The Role of Smartphones as an Assistive Aid in Mental Health

John J. Guiry[1], Lisanne Warmerdam[2], Patrick van der Hilst[2], Heleen Riper[2]
Pepijn van de Ven[1] and John Nelson[1]

[1] University of Limerick, Limerick, Ireland
[2] VU University, Amsterdam, The Netherlands

Abstract. Recent developments in wearable sensors and smartphone technology have demonstrated the applicability and viability of such devices to the successful and cost effective treatment of mental illness, particularly depression. This paper describes a software toolkit and physical activity algorithms developed at the University of Limerick that will be used to monitor and assist clinical professionals in analyzing physical activity and physiological data. The resulting information is used in the ICT4Depression project to deduce an individual's mental state, and progression through mental illness. Two trials were performed to assess the algorithms and the resulting data are discussed.

1 Introduction

Major depression is currently the fourth disorder worldwide in terms of disease burden, and is expected to be the disorder with the highest disease burden in high-income countries by 2030. Current treatment methods can reduce the burden of this disease by approximately one third [1]. ICT4Depression is an FP7 funded project that aims to reduce the disease burden significantly further. To this end the ICT4Depression consortium has set out to develop a system for the provision of online and mobile treatment of depression. Where current methods rely on direct contact with health care professionals or are Internet-based self-help therapies with a low level of interaction with the patient, the ICT4Depression system is a responsive system that allows the patient to receive a highly personalized and interactive treatment and work on their own progress anywhere and anytime.

Fig. 1 presents an overview of the ICT4Depression system. Central to the technology used is a smart phone, which is used to provide treatment to the user. This treatment consists of the provision of self-help modules, the gathering of sensor data (physiological sensors, activity sensors and various user ratings and questionnaires) and the measurement of medication adherence. This information is used in a decision support system to reason about the user's progression and to advise on further treatment if and when necessary. In addition to being able to interact with the system on the mobile phone, the user has access to a web interface which can be used to provide more extensive feedback to the system and to view information generated by the system on a larger screen.

J. Guiry J., Warmerdam L., van der Hilst P., Riper H., van de Ven P. and Nelson J..
The Role of Smartphones as an Assistive Aid in Mental Health.
DOI: 10.5220/0003885601050113
In *Proceedings of the 2nd International Workshop on Computing Paradigms for Mental Health* (MindCare-2012), pages 105-113
ISBN: 978-989-8425-92-8

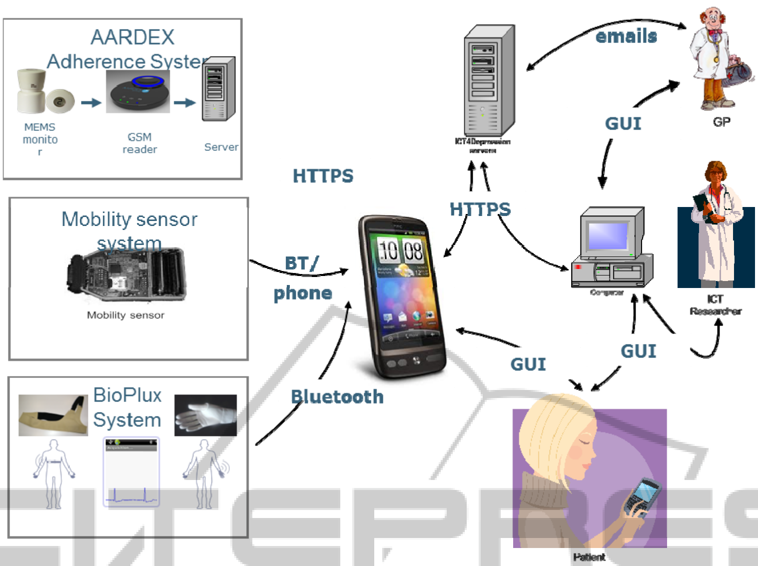

Fig. 1. Overview of the ICT4Depression System.

Sensor information plays an important role in the system as it is used in an innovative way to assess the user's treatment progression. To this end, heart rate (and variability), breathing rate and trunk acceleration are measured with a chest strap. A glove type sensor is used to measure skin conductance and blood volume pulse with the data analysed for emotive triggers. Using acceleration sensors on the mobile phone the user's physical activity is recorded. The latter plays an important role as exercise and depression are intricately linked. Various scientific studies have shown the important role physical activity plays in depression and it is widely known that depression tends to result in lower patterns of physical activity. From this perspective, it is interesting to measure the levels of physical activity for patient's diagnosed with depression to obtain an insight in the disease progression. However, it has also been shown that the reverse is true and that a regime of increased physical activity can be used to reduce the severity of the depression [2]. Several reasons for the positive effect of physical activity on mood and depression have been suggested. First, exercise may act as a diversion from negative thoughts. Second, the mastery of a new skill may be important. Third, social contacts during the activity may act as a working mechanism. And fourth, physical activity may have physiological effects such as changes in endorphin and monoamine levels, or reduction in the levels of the stress hormone cortisol which all may improve mood. Exercise has been found to be effective in the treatment of depression in more than 20 randomized controlled trials [3]. Moreover, Blumenthal reported in 1999 that 16 weeks of group exercise training was as effective as antidepressant treatment with sertraline and that the 10-month relapse rate for the group that performed exercise was 8% whereas this same rate was at 38% for the group treated with Sertraline [4].

In the ICT4Depression system exercise is recognized as a treatment in itself which is normally conducted in parallel to other treatments. This paper discusses how smart phone based sensors are used in the ICT4Depression project for the identification and monitoring of user physical activities (measured as periods spent lying, sitting, standing, walking, running, cycling and energy expenditure).

2 Physical Activity Monitoring

Physical activity monitoring using accelerometers is a well-established art which has seen a large interest from the research community in the last 20 years. Whereas research has long focused on the use of dedicated sensors rigidly attached to the user's body, recent efforts have focused on use of the accelerometers available on most modern mobile phones. Due to the high uncertainty as to the exact location and orientation of the device in a realistic setting, physical activity monitoring on mobile phones poses significant challenges. Accelerometers measure acceleration from two sources: the output signal contains both acceleration resulting from user movement and acceleration due to gravitational forces. If the orientation of the device is not known *a priori*, as is the case for a mobile phone, it is difficult to separate the two contributions to the acceleration output signal. For this reason early endeavours with mobile phones focused on step count and energy expenditure measurements [5] as both measures have the advantage that the orientation of the measurement device need not be known. Recent developments in this area of research go a step further and show promising results for sensors which can be attached to the user's body with more freedom whilst still being able to identify various physical activities [6,7]. The methods used, typically do not explicitly separate gravitational and movement components from the acceleration data. As a result, the wealth of existing algorithms cannot be re-used. The work on mobility monitors described in this paper builds on the results found in the literature, but explicitly attempts to obtain the direction of gravity in device-fixed coordinates, such that a rotation of the measured accelerations (in device-fixed coordinates) can be performed to world-fixed coordinates (with the gravity vector pointing straight down). Where this can be done with sufficient accuracy, existing algorithms can be employed to then obtain accurate insight in specific user activities.

2.1 The PA Monitor

The PA monitor was developed and tested on a Samsung Galaxy S GT-I9000 which integrates Bosch's SMB 380 TA accelerometer. This digital accelerometer falls into the differential capacitive line, whereby a change in capacitance can be mapped to changes in acceleration, and consumes 290μA while in use. The Samsung uses a 1500mAh battery, with which a mobility monitoring application will run for approximately 6 hours. Output RMS noise from the accelerometer is in the order of $0.5\mathrm{mg}/\sqrt{\mathrm{Hz}}$. Android does not allow developers to specify the sampling rate explicitly. Instead, suggestions are made to the Android platform, such as DELAY_NORMAL, DELAY_UI or DELAY_FASTEST. These determine the priority with which the accelerometer readings are processed but do not guarantee a fixed sampling rate. Using the DELAY_FASTEST attribute on the Samsung provides applications with samples at approximately 90Hz.

2.2 Data Processing

As the sampling frequency of the accelerometer is not constant, raw acceleration data from the phone are first interpolated. A lightweight linear interpolator is used to facilitate any real time requirements. Interpolation facilitates processing further down the chain, since the quantity of samples in the incoming stream becomes fixed, at 120Hz in this case. For the case of linear interpolation, let: $x = \{x_{m+1}, x_{m+2},\ldots x_{n-1}\}$ be the vector of missing data points bounded either side by the known points (x_m, y_m) and (x_n, y_n) where n>m. The n-m-1 missing data points can be found using linear interpolation between the two known points:

$$\forall i \in \langle m, n\rangle \quad y_i = y_m + \frac{y_n - y_m}{x_n - x_m}(x_i - x_m) \tag{1}$$

Next, the interpolated stream is median filtered with a 3-point median filter to eliminate any sporadic spikes in the signal. This median filtered stream is then used to fragment the acceleration signal in two using both band pass and low pass filters to give estimated vectors for the dynamic and static (gravitational) components respectively. The static and dynamic acceleration components are then fed into a physical activity state machine algorithm to derive user physical activity.

2.3 Activity Inference

Firstly, the incoming sample stream is converted to a world fixed coordinate system to overcome variations in the input signal due to changes in the phone's orientation. The transformed stream is given by: $a_{wf} = a_{df}\,R$, where R is the rotation matrix which is derived from the static component of the acceleration signal, and is defined by:

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

Once world-fixed accelerations are available, traditional physical activity algorithms can be used. The first step undertaken to achieve activity recognition involves selecting a heuristic feature set. The features chosen to distinguish between high and low energy activities are one-dimensional counts per minute (CPM) and the coefficient of variation (CV) [8], which give an indication of the energy contained in the acceleration signal and the variation in the latter respectively. Formulae for these can be found in equation 2 and 3.

$$\mathrm{CPM(k)} = \sum_{i=0}^{N-1} \frac{|a_z(k+i)|}{N} \tag{2}$$

$$\mathrm{CV(k)} = \frac{\text{Standard Dev}(|a_z(k{:}\,k+N-1)|)}{|\text{mean}(a_z(k{:}\,k+N-1))|} \tag{3}$$

where $\mathbf{a_z}$ is the component of the acceleration pointing straight down and N is the number of samples collected in a 1 minute window starting at time k.

Whereas the CPM is per definition high for high energy activities, the CV is relatively low in these cases. CV tends to be high for sedentary activities as small movements results in the CV increasing significantly. Hence these features are ideal candidates for the classification of high energy versus sedentary activities. Moreover, these features are used to distinguish between varying high energy activities, such as walking, running and cycling.

Further classification of sedentary activities is performed based on the static component of the acceleration signal which indicates the orientation of the device. This information is only useful if one also knows the orientation of the device relative to the orientation of the user. This information is obtained whilst the user is performing dynamic activities (for which activity the orientation of the user's body is relatively well known) and updated regularly to account for the changing orientation of the phone as it is being used by its owner.

3 Trials Performed

Two separate trials were conducted to assess the performance of the PA monitor. In initial short technical trials the performance of the physical activity algorithms were assessed and trial results were used to fine-tune the algorithms. At present these algorithms are being employed in a larger study which also assesses the mood of the user.

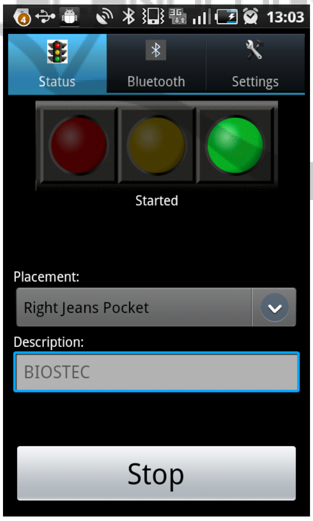

Fig. 2. GUI used for trials in Limerick.

The first trial took part in the University of Limerick, Ireland and entailed the monitoring of prescribed activities organized in a protocol lasting around half an hour. Six healthy individuals (5 males, 1 female) went through a range of activities which can be found in Table 1. The combined mean age of all participants was 30.6 years.

Activities recorded included: sitting, standing, walking at the subject's comfortable pace on a corridor, cycling on an indoor bike, treadmill walking at 5km/h & 6km/h, jogging at 8km/h, and finally running on a treadmill at 9.6km/h. A total of 327 minutes of data were collected using three Samsung Galaxy S phones per subject, which included a central controller, and two clients. Each subject was asked to place a phone in their right and left pants pockets. Both phones were controlled remotely via Bluetooth by the central controller. This program could issue commands to the client PA monitors including facilitating a synchronization request between devices. For example, if the individual performs an activity beyond the scope of the trial, the observer could issue a synch request when the subject started the next scripted activity. Both smartphones placed in the subject's pockets, sent real-time activity information back to the controller. Using Matlab, the data was labeled for each activity performed and processed to obtain a confusion matrix showing the rates of correct and incorrect classification. In case of an incorrect classification, the confusion matrix also indicates which activity was incorrectly inferred by the PA monitor. The obtained confusion matrix, which is depicted in Table 1, shows that correct classification rates lie between 82% and 91% for all activities other than sitting. Sitting is misclassified as lying as for both activities the phone (which is in the pants' pocket) is in the exact same orientation. This shortcoming can be overcome by also measuring trunk orientation which is measured by the aforementioned sensor for heart rate and breathing rate. Although this feature was beyond the scope of the described trials, use will be made of the trunk orientation in the final ICT4Depression system. The reader should also note that all rows sum to a likelihood of 1, apart from the row describing the Stand activity. This is due to the fact that the algorithms use an extra 'Transition' stage which indicates that the state machine is in between two of the listed activities. This only affects the Stand activity and occurred in 9% of the time.

Table 1. Confusion Matrix.

	Lie	Sit	Stand	Walk	Run	Cycle
Lie	N/A	N/A	N/A	N/A	N/A	N/A
Sit	1	0	0	0	0	0
Stand	0	0	.91	0	0	0
Walk	0	0	0	0.86	0.14	0
Run	0	0	0	0.13	0.85	0.02
Cycle	0	0	0	0.01	0.17	0.82

Further trials are currently underway at the VU University, Amsterdam, The Netherlands. The goal of this study was testing the feasibility of wearing the devices (mobile phone plus aforementioned chest strap and wrist strap) for prolonged period of time and the ability to reliably detect the ongoing activity (specifically posture and physical activity) from the sensors. In this study a larger cohort of volunteers are subjected to an hour of scripted activities and consecutively to 23 hours of unscripted activities. Thirty healthy volunteers were recruited for this study, aged 18-25. The scripted activities consist of sitting, standing, lying, walking, cycling and tone avoidance activities (see Figure 3). The tone avoidance task is an experiment in which the user has to react to a visual stimulation by pressing a button as fast as possible. The visual stimulation is presented as a square on a computer screen that can appear in all four corners. The user has to react by pushing a button corresponding with the opposite corner. By doing this in time, the user prevents a loud noise from sounding. This test was used to induce a stress situation in the user, which was measured through the use of heart rate, breathing rate and skin conductance sensors. However, this part of the trial falls outside the scope of this paper. Subjects engage in the scripted activities under supervision of the experimenter. They subsequently perform 23 hours of daily activities without further instructions. Subjects will be monitored during this time. During this unsupervised period, an iPod will be used by the subjects to fill out a self-report every 30 minutes. They rate how they felt, what they did, where they were and with who and how much time (in %) they spent on lying, sitting, standing, walking and biking.

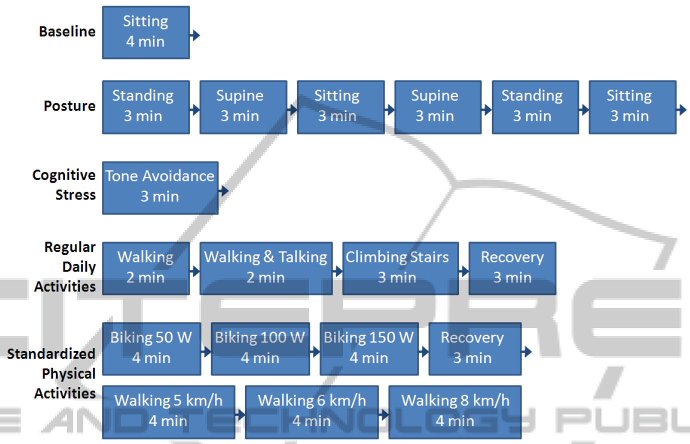

Fig. 3. Overview of elements assessed during the trials at the VU University.

Data analysis for these trials so far has focused on the physical activity aspects performed as part of the ‘Regular Daily Activities’ and the ‘Standardized Physical Activities’ as defined in Figure 3. This yields incomplete yet modestly encouraging confusion matrices as depicted below in Table 2 and Table 3. Note that ‘Climbing Stairs’ is not currently identified as a separate category in the physical activity algorithms and that ‘Recovery’ is a period of sitting.

Table 2. Confusion Matrix for User 03.

	Lie	Sit	Stand	Walk	Cycle
Sit	0.46	0.47	0.06	0.01	0
Walk	0	0	0.01	0.98	0.01
Cycle	0	0	0	0.66	0.34

Table 3. Confusion Matrix for User 04.

	Lie	Sit	Stand	Walk	Cycle
Sit	1	0	0	0	0
Walk	0	0	0	0.98	0.02
Cycle	0	0	0	0.15	0.85

The results in above tables show that the difference between static (lying, sitting, standing) and dynamic activities (walking, cycling) is accurately identified by the algorithms. For user 03, the sitting activity is often confused with standing and lying due to the fact that this particular sitting activity was a Recovery activity which took place while the participant sat on an exercise bike. As the physical activity algorithms assume that both upper legs are horizontal, the sitting activity on the exercise bike is not identified correctly. The identification of the cycling activity for user 03 shows that further features may be needed to identify the difference between walking and cycling accurately.

For user 04 results show good identification rates. Although sitting and lying are confused 100% of the time, the trunk orientation of the user would give a potentially perfect feature to correctly identify sitting. The identification of static versus dynamic activities is 100% for this participant and the correct identification of walking and cycling 98% and 85% respectively. Similar to user 03, the correct identification of cycling is still rather low whereas the correct identification of walking is similar at 98%, which suggests that the algorithms could be improved by fine-tuning the identification of cycling. As data analysis of these trials is ongoing, more extensive results, also including the other activities performed during the trial, will be published in a subsequent paper.

4 Conclusions

This paper outlines the use of mobile phones in the treatment of depression as a means of communication with the user, presentation of the treatment modules, sensor data gatherer and physical activity monitor in its own right. The focus of this paper was on the latter and two physical activity monitoring trials performed as part of the ICT4Depression project are described. The inherent challenge in measuring physical activity with a sensor whose orientation is not known, is addressed through a data transformation from device-fixed coordinates to world-fixed coordinates through the use of an approximated gravity vector. The world-fixed acceleration signal is then used to apply thresholding based algorithms to the identification of various activities. Preliminary results show that the phone can lead to a reasonable estimate of user activity although it is also clear that further work is needed to obtain accuracies similar to these obtained with traditional sensors.

References

1. Andrews et al: Utilising survey data to inform public policy: comparison of the cost-effectiveness of treatment of ten mental disorders. British Journal of Psychiatry, (2004) 184, 526-33
2. Ströhle, A.: Physical activity, exercise, depression and anxiety disorders, J Neural Transm, (2009) Vol. 116, pp. 777–784.
3. Blumenthal J. A., Babyak M. A., Moore K. A. et al.: Effects of exercise training on patients with major depression. Arch Int Med (1999) 159:2349–2356.
4. Maed et al.: Exercise for depression, Cochrane Database of Systematic Reviews ,(2008), Issue 4. Art. No.: CD004366. DOI:10.1002/14651858.CD004366.pub3.
5. Manohar, C., Mc Crady, S., Fujiki, Y., Pavlidis, I. and Levine, J.: Laboratory evaluation of the accuracy of a triaxial accelerometer embedded into a cell phone platform for measuring physical activity. 2010 Experimental Biology meeting (2010)
6. Bieber, G., Voskamp, J., and Urban, B.: Activity Recognition for Everyday Life on Mobile Phones. UAHCI '09 Proceedings of the 5th International Conference on Universal Access

in Human-Computer Interaction. Part II: Intelligent and Ubiquitous Interaction Environments. (2009)

7. Bieber, G., Koldrack, P., Sablowski, C., Peter, C., Urban, B.: Mobile physical activity recognition of Stand-Up and Sit-Down Transitions for User Behavior Analysis. Petra (2010).
8. Crouter, S. E, Clowers, K. G., Basset, D. R.: A novel method for using accelerometer data to predict energy expenditure. J. Appl Physiol (2006) 100: 1324-1331