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Correlation Between Self-Reported Mood States and Objectively Measured Social Interactions at Work: A Pilot Study

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***Abstract*—A number of clinical studies investigated associations between mood states and environmental factors. However, they mostly rely on self-reporting methods to describe past activities which, due to recall difficulties, may not be reliable. In this pilot study, we attempted to measure the amount of social interaction at workplace in an objective way and to investigate correlations with mood states. The results show correlation between social interactions and mood states both in the beginning and at the end of monitored intervals.**

Keywords- social interactions; mood states; pervasive computing.

I. Introduction

There are a number of factors that may affect the mood such as environmental conditions [16], social interactions [10, 12], location [14] and physical activities [14]. Mood changes and the factors that influence these changes are studied with respect to general well-being and also regarding mood disorders of which the best known are clinical depression and bipolar disorders. In addition, mood disturbances may affect work productivity thus causing Lost Productive Time (LPT) and consequently significant financial losses. For instance, due to workers with depression US employers incurred expense of $44 billion per year in LPT, which was $31 billion more in comparison to the workers without depression [9].

An important factor affecting the mood is social interaction [17]. Being an integral part of our life, social interaction undoubtedly affects the way we feel both in positive and negative way [10,18]. Typically, having a pleasant conversation with colleagues or receiving complements for achieved results may improve our mood, while on the other hand arguing or being criticized can provoke negative emotions. Therefore, social interaction can be perceived from workers' point of view both as a pleasant and displeasing experience.

Previous studies that were investigating mood and its determinants mostly relied on questionnaires to report social activities and their intensity. However, applying self-report methods to express past activities suffers from human subjectiveness since individuals are prone to neglect or to overestimate certain parameters related to performed activities. On the other hand, technological advancements provide means to measure and recognize activities in an objective way. The field of sensors has created a solid basis to support the development of smart environments capable of recognizing activities and inferring behavioural patterns of people. While significant results are achieved in the area of activity recognition, direct monitoring of social interactions is still very challenging task. Several attempts are made in the field of automatic recognition of social-interaction, such as the study by MIT Media Laboratory [11] that used sociometric badges to identify social activity among individuals working in the same team. However, having a dedicated device reminds the subjects that they are being monitored, which may influence their behaviour and consequently affect the reliability and objectiveness of measurements.

In our study, instead of using additional sensing to recognize social interactions, we used only mobile phones since they are widely accepted and commonly used. Phones are also adaptable for everyday usage and people are carrying the phones anyway, therefore they represent a suitable tool for conducting social interaction experiments in an unobtrusive manner. The microphone embedded in mobile phones is well suited for many context-aware applications and is also very robust source of information. Being part of every mobile phone, microphone is one of the most ubiquitous and unexploited [4] sensor that is capable of making inferences about human activity, conversation detection [19], location [3,7] and social interaction [20] from sound. Since typical social interaction involves a conversation between subjects, we based our approach on detecting the voice of subject and calculating the duration of conversation. The audio from a phone's microphone was continuously sampled and was used as the basis to quantify the amount of social interaction that participants had during the working day. We used the social interaction information about the subjects to investigate possible correlations between the amount of social interaction and subjects' self-reported mood states.

II. Related Work

A. Mood

There is a spectrum of approaches to study mood from clinical studies while relatively small number of them exploit technological solutions for mood research. A number of studies aimed at recognizing factors that influence daily mood variability and measure the intensity of these factors such as anger, cheerfulness, depression, or a combination of these factors.

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Robbins [12] investigated patterns of depressed mood periods in healthy subjects. The experimental procedure used in this study was 105 undergraduate students followed for a period of 10 days, by using a self-administered psychological diary. In reflecting upon their experience, eighty-four percent of the days were reported by subjects as having periods of depressed mood. The results showed that the peak of bad mood was usually in the evening. Subjects who reported a constant depressed mood were more likely to report higher levels of health problems and less pleasure in social interaction rather than persons who reported only depressed days involving mood swing. Volker et al. [13] assessed sleep quality by a brief self-rating questionnaire in each of three mornings after getting up from bed, to determine relation between sleep quality and diurnal variation of mood. Sleep quality was positively correlated with vigour at awakening, negatively with fatigue after awakening and during the morning, and negatively correlated with anger after awaking. Several experimental studies examined determinants of daily mood variability. According to Stone et al. [14] most mood states are strongly associated with activities and location. This study included ninety-four subjects that completed daily diaries every 15min for 1 day, where they managed to correlate most mood states with certain activities and locations.

From the above-mentioned studies a considerable work has already been done in applying methods of self-reporting and observing psychological measures to examine relationship between mood and environmental factors. However, there have not been reports of many studies that used technological solutions to investigate mood and determinants of its variations. Hasler et al. [8] examined daily activities and conversations by using Electronically Activated Recorder (EAR). The authors examined daily diary entries that monitor the sound of participants using EAR device where they found activities associated with Positive Affects (PA) such as socializing, laughing, and singing with it was not the case for activities associated with Negative Affects (NA) such as arguing and sighing. To investigate sociability at workplace, the study in MIT Media Laboratory [11] presents a detailed description of human behavior in terms of physical activity, speech activity, face-to-face interaction, proximity and social network attributes from sensor data. The approach was based on using Sociometric badges that are capable to measure physical activities, speech activity, face-to-face interaction, and physical proximity. The authors claim the possibility to identify different personality traits, perception of workload, quality of group interaction, productivity and stress from low level data collected using wearable sensors.

B. *Speaker Recognition*

Automatic speaker recognition has been investigated for more than four decades and it continues to be an open area [28]. Experimental studies reported in [1] examined the problem of speaker identification based on speech feature extraction. The authors used features called sub-band based cepstral parameters (SBC), and wavelet packet transform parameters (WPP), which allowed embedded de-noising or enhancement in the feature extraction to improve speaker identification. Applying the algorithms on two groups of speakers, the authors achieved the recognition rate of 94.8-96.4% for MFCC, 96-98.5% for SBC and 97.3-98.8% for WPP method. Ting et al. [2] also analyzed the usage of MFCC and Pitch to enhance performance of gender recognition. The authors claim that the information provided by acoustic analysis using MFCC and pitch achieved the recognition rate of 96.7%. In a similar way Kim et al. [15] claim the improvement of identification systems using PMFCC (Pitch Synchronous Mel Frequency Cepstral Coefficient) and the study confirmed that PSMFCC improved speaker identification performance in both text-dependent (44.3% - relative improvement) and text-independent (26.7%-relative improvement) experiments in comparison to the to the conventional MFCC feature. The study, described in [21], addressed speaker recognition, sound classification, and segmentation of audio. The authors used sound/speaker identification to evaluate the MPEG-7 Audio Spectrum Projection (ASP) feature for sound recognition performance in comparison to the well established MFCC. Twenty-five subjects (11 males and 13 females) participated in the experiment, where each speaker briefly read 15 different sentences and each recorded sample was cut into smaller parts. According to the results, MFCC features yielded the recognition rate of 93.24%, providing higher accuracy than MPEG-7 ASP (recognition rate 91.67%).

In contrast to previous studies, our approach exploits technological solutions, in particular smart phones, to recognize social behaviour and to investigate the correlation with subjects' mood.

III. OUR APPROACH

In this section we describe our approach to monitoring social interaction during work time and investigating correlation with self-reported workers' mood.

A. *Monitoring social activity*

Mobile phones are already part of the daily life of people, and their monitoring capabilities provide a potential to bring new insights into human social behaviour by using powerful sensors, such as accelerometers, digital compass, gyroscope, GPS, microphone, and camera. The microphone is an important and ubiquitous sensor; however it has not been explored to the extent that other sensors have. Microphone data analysis can provide inferences about human activity, location [3, 7] and social events [20] from sound. In comparison to other sensors such as accelerometers and GPS, the microphone and inference based on sound has received little attention in literature [4].

In order to recognize social interactions we relied on using the microphone embedded in smart phones. By recognizing subjects' voice we aimed to quantify the amount of social interactions during working days. The continuously recorded voice was split in 1 minute long samples and speaker was identified using short time spectrum through MFCC (Mel-Frequency Cepstral Coefficient) and GMM (Gaussian Mixture Model). MFCC feature is recognized as one the most important feature sets for audio signal processing [3, 5] and recognizing human voice [1, 2, 4, 15]. The triangular filterbank was used in our approach to multiply with the magnitude spectra of the frame where the log energies are computed. The discrete time cosine transform of the filterbank log energies are taken to find the MFCCs. In this study, we used 20 filterbanks and 19 MFCCs in order to recognize the speaker. Each minute that contained voice of monitored subjects was considered social interaction. Total amount of social interaction during working day was the sum of minutes in which the subject's voice was recognized.

B. Measuring mood

Our method for assessing mood states is based on EMA (Ecologically Momentary Assessment) which involves participants to report their psychological state several times a day [27]. The questionnaire that we used was derived from the Profile of Mood States (POMS) scale which consists of 65 items in its standard version. Concerning the fact that long and repeated questionnaires may be too cumbersome for the workers, we derived 8 adjectives (cheerful, sad, friendly, annoyed, relaxed, energetic, fatigued, tensed) with 1-5 point scale.

C. Experimental setup

In the pilot study, we recruited 3 participants (2 males, 1 female, age 28.0±1.7 years) during one working week that is 5 working days. In order to detect conversations, we collected data from participants that were wearing headset connected to a mobile phone while performing typical activities, such as working at the office, moving around a building (having a coffee break, for example) and entering and leaving different conversations with another subject. The mobile phone was a Samsung S3C6410 800MHz processor, 256 RAM and 8GB storage, where all recorded data was saved. The data collection was controlled by an application we developed which recorded audio samples in WAV format in 8 KHz 16 bit Mono PCM format. Overall, we had 102.3 hours recorded; however due to missing questionnaires and gaps in recording we analyzed 61.6 hours.

Once we have extracted conversations from the sensor data, we began building a picture of social interaction. As a part of the training phase, for each subject we recorded a voice stream for 60 seconds. The voice stream was used as training audio to compute MFCCs feature vector that is used to build a GMM of the speaker. Since the voice was recorded in noisy environments also, it was important that the MFCC feature we used to be robust to noise. We found that performance of MFCC-features was able to detect conversations with accuracy ranging from 80% to 95%. To collect the self-reported data, we used application MyExperience [25] installed in the smart phones. Typically, the questionnaires were answered in the morning, after lunch and at the end of working day (at 11:00±28min, 14:30±34min, 18:00±58min). MyExperience prompted users at 11:00, 14:30 and 18:00 everyday to respond to eight mood-related questions allowing also the user to manually invoke questionnaires in instances where she/he was unable to fill it out when the reminder prompted.

D. Privacy issues

Privacy is an important issue whenever monitoring of subjects' data occurs. Perhaps it is the most fundamental requirement for the phone sensing system. Although many approaches show considerable promise that can help with privacy problems such as privacy-preserving data mining, cryptography, they are often insufficient [22].

Subjects in our experiments were introduced to the method of recognizing social interactions and they were initially concerned about recording their voices. Recording continuously voice data at the workplace will require protecting the privacy of, not only monitored subjects, but also the privacy of the subjects that the monitored subject was interacting with. Therefore, in our study, only the monitored subjects had exclusive access to recorded (raw) data. They were asked to process the data (using a script we developed which provide only the amount of social interactions with corresponding time-stamps) and then to delete all the audio recordings. Also processing data locally, on the mobile phone and extract the useful features is an avenue we plan to implement in future experiments.

IV. Results

We analyzed intervals (with duration of 260.1±60.9 minutes) between two consecutive questionnaires regarding the correlation between the amount of social interactions and reported mood states in the beginning and at the end of monitored intervals. Table 1 reports the standardized regression coefficients of self-reported mood scores and the amount of social interactions in the following interval. As mentioned above, items in questionnaires were rated using 5-points scale while social interaction was measured in minutes. Table 2 presents the standardized regression coefficients of social interactions and self-reported mood scores at the end of monitored interval. Statistical significance was set at $P<0.05$; statistical analysis was conducted using SPSS 17.

Adjectives	***B***	***P***	**Adjusted *R*²**
Energetic	0.192	0.013	0.37
Tensed	0.086	0.035	0.26
Cheerful	0.187	0.050	0.20
Sad	-0.103	0.214	0.05
Friendly	0.074	0.406	0.02
Relaxed	-0.072	0.139	0.05
Fatigued	-0.027	0.001	0.07
Annoyed	-0.020	0.827	0.08

Table 1. Self-reported mood state in the beginning of monitored interval and the amount of social interactions

Adjectives	***B***	***P***	**Adjusted *R*²**
Energetic	2.13	0.041	0.25
Tensed	1.05	0.346	0.03
Cheerful	3.26	0.002	0.51
Sad	-1.815	0.099	0.14
Friendly	-0.806	0.475	0.04
Relaxed	-0.300	0.800	0.08
Fatigued	1.21	0.392	0.02
Annoyed	-2.734	0.018	0.34

Table 2. Self-reported mood state at the end of monitored interval and the amount of social interaction

The amount of social interaction and the items “energetic”, “tensed” and “cheerful” rated by subjects in the beginning of monitored interval were positively correlated, *P=0.013, P=0.035, P=0.05* respectively *(Table 1)*. On the other hand, the scores for items “energetic”, “cheerful” and “annoyed” reported at the end of monitored interval were correlated with the amount of social interaction within that interval, *P=0.041, P=0.002, P=0.018* respectively *(Table 2)*. In other words, the more social interactions subjects had the more cheerful and energetic they felt while reporting less annoyance. In addition, the more energetic, cheerful or tensed subjects felt initially, the more time they spent in social interactions. No other statistically significant correlations were found.

V. CONCLUSIONS

We investigated correlation between self-reported mood scores and measured social interaction. The results of the pilot study have shown that the scores for adjectives “tensed”, “energetic” and “cheerful” reported in the beginning of monitored interval were positively correlated with the amount of social interaction. In addition, items “energetic”, “cheerful” and “annoyed” rated at the end of examined interval have shown associations with time spent in social interactions. The study will be extended towards recognizing the type of social interaction that has occurred (such as arguing for example) and how it correlates with the self reported mood scores.

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