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Daily Mood Assessment based on Mobile Phone Sensing

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***Abstract*—With the increasing stress and unhealthy lifestyles in people's daily life, mental health problems are becoming a global concern. In particular, mood related mental health problems, such as mood disorders, depressions, and elation, are seriously impacting people's quality of life. However, due to the complexity and unstableness of personal mood, assessing and analyzing daily mood is both difficult and inconvenient, which is a major challenge in mental health care. In this paper, we propose a novel framework called MoodMiner for assessing and analyzing mood in daily life. MoodMiner uses mobile phone data—mobile phone sensor data and communication data (including acceleration, light, ambient sound, location, call log, etc.)—to extract human behavior pattern and assess daily mood. Our approach overcomes the problem of subjectivity and inconsistency of traditional mood assessment methods, and achieves a fairly good accuracy (around 50%) with minimal user intervention. We have built a system with clients on Android platform and an assessment model based on factor graph. We have also carried out experiments to evaluate our design in effectiveness and efficiency.**

***Keywords*-mobile phone sensor, mood assessment, behavior modeling, mobile healthcare, reality mining**

I. Introduction

As technologies and economy continue to develop dramatically, *well-being* goes well beyond keeping one from starving, cold, and physical diseases. People begin to pay more attention to other elements that affect people's feeling of *happiness*, of which mental health is an important aspect. Mood related mental problems, such as mood disorders, have become a global concern of human society.

The study of mood theory and the treatment of mood disorder has been an important topic of psychology. Different measures and treatments are applied according to different mood status and symptoms. However, the assessment of mood has long been a challenge in mood-related study. Current mood assessment is mainly based on traditional psychological measurements, like scales and psychological counseling. But these methods are faced mainly with two challenges in mood measuring.

One is the *subjectivity* of mood. Mood is with no doubt subjective, but for scientific analysis, objective mental states should be extracted from people's feelings and expressions. Self-reported data, suffering from its subjectivity, cannot serve as a reliable indicator of objective mood, without complex validation and process.

The other is *inconstancy*. In comparison with emotion, mood is relatively long-time state, but it still changes in hours or days. Therefore, it is very difficult to use traditional methods to assess mood in such frequency. Psychological scales, due to their complexity, consume a large amount of time and energy of user, which is often annoying to do everyday. Psychological counseling involves interaction between client and counselor (psychologist), and thus, it is more unrealistic to be taken frequently.

Fortunately, the rapid increasing usage of mobile phones, has opened a new possibility for daily mood assessment. Modern mobile phones are equipped with rich sensors, such as accelerometer, light sensor, sound sensor(microphone), location sensor(GPS), etc.. Besides such sensory data, the mobile phone generates soft-sensor data—SMS and call information—that can also reflect people's daily behavior. What's more, the mobile phone is usually inseparable with its user, and then it can use its hard- and soft-sensors together to profile some significant behavior patterns of people.

In this paper, we propose a novel framework for daily mood assessment using mobile phone sensor data. First, we collect sensor data on mobile phone in a smart manner, which is both efficient and energy-friendly. Second, different types of sensor data and communication events are then combined together to model people's daily behavior pattern, including physical movements, minor motions, location trace, etc.. Third, these features are used as input to model users' real-time mood. We build a general model based on factor graph to do the analysis and assessment. We finally build a prototype system for collecting sensor data and communication data from Android smartphones. We use self-report mood data as ground truth and perform the test-bed experiment on a number of users for one month to evaluate the effectiveness of our design.

The contributions of our work are as follows. First, the proposed mood assessment is carried out solely on mobile phone, without requiring any additional medical devices, and then it is convenient to be used at low cost and supports real-time dynamic mood analysis. Second, the use of mobile phone sensor and communication data improves the objectivity in mood assessment, by eliminating expression and comprehension error of psychological scale and questionnaire. Third, we build a testbed system with

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the Android phone and a back-end server, to evaluate the feasibility and efficiency of our design.

The rest of the paper is organized as follows. Section II briefly introduces some work related to this paper, including mobile healthcare and mood assessment. Section III describes the system we have built for doing mood assessment on Android platform. Section IV gives our analysis based on the collected data and the proposed model. Section V presents experimental results. Section VI concludes the paper.

II. Related Work

Our work aims at performing mood assessment by using phone-based sensing techniques. In this section, we first briefly introduce these two domains respectively, and then present some related work of combination of both areas.

Mood and Mood Assessment. Mood and mood assessment is an important topic of psychology, and a lot of work has been done in the mood theory and the methodology of assessing mood in daily mood. Thayer [1] defines mood as relatively long lasting emotional state, which is different from emotion, as mood is less specific, less tense, and less likely to be related to a particular stimulus or event. It is now widely recognized that overall mood can be viewed as production of two unrelated dimensions - energy and stress [2] [3]. In practical research, mood is often measured in three basic dimensions: displeasure (overall), tiredness and tensity [2]. Mood assessment is usually achieved using self-report methods like psychological scale. Wilhelm, *et al.* [2] has evaluated the psychometric properties of a short mood scale to assess mood states in daily life, and discusses problems brought by measures.

Mobile Phone Sensing. Mobile phones, especially smartphones, are developing rapidly in recent year, and are becoming the central devices of communication and computing in people's daily life. Along with the development of mobile phones, mobile phone sensing has also gain much popularity due to its convenience [4] [5].

However, using mobile phone as the only device for individual's daily behavior sensing is still a relatively new topic. Nathan, *et al.* [6] describes using data generated by mobile phones to discover individual and social patterns in human society . Funf[1] is a platform build on Android that can collect various kinds of mobile phone generated data for user to view, trace and analyze. Data that can be collected include sensor data, communication data and phone usage data. Cui, *et al.* [7] proposes an energy-saving method for detecting user activity using mobile phone accelerometers. Yuki, *et al.* [8] proposes a context acquisition method using a mobile phone, using location, accelerometer, sound, etc.. Context includes user activity, environment status. Constandache, *et al.* [9] identifies the possibility of using electronic compasses and accelerometers in mobile phones, as a simple and scalable method of localization without war-driving, which is another approach for location detection without energy-consuming GPS.

There is not much previous work concerning mood assessment based on mobile phones. Moturu, *et al.* [10] explores and uncovers the associations between sleep, mood and sociability by analyzing mobile-phone-generated social communication data and self-reported mood and sleep data. Tang, *et al.* [11] propose a method for quantitatively predict users' emotional states based on mobile social network. This piece of work is different from our work in that the model input is mostly social attributes, with just a few mobile phone based attributes like location, and the model target is short-scale emotion, instead of daily mood.

III. System Overview

Our system, called *MoodMiner*, focuses on daily mood assessment based on mobile phone sensors and communication events. The proposed system contains a client application based on Android platform, and a back-end server built in Java. The client application collects sensor data as well as communication logs, applies simple analysis on the data, and finally transfers the data to the server. The back-end server stores data from all users and creates personalized model that outputs daily mood based on collected data. The output mood is then fed back to the user with a configured regular period.

We next present in detail the implementation of our system. We only cover Android platform for now, but since sensor availability does not differ much on different mobile platforms, our approach can be easily adapted for other platforms.

A. Survey of Android Platform Sensors

Android [2] is a Linux based operating system for mobile devices such as smartphones and tablet computers. [3] Android consists of a kernel based on the Linux kernel, and a mobile optimized virtual machine called Dalvik. Applications on Android is usually write in Java and translated to Dalvik dex-code running on Dalvik. Starting from 2007, Android is now one of the most popular mobile operation system.

Android has built-in support for a wide range of sensors. Currently, the Android API of version 16 describes 11 sensor types[4], with new sensor types adding gradually. What's more, android phones all have sound sensor—microphone, and most of them have the ability of sensing location using GPS, WIFI, etc.. But, since Android powers a large variety of devices, and different devices run different versions of Android system, their is no guarantee of the availability of a particular sensor type on a particular device. We have

[1] http://funf.media.mit.edu

[2] http://www.android.com/

[3] http://en.wikipedia.org/wiki/Android_(operating_system)

[4] http://developer.android.com/reference/android/hardware/Sensor.html

selected several sensor types based on the usefulness for daily behavior modeling as well as availability on different devices.

Android uses broadcaster-receiver pattern to manage sensors. When an application wants to use a sensor, it first registers itself as a receiver to the system, and at the same time, it specifies a sensitivity level at which it wants to receive sensor data. Then an event is sent to the application when sensor value is changed (according to the sensitivity level) [12].

- **Accelerometer.** Android accelerometer data is calculated by measuring forces applied to the sensor itself, including the force of gravity. There are three readings corresponding to three axes of Android coordinate system: the x-axis horizontal and points to the right, the y-axis vertical and points up, and the z- axis points towards the outside of the front face of the screen [12]. Thus accelerometer reading at time t can be denoted as $(x^{(t)}, y^{(t)}, z^{(t)})$.
  Accelerometer may be the most common sensor available on Android devices, and it has relatively low energy cost. Accelerometer data can be used to detect user's physical movement, which is very important in behavior modeling. For these reasons, accelerometer plays as a central role in our system.
- **Sound sensor.** Actually, sound sensor is not an Android sensor type. However, every phone is fitted with a microphone, which can be used to sense background sound and user's voice. In fact, environmental sound can affect human mood, and human voice can disclose mood states of the speaker.
- **Location.** Location is closely related to mood, and can also provide context information for user behavior. Android platform provides both coarse and fine location services. Location can be obtained by both GPS, WIFI, or cellular network. Fine location provided by GPS can achieve an accuracy better than 3 meters; the location error without GPS may be of tens of meters, but usually acceptable for building-level localizing.
- **Light sensor.** Ambient light sensor is used in mobile phone for auto-adjusting screen brightness, controlling keypad backlight, etc.. Optical track pad on some phones also uses light sensor. In daily mood assessment, ambient light can be employed to determine the position of the phone—in bag, in pocket, or on desk—and to detect environment brightness.

B. Application Implementation

Our *MoodMiner* system consists of the following components: collecting sensor data, obtaining communication statistics, and recording user-reported mood status on daily basis.

Our system works as follows. Sensor data collecting is started as soon as the app starts. Data of different sensor types is recorded using different strategies (explained later). Collected sensor data is stored in text files on the phone (Android has built-in support for SQLite database, but its performance for frequent large-amount data reading/ writing is very poor compared to using files.) Users can report their mood states at any time, and the reported data will also be stored in text format. Each day's data will be uploaded in the next day. Communication statistic data is collected from Android system log before the upload operation. Data uploading happens automatically when the phone has a valid WIFI Internet connection. If the phone has not connected to WIFI network for a whole day, the data will then be saved on the phone until the time the WIFI connection is available.

The application can show the calculated features related to user's behavior pattern, as well as the assessed mood. These information can also be sent to other recipients given the approval of the user. The user is able to send feedback of the assessed mood, which will be used in future assessment.

Figure 1 shows the main interface of MoodMiner, which displays calculated feature values and mood.

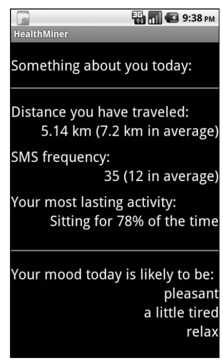

Figure 1. Information display interface of MoodMiner

C. Sensor Management Strategy

Mobile phone sensors usually cost considerable amount of energy, and intensive use of sensors will seriously affect battery life. In our system, we use different strategy to manage working cycle of different sensors, considering both energy consumption and modeling demand.

Two important and energy-costing sensory types are accelerometer and location. Accelerometer is available on most android phones, and its energy cost is considerably low among sensors. So we use accelerometer continuously in our system, for detecting users' activity as well as micro-motion (which is explained in Section IV-A). When raw accelerometer data is received, it is first compared with the previous reading. The new value is recorded only when the two values have significant difference, which indicates the physical attitude of the phone has changed dramatically (e.g. picked up by the user). Based on experiment, we only record value whose change on any axis is greater than 0.5m/s^2.

The other sensory type is location. It is measured by sensing either GPS or WIFI signal, both of which consumes a large amount of energy. We use a smart framework for location sensing, by combining location and accelerometer readings. Detailedly, the location sensor does not work continuously unless the phone is in moving state (identified via accelerometer readings); this provides better accuracy while prolonging the battery life [7].

IV. Data and Model Description

A. Problem and Feature Definition

Our approach deals with the problem of daily mood assessment using mobile phone sensor and communication data. In this section, we will give a series of definitions, and then formalize the problem.

Definition 1: **Mood.** Mood is defined as daily emotional status of a person. There are a number of structure theory about mood, most of which decomposite mood into three dimensions. Thayer [1] further states that the three dimensions are not equal - Two of them are basic dimensions and the other is a mix of two basic dimensions. We adopt Thayer's theory and choose three dimensions to represent an individual's daily mood, including *displeasure, tiredness and tensity* [3]. Degree of *displeasure* of user i in day t is donated as $d_i^{(t)}$, *tiredness* as $ti_i^{(t)}$ and *tensity* as $te_i^{(t)}$. The three values $d_i^{(t)}, ti_i^{(t)}$ and $te_i^{(t)}$ are integer values whose range is 1 to 5, with 1 for least severe and 5 for most severe. For example, $d_i^{(t)}$ can be any value of "very pleasant", "pleasant", "medium", "unpleasant" and "very unpleasant", with "very pleasant" being 1 and "very unpleasant" being 5. Overall mood of user i in day t is $m_i^{(t)}$, where $m_i^{(t)} = (d_i^{(t)}, ti_i^{(t)}, te_i^{(t)})$.

As explained above, the three dimension of mood is not totally independent. In fact, *displeasure* is an overall evaluation of mood states, whose value is affected by *tiredness* and *tensity*. Generally, people who feel less tired and more relax may feel more pleasant.

Modeling mood as three dimensions gives us flexibility to find relationships between daily behavior and a particular mood dimension, which is often more remarkable. For example, micromotion (which is explained in Section IV-A) is more related to degree of tensity than degree of tiredness. What's more, the relationship between different dimensions can help validate user-report data, and thus increases the reliability of the data.

Definition 2: **Daily behavior features.** We have defined a set of daily behavior features extracted from mobile sensor data and communication data. All features of user i in day t is denoted as $X_i^{(t)}$. Specifically, $x_{ij}^{(t)}$ is the value of feature j of user i at day t.

Next we will define the following features:

- **Location.** We have recorded the user location trace (using latitude and longitude). the recorded location is simply clustered using K-Means [13], and transformed into region.
- **Micromotion.** Micromotion is defined as the following user behavior—a user picks up the phone and does nothing useful for no longer than a few seconds. This feature is extracted using accelerometer raw data.
- **Communication frequency.** We calculate the frequency of user communicating with others using the mobile phone, considering both text messages and call logs. This feature is the accumulated number of communication times per day.
- **Activity.** We also use accelerometer data to extract user activity. Activity includes *walking, running, sitting*, and *standing* [14]. We calculate the proportion of different activities during the day.

Finally, the learning problem can be defined as:

Learning problem. Given a feature set $X_i^{(t)}$, and the previous mood state $m_i^{(t-1)}$ the goal is to establish an assessment function f that outputs mood $m_i^{(t)}$, more specifically, $d_i^{(t)}$, $ti_i^{(t)}$ and $te_i^{(t)}$. Formally, f is defined as:

$$f(X_i^{(t)}, m_i^{(t-1)}) \to m_i^{(t)}$$

Generally speaking, this can be treated as a classification problem, with the classification target being discrete ordinal levels. With the Factor Graph theory, we design an algorithm to solve this classification problem, which will be described in Section IV-C.

B. Deployment and Observation

We have deployed the application on 15 users and collected data for 30 days. Most of the users are college students and teachers, others being urban white-collar workers. Each client generates about 1 MB data per day, and the data is transfered to and stored in the central server database. We conduct a series of analysis on the data, and then present the results in this section.

We have studied the mood distribution of users. Data reveals that user-reported mood follows an approximately normal distribution, with central levels taking a large proportion (as is seen in Figure 2). This implies that for ordinary people, extreme mood is very unusual.

We have also investigated relationships between different features of a person and temporal correlation of each feature. For example, Figure 3 shows the distribution of differences between two successive time periods (two days). In this figure, horizontal axis represents the change of one's mood level compared with yesterday (0 means no change). It can be observed that daily mood has a strong time correlation, which means people tend to have similar mood as yesterday, with dramatic changes (more than 2 levels) are rarely observed.

There are also some correlation patterns observed between mood and sensor features. For example, we have studied

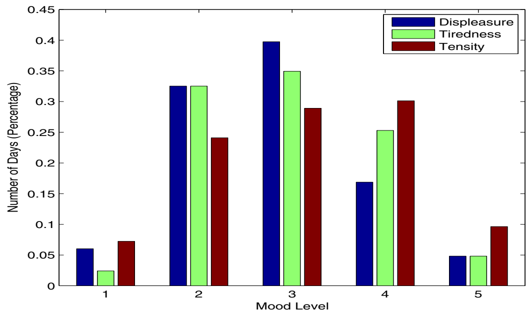

Figure 2. Mood level distribution

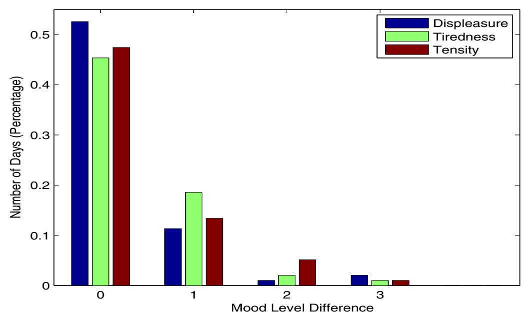

Figure 3. Distribution of mood difference of two successive days

the correlation between micromotion and mood, which is illustrated in Figure 4. It can be observed that, the amount of micromotion increases with the level of displeasure and tensity, but do not show strong correlation with the tiredness dimension of mood.

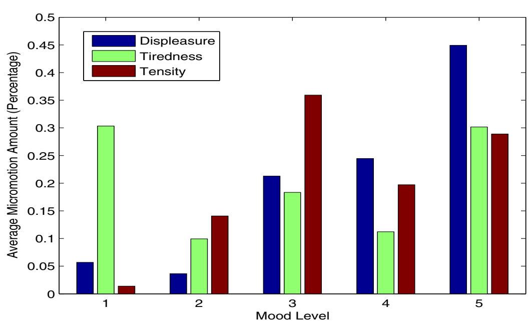

Figure 4. Micromotion distribution within different mood level

C. Model Description

Based on our data observation, we have developed a classification algorithm based on factor graph. Factor graph is a bipartite graph used for describing algorithms that deal with complicated global functions of many variables, and the global function can be factored as a product of "local" functions, each of which is a simpler function of a small subset of the variables [15], [16].

Before diving into the model, several reasonable assumptions are made based on experimental observations to simplify our model. First of all, we assume that user mood has Markov property, which means that given $m_i^{(t-1)}$, $m_i^{(t)}$ and $m_i^{(t')}$ are conditionally independent for all $t' \leq t-2$. We also assume that given $m_i^{(t)}$, all features $x_{ij}^{(t)} \in X_i^{(t)}$ are conditionally independent of each other.

Based on the observations and assumptions, we define the following factor functions:

- **Temporal correlation factor function** $h(m_i^{(t-1)}, m_i^{(t)})$. It reflects the persistence of mood. Based on Markov property, the decay of user mood can be modeled as:
$$h(m_i^{(t-1)}, m_i^{(t)}) = \alpha * e^{-\lambda \|m_i^{(t)} - m_i^{(t-1)}\|} \tag{1}$$
- **Feature correlation factor functions** $c(x_{ij}^{(t)}, m_i^{(t)})$. There are two kinds of user features: mood and behavior features. According to the assumption, we only have to consider correlations between mood and behavior features. We adopt a Naive Bayes (NB)-based strategy, so $c(x_{ij}^{(t)}, m_i^{(t)})$ is modeled using Bayes theory, and the pairs previously observed have higher values.

V. Evaluation

The dataset we obtained by the experiment contains 2,872,311 sensor data records (including accelerometer, location, etc.), 3,169 SMS records, and 5,871 call records.

The raw data is aggregated into features, with one value for each feature in one day of every subject. Self-reported mood data is aligned into the levels pre-defined, and for those who marked their mood more than once a day, we take a weighted average to be the mood value of the day, with those later reported values having higher weights.

Users are required to run the app in their phones during their active time period of a day, and they can of course stop the app when they are about to go to sleep, because sensor data during sleep does not effectively reflect daily behavior and consequently is not useful in mood assessment. Since what we address is a classification for ordinal discrete levels, we apply metrics of accuracy (percentage of days that predicted value is exactly true value) and RMSE (root-mean-square error) to measure the effectiveness of our method.

Table I
Performance of MoodMiner mood assessment

Target	Accuracy	RMSE
Displeasure	52.58%	1.446
Tiredness	45.36%	1.519
Tensity	47.42%	1.564

Discussion. The assessment model achieved an acceptable performance, with an accuracy around 50%. Error of the output comes in several aspects. First of all, because of the subjectiveness of mood, sensor data, communication data, and historical mood data may fail to reflect mood swings in some circumstances — it just changes without any indication. Furthermore, people show significant difference in daily behavior style and use pattern of mobile phone, making it difficult to build a model working well for anyone. For some people, mobile phones (though so powerful) is just a tool for making calls and receiving messages, and they would leave their phone on the desk forever unless there is an incoming call. The model may fail for these users. There are also some kinds of mobile phone data that we have not taken into consideration, like the mobile apps' usage data and other communication data apart from calls and SMS (e.g. *Talkbox*[5]). Such missing data may also affect the performance of our model.

VI. Conclusion

In this paper, we propose a novel approach to assessing individual's daily mood using mobile phone. We first extract several features from mobile phone data, and then propose a method based on factor graph for assessing mood using these features. We have built a system for data collection and model implementation. The client application works on Android platform, which collects sensor data and communication data, while the algorithm runs on the server application, which receives data and provides mood states as output. Experimental results on 15 users for 30 days shows that our system can effectively assess daily mood objectively, with minimal user intervention.

The problem of mobile phone-based mood assessment is an interesting topic in sensor data mining and still needs more exploration. For future work, more social networking information will be taken into consideration, like the mood propagation, instead of just counting communication frequency. Then the personal assessment model can be transformed into a model on a dynamic social graph. We can also integrate into our model with more context information, such as the weather and the public events of places the user visits. In sensor data processing, cross-sensor features may also help improve the performance of our model.

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References

[1] R. E. Thayer, *The Biopsychology of Mood and Arousal*. New York, NY: Oxford University Press, 1998.

[2] P. Wilhelm and D. Schoebi, "Assessing mood in daily life - structural validity, sensitivity to change, and reliability of a short-scale to measure three basic dimensions of mood," *European Journal of Psychological Assessment*, vol. 23, pp. 258–267, 2007.

[3] R. E. Thayer, *The Origin of Everyday Moods: managing energy, tension and stress*. New York, NY: Oxford University Press, 1996.

[4] N. Lane, E. Miluzzo, H. Lu, D. Peebles, T. Choudhury, and A. Campbell, "A survey of mobile phone sensing," *Communications Magazine, IEEE*, vol. 48, no. 9, pp. 140 – 150, sept. 2010.

[5] C. Seeger, A. Buchmann, and K. V. Laerhoven, "myhealthassistant: A phone-based body sensor network that captures the wearer's exercises throughout the day," in *BodyNets*, 2011.

[6] N. Eagle and A. (Sandy) Pentland, "Reality mining: sensing complex social systems," *Personal Ubiquitous Comput.*, vol. 10, no. 4, pp. 255–268, Mar. 2006.

[7] J. Cui, G. Sun, and B. Xu, "Ad-sense - activity-driven sensing for mobile devices," in *The 9th ACM Conference on Embedded Networked Sensor Systems (SenSys'11)*.

[8] Y. Arase, F. Ren, and X. Xie, "User activity understanding from mobile phone sensors," in *Proceedings of the 12th ACM international conference adjunct papers on Ubiquitous computing*, ser. Ubicomp '10. New York, NY, USA: ACM, 2010, pp. 391–392.

[9] I. Constandache, R. Choudhury, and I. Rhee, "Towards mobile phone localization without war-driving," in *INFOCOM, 2010 Proceedings IEEE*, march 2010, pp. 1 –9.

[10] S. Moturu, I. Khayal, N. Aharony, W. Pan, and A. Pentland, "Using social sensing to understand the links between sleep, mood, and sociability," in *Privacy, security, risk and trust (passat), 2011 ieee third international conference on social computing (socialcom)*, oct. 2011, pp. 208 –214.

[11] J. Tang, Y. Zhang, J. Sun, J. Rao, W. Yu, Y. Chen, and A. Fong, "Quantitative study of individual emotional states in social networks," *IEEE Transactions on Affective Computing*, 2011.

[12] Sensorevent documentation for android developers. Android Open Source Project. [Online]. Available: http://developer.android.com/reference/android/hardware/SensorEvent.html

[13] J. A. Hartigan and M. A. Wong, "Algorithm as 136: A k-means clustering algorithm," *Journal of the Royal Statistical Society. Series C (Applied Statistics)*, vol. 28, no. 1, pp. pp. 100–108, 1979.

[14] L. Bao and S. Intille, "Activity recognition from user-annotated acceleration data," in *LNCS 3001*, 2004, pp. 1–17.

[15] F. R. Kschischang, B. J. Frey, and H.-A. Loeliger, "Factor graphs and the sum-product algorithm," *IEEE Transaction on Information Theory*, vol. 47, pp. 498–519, Feb. 2001.

[16] J. Hopcroft, T. Lou, and J. Tang, "Who will follow you back? reciprocal relationship prediction," in *The 20th ACM Conference on Information and Knowledge Management (CIKM 2011)*.

[5] http://talkboxapp.com/en/home