Mobile Sensing for Wellbeing Estimation of Urban Green using Physiological Signals

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ABSTRACT

Designing for wellbeing and a better quality of life is a challenge due to individual differences and contextual influences. How a person feels may depend on inner-body and outer-body circumstances. Moreover, some places may foster while others hinder wellbeing. The objective of this paper is to identify typical patterns across characteristics of the urban environment, the user's self-reported wellbeing as well as physiological measures as indicators of wellbeing. To this end, we conducted a study with 7 participants in an urban environment covering different kinds of climate zones. In addition to multi-sensor data collection, participants were asked to provide location-specific experience samples with the help of off-the-shelf wrist accessories and a smartphone. The paper at hand presents classification results for the collected data. It furthermore analyzes the limitations of the approach and discusses the potential for future therapeutic applications that enhance the value of urban green by making use of sensory technologies.

CCS CONCEPTS

• **Human-centered computing → Ubiquitous and mobile computing systems and tools**;

KEYWORDS

Mobile Social Signal Processing, Wellbeing

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1 INTRODUCTION

Climate change comes with several challenges that need to be dealt with on different scopes. On the level of city-planning, Sponge-Cities are explored to cope with floods in China [5]. One key aspect of Sponge-Cities is urban green that does not only absorb water in order to release it again over a longer time period. Urban green also has the potential to reduce climate-induced stress on the individual. Here the research at hand comes into play. We aim to investigate to what extent an individual's wellbeing is affected by the urban environment. To this end, we record a wide range of sensor data related to environment and physiology. We report on first evaluation results focusing on the participants' Blood Volume Pressure (BVP) and subjective ratings of wellbeing.

Figure 1: Two participants taking part in the field study. The following sensor devices are visible in the photo: 1. Aspiration psychrometer, 2. Microsoft Band 2, 3. Samsung Gear S2, 4. Custom built Environmental sensor box

Urban green has not only been recognized as an important climatic mediator that might help mitigate challenges resulting from climate change. In addition, nature therapies, such as garden therapy [1] or Shinrin-yoku forest bathing [14], have provided evidence of the positive effects of green on humans' mind and physique [15]. Previous research argues for a healthy effect of natural environments even when only viewed through a window [22]. Going beyond the typical quantified-self notion "know thyself", this paper aims to employ sensory data to investigate the potential of health-transpiring environments.

There is a large body of work that employs HCI technology to enhance interaction with nature (e.g., [4]), including explorations of human-plant interactions. However, understanding what aspects of an environment influence wellbeing and integrating this knowledge dynamically into (technology) design is a challenging task. Relevant data to analyse a person's wellbeing may be acquired, for example, with mobile and stationary sensors. Sensor-data other than video or audio do not speak for themselves when viewed out of context, it is essential to request specific annotations from the user in the very moment of data recording [7]. To this end, comfortable mobile interfaces have to be provided that facilitate the input of annotations without affecting the user's experience of the outer-body environment. A number of applications draw on the interdependencies between the aesthetics of a landscape and an individual's wellbeing. Examples include navigation systems that aim to reduce environment-induced stress on the user. Contemporary approaches consider routes with beautiful scenery instead of the fastest route [17] when generating recommendations. Such applications go beyond routing and can even recommend on which side of a bus [18] passengers should sit on a bus tour to experience the most aesthetic views during their trip. Usually, these applications rely on machine learning models that are trained using image data from the categories of interest, i.e. aesthetic and non-aesthetic scenery, such as a highway. However, they do not employ objective physiological or behavioral measures to assess the user's wellbeing.

A variety of wellbeing models has been proposed in the literature [8] to capture relevant factors, such as sufficient sleep and healthy nutrition, that influence an individual's wellbeing. Besides subjective measures, usually drawing on valence-based self-reports, objective measures, such as physiological data, are employed to assess an individual's wellbeing [11, 12]. Also, the influence of an individual's environment on physiology has been researched by measuring heart rate and heart rate variability [20], skin temperature and pulse rate [13]. Climate is a key environmental influence on the human body, therefore it plays a central role in our study design. Fine grain assessment on environmental and personal factors combined so far have not been used together with machine learning to gain models that can be personalized. Nonetheless, adaption of machine learning models on mobile device is a feasible task [19]. While deep learning is becoming increasingly popular in Affective Computing [24] we rely upon handcrafted features due to the sparse nature of our data-set [23]. This leads to the main question we seek to answer: How can we model the influence between the users' urban environment and their physiological and psychological wellbeing? To shed light on this question, we conducted a field study with 20 participants. Measurements were recorded with a wide range of sensors associated with the participants' inner-body states and their urban environment. In addition, we collected self-reports of psychological parameters including valence-based ratings of the pleasantness of the moment as well as subjective assessments of thermal sensation and perceived air quality. Due to different screen sizes of smartphone and smartwatches, we provided the users with dedicated graphical user interfaces for each of these devices to conduct the labeling. Since people are usually able to distinguish easily between a pleasant and an unpleasant feeling [2], it is possible to annotate data related to wellbeing on the go. In the following, we will present the setup and results of a study to investigate dependencies between the urban environment and the user's wellbeing as a first step towards an application fostering the user's wellbeing while employing an interactive machine learning subsystem [9, 16].

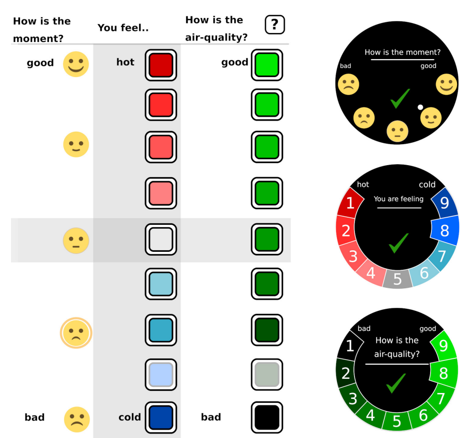

Figure 2: GUI used for self-assessment on smartphone (left) and smartwatch (right). Each version gathers wellbeing in terms of valence (5 point scale), subjective impression of temperature and air quality (9 point scales).

2 SETUP AND DATA

In each recording session, data was collected from two participants, with one participant using a smartwatch for labeling, and the other using a smartphone. The user interfaces for both devices are shown in Figure 2. In addition to the annotation devices, both participants wore fitness bands to collect physiological data. The per-person setups also varied in the addition of an aspiration psychrometer, for the detection of ambient air temperature, relative humidity and further derived variables relevant for wellbeing. Aspiration psychrometers are bulky professional devices, the established standard for measuring relative humidity. They serve as high-quality reference for low cost alternatives integrated into the custom-built sensor box as displayed in Figure 1.

Figure 3 shows the setup for acquisition of sensor data and users' self ratings. Different sensors tend to provide data at different speeds, see Table 1. Especially, on mobile devices, chunks of data at one moment would span different time periods for different sensors. Therefore, synchronization of the individual data streams is required. To record data, we employed mobile tools for the acquisition and analysis of sensory data, SSJ [6] and MobileSSI [10], which include specific mechanisms for synchronizing multi-sensor data.

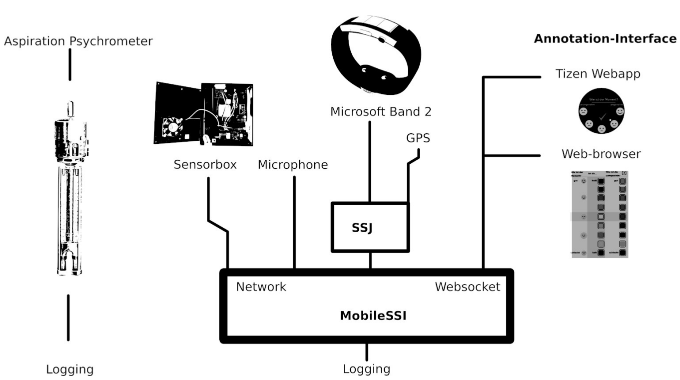

Figure 3: Setup including sensor configuration, recording software and annotation interfaces.

Sensors and Devices

While the evaluation of this paper focuses on heart-related physiological signals, the recording setup was done using a wide range of sensors that promise useful input for context-aware applications. Environment-related data were collected using microphones connected to the smartphones, GPS provided by the smartphones, and a custom-built sensor box. The sensor box contained a sensor for temperature, humidity (SHT75) and air pressure measurement (BMP280) as well as dust (SDS011) and gas (MICS) sensors. For a detailed overview, see Table 1. Person-related data were collected via a Microsoft Band 2 providing galvanic skin conductance (GSR), heart-rate (HR) and the heart's inter-beat-interval (IBI) as physiological signals. Aspiration psychrometers were used to collect temperature and humidity as an indicator of heat stress. These devices only store data locally, thus synchronization was required which was conducted retrospectively via GPS and timestamp information.

Device	Sensor	Data	SR (Hz)
MS Band 2	BVP sensor	IBI	30
		HR	1
	GSR	GSR	5
	Accelerometer	ACC	62.5
Smartphone	GPS	coordinates	5
	Microphone	audio (raw)	16000
	UI	ratings	event based
Smartwatch	UI	ratings	event based
Sensor Box	SDS011	PM2.5	0.07
		PM10	0.07
	SHT75	humidity	0.07
		temperature	0.07
	MICS	CO	0.07
		NO_2	0.07
		NH_3	0.07
		C_3H_8	0.07
		C_4H_{10}	0.07
		CH_4	0.07
		H_2	0.07
		C_2H_5OH	0.07
	BMP280	pressure	0.07
		temperature	0.07
Aspiration Psychrometer		humidity	0.5
		GPS	0.5
		temperature	0.5

Table 1: Devices involved in the recording setup.

Experience Samples - Label Acquisition

In order to gain information on the participants' wellbeing, we asked them to provide explicit experience samples about their momentary state, related to valence (5-point scale, good to bad), perceived temperature (9-point scale, hot to cold) and air quality (9-point scale, good to bad).

On the back-end side, annotations were serialized synchronously with the collected data described in Section 2. Participants were asked to annotate whenever they felt a change of the respective states. Thus, a label was valid until a new label replaced it. Overall 769 labels where annotated on the go by our participants with an average of 38 labels per session. Since those samples represent impressions for a short time period only, questionnaires including ratings related to mean and variance of wellbeing, temperature and air quality concluded each session.

Route and Sessions

The route used for recording was selected due to the variety of local climate zones including the built up "Open Mid Rise" as well as the mainly natural "Scattered Trees" and "Dense Trees" categories [3, 21] (see Figure 5). These local climate zones covered both exposure to heat in city and open meadow as well as sheltering forest. In addition to the GPS-track marking the route, Figure 4 also shows the temperature along the track for one exemplary walk. Each session took about 80 minutes for the 5 km walk. Days with

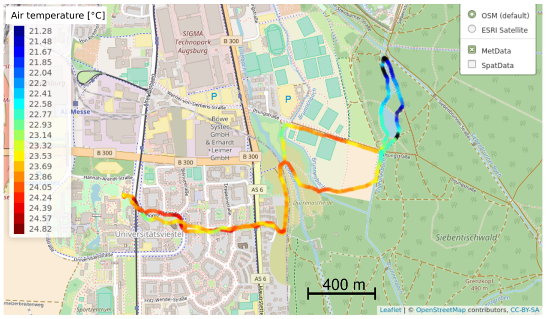

Figure 4: Plot of temperature acquired along the route in one exemplary measurement.

similar weather conditions were chosen for the study in order to reduce a weather-based bias on data. Measurement campaigns were performed under clear and calm weather conditions around noon on midsummer days to ensure maximum thermal differences between local climate zones and thus increasing the chance of capturing potential heat stress. The path used for data-acquisition is conceptualized as a loop, to prevent the participant's time walking from influencing physiological data. A total of 20 sessions with 7 participants (5 male, 2 female, average age of 25) were included in the data set used for the evaluation in Section 3.

3 EVALUATION AND MACHINE LEARNING MODELS

We utilize machine learning techniques to cope with the complexity of the data while searching for meaningful patterns across physiological data (using a BVP sensor), characteristics of the environment and the users' self-reported wellbeing. Since the environment is a key independent variable in our study's design, we test the influence of environment on physiology by discriminating different climate zones using physiological data. An important objective of our approach is to investigate to what extent the user's experience in terms of wellbeing, temperature and air quality may be predicted from the recorded physiological data. The user's subjective ratings for pleasantness of the moment, perceived temperature and air quality were used as a golden standard in the training and evaluation process. Once a model is trained, it can directly be employed to generate context information for an application in real-time [10]. In addition, the ability to process data directly on the device is an important prerequisite to respect the user's privacy, that again is a desirable feature when processing health related, physiological data. In the following we describe the steps involved in our data processing pipeline.

Figure 5: Occurring local climate zone types: Open Mid Rise (City), Scattered Trees (Meadow), Dense Trees (Forest).

Feature set for Machine Learning

In order to calculate features for our classification approach, we rely on data provided by the Microsoft Band 2, which provides inter-beat-interval (IBI) and heart rate (HR) that are analyzed in the following. Usually, physiologically measurable effects of a change in the state of mind (such as an spontaneous increase in valence) are slightly delayed and rather long-lasting. Therefore, we employ a range of statistical features over multiple data samples to cover the characteristics of the input signal over an extended time period. To assess the contribution of each statistical feature to the overall classification result, a Sequential Forward Selection (SFS) was applied. The results of this SFS are shown in Table 2. SFS identifies the most useful single feature to which the next best feature is added subsequently. Recognition rate at rank 2 therefore is achieved using feature 1 and 2. The full feature set is used for the training of all models presented in the following section. In Table 2, the score peaks the first time at rank 9 with a score of 0.5. A closer look at the results of the SFS reveals that mostly IBI-Features are used to reach peak performance, which indicates that the heart's inter-beat-interval conveys more valuable information than the heart rate in our case. HR (1.0 Hz) and IBI (5.0 Hz) features are calculated on the same time slice, consisting of a 10 second frame containing new data, and a 240 to 380 seconds overlap containing old data.

rank	feature	score	rank	feature	score
1	IBI_MAXPOS	0.40	12	HR_ZEROS	0.50
2	HR_MAXPOS	0.43	13	IBI_PEAKS	0.50
3	IBI_MIN	0.43	14	IBI_MINPOS	0.49
4	IBI_STD	0.43	15	HR_STD	0.41
5	HR_PEAKS	0.43	16	HR_RANGE	0.35
6	IBI_ZEROS	0.43	17	IBI_LEN	0.34
7	IBI_MAX	0.42	18	HR_LEN	0.34
8	IBI_ENERGY	0.45	19	HR_MEAN	0.33
9	HR_MINPOS	0.50	20	HR_ENERGY	0.33
10	IBI_MEAN	0.48	21	HR_MAX	0.34
11	IBI_RANGE	0.50	22	HR_MIN	0.31

Table 2: Sequential Forward Selection (SFS) of Features

Machine Learning Models

The models described in this section were evaluated using a two-fold cross-validation. As a classificator we chose Support Vector Machines (SVM). Since SVM's are sensitive to unbalanced sample distributions across classes, random undersampling was used. An important factor for real-time applications is the responsiveness. Therefore, we aim at keeping the frame sizes as low as possible, which enables classification results at a higher frequency and thus increases the responsiveness of the system.

Environmental Context. In the first experiment, we investigate to what extent it is possible to infer the outer-body environmental context from the recorded physiological data. We are modeling this outer-body environmental context by means of the landscape the user is currently situated in. Consequently, it is the goal of our model to distinguish between the three classes *forest*, *meadow*, and *city*. This helps us counter-check if there is an influence of the environment on the participants' physiology. The labels were gained by manually defining the different landscapes on the route and automatically establishing a mapping with the GPS coordinates of the user. This mapping is also shown in Figure 5.

	Environment (SVM)			
	Forest	**Meadow**	**City**	**Acc. %**
Forest:	132	16	12	82.50 %
Meadow:	10	61	89	38.12 %
City:	12	87	61	38.12 %
Average				**52.92 %**

Table 3: User related model trained over 945 samples, 10 seconds frame, 240 seconds overlap.

To gain a sufficient number of samples for training and to maintain responsiveness, the frame size was set to 10 seconds. Using additional 240 seconds of preceding data enables us to increase the model's accuracy, see Table 3. Overall 52.92 % average accuracy was achieved, with 82.50 % accuracy for the *forest* class and 38.12 % for *meadow* and *city* classes.

	Valence (SVM)					
	1	**2**	**3**	**4**	**5**	**Acc. %**
1 (good)	575	56	96	92	40	66.94 %
2	40	541	199	89	55	62.98 %
3	147	172	148	179	213	17.23 %
4	114	149	120	307	169	35.74 %
5 (bad)	137	104	109	177	332	38.65 %
Average						**44.31 %**

Table 4: User related model trained over 4295 samples, 10 seconds frame, 240 seconds overlap.

Environment Related Wellbeing. As a golden standard for the inner-body state, we rely on the users' self assessment as described in Section 2. Hereby, we distinguish between the valence of the moment (see Table 4) and the perceived air quality and temperature, labeled as positive or negative by the user on scale from 1 to 9 (see Table 5). To be able to train models with a sufficient number of samples, classes with few associated annotations were merged. Thus, the last class of the air quality and temperature rating in Table 5 consists of user ratings of 8 and 9. This results in a classifier scoring at 44.31 % accuracy on the five-class valence problem, as depicted in Table 4. Here the first classes, with label 1 and 2, perform best at over 60 %, while the classes of label 3 scores lowest at 17.23 %.

Temperature		**Air Quality**	
Rating	**Acc. %**	Rating	**Acc. %**
1 (hot)	27.16 %	**1 (good)**	29.64 %
2	36.21 %	**2**	37.52,%
3	38.27 %	**3**	27.95,%
4	27.57 %	**4**	22.70,%
5	39.92 %	**5**	19.70,%
6	21.40 %	**6**	36.96,%
7	33.33 %	**7**	26.45,%
8,9 (cold)	34.16 %	**8,9 (bad)**	51.97 %
Average	**32.25 %**	**Average**	**31.61 %**
1944 samples, 10 s frame, 240 s delta		4264 samples, 10 s frame, 240 s delta	

Table 5: Environment related models based on self-assessment. Class count was reduced due to unbalanced annotation distribution.

Perceived temperature-ratings were correctly classified with an average of 32.25 % on this 8 class problem. The class with label 5 performed highest at 39.92 % while the class of label 6 scored lowest at 21.40 %. The 8 class model predicting perceived air quality scores at an average of 31.61 % accuracy with the aggregated rating's class (8,9) scoring highest at 51.97 % and the class of label 5 scoring lowest at 19.70 %.

4 DISCUSSION

In the beginning we argued that environments influence the user's wellbeing, that again can be measured using physiological data. Machine learning helped us tackle the complexity involved in the interplay of environment and affect and make this context information more accessible for future applications. Considering the concrete classification results, the three class environment classification is reasonably possible with 52.92 % recognition rate, especially in classifying *Forest* with 82.50 % accuracy. Within the environment model the classes *City* and *Meadow* are often mistaken for each other, while being rarely confused with the class *Forest*. Scores of classification based on self assessment are considerably lower, but clearly above chance. Recognition on self-rated valence reaches 44.31 % those on air quality 31.61 % and temperature is recognized at a rate of 32.61 %. Both environment and user related models might be interpreted so that the cooling effect of the forest and the decrease in stress on the body is an important factor for identifying the surrounding via physiological data. Thus, results are promising, considering the distinction of different environments using physiological data, suggesting that it is possible to integrate the detection of an environment class (e.g., forest) with relaxing influence into wellbeing applications. Considering practical use, in contrast to most environmental sensors, BVP sensors are commonly integrated in consumer grade hardware (smartwatches and fitness bands). Therefore, they are a good candidate for gaining context information.

5 CONCLUSIONS AND FUTURE WORK

We presented the setup, data collection and uni-modal evaluation of an approach for recognizing subjective and environment related contexts on mobile devices. First results show that classification based on physiological data can convey valuable hints on wellbeing within urban environments especially regarding the classification of forest. This might be possible due to the cooling effect of the forest and the decrease in stress on the body. Future work on personalized models of heat comfort can build upon the presented approach.

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