A Wearable System for Mood Assessment Considering Smartphone Features and Data From Mobile ECGs

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Abstract
Traditionally, mood is assessed by either considering physiological data or smartphones-based self-reports. Physiological data is objective and continuous, but difficult to be collected in-field and lacks a subjective component. Smartphones provide subjective feedback and objective data, but lack physiological data. We propose to combine smartphones as a rich sensor system and smartwatches as a wearable heart rate monitor. Both serve as a platform for reporting mood states. Within an explorative user study with six subjects over four weeks, we collected smartphone data and heart rate in addition to subjective ground truth via self-reports. We assessed all three mood dimensions *valence*, *energetic arousal* and *calmness*, but only consider *valence* in the context of this paper. Analyzing the information gain, we identified the relevance of temporal features (daytime, weekday, type of day) as well as the heart rate. Decision tree classifiers trained on the first three weeks and tested on the fourth achieve recognition accuracies of up to 0.91.

Author Keywords
Mood Assessment; Mood Recognition; Mobile Sensing; Wearable; Smartphone; Smartwatch; Heart Rate

ACM Classification Keywords
J.4 [Social and Behavioral Sciences]; I.5.m [Pattern Recognition]

Introduction

Mood assessment is one important aspect in social sciences as it can support monitoring and identifying state changes, e.g. of patients suffering from personality disorders [8]. Traditionally, it is assessed via self-reports on smartphones or via physiological devices such as ECG monitors. In lab settings, physiological devices yield fairly good results [15]. However, this approach is difficult to be transferred into real-world settings as clinical ECG devices are neither mobile nor wearable.

We propose to combine smartphones and on-body ECG sensors [3]. Smartphones are well-integrated into everyday life and a rich sensor systems which is able to gather a vast amount of personal data. Moreover, environmental influences or contextual data such as recent events or interactions can be logged. Wearable sensors, e.g. the personal smartwatch or a mobile ECG sensor, provide additional measurements.
We choose *Moto 360* smartwatches as personal wearables and *ekgMove*[1] as a fallback option in case of malfunctions and as a comparative means. Within a user study, we assess mood and explore the applicability of smartphone and heart rate features for subjective mood recognition.

Related Work

Physiological Approaches
Mood and biophysical human reactions have been shown to correlate [16]. Heavily investigated are heart rate (HR) and heart rate variability (HRV).
Ark et al. [1] compared the six basic emotions of Ekman [9] shown via facial expressions with HR, among others. They achieved recognition accuracies of up to 0.66.

[1] http://www.movisens.com/en/products/ecg-and-activitysensor/

Nardelli et al. [15] studied correlations between valence and arousal (*circumplex model of affect* [18]), and HRV to recognize mood in-lab. They achieved a recognition accuracy of 0.85 on the valence dimension.
Valenza et al. [20] investigated correlations between four emotional states, using valence and arousal, and the HR. They achieved an accuracy of 0.79 in-lab. In another project, the authors analyzed correlations between five values of each valence and arousal and HR and HRV, among others [21]. They gained an accuracy of over 0.9 in-lab.
Overall, related work showed that HR and HRV support the distinction of affective states, especially in lab settings.

Mobile Approaches
Mobile devices offer a variety of sensors which allow to infer contextual information. Several projects investigated their applicability for recognition of affective states.
One well-known example is *Emotion Sense* [11]. It gathers ground truth via self-reports and collects smartphone data in the background. Afterwards, the app seeks correlations. The authors want to make self-reports obsolete by having found enough "psychological markers" in the data.
Another project is *MoodSense* [13] which focuses on communication and interaction and used apps. They rely on the *circumplex model of affect* and apply self-reports. Their approach achieved an initial accuracy of 0.66 which could be improved to 0.93 after a two months training phase.
Mappiness [14] analyzes correlations between mood and environmental data. This app asks for self-reports at random moments while logging GPS positions. Afterwards, each location is associated with objective spatial data and correlations to the self-reports are reviewed. The results show that on average a participant is happier outdoors than in urban environments [14].
As shown, smartphones can reveal information related to affective states and are suitable sensing systems.

Sensor	Features
Location	Cell ID (CID); Location Area Code (LAC)
Current app	App running in the foreground; empty if screen is locked
Microphone	Max. absolute amplitude
Message history	Unique caller ID*, folder (inbox, sent), message length
Call history	Unique caller ID*, type (incoming, outgoing, missed), duration
Ambient light	Light level in Lux
Connectivity type	Wifi, mobile or none
Calendar entries	ID of current entry; calendar name
Activity type	Physical activity (Google Activity Recognition API[a])

Table 1: Selected sensor sources and derived features. * marks hashed values.

[a] https://developers.google.com/android/reference/com/google/android/gms/location/DetectedActivity

Mood Assessment System – Design

Our approach is based on the mood assessment app *MoA*[2] [2]. It was extended to a two-part app designed for Android and Android Wear as proposed in [3].

Data Assessment
Smartphones provide access to a wide range of sensors. Table 1 lists the sensors considered in our approach. All data is sampled at 1Hz. The smartwatch collects HR with about 12Hz. The ekgMove samples HR with up to 1024Hz.

Mood Assessment
In addition to sensor values we assessed ground truth of mood using self-reports. We selected a three-dimensional model for which a digitalized, standardized questionnaire exists. This model describes mood as a combination of *valence* (V, positive-negative), *calmness* (C, restless-relaxed) and *energetic arousal* (E, tired-awake) [19, 22]. It is based on the *Multidimensional Mood Questionnaire (MDMQ)* and consists of a six-item short scale to measure the three dimensions. Figures 1 and 2 show the mood assessment on (a) a smartphone and (b) a smartwatch.

Self-reports were prompted time-triggered, event-triggered or voluntary.
Time-triggered: every full hour between 9a.m. and 10p.m.
Event-triggered: if one of the following situations occurs: *a)* a calendar entry starts or ends; *b)* connectivity is lost or re-established; *c)* a message is sent or received; *d)* a call has ended (incoming or outgoing).
Voluntary Subjects were free to report their mood anytime.

We added constraints to avoid too many prompts. *a)* connection changes can only trigger prompts once per five minutes and only if the screen is active; *b)* the time span between two prompts is at least 15 minutes.

Mood Assessment System – Evaluation

We conducted a user study to evaluate our app in a real-world setting. Based on collected data we investigated the use of smartphone features and HR for mood recognition.

Study Design
-Subjects-
We recruited six subjects aged between 22 and 28, two of them female. The age and gender distribution seems reasonable: most wearable users are between 18 and 34, and men and women are equally likely to equip wearables (cf. *Nielsen's Connected Life Report* from March 2014[2]). Four subjects are students, two employed in local businesses. All of them participated voluntarily and were not paid.

One subject used their own Android phone and their own Moto 360 smartwatch. Four of them used their own Android phone but a Moto 360 provided by us. One possessed their own Moto 360, but an iPhone. For this subject, we provided a Google Nexus 4 phone. The subject was free to use it as their own, i.e. use their own SIM card and install desired apps. Moreover, every subject received an ekgMove.

-Procedure-
The study lasted four weeks. We met the subjects the day before and after the study.

In the first meeting we explained the background of our study, the data that will be collected, and what the subject has to do or must not do. The subjects were supposed to use their smartphone as usual. In addition, they were instructed to wear both the smartwatch and the mobile ECG during the day. They were asked to take them off if necessary, e.g. while doing sports to avoid artifacts in the data.

[2] http://www.nielsen.com/us/en/insights/news/2014/tech-styles-are-consumers-really-interested-in-wearing%2dtech-on-their-sleeves.html

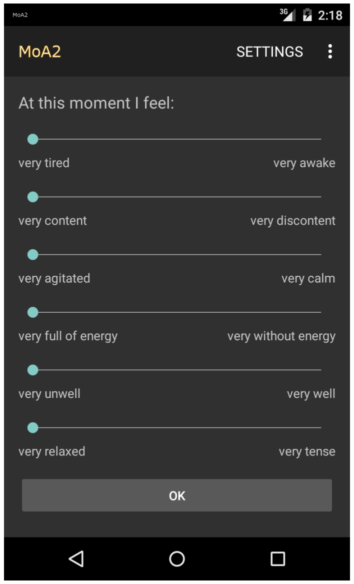

Figure 1: Screenshot of the Android app.

Figure 2: Exemplary screenshot of one of three screens of the Android Wear app.

However, they were asked to run our app as often as possible. They were asked to answer the MDMQ whenever a self-report prompt appears. We informed our subjects that they might drop out of the study whenever they want if they feel uncomfortable. Next, we asked the subjects to sign a consent form. Afterwards, we installed our app on the subject's Android phone and set up the Moto 360 smartwatch and the ekgMove. We explained how to wear both for correct measurements so that subjects could put both of them on and off by themselves.

In the final meeting each subject was asked to fill out a feedback questionnaire. We asked for demographic data and their experience of using our app. Afterwards, we handed out the *System Usability Scale (SUS)* [6] to assess the usability. At the end, we asked about the comfort of using the app both quantitatively and qualitatively. Within this meeting we also exported the collected data.

Usability and User Experience Feedback
We analyzed the quantitative and qualitative user feedback in terms of usability and user experience.

Our app gained a median SUS score of 88.75 which results in an adjective rating of *excellent* [4].
Five subjects reported that the usage of our app was pleasant. All subjects found the introduction to the app easy. Two subjects rated the mood report via smartphone as easy, three as neutral and one as complex. Fittingly, four of them solved this task fast, two neutral. Three subjects rated the mood report via smartwatch as easy, two neutral and one complex. However, four subjects said it could be done fast, though two said the duration was higher.
Three subjects rated our app as helpful, the others were neutral about its general usability. Five subjects liked that our app can be used easily due to its simple interface with one frame containing everything relevant. Two of them disliked the increased battery consumption or short battery life, respectively. This applies especially to the smartwatches.
Three subjects reported that the complexity of using the ekgMove was easy, two were neutral about it, and one said it has been complex. Nevertheless, three of them rated the comfort of wearing it as uncomfortable.
Overall, the feedback confirms a high usability and comfort of our approach and its suitability for in-field studies.

Overview of Collected Mood Data
The focus of our user study was to collect mood data. First of all, we got an overview of the reported mood values per subject. We identified Min, Max, Mean and Standard Deviation (SD) for each of the three dimensions as shown in Tables 3, 4 and 5. Apparently, most subjects used the full range from 0 to 6 to state their valence, energetic arousal or calmness. However, subject 2 and 6 did not max out both valence and calmness which might influence the accuracy of a mood recognition system.

Next, we analyzed response times and prompting triggers to get a better understanding of the prompting of our app and the response behavior.
On average, subjects needed 60s (± 20.6s) to react to the prompt and answer the mood questionnaire. Taking into account that the study lasted four weeks this means that the subjects tried to react to our notifications in a timely manner.
A proportion of prompt triggers is shown in Table 2. Primarily, each subject answered the mood questionnaire due to time-triggers. However, especially calendar events and phone calls as well as the connectivity state of the device resulted in prompting self-reports for many subjects. SMS were barely important. Two subjects received none at all.
All subjects chose to voluntarily report their mood but with varying frequency.

Valence				
Subj.	**Min**	**Max**	**Mean**	**SD**
1	1	6	3.32	0.92
2	2.5	6	5.38	0.76
3	0	6	4.63	1.02
4	0	6	4.1	1.07
5	0.5	6	4.62	1.1
6	0	4.5	2.22	0.93

Table 3: Overview of the valence values per subjects.

Energetic Arousal				
Subj.	**Min**	**Max**	**Mean**	**SD**
1	0	5	2.72	0.83
2	1	6	4.54	1.06
3	0	6	4.11	1.28
4	0.5	6	3.98	1.25
5	1	6	4.18	1.16
6	0	6	3.46	1.42

Table 4: Overview of the energetic arousal values per subjects.

Calmness				
Subj.	**Min**	**Max**	**Mean**	**SD**
1	0.5	5,5	3.17	0.91
2	3	6	5.46	0.78
3	1	6	4.02	1.1
4	0,5	6	4.03	1.14
5	0.5	6	3.94	1
6	2	6	4.83	0.84

Table 5: Overview of the calmness values per subjects.

Subject	**1**	**2**	**3**	**4**	**5**	**6**
Start of calendar event	4%	19%	8%	3%	10%	13%
End of calendar event	3%	11%	1%	3%	6%	7%
End of phone call	1%	3%	11%	16%	15%	3%
Connection lost	10%	10%	$<$1%	5%	3%	6%
Connection renewed	3%	1%	1%	6%	3%	5%
New SMS message	2%	0%	1%	6%	6%	0%
Voluntary	8%	10%	26%	1%	7%	5%
Time-dependent	67%	46%	52%	59%	51%	61%

Table 2: Percentage share of all trigger types that caused self-report prompts.

Explorative Analysis
We analyzed the collected data exploratively and examined classifiers built upon this data to rate its usefulness.

-Preprocessing-
In preparation of further analysis, we preprocessed some features. The timestamp has been replaced by *day of week* (e.g. Monday or Friday), *type of day* (weekday vs. weekend) and *daytime* (e.g. noon or evening). The lux values of the *ambient light level* have been factorized into categories according to the Microsoft Developer Network[3] (e.g. pitch black or direct sunlight). The recognized *activities* were categorized as motion or stillness. The measured *HR* values were divided into blocks of ten, i.e. values between 50 and 59 are stored as 50, values between 60 and 69 as 60, etc.

We decided to focus our mood analysis on the *valence* dimension as it is frequently considered separately in related work [15, 20]. *Valence* values were split up into three categories: *low*, *neutral*, and *high* as used in [23].

The values 0 to 1.5 were replaced by *low*, the values 2 to 4 by *neutral* and the values 4.5 to 6 by *high*. We chose these ranges as they allow a fair share between low, neutral and high: all of them cover about the same range except for the middle value, 3, which was assigned to neutral. Table 7 gives an overview of the distribution of valence values per subject.

We exported HR measurements from the ekgMove sensors using the movisens *SensorManager*. Based on these measurements, we extracted HRV using the movisens *DataAnalyzer*. These features are namely HrvHf, HrvLf, HrvLfHf, HrvPnn50, HrvRmssd, HrvSd1, HrvSd2, HrvSd2Sd1, HrvSdnn, HrvSdsd which are described in detail in the DataAnalyzer manual[4]. Afterwards, the extracted HRV features were synchronized with the reported valence via their timestamps. To get a glance of the quantity of the HRV measurements, we counted the number of values as shown in Table 8. Apparently, there is a strongly varying quality depending on each subject. This might be caused by wrongly worn sensors or incorrect usage of the sensors.

-Feature Ranking-
After the preprocessing, we analyzed the importance of the collected and generated features. For this purpose, we calculated the *information gain* of each smartphone feature and the smartwatch HR measurements. Table 6 shows the five best features per subject. Although all values are rather small, temporal attributes (*day of week*, *daytime*) and the smartwatch's *HR values* have the highest information gain. They can be considered most relevant among the set of features. Interestingly, all of them can be collected using the smartwatch only what should be investigated further in future experiments.

[3] https://msdn.microsoft.com/en-us/library/windows/desktop/dd319008%28v=vs.85%29.aspx

[4] http://www.movisens.com/wp-content/downloads/DataAnalyzer_Manual_EN.pdf

Subject 1		Subject 2		Subject 3	
0.105	day of week	0.094	day of week	0.061	day of week
0.063	daytime	0.066	daytime	**0.046**	**heart rate**
0.04	type of day	**0.023**	**heart rate**	0.028	daytime
0.022	**heart rate**	0.005	type of day	0.013	type of day
0.003	location	0.001	number of calendar entries	0.002	number of calendar entries
Subject 4		**Subject 5**		**Subject 6**	
0.07	day of week	0.078	day of week	0.122	day of week
0.036	daytime	0.067	daytime	0.031	daytime
0.013	**heart rate**	**0.032**	**heart rate**	**0.029**	**heart rate**
0.008	type of day	0.023	type of day	0.003	location
0.003	number of calendar entries	0.005	location	0.001	type of day

Table 6: Top 5 of the 13 features with the hightest information gain per subject.

Subj.	Low	Neutr.	High
1	11	304	46
2	0	26	290
3	11	83	293
4	7	162	170
5	2	82	144
6	59	127	4
Avg.	15	131	158

Table 7: Number of times each valence level was reported by each subject and on average.

Subject	Number
1	826
2	5,716
3	7,095
4	2,353
5	43
6	3,971
Avg.	3,334

Table 8: Number of HRV values extracted from ekgMove per subject and on average.

Mood Recognition
To explore how well the gathered features can be used to recognize mood we trained and tested personalized decision tree classifiers.

For each subject, we built three different types of decision tree models based on:

1. all *smartphone* features
2. all *smartphone* features *plus* Moto 360 *HR* values
3. all *HRV* features extracted from ekgMove ECG values

There are slight variations among the decision trees we used. For subject 1, 2, 5 and 6 we built J48 decision trees based on the C4.5 algorithm [17] for all models. Due to computational limitations we had to use a SimpleCART [5] for subject 3 and a LADTree [12] for subject 4 for the first two models and J48 for the third. All trees have been trained with data of the first three weeks and tested with the data of the fourth. The results are displayed in Figure 3.

For subject 1, 3 and 6, the models trained on *smartphone data* yielded better recognition accuracies than those based on *HRV data*. The model considering smartphone and smartwatch data achieved the highest recognition rates of all three models for subject 2. For subject 4 and 5 the accuracies of the HRV-based trees could not be reached.

On average, all models achieved almost the same recognition accuracy: decision trees based on *smartphone data* achieved 0.69, those for *smartphone data and smartwatch HR* 0.68 and those based on *ekgMove HRV data* 0.68.

It is visible that the influence of HR measurements, gathered by Moto 360, as well HRV, extracted from ekgMove, on the recognition accuracy varies for each subjects and is related to their number of measurements (cf. Table 8). Subject 5 is a prominent example with almost no HRV data but high recognition accuracies for the *HRV*-based model.

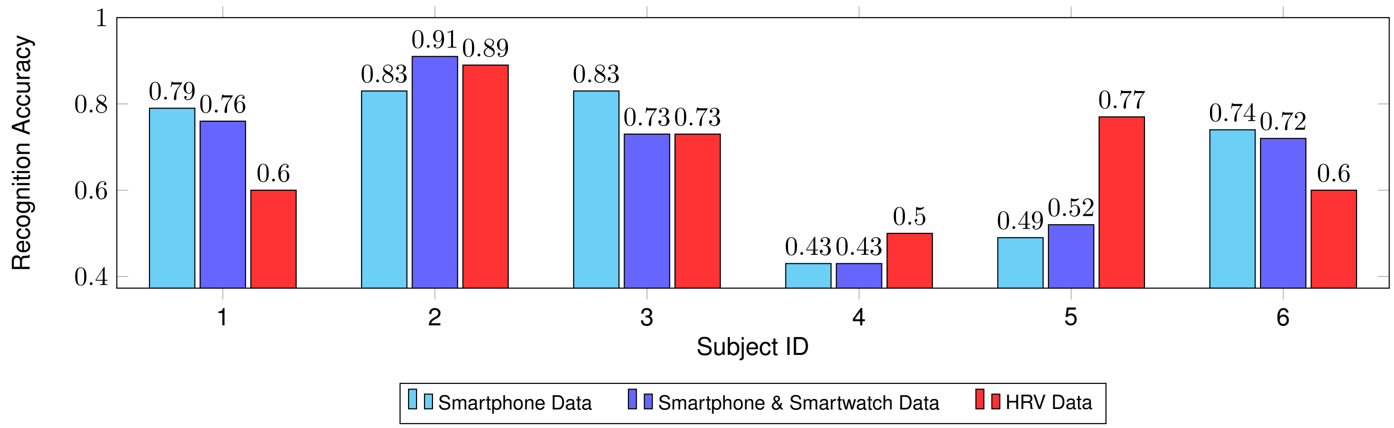

Figure 3: Visualization of the recognition accuracies for all three different dataset types.

We expected higher recognition accuracies for the model built upon *HRV data* as it proofed useful in related work [15] in which authors reported a recognition accuracy of 0.85 on the valence dimension in a controlled environment. Though, this rather low value can be explained by considering artifacts like movement which influence both the quality of the measurement itself and the derived HRV values.

Overall, the approach looks promising. Recognition accuracies are comparable to those of *MoodSense* which achieved 0.66 first and 0.93 after a two month training period. However, high recognition accuracies are to be treated carefully. As shown in Table 7, the valence classes are usually not equally distributed. Predicting the most common class may already yield high recognition accuracies.

A mood recognition running on personal wearables and based on their measurements appears possible. At least for some subjects, it is sufficient to rely on data gathered by the Moto 360 and neglect additional sensors such as ekgMove.

Conclusion

We presented a first approach to realize a mood assessment combining smartphone and physiological data as introduced in [3]. Physiological data was collected using a commercial smartwatch (Moto 360) and, as a fallback, a wearable ECG monitor (ekgMove). In an explorative study we collected data from six participants over four weeks. As ground truth for mood subjects were asked to answer the MDMQ digitally via smartphone or smartwatch.

Subject feedback confirms a high usability of our app with a median SUS score of 88.75 and reports a high comfort of wearing the Moto 360 in contrast to the ekgMove.

To examine the quality of the gathered data and the usefulness of smartphone and ECG data, we ran different analyses. Within this paper, we only considered the *valence* dimension of mood. Temporal attributes (daytime, weekday, type of day) and HR showed a high information gain and appear relevant. It is worth notable that all of them can be gathered using smartwatches only. Decision trees trained on the first three weeks and tested with the fourth show high recognition accuracies of up to 0.91. These results have to be interpreted with caution. In case of imbalanced datasets, the recognition accuracies might already be very high by just returning the most common class. However, this knowledge can be used to build reliable classifiers for the most common mood to implement an anomaly detection system, e.g. for monitoring state changes of patients suffering from depression.

Based on user feedback and our explorative analysis, we conclude that our app in combination with a commercial smartwatch is applicable for mood assessment in real-world settings.

Future work should investigate the combination of temporal attributes and HR in a longer time frame and with a higher number of subjects. A clinical setting with patients suffering from mood-related personality disorders might be interesting to investigate. In addition, it might be useful to examine new sensor sources, e.g. the microphone (noise level) and ambient light sensor of the smartwatch as they might yield better results than the corresponding sensors embedded in the smartphone. Moreover, location should be considered in a more complex way. Instead of only considering the raw location, the land use could be considered [7] or locations could be categorized, e.g. as shops and restaurants, related to the Google Places API[5] as used in [10].

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[5] https://developers.google.com/places/

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