Correlation of significant places with self-reported state of bipolar disorder patients

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***Abstract*—Capabilities of smartphones can be utilised to monitor a range of aspects of users' behaviour. This has potential to affect a number of areas where users' behaviour is considered relevant information. Most notably, healthcare in general and mental health in particular are excellent candidates to utilise capabilities of smartphones, since mental disorders typically have a strong behaviour component. This is especially true for bipolar disorder, where mobility and activity of the patients is considered an indicator of a bipolar episode (depressive or manic). In this work we report on results of using capabilities of smartphones to monitor mobility of the patients, monitored over the period of 12 weeks. Through the continuous discovery of Wi-Fi access points we have inferred significant places (where the patient spent majority of the time) for each patient and investigate correlation of these places with patients' self-reported state. The results show that for majority of patients there exists negative correlation between time spent in clinic and their self-assessment score, while there is a positive correlation between self-assessment scores and time spent outside the home or clinic.**

Keywords-smartphone sensing; bipolar disorder; mobility; self-assessment; correlation;

I. INTRODUCTION

The last decade has shown an exponential growth of a number of scientific disciplines, including Ubiquitous Computing, where the main idea is to provide an environment where computing systems are everywhere and anywhere. These computing systems support human to computer interaction and facilitate the relationship between these two worlds. The remarkable development of systems that followed this philosophy resulted in an increasing integration of technological products in everyday life and in specialised settings. One of these aspects is healthcare, where use of computing devices has revolutionised diagnosis for somatic diseases, including use of imaging techniques such as Computed Tomography (CT) in computer aided diagnosis (CAD) or processing of vast amount of data to discover new bio-markers in bio-informatics. These advancements have had tremendous impact on aiding diagnosis of primarily somatic diseases. The impact of these advancements has been felt less in area of diagnosing mental disorders. One the main reasons is that currently there are no strong bio-markers that can indicate presence of a mental disorder and neither imaging techniques that can reliably discern mental diseases.

However, one significant difference between somatic diseases and mental disorders, in addition to lack of reliable bio-markers for the latter, is that mental disorders have a strong behaviour component. The symptoms of a mental disorder, such as depression, schizophrenia or bipolar disorder, are directly manifested on the behaviour of the patients. Considering the capabilities of smartphones in monitoring diverse aspects of human behaviour, the potential of smartphones to monitor and detect changes in patients' behaviour as a result of the disease, becomes evident.

In this paper, we report on the results of exploiting capabilities of smartphones to detect a particular aspect of patients' behaviour, namely their mobility patterns through the discovery of significant places. In this work, a significant place is a physical place where patients spent majority of their time, including home, clinic or other places outside home and clinic. In order to understand significant places we rely on continuous scanning and recording of Wi-Fi access points from the smartphone app we have developed for the purpose of the trial. In total, 10 smartphones were given to 10 patients that were already diagnosed with bipolar disorder and were monitored during a 12-week trial. During our research there was not a distinction between an intervention group and a control group, the patients were all of the same type. Each of them was monitored 24 hours a day and 7 days a week. During the monitoring period they underwent psychiatric evaluation every 3 weeks and also reported their psychological state every day, through questionnaires prompted by the monitoring app on the smartphone. We report on the correlation between discovered significant places and patients' self-reported psychological state.

A. *Trial Setup*

The trial was setup at a psychiatric hospital located in Hall in Tirol, Austria. The trial was uncontrolled, not randomized, mono-centric, observational study, approved by the ethics board of the Innsbruck University Hospital. Inclusion criteria were: age between 18 and 65, ability and willingness to use smartphones, being "contractually capable", and a diagnosis of bipolar disorder categorised by ICD-10, F31 (International Classification of Diseases and Related Health Problems), with frequently changing episodes.

The trial did not interfere in any way with the patients' therapy and patients were fully unconstrained in using the smartphone; that is, there were no restrictions to use the phone in a particular manner or at a specific part of the body. Out of 12 patients that were recruited (11 female, 1 male), 10 patients underwent the full trial, while two patients dropped early. The patients were aged between 18 and 65 and each filled in a daily questionnaire prompted by the smartphone app that allowed capturing patients' subjective psychological state. Other details of the trial are reported in our previous publications [1-3].

For the rest of the paper we initially review related work in this area and provide a description of the approach, followed by the results and concluding remarks.

II. Related Work

A number of research works have focused on the extraction of significant places from mobility traces [4-6]. Most of the approaches rely on location technologies such as GPS or GSM trajectories to identify locations of interest along with the semantics of the place. Ashbrook et al. [7] investigated use of an agent able to learn user's most frequent locations and from this information be able to predict most likely places where the user will go next. For this work, they have relied on GPS measurements that relate with the user's physical locations and made use a Markov model to predict next location. GPS data was clustered using k-means algorithm, however our approach is based on far less precise Wi-Fi localisation. Another approach in this area is from the work of Liao et al. [8] where the authors have studied modelling different types of places, also considering user's activities when they move between places. Their approach incorporated much more information, such as users' activity at a particular location and based on this information a place was deemed significant or not. While, our approach is based on temporal analysis only, since the nature of the patient trial was such that we could not gather further information about the activities the patient performed. Other approaches to understand user's mobility from mobile sensors have relied on Call Detail Records (CDR), such as work presented in [9]. The authors used CDRs from a cellular network to estimate the important places in the lives of large populations of people and especially identify home and workplace. This is relevant work, however it relies on acquiring information from the mobile operator, rather than information that can be acquired from the mobile device.

Research work in clustering users' location is one aspect, while smartphone and wearable monitoring in medicine is another aspect of this work. In this regard, work carried out in [10] has used smart textiles, coupled with a smartphone in order to monitor patients' behaviour. While work presented in [11] has relied on wireless sensor networks and smartphones in order to fuse self-reported patient information with the objectively measured data. As highlighted in [12] the manner in which the patients are treated has significantly changed due to arrival of mobile technology; where, healthcare institutions have changed their relationship with patients and are able to monitor them also outside of the traditional hospital walls. Wearable technology in healthcare has been explored in a number of research papers. An overview of the wearable technology in health is provided in [13] and [14]. However, in terms of smartphones there is clear focus of the systems in supporting self-monitoring and subjective information capture. Examples of these systems are presented in [15] and [16], where authors have used phone messaging to provide feedback to the patients. Other systems, like [17], [18], and [19] similarly rely on self-reporting, implemented using smartphone applications. Burns et al. [17], for instance, introduce an app for mood prediction of depressive patients. However, it requires constant interaction and feedback of the patient. Furthermore, 'True- Colours' [18] and the "Optimism App" [19] were developed to log self-reported mood, activities and quality of sleep in order to monitor depression and state changes. LiKamWa et al. [20] also display an approach, which infers mood through analysing mobile phone usage.

III. Our approach

The analysis in this work can be divided in two parts, namely: discovering principal places where the patients spend majority of the time based on Wi-Fi traces and correlation of these places with self-reported patient state over the monitoring period.

The data we gathered from the mobile phone were the following: the name of the network (SSID); and, the MAC address that identifies this network (BSSID). In addition, there was a prompt for the patient to fill in a clinical questionnaire in order to capture the patients' subjective state, through Ecological Momentary Assessment (EMA).

In terms of Wi-Fi we processed temporal information and MAC addresses in order to get information about the principal locations the patient had spent their time during the monitoring period. Through processing of the data using unsupervised machine learning algorithms, our intention was to understand clusters that would have uncovered patients' most significant places. The clusters that we wanted to find had a density based nature, thus DBSCAN clustering algorithm was an appropriate choice. Figure 1 presents an example where patients' location clusters are presented using DBSCAN algorithm. The x-axis represents how many Wi-Fi networks were discovered and the y-axis represents the time, namely hours of the day, where every triangle represents a single MAC address grouped in coloured clusters.

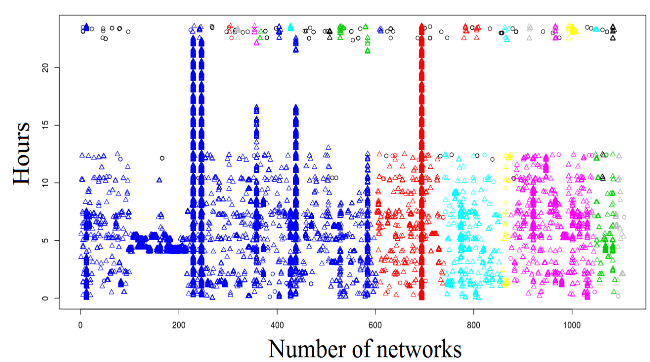

Figure 1. Clusters of principal locations of P0802

As it can be seen from the Figure 1 there are five main clusters that correspond to 5 significant locations of the patient. The blue cluster is the densest, corresponding to a place where patient spent majority of time. This Wi-Fi cluster refers to patient's home when considering temporal information of the discovered BSSIDs (during the whole nights). However, a number of patients have spent a significant time in the clinic, which was then reflected in their Wi-Fi clusters. For example, patient P0402 had spent majority of time in the clinic and the resulting Wi-Fi clusters are shown in Figure 2.

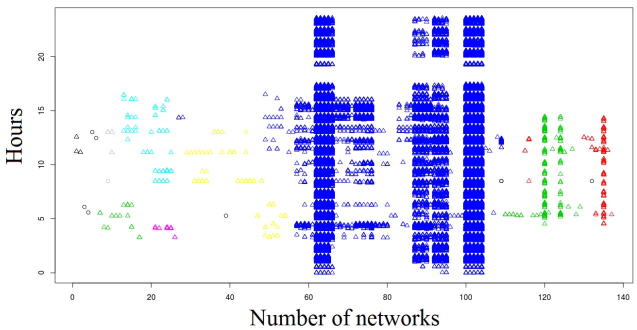

Figure 2. Clusters of P0402 significant locations

Figure 2 shows location clusters of patient P0402 having one significant location and other much smaller location clusters. The main cluster refers to the clinic, based on the Wi-Fi fingerprints we previously acquired at the clinic.

In order to understand the correlation, we have also analysed patients' self-reports in order to see if there is a correlation between the self-reported patient state and their significant location. The idea behind self-reports was to get information directly from the patients, through ecological momentary assessment (EMA) in order to understand subjective physical and psychological state. This information was recorded through a daily questionnaire derived from clinical questionnaires. From the set of questions presented in the daily questionnaire, one set of questions were defined in consultation with the psychiatrists and the other set was taken from standard clinical questionnaires of depression (HAMD) and mania (YMRS). The overall questionnaire focused on 4 aspects, namely information about time spent in outdoors and indoor activities, sleep quality and duration, whether the patient had meals and finally the patient was asked to report their level of depression and/or mania.

For this work we were interested in the last aspect, namely self-reported levels of patient state, while other aspects of the questionnaires will be subject of another research work. The scale followed the choice of answers "Mostly", "Often", "Sometimes" and "Rarely". The questions and answers were in German since the patient trial took place in Austria and it involved German-speaking patients.

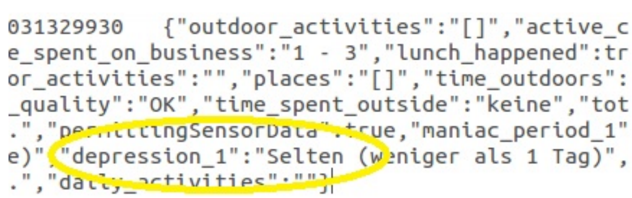

Figure 3. Patient's self-reported state

Figure 3 shows an example of a self-reporting. The yellow circle highlights the information we used for our analysis, in this case the patient answered "Selten" (meaning "rarely" in German language). Our aim was to investigate correlation between the patients' self-reported psychological state and the time they have spent in a significant location. For the study we used patients' subjective psychological state that we extracted from the self-reports on one hand; and on the other hand we extracted significant locations for the patients using scans of Wi-Fi access points. Using DBSCAN to cluster the Wi-Fi scans we were able to infer the number of major clusters, however this did not provide information whether these major clusters referred to their home location, stays in clinic, some other significant place. The main distinction was between patients' stay in the clinic and patients' stay at a significant other location, which most likely has been patients' home, based heuristics, such as sleeping patterns. Therefore, we have used Wi-Fi fingerprints at the clinic to provide distinction between the time spent at the clinic and time spent at other significant locations.

In order to smooth out daily variations of self-reports, we chose a period of 3 days to calculate self-reported patient state score. In this manner we have handled the data as follows: regarding the self-reported depression score we normalized data to a value between -1, when the patient answered he felt depressive "Mostly" or "Often", to score of 1 when the patient felt depressive "Sometimes" or "Rarely". We have grouped these scores in sets of three (one score for every day) and used majority voting to assign a value to the overall set. For example, the set of three days was assigned score of -1 if in 2 out of three days the patient has felt depressive. Using this information, we can look for possible correlations between these values and the patients' presence in a significant location. For patients' locations, we have calculated the percentages of the time spent in a location considering the three-day interval. Pearson's correlation coefficient was our measure of correlation between patients' self-reported state and their presence in an identified significant location. Each correlation result was checked, to ensure statistical significance using a one tailed p-value test.

We analysed the cases where we had both data for the patients, that is: self-reports during the three-day interval and Wi-Fi scans during that period. Therefore, out of our 12 initial patients, 7 were suitable for our study, having both data, while other patients were excluded due to lack of either or both data. The results of the study are presented in the next section.

IV. Results

As explained in the previous section, our aim was to find out if there are any correlations between the patients psychological state and the time spent in a significant location, either clinic, home or outside.

From the results in Table I, it is evident that in general there is a weak correlation between the variables. However, a number of trends become evident. Majority of patients (namely patients P0102, P0202, P0402, P0602 and P0802) show negative correlation of self-reported state and duration of stay in the clinic. This means that longer stays in clinic meant that the patients were reporting lower mood scores, namely they were feeling more depressed or vice versa. This can be explained by the fact that patients that are more severely depressed tend to stay longer in the clinic.

On the other hand, a positive trend can be observed between self-reported patient's state and their stay outside the clinic or home, indicated as 'Other' in Table I.

TABLE I. Correlation results between self-reported patient state and discovered significant places (n/a* no data available)

	correlation coefficient (*r*) *p<0.05*		
ID	*Clinic*	*Other*	*Home*
P0102	-0.03	0.14	0.05
P0202	-0.53	0.53	n/a*
P0302	0.24	-0.25	-0.1
P0402	-0.25	0.21	n/a*
P0602	-0.26	0.27	n/a*
P0802	-0.07	-0.25	0.22
P0902	0.08	0.09	-0.12

Majority of patients (namely P0102, P0202, P0402, P0602 and P0902) show positive correlation between the self-reported patients' state and time spent at other locations, outside home or clinic. Concerning home location, it is important to note that there were only four patients with Wi-Fi data for their home location. As such, no definite conclusion can be made regarding correlation of patients' self-reported state and time spent at home.

V. CONCLUSION

The work in this paper has shown that there exist correlation between significant places representing mobility of the patients and their self-reported psychological state. From the seven patients that underwent the study, the results show positive correlation between self-reported psychological state and time spent outside clinic or home for majority of the patients. While, on the other hand, the results show negative correlation between the time spent in the clinic and self-reported psychological state. For this study, there was insufficient data to conclude definite correlation between time spent at home and self-reported psychological state of the patients. These results provide an indication of behaviour of patients' with bipolar disorder, with respect to their significant locations, which may be used as an input to further augment the diagnosis.

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