Social and sentiment sensing and assisting using on-body sensors

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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 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 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 share of the population and have drawbacks such as high cost, weight, non-portability, and sometimes involve invasive implantation.

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, (3) exploit environmental signals such as RSSI or RF-signal strength for sentiment sensing, (4) predict the evolution of sentiment from the time series of past observations,

(5) develop memory, time, and computation efficient methods to perform such analysis on a smartphone and, (6) 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, if necessary, we may 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 placement. 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].

We will in addition 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 is 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 a 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 environment. 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 a predictive model of sentiment from the signal. We will test the model on signals coming from participants of our study. We will also develop a feedback algorithm that will provide user information about current sentimental state, and possibly future predicted one. Hopefully, the user will benefit from such feedback. Additional components we plan to pursue is the development of efficient prediction and feedback methods, that could be executed on a smartphone.

We hypothesize that we will be able to collect sensor information of users, and their true or approximated sentimental state. We also assume that it is possible to predict sentiment from signals of sensors. Both assumptions are reasonable as similar tasks were already performed by both PIs in other contexts.

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.

WP-1: Review of recent advances in sentiment recognition

Estimated effort	6 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.

	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Q11	Q12	
Recent advances													
WP-1	25	25	20	20	20	20	20	15	10	10	10	5	200
Sensing system													
WP-2.1	100												100
WP-2.2	50	50											100
WP-2.3	25	75											100
WP-2.4		50	50										100
WP-2.5				30	30	40							100
Experiments													
WP-3.1			130	70									200
WP-3.2							50	30	30	45	30	15	200
WP-3.3									60			40	100
Analysis													
WP-4.1				80	20								100
WP-4.2					130	70							200
WP-4.3						70	130						200
WP-4.4								100	55	45			200
WP-4.5										50	100	50	200
Prediction													
WP-5.1								55	45				100
WP-5.2										50	60	90	200
Sum	200	200	200	200	200	200	200	200	200	200	200	200	2400

Table 1: Occupation (1PM) subject to the quarterly period and project task.

WP-2: Development of sentiment sensing systems

WP-2.1: Development of the basic recognition system

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

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.

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.

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*

[1] http://www.nre.bccn.uni-goettingen.de/index.php?id=82
[2] https://www.ibr.cs.tu-bs.de/projects/inga/

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-2.5: Development of a mobile sensing system for continuous sampling

Estimated effort	3 PMs
Precondition	WP-2.1,WP-2.2,WP-2.3,WP-2.4
Milestone	*Android mobile sensing application*

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. This application will be instrumented in WP-3.2. The purpose of this application is the study of sentiment and the potential of user feedback to alter sentiment related behaviour over a longer period of time. In particular, correlations between distinct sensor types, exploited in WP-4, will be utilised to mitigate missing sensor readings (e.g. from medical sensors) with sensor readings from other sensors.

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*

Utilizing the sentiment sensing system developed in WP-2, we will collect data from medical, smartphone, body and environmental sensors for our sentiment analysis in 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 experiment design. The subjects

[3] http://www.ettus.com

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]. The purpose of this workpackage is the generation of data for the development of accurate classifiers for sentiment prediction given all available sensor modalities and the identification of possible correlations between sensor classes.

WP-3.2: Mobile 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.

WP-3.3: User interaction and feedback

Estimated effort	3 PMs
Precondition	WP-3.2
Milestone	*Report on the efficiency of the installed feedback mechanisms*

In this workpackage, the efficiency and performance of the implemented feedback mechanisms of the app implemented in WP-3.2. In particular, this feedback is generated by user questionaires. In the questionaire design and execution we will receive support

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

from the Institute of Psychology at TU Braunschweig, let by Professor Simone Kauffeld[6]. Two feedback rounds are implemented in the middle and at the end of WP-3.2 in order to enable adaptation of the feedback in the second phase.

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.

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.

[6] https://www.tu-braunschweig.de/psychologie/abt/aos/mitarbeiterinnen/kauffeld/index.html

WP-4.3: 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*

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-4.4: 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-4.5: Sensor output analysis and fusion

Estimated effort	3 PMs
Precondition	WP-2.1,WP-2.2,WP-2.3
Milestone	*Analysis and fusion of output from all sensors.*

In this workpackage we will analyze the sensor data and evaluate their redundancy. This study will be used to develop methods to fuze data from all sensors into a single coherent and compact stream. We will develop methods to remove noise and outliers readings. These tools will be used to process sensor data before feeding it into sentiment prediction models.

WP-5: Prediction of sentiment based on past data and provide feedback for future

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*

We will analyze long sequences of sensor-input and sentimental-state. Our goal is to find long-correlations between the state of the sentiment across in various time scales (minutes, hours, days). Based on these results we will develop models to predict sentiment based on both current sensor data and previous (or historical) sentiment, either predicted (or also given via interface).

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*

We will develop few feedback methods to users about current and future predicted sentiment. Our goal is to build an automatic system that will find an optimal feedback mechanism to achieve certain goals, defined by the user. We plan to build on recent advances [73] in multi-armed bandit algorithms based on context which are optimizing exploration of methods and exploiting them.

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. We envision a relation in which Goettingen take the lead on sensor deployment and analysis, and Technion on analysis and building prediction models. We plan to close the loop, and use the models and analysis-outcome to better improve sensor usage. Smartphones and body sensors will be deployed on both locations. We will to assign a student in each institute, and plan for them to work as a team.

The researchers plan to have periodic phone meetings, and visit each other every six 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 a 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].

Developing Prediction Models

Koby Crammer have been working on developing prediction models since his PhD. He developed new methods for assigning one category [66, 65, 68, 67, 64, 84, 93, 92, 94] or more [69, 86] to a given input. The task of predicting sentiment (or composed sentimental state) from sensor input share some properties with these problems.

Koby also worked extensively worked on developing new learning methods and models to predict sequential data and taking correlations into account. These methods have been used in text analysis [85, 87], speech analysis [77, 70] and bioinformatics [62, 61, 83].

Developing Efficient Algorithms

Since 2008 Koby have worked extensively on new adaptive models and algorithms that are very time and memory efficient. This worked is based on earlier work [71] on online learning. The methods were designed for predicting a real number [74, 89], single bit from an input [75, 72, 76], one out for few [64, 81], or many decisions simultaneously [88, 77]. Additional work pursed are new efficient methods for large scale learning [93, 94].

Koby have also developed new methods that are efficient in interaction with annotation, and specifically human annotation. These methods can require annotation only for parts of the input [82, 90, 91], or they actively choose what inputs should be annotated [80, 73, 88].

Detecting outliers

Koby Crammer developed few models to detect outliers in data or finding a small subset of measurements that can be representative and coherent. The methods are either working by enclosing a large subset of inputs in a small ball [78], using non-convex loss functions [63], or rate-distortion methods from information theory [79].

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

The applicants were introduced to each other by a third researcher. They communicated tightly and continuously for both setting the project goal and methods, and, clearly, writing this application.

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

H2020 project, one of the ICT ones, need to find proper calls.

K: do you know specific ones?

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

Technion will make use of the machine learning computing cluster composed of more than 50 nodes. If there will be a need, Technion will make the proper adaptation of the cluster to the possible requirements of the project.

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