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Activity recognition with smartphone support

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ABSTRACT

In this paper, the authors describe a method of accurately detecting human activity using a smartphone accelerometer paired with a dedicated chest sensor. The design, implementation, testing and validation of a custom mobility classifier are also presented. Offline analysis was carried out to compare this custom classifier to *de-facto* machine learning algorithms, including C4.5, CART, SVM, Multi-Layer Perceptrons, and Naïve Bayes. A series of trials were carried out in Ireland, initially involving $N = 6$ individuals to test the feasibility of the system, before a final trial with $N = 24$ subjects took place in the Netherlands. The protocol used and analysis of 1165 min of recorded activities from these trials are described in detail in this paper. Analysis of collected data indicate that accelerometers placed in these locations, are capable of recognizing activities including sitting, standing, lying, walking, running and cycling with accuracies as high as 98%.

1. Introduction

Novel approaches to the ubiquitous identification of physical activity are beginning to emerge as a modern day necessity. Overwhelming evidence exists to suggest that physical inactivity can greatly increase the likelihood of several non-communicable diseases, including, coronary heart disease, type II diabetes and even particular forms of cancer. A recent Lancet publication [1] estimates that physical inactivity causes 9% of all premature deaths worldwide. This figure represents over 5.8 million deaths in 2008 alone. Furthermore, eradicating physical inactivity would increase life expectancy of the world's population by an average of 0.68 years.

This sentiment is echoed in publications by the U.S. Department of Health and Human Services, which found a strong correlation between increased physical activity and a lower risk of heart disease, stroke, high blood pressure, type II diabetes and even particular forms of cancer. Research conducted by Heidenreich et al. [2] and Dall et al. [3] documents the financial burden caused by such diseases. Heidenreich et al. found the total cost in 2010 of coronary heart disease among Americans to be $108.9 billion, while Dall et al. estimated the 2007 cost of Americans suffering type II diabetes to be in excess of $159 billion. Furthermore, the prevalence of cardiovascular disease and stroke is predicted to increase by an average of 20.75% among the American populous by 2030. A similar report by Leal et al. [4] places the 2003 total cost of coronary heart disease in the EU area at €44.7 billion ($56.5 billion, at 2003 rates[1]), which includes €294 million ($371 million, at 2003 rates[1]) for Ireland.

Thus, a compelling case exists to monitor physical activity, or the lack thereof, in a manner which strives to be unobtrusive, yet objective. Such a monitor can play a significant role in a shift towards user driven preventative healthcare. Traditionally, logging bouts of physical activity has proven tedious and cumbersome, with many individuals relying solely on biased self-report methods. Recently, several MEMs sensors have emerged as potential candidates in the determination of human activity, including the accelerometer.

In this paper we compare several activity recognition classifiers, including a custom built classifier with the goal of recognizing six key activities, using two accelerometers. The comparison was performed with data collected in trials from 30 volunteers.

2. Background

Numerous standalone devices already exist in the market which use a dedicated, embedded device, often strapped to the user,

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[1] European Central Bank – Statistical Data Warehouse, Historical €/$ Exchange Rate (Referencing value as of 31/12/2003). Available at: http://sdw.ecb.int/ [accessed 31.01.13].

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typically using belts or tape, e.g. the ActiGraph[2] or ActivPal[3] devices. Recently however, the feasibility of smartphones to the field of physical activity monitoring has become increasingly apparent.

Yang [5] attempted to use motion recognition from a phone's accelerometer for use in physical activity diary applications. Yang uses a Nokia N95 to sample the accelerometer at approximately 36 Hz, for activities including sitting, standing, walking, running, driving and cycling. The samples were then uploaded to a server for later annotation and post analysis. Yang used the WEKA learning toolkit to compare the accuracy rates of C4.5 Decision Trees, Naïve Bayes, k-Nearest Neighbour, and Support Vector Machines. The study found that vertical and horizontal features have greater impact on recognition rates than magnitude features alone. Using tenfold cross validation, this feature set coupled with the C4.5 algorithm achieved 90.6% accuracy.

Bieber et al. [6] used Sony Ericson phones including the w715 to recognize stand-up and sit-down transitions. Recognition rates of up to 90% were achieved, dependent on the type of clothing worn. However, Bieber did not test other activities of daily living outside of these stand-up and sit-down transitions.

Finally, studies have also focused on orientation independence of a monitoring device. Mizell [7] suggested that the orientation constraint associated with existing mobility devices could be relaxed somewhat. The author also proposed that tracking the magnitude and direction of the vertical component was sufficient for the majority of activity recognition. The magnitude contained in the horizontal component may also be calculated, but not the direction. Thiemjarus et al. [8] classified activities on a smartphone with the help of the mean gravity vector. Thiemjarus claims accuracies varying from 83% to 90%, although it is clear that difficulties were encountered when differentiating between lying and sitting activities. Results were validated against an earlier experiment where five subjects performed scripted activities.

Although standard classifiers often perform well in recognizing physical activity, the limited resources available on smartphones make training difficult. For this reason, the authors have also investigated the use of custom classifiers, which gives total control over the training phase.

3. Sensor setup

Both a Samsung Galaxy S GT-I9000 and a PLUX chest sensor were used to gather tri-axial accelerometer readings from the thigh and sternum respectively. The Galaxy S integrates Bosch's SMB 380 tri-axial, capacitive accelerometer, which consumes 290 μA while in use. This device largely fulfils the ubiquitous, unobtrusive sensing requirements desired by mobility monitoring applications.

For the purposes of this scripted trial, the smartphone was placed loosely in the participant's trouser pocket, and acceleration data stored on the SD card. The pocket chosen and initial orientation of the device were left entirely at the participant's discretion. The chest sensor was placed inside a chest strap which was then worn comfortably by the participant, which ensured device orientation remained fixed. It is highly likely that such a sensor will be embedded in clothing in the near future, as has been demonstrated in existing European FP7 projects, including eCAALYX [9]. A Bluetooth Serial Port Profile connection was created between the phone and the chest sensor. Thus, the phone acted as a data server, whereby raw sensor data from both sensors was collected for later preliminary processing and activity inference on the participant's smartphone. Typical sampling rates were in the range of 90–100 Hz for the phone, and 500 Hz for the chest sensor.

4. Signal processing

Initial data processing is undertaken on the smartphone itself, with the aim of synchronizing the raw acceleration signals from both phone and chest sensor. To this end, a common fixed sampling rate is defined a priori between the Android device and the dedicated PLUX chest sensor. Thus, data from the smartphone's accelerometer is interpolated in real time. Similarly, chest sensor data is downsampled from a fixed 500 Hz to 120 Hz. This interpolation and downsampling process facilitates subsequent signal processing, including low and bandpass filtering.

Once interpolation completes, the static component due to gravity is isolated from the dynamic components caused by movement. A cut off frequency of 0.7 Hz is chosen for the lowpass, while the range from 0.25 Hz to 10 Hz is chosen for the bandpass. Since raw accelerometer data from both devices are aligned to differing coordinate systems, a rotation to a world fixed coordinate system is carried out to facilitate further analysis and activity classification. The equation used for this rotation can be found in Eq. (1).

$$\begin{bmatrix} 1+(1-\cos(\varphi))\times(x^2-1) & -z\times\sin(\varphi)+(1-\cos(\varphi))\times x\times y & y\times\sin(\varphi)+(1-\cos(\varphi))\times x\times z \\ z\times\sin(\varphi)+(1+\cos(\varphi))\times x\times y & 1+(1-\cos(\varphi))\times(y\times y-1) & -x\times\sin(\varphi)+(1-\cos(\varphi))\times y\times z \\ -y\times\sin(\varphi)+(1-\cos(\varphi))\times x\times z & x\times\sin(\varphi)+(1-\cos(\varphi))\times y\times z & 1+(1-\cos(\varphi))\times(z\times z-1) \end{bmatrix} \tag{1}$$

where x, y and z denote a unit vector, and φ is the rotation angle required to rotate the y-axis of the device coordinate system, to the corresponding world fixed coordinate system.

An activity inference algorithm is then executed, which begins by computing features, including activity counts, the highest frequency found, and the angles of both devices to the vertical, gravitational axis. As the orientation of the phone can vary somewhat in a user's pocket, efforts are made to enhance angular measurements by tracking the mean gravity vector when participants begin walking. When participants transition from walking, it is inferred unconditionally that they are now standing, and a simple rotation may be required, to reflect the phone's new orientation. The algorithm waits for the presence of at least 15 s of walking, before updating the gravity vector with this data. Fifteen seconds was deemed appropriate, as this incorporates a number of gait cycles. A window of acceleration samples is logged until this bout of walking ceases. Enough information now exists to update the gravity vector. The algorithm crops 15% of samples from either side of the movement buffer before computing both the mean gravity vector and mean angle. This cropping was deemed appropriate to avoid overlaps with other activities, such as suddenly sitting down. Instantaneous angles are then updated to reflect this new mean angle, thus eliminating spurious angles generated during the prior feature generation phase.

The activity inference algorithm computes time domain based activity counts in one second windows. Signal decomposition in the frequency domain is also undertaken for the thigh every fifteen seconds. Frequency bands containing the highest energy are recorded for each of these intervals. Together, both activity counts

[2] ActiGraph – Activity Monitoring Devices. Available at: http://www.theactigraph.com/ [accessed 30.03.12].

[3] PAL Technologies Ltd – ActivPal. Available at: http://www.paltech.plus.com/products.htm [accessed 30.03.12].