Using acceleration signatures from everyday activities for on-body device location

Kai Kunze, Paul Lukowicz
Embedded Systems Lab (ESL), University of Passau
{kai.kunze, paul.lukowicz}@uni-passau.de
http://wearable-computing.org/

Abstract

This paper is part of an effort to facilitate wearable activity recognition using dynamically changing sets of sensors integrated in everyday appliances such as phones, PDAs, watches, headsets etc. A key issue that such systems have to address is the position of the devices on the body. In general each devices can be in a number of different locations (e.g. headset on the head or in on of many pockets). At the same time most activity recognition algorithms require fixed, known sensor positions.

Previously we have shown on a small data set how to recognize a set of on-body locations during a walking motion using an accelerometer signal. We now extend the method to work during arbitrary activity. We verify it on a much larger data set with a total 9 hours from real life activity by three divers users ranging from a 70 year old housewife to a 28 year male student.

1 Introduction

Most state of the art context and activity recognition techniques rely heavily on a fixed number of sensors with known position and orientation. The work presented in this paper is part of our effort to get rid of exactly those limitations. The idea is to use sensors integrated into everyday objects, garment and other devices the user might carry with him, like mobile phone, glasses etc. Of course, the obvious problem is to determine where on the body these appliances are. Note that devices location itself can also be relevant as context information (e.g. if the user has a headset in his ear or in a pocket).

Our approach to this challenge is to infer on-body position of appliances using inertial sensors. In previous work we have demonstrated on a small data set, that 4 locations (wrist, head, torso and trouser pocket) can be distinguished from the acceleration signal when the user is walking [2]. The main contributions of this paper over the above previous work are (1) to extend the method to work with arbitrary every day activities not just walking by improving the feature selection and recognition procedure, (2) to perform evaluation on a large (9 hours) data set recorded from real life activities and (3) to have studied 3 divers subjects: a 70 year old housewife, a 50 year old female office worker and 28 year old male student.

(a) (b)

Figure 1: Experimental setup during kitchen work (a) and packing (b).

Related Work The work that comes closest to ours, considering the modality of acceleration, has been presented by Lester et. al [3]. They introduced a method to determine if two devices are carried by the same person. In addition Gellersen et. al have shown how a group of devices can be coupled by being shaken together. Furthermore there were a number of attempts detect whether an appliance such as a mobile phone is on a pocket in the hand or on the table [1].

2 The Experiments

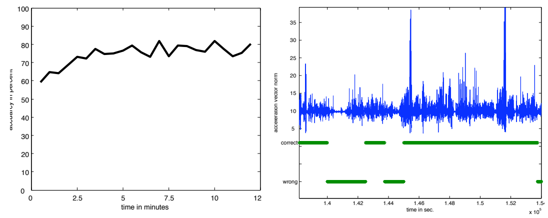
Method Overview Our approach is based on the fact that different body parts show different movement patterns and varying degrees of freedom. We evaluated over 35 features and have found the following 6 to best capture those differences: the standard deviation, zero crossings and mean of the norm of the acceleration vector minus the gravitational pull g_0 ($|\sqrt{x^2+y^2+z^2} - g_0|$), the sum of the norm of the differences in variance for the normalized axes divided by the variance of norm of the acceleration vector($\frac{|var(x_n)-var(y_n)|+|var(x_n)-var(z_n)|+...}{var(norm)}$), the number of peaks in the absolute value of the three axis using hill climbing with a threshold and the median of these peak highs. The first step is the computation of those features in a 2.5sec jumping window (overlapping 1.25 sec.). We then apply another window on top of the already windowed features and feed them into a continuous Hidden Markov Model with 5 hidden states. Exploring different window sizes, we get the best recognition rates using a 6 min window (see figure 2a). As an alternative aprpoach frame by frame classifaction with the C4.5 classifier has also been applied to the 2.5 sec windows, followed by a majority decission over up to 10 - 15 samples. However this approach has proven to be much worse then the above HMM classifier.

Experimental setup We conducted 3 experimental trials with 3 different test subjects, each trial over 1 hour. This leaves us over 9 hours of recorded data. The trials did not follow a predefined protocol, instead we recorded real life activities in four different scenarios: Kitchen work, washing and ironing cloths, packing and office work. The data includes a wide range from activities from drying dishes over folding shirts to making coffee. As mentioned before, the test subjects were quite diverse in age and occupation.

For the experiments, we used the X-Bus Master system, attached to it 5 motion sensors equipped with 3 axis accelerometers and gyroscopes. So far, we just consider the accelerometer data for inference. The on-body locations for the sensors are as follows: on the right wrist, the left side of the head, the torso (breast pocket), the front and back trousers pocket. We picked these locations, as they are the most likely places to wear applainces and accesories such as a mobile phone, watch, a headset, keys or smart cards on the body.

3 Results and Discussion

The classification rate as a funtion of the HMM sliding window is shown in 2a. The maximum accuracy achieved for 6 min windows is 82 %, with roughly 80% being reached already after less then 5min. For a typical pattern recognition problem this might be considered quite low. However, here we need to consider the fact that we are looking at data from unconstrained every day activity, which includes a certain percentage of time where there is no significant movement of some body parts or the motion might be atypical.



(a) (b)

Figure 2: The training curve in 3 varying the sliding window sizes and the norm of the acceleration vector from the wrist, plotted against the classification of the HMM classifier in 2a. The classifier fails to predict the right class when there is little movement.

This in turn means that in some windows it is theoretically impossible to get a correct classification.

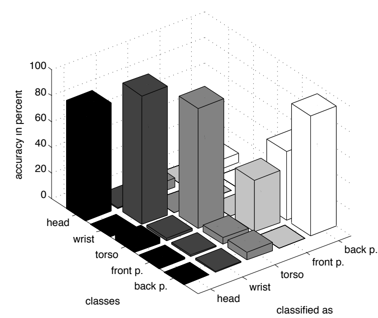


Figure 3: The confusion matrix of the HMM classifier.

This is illustrated in Figure 2b, where the HMM classification can be seen to be wrong during phases in which there is a lack of movement. Looking at the confusion matrix in 3, it is also clear that the most significant confusion is between the front and the back trousers pocket. These are locations where confusions are to be expected and the value of having them as separate locations is not clear. If we combine the two pocket classes into one, the accuracy increases to 92 %.

References

[1] H. W. Gellersen, A. Schmidt, and M. Beigl. Multi-sensor context-awareness in mobile devices and smart artifacts. *Mob. Netw. Appl.*, 7(5):341–351, 2002.

[2] H. J. Kai Kunze, Paul Lukowicz and G. Tröster. Where am i: Recognizing on-body positions of wearable sensors. In *LOCA'04: International Workshop on Location- and Context-Awareness*, London, UK, 2005. Springer-Verlag.

[3] J. Lester, B. Hannaford, and G. Borriello. "are you with me?" - using accelerometers to determine if two devi ces are carried by the same person. In A. Ferscha and F. Mattern, editors, *Pervasive Computing*, 2004.