Experimental Analysis of Cost-Effective Mobile Sensing Technologies for Activity Analytics in Elderly Care

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Abstract – The advances in sensor technology over recent years has provided new ways for researchers to monitor the elderly in uncontrolled environments. Sensors have become smaller, cheaper and can be worn on the body, potentially creating a network of sensors. Smart phones are also more common in the average household and can also provide some behavioural analysis due to the built in sensors. As a result of this, researchers are able to monitor behaviours in a more natural setting, which can lead to more useful data. This is important for those that may be suffering from mental illness as it allows for continuous, non-invasive monitoring in order to diagnose symptoms from different behaviours. However there are various challenges that need to be addressed ranging from issues with sensors to the involvement of human factors. It is vital that these challenges are taken into consideration along with the major behavioural symptoms that can appear in an Elderly Person. For a person suffering with Dementia, the application of sensor technologies can improve the quality of life of the person and also monitor the progress of the disease through behavioural analysis. This paper will consider the behaviours that can be associated with dementia and how these behaviours can be monitored through sensor technology. We will also provide an insight into some sensors and algorithms gathered through survey in order to provide advantages and disadvantages of these technologies as well as to present any challenges that may face future research.

***Index Terms* — Internet of things, healthcare, behaviour analytics**

I. INTRODUCTION

To begin to understand Dementia and the related behavioural symptoms, we must first understand the disease. Currently it is estimated that 1 in 5 people over the age of 65 will develop Dementia. At present it is estimated that there are more than 850,000 people living with some form of the disease [1]. There are two major symptom groups of Dementia: symptoms of behavioural and psychological signs as well as symtpoms of cognitive dysfunction [2]. The symptoms of Dementia that contribute to the behavioural changes in a person are physical movement and speech. An example of a behavioural change caused by Dementia is increased agitiation in a person [3]. Communication challenges can arise in a person suffering with Dementia as speech can be affected. Maintaining effective communication allows for the increase in the quality of life for a person as sufferers of Dementia can struggle to find appropraite vocabulary. Difficulties with speech and communication can cause depression and anxiety as well as other behavioural symtpoms of Dementia [4].

Alternative behavioural symtpoms of Dementia include sleep distrubances, withdrawal and apathy. Symtpoms of Dementia can also vary between individual people in repeated occurances. There can also be clusters of behavioural symptoms that occur which complicates the process of characterizing symptoms [3]. In certain situations, clinical applications monitor a persons behaviour through direct observation. However, these applications only determine if a symptom is present or absent, few applications consider the behavioural symtpoms insensity when it is present [3].

Typically, in order the improve the quality of life of a person who suffers with Dementia, direct observations of real life settings and behaviour change principles are used. At present, there are various theoretical and computational frameworks that are used in critial care and hospitall environments by modelling various Dementia bevahioural excesses (wandering, disruptive vocalisations), behaviour deficits (inontinence, self-feeding) and also mood changes (depression, anxiety) [5]. However, these frameworks require large-scale ambient sensing systems to be deployed. These are expensive to implement and are therefore only viable in hositpal environments.

Over the past decade, the use of pervasive healthcare applications ahs become commonplace [6]. Many of these applications take advantage of the recent techological advancments in mobile and wearable technoligies. The device manufacturers are costnatly adding improvments and new innovations to these devices, giving us additional proccessing power, storage and also adding new sensors into these devices. Pervasive healthcare applications devoleoped to use these devices can provide assistance to those suffering with disabilties such as communication issues. They can also be used to monitor behaviour of a person and detect anomalies. In Dementias case, it differs from other diseases as the carer can also benefit from the use of applications on smart devices. These applications can function in an assistive manner, providing prompts to the user, alerting them to take medicine. Human computer interaction is also another role the applications can take on, allowing the sensors in the device to monitor cogntivie decline or behaviour. Monitoring the activies of a person, such as sitting down or drinknig some water, can be essential for the evaluation of the progression of Dementia for individual people.

Over the last few years, the advancments in Internet of Things (IoT) related technologies has provided various opportunities to build Quality of Life (QoL) profiles for individuals with a higher valdity and reliability [7]. We have been able to do this by monitoring lifelogging data that has been captured by various IoT technologies (sensors, mobile apps, web-objects etc) with a constant connection and interaction in a pervasive network. Currently, persons with long-term conditions and chronic diseases require an intense interaction in a hospital environment with a clinician. These interactions can be time consuming and the results of the assessment may be subjective. As a result of this, the cost to the hospital is higher and therefore not sustainable [8]. By employing IoT technologies for home-based Dementia care, we can achieve improved accuracy in monitoring and deep analysis of Dementia related behaviour such as: gradual loss of memory, difficulty in performing familiar or complex tasks, changes in mood and disorientation. By using IoT technologies, we can also consider sensitivity, social and emotional factors that will help when worknig with various persons at different stages of the disease.

At present there isn't a great deal of evidence-based literature for guiding strategy implementations in order to ensure an early diagnosis or to design optimal services for people that suffer with the disease. The aim of this paper is to highlight the experiment protocol that will be used for future experimentation on those with mild cognitive impairment and to discuss the results obtained through healthy participants.

The remainder of this paper is structured as follows: Section II is focused on the current research in the field, Section III is the discussion of the experiment and the results, Section IV is focused on future research followed by the conclusion in Section V.

II. CURRENT RESEARCH

In the literautre, various sensors and how they have been used to detect behaviour were looked at extensively as [9] displays. The behaviours associated with Demenria as well as the related symtpoms are classified under 6 neuropsychiatric symptoms [10]: 1) Anomalous Motor Behaviour, 2) Depression, 3) Anxiety, 4) Weight Loss, 5) Irritability, 6) Agitation. Through the use of wearable technology it is possible to monitor these symptoms. Our research focused on Anomalous Motor Behaviour (AMB), Depression and Anxiety.

A. Anomalous Motor Behaviour

AMB refers to behaviours that are displayed through a persons movements. These can include location-based behaviours such as wandering which is monitored by using GPS as well as falling which can be monitored through fall detectors and accelerometers. AMB is monitored through a range of sensor technolgoies from non-medical grade sensors to blind video monitoring [10].

Over the last few years wearable trackers have been created to monitor a persons phsyical activity. Devices such as the FitBit and Nike+ Fuelband are gaining public attention due to their ability to record exercises, heart rate and calories burnt [11]. Lifelogging physical activity data is typically more difficult to manage. Methods typically require the use of machine learning algorithms and sesnors to analyse the physical activity, the patterns in the movement and the intensity of them. However these methods require the use of raw data to analyse human behaviour [12], [13]. To maintain a high accuracy when logging phyisical activity data, body sensors may have to be worn. However in real environments, these may not the the cost-effect solution [14].

An accelerometer-based approach was proposed by Aguiar [15] for fall detection using smart phones. The paper discusses the neccesity to monitor falls in the elderly as 40% of all mortalities in the elderly are caused by falls. Previous fallers also have a two-thirds chance of falling again within the next year. Kim [16] proposes a method using tri-axis acceleration sensors to the behaviour of the eldy by tracking their daily activities. Physical activities were categorised into low and high levels. Low level refers to movements such as walking, running and lying. High-level activities are typically predicted using time and place, sleeping being an example.

A fall detection system for andiroid smart phones is proposed by Yavuz [17] that includes different algorithms and accelerometers in the device in order to create the fall detection system. A 1-D Fourier frequency has been suggested as insufficient for detecting falls using accelerometer signals. An alternative method using wavelet transformation is proposed as thus allows for temporal localization of frequency components.

Solutions for fall detection can sometimes have disadvantages as display with the "Social Alarm" [18] as this requires the user to press a button after a fall. A popular solution for fall detection, is to wear a fall detector that is based on accelerometers and tilt sensors. This would have to be worn constantly, especially in places such as showers which has the highest risk of a fall. Video based techniques rely on image processing of a persons movement in real-time in order to analyse [18]. Video based techniques present challenges as monitoring and entire house present challenges and can raise privacy concerns. Another example shown in [10] uses video capture to detect changes in body mass in order to help ensure that elderly people have had sufficient nutrition in their diet.

B. Anxiety

An application to detect anxiety through wearable sensors is proposed by Miranda [19]. Three devices are used to monitor the heart rate and spontaneous blink rate. An algorithm coded in Java and based on the approach by Ishimaru [20] was used in their custom application, with some modifications. Readings from sensors were tracket in order to detect when the data produces a peak value in the event of a blink.

Body sensor networks for continuous longitudinal agitation assessment is proposed by Bankole [21]. Eight wireless interial body sensors were to gather the data from persons while they perform typical daily activities. The various motion capture abilities provided by the sensor network allow for six degrees of freedom, sensing frequencys with a resolution of 12-bits. The allows for a higher resolution when analysing a persons' movements and potentially a higher precision in the assesments of agitation. It is essential to for us to be able to notice the differecne between normal movements and agitated movements.

The stress a person suffers during a job interview was studied by Lu [22]. Three tasks were created with the assistance of behavioural psychologists. The persons voice is assumed to be under stress once a stressor is present and neutral when one is not as with SUSAS (Speech under Simulated and Actual Stress) and other previously performed studies [23]–[25]. Audio was collected using a Google Nexus One Android smartphone and a microconel microphone array. Video data is collected by recording the interviewee and interviewer.

C. Depression

Each participant was given an Android smartphone in the study by Gruenerbl [26]. The smartphone ran a logging application developed by their group. This application contained a data logger that used a standard Android API, which the participant had the option to disable. The application also used a self-assessment questionnaire which would display at the end of the day. After the questionnaire the participant would be asked if they were comfortable with the days data being logged, which would then be stored on an external SD card for periodic examination.

MoodTraces, an Android application which samples phone sensors to retrieve the users location was used in the study by Canzian [27]. Additional information about the phones usages and user activities are also collected, however they are not analysed in this work. The activity information collected is used to help ensure the sampling process is efficient. Daily questionnaires are also collected from users in addition the the sensor-based data.

Mobilyze was used by Burns [28] which is an 8 week multimodal intervention for depression. This included sensing using mobile phones combined with ecological momentary intervention, an intervention website for training in behavioural skills and email and telephone support from various coaches that had been assigned to participants. The system uses sensors that are housed in the mobile phone to perform observations of participants and their environment. It also used an algorithm to learn from the relationship between sensor data and particiapnts recorded activities.

Depression can also be detected throguh the use of sleep monitoring applications [29]. The most accurate devices for this are Polysomnography devices, however these have a significant price tag as well as a requirment to have profressionals monitor the data. Tri-axial accelerometers were used to send the data wirelessly to be processed using a laptop. The advtange to using this approach is that sensors will still monitor the person even if they have been knocked out of place. The true orientation of the accelerometer also does not have to be determined in order to function.

III. EXPERIMENT

The experiment will focus on a series of physical movements and activities performed by the participant as well as some physical factors, for example heart rate. These various physical tests will be monitored using a series of shimmer devices in order to collect the relevant data. Shimmer devices contain accelerometers and ECG which will be used for this study. Healthy controls under the age of 65, with no sign of mild cognitive impairment were used in this study. Activities performed by participants are split into three categories: Physical Activity, Physical Movement and Physical Factors.

The various activities will be performed over a duration of 20 seconds, 40 seconds and a minute. This is to allow us to decide what length of time is appropriate to gather sufficient data that will produce measurable results. Activities and movement may have to be repeated multiple times during the allocated time. The objective is to look at the peaks as well as the minimum and maximum points in the data to determine changes in behaviour. Shimmer devices will be attached to the body on the wrist, the waist, the ankle using straps that come with the device. An ECG will also be set up to monitor heart rate.

Physical Activity

Picking Up Object – This activity will involve picking up a relatively small object such as a pen, or a piece of fruit, or a bowl off a table or counter and then placing the object back down.

Bending over to pick up an object – This activity will involve the participant bending/kneeling down to pick up a box off the floor, standing upright, then bending back down to place the object back on the floor and finally standing upright again.

Opening and Closing a door/cupboard – The participant will use either their left or right hand to open and close a door.

Sitting down – Participant will sit down in a chair.

Standing Up from sitting down – Participant will stand up from the sitting down position.

Lying down – Participant will lie down on a bed/sofa.

Standing Up from Lying Down – Participant will stand up from the lying down position.

Taking a Drink of Water – Participant will use their left or right hand to take a glass of water and drinking it.

Walking – Participant will perform a small walk up and down a room.

Walking Upstairs – Participant will walk up and down a staircase.

<u>*Physical Movement*</u>

Waving – Participant will perform a waving motion using their right hand.

Hand Shake – Participant will perform a hand shaking motion using the right hand.

<u>*Physical Factor*</u>

Heart Rate – Participants heart rate will be monitored using an ECG.

<u>*Data Collection*</u>

Data collection will be performed using an ECG in order to check for fluctuations in heart rate and the shimmer device, as this can monitor movement using its accelerometer. Three devices will be used which will be placed in key locations on the body.

Wrist Accelerometers – An accelerometer will be attached to the wrist to monitor the movements during activities such as "Picking Up and Object".

Waist Accelerometers – An accelerometer will be attached to the waist in order to monitor movements that involve bending down or lying down.

Ankle Accelerometers – An accelerometer on the ankle will be used to monitor the participants walking.

Heart Rate Monitors – A heart rate monitor will be attached to the body in order to see if elevated heart rates arise during stressful situations, and to compare it with and features that are selected from data from other devices that may indicate anxiety or depression.

The shimmer devices connect to a Samsung Galaxy S6 using bluetooth. They are controlled using Multi Shimmer Sync Evaluation for Android. This applicatin allows for the streaming and logging of data from multiple connect devices. Each shimmer device connect to the application can be configured such as modifying the sampling rate.

IV. FUTURE WORK

V. CONCLUSION

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