Quantifying the Mental State on the Basis of Physical and Social Activities

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Abstract
We demonstrate the idea of "Thermometer for the Mind": the mental state estimating system by a user's activity log derived from wearable devices. While it is well known that physical and social activities are correlated with the mental state, our aim is to build an application which tracks daily activities automatically, estimates the mental state and visualizes it in an easily understandable way. As a preliminary experiment, we investigated how information about physical activity from a smartphone (step counts) and social activity from a Web service (Twitter post counts) can be used to estimate a user's mental state. The method is evaluated on one participant's 5 months recording. The classification accuracy for 3 classes (mood is low, middle and high) is 60%.

Author Keywords
Activity recognition; depression; mental illness; personal health system; mobile application

ACM Classification Keywords
H.5.m [Information interfaces and presentation (e.g., HCI)]: Miscellaneous

Introduction
Mental illness, especially depression is one of the most pressing concerns all over the world. According to the research by WHO in 2012, more than 350 million people

Figure 1: A screen shot of Thermometer for the Mind App.

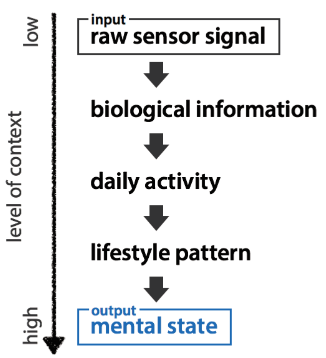

Figure 2: A flow image to estiamte the mental state

could suffer from depression [1]. If the recognition of depression is late, the symptom will be serious and the duration of therapy will be long towards several years. Knowing our mental state is important. Yet, the appearance of symptoms of mental illnesses is hard to detect compared with symptoms of common physical illnesses. You can check whether you have caught a cold or not by measuring the body temperature with a thermometer. However, there is no simple tool which can quantify your mental state. You can't measure how much you feel depressed in an objective way.

The goal of our research is 1) estimating the mental state by the user's biological information and activity log derived from several wearable devices and 2) visualizing it to make it easy to understand. Contributions of this paper are two folds. First, we present the concept of Thermometer for the Mind, which is an idea of estimating and visualizing the mental state. Second, we show the preliminary data analysis of mental state estimation. We have recorded one participant's step counts (as one of the measurements of physical activities) and Twitter post counts (as one of the measurements of social activities) with his self-assessment ground truth for 5 months. We have obtained the classification accuracy of 60% for 3 classes, which might not be enough. Yet, the result and the feature plot show the potential of physical and social activities as features for estimating the mental state.

Related work

There is a large corpus of work focusing on mental illnesses, and these approaches can be grouped into 3 categories.

The first category is to find the relation between mental states and activities. Pereia et al. have proved that the relation between physical activity and depressive symptoms is bidirectional. Physical activity can help reduce the risk of depressive symptoms in the general population and depressive symptoms in early adulthood can be a barrier to activity [7]. There is also an opinion survey in U.S. which shows social activities and emotional wellbeing is related. According to Gallup-Healthways Well-Being Index, Americans feel happy on days when they spend 6 to 7 hours socializing [4].

The second is to develop a personal health monitoring system like MONARCA by Bardram et al. [2] and MoodRhythm by Voida et al. [9]. These applications are designed for bipolar. They track the user's daily rhythms by active and passive methods (e.g. mood by self-assessment, physical and social activities by sensor logs on a smartphone) and visualize them to the user and the physician.

The last is to detect depression by functional brain imaging. Some researchers have investigated functional changes of brain oxygenation in prefrontal brain area during a verbal fluency task by using near-infrared spectroscopy (NIRS). They have proved that depressive patients had significantly lower brain activation during the task although there are no significant differences in behavioral tasks [5] [8].

The aim of "Thermometer for the Mind" is combining them. It records a user's activities that are related to the mental state with wearable sensors, and detects the symptom of depression easily compared with functional brain imaging.

Concept – Thermometer for the Mind

Figure 1 shows a screenshot of "Thermometer for the Mind" App. The application scores a user's mental state and map it onto a single scale like a temperature. We use the analogy of thermometer for visualization because everyone should have gone through hardships with fever, and they can understand how much tired the patient is by this format.

The system estimates the mental state according to the flow as shown in Figure 2. First of all is detecting biological information (e.g. step counts, blinks, heart rate) by raw sensor signals of wearables (e.g. accelerometer, electrooculography sensor). We see the potential of J!NS MEME as a detector of blinks and eye movements, Apple Watch as a heart rate monitor and smartphones as a location logger. They also have tough batteries which run almost full of one daytime. They are designed for everyday everywhere use. The next step is to estimate the user's activity (e.g. reading, talking, cycling) by biological information. Activity recognition by the combination of blinking frequency and head motion can be applied in this step [3] [6]. If the system can recognize almost all of our daily activities, our lifestyle (e.g. work-life balance, social-private balance) will be appeared in activity log. The system finally estimates the mental state by monitoring the change of lifestyle.

Preliminary Data Analysis

Estimating Mental States by Steps and Tweets per Day
To evaluate the potential of physical and social activities, we estimate the mental state with the data we can record every day at the moment. Two features are calculated for each day, and mental states of days are classified into 3 classes (mood is low, middle, high) by k-nearest neighbor (k=7).

The first feature is step counts derived from a smartphone as a measurement of physical activity. We use Moves [1], which is an activity tracking App. We export summaries for each day. Then the moving mean (an average of the day and last 6 days) is calculated and used for a feature.

The second feature is Twitter post counts [2] as one of the measurements of social activities. We use data on the Web for the preliminary analysis because logs on the Web can be collected easily and it's still difficult to record all conversation in the real life. We fetch all tweets for each day. Then tweets which contain URLs are removed because most of them are not conversation and sometimes they are posted automatically by other services. Finally, the moving mean is calculated and used as a feature.

[1] https://www.moves-app.com
[2] https://twitter.com

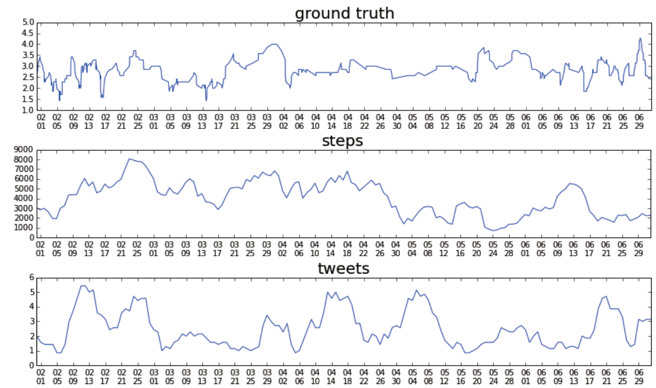

Figure 3: An overview of one participant's 5 months recording.

Experimental Setup
We recruited one participant to track his mental state, steps and tweets. He had suffered from depression since October 2014 and was in the convalescent stage during the recording. The experimental task was to report his mental state (self-assessment, from 1 to 5). The daily average x is used as ground truth. We remapped it to 3 classes (low: 1.0 <= x <= 2.5, middle: 2.5 < x < 3.5 and high: 3.5 <= x <= 5.0) for the classification. the period of the experiment was 5 months, and actually evaluated day was 131 days. The classification method was evaluated by 10-fold cross-validation. Figure 3 shows an overview of ground truth and features by physical and social activities.

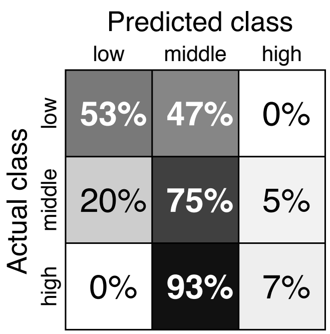

Figure 4: A confusion matrix of the evaluation. The classification accuracy is 60%.

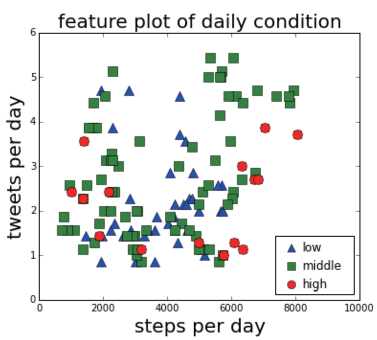

Figure 5: A plot of physical and social features for each day.

Results and Discussions

Figure 4 is a confusion matrix of the classification result. The accuracy of classification is 60%. Low and middle conditions are confused, and a lot of high conditions are classified as the middle. Yet, no low condition and high condition are confused with each other. All samples are classified into correct or neighboring classes. Figure 5 is a feature plot for each samples. Low mood samples tend to be plotted at few steps and few tweets position. There is no low mood sample where the step counts are over 6000.

Conclusion and Future Work

We showed the concept of "Thermometer for the Mind" and proposed the mental estimating method by step and tweet counts per day. The classification accuracy 60% for 3 classes is not enough. Yet, the feature plot shows the potential of physical and social activities as features to estimate the mental state. A possible improvement of this system is to estimate higher level information (activities and lifestyles) and using them for mental state estimation. We are also going to get feedbacks from specialists about which feature can be related to our mental state and what kind of information can be useful for the diagnosis.

REFERENCES

1. 2012. WHO | Depression. (2012). http://www.who.int/mediacentre/factsheets/fs369/en/.
2. Jakob E Bardram, Mads Frost, Károly Szántó, Maria Faurholt-Jepsen, Maj Vinberg, and Lars Vedel Kessing. 2013. Designing mobile health technology for bipolar disorder: a field trial of the monarca system. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. ACM, 2627–2636.
3. M Haak, S Bos, S Panic, and LJM Rothkrantz. 2009. Detecting stress using eye blinks and brain activity from EEG signals. *Proceeding of 1st Driver Car Interaction and Interface* (2009).
4. James Harter and Raksha Arora. 2008. Social time crucial to daily emotional wellbeing in U.S. *GALLUP* (2008).
5. MJ Herrmann, A-C Ehlis, and AJ Fallgatter. 2004. Bilaterally reduced frontal activation during a verbal fluency task in depressed patients as measured by near-infrared spectroscopy. *The Journal of neuropsychiatry and clinical neurosciences* (2004).
6. Shoya Ishimaru, Jens Weppner, Kai Kunze, Andreas Bulling, Koichi Kise, Andreas Dengel, and Paul Lukowicz. 2014. In the Blink of an Eye – Combining Head Motion and Eye Blink Frequency for Activity Recognition with Google Glass. In *Proceedings of 5th Augmented Human International Conference*. 150–153.
7. Snehal M Pinto Pereira, Marie-Claude Geoffroy, and Christine Power. 2014. Depressive symptoms and physical activity during 3 decades in adult life: bidirectional associations in a prospective cohort study. *JAMA psychiatry* 71, 12 (2014), 1373–1380.
8. Tomohiro Suto, Masato Fukuda, Makoto Ito, Toru Uehara, and Masahiko Mikuni. 2004. Multichannel near-infrared spectroscopy in depression and schizophrenia: cognitive brain activation study. *Biological Psychiatry* 55, 5 (2004), 501–511.
9. Stephen Voida, Mark Matthews, Saeed Abdullah, Mengxi Chrissie Xi, Matthew Green, Won Jun Jang, Donald Hu, John Weinrich, Prashama Patil, Mashfiqui Rabbi, and others. 2013. Moodrhythm: tracking and supporting daily rhythms. In *Proceedings of the 2013 ACM conference on Pervasive and ubiquitous computing adjunct publication*. ACM, 67–70.