Do the dynamics of the city environment influence us, and how?

Answer through the Machine Learning Approaches

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Abstract. As a part of research with a team at the ETH Zurich, Switzerland, we investigated a detailed answer to the question "Do the dynamics of the city environment influence us and how?" We adopted Data Science and Machine Learning approaches for investigating such relationship between the dynamics of the city environment and the human perception. A complex and messy dataset was analyzed and resolved for this purpose. The machine learning analysis and its results will focus on answering the following questions: (1) What are the factors that need to be accounted for from the city environment? (2) How can we collect and process messy and complex datasets? (3) Can we predict the citizen's perception based on an environmental condition? (4) Are we able to infer a detailed relationship between a citizen's perception and the city environment? (5) What are the significant factors that influence a citizen's perception? (6) Does the citizen exhibit positive or negative emotion towards a certain environment? Our investigation through Data Science and Machine Learning approaches answers these questions in detail using data preprocessing techniques such as stationary wavelet transforms; physiological signals processing; and quantification and information fusion. We discover knowledge (answers to the questions) through the use of data science tools like decision tree, fuzzy unordered rule induction algorithm, feature analysis, self-organizing map, deep learning, spatial and non-spatial statistics, and plotting correlation maps. Our results reveal qualitative answers to the above questions such as highly sensitive of human's perception of the environmental conditions, the essential drivers such as temperature and illuminance, and field of view.

Keywords: Signal Processing; Urban Environment; Machine Learning; Data Science; EEG Signal; Fuzzy System; Self-Organizing Map; Deep Learning.

1 Introduction

This research study was conducted in the City of Zurich, Switzerland and Weimar, Germany which deals with researching the question: what causes one's experience and perception to fluctuate in an urban environment [3], [6]. Zurich continually ranks in top place in the world's most livable cities [5]. Hence, our objective was to analysis the human perception indicator, pattern and factors of influence in some of the most livable city. With rapid urbanization in developing countries, this question is vital for both developed as well as for developing cities because this research questions and their answers/solutions entail relevance to the topics of environment/climate impact on humans and the built environment and urban spaces impact on humans

1.1 Research Questions

The research in [3] tried to answer the following question using data science and machine learning techniques. The machine learning analysis and its results will focus on answering the following questions: (1) What are the factors that need to be accounted for from the city environment? (2) How can we collect and process messy and complex datasets? (3) Can we predict the citizen's perception based on an environmental condition? (4) Are we able to infer a detailed relationship between a citizen's perception and the city environment? (5) What are the significant factors that influence a citizen's perception? (6) Does the citizen exhibit positive or negative emotion towards a certain environment?

1.2 Experiment (description of the study)

To answer the mentioned question the following phases were adopted. We designed an experiment to record environmental variables and human physiological signals where participants were asked to walk along a predefined path in both cities Zurich and Weimar [3]. In order to understand, measure, and predict the impacts of *urban morphology* (UM) on the perception of citizens, we developed a three-tiered empirical study. The purpose of was to draw upon the participants' experiences in a real-world experiment [6], along with two controlled experiments using a 360-degree video and a grey-scaled 3D virtual reality (VR) model of the city [2]. All three experiments are conducted using the same predefined path in each of the two cities (Fig 1).

Along with environmental variables such as temperature, humidity, illuminance, the field of view (area), and dust, we recorded the implicit perception of the participants by simultaneously measuring *electro-dermal activity* (EDA) data collected via wearable devices. The EDA data is processed to quantify the frequency, duration, and location of arousals along the experimental path to show a measure of excitation in terms of implicit perception provides the "raw" arousal-based perception from participants

2 Data Pre-processing

We also consider the impacts of urban environment features on perception, including temperature, illuminance, sound, and dust using data collected via a "sensor-backpack," specially designed for the use in the real-world participant studies [4]. The data produced from this experiment is highly complex; the seven sensors have varying frequencies and varying temporal dependencies. We, therefore, developed an information fusion mechanism to combine the spatial-temporal data to produce a structured dataset. The preprocessed dataset was analyzed using four state-of-the-art

Machine Learning algorithms. The quantified physiological responses in other words "human perception" was quantified using Ledalab tool [1] and the data was being paired with the sensor-based environmental measurements for processing using Machine Learning based knowledge discovery approaches. A comprehensive framework is offered in [6].

Fig. 1. (a) Predefined walking path (Wiedikon, Zürich, Switzerland); (b) a participant with sensor backpack [4] (Figure adapted from [6]).

3 Machine Learning and Data Science Tools

The Machine learning approaches to deal with problems include classification, fuzzy rule-based inference, feature selection, and clustering to derive underlying relationships between participants' physiological response and environmental conditions. The results indicate that the participant's implicit responses are affected by both urban morphological features measured as participant field-of-view and street width as well as the dynamic environmental features temperature, noise levels, illuminance and traffic speed.

Complex as it seems the question as to how to investigate this relationship between the urban environment and its perception of humans, the machine learning emerges as a viable tool to reveal this mystery. Machine learning application also compels to bring with it the additional necessary tools like signal processing and data fusion techniques. In its entirety, data related to the environment (weather sensor data) and human's experience (biofeedback sensor data) processed and fused together to generate a high-level dataset that was explored by the machine learning tools to revealed various relations between the environment and human's perception (see Fig 2) [6]. As well as the importance of variables is shown in Fig. 3.

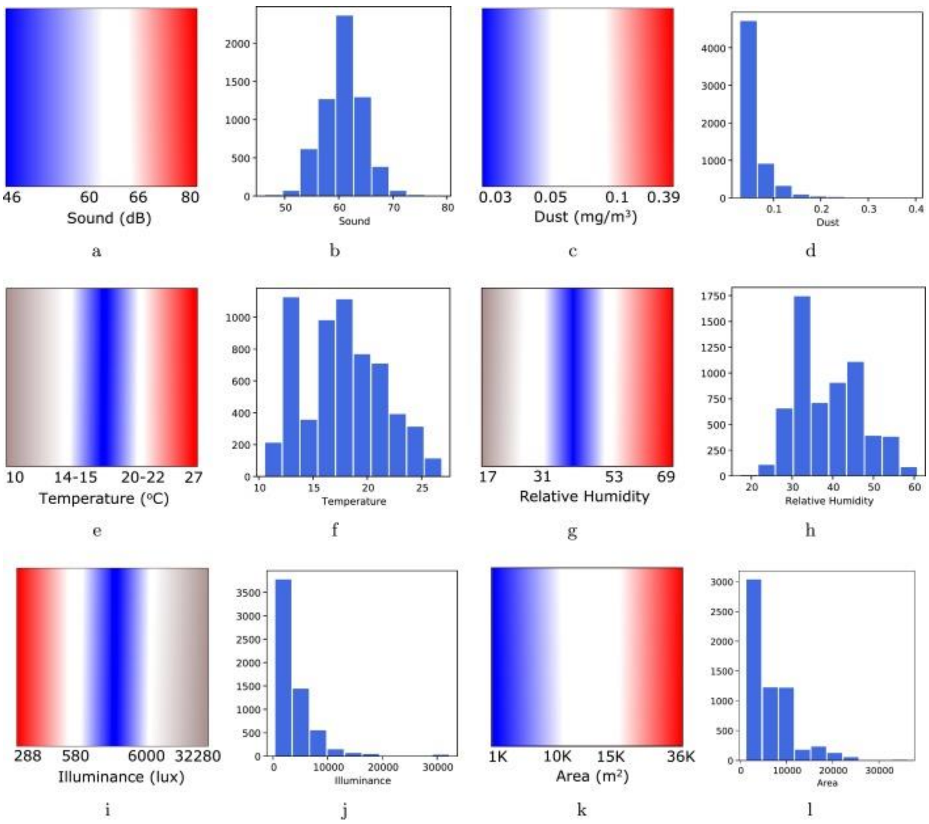

Fig. 2. Visual interpretation of the fuzzy rules. The color "red" indicates the range for which the fuzzy rules finds philological repose high, i.e., an indicator of aroused physiological state. The color "blue" indicates the range for which the fuzzy rules finds phycological repose high, i.e., an indicator of normal physiological state. The color "white" indicates a range of fuzziness. The color "gray" indicates the range for which rules do not provide any conclusive information (Figure adapted from [6]).

The subsequent experiments are further abstractions of the real-world experiment to emphasize and evaluation the impact potential of urban morphology. For example, the 360-degree video holds all dynamic environmental variables constant, and the grey-scaled 3D block geometry VR model purely focuses on participant response to the change in geometry, eliminating the influence of aesthetic qualities. The three experiments enable us to identify the "hot spots" of arousal as a function of pure urban form, thus gaining insight for how human perception is linked to UM using plots of UM architectural features [2], [7]. Additionally, a spatial statistics analysis helps to investigate whether similar built environment have an identical impact on the human's perception [8].

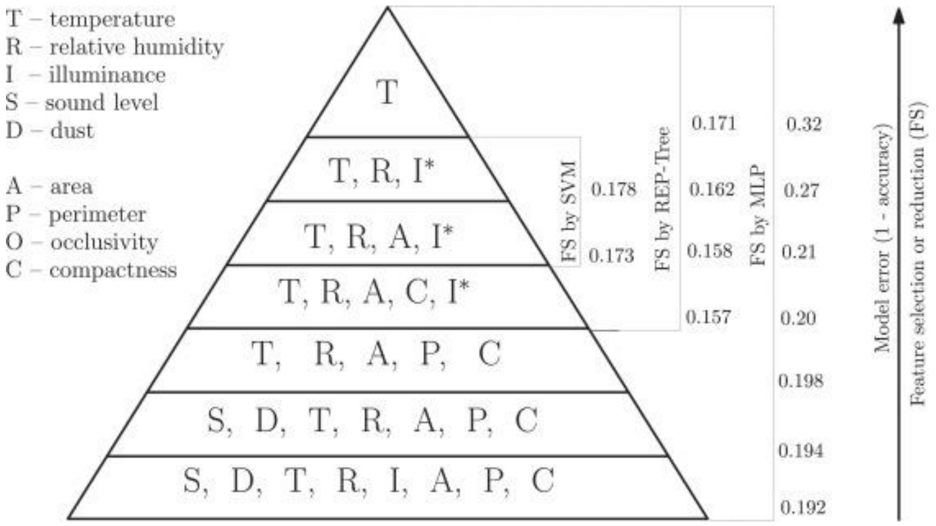

Fig. 3. Hierarchy of feature importance. The symbol I* appeared only in the REP-Tree based feature selection. The feature set {T, R, A, I} appear in all three predictor's results (Figure adapted from [6]).

The question of whether to rely on a fixed threshold or to have a flexible threshold for determining the physiological arousal level during the signal processing was a major challenge. Although the fixed threshold gives an indicative arousal level, the flexible threshold looks more intuitive than using fixed thresholds since the different person may have different environmental conditions acceptability.

How much control do we have when we relate to the human's perception with the only built environment? This question posed an additional challenge. While investigating this, weather condition needs to be eliminated. Thus, the Virtual Reality experiment helped in increasing the abstraction level and helped in examining the direct impact of the built environment over the human's experience [2].

4 Deep Learning Approach

In this work, we investigated, deep learning to investigating the further relation between the visual features of the built environment on human's perception [9]. It offers a direction that provides answers that are precise and with the accord of visual perception. It begins with processing images, extracting features of the built environment, clustering them in different groups, and investigating the subjective (rating votes) and objective (biofeedback) scores. Further, feeding them (high-level information in the form of cluster images) to a convolutional neural network for extrapolating a street scale experiment to city-scale experiment and one city to another city (Fig. 4 and Fig. 5).

Road: 0.356
Sidewalk: 0.017
Building: 0.228
Wall: 0.001
Fence: 0.002
Pole: 0.0030

Traffic light: 0
Sky: 0.254
Person: 0.024
Rider: 0
Traffic sign: 0.006
Vegetation: 0.020
Terrain: 0.002

Car: 0.061
Truck: 0
Bus: 0.005
Train: 0.013
Motorcycle: 0
Bicycle: 0.002

Fig. 4. Example of a VR frame evaluated using Convolutional Neural Network (CNN) as Network trained over CITYSCAPE dataset [10] (Figure adapted from [9]).

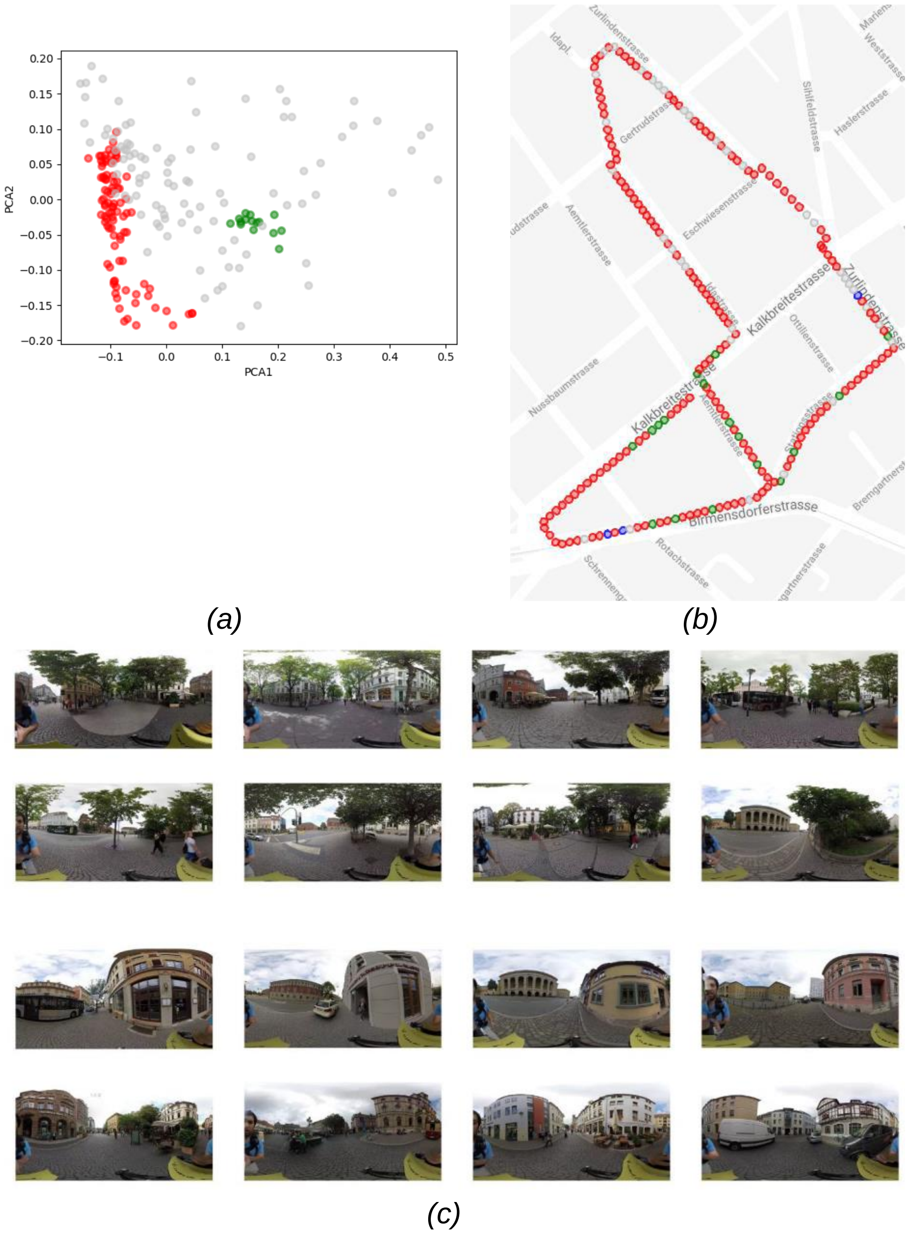

Fig. 5. A cluster of two-level of Physiological arousals and their map on the path. The cluster of types of images and their architecture feature analysis using CNN related to low physiological arousal [red dots on the map (b) and images are Upper two rows in (c)] and physiological arousal [green dots on map (b) and images are lower two rows in (c)].

5 Conclusions

Complex as it seems the question as to how to investigate this relationship between the urban environment and its perception of humans, the machine learning emerges as a viable tool to reveal the underlying relationships. Machine learning application also compels to bring with it the additional necessary tools like signal processing and data fusion techniques. In its entirety, data related to the environment (weather sensor data) and human's experience (biofeedback sensor data) processed and fused together to generate a high-level dataset that was explored by the machine learning tools to revealed various relations3 between the environment and human's perception.

The question of whether to rely on a fixed threshold or to have a flexible threshold for determining the physiological arousal level during the signal processing was a major challenge. Although the fixed threshold gives an indicative arousal level, the flexible threshold looks more intuitive than using fixed thresholds since the different person may have different environmental conditions acceptability.

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The deep learning was investigating the relation between the visual features of the built environment on human's perception. It offers a direction that provides answers that are precise and with the accord of visual perception. It begins with processing images, extracting features of the built environment, clustering them in different groups, and investigating the subjective (rating votes) and objective (biofeedback) scores. Further, feeding them (high-level information in the form of cluster images) to a convolutional neural network for extrapolating a street scale experiment to city-scale experiment and one city to another city. Additionally, a spatial statistics analysis helps to investigate whether similar built environment have an identical impact on the human’s perception.

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