Urban Emotions and Cycling Experience – Enriching Traffic Planning for Cyclists with Human Sensor Data

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Abstract

Even though much research has been conducted on the safety of cycling infrastructures, most previous approaches only make use of traditional and proven methods based upon datasets such as accident statistics, road infrastructure data, or questionnaires. Apart from typical surveys, which are known to face numerous limitations from a psychological and sociological viewpoints, the question of how perceived safety can best be assessed is still widely unexplored. Thus, this paper presents an approach for bio-physiological sensing to identify places in urban environments which are perceived as unsafe by cyclists. Specifically, a number of physiological parameters like ECG, skin conductance, skin temperature and heart rate variability are analysed to identify moments of stress. Together with data gathered through a People as Sensors app, these stress levels can be mapped to specific emotions. This method was tested in a pilot study in Cambridge, MA (USA), which is presented in this paper. Our findings show that our method can identify places with emotional peaks, particularly fear and anger. Although our results can be qualitatively interpreted and used in urban planning, more research is necessary to quantitatively and automatically generate recommendations from the measurements for urban planners.

Keywords:

people as sensors, physiological parameters, emotions, bicycle safety, mapping

1   Introduction

There is overwhelming evidence from the literature and practice (see Gössling (2013) for a review of Copenhagen's bicycle policy) that a consistent pro-bicycle policy is essential for any successful promotion of cycling. Pucher et al. (2010) provide an extensive overview of the effectiveness of policy interventions. In line with other authors (Aldred & Jungnickel, 2014; Lanzendorf & Busch-Geertsema, 2014; Rietveld & Daniel, 2004), they argue for multi-facetted approaches that are built on adequate infrastructure, information and education, as

well as the development of a bicycle-friendly mobile culture. Thus, successful bicycle policies combine infrastructure with soft measures, the former being decisive for the potential impact of the latter. The anticipation of the specific needs of cyclists is also crucial for the success of cycling-promotion strategies (Fernández-Heredia et al., 2014).

Recent trends show that cycling is enjoying increasing popularity, especially in urban environments, on the one hand as a newly propagated, urban lifestyle, and on the other hand as a key component in sustainable mobility. Indicators for this increasing relevance in urban planning are the growing numbers of bicycle-sharing schemes (Freese et al., 2014) and comprehensive bicycle-promotion strategies (Winning et al., 2012), to name just two examples. Consequently, cities of various sizes are striving to provide adequate cycling infrastructures to make urban cycling even more attractive. Known factors that influence the impact of such investments are the quality of the road infrastructure, the accessibility and connectivity of bicycle networks, the topography, and traffic safety. This last is often difficult to capture, especially with respect to subjectively-perceived safety. In order to gain a more holistic picture of how cyclists perceive the road space, different methods need to be merged, with the geographical space being the common reference.

Yet, even though numerous previous research efforts have tried to analyse the safety of cycling infrastructures, the majority of these approaches are based only on traditional and proven methods that employ datasets like accident statistics, road infrastructure data, or conventional questionnaires. Consequently, the question of how to best analyse perceived safety is still widely unexplored, other than through typical surveys, which are known to face numerous limitations from psychological and sociological viewpoints: the assessment of people's emotions and intrinsic perceptions is an inherently difficult and an unsolved problem in psychology.

Thus, we aim to leverage current developments in the field of emotion-sensing, where we are currently witnessing rapid progress in the areas of wearable computing and context-sensitive analytics. These technological innovations allow for the passive sensing of bio-physiological parameters, and their use complements established assessment approaches such as indicator-based models that calculate "bikeability" indices (Loidl & Zagel, 2014; Winters et al., 2013) and the collection of in-situ feedback (Senatsverwaltung für Stadtentwicklung Berlin, 2013). Loidl (2016) provides an overview of spatially-enabled communication frameworks about the road space, and Forsyth & Krizek (2011) embed cyclists' perceptions in an urban design context. However, so far little research has been done on the additional benefit of psycho-physiological in-situ measurements for bicycle policies aimed at specific target-groups. Insights gained through the integration of new algorithms and tools with in-situ sensor data serve as a basis for informed decisions in urban and transport planning.

This paper presents an approach which is an inherent part of the Urban Emotions concept (Resch et al., 2015b), in which bio-physiological data is sensed in urban environments to identify areas in which cyclists feel distinct emotions. This information can then be correlated with concrete urban planning requirements. The method was tested in a pilot study in Cambridge, MA (USA). The aim of this field test was to set the stage for a large-scale follow-up investigation with a more extensive sample size, from which general conclusions can be deduced and transferred to achieve a city benchmark.

With our method, it is possible to detect bicycle riders' emotions directly in situ, i.e. while they are riding their bicycles, and we assign inputs from the "People as Sensors" app (subjective observations) to physiological sensor data (objective measurements). The vision of this research is to use physiological sensing devices, to collect data in situ, to combine it with other data sources like social media channels, and to create a people-centric view for bicycle-traffic planning.

2   State of the Art

The proposed approach is located at an intersection of technical and planning domains. Therefore, related work from these areas – on People as Sensors, and GIS-based bicycle planning – is discussed in the following sub-sections.

People as Sensors, Social Media Emotions and Emotion Measurement

"People as Sensors" describes a human-centric measurement model that allows the sharing of information and local knowledge about citizens' personal environments (Resch, 2013). Recently, a number of reporting and eDiary apps have been introduced, many of which address general urban management issues (MySociety, 2010). More specifically, a number of approaches to collect citizens' feelings at virtually any location at any time have emerged. One example is the "Mappiness" app, which aims to understand how citizens' feelings are affected by features of their current environment, including air pollution, noise and green spaces (MacKerron & Mourato, 2012). Viewed from the discipline of emotion psychology, one major shortcoming of these approaches is the induced bias due to conditioning effects, user interfaces that are too complex, and the cognitive processes involved (apps collect cognitively-generated input rather than authentic emotions).

In addition to these app-based approaches, emotion-sensing using wearable physiological sensors has recently gained much interest in scientific research in various disciplines. Current sensor technologies for examining emotions assess parameters like electroencephalogram (EEG), electrocardiogram (ECG) and electrodermal activity (EDA) by measuring skin conductance level (SCL) together with skin temperature (Kanjo et al., 2015). Currently, EDA seems to be the most reliable parameter from which to derive emotions. Zeile et al. (2013) have shown in several case studies that reliable results can be obtained for urban planning. However, quantitative validation of the results is still lacking.

From a "Collective Sensing" viewpoint, a number of approaches have been developed for extracting emotional information from social media data. However, these approaches do not work reliably because they have been designed for edited text, using simple methods like word-matching. Examples of these approaches include Kouloumpis et al. (2011) and Hauthal & Burghardt (2013). A promising recent approach seems to be TwEmLab, a semi-supervised learning approach that identifies distinct emotions in Tweets and other social media posts in an intelligent space-time-linguistics algorithm (Resch et al., 2016). This approach can also cope with the fact that social media posts contain a large number of slang words,

abbreviations, emoticons, irregular punctuation, "yoof speak", or other lexis that cannot be found in standard dictionaries, which most other approaches use (Eisenstein, 2013).

The Urban Emotions approach presented in this paper advances previous research by 1) combining subjectively contributed emotions with technical measurements from wearable sensors, and 2) providing a simple mobile app interface that is dedicated to scientific purposes and designed in accordance with guidelines and requirements from the field of emotion psychology (Resch et al., 2015a).

Bicycle Safety and GIS

Bicycle mobility can be modelled and analysed from various perspectives in geographical information systems. GIS environments serve as integrated platforms that facilitate the detection of, and analyse the dependencies between, cyclists, other road users, the built environment, and non-physical descriptions of the road space (Loidl, 2016).

Current research on perceived bicycle safety focuses mainly on bicycle–vehicle interactions (Chaurand & Delhomme, 2013; van der Horst et al., 2013) and the influence of the built environment (Dozza & Werneke, 2014; Jensen et al., 2007). Both aspects can be represented in a GIS for analysis and modelling purposes. Spatial models that assess the quality of the road space in terms of perceived safety (Klobucar & Fricker, 2007; Parkin et al., 2007) or safety performance in general (Loidl & Zagel, 2014; Winters et al., 2013) help planners to implement targeted counter-measures and better address the concerns and requirements of existing and prospective cyclists. Until now, most approaches have relied on models that are validated against epidemiological data that is aggregated and abstracted. Thus the relation between concrete, physical situations and perceived safety on an individual basis is still unknown.

3   Case Study: Analysing Cyclists' Emotions

It is widely acknowledged that human sensors can help planners in urban environments to get a better impression of daily processes in the city. Our pilot study, which we carried out in the cities of Cambridge and Boston, MA (USA), aims to verify the potential of using crowdsourcing mechanisms in combination with the collection of physiological data for planning urban cycling infrastructures.

Participants

The participants in our experiment were invited to take part by email via the Harvard University community. The invitation was shared on a number of social media channels (Facebook, Twitter) and spread virally to a large number of people in the Boston metropolitan area. Twelve participants were recruited to take part in the experiment for the test period (13–20 September 2015). Even though the number of participants seems to be at the lower limit for producing reliable results, our results (see section 0) show that both qualitative and quantitative interpretation of the data is possible, although the quantitative analysis (statistical interpretation of physiological measurements) may be more robust with

larger sample sizes. Furthermore, our test area was small enough for the given sample size, allowing all participants in the test to cover the entire area throughout the study.

The composition of the group was 5 female and 7 male cyclists who were between 25 and 45 years old. All except for 2 used their bikes in their daily routine and thus had extensive experience of cycling in the traffic conditions in the Cambridge/Boston area. Two participants were only occasional bicycle-users. They used the cycle-renting system "Hubway", which is highly popular in the greater Boston area and provides 1,300 bicycles at 140 stations.

Equipment

To reliably assess emotions and stress levels, several sensor data sources have to be combined (see data analysis in section 0). Accordingly, all people were equipped with the following sensors (the authors assisted the participants in adjusting the sensors correctly):

- Zephyr *Bioharness 3* chest belt to measure electrocardiogram (ECG) at a sampling rate of 250 Hz, pulse at a sampling rate of 1 Hz, and respiration rate at a sampling rate of 1 Hz.
- Bodymonitor *Smartband* to collect electrodermal activity (EDA) data at a sampling rate of 1 Hz.
- *People as Sensors* app (Resch et al., 2015) running on an HTC Desire 500 (the smartphone was provided by the authors and mounted on the handlebars).
- *GoPro Hero 4* to capture video footage of the test route and to compare the physiological stress triggers with the real situation through visual comparison.

Test Phase

Once equipped with the sensors, the participants were instructed on how to use the People as Sensors app and how the test phase would be carried out. Thereafter, the experiment was divided into three stages.

Phase 1 consisted of a 3-minute resting phase, in which the participants were instructed to breathe deeply and regularly, and not to talk or move. This was done to level out the baseline of each participant's physiological measurements – in other words, to assess the individual physical condition of each participant, which is essential for producing valid results in the subsequent data-analysis phase.

Phase 2 served to calibrate the participants' physical conditions while cycling. Therefore, all cyclists were asked to go up and down the same route – a small, low-traffic, dead-end street. They were instructed to ride in a relaxed fashion, slower than on a normal ride, avoiding all peaks of exhaustion. In this way, we could level out the baselines of the measurement parameters (ECG, EDA and heart rate variability) for an individual's physical condition, which served as reference value for all measurements.

Phase 3 was the actual test ride, a freely chosen route through the cities of Cambridge and Boston with a duration of at least one hour. During the ride, measurements were collected continuously by the physiological sensors and the camera. Throughout the measurement

phase, participants were able to enter their subjective impressions and observations into the People as Sensors app at any time. Additionally, the app notified them if a stress event was detected by the sensor and asked them to enter their feelings (happiness, sadness, fear, anger/disgust, surprise) and the context (traffic, safety, etc.), according to the procedure described by Resch et al. (2015). Furthermore, a geofencing algorithm notified the user when they entered a pre-defined area (Central Square, Harvard Square, Harvard Bridge, etc.) to ask for their impressions of the place.

The use of the People as Sensors app was necessary to ground-truth the sensor measurements, i.e. to assign an emotion and a context to the sensor measurements, which is still not possible in an automated fashion through pure signal analysis (Resch et al., 2015a). Geotags (smartphone positioning using GPS and wireless mobile networks) and timestamps (smartphone system time) were automatically added to all measurements.

After returning to the starting point, the participants were asked to go through a 5-minute recovery phase, to assess how quickly their organism returned to its normal physical condition.

Data Analysis

According to the current state-of-the-art in physiological sensor data analysis, only negative arousal can be accurately identified by analysing the physiological parameters skin conductance level and skin temperature. This negative arousal is an indicator for a stress event as, according to emotion researchers, skin conductivity increases and skin temperature decreases when a negative experience occurs (Kreibig, 2010, p. 401; Rodrigues et al., 2014, p. 94): "[if] for instance a test person has the experience of anger or fear – a negative emotion – skin conductance (the difference between sweat production and absorption of the skin) increases and skin temperature in the extremities decreases" (Zeile et al., 2015, p. 217).

To extract stress events from the physiological measurements, we calculate the first derivation for skin conductivity and skin temperature to decreasing or increasing slopes. To detect negative arousal, it is only necessary to know whether the skin conductance level is increasing; the scoring value for this event is "+1", and the skin temperature has to decline (scoring value is "-1"). At the end of the evaluation, two binary-coded columns have to be interpreted (see Figure 1). A stress event is identifiable if a signal shows decreasing skin temperature three seconds after the skin conductance level has risen significantly (Papastefanou, 2009).
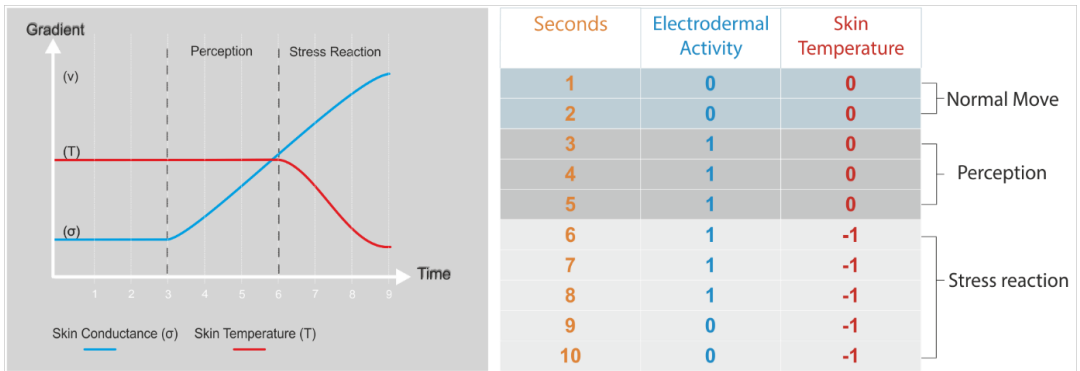
Figure 1: Typical course of physiological measurement of skin conductance (blue) and skin temperature (red) (left-hand side), scoring and 3-second delay pattern of stress reaction (Bergner et al., 2013)

After collecting the physiological data, all the datasets were analysed using the following sequential steps, according to the procedure shown in Figure 2:

- Identification of the points of negative arousal by analysing the gradient of EDA (Map 1)
- Verification of the detected points of negative arousal with the help of simultaneous video tracks (Map 2)
- Addition of the events from the People as Sensor app (Map 3)
- Merging of all results with identified incidents and points of negative arousal (Map 4)

Figure 2: Schematic maps for identifying potential danger spots, combining datasets collected from all participants

Results

Figure 3 shows the analysis results for all participants combined. Visual analysis of the individual cyclists' results reveal several places in which negative arousal was measured. Some critical intersections can also be identified.

In the aggregated results for all cyclists, hotspots could be identified (see Figure 3). Correlating these hotspots with the People as Sensors inputs and the physiological measurements revealed unfavourable traffic conditions, such as large numbers of vehicles, bad street design, violations of the highway code, especially cars overtaking without respecting the safety distance, long waiting times at crossroads, and damaged road surface.
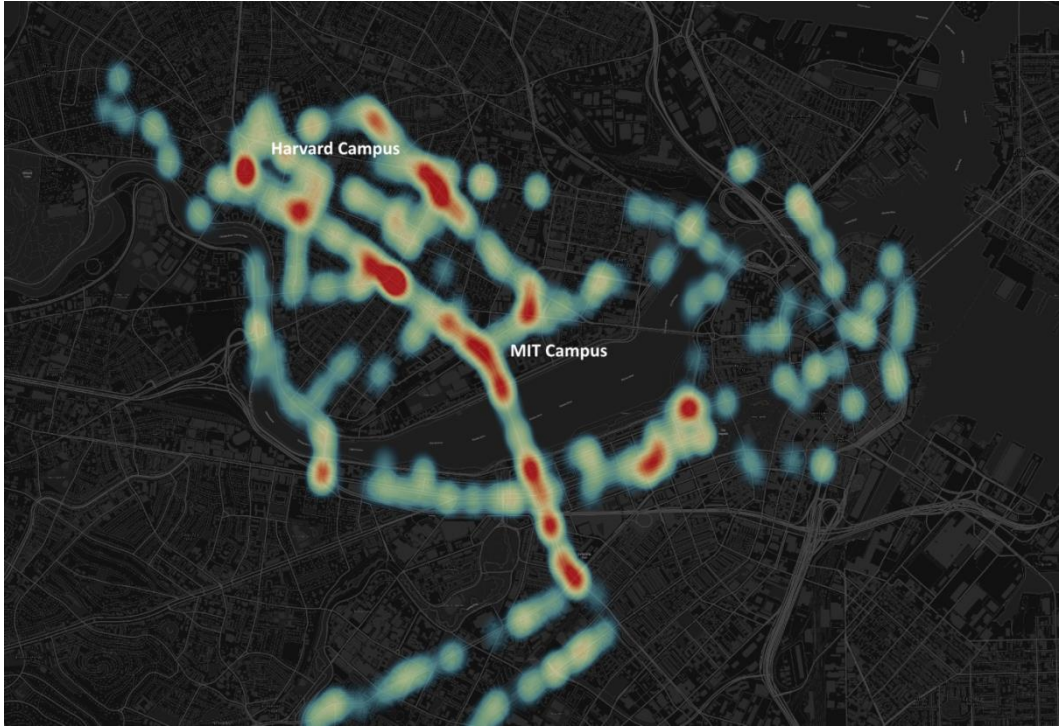

Figure 3: Visualization of EDA for identifying areas of negative arousal during the test rides.

The map of hotspots (Figure 3) provides an initial impression, showing areas with more intense moments of stress and ones where the cyclists are more "relaxed".

For precise information regarding which incidents or triggers aroused negative feelings, we can refer to the recorded camera tracks and the geotagged emotions of the People as Sensors app. Comparing the duration of the negative arousal and the actual trigger of the arousal is also useful. See Figure 4 for an example of this type of analysis. Concretely, we detected 22 individual triggers in the video track for one of the cyclists. These triggers include cars passing close by, long waiting times in heavy traffic, and damaged road surface. The Smartband additionally identified a few other points of georeferenced stress triggers (moments of stress), which indicates that there is no 100% match of sensor measurements with visible real-world events. However, this combination of the different data-acquisition mechanisms delivers a new view of the city and of potential planning deficiencies.

Figure 4: Comparative analysis of the data of rider 5. "Moments of stress" (MOS) show the negative arousal situations. "Triggers from video recording" identify critical situations from the GoPro Tracks. "MOS and Triggers" combines triggers from the video recording and instances of negative arousal. "People as Sensors" illustrates georeferenced, subjective, perceived emotions.

The "Moments of Stress" (Figure 4, upper-left) shows the negative arousal identified by the Smartband wristband sensor in terms of the duration of the stress events. With the help of the video analysis, critical situations can be identified in the physiological measurements. A closer look at cyclist 5's video reveals the triggers for negative reactions in 29 situations (Figure 4, upper-right): damaged road surface, dangerous intersections, physical obstacles, overtaking, or pedestrians crossing (videos are available on Urban Emotions Youtube Channel, 2015). The lower-left map in Figure 4 shows MOS and triggers combined, representing a consolidated indicator for negative arousal.

Finally, the lower-right map in Figure 4 illustrates all subjectively-perceived emotions which were triggered, collected and georeferenced by the People as Sensors app. These represent an additional information layer for identifying specific places of stress. The People as Sensors app generates an individual, subjective impression of the rider's environment. Using this app, the basic emotions of anger, joy, fear and sadness, which were assigned by the cyclists to distinct locations, can be enriched with a personal comment. In combination with the identified moments of stress and the information extracted from the video footage, these user inputs can therefore add meaning to the pure measurements ("ground-truthing"). The textual comments range from simple comments ("street bump", "traffic" or "green wave") to differentiated statements on particular traffic situations, including concrete suggestions for improvement.

4   Discussion and Conclusions

This paper presents the results of a case study in which bicycle traffic safety was assessed using a combination of physiological sensors, People as Sensors inputs, and video footage. Using this method, it is possible to detect cyclists' emotions directly in situ. We assigned inputs from the People as Sensors app (subjective observations) to physiological sensor data (objective measurements) and validated our conclusions using video footage.

The results in their current state can be used as a source of information to help improve bicycle traffic planning and to mitigate traffic risks for cyclists. The intermediate results of our methodology (sections 0 and 0) can all be used to identify planning requirements, while the final integrated analysis results can be employed specifically to identify hotspots in urban planning deficiencies. From a planning point of view, the insights gained in the course of this research create a new layer of information about urban processes, and the Urban Emotions approach can help to reveal an unseen perspective and give better insight into the "city as an organism".

Although our results can be qualitatively interpreted and used in urban planning, more research is necessary to quantitatively and automatically generate recommendations for urban planners from the measurements. First of all, the process of emotion-extraction has to be made more robust. With our current sensing setup, we are able to achieve a clear classification of only one emotion, which is then mapped to the parameters of skin conductance level and skin temperature to identify negative arousal. The ground-truthing process (identifying a particular emotion) is still done in a semi-automated manner only, using the individual inputs from the People as Sensors app and visual comparison with the video tracks. In the future, we would like to be able to identify these emotions in a fully automated fashion through combination with new sensor parameters (respiratory and cardiovascular measurement parameters, like additional heart rate (AHR) and EEG). In this regard, greater cooperation with psycho-physiological experts will be necessary. Accordingly, field tests and lab trials are currently being set up in conjunction with emotion psychologists, aiming to develop a more sophisticated sensor-fusion method.

In using physiological sensing devices and collecting data in situ in combination with data from sources such as social media channels, the Urban Emotions approach establishes a new and innovative model for citizen-centric planning processes in the city.

Acknowledgements

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