Mobile physical activity recognition of Stand-Up and Sit-Down Transitions for User Behavior Analysis

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ABSTRACT

Sufficient physical activity is required for everybody, especially for elderly people. Monitoring of physical activity is possible in daily life by using mobile sensors such as acceleration sensors. The recognition of periodic activity types like walking, cycling, car driving etc. is easy to perform. However, the identification of transitions between physical activities is difficult, because those events are nonrecurring and unique. The estimation about the share of standing or sitting during work is interesting for the design of the modern workplace. Human ergonomics demand for a limitation of standing work; this may even be enforced by the legal protection of working mothers to improve the working condition. The recognition of standing and sitting is furthermore useful within the home living area design. Hereby a detection of staying, sitting and walking supports the assessment of the activities of daily life. This paper addresses the methodology of mobile physical activity recognition of transitions between sitting and standing by using only one three-dimensional acceleration sensor. The recognition is performed by using a synthetic kernel signal and a correlation of the measurement signal. For the evaluation, a detection application has been developed which uses the build-in sensors of a standard mobile phone. The evaluation included 12 subjects and the result shows that mobile recognition of activity transitions is possible.

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

Algorithms, Design, Measurement, Reliability, Human Factors

Keywords

Activity Monitoring, Acceleration Sensor, User State Detection, Assistive Technologies, physical activity transitions, DiaTrace

1. INTRODUCTION

The world health organization WHO recommends a physical activity of e.g. 30 minutes of moderate-intensity physical activity 5 days per week [1].

Physical activity is important for people of every age and physical condition and should be an integrated module of human behavior in daily life. On the other hand, overplay of sport or excess of only one type of physical activity causes negative effects as well.

Objective instruments for physical activity recognition are available only under laboratory conditions. In everyday life, mobile monitoring systems are needed in that kind that they are able to distinguish between basic activity types such as resting, walking, jogging, running, cycling etc. and the transitions between them. Hereby the transition of sitting and standing is very important.

The identification of the activity behavior and the occurrence of transitions between standing and sitting in daily life might provide additional information for the assessment of the constitution of elderly people. Very old people do often not leave the apartment and the single physical activity is to stand up and to walk between kitchen, living room and bedroom. Hereby the occurrence of sitting and standing periods is relevant for the pattern of daily life and identification of abnormalities. The amount of sitting and standing periods is also relevant for pregnant women. The legal protection of working mothers, enforced by several countries (e.g. MuSchG, Germany), requires a limitation of standing work. Hereby it is necessary to estimate the time relation of standing and sitting. But also for non pregnant workers, a well balanced change of sitting or standing work is recommended under ergonomic aspects [2].

Physical activity recognition in mobile surroundings can be performed by using acceleration sensors. These sensors are very small and already used for step counters. Acceleration sensors are also integrated into home consumer produces like notebooks (for hard disk drive protection by free fall detection), or mobile phones and digital cameras for autorotation of photos.

In this paper we first describe the current work in the field of physical activity recognition by acceleration sensors. In the next section we introduce a novel method of transition detection between standing and sitting. The following paragraph describes the evaluation of the transition recognition and the discussion

about the received results. The paper closes with a summary and the outlook on further research and next steps.

2. RELATED WORK

In general, the application of double labeled water is regarded as the gold standard for physical activity assessment [3]. There, the energy consumption can be determined over a period of several days. This method is not useful for the identification of activity types, duration, iteration or distribution. Physical activity recognition by optical sensors is useful for surroundings with available infrastructure. For mobile and daily life, physical monitoring by using three dimensional acceleration sensors is very suitable. Physical activity monitoring by 3D acceleration sensors started in the 90s, continued by the work of Massachusetts Institute of Technology MIT, USA in 2001 [4]. Hereby multiple sensors were used, mounted on foot, knee, hip, elbow and wrist [5]. Intel Research, USA, developed an aligned hardware for physical activity recognition [6] and developed an automatic feature extraction algorithm for physical activity recognition in daily life [7]. Carnegie Mellon University and TU Munich started to work on rich sensor systems, which can be worn at a wrist (eWatch) [8]. The development of new algorithms, especially designed for standard mobile devices with low sampling rate and quantization lead to the usage of physical activity recognition on mobile phones, e.g. by Fraunhofer, Germany, DiaTrace [9].

In [11], a sensor was fixed mounted at the body's chest and hereby a detecting and monitoring of body postures like sitting, standing and lying, as well as periods of walking during activities of daily living as possible. The sensor is composed of one gyroscope and two accelerometers to measure angular velocity and accelerations of the trunk in vertical and frontal directions. Instead of detecting standing and sitting directly, transitions between these states were recognized by typical patterns in the sensor data. Features like vertical displacement, changes in trunk tilt as well as the order of acceleration and deceleration phases with their respective maximum and minimum values were calculated and used for classification. Knowledge about the mounting and additional information about the orientation of the sensor kit relative to the room reference provided by application of the gyroscope data on the acceleration data allows ruling out a set of movements which cause similar patterns. For example, a single step forward would likely lead to an acceleration phase followed by deceleration and a displacement similar to a stand up transition, but in horizontal direction.

A major disadvantage of this presented system is the remaining need to wear a special device for recording, a fixed mounting position of the sensor system as well as the necessity to stay in range of a wireless link to a computer which performs the analysis. Another approach is introduced in [12], where body postures and motions are recognized by four triaxial accelerometers fixed at sternum, wrist, thigh and lower leg. The observed subjects wore a data recorder of 700g weight in a bag fastened at a belt. Data analysis was performed after the complete dataset was recorded. The recognition of standing and sitting is based on information about the orientation of different body parts. As standing and sitting are states of relative rest, the influence of external accelerations on the determination of orientation is minimal. After a person was equipped with the complete apparatus, he or she had to strike determined poses for several seconds under laboratory conditions. These datasets were used for comparison with data recorded later in more natural surroundings. The sensor output was averaged over time frames of more than 20 seconds and then assigned to the training data with the least distance. The system performed well under laboratory conditions, but was of limited use in more natural environments.

2.1 Physical Activity Recognition

The movement of the human body can be measured by acceleration sensors. The fastest movement a human is able to perform with his extremities is about 16 Hz [10]. This leads to a sampling rate of 32 Hz for physical activity recognition for humans. The internal sensor of the mobile phones used in this study allowed a sampling rate of 20 Hz. Even 20 Hz is less than the optimal sampling rate, it is sufficient for activity recognition. The phone sensor measures in a range of ±2.3 g with the quantization of 6 bit per g. The range is adequate for stand-up and sit down movements.

For the detection of transitions between stand up and sit down we were using a signal matching. The basic principle to locate stand-to-sit and sit-to-stand transitions in the input data is to find characteristic waveforms. Theses features were caused by acceleration and deceleration phases during the transition. As an accelerometer measures acceleration by displacement of a mass due to influence of an external force, the earth gravitational field will permanently cause an acceleration measurement of one g directed away from the earth center. Every sample is therefore a composition of the earth gravitational vector and other additional accelerations. A decomposition of the influencing vectors is only possible if information about the orientation of the sensor body frame relative to the earth gravitational field is available. Because a sit-to-stand transition starts with an upwards acceleration its vector points nearly in the same direction as the gravitational vector. The value of the measured samples will therefore be slightly higher than one g. As the vertical speed of the subject after the transition will be zero, the first phase is followed by a second phase of deceleration. Now the additive acceleration vector points in the opposite direction relative to the gravitational vector. The values of the sampled vectors will therefore be less than one g. Obviously, for stand-to-sit transitions it is vice versa.

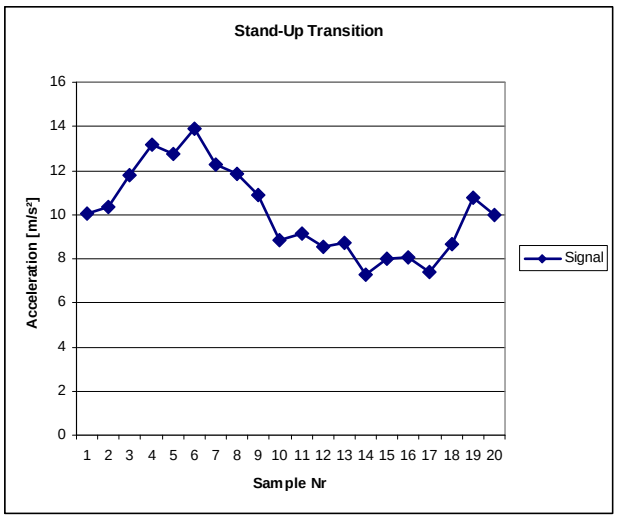

Figure 1 *Values of acceleration measured by a mobile phone with integrated acceleration sensor during a stand-up transition sampled with a frequency of 20 Hz.*

The displacement of the sensor during the transition can be calculated by the second integral of the sampled acceleration function denoted by *a[t]*, where *v* means speed and *s* the displacement.

$$v = \left(\sum_{t_1}^{t_2} a[t] * dt \right) + v_0$$

$$s = \left(\sum_{t_1}^{t_2} v[t] * dt \right) + s_0$$

Depending on body size and height of the seat, it is commonly settled around 0.3 meters if the sensor is attached at one of the upper body parts. This data could be determined by the field tests, described in the following chapter. Because the displacement is fixed for a given pair of subject and seat, the values of acceleration depend mainly on the duration of the transition. While healthy young people stand up in approx. 1s, generating a sharp waveform as described, elderly or disabled people likely need more than two seconds where the low accelerations lead to a very flat curve in the sensor output.

The software presented in this paper detects sit-to-stand and stand-to-sit transitions primarily by recognition of the described waveforms. The big benefit of suitability for daily use gained by utilizing a mobile phone for data acquisition and analysis comes along with some difficulties: As only one sensor is available, data about body postures expressed through relative orientations of different limbs is not determinable. The system is therefore limited to detecting acceleration patterns caused by state transitions. For this application the vertical parts relative to the room reference of the sampled acceleration vectors are of major interest. The only restriction of wearing the mobile phone was to carry it in a trouser pocket so no a priori orientation data could be used. In a resting position, no additional accelerations occur and the measured gravitational vector equals the vertical axis of the room reference. During the transition the mobile phone is rotated about 90 degrees when placed in a trouser pocket and a set of accelerations pointed in different directions add up to the gravitational component. To gain at least a minimum of orientation data the input was segmented in frames of 5 samples, which corresponded to a time slot of one quarter second. For each frame, the mean and variance of the acceleration values were computed to distinguish between phases of rest and activity. If a period of activity enclosed by phases of rest and with acceptable duration was detected, the according data window undergoes further analysis. For the terminal segments of rest before and after the transition, the direction of the gravitational vector was calculated. This provided information about angle and rotational plane of the performed rotation. As we assumed the mobile phone to be located in a trouser pocket, state transitions which caused rotations of less than 60 or more than 120 degrees where not examined further. To minimize the influence of accelerations in horizontal directions the sampled acceleration vectors were projected into the plane defined by the point of origin of the sensor coordinate system and the two gravitational vectors taken before and after the transition. The next step was to detect the characteristic waveform mentioned above in the values of the projected acceleration vectors. To achieve this, a set of kernel functions with different lengths were generated out of third degree polynomials and then cross correlated with the sampled and projected acceleration signal.

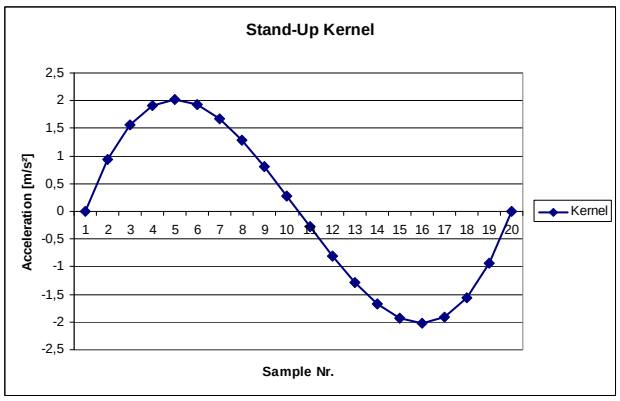

Figure 2 *Kernel generated for detection of stand-up transitions with duration of approx. 1 second.*

A correlation coefficient near one indicates a sit-to-stand transition, near minus one a stand-to-sit transition using our polynomials which model stand up events. In a last step the section of the signal which caused the highest correlation with one of the kernels is taken to calculate the displacement of the transition. If it is in the range of 0.3 meters, the transition will be classified as either stand-to-sit ore sit-to-stand transition.

3. ARCHITECTURE

This leads to a slim infrastructure for motion tracking as follows:

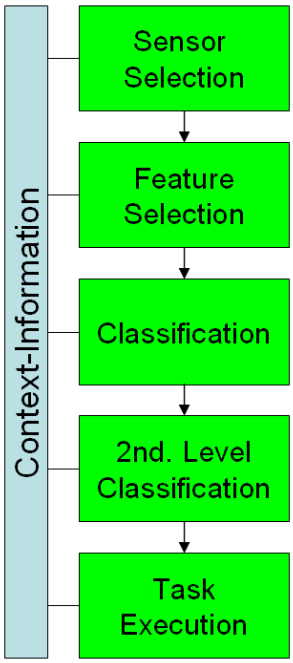

Figure 3: Generic architecture for motion tracking

4. PROTOTYPE

4.1 Mobile Phone Application

The presented algorithm for feature extraction and transition classification was implemented on a standard mobile phone, which is equipped with a 3D-acceleration sensor. The phone, a SonyEricsson w715, samples movements with a frequency of 20 Hz by 6 bit resolution per g. The phone is equipped with wifi connectivity, so a control of a wifi switch by the detection of stay up or sit down was possible. The features and classification were generated on the device and in real time. Every detected transition generated an output by sound and http-post – message, so easy annotations of tests were possible.

5. EVALUATION

5.1 Algorithm Evaluation

The aim of the evaluation is to determine the accuracy of the transition detection between stand-up and sit-down movements. Therefore, we designed three types of tests. At each test, the sensor platform was a standard mobile phone with a J2ME-Java virtual machine. The phone was worn in the front pocket of the trousers.

The first test was focusing on the recognition rate for a subject, who tried to reach an optimal recognition rate. The subject was a member of the research team, male, age 44, normal weight. The test consisted of 12 sit-down and 12 stand-up movements. The recognition rate was 100%.

The second test was focusing on false detections during a normal office working day, consisting of walking, climbing stairs, working with computers, business meetings etc. Within the tests, no sit-down or stand-up movement, fulfilling the requirements mentioned above, was performed. The test was performed for three hours by three subjects. The subjects were male, age between 25 and 35, normal weight. No false detection of the activity "sit-down" or "stand-up" was detected.

The third evaluation included 12 subjects, who were performing the sit-down and stand-up movement (12 times each) without knowing the reason for the test. Two subjects were female, all in the age between 10 and 45 years, normal weight. The evaluation showed an average recognition rate of 70%. The recognition rate varied between subjects wearing wide trousers or jeans. Subjects wearing jeans showed a recognition rate of 90%.

5.2 Discussion

Proof-of-Concept

The evaluation showed that it is possible to detect typical activity patterns with the proposed system. Test 1 showed that the eligibility can be demonstrated very well.

Misdetection

The applied algorithm shows a good performance regarding misdetection. This is possible because of the movement vector. The tests didn´t include stair-climbing or tests with a lift, here might by some misdetection possible.

Application

The third part of the evaluation shows that the applied correlation analysis is not fully suitable for everyday use. As can be seen in chapter 4, the test-signal is describing a short sequence of rest which usually occurs after a sit down or a standing up movement. Some subjects were still moving their hips right after a sit-down or began to walk after a stand-up. These seamless activities are hardly detected by the presented kernel.

We assume that the presented method of transition detection is a further component of comprehensive physical activity recognition. The classification of physical activities must be backed up with a second level classification with tests the further state of the user. To give an example, if a user walks, he must be stand up before, a user who drives his car is also sitting. The inclusion of the likelihood of the activity might improve the accuracy.

6. CONCLUSIONS AND OUTLOOK

Mobile physical activity recognition of basic periodic movements, e.g. walking, cycling, running etc. is available today. In this paper we presented a novel method for mobile recognition of stand-up and sit-down transitions for user behavior analysis. This method is based on an algorithm which can be used on standard mobile devices such as cell phones with integrated acceleration sensors. The transition movement of stand-up and sit-down influences the vertical displacement as well as the sensor device orientation. Even the sensor quality is insufficient for the calculation of true physical parameters, the wave shapes can be used for transition detection. The presented activity recognition algorithm uses the identified features of characteristic stand-up or sit-down movements. The evaluation showed that within the test environment no misdetection occurred, the recognition rate by twelve subjects was about 70%. The evaluation also shows that the clothing is a significant factor for the recognition rate. If user were wearing jeans, the accuracy was about 90 %. The used algorithm shows weak recognition rate for fluent, seamless activities, e.g. a stand-up with immediate begin of walking.

Our next steps of research will be to identify additional patterns for the fluent movements. Furthermore we plan to work on additional probabilistic models which use the previous or subsequent activity types for higher transition recognition rates. The consideration of the state of activity prevents missing transitions.

We hope that in future the monitoring application will be used for ergonomic aspects within inappropriate working conditions and support the health condition of elderly people as well.

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