Consistent Excitement Correlates with Happiness - Predicting Mood Through Body Sensing with Smartwatches

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Abstract

We built a body sensing system using commercially available smartwatches to collect individual mood states and correlate them with body sensing data. In particular, in this first prototype we collected acceleration, heart rate, and light level data from the smartwatch, and location through the GPS sensor of the smartphone. We also polled users on the smartwatch for a week four times per day asking for their mood state. We found that the higher the heart rate, the higher the level of activity sampled through changes in x,y,z coordinates of the accelerometer, and the more consistent the movement, tracked as lower variance in the x-coordinate of the accelerometer was, the higher the individual self-reported level of pleasance and activation was. This system is a first step towards building an automated mood tracking system to be used for better teamwork.

Introduction

Frequently we are working ourselves into a rage without being aware of it. Or we might get angry and become upset about out teammates without an obvious cause. What if we had an early warning system that alerts us before we are getting all stressed out, so we can calm down by taking a break, or taking a walk in the park?

Based on the premise that your body tells you how happy or unhappy you are, we propose a body sensing system that automatically recognizes individual mood state and proposes corrective action. Using commercially available Pebble smartwatches we built a body sensing system that can measure individual mood states and interactions between people. Our prior research analyzing e-mail archives (Gloor 2015), and interpersonal interaction using sociometric badges (Gloor et al 2012) has shown that communication patterns of individuals and teams can be calculated automatically from communication archives, and that positive mood states and particular modes of interaction are associated with higher quality teamwork.

As there exists a ripple effect of positive emotional contagion, where group members experience improved cooperation, decreased conflict, and increase perceived task performance (Barsade 2003), knowing the mood state of one's co-workers will increase positive emotional feelings in the whole group.

Research Setting

Our system is based on years of experience working with sociometric badges developed at MIT's Media Lab, which record location, speech, and energy levels of people wearing them, and also note when members of workgroups are interacting in person. These badges are a powerful tool for gathering data on workplace interactions, but are relatively expensive and can be difficult to use in long-term studies.

Researchers have also been using smartphones to track mood of their owners over extended periods of time and correlated it with their location (Sandstrom et al. 2016, Doherty et al. 2014).

The goal of this project is to develop a lightweight, inexpensive, and non-intrusive sensor system that is easy to use over extended time periods, using smartwatches instead of sociometric badges. We are integrating the smartwatch with each subject's smartphone to access the phone's location sensing and data transmission capacity, as well as its processing power. The smartwatches also provide data on lighting level and heart rate. Unlike the badges, the watches are designed to be worn constantly, naturally and non-intrusively, and their rechargeable batteries have robust charge length. Their displays also enable easy two-way communication to give status updates to wearers.

Figure 1 below illustrates the target architecture, consisting of three components:

The ***smartwatch*** uses its built-in accelerometer, light sensor, microphone, and heart rate sensor to gather data. Location is detected by the ***smartphone***. Data from both is uploaded instantaneously to a server.

Mood states of users are polled at random times 4-7 times per day for 2-3 weeks. This information can be used to train to a machine learning system to correlate sensor data with wearers' mood states. After the training phase, mood can be shown to the user based on smartwatch sensor readings.

Collaboration patterns of face-to-face and email interaction between work group members will be compared against best practices identified in prior research, with organizational performance metrics also be used to assess collaboration effectiveness.

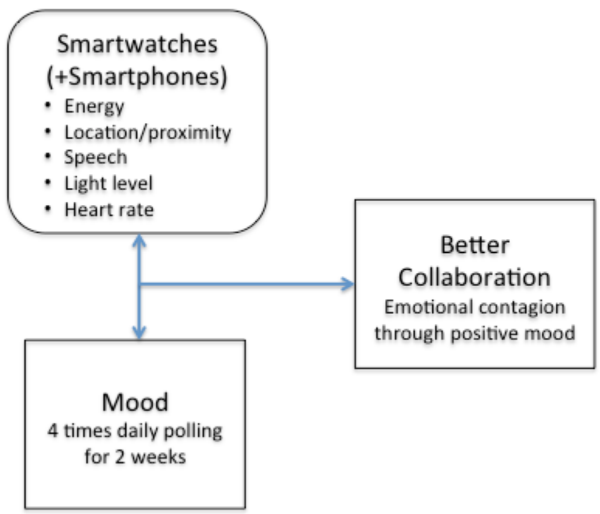

Figure 1. Smartwatch-based sensor system

Recording Mood States

The smartwatches enable us to easily record the mood states of the smartwatch wearer using experience-based sampling (Hurlburt & Schwitzgebel 2007). Hurlburt and Schwitzgebel (2007) found that polling users repeatedly to ask them about their mood states was a reliable way to assess their emotional state.

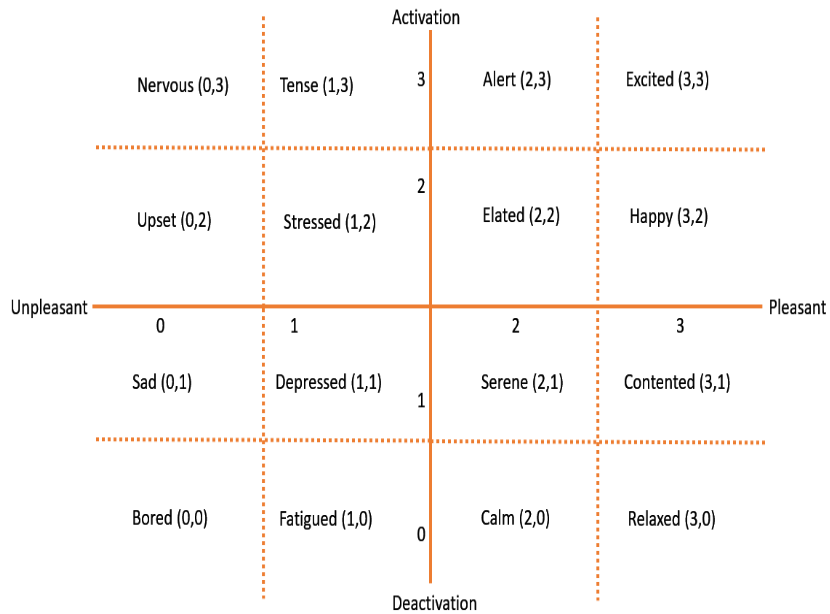

Figure 2. Two-dimensional mood state grid

We implemented a four-by-four grid in the two dimensions pleasance and activation (Rafaeli et al 2007) (Barrett 2006), see figure 2. This means that in two steps we can collect sixteen different mood states as combinations of four levels of pleasance and four levels of activation.

System Architecture

A team of students of the 2016 COINs collaborative innovation networks seminar (Gloor et al 2016) with team members from University of Cologne, University of Bamberg, and Jilin University, Changchun China[1] built the basic smartwatch software infrastructure for the Pebble smartwatch and tested it in a laboratory setting.

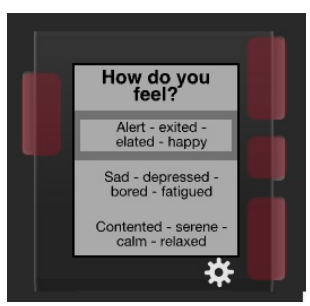

Figure 3. Pebble smartwatch Happimeter App

The basic system includes four software components:

1. The “happimeter” Pebble app to collect data from the accelerometer, light sensor, microphone, and heart rate sensor in the smartwatch and location from the smartphone.

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[1] The team members are Pascal Budner (Cologne), Cihan Öcal (Cologne), Jan Marc Misselich (Cologne), Ines Rieger (Bamberg), Joscha Eirich (Bamberg), Anne Schleicher (Bamberg), Xia Yu (Rain) (Jilin) Liqi (Jilin), Gavin (Jilin)

2. The “happimeter” Pebble app also polls users 4-7 times per day by vibrating the smartwatch, and asks them to enter their mood states (figure 3) (Hurlburt & Schwitzgebel 2007).
3. On the smartphone the “happimeter” Pebble app runs in the background and continuously transfers sensor data to a server.
4. A responsive web site shows users their sensor data. We are also adding a comparison of individual sensor and mood data to that of their peers. In prior studies, users have valued such mirroring feedback, and it increased their motivation to continue participating.

Figure 4 illustrates the Web site giving immediate user feedback from the mood poll and the sensor readings.

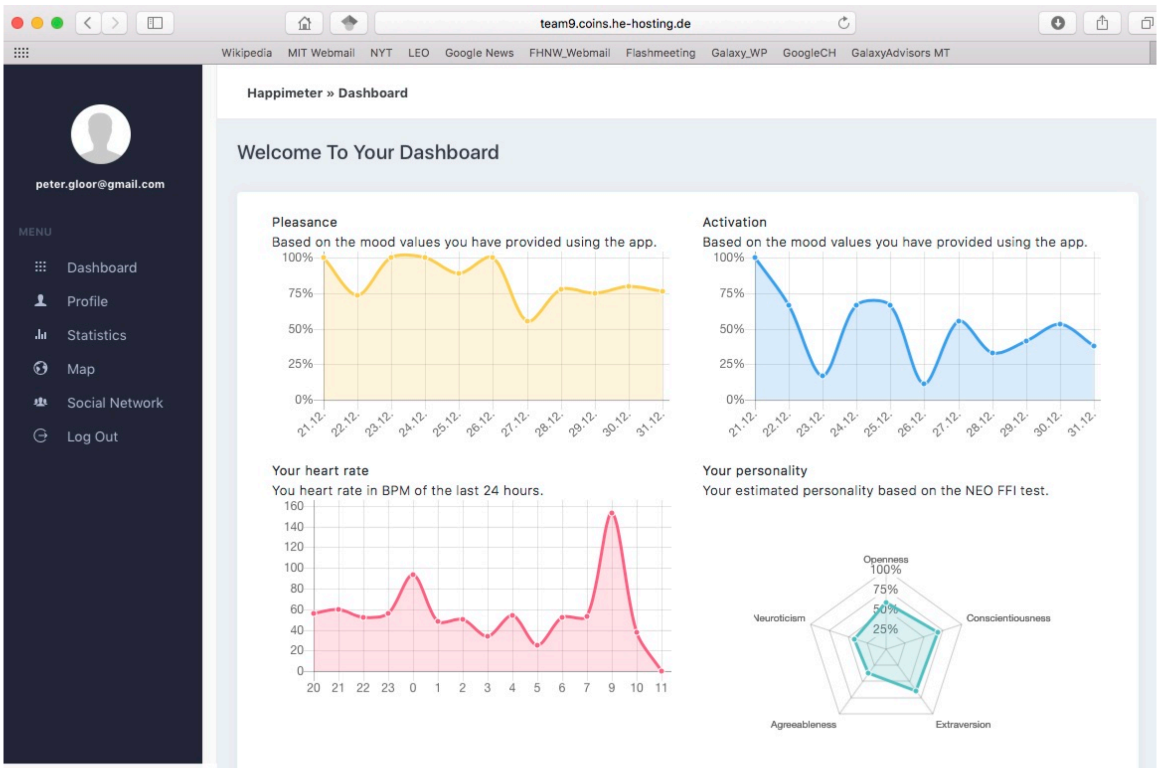

Figure 4. Responsive Web site giving user feedback

We will also build a machine learning system to train the smartwatch to predict mood state based on the smartwatch sensor readings. In this initial pilot we will train the system with data from 20-30 students, wearing the smartwatch and responding to the mood survey for 2-3 weeks. After initial training, the smartwatch will automatically show the mood of its wearer, calculated from the sensor readings of the smartwatch.

Preliminary Results

In an early ”proof-of-concept” six individuals were wearing the Pebble smartwatch for one week, and recording their mood using the “happimeter” app described above to record their mood along two dimensions, pleasance and activation. At the same time, the “happimeter” app was also recording their sensor readings (accelerometer, light level, heart rate, location). Table 1 shows the results. We found positive significant correlations between the sum of happiness and activation and heart rate (avgbpm), and the total level of activity measured through changes in velocity (vmc). We also found negative correlation between changes in activity level measures through the variance of the x-coordinate of the accelerometer.

Correlations

		avgbpm	activity	acc_var_x	vmc
pleasant	Pearson Correlation	.178	.029	-.278*	.248*
	Sig. (2-tailed)	.122	.800	.014	.030
	N	77	77	77	77
activation	Pearson Correlation	.179	-.246*	-.140	.105
	Sig. (2-tailed)	.119	.031	.224	.366
	N	77	77	77	77
happy+activ	Pearson Correlation	.258*	-.182	-.289*	.242*
	Sig. (2-tailed)	.024	.113	.011	.034
	N	77	77	77	77

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Table 1. Correlations between smartwatch sensor readings and self-reported mood

Figure 5 resumes the main findings. The higher the heart rate, the more steady the movement of the user, and the more the user moves around, the happier and more activated the user is. A faster heart rate in expectation of a pleasant surprise is not all that surprising, nor that the more a user moves around, instead of sitting in a corner, the more positive her mood. However it also seems that a steady movement, shown as low variance in acceleration, is also an indicator of positive mood.

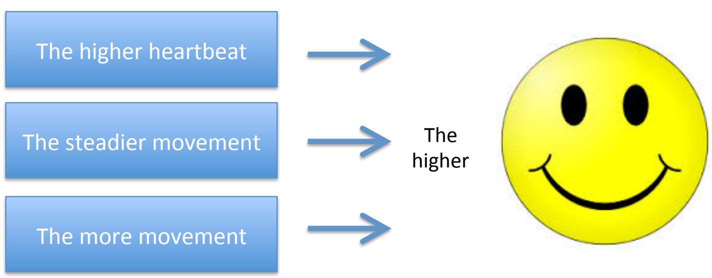

Figure 5. Predicting mood from sensor data

As a side result we also found that the lower the activity of the user is, the higher his self-reported activation is.

Discussion and Future Research

Unfortunately Pebble was bought in November 2016 by Fitbit, and discontinued production of their smartwatch, while maintaining the Cloudpebble software development platform. We bought a supply of smartwatches for our experiments, but for future work we might have to port our platform to other types of smartwatches.

Such studies require collection of data from the smartwatch sensors, data on communication patterns inside work groups, and performance metrics for those groups. In future work communication data will be collected by mining e-mail/Skype/phone archives, which our group has been doing for 15 years. Face-to-face interactions will be discerned by smartphone proximity. We can then use this sensing system to track work group mood, interactions, and quality of group work output. The long-term vision is that smartwatches can become a key element of team coordination providing valuable feedback to adjust collaboration behavior based on people's moods and the kind of tasks a work group is tackling.

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