University of Bristol

DEPARTMENT OF COMPUTER SCIENCE

Context Awareness by Analysing Accelerometer Data

Cliff Randell Henk Muller

August 2000 | CSTR-00-009

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Cliff Randell Henk Muller
Department of Computer Science, University of Bristol, UK.
cliff@cs.bris.ac.uk, http://wearables.cs.bris.ac.uk/

Abstract

In this paper we describe continuing work being carried out as part of the Bristol Wearable Computing Initiative. We are researching processing techniques for data from accelerometers which enable the wearable computer to determine the user's activity.

We have experimented with, and review, techniques already employed by others; and then propose new methods for analysing the data delivered by these devices. We try to minimise the number of devices needed, and use a single X-Y accelerometer device.

Using our techniques we have adapted our GPS based Tourist Guide wearable Computer application to include a multimedia presentation which gives the user information using different media depending on the user's activity as well as location.

1 Introduction and Background

This is a condensed version of a technical report. [1]

Our interests in wearable computing are centred around determining the context of the user and developing applications which make use of this information. We are exploring the concept of situated computing [2] by using sensors to determine the where, what and how of the user. We have used GPS and 'Pingers' [3] to provide location awareness and we are now investigating the use of accelerometers to provide activity awareness.

Previous research in this field, such as the wearable Context-Awareness Component [4], and Sensor Badge [5] employed accelerometers to detect basic activities such as sitting/standing/walking/running. More complex projects included the Acceleration Sensing Glove [6] using multiple hand mounted accelerometers, and Technology for Enabling Awareness [7] which combined accelerometers with a variety of other low-level sensors.

To minimise complexity, size and power consumption, we have researched data processing techniques which provide a higher level of activity analysis without the use of multiple sensors.

2 Architecture

The Crossbow ADXL202 Accelerometer Evaluation Board is designed specifically to help the designer understand these devices and provides a compact module which can be interfaced to any PC with a RS232 serial interface. It provides outputs corresponding to the X and Y G-forces applied to the board. To enable testing to take place for long periods with a minimal infrastructure we have interfaced this with a Matsucom onHand PC. (see Figure 1). The sensor is worn in a trouser pocket.

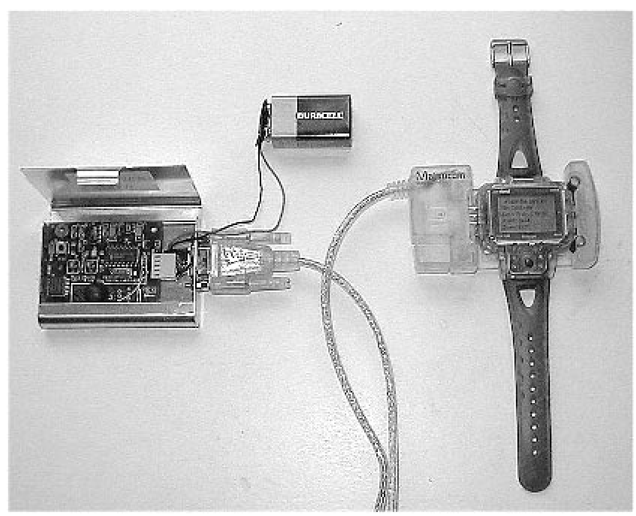

Figure 1. Accelerometer with onHandPC.

Our planned wearable consists small computer connected to a variety of sensors using an event manager. In a steady state the main processor is switched off and the sen-

*This work is performed in collaboration with, and with support from, Hewlett-Packard Research Laboratories, Europe

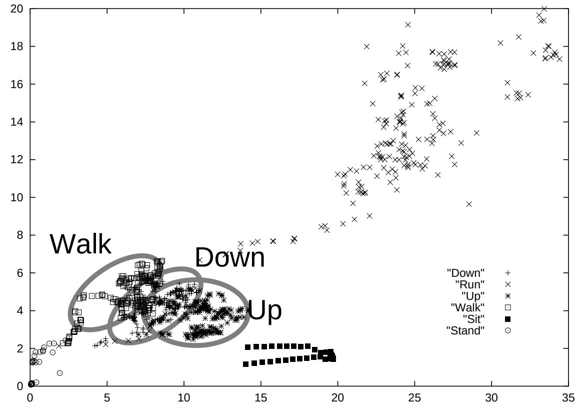

Figure 2. RMS X vs Y for six activities

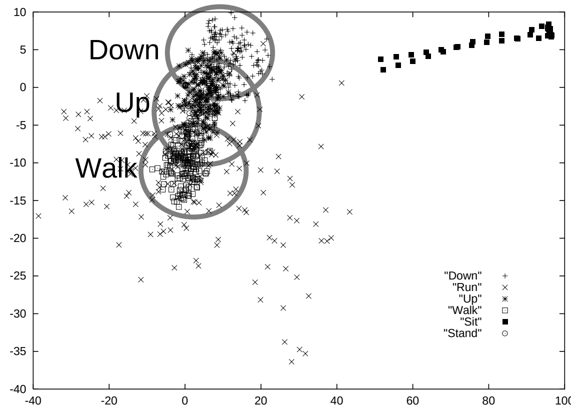

Figure 3. Integrated X vs Y for six activities

sors are the only active parts. The sensors are programmed by the main processor to power-up the main processor when an interesting situation arrives. In order to program the sensors, the main processor combines the requirements from the various application programs, and programs each sensor to send an event in a particular case [8].

We embed our accelerometer in this architecture so that the accelerometer sensor analyses the user's behaviour, and outputs the states 'Sitting', 'Walking', etc. For example, an application program could register an interest in the event that the users activity changes from Walking to Sitting. It would then wake up the main processor, and because the user is now be able to look at a screen, display relevant information.

3 Data Processing

We collect samples at a relatively low frequency (5 Hz; to aid in low power design), and from only two data sources - the X and Y axes of the accelerometer. From these samples we extract 4 features. These features can be calculated cheaply; they can work across a range of people; and are robust. We then use a clustering algorithm - a neural network - in order to infer what the user is doing.

In order to experiment with various features and clustering algorithms, we have first collected a ground-truth of 10 people performing various activities: **Walk**ing, **Run**ning, **Sit**ting, walking **Up**stairs, **Down**stairs, and **Stand**ing. We use this ground truth to train and evaluate our system.

3.1 Feature extraction

As can be expected some activities are easy to distinguish, however distinguishing between walking and walking upstairs is more difficult. We have studied various features that can be extracted from the sensor data cheaply. It turns out that extracting a total of 4 features from the 2 sensors is sufficient: the RMS and integrated values of both sensors over the last 2 seconds. We have determined that using this technique it is unnecessary to carry out any further analysis such as determining frequency components.

Figure 2 shows a scatter plot of 6 types of By plotting the RMS values we observe a lot of overlap between walking, and going up Figure 3 shows a scatter plot of the same activities, However by plotting the RMS values against the mean values there is again overlap, but

It is important to stress that the features discussed are person and clothing specific. The strength of these features is that for every person that we have data for, these four features allow the recognition of the user's activities. However, one person walking can give the same results as another person running. Repeated testing has also shown that different results are obtained with the same person wearing different clothing e.g.tight jeans or baggy chinos.

3.2 Neural Network Analysis

To determine the nature of the clusters, we use a neural network with 4 inputs and single layer of neurons. Outputs were taken for each activity we are interested in. Back-propagation was used to adjust the values of the network. using the transfer function between the output and the input medial layers:

$$z = 1/(1 + e^{-z})$$

This provided a simple arrangement which could be incorporated into the onHand PC, and later transferred to our 486 Linux based Cyberjacket.

We initially trained our network on a ground truth, and analysed the results after further person specific training. Our initial results shown that we can infer the user's activity with a high accuracy (85-90%). Verifying which 10-15% is "wrongly" classified, we observe that this is often

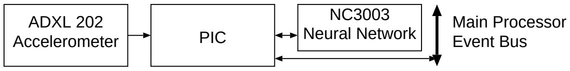

Figure 4. Final sensor design

the person going upstairs via a small landing. Landings are difficult to resolve: the real activity is walking, whereas it is labelled as going upstairs in our ground truth. A temporal filter can take those errors out, but this will make the system sluggish in its response. The actual accuracy of detecting peoples activities is around 95%; with a temporal filter we can increase that further.

3.3 Final implementation

In order to implement our sensor we propose to connect our accelerometer up to a small neural network chip [9] and a PIC. (Figure 4). We will trigger a measurement and calculation every 200ms, and the PIC will send an event over the event bus to the main processor if the activity has changed. The sensor

This sensor is programmed in two ways:

1. The main processor can order the sensor to train (given that the main processor has told the user to perform a certain activity).

2. The main processor can order the sensor to monitor the user's activity, and to only inform it when the activity changes for more than x seconds.

4 Application - the Well-Behaved Wearable

We have previously developed a Tourist Guide application for our Cyberjacket incorporating a CardPC; GPS receiver; hand held display and audio interface. Web pages and audio notes were rendered using this configuration dependent only on location. A drawback of this design was the untimely rendering of media information e.g.a distracting audio commentary being played while hurrying across a busy road.

As a first example of the potential use of a single accelerometer, we control the media rendering to ensure that the presentation of information is appropriate to the user's activity and consistent with the sensed event. For example, we do not wish to render any information if the user is running; we also know that if the user is not moving then an event triggered by a change in location cannot be generated. A simple set of rules can thus be formulated to form an etiquette for our wearable computer.

We thus designed our application to operate according to the users activity. Events signifying interesting locations with associated web pages and/or commentary can only be triggered while the user is walking. The commentary is played to alert the user to the place of interest, and the web page is only displayed once the user has stopped walking. The application is suspended when the user is running.

This arrangement improved our user interface and reduced the irritation factor caused by the untimely and inappropriate rendering of information. We are now considering the potential of developing a more complex set of rules which could be implemented with additional sensors such as microphones to determine when the user is speaking and/or being spoken to.

5 Results and Conclusions

We have demonstrated that with a single X-Y accelerometer we can distinguish various activities of the user, even very similar activities. We have experimented with many features, but stuck with two that can be calculated cheaply: RMS and integration of the last 2 seconds of measurements. We then use a clustering algorithm, a neural network, to infer the user's activity.

As an initial application we have added the activity sensor to our Tourist Guide in order to use the appropriate output mechanism i.e.be quiet when the user is running; enable events and only use audio when the user is walking; use graphics when the user is standing or sitting. We will incorporate walking up/downstairs when guiding the user around. This will give us vital clues as to where the user is going on a small scale, and giving them immediate feedback that they are going the wrong way.

We have thus shown that the use of context sensors to determine the user's activity can provide a valuable source of data which has the potential to improve the behaviour of wearable computers.

References

[1] C. Randell and H. Muller. Context awareness by analysing accelerometer data. http://www.cs.bris.ac.uk/Tools/Reports/techreport.html.

[2] R. Hull, P. Neaves, and J. Bedford-Roberts. Towards situated computing. In *Proceedings of The First International Symposium on Wearable Computers*, pages 146–153, October 1997.

[3] C. Randell and H. Muller. The shopping jacket: Wearable computing for the consumer. In *Proceedings of The Second International Symposium on Handheld and Ubiquitous Computing*, September 2000.

[4] A. Schmidt, H.W. Gellersen, and M. Beigl. A wearable context-awareness component. In *Proceedings of The*

Third International Symposium on Wearable Computers, pages 176–177, October 1999.

[5] J. Farringdon, A.J. Moore, N. Tilbury, J. Church, and P.D. Biemond. Wearable sensor badge & sensor jacket for context awareness. In *Proceedings of The Third International Symposium on Wearable Computers*, pages 107–113, October 1999.

[6] J.K. Perng, B. Fisher, S. Hollar, and K.S.J. Pister. Acceleration sensing glove. In *Proceedings of The Third International Symposium on Wearable Computers*, pages 178–179, October 1999.

[7] The TEA Consortium. Technology for enabling awareness. http://tea.starlab.net/.

[8] H. Muller and C. Randell. An event-driven sensor architecture for low power wearables. In *Workshop on Software Engineering for Wearable and Pervasive Computing*, June 2000.

[9] Neuricam. Nc3003 totem digital processor for neural networks – data sheet. http://www.neuricam.com/, December 1999.