idea of a dedicated terminal. Each event, e.g. pressing a button, screen touch event, or sensor readout has to be transmitted to a hub, the smart phone. On the phone, the data will be processed and events will be sent back to the watch wirelessly. Hereby the phone might transmit the vibration event or the screen content. The watch needs no extra computational power which helps saving battery energy. If

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acceleration data are to be read out permanently (e.g. for activity recognition) the transmission needs significant more energy than an onboard data processing would consume.

2.2 Activity Recognition

The integrated acceleration sensor of a smart watch enables the feature of physical activity recognition. Because of the location of the watch, the integrated sensor measures the acceleration force of the wrist. The wrist is not the ideal location for physical activity recognition in comparison to the hip. If the user is shaking the hip, the acceleration data are a good indicator that the whole body is in motion. In [2], [3] is shown that the pattern of a hip movement correlates to the basic activities such as walking, cycling, car driving or jogging.

The wrist movements are very complex and are significantly different to the hip movements. Nevertheless Polar could proof by AW200 that easy activity recognition for walking and different states of running is possible on a commercial product [4]. Hereby an acceleration and air pressure sensor were integrated into the watch. The research project eWatch [5] designed an activity monitoring system that uses additional sensors, e.g. light and audio. WristQue by MIT, USA [6] is a research prototype with integrated location sensor, temperature and humidity. The focus of InfoPulse [7] is to act as a handsfree email reading device, perfect to catch a quick glance without distracting too much from a user's primary task. Texas Instrument introduced the Chronos [8], a very inexpensive smart watch, which is based on the embedded system MSP430 that provides an SDK for individual programs. Newer smart watches are Bluetooth enabled and some are water resistant. These smart watches are designed to be worn 24 hours a day and allow a long shower or a bath in the swimming pool.

2.3 Inactivity Recognition

The major difference in activity recognition between a smart phone and a smart watch is the wearing behavior. If the user returns to his home, he will put off the phone. A smart watch can be worn constantly at the wearer’s body, no matter if he is doing sports or is at rest or sleeps.

Some systems are available that are detecting sleep or resting by wearing a sensor at the wrist. The Actiwatch is an actigraphy based data logger designed for rest activity patterns, quantify physical activity or sleep [9]. Another watch-based sleep recognition solution is the Sleeptracker [10] that detects sleep and allows a wake up at the estimated optimum time. Some other solution for sleep detection exists whereas some other sensor technology is used, e.g. EEG signals.

2.4 Acceleration Sensor

The performance of acceleration sensors can be measured in accuracy, quantization, sampling rate, sampling stability, range, noise, and energy consumption [11]. Early types of acceleration sensors were metal balls within a coil environment that generated electric charge or an induction field while it was moved. Other system concepts were piezo crystal based; hereby a weight pressures on a piezo crystal that response to applied mechanical stress by electric charge. Accelerometers can also use strain gauges. Earthquake observatories were using optical levers or mechanical linkages to amplify the small motions. Nowadays, the acceleration sensors are using electronics. The most common sensor for home consumer products, e.g. phones, cameras, cars etc. is a MEMS, micro-electro-mechanical system, which is very cheap and low on power consumption. The usage of the MEMS in smart watches is a tradeoff between performance, energy consumption, size and costs. The MEMS-sensor in itself provides usually a high frequency sampling rate, e.g. more than 1000 Hertz. Due to the operating system and power requirements, the sampling rate is self-adjusting (Android) or is limited to a lower frequency. [2] was using 75 Hz, [14] suggested 100 Hz, [15] was using 36 Hz, [16] only 20 Hz. It is obvious that a high sampling rate provides more data than a lower rate, a good compromise in sampling rate seems to be at 32 Hz [11]. One quality criteria of an acceleration sensor is the accuracy. We assume that the MEMS sensor show a hysteresis effect to the measured signal. Furthermore, the data shows an offset and a not linear gain. Sensor data sheets and trials show a tremendous offset of each axis. This offset can be around 0.5 m/s^2, often the amplification factor shows an error of 2-3 percent. The offset is usually too high for physical way-time calculations. The following paragraph will discuss what requirements are necessary for activity and inactivity recognition for acceleration sensors.

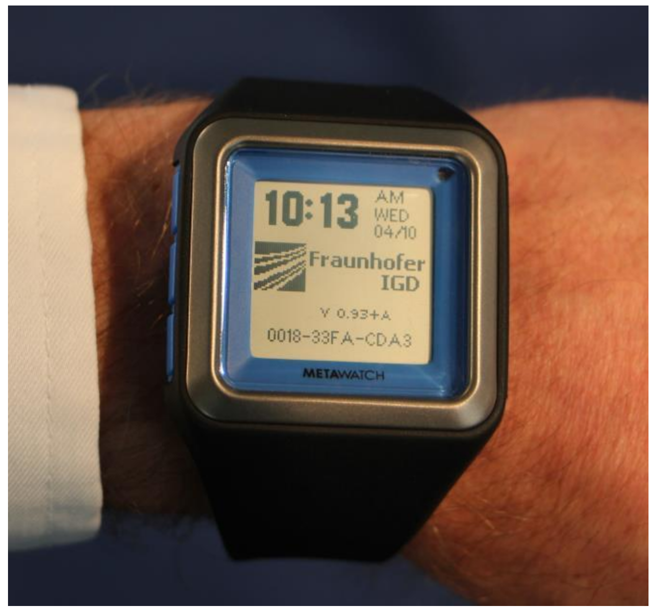

Figure 1: Smart Watch with integrated sensor, connectivity and micro matrix display

3. CHALLENGES

For adequate activity recognition, the sensor has to provide reliably sensor information. Because the most important sensor for activity monitoring is the acceleration sensor, it is necessary to know what the key features are.

The sensor requirements are distinguished between the application fields of

- Activity monitoring for health and wellness applications
- Inactivity recognition
- Gesture recognition and interaction
- Industrial monitoring concerning health issues of harmful hand or arm vibrations

In [11], significant features for activity monitoring are described but some new features for inactivity are to be worked out in order to detect a fall of a person, and to differentiate states of unconsciousness, sleep or a nap. In case of inactivity, some new features and requirements to the sensor are necessary.

Some smart watches provide an integrated light sensor. The light condition which surrounds a person is an important factor for the estimation of his activity state. Some light sensors are measuring the RGB-light proportions which indicate if artificial light or sunlight is ambient. This sensor provides important information in hospital environment but in every day live it seems to be different. Here, people do a nap while it is light or sleep in front of the T.V. at night by a full light condition. If the user is wearing a shirt with long leaves, the detected light is different to the real light condition. Furthermore, often the geometrical constellation of the integrated light sensor of the smart watch cannot detect the ambient light but only the light which shines directly into the light sensor.

4. ACTIVITY UNIT

The acceleration sensor is the most important sensor for activity recognition. The sensor detects three dimensional acceleration forces that are typically measured in a Cartesian coordinate system. The axes are x, y, and z and they are orthogonal to each other.

If the sensor is motionless, only the gravity g is affecting the sensor data. The acceleration values are in a specific relation to reach other, no matter which orientation the sensor shows. If the variables x, y, z are the sensor values in g (9.81 m/s^2), the motionless sensor shows:

$$1g = \sum (x^2 + y^2 + z^2)^{0,5}$$

If the sensor will be accelerated, the right term of this equation can't be used to determine the average acceleration. One reason is that the gravity g is not constant over the world (pole and equator have different gravity influence). Furthermore, the sum of the squared acceleration values is not corresponding to the acceleration, if one average acceleration value of one axis is negative. In addition, the sensor offset of each axis is affecting the equation so a possible error occurs.

We developed the algorithm of a new feature. This feature defines the mean acceleration of the sensor in the three dimensional space per second. The feature is called "activity unit (AU)" and describes the acceleration force. This feature is defined in m/s^3; hereby meter and seconds are elements of the international system of units [17].

The gravity constantly influences every material on earth, that's why the activity unit considers only the additional acceleration forces. Furthermore we introduce the simplification that the acceleration force of interest is not vectored. In contrast to the physical jerk that describes the rate of change of acceleration [18], the AU is a scalar magnitude, normalized to the time interval of one second. The jerk represents only the derivative of acceleration with respect to time. The jerk does not consider if the present acceleration is zero, low or high; only the change of acceleration is regarded.

In contrast to the jerk, the AU is respecting the present level of acceleration while the change of acceleration occurs. To give an example, the jerk would be the same (zero) in the case that the sensor is motionless or in the case that the sensor is accelerated with a constant value. The AU is zero in case of the motionless sensor too, but in the case of the accelerated sensor - it is different. Hereby the AU represents the difference of the current acceleration to the average acceleration condition.

This leads to the following definition of the activity unit:

$$1AU = \frac{1}{N}\sum_{n=1}^{N}((x_n - x_{mean})^2 + (y_n - y_{mean})^2 + (z_n - z_{mean})^2)^{\frac{1}{2}}$$

The variables x, y, z are the sensor values in m/s^2. x_n, y_n, z_n, are the sensor values, received by each readout cycle n. N is the number of readout cycles per second. x_{mean}, y_{mean}, z_{mean} are the averages of the sensor values of each axis. These values describe the constant force to the sensor and can be determined by the inclusion of a moving average.

For a motionless sensor, only the gravity forces are affecting the measured values and these forces are constant. Because of the moving average, the algorithm will detect no force after a while, zero AU. If a translation occurs, the acceleration will be detected and measured. If the sensor will be rotated, the sensor detects different gravity force for each axis.

If the sensor is motionless after the turn again, the algorithm should detect no acceleration force after a defined time interval. This is performed by the implementation of the moving average algorithm. We assume that a sensor will be read out with 32 Hertz. If the sensor is turned by 90 degree, we require that the acceleration force of one axis, that had no gravity influence before, will adapt to the gravity force of one tau (63.2 percent) within 2 seconds. The two second period will provide 64 data-triples which is a usable window frame length for activity recognition [11]. The time requirement leads to the average factor of a=0.95 by the following average algorithm, the given average is analog to y_{mean} and z_{mean}:

$$x_{mean}(n) = x_{mean}(n-1) \cdot a + x(n) \cdot (1-a)$$

Hereby x(n) is the current sensor value, the factor *a* is an absolute term and $x_{mean}(n)$ is the calculated average. n describes the readout cycle. $x_{mean}(n-1)$ is the calculated average of the readout cycle *n-1*. If parameter "a" would be set on a = 0, the algorithm for AU is directly matching the jerk.

The sensor values of the x, y, and z-axis are represented by the SI-unit m/s^2, so 1 AU is 1 m/s^3 (m/s^2 per second).

Because of the consideration of the mean acceleration of each axis for the AU value, the constant sensor offset and constant gravity influence can be ignored. This is a very powerful feature of the equation because some acceleration sensors are charged with a high offset. AUs can be summed up to estimate the physical activity, hereby the sum of the AUs are a rough indicator how active the wearer has been throughout the day. Furthermore, the AU can be used to estimate the noise of the sensor.

The AU can be used as a very important feature for physical activity recognition.

5. APPLICATIONS

5.1 Wearing Detection

When smart watches detect no physical activity, there is the obvious assumption that the user is not active. Even the human body seems to be calm; the wrist sensor measures a significant higher activity than if the sensor would be dismounted. This effect can only be noticed when the sensor noise is very low.

The defined AU is a good parameter for the estimation of the noise level of the sensor. When the smart watch is motionless and lies on a table, the typical AU-value of a sensor (e.g. Meta Watch Strata [19]) in 6 bit / g – quantization mode) is approx. 0.4 m/s^3. If the same watch is in 10 bit / g – quantization mode, the assessed AU value is much lower and is approx. 0.04 m/s^3.

If the smart watch is set in 10 bit / g – quantization mode and the user is stretching the arm and hold the watch motionless, the system will measure approx. 0.16 AU. In comparison to the value of 0.04 AU we received from the watch on the table, we can identify the arm stretching condition. The received values are only possible if the sensor is working in the 10 bit / g mode. A 6 bit / g mode would provide a noise of 0.4 AU if the arm is stretched out whereas no difference of the wearing condition is possible.

The introduced algorithm for activity units is an important feature in the time domain. For the frequency domain, it is necessary to analyze the spectral distribution of the movements. The Fourier transformation enables the analysis if the signal is overlaid with a white or a colored noise. If the sensor is totally motionless, the sensor noise is stochastically distributed (white noise). Any light micro movement is influencing the spectrum, the noise will be colored.

Figure 2 (smart watch is set in 10 bit/g mode, 32 Hz) shows the noise while the smart watch is lying on a table, the figure 3 shows the noise while the watch is worn at the wrist of a user. When the smart watch is on the table, we recognize that noise in the Fourier spectrum is stochastically distributed.

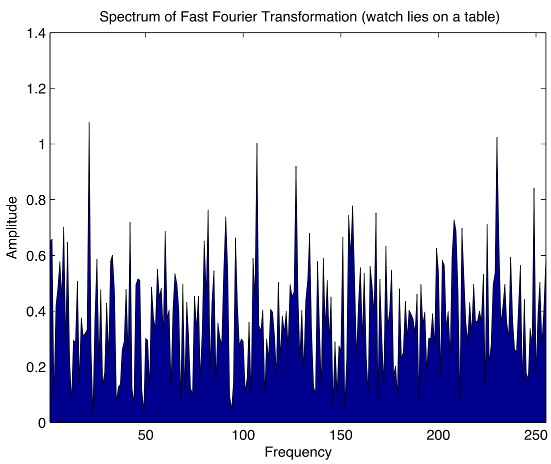

Figure 2: Frequency spectrum while smart watch is lying on a table

In figure 3 we can clearly see a main frequency and the influence of little movements to the spectrum. Depending on the manufacture and sensor type, the sensor of the smart watch can be configured into a different modus, especially quantization and sampling rate. Setting the smart watch into the highest sensitivity mode, the effects of white noise and colored noise become more visible.

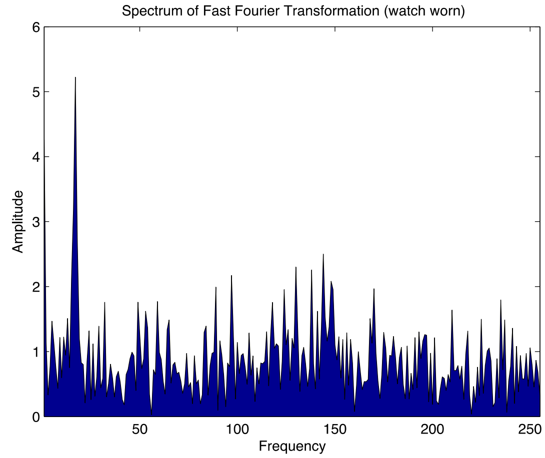

Figure 3: Frequency spectrum while smart watch is worn and arm is stretched out

Usually, when a user is wearing a watch, the arm is not stretched out. The feature AU provides only a slightly higher value that for the lying on a table. In combination with the features of the frequency domain and the recognized effects of colored noise we can do to the assumption that we can detect if the smart watch is worn or not.

On one side we are considering the AU value by using a defined threshold (depending on the Smart Watch model), to distinguish between worn or laid down. On the other side we are considering the frequency band of the Fourier spectrum. We are adding the Fourier magnitudes of each band (low band and high band) and are calculating the quotient. Here we are also considering a threshold of the quotient as the indicator of worn or laid down.

5.2 Sleep Detection

When a person sleeps, the smart watch is permanently measuring micro activity of the body. Our algorithm detects an activity of approx. 0.05 AU while sleeping, depending on the position of the wrist, mattress and physical condition (weight, BMI etc.). If the user turns from side to side while he is sleeping, the smart watch detects a very high AU value. Together with other features, the AU can be used to detect if the user sleeps or is wake.

The following figure 4 shows the 24h diagram of a user from 12 p.m. to 12.p.m. (x-axis). The y-axis is the degree of inactivity. The red graph illustrates the automatically detected sleep, the green graph shows the detected activity period.

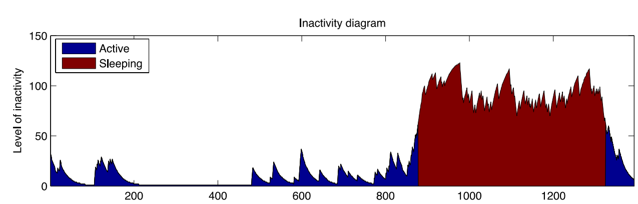

Figure 4: Sleep recognition with a smart watch

The requirements to the sensor for sleep recognition are low. We identify that a quantization of 6 bit / g and a sampling frequency of less than 1 Hz is sufficient for sleep detection. This requirement leads to very low energy consumption for the smart watch.

5.3 Heart Rate Detection

The sensitivity of the smart watch allows the recognition of the heart rate. We implemented an application of an android phone that determines the heart rate whenever the user holds the smart watch to his chest.

Figure 4: User holds his smart watch to his chest

The heart rate detection algorithm uses the AU - values. Therefore we performed an autocorrelation, using a set of 640 AU – samples that took 20 seconds because the sampling rate is 32 Hz. When the acceleration sensor is in 8 bit /g mode, the algorithm is detecting the heart rate; in the 6 bit / g mode the signal is very noisy and we hardly detect a pulse. (Maybe we have to collect a larger data set for the correlation.)

Figure 5 shows the corresponding signal with the heart rate. Hereby the period length is about 30 samples, which relates to approx. 60 beats per minute.

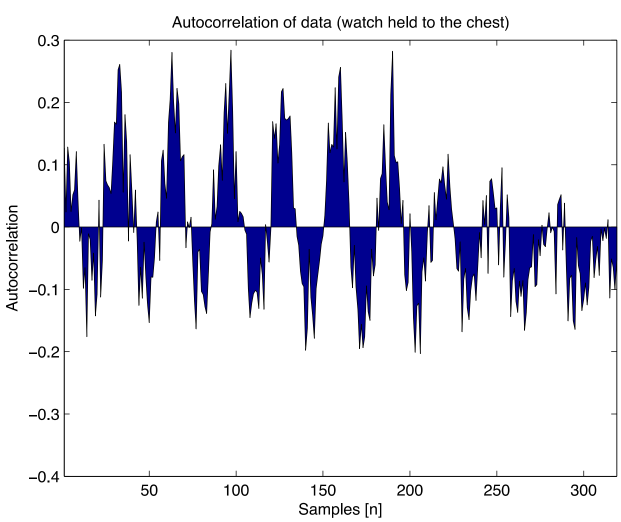

Figure 5: Autocorrelation of detected heart rate signal

5.4 Industrial Applications

Smart watches are mobile devices with a small display and a vibration feedback to indicate incoming messages. Because of the sensor functionality, smart watches can be used to support indoor navigation features in construction or maintenance work. In construction environments, the environment might be noisy and dirty. If a worker needs guidance to a place of interest, he can be guided by vibration signals of the smart watch.

Within the research project eKon, we are developing new indoor navigation technologies in the context of ship construction and maintenance. The research project eKon is funded by the German Federal Ministry of Economics and Technology. Hereby, Smart watches are useful interaction devices for model based navigation, while the 3D plans of the environment are known. Smart watch supports inertial navigation as well because of the capability of a distance measuring functionality (pedometer).

In some working environments, machines are transferring vibrations to the hand or arm of the worker. The Control of Vibration at Work Regulations 2005 (the Vibration Regulations), came into force on 6 July 2005 in Great Britain by the HSE [13]. The Control of Vibration is based on a European Union Directive to protect workers from risks to their health and safety from vibration. Hereby the regulations on hand-arm vibration define a maximum of daily exposure value of 5 m/s^2 A(8); and a daily exposure action value of 2.5 m/s^2 A(8). The maximum vibration force on hand or arm might be very high, common devices provide a measuring range of approx. +/-500 g, some others +/- 1000 g. In comparison, the standard MEMS sensor has a range of max. +/- 16 g. The direct exposure to the arm or hand cannot be measured exactly by standard MEMS sensors. However the smart watch is able to perform pattern recognition of the acceleration signals that allows the identification of the used tools and their using duration. We expect that the smart watch will be used for monitoring the hand and arm vibration exposition in combination with the recreation time in the near future.

6. CONCLUSIONS AND OUTLOOK

Smart watches are wrist watches with computational power, sensor functionality and connectivity to the internet. Smart watches allow a new mobile assistance and are affecting our business and social life.

Because of the haptic feedback of information by vibration signals or micro display messages, smart watches enable a user support especially in home environments, construction or maintenance environment, or indoor navigation in ships and submarines. The smart watch with its integrated and body worn sensors enable a constant monitoring during day and night. Hereby it is necessary that the sensor is sensitive and reliable for the desired application.

The paper introduced a gravity free parameter for the acceleration in the three dimensional space, the activity unit (AU). The AU consists of standardized SI-units and allows a reproducible metric for activity estimation.

The work presents an algorithm to distinguish if the user is wearing the smart watch or not. The smart watch is also able to detect the heart rate if the user holds it to his chest. Hereby the requirement to the acceleration sensor is a sampling rate of 32 Hz and a quantization of 10 bit / g.

Other applications show the ability of sleep detection by smart watches. Sleep detection and physical activity recognition require a 6 bit / g quantization.

Further work will be done in research of micro activity in periods of physical inactivity. We are convinced that smart watches will provide additional mobile assistance to the user that we can´t even imagine today.

7. ACKNOWLEDGEMENTS

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