Context Awareness via GSM Signal Strength Fluctuation ⋆

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Abstract. In this paper we demonstrate how a cell phone can infer contextual information such as mode of travel by monitoring the fluctuation of GSM signal strength levels and neighbouring cell information. We show that these signals are stable enough to reliably distinguish between various states of movement such as walking, travelling in a motor car and remaining still. We present preliminary results for a metropolitan environment.

1 Introduction

The ability for computer programs to provide behaviour reflective of the current context that they are being used in has long been a goal of the pervasive and ubiquitous research communities. In this paper we demonstrate how context-awareness may be achieved by using fluctuations in GSM signals and neighbouring cell information. We show that the behaviour of these signals is sufficiently stable to distinguish between walking, remaining still and travelling via a motor car.

On a cell phone this type of context knowledge enables behaviour such as diverting calls to an answer phone whilst travelling in a car or raising the volume of the ring tone when walking. Manalavan et al. [3] demonstrated that by informing the remote caller that a person was currently driving it was possible to mitigate the risk associated with driving and using a cell phone. The approach to sensing context presented in this paper will enable a low cost implementation of such applications.

There has been much research focusing on the ability to sense context in an unobtrusive manner [2, 4]. Other work demonstrated that by using signals from a 2D accelerometer it was possible to distinguish between various states of movement such as walking, climbing stairs and running [5]. The Sensay project [6] used three accelerometers to capture the motion of the user and a microphone was used to sense the level of ambient noise and adjust a the ring tone volume accordingly. Various strategies have been used to classify data, for example at MIThril [7], DeVaul et al combined a multi-component Gaussian mixture model

⋆ This research was funded by the UK Engineering and Physical Science Research Council, Equator Interdisciplinary Research Collaboration EPSRC GR/N15986/01 (http://www.equator.ac.uk).

Tom Pfeifer et al. (Eds.): Advances in Pervasive Computing 2006
Adjunct Proceedings of Pervasive 2006, Dublin, 7-10 May
books@OCG.at Vol. 207, ISBN 3-85403-207-2

with a Markov model to classify accelerometer signals [1]. Our approach differs from this work in that we do not require any additional hardware, and in particular no accelerometers, whilst being able to distinguish between states of activity such as walking, driving and remaining still.

The rest of this paper is structured as follows. Section 2 discusses the behaviour of GSM signals and presents an artificial neural network for classifying the GSM signals. Section 3 discusses preliminary results and provides an overview of future work.

2 Context Sensing

We aim to distinguish between different states of movement such as walking, running and remaining still using GSM cellular signal strength levels and neighbouring cell information. In Section 2.1 we discuss the behaviour of GSM signals. In Section 2.2 we present an artificial neural network for fusing GSM signals. In Section 2.3 we discuss the performance of the neural network.

2.1 Available Data

In order to provide support for roaming, GSM cell phones monitor six or seven neighbouring cells. This list of neighbouring cells will typically vary minimally when the cell phone is static. However, whilst moving the rate of change will be more apparent, particularly in metropolitan environments with a large number of cells. Hence a change to neighbouring cells and signal strength levels typically indicates a change to the position of the cell phone.

In order to assess this behaviour we collected GSM trace data from indoor and outdoor settings in metropolitan environments. Volunteers were equipped with Orange SPV C500 cell phones capable of monitoring the signal strength levels for the current serving cell and up to six neighbouring cells. When outdoors, GPS receivers were used to collect a ground truth for the samples. Samples were collected once per second.

Figure 1a shows the total signal strength fluctuation across all monitored cells during a rolling 15-second time period whilst walking, remaining still and travelling in a motor car. Figure 1b shows the number of distinct cells monitored. Figure 1a show it is relatively easy to distinguish between walking and remaining stationary by looking at signal strength fluctuation alone. However, at times, walking and travelling in a motor car share similar signal strength patterns. By comparing the fluctuation with the GPS traces we found that the drops between high spikes of fluctuation typically occurred whilst waiting at areas of traffic flow control or road junctions. Hence the graph reflects the stop-start nature of driving in metropolitan environments. Whilst travelling at constant but low speeds (sub 30mph) we found the signal strength fluctuation patterns to be similar to those obtained whilst walking. Again this is reflective of the current speed of travel. However this does not represent the current mode of travel.

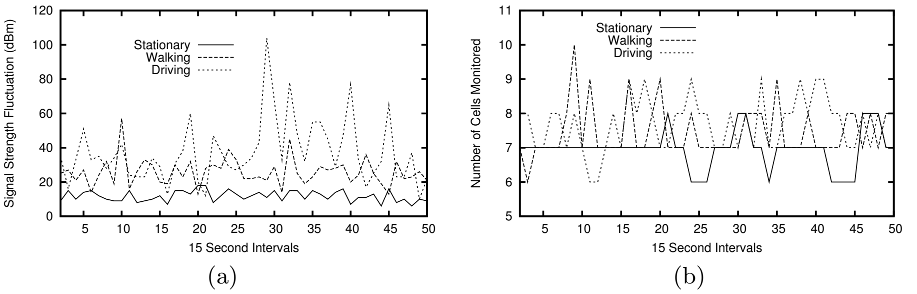

Fig. 1. (a) Signal Strength fluctuation when stationary, walking and travelling in a motor car. (b) The number of distinct cells monitored during the 15-second intervals.

In terms of changes to the neighbouring cells we once found that when stationary typically only six or seven distinct cells were seen. Typically more were seen when walking or driving and again both of these modes of travel shared similar patterns. We suspect that although a greater distance was covered in the motor car than when walking, both saw similar numbers of cells because of a hardware limitation on the cell phone and the need to avoid repeated changing of the neighbouring cells (thrashing). Hence moving at a slower speed through a metropolitan environment gives the cell phone more opportunity to detect and assess the suitability of neighbouring cells.

2.2 Initial Neural Network Implementation

In order to distinguish between different states of movement we use an artificial neural network. The network inputs are: *(i)* the sum of signal strength fluctuation across current serving and neighbouring cells and *(ii)* the number of distinct cells monitored over a given time interval. The network outputs the current mode of travel for the given input values. The network uses a single layer of eight hidden units. Weights are learnt using back propagation. The network was trained by repeatedly presenting data collected during each method of movement.

2.3 Preliminary Results

We have found that once trained the neural network performs well, able to distinguish between different modes of movement. Table 1a shows the confusion matrix for sensing the three tasks. A total of three hours trace data from each environment was used to evaluate performance. We used ten minutes of this data for training the neural network and the remainder for testing. It is quite clear that distinguishing between remaining stationary and other modes of travel produces good performance, only occasionally positioning the user as walking. Again when walking good performance levels were achieved. However travelling in a motor car resulted in placing the current mode of travel as predominantly

Table 1. Confusion Matrix. Each row is an activity performed; each column indicates what the interpretation was.

	Stationary	Walking	Driving
Stationary	90 %	10 %	0 %
Walking	15 %	79 %	6 %
Driving	11 %	54 %	36 %

(a) Without Task Knowledge

	Stationary	Walking	Driving
Stationary	96 %	4 %	0 %
Walking	3 %	91 %	6 %
Driving	5 %	15 %	80 %

(b) With Task Knowledge

walking. This was expected, the pattern of signal strength fluctuation whilst driving was erratic, periods of high fluctuation were found between periods of low fluctuation. These drops were similar to those found whilst walking and on occasion remaining stationary.

This is due to the neural network effectively outputting a speed of travel that has been mapped to a method of movement via the training data. Typically the greater the fluctuation in signal strength levels and changes to the neighbouring cells the greater the speed. However, whilst travelling in a motor car the speed of travel fluctuates between stationary (waiting at traffic lights), walking speed (traffic congestion), and normal (clear roads). This results in the network occasionally indicating other modes of travel. We are able to address this issue by refining the network to include additional information about the task being sensed. For example, we can remove changes to the mode of travel that occur for short periods of time by using the knowledge that a typical a car journey is not ended and a new one started in a 15-second time period. Hence short periods of low signal strength fluctuation can be ignored when placed between periods of high fluctuation.

The results of this task-based approach are shown in Table 1b. This shows that by complimenting the output of the neural network with information about the task to be sensed it is possible to accurately determine current mode of travel. This addresses the issues of placing the user in different modes of travel whilst travelling in a motor car. A performance increase is also gained when sensing walking and remaining stationary.

Initial experiments using the same trained neural network in other metropolitan environments have shown positive results. When testing in environments with different cellular network structures such as rural locations we found the network to need retraining. For example, signal strength fluctuation is not as apparent in rural areas hence using the same neural network for both metropolitan and rural areas may result in walking being detected as remaining stationary. This can be addressed by adjusting the sensitivity of the network in accordance with the current environment.

3 Conclusions and Future Work

In this paper we have demonstrated that by monitoring GSM signal strength levels and neighbouring cell information it is possible to distinguish between different modes of travel. We classify signal patterns using a neural network. An advantage of a neural network solution is that once trained, the network can be easily implemented on a cell phone and run in real time. As a proof of concept we have implemented the trained network on an Orange SPV C500 cell phone. Although not able to sense all gestures that can be distinguished with an accelerometer, this approach to *context sensing* requires no changes to existing hardware. On a cell phone this type of knowledge enables contextual behaviour such as extending the call alert vibration period when walking to avoid missing notifications between strides, or routing calls via a *hands free* system when travelling in a motor car.

We have shown that our strategy works using GSM (2G) networks, and we see no reason why it would not work on UMTS (3G). Hand-off, and hence monitoring cell strength is essential to any mobile network.

At present our system works well in built up areas but in rural areas the network requires retraining. We are currently working on passively sensing the class of environment; indoor or outdoor and rural or metropolitan. Initial experiments have shown that changes to the list of neighbouring cells can be used to infer the current type of environment. This would enable the same neural network to operate effectively in heterogeneous environments.

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