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HOT SPOTS IN CITIES - CLASSIFYING EMOTIONS DURING PHYSICAL OUTDOOR ACTIVITIES IN URBAN AREAS

H. Dastageeri , S. Schneider [1], M. Alfakhori, V. Coors

University of Applied Sciences Stuttgart, Schellingstr. 24, 70174 Stuttart, Germany -
(habiburrahman.dastageeri, sven.schneider, muhammad.alfakhori, volker.coors)@hft-stuttgart.de

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ABSTRACT:
Determining emotions of people during different activities (e.g. surfing the web or walking and driving in urban areas) is of high interest to many industries such as the advertising and marketing industry (Imotions, 2022) or city developers and planners (Zeile et al., 2015). However, as the authors have explained in their previous works (Schneider et al., 2020, Dastageeri et al., 2019, Kohn et al., 2018), it is very difficult to determine emotions using surrogate measurements. This is compounded by the fact that many people have trouble to name their emotions correctly as they are often mixed and hardly ever occur as a single and distinct emotion. In order to improve the attractiveness of cities not just based on general presumptions about how citizens would react to certain changes in the urban environment, but based on physical measurements, previous works have shown approaches to do that (Schneider et al., 2020, Dastageeri et al., 2019). They have developed a first attempt to correlate measured physical parameters such as heart rate and skin conductivity (among others) which are triggered by location and environment to emotional states using machine learning. To correlate locations to emotions is an important aspect for city planners, as a person’s emotion for a location defines the personal relationship to a place which can help to gauge the attractiveness of a place and give indicators about where to improve the city or place.

1. INTRODUCTION

Determining emotions of people during different activities (e.g. surfing the web or walking and driving in urban areas) is of high interest to many industries such as the advertising and marketing industry (Imotions, 2022) or city developers and planners (Zeile et al., 2015). However, as the authors have explained in their previous works (Schneider et al., 2020, Dastageeri et al., 2019, Kohn et al., 2018), it is very difficult to determine emotions using surrogate measurements. This is compounded by the fact that many people have trouble to name their emotions correctly as they are often mixed and hardly ever occur as a single and distinct emotion. In order to improve the attractiveness of cities not just based on general presumptions about how citizens would react to certain changes in the urban environment, but based on physical measurements, previous works have shown approaches to do that (Schneider et al., 2020, Dastageeri et al., 2019). They have developed a first attempt to correlate measured physical parameters such as heart rate and skin conductivity (among others) which are triggered by location and environment to emotional states using machine learning. To correlate locations to emotions is an important aspect for city planners, as a person’s emotion for a location defines the personal relationship to a place which can help to gauge the attractiveness of a place and give indicators about where to improve the city or place.

2. PROBLEM STATEMENT

The challenge of detecting emotions is that measurements of physical parameters relating to different emotional states have to be executed in an inconspicuous and subtle manner. Even by just providing the information to the subject that emotions are going to be tracked may distort the results. The alternative of questionnaires also leads to insufficient and unsatisfactory results as questionnaires can only take place after a study. The subjects need to recall their emotions to describe their feelings which would be a rough approximation at best.

One key challenge is that measurement needs to be performed on site as the effect of the specific urban locations needs to be taken into consideration. This approach counteracts most of the previous studies in this field. Classically so far, emotions are mainly tracked under laboratory conditions within a controlled environment regarding lighting conditions, temperature, sounds, visual stimuli, and physical activity (Saganowski, 2022). Contradicting to this, measuring emotions outdoors during physical exertion is of great interest for gauging the perception of the environment and how it makes a subject or a person feel at a certain location. Furthermore, the external and unpredictable stimuli that a subject is exposed to outdoors and how they react to them, is the focus of this and previous work.

3. METHOD AND CHALLENGES

Our approach is to use sensors that are housed inside everyday devices to which the subject is used to (e.g. smart watch, fitness tracker). Due to this, the process of tracking the subjects is less cumbersome. The subjects are not as focused on the fact that they are under surveillance, so it increases the chance of measuring unadulterated data.

Corresponding to the challenges the measured data of previous studies needed to be examined, especially the questionnaire as well as the parameters need to be evaluated thoroughly in order to assess their contribution to the classification of an emotional state. In the questionnaire, we used NASA-TLX to measure the mental, physical, and temporal demand along with performance, effort, and frustration. The results were taken into consideration together with the following physiological parameters: heart rate (HR), AppleWatchPulsClass, sound level of the surroundings,

[1] Corresponding author

VO_2max, and cardio fitness level. Because of the noise caused by the outdoor environment, we chose not to use skin conductance level (SCL) and eye tracking. To be able to classify the emotional state, we used the Self-Assessment Manikin (SAM) (Figure 1, (Bradley and Lang, 1994)) which was assigned five levels representing different emotional states. SAM was used deliberately instead of a word description of emotions. Previous works have shown (Schneider et al., 2020, Dastageeri et al., 2019) that it is hard for subjects to describe their emotions in words or classify them in just one word.

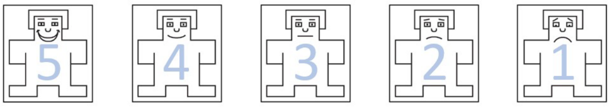

Figure 1. Numeration of the SAM scale

4. DATA ANALYSIS

In this work the authors extended their previous work by differentiating between three modes of physical activity: sitting, walking and running. For each mode, training data were collected of 10 subjects; 3 female, 7 male, age 17-46 of different physical condition. Using the Open Affective Standardized Image Set (OASIS) four pictures were selected which could nearly cover the whole arousal and valence spectrum. Based on that pictures locations were carefully selected in and around Stuttgart which resembled the pictures.

To be able to classify the emotions for each of the methods to one of the five SAM-levels, Machine Learning (ML) was used. For classification, four methods were chosen: Perceptron, Decision Tree, Naive Bayes, and Support Vector Machine. Each method has its advantages and disadvantages. To counteract that issue, the methods were combined into ensembles. The assumption is that the methods together will generate better results than each method alone. The following three ensembles were used: Random Forest, AdaBoost and Bagging.

A confusion matrix was generated for each method to calculate accuracy, precision and recall in order to derive the F-scores to quantitatively evaluate the ensembles. Based on the confusion matrix, we used F1-score (Olson and Delen, 2008) and $F\beta$-score metrics for evaluation of the ensembles. Using F-beta allowed us besides calculating the harmonic mean in F1-score also providing flexibility in prioritizing between precision and recall. We used a beta score of 0.5 which lends more to precision as β>1 lends more to recall (Pedregosa et al., 2011).

Some ML methods allow to set up model parameters called hyperparameters which also the ensembles allow. Hyperparameter for ML methods and ensembles were tuned to find optimal values. For ML methods, we tuned the respective models using RandomSearch-CV of the free software ML library Scikit-learn. Randomly from a set of preset parameters, the hyperparameters were chosen so that they had the highest values based on an internal scoring process. For the ensembles Random Forest, AdaBoost, and Bagging, a specific tuning method for each model was used: Random Forest Randomized Search, AdaBoost Randomized-Search, and Bagging Randomized Search (Paper, 2020).

The best results of our study were provided by Random Forest with Randomized Search. That also reflects the work of (Fernandez Delgado et al., 2014) who tested 170 classifiers on 121 real world data sets. Their bottom line was that Random Forest, Support Vector Machines, and Kernel Perceptions usually perform well.

5. IMPLEMENTATION

The presented approach was implemented as a web app in Python using the open-source app framework Streamlit [1] (Dastageeri, 2022). The user interface allows users to choose the ML model which will be calculated directly on the server. The resulting SAM level will be shown on the fly on the web app as well as sent to another PHP web app that process the numeric value and provides it for further processing, if needed.

The crucial part of this approach was collecting, labeling, and preparing the training data. That process for high quality training data was cumbersome and time consuming. However, it may be of interest to investigate in future whether persons with similar bodies and mental constitution have similar parameters and if training data can be transferred among a certain group of participants.
The results of this approach is a proof of concept that needs to be elaborated more in future work. Because the aim of this work is to simplify the process of classifying emotional states during physical outdoor activities, it was important to provide a solution that could be applied using mobile unobtrusive sensors. In the future, the final goal is to be able to provide a more general solution.

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