A multi-sensor monitoring system for objective mental health management in resource constrained environments

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Abstract

Neuropsychiatric conditions account for one third of years lost to disability among adults worldwide and in the United Kingdom account for almost half of all health issues for people under the age of 65. At the same time, mental health budgets (especially in low- and middle-income countries) are increasingly stretched denying care to those that need it. The WHO predicts that unipolar depressive disorders will become the leading cause of disabilities worldwide by 2030. This paper describes a smartphone-based system that allows remote real-time monitoring of psychiatric patient symptoms, behaviour and physiology to enable allocation of psychiatric resources most efficiently. We present preliminary results from an ongoing study of over 100 participants showing qualitative differences between healthy controls and pathological subjects.

1   Introduction

This article describes an open source[1] smartphone-based system that allows remote real-time monitoring of psychiatric patient symptoms, behaviour and physiology to enable allocation of psychiatric resources as well as patient self-monitoring.

The World Health Organization (WHO) reports that neuropsychiatric conditions account for around one third of years lost to disability among adults aged over 15 years [1]. In the United Kingdom it is estimated that mental health issues account for almost half of all health issues for people under the age of 65 with a 17% prevalence, most cases being depression or anxiety disorders [2]. Similar statistics are seen in absenteeism from work [3, 4] and proportion of incapacity benefit claimants where over 70% are for mental and behavioural disorders [5].

The UK National Health Service (NHS) spends over £12bn annually on mental health services, but this still represents only 13% of the total NHS budget [2]. With budgets still being cut since the recession this relatively small amount is being increasingly stretched. In this setting, it is crucial to be able to allocate the available resources appropriately so that the patients receive the care that they require.

Mental illness also has an indirect effect on life-expectancy for sufferers with a similar effect to smoking and more than obesity [2]. Mental health conditions often co-occur with chronic medical conditions and if not effectively treated can lead to even higher health care costs [6]. The indirect costs can be much higher still including social care, education, housing and criminal justice [4, 7]. There is also an inverse correlation between education and common mental disorders [8] and some evidence for an inverse correlation with income [2].

Mental health is an area of healthcare that still largely relies on traditional and subjective methods of diagnosis performed using checklist type criteria [6] often based on the Diagnostic and Statistical Manual of Mental Disorders (DSM). Mental health professionals are acutely aware that new objective tools are needed to assist their assessment protocols.

Mental health is often considered within the context of high-income countries, but there is increasing awareness of mental health as a major burden globally in low- and middle-income countries. The WHO predicts that unipolar depressive disorders will become the leading cause of disabilities worldwide by 2030 [1] (from 3rd place in 2004). It has been reported that as many as 17.5% of adults in China may suffer from mental health problems [9] yet diagnosis remains highly subjective and requiring well-trained individuals [10]. Prevalence and awareness of the problem in teenagers and young adults (who are the key smartphone demographic) is also growing [11]. Additionally almost a third of countries (31%) do not have an allocated budget for mental health at all and of those that do, many in Africa and southeast Asia spend less than 1% of their small health budgets on mental health services [12].
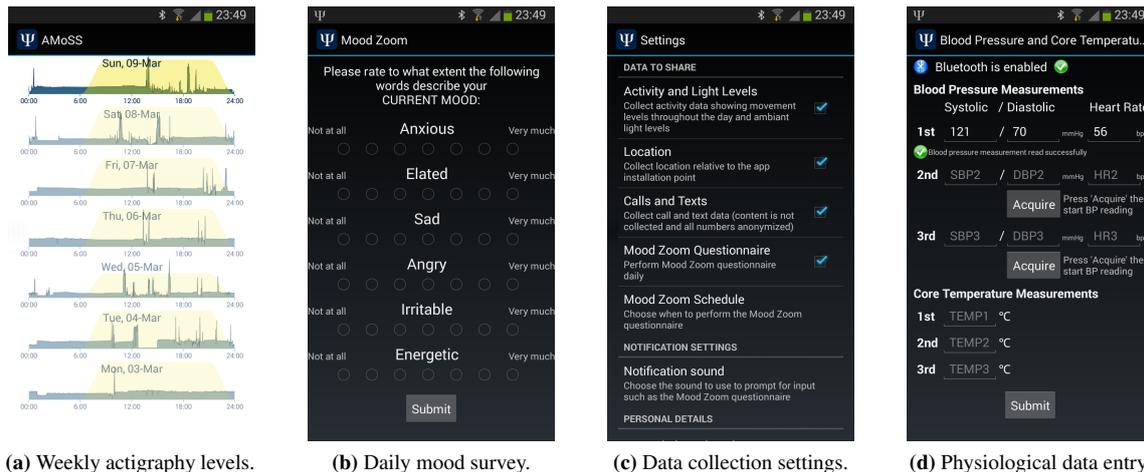
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[1] Source code for the Android data collection app described in §3.1 is available from http://amossstudy.bitbucket.org/

(a) Weekly actigraphy levels.   **(b)** Daily mood survey.   **(c)** Data collection settings.   **(d)** Physiological data entry.

Fig. 1: Data collection Android app screen-shots. The main screen (a) shows an overview of the recorded actigraphy levels over the last week. Screen (b) shows the simple mood monitoring survey (mood zoom) that is filled in on a daily basis to track participant's mood levels. The settings screen (c) gives participants full control over the data being collected and physiological data can be collected in screen (d) either through connection to external Bluetooth devices or manual entry.

2 Related Work

Most previous work in objective measures for mental health have focused on devising new survey tools to aid physicians in managing their caseload [6]. While this is valuable from a triage perspective it is not practical for real-time monitoring.

Two EC FP7 funded projects are currently addressing the topic of multi-parametric monitoring of bipolar disorder. The PSY-CHE (Personalised monitoring SYstems for Care in mental HEalth) project uses textiles with integrated sensing devices for data acquisition but have only published preliminary results on 3 subjects [13]. The MONARCA project is developing an Android-based monitoring platform using accelerometry and location data demonstrating a bipolar state recognition accuracy of 80% on a very small cohort of 12 bipolar patients [14].

Our previous work by Osipov *et al.* [15] showed that classification of subjects with schizophrenia from healthy controls achieved 90% accuracy using actigraphy alone. This was promising preliminary work but the limited sample size and types of data restricted it to a retrospective analysis so we designed the large study presented here with the most complex set of physical and social activity metrics published to-date.

3 Methods

This article presents preliminary data from the Automated Monitoring of Symptom Severity (AMoSS) study run by the Department of Psychiatry at the University of Oxford. The study will recruit 130 subjects, 50 with bipolar disorder (BP); 30 with borderline personality disorder (BPD); and 50 healthy controls (HC). Currently 50 subjects have been recruited (16 BP, 9 BPD and 25 HC). The study was approved by the local NHS research ethics committee (REC reference 13/EE/0288) and all participants provided written informed consent.

3.1 Mobile Phone App

Participants are provided with an Android based smartphone (Samsung Galaxy S III) which records the following data through a custom app developed in-house specifically for the needs of this study (screen-shots shown in Fig. 1):

1. Actigraphy levels
2. Ambient light levels
3. Social network activity measured by phone calls (time and duration) and text messages (time and length)
4. Daily self reported mood surveys (known as *mood zoom*)
5. Participant physiology (blood pressure and temperature can be manually entered or read from Bluetooth connected devices; continuous heart rate and related signals derived from Bluetooth ECG or pulse oximetry devices)

3.2 Clinically Validated Surveys

In order to track psychological state, participants also complete the following clinically validated psychiatric questionnaires on a weekly basis. These surveys are performed through the True Colours monitoring system [16, 17] which is integrated with the NHS infrastructure in Oxford. True Colours enables completion of pre-defined surveys via either email or text message.

1. 16-item quick inventory of depressive symptomatology (QIDS) [18]. The QIDS questionnaire is a 16 question diagnostic and monitoring tool for depression.
2. Altman self-rating mania scale [19]. The Altman questionnaire is a 5 question tool is designed to measure the presence and severity of manic symptoms.
3. A brief measure for assessing generalized anxiety disorder (GAD-7) [20]. This is a 7 question tool designed to assess symptoms of generalized anxiety disorder.
4. The EuroQol EQ-5D [21]. The EQ-5D is a 6 question quality of life questionnaire providing a quality of life score based public ratings of the possible responses.
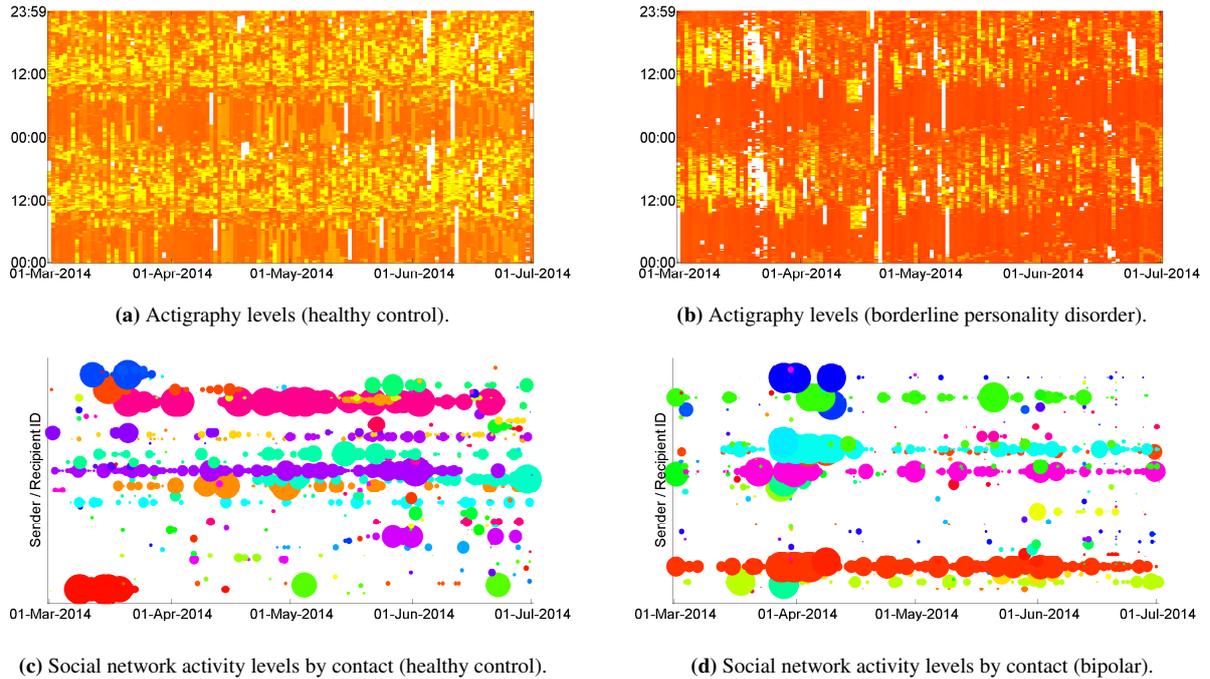
(a) Actigraphy levels (healthy control).

(b) Actigraphy levels (borderline personality disorder).

(c) Social network activity levels by contact (healthy control).

(d) Social network activity levels by contact (bipolar).

Fig. 2: Preliminary results from data collection. Daily actigraphy levels over 4 months are shown for (a) a healthy control and (b) a BPD participant where lighter colours indicate greater activity. It can be observed that the data from the HC displays a greater degree of regularity than the data from the BPD participant which appears much more disorganised. Social network activity levels as a sum of the number of text message characters and phone call seconds are shown for (c) a healthy control and (d) a bipolar participant. These show activity levels per unique contact on the y-axis where the size of each point represents the level of social interaction with that contact per hour and each colour represents one contact.

3.3   Hardware Actigraphy and Physiology Sensors

In addition to the above, participants are provided with a Fitbit One™ wireless activity and sleep tracker and a GENEActiv Original wrist-worn accelerometer to provide improved actigraphy as the phone may not always be carried on the person.

The Fitbit One™ transmits data to the Fitbit server via the smartphone at a resolution of 1 minute. The GENEActiv device stores the data internally for 28 days recorded at 25 Hz.

Participants also took their own temperature and blood pressure at specific times in the study. Furthermore, an electrocardiogram was worn for a limited period of time by each participant and selected participants wore a pulse oximeter overnight.

4   Preliminary Results

Since data collection is ongoing, it is not possible to provide quantitative results at this stage. Fig. 2(a-b) shows actigraphy levels for a healthy control and a borderline personality disorder participant. The most striking feature immediately obvious is that there is a degree of regularity in the data for the healthy control while the data from the BPD participant appears more disorganised, as was observed by Osipov *et al.* [15].

Fig. 2(c-d) shows the social network activity levels for a healthy control and a bipolar participant as total activity level

per unique contact[2]. Again it can be seen that there appears to be more irregularity in the data from the BP participant.

5   Discussion and Future Work

An Android-based smartphone provides a convenient platform for mental health monitoring due to the number of high quality sensors readily availability and the high adoption rates. The techniques could equally be applied to the Apple iOS platform. However the mobile phone cannot provide the same level of data as a wearable device such as the GENEActiv wrist-worn accelerometer. An open question is how well the mobile phone data correlates to the wrist-worn accelerometer. However, the richness of data made possible through the smartphone platform and ready availability enables large scale studies in resource poor regions at relatively little cost.

Future work is focusing on fusing features from all the recorded signals to derive clinically useful and actionable metrics of precipitous deterioration in condition. Although we are collecting basic social network data through phone calls and text messages we will extend this to perform topic modeling on text message content. A further extension will be to couple this with topic modeling of social network posts on Facebook and Twitter for users that are active on these platforms.

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[2] A unique ID for each contact is created non-reversibly.

6 Conclusions

This paper has presented an open-source method for collecting rich data from mental health patients to aid diagnosis and management. Recruitment is about half of the total at the time of writing and data collection will likely last for another year and a half. The data collected to-date shows preliminary promise and there is scope to extend the study to collect rich social network data from multiple sources.

Acknowledgements

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