Detection of Behavior Change in People with Depression

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Abstract

Major Depressive Disorder (MDD) is the most common mental health disorder and remains a leading cause of disability and lost productivity with huge costs for society. MDD has high rates of relapse and recurrence, and it has strong correlations with feelings of low social support and disrupted sleep. However, MDD is also commonly misdiagnosed by primary care providers, which leads to delayed treatment and unnecessary suffering. Changes in technology now make it possible to cheaply and effectively monitor social and sleep behaviors, offering the potential of early detection of the onset of MDD. We report on the design of Big Black Dog, a smartphone-based system for gathering data about social and sleep behaviors. We also report on the results of a pilot evaluation to understand the feasibility of gathering and using data from smartphones for inferring the onset of depression.

Introduction

Each year 7% of Americans experience an episode of major depression [NIMH, 2011]. As a leading disability, depression has huge costs in terms of reduced productivity and absenteeism [RAND, 2008]. Most people seek help from their primary care provider (PCP); however, PCPs fail to recognize depression symptoms 65% of the time [Jencks, 1985; Coyne et al, 1995]. The delay in diagnosis and treatment increases the time people suffer from this condition. Research has shown that early detection of a first episode or of a recurrent episode can have a major positive impact [Halfin, 2007; Kupfer et al., 1989].

MDD has high rates of relapse and recurrence, and it has strong correlations with feelings of low social support and disrupted sleep. For example, a lack of social support has been found to predict depression as well as many other health related issues [Sias and Bartoo, 2007]. Past work has also found that sleep disorders are correlated with depression [Livingston et al., 1993], and disrupted sleep has been found to predict recurrences [Perlis et al., 1997].

The meteoric adoption of smartphones offers a tantalizing opportunity, in that many people now carry a networked, sensor-rich device almost everywhere they go. These changes make it possible to cheaply and effectively monitor people's activities and behaviors, which could then be used to detect the early onset of MDD.

Towards this end, we have developed a system called Big Black Dog (BBD) to detect the onset of major depression, allowing for earlier diagnosis and treatment of first episodes, relapses, and recurrences. Our angle of attack is to capture data about and model social behaviors and sleep behaviors. This paper reports on the design and on a pilot study to understand the feasibility of our approach.

Related Work

Researchers have investigated a number of behavioral signals to detect the mental state of people, using such approaches as brain signals (Stewart et al., 2010), heart rate (Vikram et al. 2002) blood pressure (Shinn et al., 2001), voice prosody (Cohn et al., 2009; France et al., 2000), and facial expression (Cohn et al., 2009) as proxies for psycho-physiological information. EEGs, heart rate trackers, and skin conductors provide rich streams of data; however they are cumbersome to wear, often difficult to use, and typically limited to being used in clinics.

Text mining has also been investigated as a method to detect depression. De Choudhury et al. used tweets to detect depression (De Choudhury et al., 2013). Important indicators included a decrease in social activity, raised negative affect, highly clustered ego networks, heightened relational and medicinal concerns, and greater expression of religious involvement.

Smartphones offer rich a set of built-in sensors including accelerometers, location (GPS, WiFi ID, signal strength), light, and microphone. In past work, we used call logs, text logs, and contact list data to model social behaviors. In other past work, we used smartphone sensor data to model sleep quantity and sleep quality. BBD uses many of the same features from these two systems and applies them in a pilot study specifically for depression.

The most relevant piece of past work is Mobilyze (Burns et al., 2011), a smartphone app that collects sensor data to detect the user's cognitive state. Mobilyze uses machine learning models to predict mood, emotions, cognitive/motivational states, activities, environmental context, and social context. This system has been used for intervention and not for depression detection.

Our research builds on this previous work, focusing on detecting the early onset of depression. Unlike Mobilyze that constantly prompts users for ground truth data, we only ask for a weekly survey. Our goal is to track behavior without any effort from the users. In the following sections, we report on design of the BBD mobile application followed by the pilot study and primary results.

Overview of the Data Collection app

We designed and implemented BBD as an Android app that uploads captured data every day to our server (see Fig. 1). BBD collects sensor data that might reveal behavioral and environmental factors, including noise amplitude (from microphone), location, WiFi SSIDs, light intensity (from ambient light sensor), and movement (from accelerometer). To minimize power consumption, each of these sensors captures data on a relatively light duty cycle (see Table 1). If the battery charge decreases below 30%, the phone samples the information less frequently. If the battery is very low (below 15%), we pause the logging.

BBD also captures device states, such as screen on/off, apps currently running, and the battery-charging state. For example, "screen on" in the middle of night is a signal that a user is probably not asleep. Lastly, BBD collects daily call logs and text messages from the phone.

BBD stores captured data in a database in the protected storage area of the phone. It creates a new database each day and uploads the previous database to the server. This strategy reduces the risk of data loss and complications that can come when attempting to upload large files.

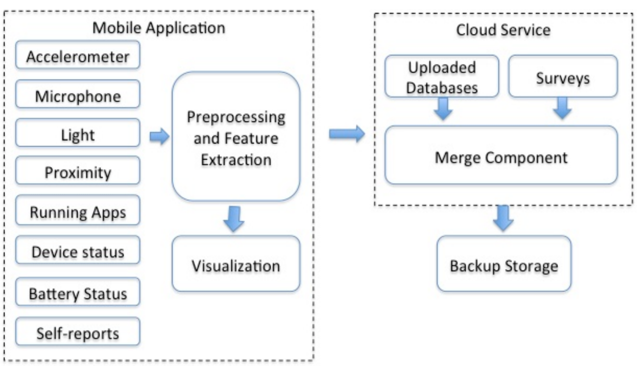

Figure 1. System overview of BBD.

Raw data	Frequency	Low Battery	Very low Battery
Sound (1hz)	Every 2 minute (1min break)		Stop
Apps	When the screen is turned on, every 10 second		Stop
Acceleration (5hz)	Every 2 minute (1min break)		Stop
Light (1/5hz)	Every 2 minute (1min break)		Stop
Location	Every 10 minutes, if (motion = true)	Stop	Stop
WiFi	When the location provider is "network"	Stop	Stop

Table 1. Types of sensor data and their frequency collected by the BBD mobile app

Pilot study

Before our pilot study, we met with three groups of psychiatrists (both research and clinical) to discuss the overall goal of the study and to hear their critique and insights. Their reaction was very positive and they showed interest in tools that can help them help their patients. They also raised some concerns, and offered some suggestions for a user study. The main concern was the challenge of finding and recruiting people who are likely to get depressed. Instead, they suggested reversing the focus, seeing if we could do a small study with people who were already depressed and starting a treatment, and then see if our system could monitor improvements in their state. Another suggestion was to change the focus to look at people who are going off medication and have a high likelihood for becoming depressed.

For our pilot study, we opted for the former, aiming to detect changes in behavior in people who had just started medical treatment for depression.

Participant Recruitment

After getting approved by our IRB, we distributed a flyer in a mental health clinic and asked the psychiatrists to inform the potential patients about the study. Patients could contact us via email or phone call. Participants had to be 18 or older, had been diagnosed with major depression, and were about or had recently started medication. Once contacted, we performed a preliminary screen to confirm that all requirements were met. We then visited the participants in their home, provided a detailed description of the data we planned to collect, discussed the risks of their participation, got their informed consent, provided them with a phone or installed software on their Android phone, provided some training on how to submit the ground truth data, and provided them with contact information so they could easily reach us. Participants were paid $100 per month for their participation.

Data Collection

Three (2 females and 1 male) out of 26 people were eligible for our study. Three members of the research team (2 males and one female) participated in the pilot for few weeks to acquire a baseline for non-depressed behavior. Participants were asked to fill out a weekly self-report, based on the CES-D survey instrument (Hann et al., 1999). The CES-D asks questions like "My sleep was restless" and "I felt that people dislike me." Higher scores mean more likely to be depressed. Participants were also asked about alcohol consumption, smoking, and medication. We collected about 4 months of data from participants. In total, 65 surveys were filled out, 42 from the patients and 23 from the researchers.

We then extracted features from the raw data and aggregated them on a daily and weekly basis. The following sections describe the process of feature extraction followed by data analysis.

Feature Extraction and Data Analysis

Given the small sample size, our goal is not to claim statistical significance, but rather to find potentially promising features that we could focus on for future, larger studies. As such, we emphasize that the analysis below should be viewed as preliminary results.

From the raw data, we extracted 473 features (see in Table 2). We were interested in probing what type of signals and what combination of features might give insight into the mental state of the patients. We also added the weather features as an external factor that could affect people.

Category	Modality	Feature parameters
Sensing channels	Noise level	{Min., Med., Max., Avg., Std., peaks} of sound amplitudes
	Movement	{Min., Med., Max., Avg., Std., peaks} of the changes of acceleration
	Light intensity	{Min., Med., Max., Avg., Std., peaks} of light intensities
		{Min., Med., Max., Avg., Std., peaks} of screen proximities
	Phone usage	Number of tasks and processes, frequency of change in tasks and processes, time between changes
		Frequency and duration of screen on and off
	Location	Time at/away from home, number of places visited, travel distance
	Social communication	Number of incoming and outgoing calls and text messages, number of contacts, duration of incoming and outgoing calls, etc.
Segmented features	Seg 1 00:00 – 4:00 Seg 2 4:00 – 8:00 Seg 3 8:00 – 12:00 Seg 4 12:00 – 16:00 Seg 5 16:00 – 20:00 Seg 6 20:00 – 24:00	Segmentation of all features including noise, movement, location, phone usage, light intensity, and social communication
Aggregated features	Daily	The sum of each feature value on a daily basis
	Weekly	The sum of each feature value on a weekly basis
External sources	Weather features	Temperature (min, max, mean), cloudiness, humidity(min, max, mean), precipitation, events(rain, snow, wind), etc.

Table 2. The list of extracted features from sensor data

In the analysis of the data, we were interested in finding:

- What behavioral features correlate with the mental state of general population and patients in particular? Common features in both cases could be the ones to watch in detection of the onset of depression.

- How behavioral parameters correlate with the mental condition of men and women? These observations could indicate what factors should be considered in models for detection of depression.

- How much change in behavior (compared to the norm) can be alarming and indicate an upcoming depression episode?

To answer these questions, we built ten different datasets (see table 3) from the collected data based on the factors that seemed to affect the behavior and the analysis outcomes. The five original datasets included the unified dataset (O-1) with patients and non-patients data, the patients' dataset (O-2), the non-patients dataset (O-3), the male dataset (O-4) and the female dataset (O-5) including both patients and non-patients.

Dataset	Patients	Non-patients	Male	Female	Data points
O-1	X	X	3	3	153
O-2	X		1	2	57
O-3		X	2	1	96
O-4	X	X	3	0	61
O-5	X	X	0	3	92
B-1	X	X	3	3	153
B-2	X		1	2	57
B-3		X	2	1	96
B-4	X	X	3	0	61
B-5	X	X	0	3	92

Table 3. Different datasets built for the analysis

We also calculated what we call behavior baselines that were computed based on the average of feature values for each participant. The goal was to acquire the average/base behavior for each person in order to detect significant changes as a result of e.g., depression. The reason for doing that is the fact that each person's routine and daily life is different from others. We built five corresponding baseline datasets (B-1 to B-5) from the original ones by subtracting the original feature values from the average values calculated in the baseline.

We then used correlation analysis and pattern mining to analyze our 10 datasets. These methods are best suited for our purpose in finding behavioral features and parameters that reveal information about change in the mental condition. The following sections report on our results.

Correlation Analysis

For our first analysis, we wanted to see if specific features correlated well with specific CES-D questions. That is, even if we cannot fully model depression, we might be able to model specific behaviors related to depression.

Although there were high and significant correlations between feature values and the CESD score in all datasets, we found that the numbers in the baseline datasets were more interesting as they showed the value compared to the normal/average behavior of each person. For example, a significant correlation (r=0.5) between the time at home and the CESD among females in B-5 was observed, which might mean that females tend to stay at home more often when they feel more depressed, compared to their regular routine. We did not observe this correlation in the original female dataset (O-5). Humidity, on the other hand was common in both datasets (r=0.4) suggesting females might feel worsening in their condition during rainy weeks. This value was the opposite in male dataset (B-4) with r=-0.5 for humidity.

Another possible point of interest was the negative (-0.5) correlation between the number of ingoing and outgoing calls in the male baseline dataset (B-4). It may be the case that male participants tend to have fewer calls than usual as they feel more depressed

Extraction of change in behavior patterns

To get a sense as to how higher level behavior changes with mental state, we generated three main behavior parameters, namely social interaction, mobility, and phone usage. The values were aggregations of relevant lower level features. The social interaction parameter includes aggregation of call, text, and noise features, mobility includes location and WiFi features, and phone usage is a combination of app use and the status of the phone screen.

We used Tertius algorithm (Flach, 1999) on our baseline datasets to find change in behavior parameters that correspond to changes in the mental state. The level of change compared to the baseline could vary from -3 to 3 with -3 as three times lower than the average and 3 being three times higher than the baseline. For example, if the social interaction feature for one participant has a value equal to 2, it means that the level of social interaction in the corresponding week has been twice as high as usual for that person.

The first patterns were extracted from the entire dataset (B-1) including both patients and researchers. With a confirmation value over 0.5, we observed mild decrease (-1) in social interaction, phone usage and mobility corresponding to increase in the level of depression (1-3 times higher CESD score). These patterns were repeated in the non-patients data (B-2) as well. In general, the observed changes are aligned with our expectations; however, the change in the parameters is mild (-1) regardless of the level of change in the CESD score (1-3).

The patterns in the patient's data (B-2) on the other hand showed the opposite. The increase in level of CESD corresponds to increase in the behavioral parameters. This observation can be explained by the fact that 2 of our patients were female. As shown in table 6, for female participants (gender=1), increase in outgoing communication corresponds to higher level of depression. This pattern is the opposite among males.

We also extracted patterns in the segmented features from midnight to 4am that relate to sleep behavior. Although the confirmation values are low, the extracted patterns follow our general intuition. For example, the decrease in mobility and phone usage corresponds to a more restful sleep (-1), while the increase in social interaction corresponds to a more restless sleep (1). These observations suggest that we might be able to infer the sleep quality of patients from their smartphone data.

Data set	Conf. value	Patterns
B-1	(0.42 -0.58)	social_interaction = -1 and phone_usage = -1 => CESD = 1 or CESD = 2 or CESD = 3
	(0.42 – 0.58)	mobility = -1 and phone_usage = -1 => CESD = 1 or CESD = 2 or CESD = 3
	(0.47 – 0.5)	phone_usage = -1 => CESD = 2 or CESD = 3
B-3	0.39	mobility = -1 and phone_usage = -1 => CESD = 2 or CESD = 3
	0.38	phone_usage = -1 => CESD = 2 or CESD = 3 CESD=3
	0.32	social_interaction = -1 and mobility = -1 => CESD = 1 or CESD = 2 or CESD = 3
	0.30	social_interaction=-1 => CESD=2 or CESD=3
B-2	(0.39 - 0.43)	social_interaction =1 and phone_usage = 1 => CESD = 1 or CESD = 2
	(0.39 -0.43)	mobility = 1 and phone_usage = 1 => CESD=1 or CESD = 2
	(0.35 - 0.42)	gender = 1 and phone_usage = 1 => CESD=1 or CESD = 2
	0.38	phone_usage = 1 => CESD = 1

Table 4. Extracted patterns from different baseline datasets

Conf. value	Patterns related to sleep (B-1)
0.27	mobility_seg_1 = -1 and phone_usage_seg_1 = -1 => Restless sleep = -1
0.23	mobility_seg_1 = -1 => Restless sleep = -1
0.22	social_interaction_seg_1 = -1 and phone_usage_seg_1= -1 => Restless sleep = -1
0.19	mobility_seg_1 = 1 => Restless sleep = 1
0.19	social_interaction_seg_1 = -1 => Restless sleep = -1
0.18	phone_usage_seg_1 = -1 => Restless sleep = -1
0.17	social_interaction_seg_1 = 1 => Restless sleep = 1

Table 5. Extracted patterns related to sleep

Conf. value	Call patterns in the unified dataset (B-1) (male = 0 and female = 1)
0.14	gender = 0 and outgoing_calls = -1 and duration_total_incoming_calls = -1 => CESD = 1
0.13	gender = 1 and outgoing_calls = 2 => CESD = 2 or CESD =3
0.13	gender = 1 and incoming_calls = -1 and duration_total_outgoing_calls = 3 => CESD = 3
0.12	gender = 0 and incoming_calls = -1 and duration_total_incoming_calls = -1 => CESD = 1

Table 6. Gender-based patterns in social communication

Conclusions

We reported on our preliminary study on detection of behavior change in people with depression. Interesting observations include differences in behavior between male and female participants, detecting restless sleep from phone signals, and correlation between decreased social activities and increased CESD score. The noise and variation in our results emphasize the effect of individual factors such as lifestyle and personality on behavior patterns. However, features related to mobility and social activities seem promising in detecting change in personal behavior. In our next study, we will focus on change in individual and personal patterns.

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