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A Spatially Explicit Classification Model for Affective Computing in Built Environments

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***Abstract*—We explore a wearables and sensors centric approach for collecting data in built environments. In addition, we propose a design methodology as a focus to assist in the design of applications and experiments for affective computing. The implications of such systems is to aid in the reproducibility of experiments and better intelligent systems.**

1. Introduction

Generally speaking, affective computing is the study and development of systems and devices that can recognize, interpret, and process human emotions or affects [1]. Built environments are human-created settings which provide the infrastructure for human activity. These environments have been commonly defined as the human-made space in which people live, work, and recreate on a day-to-day basis [2]. Architects and planners focus on creating built environments using a variety of forms and features which are designed to support society through functional approaches and human-centered use [3], [4]. Recently, there is increasing interest in exploring the association between built environments and mental health and other affects [5]. We believe an affective computing approach to questions on how built environments influence human emotions or affects, is extremely relevant.

Through this study, we consider the motivation for using wearables and sensors as tools in studying human emotion given built environments. The association between affective computing and wearables goes back to the earliest days of research in Affective Computing [6]. In addition, there have been affective computing studies focused on detecting stress in participants [7]. Recent advances in wearables and sensors are suggestive of how we might collect data in order to answer questions on how built environments influence human emotions. First, there is a general trend toward the growing availability, capabilities, and lowering costs of computing resources to process large quantities of data. Second, there is the growing sophistication and abilities of wearables and Internet of Things (IoT) devices. For example, sophisticated wearables such as the Empatica E4 can be used to collect a plethora of detailed physiological data in a non-entrusive manner [8]. In addition, commercial wearables such as the Garmin's vivosmart have purported abilities to detect stress in a user [9]. Therefore, using existing and new capabilities of wearables and sensors in examining human affects in built environments is worth serious consideration.

We believe research shows persistent interest in how built environments can impact human affects and how wearables and sensors can be used to detect human affect within such environments. Therefore, we shall focus on the following points. First, that the uses and applications of affective computing systems associated with built environments focuses on arousal detection. Second, we briefly examine an experiment that will motivate guidelines for future work that is unobtrusive, effective, and likely to be more effectively used by participants in research. Third, as a guideline for affective and intelligent systems in a built environment context, we propose an approach and design for geospatial zone classification. Finally, we will briefly consider future work and present the need for interdisciplinary approach and collaboration.

2. Arousal Detection in Built Environment

2.1. Motivation for Arousal Detection in Built Environments

Arousal can be defined as an elevated or different physiological state different from the average base physiological state such as average heart rate [10]. Measuring other physiological phenomenon such as such as emotions and human affect is difficult and complicated. In addition, it is an open problem in correlating emotions to a physical space due to the complexity of the problem. The authors acknowledge these challenges and believe framing the problem via the detection of arousal is an important first step in detecting human affect in built environment using wearable and associated sensors.

The detection of arousal using wearables and sensors will be useful in gaining insights into understanding built factors as an influence on human affects, and allowing researchers more sophisticated tools to test different strategies to alter emotion within a built environment [11]. Recent

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advances in wearable sensors [12] and data analytics means we are now able to collect new kinds of data in order to measure the relationship between built environments and human affective responses.

We believe the detection of arousal with the use of wearables and sensors can help researchers investigate several issues of contemporary interest to landscape architects, planners and engineers. First, it is well known that perceived or actual unsafe built environments can adversely affect human mental health [13], [14], [15]. In addition, there are risks from urbanization worth exploring in this context. Studies suggest that there is a correlation between physical environment and human physical and mental health [16], [17], [18], [19], [20]. There is also reason to believe that natural elements in a built environment improve mental and physical health [21], [22], [23]. Research by Ulrich and Parson et. al suggests that exposure to nature contrasted with built environments influences human affect and behavior [21], [22]. The decline of nature globally due to rapid urbanization suggests a decline in public health [24], and consequently, this has the potential to increase the risks for adverse conditions such as stress and mental fatigue [21], [23], [25], [26], [27]. Therefore, an affective computing approach to the detection of human arousal in built environments should be the focus in collecting data to address these various concerns.

2.2. Detecting Arousal in Built Environment

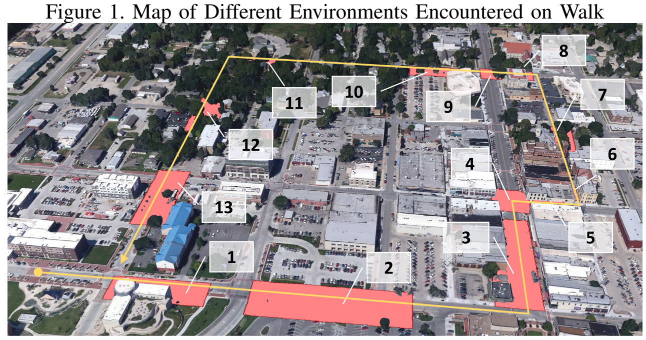
The authors have already added to the literature in the detection of arousal in built environments, primarily using geospatial affective computing techniques [28].

Preliminary work has focused on measuring how different environments encountered on a walk can be associated with physiological changes and differences. Specifically, Ruskamp [29] examined how different environmental characteristics affected arousal responses in participants at Manhattan, Kansas. The study had 17 college age students each fitted with an Empatica E4 and polar sensor. Each participant was asked to walk a predetermined route which was chosen for specific environmental characteristics. For instance, a darkened alley, poorly lit street, well lit sidewalk, and areas with more vegetation features present such as trees. These environmental characteristics were denoted by zones. Please see the map below of different environments encountered on the walk.

After participants individually walked the route, each participant was given a survey and in order to rate perceived safety of each zone on a likert scale. The data outside of zones in the survey are not rated by participants. The responses in the survey were reported to be statistically significant by Ruskamp and Chamberlain [29]. Further reinforcing the connection in literature that built environments are associated with human affect.

Using Ruskamp's data, the present authors examined the same data and experiment through an affective computing context. First, normalized heart rate collected from participants was examined and the mean for all participants was

Figure 1. Map of Different Environments Encountered on Walk



calculated for each question zone given the 95% confidence interval. Each question zone corresponds to a specific environment of interest.

Figure 2. Mean Normalized HR and 95% Confidence Interval by Different Environments Encountered

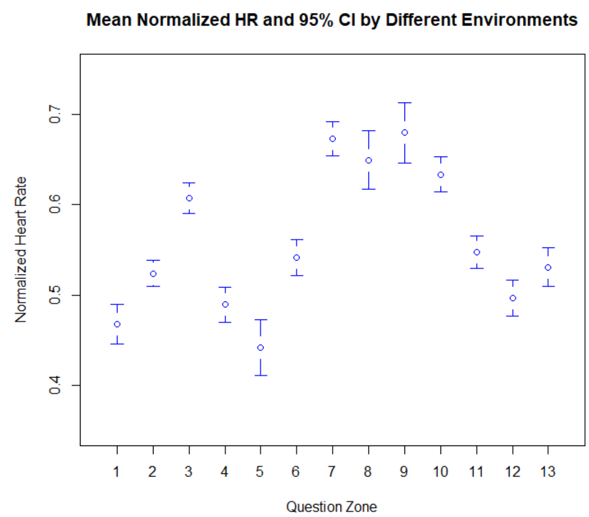


Figure 2 demonstrates statistically significant differences between the normalized HR by zone. We believe this is suggestive that different environments can have an influence on human physiological responses. Consequently, we looked at the control portion of the data to gain a baseline heart rate for each participant to compare against the data collected from the participant when they were walking the route. For the control, the user was asked to calmly walk from a predetermined starting point at a hotel to the beginning of the route. This 2 minute data collected on each participant was used to calculate the baseline for psychometric signals such as average heart rate. For each participant, the data from walking the route was smoothed using the mean heart rate and standard deviation grouped by every 30 seconds. This data was given to a neurophysiologist who looked at the smoothed and post survey data and gave an expert annotation of whether or not a participant was experiencing an arousal event for each zone. The authors applied standard classification machine learning algorithms to the expert annotated data. The results are nascent and very preliminary, but suggest machine learning can be used to detect arousal in built environments using annotated data.

2.3. Proposed Guidelines and Open Questions

For studies applying affective computing to built environments, we argue that research should heavily consider adopting a geospatial approach toward data collection, that allows scientists to analyze data obtained from wearables and sensors in association with elements one experiences in space. It is very desirable to conduct similar experiments in as many different built environments as possible. In addition, seasonality, time of day, weather, and other natural environmental factors should be considered. Collecting such data over a long term duration may provide an opportunity to better estimate baseline data, identify significant events and increase the reliability of data models. The present approach used expert defined user annotated data. We proposed that future experiments consider additional sensors that allow participants to directly annotate their responses in real time, not just post experiment in a questionnaire survey. We believe experiments using wearables and sensors are demonstrably unobtrusive, effective, and likely to be used by participants in experiments with considerable ease.

3. Design for Arousal Detection in Built Environments

As a guideline for affective and intelligent systems in a built environment context, we propose an approach and design for geospatial zone classification. Built environments are not found in laboratory settings. Consequently, measuring how differing environment spaces influence human affects requires an approach that allows researchers to measure physiological data in that space. Wearables and sensors in an affective computing context allows researchers in built environments a viable approach and can be used to detect a plethora of physiological phenomenon. Studies have demonstrated that wearables can be used in the detection of stress [30]. In addition, physiological data, such as heart rate, heart rate variability, electrodermal activity (EDA), facial expressions, have been used in classifying human affect [31], [32], [33], [34]. We propose that experiments conducted in the built environment domain space utilize wearables in order to collect data and use classification methods to detect human affect.

3.1. Data Provenance

We now briefly consider the nature of data that have been or could be collected by wearables in a built environment. For illustrative purposes, consider again, the study by Ruskamp [11] which relied on the Empatica E4 sensor. The sensor collected data such as time, heart rate, temperature, and EDA. The study also collected additional data from participants through a survey asking them to rate different environmental zones. In addition, it is possible to process and annotate data by an expert for the presence of arousal or not. In the future, it might be possible to measure participant response in real time through input devices such as a mobile phone or another sensor to directly annotate the levels of arousal they are experiencing as they walk through different environments. Therefore, data provenance from expert annotated data is likely to be different from user annotated data. In other words, the expert annotated or user annotated scenario represents a different kind of data provenance which we shall now briefly describe.

For expert defined annotation data of arousal, it follows that it is likely to be discrete data. That is, ordinal or binary data. Conversely, participant annotated arousal data could be continuous data that vary according to some scale. Also described as nominal data. In both scenarios, arousal is a classification target that will determine what sort of processing and analysis that will be appropriate [35]. Let us now briefly consider how these data are likely to be designed.

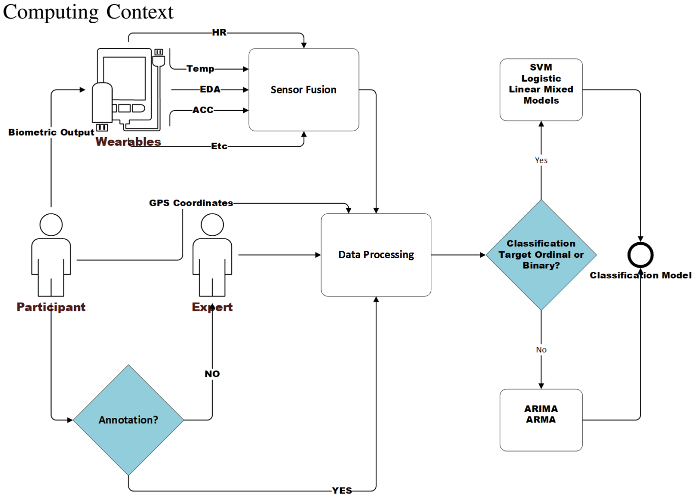
3.1.1. Ordinal and Binary Data. Ordinal and binary data are likely to represent expert defined annotation of arousal. Specifically, the ground truth values that researchers elicit from subject matter experts that are holistic, subjective assessments of environmental arousal-induction level per geospatial zone. These are (1-10) Likert scale values elicited using annotation or survey questions and correspond to discrete classification targets, namely ordinal values. Similarly, expert annotation of arousal can take on a value of either 0 or 1 for each row of observation where 0 indicates the absence of arousal and 1 the presence. Concretely, the presence or absence of arousal as defined by expert annotation is binary and survey question results are discrete categorical variables [36].

3.1.2. Nominal Data. In contrast to ordinal and binary data, nominal data are likely to be collected from users themselves. That is, values that researchers elicit from users directly that are holistic, subjective assessments of environmental arousal-induction level per geospatial zone. However, in these experiments, putative arousal annotations by users are treated as additional input variables - channels of input observed over time. A user records these annotations *in situ* during a walk, by using a mobile phone with a slider or handheld mechanical device to indicate arousal levels to their environment. For example, a device could record a continuous range of values, sampled at a precision of 0 to 1000 numeric values to indicate arousal. Because these variables are sampled using analog devices and converted to digital format, they are treated as continuous-valued [37].

3.2. Data Processing and Analysis

The following is a proposed design for using wearables and sensors to detect arousal in an affective computing context. First, the participant is provided a wearable which records their biometric data. Second, sensor fusion occurs by combining the input channels heart rate (HR), electrodermal signal (EDA), and temperature (temp) taken from the participant via the wearable or mobile phone. In addition, there could be other signals such as an accelerometer or another input of interest. Separately, GPS data are also of interest. Third, data are annotated by the participant either through a Likert survey or another sensor provided to the participant which records a numerical value to indicate stress. Otherwise, a domain expert will examine the data present in the sensor fusion and determine the presence or absence of stress. Fourth, data processing occurs which prepares data for analysis. The last step considers if the classification target is ordinal/binary/nominal and then applies the appropriate classification method. For example, if data is binary then it is likely Support Vector Machines (SVM), Logistic Regression (Logistic), or Linear Mixed Models are appropriate. The final result will be a classification model which can then be used to build an affective intelligent system.

Figure 3. Arousal Detection using Wearables and Sensors in Affective Computing Context



4. Summary

Advances in affective computing and machine learning techniques using wearables and sensors offer a unique opportunity to explore existing and open questions in new ways. In addition, it presents many new questions as well. For many years, research has focused on the value and benefits of various characteristics of the built environment, including the presence of vegetation, lighting, public spaces, amongst others. However, many of these studies were conducted in controlled environments and, as a result of developing robust experimental design, were limited in the number of variables and interactions they could test. By harnessing the capacity of advanced wearables and employing the design methods suggested in the previous section, we are confident that a carefully designed affective computing approach can help researchers better understand the innumerable variables of design and planning, and their relationship to human health and well-being.

4.1. Open Questions and Future Work

Several major questions remain: 1) Can we differentiate effects between various design characteristics and identify strong correlation between those and arousal? 2) Does an affective computing approach offer additional insight that traditional research methods (and related findings) for studying built environments have not addressed? 3) Can affective computing be used to understand the difference between effects from environmental characteristics, social interactions and if those are mutually exclusive in different contexts? 4) Are there particular cultural differences or individual circumstances that influence results? 5) What patterns exist between daily behaviors and built environment, and are they influencing one another? 6) What is the most ethical way to commercialize affective systems designed for built environment spaces?

Arguably, the most important step moving forward is to expand collaborations and the interdisciplinary approach to studying built environments in an affective computing context. Researchers and industry should seek to address these questions by working together. Through our research, we hope to address these questions in the long term, but our first aim is to develop reproducible results by aiding researchers in suggesting and designing reliable experiments by relying on the ever increasing power of wearables and capabilities of affective computing.

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