Reflecting on Mood and Movement

Brett Clippingdale
School of Information
University of Michigan
Ann Arbor, MI USA
clipping@umich.edu

Martha E. Pollack
School of Information
University of Michigan
Ann Arbor, MI USA
pollackm@umich.edu

Mark W. Newman
School of Information
University of Michigan
Ann Arbor, MI USA
mwnewman@umich.edu

Michael A. Fauman
Department of Psychiatry
Medical School
University of Michigan
Ann Arbor, MI USA
mafauman@umich.edu

CHI 2009, April 4 – April 9, 2009, Boston, MA, USA
ACM 978-1-60558-247-4/08/04.

Abstract
We are developing a system for self-reflection and mood monitoring ultimately focused on the treatment and clinical management of depression. We plan to analyze movement sensor data to infer internal, mood states from individuals' externally-observable behavior, and then present this as feedback to help individuals develop a greater awareness of their moods throughout the day. Coupled with *in situ* experience sampling, we hope to stimulate reflection with informed self-analysis, helping people with depression become more aware of the changes in their mood states, and giving therapists a more complete picture of the status of their patient's mood in real-time. By better understanding their moods, individuals and their therapists can hopefully monitor how the individuals are responding to treatment and can detect relapses at an early stage allowing for a more effective therapeutic intervention.

Keywords
Reflection, HCI, experience sampling, depression, affect, ubiquitous computing, sensors, GPS.

Introduction
Depression is a serious problem in the United States. Major depressive disorder (MDD), for example, affects 4.9-17.9% of the adult population. MDD is a severe, often recurrent mental disorder that includes disturbances in mood, thought, behavior, activity, and

physical health [8,14]. Left untreated, it can lead to significant morbidity and mortality. Clinical interventions such as psychotherapy and medication have been shown to treat major depression to remission in at least 40% of cases [7]. However, effective treatment depends on timely and accurate diagnosis, effective monitoring, and patient and caregiver cooperation. Typically, initial diagnosis, treatment and monitoring are done in weekly or biweekly meetings between the patient and clinician. There is currently, however, no effective method of real time monitoring between therapy sessions. This becomes even more important once a patient responds to treatment because the time between sessions may be stretched even further. Therefore, the therapist may not detect those patients who relapse between sessions, unnecessarily increasing patient suffering and prolonging treatment.

We are exploring what manual logging and sensor data can reveal about a person's psychological state in real-time, what correlations exist between sensed physical activity, location, and mood, and how we might present this information to individuals and therapists to help them monitor depression and the response to various kinds of treatment. Two main goals of psycho-therapeutic interventions are to introduce self-reflection and to foster behavior change. Technologies for self-reflection have been shown to positively impact general behavioral change [e.g., 2,11]. We plan to provide those who suffer from mood disorders with additional information to enable and stimulate self-reflection.

For severe forms of depression, such as MDD, both patients and therapists could use that information as a basis for the initiation or modification of a therapeutic approach. For minor depression, that information may lead to therapist-mediated reflection that helps individuals develop insight and use cognitive methods to manage their depression.

In addition to the potential benefits of improved self-reflection, monitoring real-time information about psychological state and behavior has a number of potential benefits for clinical treatment. First, diagnosis may improve with the identification of mood and behavior patterns that would not otherwise emerge during clinical visits. Second, treatment plans could be more effective when informed by understanding what behavior patterns lead to undesirable outcomes. Third, real-time monitoring of psychological state and behavior may provide better understanding of the efficacy of treatment plans. Finally, this information may empower patients to feel more self-aware, in control, and able to manage their own mood. Clinical benefits such as these could result from automatic diagnosis and tracking that infers mood or condition from raw sensor data, or could result from *mediated reflection*. In the latter case, patient and care provider take advantage of sensed activity patterns in order to engage in a more productive conversation about the patient's experience. In particular, we believe that trained professionals (e.g. psychiatrists, psychologists, social workers, etc.) could benefit from more information about a patient's daily fluctuations in behavior, mood, and other signals.

Background and motivation

Our initial work seeks correlations between coarse physical movement, location, and mood, with a particular focus on depression. This is not an entirely new approach. Affective computing [12] has had some

success, mostly in laboratory-based studies, inferring emotional state from video, speech, computer use, and biometrics. More relevant to our project is the sensor-based depression research already done by others. In particular, accelerometer-based "actigraphy" has been used for decades to analyze the degree and temporal distributions of fine motor movement, revealing a strong correlation between depression and the disruption of circadian rhythm [13]. However, we'd like a more general understanding: as sensors become more ubiquitous and acceptable in everyday life, we wish to understand what other sensed information might provide similar correlations with various moods, especially depression. We also seek ways of gathering information with sensors that are less invasive and obtrusive than those used for actigraphy.

Our *in situ* experience sampling method [4] for collecting mood data via SMS text messaging is novel; however, others have done SMS-based experience sampling and diary studies for other purposes; examples include Momento and MyExperience [1,5].

Study and Goals

We completed a pilot study with 5 subjects, and plan to follow with a larger study of 40 subjects. In these initial studies, our subjects are students. Once we are confident of our methodology, we will conduct a larger, longitudinal study composed of subjects drawn from a clinically depressed population. While our broad goal is to understand how monitoring behavior and mood can improve outcomes for people suffering from depression, our initial study investigates a more constrained question: what can sensors reveal about a person's psychological state, and what correlations exist between sensed physical activity and mood? As a first step, we monitor gross physical motion using GPS-based position to determine when, and how often, individuals leave home, how far they travel, and how many places they go, as well as to which ones. We augmented this with experience sampling, using cell phone-based SMS for psychometric testing as a means of determining each person's mood throughout the day.

Methodology

At the initiation of the study (before collecting any other data), each participant completed a long-form standard psychometric mood evaluation (see discussion below). Each subject then carried a GPS data-logger and his or her own cell phone; the cell phone served as an experience sampling platform with queries to determine participants' mood through periodic psychometric surveys delivered via SMS. At the end of each trial, we interviewed each subject to learn their own view of the links between location, movement, and mood. This information will be used as a comparison against the correlations that are found using automated analyses, which are still being defined.

To gauge each subject's mood, we used the Profile of Mood States (POMS) psychometric test [10], which measures mood along 6 axes: tension-anxiety, depression, anger-hostility, vigor-activity, fatigue, and confusion-bewilderment. At the beginning of the study, we asked each subject to complete the standard form POMS test, in which the subject rates how much they are feeling 65 items (e.g. lively, on edge, resentful, annoyed) on a 5-point Likert scale. Then, during the study, we used an adaptation of the POMS test called POMS-15, a reduced 15-item form of POMS [3]. POMS-15 yields scaled values for 5 mood factors (discarding the confusion-bewilderment axis). Of the rigorous

mood-assessing psychometric tests, POMS-15 is the most compact of which we are aware, requiring just 3 questions per measured mood axis.

Because we wished the study to be as non-invasive as possible, we used technology that subjects already have; in this case, we did the psychometric testing via SMS text messaging over the subjects' own cell phones. We sent queries throughout the day, polling over a random distribution of the POMS-15 items. Part of the purpose of this feasibility study is to understand how to best present these messages, when, and how often; exit interviews suggest a wide range of preferences/tolerances.

To track location and movement, we supplied each participant with a QSTARZ BT-Q1000P portable GPS logger. These devices are quite small and unobtrusive, roughly comparable to a very small cell phone. We asked each subject to put it at the top of their backpack, in their purse, or mounted on a supplied hip-clip. We left the GPS unit with our participants for the duration of the study, and required only that they carry it with them whenever they left their homes. We also sent SMS messages each morning to remind them to carry it with them. At the end of each trial, we downloaded the data and began analysis.

We are interested in examining the collected data both quantitatively and qualitatively. Like the actigraphy studies, correlations between sensor data and mood are calculated using quantitative statistical methods. We are also interested in examining the data qualitatively; for example, does a particular individual have positive or negative associations with particular locations they frequent? When feeling depressed, do they tend to go to Ben & Jerry's, or do they bypass their usual latté detour on their way to work? Do certain location-based behaviors (e.g., a visit to the gym) precede improvements in mood?

Discussion

Our initial study is intended to lay the groundwork for our broader goal of helping depressed individuals cope with their mental illness more effectively. By looking for connections between sensed activity and mood, we hope to gain insight into how best to interpret and present information about individuals' behavior to support self-reflection, mediated reflection, and clinical interventions. The specific forms of those reflections remain an area of future work. However, there are near-term benefits that we believe can be realized as outcomes of this study.

Merely by answering the POMS-15 questions with their cell phones, subjects are forced to reflect upon their moods. This creates a critical distance between their thoughts and their feelings, inviting a more analytical and self-directed approach to managing their mood trajectories. Currently, the data are collected at a server and analyzed for correlations with the recorded GPS data only at the end of the study. However, we hope to eventually make the analysis local and immediate (perhaps with processing directly on a smart phone that communicates with an external or on-board GPS, as well as other sensors), thus creating a real-time mood monitor. By exploiting communication features and addressing privacy issues, it may be possible to share this data, enabling interventions by caregivers.

By providing individuals with a clearer picture of their internal psychological states throughout the day, we hope to allow them to become more emotionally aware, and to empower them to make better choices about how to handle their moods. By eliciting feedback directly from the subjects, we hope to encourage deeper reflection about their emotional states, possibly leading to greater emotional well-being. We envision providing feedback with peripheral awareness via cell phone, similar to UbiFit [2] and Affective Diary [9]. By doing experience sampling of mood while providing this awareness, the system may reinforce or contradict the user's mood assessment, thus creating a feedback loop that may affect the responses to our mood queries. While this may represent a threat to the validity to our mood data, we consider it an integral part of our goals for self-reflection by the individual, where improved awareness may lead to corrective action, whether self-directed or therapist-mediated. This is similar to the *affective loop* described by Höök: "The user's emotions are influenced by those emotions expressed by or through the application, and vice versa" [6]. Although helpful insofar as it encourages reflection, it may, however, undermine an individual's confidence in their ability to understand their own moods.

As the study expands to consider the clinically-depressed, we will be particularly interested in helping subjects and caregivers monitor therapeutic treatments, whether in the form of exercise, conscious mood management, cognitive therapy, medication, or some combination. This might enable help in the form of direct interventions and better, timelier awareness of patient health than might otherwise be available only from patient self-reporting. We also believe this will be an interesting space for interface design and data visualization. Finally, when used to monitor response to medication, the system may help doctors to find the unique lower bound of effective dosage for patients with depression, Alzheimer's, Parkinson's, or other diseases that exhibit externally-observable behaviors.

There are many interesting questions that we hope to address, depending on the results. Not only should we be able to provide feedback to enable self-reflection for individuals with depression, but without any *a priori* knowledge we may be able to determine, from sensor data alone, whether a person suffers from, or is at risk for, depression. Finding definitive correlations is challenging for the general population; with significantly depressed patients where mood and activity signals are stronger, the relationship is presumably clearer, and it may even be possible to detect the onset of a major depressive episode. Unlike actigraphy-based sensing, coarse movement alone probably cannot provide a generalized depression screen; each individual will have a unique baseline and context. However, preliminary data suggest it may be possible to discover mood trajectories when individuals are monitored for a longer period of time; we may also add sensors that monitor other correlates of depression, such weight and sleep changes. This work may also benefit non-depressed individuals. For example, data from the pilot study suggest the system may also help individuals reflect on their anxiety and in the treatment and management of anxiety disorders.

Eventually, we will devise studies with richer sensor environments, monitoring individuals' biometric data, physical location, and performance of various activities within the home. We don't know what sensed information will show correlations between which

moods (let alone causative effects), but we hope that exploratory data analysis, especially using techniques from AI (e.g. clustering and self-organizing maps for highly dimensional data), will reveal some surprising links that traditional analysis might fail to discover.

Conclusion

As mobile sensors become cheaper, smaller, and more ubiquitous, new possibilities are opening up for monitoring users' activity patterns. One promising application for such monitoring is enabling reflection and clinical intervention for mental illnesses such as depression. In this workshop paper, we have outlined our near-term goals to develop techniques for depression monitoring using portable sensors. Through an initial study comparing GPS-based location traces with periodic self-reports of mood, we hope to gain insight into the links between behavior (specifically movement between locations) and mood. As the work progresses, we plan to build on this to develop tools and interventions for combating depression. We expect that improved self-awareness, regular reflection about mood, and monitored therapy/treatment may enable higher life quality, especially for those who suffer bouts of major depression.

References

[1] Carter, S., Mankoff, J., Heer, J. Momento: support for situated ubicomp experimentation, Proc. CHI 2007.

[2] Consolvo, S., McDonald, D., Toscos, T., Chen, M., Froehlich, J., et al. Activity Sensing in the Wild: A Field Trial of UbiFit Garden, In Proc. CHI 2008, ACM Press.

[3] Cranford, J. A., Shrout, P. E., Iida, M., Rafaeli, E., Yip, T., Bolger, N. A procedure for evaluating sensitivity to within-person change: Can mood measures in diary studies detect change reliably? Personality and Social Psychology Bulletin, 2006, 32:917-929.

[4] Csikszentmihalyhi, M., Larson, R. Validity and Reliability of the Experience-Sampling Method. Journal of Nervous and Mental Disease, 1987, 175:526-536.

[5] Froehlich, J., et al., "MyExperience: A System for In Situ Tracing and Capturing of User Feedback on Mobile Phones," Proc. of MobiSys '07, pp.57-70.

[6] Fagerberg, P., Ståhl, A., and Höök, K. Designing Gestures for Affective Input. In Proceedings of Mobile Ubiquitous and Multimedia (MUM) (Norrköping, Sweden, 2003).

[7] Insel, T.R. Beyond Efficacy: The STAR*D Trial. Am J Psychiatry. 2006 Jan;163(1):28-40.

[8] Kessler RC, McGonagle KA, et al. Lifetime and 12-month prevalence of DSM-III-R psychiatric disorders in the United States. Results from the National Co-morbidity Survey. Arch Gen Psychiatry 1994;51:8–19.

[9] Lindström, M., Ståhl, A., Höök, K., Sundström, P., Laaksolathi, J., Combetto, M., Taylor, A., and Bresin, R. 2006. Affective diary: designing for bodily expressiveness and self-reflection. Extended Abstracts CHI 2006. ACM, New York, NY, 1037-1042.

[10] McNair, D. M., Lorr, M., Droppleman, L. F. (1992). EdITS manual for the Profile of Mood States. San Diego, CA: Educational and Industrial Testing Service.

[11] Mamykina, L., Mynatt, E., Davidson, P., and Greenblatt, D. 2008. MAHI: investigation of social scaffolding for reflective thinking in diabetes management. In Proc. CHI 2008. ACM Press, 477-486.

[12] Picard, R.W. Affective Computing. MIT Press, 1997.

[13] Teicher, M.H., Lawrence, J.M., et al. Increased activity and phase delay in circadian motility rhythms in geriatric depression. Preliminary observation. Arch Gen Psychiatry, 1988, 45: 913–917. 16.

[14] Weissman, M.M., Bruce, M.L., Leaf, P.J., et al. Affective disorders. Psychiatric disorders in America: the Epidemiologic Catchment Area Study: The Free Press. New York; 1991. p. 53–80.