Multi-sensor Activity Context Detection for Wearable Computing.

CONFERENCE PAPER · JANUARY 2003

DOI: 10.1007/978-3-540-39863-9_17 · Source: DBLP

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Multi-Sensor Activity Context Detection for Wearable Computing

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Abstract. For wearable computing applications, human activity is a central part of the user's context. In order to avoid user annoyance it should be acquired automatically using body-worn sensors. We propose to use multiple acceleration sensors that are distributed over the body, because they are lightweight, small and cheap. Furthermore activity can best be measured where it occurs. We present a hardware platform that we developed for the investigation of this issue and results as to where to place the sensors and how to extract the context information.

1 Introduction

For wearable, context-aware applications there are many ways to characterize the user's context. Depending on the application the user's physical activity, his state (e.g. stressed/nervous, etc.) his interaction with others or his location might be of interest. Among all these the user's physical activity is of prime importance. E.g. knowing that the user is writing on a white board tells the application, that he is most likely involved in a discussion with other people and may not be disturbed. Similarly, when the user is sitting and typing on a computer keyboard he is probably working, but may be more open for interruptions.

Since the goal of context-aware applications is to reduce the load of the user and adapt to them seamlessly, context information cannot be supplied by the user. Instead it should be sensed automatically using sensors. While it would be possible to incorporate sensors in the environment, this would make it impossible to use the context information for mobile devices and applications outside the 'augmented' environments. For the recognition in a mobile setting, the sensors should be attached to the body of the user. This also allows for very cheap sensing, since activity is measured directly where it occurs.

For truly wearable applications, the sensors have to satisfy two basic requirements. Firstly they should be unobtrusive to wear, ideally integrated into clothing, so that the user does not need to worry taking them with him. Secondly, they should be small and cheap, so that they can be integrated in many pieces of clothing or wearable devices without adding too much to the cost and size. We propose to use miniaturized accelerometers. They can be produced in MEMS technology making them both very small and cheap. Already today, there are devices available that integrate them [1].

For the application of accelerometers to activity recognition there are two principal questions to answer: firstly, how many sensors are required to recognize a given activity with a desired precision, and secondly where to place these sensors on the user's body.

For general activities, a single sensor will not be sufficient. Accelerometers measure motion, which can only be sensed where it occurs. E.g. the activity 'writing on a white board' includes standing in front of the board, which can well be measured at the legs, and writing on it, which is an activity of the right (or left) hand. Hence, for activities of a certain degree of complexity multiple sensors will be required.

There are two principal contributions in this paper. Firstly we have developed a hardware platform, that allows to record acceleration data from many places on the human body simultaneously (section 3). Using this platform and a naïve Bayes classifier (section 4) we conducted experiments to investigate the required number of sensors and their placements (sections 5 and 6). The paper concludes with a summary and discussion of the findings and future work (section 7).

2 Related Work

Recognizing general human activity or special motions using body-worn acceleration sensors is not a new problem. Apart from the extraction of the actual activity or motion, there are also interesting applications, that use this technology.

Recognizing general user activity has been tried by various authors. Randell and Muller [2] and Farringdon et al. [3] have done early investigations of the problem using only single 2-axis accelerometers. Van Laerhoven et al. [4] try to distinguish user-selected activities using a larger number (32) of 3D acceleration sensors. Unlike in our approach, they try to find recurring patterns in the data and do not model the activity explicitely. Furthermore they do not assume that the sensors have any fixed location, instead their sensors are attached to the clothing and can thus move relative to the user's body. Kern et al. [5] model activities explicitly, but use relatively few sensors and do not address placement issues in their applications. [6] compares the both approaches. Loosli et al. [7] use two acceleration sensors attached to the user's knees to investigate classification issues.

There are also more specialized applications for motion recognition using body-worn acceleration sensors. Chambers et al. [8] have attached a single acceleration sensor to the user's wrist to automatically annotate Kung-Fu video recordings. They focus on the recognition of complex gestures using Hidden Markov Models. Benbasat and Paradiso [9] have used a 3D accelerometer and a 3D gyroscope for recognizing human gestures.

Body-worn acceleration sensors have been used in a variety of applications. Sabelman et al. [10] use them for offline analysis of the user's sense of balance. Morris and Paradiso [11] use a variety of sensor that are built into a shoe for online gait analysis. Golding and Lesh [12] and Lee and Mase [13] both use a variety of different sensors for location tracking. Kern et al. [5] employ multiple acceleration sensors to recognize the user's activity and use that information to annotate meeting recordings. Kern et al. [14] use similar information from a single acceleration sensor to mediate notifications to the user of a wearable computer depending on his context.

3 Acquisition System

In order to acquire useful information in real settings it is inevitable to design, construct and build a wearable sensing platform.

3.1 Use Cases and Requirements

Before constructing the platform we considered potential application domains in which we would like to be able to use the platform. We have seen in previous work that it is feasible to construct systems for use in lab environments [9]. However we wanted to build a platform that allows recording and recognition beyond the lab in real world environments. The anticipated usage scenarios are in the domain of sports (e.g. climbing a wall, playing a badminton match, inline skating, long distance running, and playing a basket ball match) and manual work (delivering goods, rescue workers, production workers). The following set of requirements – many of them more practical as technical – was extracted.

Robustness & Durability When assessing the scenarios we realized that in all cases a robust and durable platform is paramount.

Mounting Sensors Attaching the sensors to the body at a desired position and fix them to keep them in this position during an activity became a further vital issue on which the practical usability relied.

Freedom of Movement In most scenarios it is important not to restrict the user's degree and range of freedom with respect to movements.

Time and Storage To create useful data sets we recognize that the time interval over which data can be logged has to be fairly long. In our case we decided that we require logging capabilities for more than one hour and potentially for several hours.

Sampling Rate Based on our own previous experience and work published [4] we aimed for a sampling rate of about 100 Hz per sensor.

Number of Sensors For estimating a useful number of sensors we assumed having three dimensions of acceleration at each larger body segment. As initial target we set 48 accelerometers and the potential for 192 accelerometers.

Energy Consumption As the user should be able to work or to do sports with the device over a longer period of time the energy consumption must be low enough to not jeopardize other requirements by the size and weight of batteries.

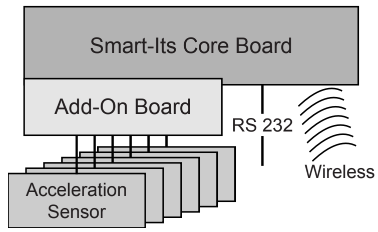


Fig. 1. Architecture of an acquisition module based on one Smart-It

The platform was deliberately designed as an experimental setup. Its main function is to provide us with real data recorded during a particular activity. Thus, properties such as robustness and durability and ease of mounting sensors had a higher influence on the design than unobtrusiveness.

3.2 Components and Architecture

The acquisition system is a modular design based on the smart-its platform [15, 16]. The smart-its core board provides communication (wired or wireless) to a host system which stores the data and has a specifically designed add-on board attached. The actual acceleration sensors are mounted on small boards which are wired up to the add-on board. See figure 1 for an overview of the architecture.

The acquisition system can be attached to a notebook computer or a PDA via serial line. In cases where it is not possible or practical to wear additional components the system can be connected wirelessly to a nearby smart-it connected to a computer (e.g. for a badminton scenario: the player only wears the acquisition system and the data is transmitted wirelessly to a computer next to the field.)

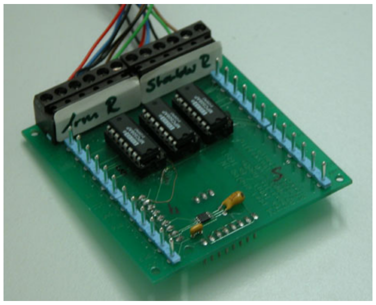
3.3 Smart–Its Core Board

The smart-it core board is a small embedded microcontroller system build around a PIC microcontroller (PIC16F877 or PIC18F252) that offers serial RS232 communication, a wireless link with 19200 bits/s, 8K of non-volatile RAM, a power supply circuit (Batteries or external voltage), and an extension connector for the add-on Board.

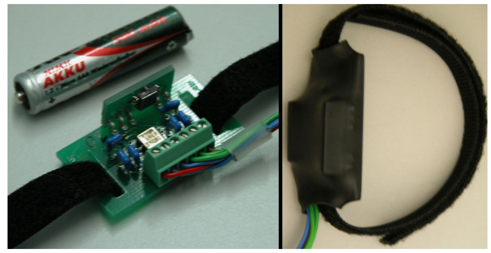
For the onboard components there are also libraries available (e.g. RAM, communication). There are also software templates on which further software can be developed. The smart-its core boards are designed as building blocks to ease prototyping of Ubiquitous Computing systems [15, 16].

3.4 Multiplexer Add–On Board

To make the system cheaper, ease programming, and to allow a high sampling speed we decided to use acceleration sensors with analog outputs. As the core



(a) add–on board to read 24 analog channels with 2 3D acceleration sensor nodes attached



(b) Left: A single sensor board with 4 channels of acceleration. Right: the sensor with Velcro strap covered by shrink wrap

Fig. 2. Acquisition Platform

board only has 5 analog inputs a multiplexer was required. The microcontroller only offers 10 bit resolution in the analog to digital conversion. To experiment and asses the value of a higher resolution conversion we included a 16 Bit analog digital converter (ADS8320).

The add-on board has 24 analog inputs, set up as 6 groups of 4 inputs. Each group has one connector that also offers power and ground. Each analog input is connected to one of the inputs of one of the 3 analog multiplexers (each with 8 inputs and one output). The output of each multiplexer is connected to an analog input of the microcontroller. For one of the multiplexers the output is also connected to the external analog digital converter. The controls (for the converter and the multiplexer) are connected to the smart-its core board. See figure 2(a).

A library is realized that allows to read each of the external channels. Given the reading time and the time to switch between channels a sampling rate of about 100Hz per channel can be achieved.

3.5 3D Acceleration Sensor Node

For the sensor nodes we used 2 ADXL311 mounted on 2 small PCBs which are attached to each other in a 90 degree angle to effectively obtain 3D acceleration data. See figure 2(b).

The base PCB is about 40mm by 20mm and contains all the signal condition components and one of the accelerometers. The board mounted upright is about 20mm by 10 mm and contains only the ADXL311. The assembled size of a node is 40mm by 20mm by 10mm. We did deliberately not reduce the size of the nodes in order to be able to have very robust screw-on connectors on the board. We also included rectangular holes directly into the PCB to ease fixing of straps. To increase the robustness the node can be covered (after fixing the straps and cable) by shrink wrap. See figure 2(b) for a picture of a complete, wrapped sensor board.

4 Recognition Algorithm

To classify the acceleration data into distinct classes we employ a Bayesian classifier. In this section we give a brief overview over the classification algorithm and introduce the features we use.

4.1 Bayes Classification

Bayesian classification is based on Bayes' rule from basic probability theory. Other, more complex, classifiers are of course possible for this task and will be investigated as part of future work.

Bayes' rule states, that the probability of a given activity a given an n-dimensional feature vector $x =< x_1, ...x_n >$ can be calculated as follows:

$$p(a|\mathbf{x}) = \frac{p(\mathbf{x}|a)p(a)}{p(\mathbf{x})}$$

$p(a)$ denotes the a-priori probability of the given activity. We assume them to be uniform for the purpose of this paper. The a-priori probability $p(\mathbf{x})$ of the data is just used for normalization. Since we are not interested in the absolute probabilities but rather in the relative likelihoods, we can neglect it.

Assuming, that the different components x_i of the feature vector $\mathbf{x}$ are independent, we obtain a naïve Bayes classifier which can be written as:

$$p(a|\mathbf{x}) = \frac{p(a)}{p(\mathbf{x})} \prod_{i=1}^{n} p(x_i|a)$$

We can compute the likelihoods $p(x_i|a)$ from labelled training data. We represent these probability density functions as 100 bin histograms.

4.2 Features

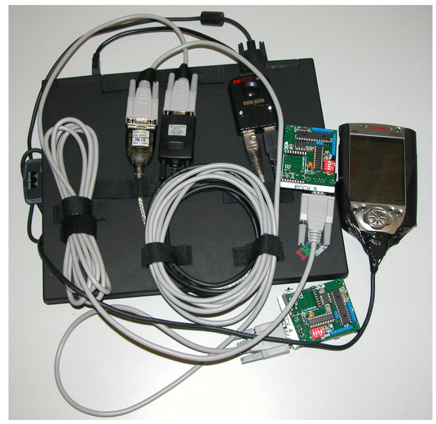
The above algorithm does not work well just using the raw data samples [12]. Its performance can be considerably increased by the use of appropriate features.

As features we use the running mean and variance, computed over a window of 50 samples. Given that our data is sampled at a rate of 92Hz, this corresponds to roughly 0.5 sec. For every new data vector the window is advanced by one. Thus we can make a new classification every time we receive a new data vector.

5 Experiments

This section describes the experiments we performed. It introduces the experimental setup, including the number and placement of the sensors, and the gathered data in detail. The obtained results are discussed in the next section.

(a) Recording Setup Mounted on a User



(b) Recording Setup: Laptop with IPAQ for Online Annotation and 2 Smart–Its

Fig. 3. Recording Setup

5.1 Experimental Setup

All data is recorded on a laptop that the user carries in a backpack. The sole user interface is a Compaq IPAQ that is attached to the laptop via serial line. It allows to start/stop the recording application and to annotate the data online with the current activity. Figure 3(a) shows the user with the mounted sensors wearing the backpack, holding the IPAQ in his hand.

For the desired number of sensors we need two complete sets of sensors with six sensors each. Each set, consisting of a smart-it, an add-on board, and six 3D acceleration sensor nodes is attached via a serial port to the laptop (see also figure 3(b)). Every sensor is sampled with approx. 92Hz.

Activities Our goal in this paper is to recognize everyday postures and activities. First of all, this includes basic user postures and movements that allow to roughly classify the user's activity. These are *sitting*, *standing*, and *walking*.

Apart from these basic postures and movements, it would also be interesting to know, what the user is currently occupied with. We hence included *writing on a whiteboard* and *typing on a keyboard*. The former indicates that the user is engaged in a discussion with others, while the latter indicates that the user is working on his computer.

Finally, social interactions are very important and interesting information. We hence include *shaking hands* to determine, if the user is currently interacting

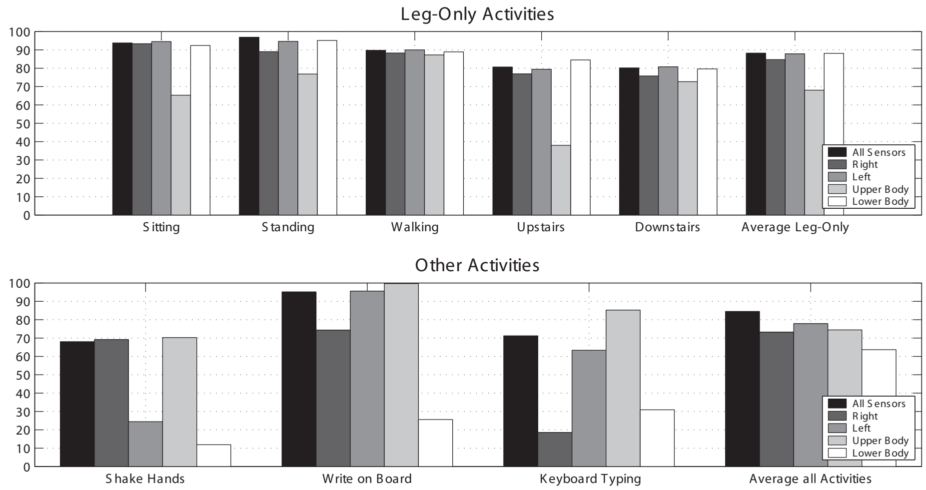


Fig. 4. Recognition Rates for All Sensors and Different Body Parts

with somebody else. Kern et al. [5] use this as one of the cues for annotating meeting recordings.

Number and Placement of Sensors In order to capture all of the above postures and activities, we decided to add sensors to all major joints on the human body. More precisely on the following six locations: just above the ankle, just above the knee, on the hip, on the wrist, just above the elbow, and on the shoulder.

In order to capture also 'asymmetric' activities, such as writing which use only one hand, we duplicate these six sensors on both sides of the body, resulting in a total of 12 3D acceleration sensors.

The sensors are fixed using Velcro straps, such as depicted in figure 2(b). Figure 3(a) shows the complete setup of all sensors attached to a user.

Experiments Using the above setup, we have recorded a stretch of 18.7 minutes data. It covers the activities mentioned above namely *sitting*, *standing*, *walking*, *stairs up*, *stairs down*, *shaking hands*, *writing on the whiteboard* and *keyboard typing*. The data can be downloaded under http://www.vision.ethz.ch/kern/eusai.zip.

6 Results and Discussion

In this section we present and discuss the results we obtained from the experiments that are described in the preceding section.

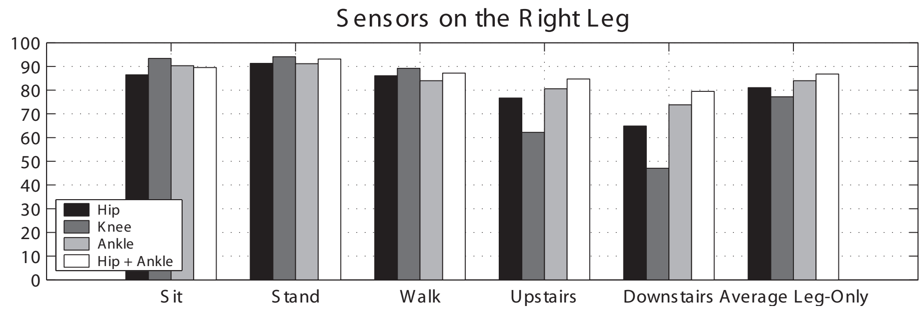


Fig. 5. Recognition Rates for Different Sensors on the Right Leg

6.1 Overall Recognition

Figure 4 shows the recognition rates using different sub-sets of the available sensors. 'All Sensor' recognition rates were obtained using all available 12 sensors for recognition. 'Left' and 'Right' use only right and left sensors respectively (six sensors each). While the 'upper body' refers to the sensors on both shoulders, elbows, and wrists, the 'Lower Body' refers to the sensors on both sides of the hip, both knees, and ankles.

The average recognition rate over all eight activities (the last set of bars) shows that the results get better the more sensors are used.

Comparing the upper and the lower parts of the body, we note that the recognition rate for the lower body is significantly lower, because the 'other' activities (*writing on the whiteboard*, *shaking hands*, and *typing on a keyboard*) cannot be recognised well. This is natural, since the main part of these activities does not involve the legs. As expected the 'leg-only' activities (*sitting*, *standing*, *walking*, *upstairs*, *downstairs*) are better recognised using the lower part of the body. However, the upper part still performs reasonably. Apparently the overall body motion for these activities can be captured using sensors on the upper part of the body.

When comparing the right and left side of the body, we note that for the leg-only activities both sides are nearly equal in recognition rate. However the recognition rates for the other activities are quite different. Since *shaking hands* is a right-handed activity in which the left side of the body plays only a minor role the right set of sensors obtains the best results. Quite interestingly *writing on the white-board* cannot be recognized well with the right set of sensors but rather with the left side, which is due to the position of the left arm which seems to be more discriminative. The low performance of the right side on the *keyboard typing* activity seems also quite interesting: since the right hand was used to annotate the data using the IPAQ the right side is not very discriminant.

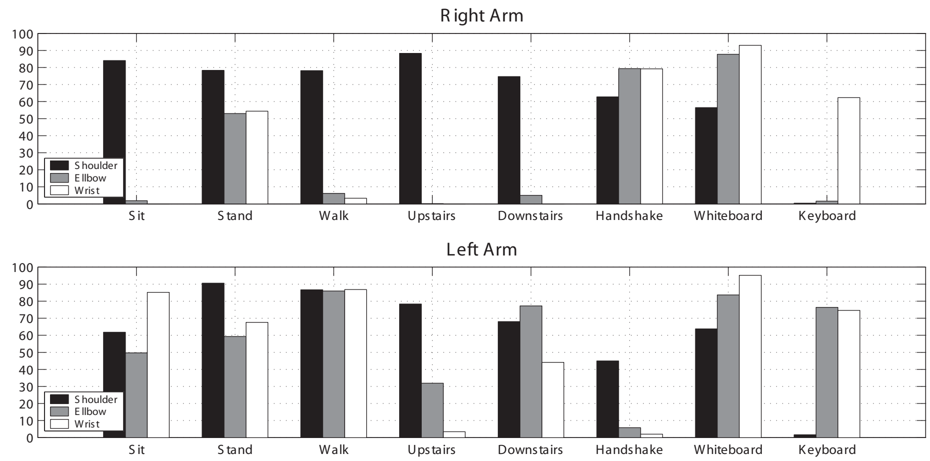


Fig. 6. Recognition Results for Single Sensors on the Arm

6.2 Sensors on the Leg

Figure 5 shows the recognition results for different sensors on the right leg. For the relatively simple motions of *sitting*, *standing*, and *walking* it seems to be sufficient to use one sensor only. Also, the difference between the individual sensors is quite small. Thus the placement can be chosen quite freely.

However, for more complex activities such as walking up- and downstairs, the placement considerably influences the recognition performance. The sensor attached to the ankle is the most discriminative, followed by the hip and (with a little distance) the knee. Combining different sensors, e.g. the hip and the ankle ones, improves the recognition rate. Thus, for more complex activities than the ones used here, the combination of different sensors might be crucial for successful recognition.

6.3 Sensors on the Arms

Figure 6 shows the recognition results for single sensors on both arms. One of the most interesting results here is that the sensors placed on the shoulders are well suited to recognize the legs-only activities. Furthermore, we note, that typing on a keyboard is best recognized using sensors on the wrists. This seems natural, since it is an activity of the hands only.

When comparing the right and the left arm, the sensors on the elbow and wrist of the right arm perform worse for the leg-only activities. This is again due to the fact that the right hand was used to annotate the data using the IPAQ, which makes the activity of the right arm similar for all leg-only activities. Shaking hands is a right-handed activity and thus cannot be detected well on the left arm.

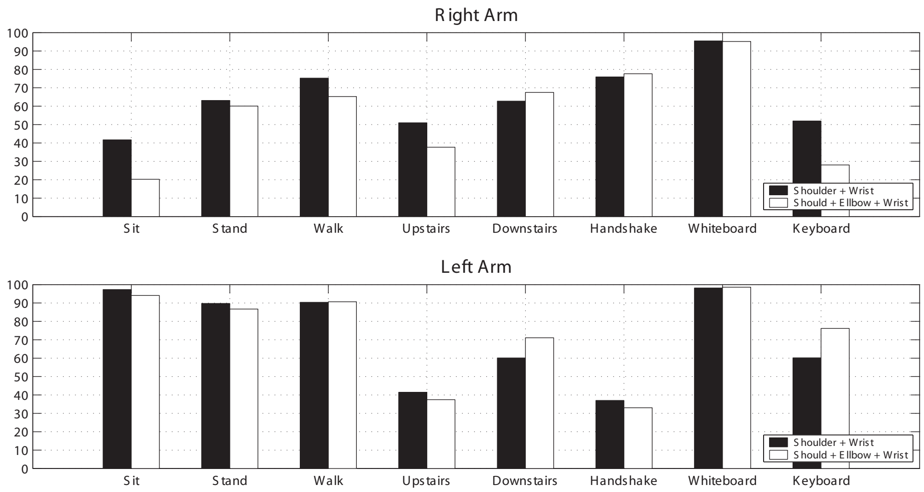


Fig. 7. Recognition Results for Combined Sensors on the Arm

Considering the sensor placement, the position just above the elbow does not add significant information. Although the recognition rate for the elbow sensor is partly better than either the shoulder or the wrist, it does not contribute to or outperform the combination of the two. Figure 7 shows that the recognition rate using shoulder and wrist sensors cannot be further increased by adding the sensor at the elbow.

7 Conclusion

The user's physical activity is central for context-aware user-centred applications. In this paper we concentrated on context extraction using body-worn sensors. More specifically we propose to use multiple acceleration sensors, since they are lightweight, small, and inexpensive.

We have presented a hardware platform, that allows capturing 3-dimensional acceleration data from up to 48 positions on the human body. It is especially designed for robustness, allowing for recording even very dynamic activities, such as playing badminton or climbing.

We have conducted experiments to investigate the number and placement of sensors. We therefore recorded data of the activities *sitting*, *standing*, *walking*, *stairs up/down*, *writing on a whiteboard*, *shaking hands*, *typing on a keyboard*.

As expected, the combination of multiple sensors generally increases recognition performance. For more complex activities, such as *stairs* or *writing on a whiteboard*, multiple sensors are not only helpful but rather mandatory for good recognition performance.

The placement depends of course very much on the activity. For 'leg-only' activities, such as *walking* or *stairs*, sensors on the legs, e.g. hip and/or ankle, are sufficient. For those activities a single sensor mounted on the shoulder also obtained good recognition performance. For more complex activities such as *writing on a whiteboard*, sensors both on the upper and lower part of the body are required. In our experiments a sensor placed just above the elbow did not seem to add significant information.

Right and left arm work relatively independently. The recognition rate can thus get confused, if either is temporarily engaged in another activity. Our experiments showed that the right arm was not very discriminative, because it was used to hold the IPAQ for annotation. In order not to confuse the recognition by such effects both arms should be equipped with sensors.

Several issues still need to be addressed. E.g. the influence of the features used for recognition and the recognition methodology itself should be addressed. Also, more complex activities should be investigated. At the moment it is not known how much actually can be inferred about the user using acceleration sensors only. The results and the platform presented in this paper are but a first step to investigate this topic.

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