Social and sentiment sensing and assisting using on-body sensors

Stephan Sigg,
University of Goettingen, Germany
stephan.sigg@cs.uni-goettingen.de

Koby Crammer
Department of Electrical Engineering, Technion
koby@ee.technion.ac.il

Keywords *Sentiment sensing, Mobile sensing, Machine learning, Data analysis*

Topic, objectives and justification of the project

Emotional states are closely linked to Physical health [42], such as anger, which increases the danger of heart disease [49] or mood which impacts health-relevant behaviour, ageing and can also act as a predictor of mortality [50]. In addition, mental health is linked to emotion regulation [23], whereas stress, especially when pertaining, has significant impact on the brain, cognition and work performance [31]. On the other hand, positive affect benefits the immune system [49] while happyness and satisfaction are good indicators for and even foster work performance, health, and also success in private life [32].

Sentiment and emotion can be detected from Physiological signals with sensors such as Electromyograms (EMG, muscle activity), Electrodermal Activity (EDA, electrical conductivity of the skin surface), Electrocardiogram (EKG or ECG, heart activity), Electrooculogram (EOG, eye movement) or Electroencephalography (EEG, brain activity) [9]. These kind of sensors, however, are accessible only to a small amount of people and have drawbacks such as high cost, weight, non-portability, and sometimes involve invasive implantation. Furthermore, for a human utilising these tools, they constitute additional devices to carry around.

Recent work shows that it is also possible to detect sentiment from gesture and pose [16]. With the verge of the Internet of Things and increasing amount of mobile and body worn devices and sensors in everyday life, a multitude of sensors is available nowadays which has the potential to capture body movement and pose.

The focus and contribution of this project is to (1) recognise emotion from medical sensors, (2) exploit the potential of cheaper smartphone and on-body IoT sensors for sentiment sensing by identifying correlations in sensor data traces with medical sensors, (3a) exploit environmental signals such as RSSI or RF-signal strength for senti-

ment sensing and, (3b) predict the evolution of sentiment from the time series of past observations. (4) develop memory, time, and computation efficient methods to perform such analysis on a smartphone. (5) develop and experiment with sentiment feedback methods.

The outcome of the project will be a sentiment sensing and feedback framework comprising medical, body, smartphone and environmental sensors together with a prototype implementation

Current state-of-the-art in an international perspective

Emotion research or affective science investigates affect expression and detection [9]. In this context, the recognition of emotion has been considered from facial expressions [20], voice [25] as well as body language and posture [35, 19]. Especially the latter is of greater interest for this project and is discussed below. There is also some body of work on utilising text mining for sentiment sensing as briefly discussed in the next section.

Sensing of sentiment from textual corpus

Sentiment mining is an active research topic in recent years [27, 10]. Also referred to as opinion mining, it considers indirect sources and requires actual active involvement of subjects [36, 60]. In particular, there is an active body of work in the direction of mining textual input (via sentiment-expressing words or phrases) in online social networks with the help of natural language processing and computational linguistics [30]. We will, however, not consider the mining of text in the scope of this project but rather focus on sentiment sensing from physical sensors. Nevertheless, we may use text analysis to provide a supervision independent signal to build such a system. That is, if necessary, we will exploit textual input to better tune the parameters of our sensor-based sentiment analyzer.

Sentiment sensing from body movement and pose

Emotion can be inferred from body gesture and pose [24] at least as accurately as from face [4, 12, 33]. The role of human body in emotion expression has received support through evidences from psychology [54] and nonverbal communication [18].

The importance of bodily expression has also been confirmed for emotion detection [53, 51, 5]. Walter and Walk [54] revealed that emotion recognition from photos of postural expression, in which faces and hands were covered, was as accurate as recognition from facial expression alone. Dynamic configurations of human body even hold greater amount of information as indicated by Bull in [8]. He proved that body positions and motions could be recognised in terms of states including interest/boredom and agreement/disagreement. Some other studies went further by looking for the contribution of separated body parts to particular emotional states [16, 34]. Emotion can be recognised from non-trivial scenarios, such as simple daily-life actions [15, 7] or recognition ability of infants [28].

Some researchers [35, 19], were able to detect boredom, confusion, delight and frustration utilising pressure mats. Such mats, however, are not portable and are therefore not applicable in our setting. Instead, we aim to detect sentiment from body or environmental sensors.

Also, the sensing of attention has been investigated previously. Attention is an important measure in Computer-Human interaction. It determines for an interactive system the potential to impact the actions and decisions taken by an individual [58]. In the literature, we find various definitions that classify attention as well as its determining characteristics [57, 55]. While the tracking of gaze is a commonly utilised measure of attention [59], also other observable features may indicate attention. In general, aspects such as saliency, effort, expectancy and value are important indicators of attention [56, 55, 58, 22]. This model was later extended to put a greater stress on the effort a person takes towards an object [21]. The authors also discuss various aspects of attention and identify as most distinguishing factors changes in walking speed, direction or orientation.

Shi et al [43] investigated, how these properties, in particular location of a person, walking direction and walking speed or changes therein can be utilised for the monitoring and detection of attention from fluctuation in received signal strength.

Sensing activity, motion and pose from inertial and environmental sensors

Activity recognition comprises the challenge to recognise human activities from the input of sensor data. Traditionally, acceleration has evolved as the standard modality for activity recognition both for high diffusion and convincing recognition rates [41, 11]. General research challenges for activity recognition regard the accurate classification

of noisy data captured under real world conditions [6] or the automation of recognition systems [39]. The classification accuracy is highly dependent on the accurate sensor location. The integration of sensors in clothing as well as the recent remarkable progress in the robustness to rotation or displacement have improved this situation greatly [13]. However, a subject is still required to cooperate and at least wear the sensors [14]. This requirement can not be assured generally in real-world applications. In particular, even devices as private as mobile phones, which are frequently assumed to be constantly in the same context as its owner [38, 52, 29], can not serve as a sensor platform suitable for continuous monitoring of an individual's context. Dey et al. [17] showed that users have their mobile phone within arms reach only 54% of the time. This confirms a similar investigation of Patel et al. [37] which reported a share of 58% for the same measure.

We will therefore also consider environmental sources, in particular signal strength information from WiFi or 2-3G systems for their ubiquitous availability. In particular, good accuracy has been achieved recently with systems exploiting fluctuation in received radio signals. Pu and others [40, 26] showed that simultaneous detection of gestures from multiple individuals is possible by utilising multi-antenna nodes and micro Doppler fluctuations. They utilise a USRP SDR multi antenna receiver and one or more single antenna transmitters distributed in the environment to distinguish between a set of 9 gestures with an average accuracy of 0.94. Their active device-free system exploits a MIMO receiver in order to recognise gestures from different persons present at the same time. By leveraging a preamble gesture pattern, the receiver estimates the MIMO channel that maximises the reflections of the desired user.

A main challenge was for them that the Doppler shift from human movement was several magnitudes smaller than the bandwidth of the signal employed. The authors therefore proposed to transform the received signal into several narrowband pulses which are then analysed for possible Doppler fluctuation. The group recently discussed application possibilities of their system [1].

In a related system, Adib and Katabi [3] employ MIMO interference nulling and combine samples taken over time to achieve a similar result while compensating for the missing spatial diversity in a single-antenna receiver system. In their system, they leverage standard WiFi hardware at 2.4GHz.

Later, this work was extended to 3D motion tracking by utlising three or more directional receive antennas in exactly defined relative orientation [2]. In particular, the system is able to track the center of a human body with an error below 21cm in any

direction and can also detect movement of body parts and directions of a pointing body part, such as a hand. This localisation is possible through time-of-flight estimation and triangulisation. Higher accuracy of this estimation is granted by utilising frequency modulated carrier waves (sending a signal that changes linearly in frequency with time) over a bandwidth of 1.69GHz. Impact of static objects could be mitigated by subtracting successive sample means whereas noise was filtered by its speed of changes in energy over frequency bands.

Research approach, methods and hypotheses

We plan to apply the machine learning approach in which prediction and feedback tools are built based on data. Specifically, we plan to install and employ a wide range of sensors, some on-body, some are already installed on everyday smartphones, and some are located in an environmental. We will collect data from these sensors and analyze it, where the goal is to find a small, cheap and efficient subset of sensors which provides a robust and stable signal for prediction. Next, we will build a prediction system of sentiment based on this signal. We will use the collected signals and true sentiment to generate with a predictive model of sentiment from signal. We will test the model on signals coming from participants of our study. We will also develop a feedback algorithm that will provide the user information about current sentimental state, and possibly future predicted one. Hopefully, the user will benefit from such feedback. Additional component we plan to pursue is the development of an efficient prediction and feedback methods, that could be executed on a smartphone.

We hypothesize that we will be able to collect sensor information on users, and their true or approximated sentimental state. We also assume that it is possible to predict sentiment from signals of sensors.

Detailed work programme including time schedule

The expected time schedule is depicted in table 1. A detailed description of the distribution of work packages to personnel is given in the following. The figures represent three person months (equal to one person quarter). The notation '40' represents an allocation of 40 percent of one person quarter.

Workpackages	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	
Recent advances WP-1	20	20	20	15	10	10	5		100
Sensing system WP-2.1	100								100
WP-2.2	50	50							100
WP-2.3	30	70							100
WP-2.4		60	40						100
Experiments WP-3.1			140	60					200
WP-3.2				100	100				200
Sentiment analysis WP-4.1				25	75				100
WP-4.2					15	95	90		200
WP-4.3						50	50	100	200
Sentiment prediction WP-5.1						45	45	10	100
WP-5.2							10	90	100
Sum	200	200	200	200	200	200	200	200	1600

Table 1: Work schedule. The table specifies the occupation (1PM) subject to the quarterly period and project task. The figures specify the percentage by which the workload is divided between the work packages.

K: where we should add detecting and removing sensor outliers? develop efficient algorithms? usage of text for developing models?

WP-1: Review of recent advances in sentiment recognition

Estimated effort 3 PM

Precondition –

Milestone *Follow-up related work and recent developments*

In this workpackage we will follow up recent developments focusing sentiment sensing and opinion mining. This is an ongoing task which is distributed over the whole project duration.

WP-2: Development of a sentiment sensing system

WP-2.1: Development of the basic recognition system

Estimated effort	3 PMs
Precondition	–
Milestone	*Sentiment sensing system with interfaces for various sensor types; Android mobile sensing application*

In this workpackage we develop a sensing system to attach medical, body, smartphone and environmental sensors. The system will comprise interfaces for various sensing sources and cover of mobile clients to collect data samples and a server backend where the data is collected and processed. We perform preliminary analysis of the data collected from various sources to evaluate various aspects of them, such as, robustness, noise, and redundancy. An application for android mobile devices will be developed for mobile data collection. The application will incorporate smartphone sensors and enable the addition of further body sensors, for instance, via bluetooth. In addition to the collection of data, the application will enable feedback to the user based on the sensed patterns. For instance, possible feedback would be recommendations conditioned on sensed sentiment.

WP-2.2: Integration of medical sensing equipment

Estimated effort	3 PMs
Precondition	WP-2.1
Milestone	*Integration of medical sensor equipment to the sentiment sensing system*

In this workpackage we integrate medical sensors (EMG and EOG) with the developed framework. We will have access to the medical sensors via a cooperation with the medical center at Georg-August University Goettingen, in particular with the Neurohabilitation Engineering Group of Professor Dario Farina[1]. We will develop methods to predict the output of the medical sensors from smartphone and other sensors in WP-4.2 for the use in our sentiment prediction system.

---

[1]http://www.nre.bccn.uni-goettingen.de/index.php?id=82

WP-2.3: Integration of smartphone and body sensors

Estimated effort	3 PMs
Precondition	WP-2.1
Milestone	*Integration of smartphone and body sensors to the sentiment sensing system*

In this workpackage we integrate smartphone and body sensors with the developed framework. Our focus will be on the integration of acceleration data from smartphones and sensor nodes. In particular, we will utilise INGA[2] sensor nodes to which we have access through a cooperation with TU Braunschweig, Germany. In addition, heart rate and accelerometer sensors, for instance, from fitness wristbands will be incorporated. We will evaluate the amount of sensor information such that we will be able to minimize usage of the phone's resource, and extend battery life.

WP-2.4: Integration of environmental sensors

Estimated effort	3 PMs
Precondition	WP-2.1
Milestone	*Integration of USRP software radio nodes to the sentiment sensing system*

In this workpackage we integrate USRP[3] devices with the developed framework. For this, we can utilise 8 fully equipped USRP-1 devices and transceivers for the 800 MHz range available at the chair for Computer networks at Georg-August University Goettingen.

WP-3: Experiments

WP-3.1: Generation of experimental data samples

Estimated effort	6 PMs
Precondition	WP-2
Milestone	*Generation of a data set for sentiment analysis*

Utilising the sentiment sensing system developed in WP-2, we will collect data from medical, smartphone, body and environmental sensors for our sentiment analysis in

---

[2]https://www.ibr.cs.tu-bs.de/projects/inga/
[3]http://www.ettus.com

WP-4. We will consider two classes of medical sensors, for instance, EMG and EOG, acceleration data from the INGA and smartphone sensors as well as RF-signal information captured by USRP devices. We aim at collecting a body of data from 30-50 subjects in laboratory settings in which a series of standard tasks will be conducted by the subjects while the sentiment classes are induced by the experiement design. The subjects will be recruited from students and University staff as well as from patients or medical test persons in cooperation with the medical center at University of Goettingen. At least three sentiment classes will be considered, such as happiness, stress, and tiredness. The experimental setting will be designed to induce these sentiment classes in role-play and interactive games. To generate ground truth, participants we will collect feedback after the experiments. In the test design and execution we will receive support from the Institute of Psychology at TU Braunschweig, let by Professor Simone Kauffeld[4].

WP-3.2: Data collection from smartphones

Estimated effort	6 PMs
Precondition	WP-2
Milestone	*Generation of a data set for the prediction of sentiment*

We will collect acceleration data from smartphone and body sensors for our sentiment prediction considered in WP-5. In this experiment, the accelerometer data from 10-20 persons will be collected over a period of 6 months both in Israel and Germany. These individuals, recruited from students and staff of both universities, will be equipped with body sensors measuring acceleration data as well as with portable medical sensors. In order to reach dense sampling, we will consider the use of fitness trackers[5] and monetary reward systems. During the experiments, in order to improve our confidence on the ground truth, users will occasionally be asked for feedback by the application. In addition, users will receive recommendations based on the sensed sentiment patterns.

---

[4]https://www.tu-braunschweig.de/psychologie/abt/aos/mitarbeiterinnen/kauffeld/index.html
[5]for instance https://www.fitbit.com/de/chargehr

WP-4: Sentiment analysis

WP-4.1: Sentiment analysis from medical sensors

Estimated effort	3 PMs
Precondition	WP-3
Milestone	*Suitable features and a classifier for sentiment from at least two types of medical sensors*

In this workpackage we investigate the identification of sentiment from data of medical sensors. We will develop new learning methods for detecting sentiment from EMG and EOG data. These methods will take into consideration the special nature of these signals. In addition,

WP-4.2: Sentiment analysis from body and smartphone sensors

Estimated effort	6 PMs
Precondition	WP-3, WP-4.1
Milestone	*Correlations between features from medical ans smartphone sensors and a classifier for sentiment from these sensors*

We will in this workpackage develop suitable features for the prediction of sentiment from body and smartphone sensors. Our goal is to have a small number of predictive features. In particular, similarly to previous work regarding movement, gestures and pose as indicators of emotion, classifiers for the detection of such classes will be developed and linked to the classification of sentiment. In addition, building on the results from WP-4.1 we will further investigate correlations between sensor readings of medical and acceleration sensors in order to give an estimation to which extent medical sensors can be substituted by cheaper acceleration sensors for the application in large scale on-phone sensing applications.

In addition, in this workpackage, we focus the analysis of sentiment over an extended period of time. In particular, we investigate the identification of typical sentiment patterns from the observed sensor data. From this, we focus on the prediction of sentiment based not only on current sensor input, but also on recent historical data. That is, modeling the state-of-mind of a person, and use it to improve prediction of future state-of-mind. In particular, similar to our previous work [46, 45], we consider the use of alignment matching approaches to identify approximately similar sub-patterns in sentiment time series and to predict probable continuation of these patterns.

WP-4.3: Sentiment analysis from environmental sensors

Estimated effort	6 PMs
Precondition	WP-3
Milestone	*Features and a classifier for sentiment from received RF-signals*

We will in this workpackage develop features for the prediction of sentiment from received RF signals. Building on our and other previous work detecting movement and gestures from received RF-signals, we will detect gestures, movement and pose of individuals. Then, we will devise new methods to predict from the output of these prediction regarding physical state (movement, gestures and pose) mental state, such as emotion and sentiment.

WP-5: Prediction of sentiment based on historical data

WP-5.1: Integrating past sentiment

Estimated effort	3 PMs
Precondition	WP-3, WP-4
Milestone	*A document describing the potential of sentiment analysis of long sensor traces*

TODO

WP-5.2: Generating user feedback

Estimated effort	3 PMs
Precondition	WP-5-1
Milestone	*A document describing the potential of sentiment prediction from long sensor traces*

In this workpackage, we consider the generation of user feedback. In particular, we intend to influence the user's sentiment with such feedback. Examples are the enforcement of stress-reducing behaviour or recommendations on behaviour to improve health or well-being.

> K: modify wp5 : wp5.1 use previous sentiment wp5.2 feedback

Type and extent of the cooperation and division of tasks between the partners

Goettingen's expertise lie in mobile pervasive sensing systems, distributed, networked systems and compressive sensing. Technion's expertise lie in the design of new methods for data analysis, building predictive models, and devise highly efficient methods.

K: to add more about who will do what and the interface bewteen the two institutes

The researchers plan to have periodic phone meetings, and visit each other every 6 months. We hope that our Goettingen's students will be have long visit in Technion in vice-versa. This will not only advance the project, but will also serve, as a way to deepen their network and the connections between the two institutes.

Anticipated results

This project will generate an initial body of knowledge on the recognition of sentiment from various sensor types. In particular, in the scope of the project, a prototype implementation for a mobile sentiment recognition app is developed and a corpus of sensor readings together with the associated ground truth is provided. The results will provide insight into the potential of sentiment sensing and prediction from medical, smartphone and body sensors.

Relevant preceding work of the applicants

Prediction of sensor readings

Stephan Sigg has been working on the prediction/continuation of time series from sensor readings from 2005 through 2009. In this analytic work he showed that the order in which processing operations are applied to sensor readings impacts the overall error probability for the prediction algorithm, regardless of the actual prediction approach utilised. A stochastic model to estimate this impact has been presented which was evaluated in simulations and case studies [45]. In addition, a novel class of context-prediction methods based on alignment approaches [46] was derived which was shown to outperform traditional approaches on nominal data sequences. This approach has

been re-used by various groups for the prediction of contextual information. Its complexity has been derived analytically and was compared to alternative context prediction methods [45]. The method was applied to readings of inertial sensors, GPS readings and long-time weather data.

Recognition of human activities from on-body and RF sensors

Since 2009 Stephan Sigg considers the use of fluctuations measured on the Radio Frequency (RF) channel for the recognition of activities and gestures. The derived systems exploit multi-path propagation as well as the reflection and blocking of electromagnetic signals. Movement is reflected in the signal strength and fluctuation patterns of a received signal. One benefit of such device-free approaches is that it is not necessary for individuals to actually wear a transmit or receive device. It was shown that the localisation and recognition of simple activities is possible from continuous signals whereas the accuracy is comparable to recognition systems that rely on body-worn accelerometers [47]. These considerations have been extended to passive systems which utilise ambient signals [48]. Recent results show, that it is further possible to detect directed attention from fluctuations on the RF-channel by interpreting body movement captured from RF-readings [43]. Such gestures can be detected based on WiFi RSSI using only time-domain features on an off-the-shelf mobile phone [44].

Brief details of the type and the extent of previous cooperation between applicants

tbd

Perspectives with respect to possible follow-up projects between the partners with funding from other sources

tbd

Funding of the project including own contribution

The project teams consists of the project researchers Dr. Koby Crammer and Dr. Stephan Sigg as well as two PhD students (to be appointed for this project) and two

student assistants.

UGOE Dr. Stephan Sigg (externally funded), 2 years

UGOE 1 research staff member, TV-L 13, 75% project + 25% external, 2 years

UGOE 1 student assistant, 40 hours/week, 2 years

Technion Dr. Koby Crammer (externally funded), 2 years

Technion 1 research staff member, TV-L 13, 75% project + 25% external, 2 years

Technion 1 student assistant, 40 hours/week, 2 years

References

[1] Bringing gesture recognition to all devices. In *Presented as part of the 11th USENIX Symposium on Networked Systems Design and Implementation*, Berkeley, CA, 2014. USENIX.

[2] F. Adib, Z. Kabelac, D. Katabi, and R. C. Miller. 3d tracking via body radio reflections. available online: http://witrack.csail.mit.edu/witrack-paper.pdf, 2014. Usenix NSDI'14 - to appear.

[3] Fadel Adib and Dina Katabi. See through walls with wi-fi. In *ACM SIGCOMM'13*, 2013.

[4] Matthias Rauterberg Anh-Tuan Nguyen, Wei Chen. The role of human body expression in affect detection: A review. In *10th Asia Pacific Conference on Computer Human Interaction (APCHI 2012)*, 2012.

[5] Anthony P Atkinson, Mary L Tunstall, and Winand H Dittrich. Evidence for distinct contributions of form and motion information to the recognition of emotions from body gestures. *Cognition*, 104(1):59–72, 2007.

[6] L. Bao and S. S. Intille. Activity recognition from user-annotated acceleration data. In *Proceedings of PERVASIVE 2004*, volume LNCS 3001, 2004.

[7] Daniel Bernhardt and Peter Robinson. Detecting affect from non-stylised body motions. In *Affective Computing and Intelligent Interaction*, pages 59–70. Springer, 2007.

[8] Peter E Bull. *Posture and gesture.* Pergamon press, 1987.

[9] Rafael A Calvo and Sidney D'Mello. Affect detection: An interdisciplinary review of models, methods, and their applications. *Affective Computing, IEEE Transactions on*, 1(1):18–37, 2010.

[10] Erik Cambria, Bjorn Schuller, Yunqing Xia, and Catherine Havasi. New avenues in opinion mining and sentiment analysis. *IEEE Intelligent Systems*, page 1, 2013.

[11] Hong Cao, Minh Nhut Nguyen, Clifton Chun Wei Phua, Shonali Krishnaswamy, and Xiaoli Li. An integrated framework for human activity classification. In *Proceedings of the 14th ACM International Conference on Ubiquitous Computing (UbiComp 2012)*, 2012.

[12] Ginevra Castellano, Loic Kessous, and George Caridakis. Emotion recognition through multiple modalities: face, body gesture, speech. In *Affect and emotion in human-computer interaction*, pages 92–103. Springer, 2008.

[13] Ricardo Chavarriaga, Hamidreza Bayati, and Jose del R. Millan. Unsupervised adaptation for acceleration-based activity recognition: robustness to sensor displacement and rotation. *Personal and Ubiquitous Computing*, 2011.

[14] Gabe Cohn, Dan Morris, Shwetak N. Patel, and Desney S. Tan. Humantenna: Using the body as an antenna for real-time whole-body interaction. In *Proceedings of ACM CHI 2012*, 2012.

[15] Elizabeth Crane and Melissa Gross. Motion capture and emotion: Affect detection in whole body movement. In *Affective computing and intelligent interaction*, pages 95–101. Springer, 2007.

[16] Marco De Meijer. The contribution of general features of body movement to the attribution of emotions. *Journal of Nonverbal behavior*, 13(4):247–268, 1989.

[17] Anind Kumar Dey, K. Wac, D. Ferreira, K. Tassini, J.-H. Hong, and J. Ramos. Getting closer: An empirical investigation of the proximity of user to their smart

phones. In *Proceedings of the 13th international conference on Ubiquitous computing*, 2011.

[18] Allen T Dittmann. The role of body movement in communication. *Nonverbal behavior and communication*, pages 69–95, 1978.

[19] Sidney D'Mello and Art Graesser. Automatic detection of learner's affect from gross body language. *Applied Artificial Intelligence*, 23(2):123–150, 2009.

[20] Paul Ekman and Wallace V Friesen. *Unmasking the face: A guide to recognizing emotions from facial clues*. Ishk, 2003.

[21] Alois Ferscha, Kashif Zia, and Benedikt Gollan. Collective attention through public displays. In *2012 IEEE Sixth International Conference on Self-Adaptive and Self-Organizing Systems (SASO)*, pages 211 –216, 2012.

[22] Benedikt Gollan, B. Wally, and Alois Ferscha. Automatic attention estimation in an interactive system based on behaviour analysis. In *Proceedings of the 15th Portuguese Conference on Artificial Intelligence (EPIA2011)*, 2011.

[23] James J Gross and Ricardo F Muñoz. Emotion regulation and mental health. *Clinical psychology: Science and practice*, 2(2):151–164, 1995.

[24] Akhil Jaggarwal and Roxanne L Canosa. Emotion recognition using body gesture and pose. Technical report, 2012. available online: http://www.cs.rit.edu/~axj4159/papers_march/report_1.pdf.

[25] Patrik N Juslin and Klaus R Scherer. *Vocal expression of affect.* Oxford University Press, 2005.

[26] Youngwook Kim and Hao Ling. Human activity classification based on micro-doppler signatures using a support vector machine. *IEEE Transactions on Geoscience and Remote Sensing*, 47(5):1328–1337, 2009.

[27] Adam DI Kramer, Jamie E Guillory, and Jeffrey T Hancock. Experimental evidence of massive-scale emotional contagion through social networks. *Proceedings of the National Academy of Sciences*, page 201320040, 2014.

[28] Ingrid Lagerlöf and Marie Djerf. Children's understanding of emotion in dance. *European Journal of Developmental Psychology*, 6(4):409–431, 2009.

[29] Nicholas D. Lane, Emiliano Miluzzo, Hong Lu, Daniel Peebles, Tanzeem Choudhury, and Andrew T. Campbell. A survey of mobile phone sensing. *IEEE Communications magazine*, 48(9):140–150, September 2010.

[30] Bing Liu and Lei Zhang. A survey of opinion mining and sentiment analysis. In *Mining text data*, pages 415–463. Springer, 2012.

[31] Sonia J Lupien, Bruce S McEwen, Megan R Gunnar, and Christine Heim. Effects of stress throughout the lifespan on the brain, behaviour and cognition. *Nature Reviews Neuroscience*, 10(6):434–445, 2009.

[32] Sonja Lyubomirsky, Laura King, and Ed Diener. The benefits of frequent positive affect: does happiness lead to success? *Psychological bulletin*, 131(6):803, 2005.

[33] Hanneke KM Meeren, Corné CRJ van Heijnsbergen, and Beatrice de Gelder. Rapid perceptual integration of facial expression and emotional body language. *Proceedings of the National Academy of Sciences of the United States of America*, 102(45):16518–16523, 2005.

[34] Joann Montepare, Elissa Koff, Deborah Zaitchik, and Marilyn Albert. The use of body movements and gestures as cues to emotions in younger and older adults. *Journal of Nonverbal Behavior*, 23(2):133–152, 1999.

[35] Selene Mota and Rosalind W Picard. Automated posture analysis for detecting learner's interest level. In *Computer Vision and Pattern Recognition Workshop, 2003. CVPRW'03. Conference on*, volume 5, pages 49–49. IEEE, 2003.

[36] Bo Pang and Lillian Lee. Opinion mining and sentiment analysis. *Foundations and trends in information retrieval*, 2(1-2):1–135, 2008.

[37] Shwetak N. Patel, J. A. Kientz, G. R. Hayes, S. Bhat, and Gregory D. Abowd. Farther than you may think: An empirical investigation of the proximity of users to their mobile phones. In *Proceedings of the 8th international conference on Ubiquitous computing*, pages 123–140, 2006.

[38] K. Patridge and P. Golle. On using existing time-use study data for ubiquitous computing applications. In *Proceedings of the 10th International Conference on Ubiquitous Computing*, pages 144–153, 2008.

[39] Thomas Ploetz, Nils Y. Hammerla, Agata Rozga, Andrea Reavis, Nathan Call, and Gregory D. Abowd. Automatic assessment of problem behavior in individuals with developmental disabilities. In *Proceedings of the 14th ACM International Conference on Ubiquitous Computing (Ubicomp 2012)*, 2012.

[40] Qifan Pu, Sidhant Gupta, Shyam Gollakota, and Shwetak Patel. Whole-home gesture recognition using wireless signals. In *The 19th Annual International Conference on Mobile Computing and Networking (Mobicom'13)*, 2013.

[41] Nishkam Ravi, Nikhil Dandekar, Preetham Mysore, and Michael L. Littman. Activity recognition from accelerometer data. In *Proceedings of the 17th conference on Innovative applications of artificial intelligence - Volume 3*, IAAI'05, pages 1541–1546, 2005.

[42] Peter Salovey, Alexander J Rothman, Jerusha B Detweiler, and Wayne T Steward. Emotional states and physical health. *American psychologist*, 55(1):110, 2000.

[43] Shuyu Shi, Stephan Sigg, Wei Zhao, and Yusheng Ji. Monitoring of attention from ambient fm-radio signals. *IEEE Pervasive Computing, Special Issue - Managing Attention in Pervasive Environments*, Jan-March 2014.

[44] Stephan Sigg, Ulf Blanke, and Gerhard Troester. The telepathic phone: Frictionless activity recognition from wifi-rssi. In *IEEE International Conference on Pervasive Computing and Communications (PerCom)*, PerCom '14, 2014.

[45] Stephan Sigg, Dawud Gordon, Georg von Zengen, Michael Beigl, Sandra Haseloff, and Klaus David. Investigation of context prediction accuracy for different context abstraction levels. *IEEE Transactions on Mobile Computing*, 11(6):1047 –1059, june 2012.

[46] Stephan Sigg, Sandra Haseloff, and Klaus David. An alignment approach for context prediction tasks in ubicomp environments. *IEEE Pervasive Computing*, Oct-Dec 2010, 2010.

[47] Stephan Sigg, Markus Scholz, Shuyu Shi, Yusheng Ji, and Michael Beigl. Rf-sensing of activities from non-cooperative subjects in device-free recognition systems using ambient and local signals. *IEEE Transactions on Mobile Computing*, 13(4), 2013.

[48] Stephan Sigg, Shuyu Shi, Felix Buesching, Yusheng Ji, and Lars Wolf. Leveraging rf-channel fluctuation for activity recognition. In *Proceedings of the 11th International Conference on Advances in Mobile Computing and Multimedia (MoMM2013)*, 2013.

[49] Timothy W Smith, Kelly Glazer, John M Ruiz, and Linda C Gallo. Hostility, anger, aggressiveness, and coronary heart disease: An interpersonal perspective on personality, emotion, and health. *Journal of personality*, 72(6):1217–1270, 2004.

[50] John F Todaro, Biing-Jiun Shen, Raymond Niaura, Avron Spiro, and Kenneth D Ward. Effect of negative emotions on frequency of coronary heart disease (the normative aging study). *The American journal of cardiology*, 92(8):901–906, 2003.

[51] CCRJ Van Heijnsbergen, HKM Meeren, J Grezes, and B de Gelder. Rapid detection of fear in body expressions, an erp study. *Brain research*, 1186:233–241, 2007.

[52] Alexander Varshavsky and Shwetak N. Patel. *Location in Ubiquitous Computing*, pages 285–319. Ubiquitous Computing Fundamentals. Taylor and Francis Group, 2008.

[53] Harald G Wallbott. Bodily expression of emotion. *European journal of social psychology*, 28(6):879–896, 1998.

[54] K. Walters and R. Walk. Perception of emotion from body posture. *Bulletin of the Psychonomic Society*, 24(5), 1986.

[55] C.D. Wickens. *Processing resources in attention*. Academic Press, 1984.

[56] C.D. Wickens and J.S. McCarley. *Applied attention theory*. CRC Press, 2008.

[57] F. Wu and B.A. Hubermann. Novelty and collective attention. In *Proceedings of the National Academics of Sciences*, volume 104, pages 17599–17601, 2007.

[58] Yongchun Xu, Nenad Stojanovic, Ljiljana Stojanovic, and Tobias Schuchert. Efficient human attention detection based on intelligent complex event processing. In *Proceedings of the 6th ACM International Conference on Distributed Event-Based Systems*, DEBS '12, pages 379–380, 2012.

[59] Tomoko Yonezawa, Hirotake Yamazoe, Akira Utsumi, and Shinji Abe. Gaze-communicative behavior of stuffed-toy robot with joint attention and eye contact based on ambient gaze-tracking. In *ICMI*, pages 140–145, 2007.

[60] Zhongwu Zhai, Hua Xu, Bada Kang, and Peifa Jia. Exploiting effective features for chinese sentiment classification. *Expert Systems with Applications*, 38(8):9139–9146, 2011.