An Approach of Spatial Emotion Recognition Oriented to Urban Design Decision

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Abstract: The user spatial emotion is an important index to assess the quality of the space, and the physical characteristics of the space are an important factor affecting the spatial emotion. This article analyses the various emotion recognition techniques and spatial feature extraction methods proposed in the past 20 years. Based on related studies, this paper explores the relationship between spatial emotion and physical characteristics, and introduce a new way to obtain the user physiological signals through wearable physiological sensors, and uses machine classifiers to build emotion recognition models. Finally, we propose a framework of coupling relationship between spatial emotions and physical characteristics to provide decision-making suggestions for the built spaces and new projects.

1. Introduction

With the help of new techniques and data analysis methods, user emotions can be recorded and identified in real time. The main methods applied include media text analysis, questionnaire survey, virtual space experiment in a laboratory, field experiment aided by wearable biosensors, and comprehensive methods. This paper proposes a new approach to evaluate the urban public spaces. The main processes conclude obtaining user physiological signals using portable physiological sensors, conducting feature extraction, reduction, and fusion, and using machine classifiers to build emotional recognition models, finally, proposing a space-positive emotion coupling index system for space design and management decision-making.

2. Related Works

In terms of text analysis method, Schöning J. & Bonhage C. E. used social network analysis and examined text expressing emotions from networks, including Twitter and Facebook to assess emotions of users in different urban spaces aided by GPS[1]. The biosensor signal recognition method utilized commercial or professional wearable equipment to record physiological signals of participants in urban spaces and obtain emotion mapping through data preprocessing, feature extraction, and emotion classification[2][3][4]. Other research employed wearable sensors to record physiological signals and simultaneously required participants to submit descriptions of emotions or self-report via smart phones at designated locations tracked by GPS [5][6][7][8]. Geiser M. and Walla P. applied virtual urban space to collect participants' physiological signals in the laboratory and obtained urban emotional maps[9]. Bergner, BS, et al., conducted a quantitative study on emotions of pedestrians in a natural environment, and attempted to compare different responses of different groups[10]. In addition to emotional research, researchers applied image segmentation technology and machine-learning technology to analyze a large number of streetscape photos and study urban space quality or changes [11] [12]. In each process different methods will produce different results. Related studies have formed some consensus results, but overall, there is a lack of comparability and the possibility of integration between different studies (Table 1).

Table 1: Experimental methods, modeling and results of related works.

Year	Author	Participants	Signals	Emotions Recognized	Classifer	Features	Results
2016	Olsen, A.F.; Torresen, J	10	smartphone accelerometer data	valence, arousal (3 levels)	SVM	mean, standard deviation, standard deviation of mean peak, mean jerk, mean step duration, et.al	arousal 75% SVM, valence 50.9%
2016	Kyriaki Kalimeri; Charalampos Saitis	9	EEG and EDA	five predefined categories	random forest classifier	182 EEG features, Six EDA features	79.30%
2016	Supriya Choudhury	100	questionnaires for emotions		KNN	expression of emotions	38.6%,45%
2017	Sandstrom, G.M., et al	18000	Self-reporting	valence, arousal(binary)	deep neural network	Data of Self-reports	68% (valence)
2018	Varun Kumar Ojha, et al		Urban environment; Human perception		REP-Tree	Environmental temperature (°C) Relative humidity (%) ,Illuminance Spatial-temporal Electro-dermal activity (EDA)	87% (binary-class)and 80% (multiclass classification)
2019	Dong, L., et al	50		valence, arousal (5 levels)	neural networks, DT	shaking time, severity of shaking, times of shaking, time of portrait orientation, et.al	71.67%, 72.37%
2019	Laura Fiorini a, et al	15	ECG, GSR and BA signals		K-Means, K-medoids and SVM, DT	RR mean, SDNN, HR mean, SD mean, RMS, SD, pNN 50, VLF peak, VLF power, et. al	77% and 85%
2020	Hashmi, M.A., et al	40 (26/14)		sadness, happiness, anger, surprise, disgust, fear	SVM	mean, median, standard deviation, max, min, index of max/min, skewness, kurtosis, entropy, root mean square, energy, et. al	95% , 86.45%

3. Methods

The study's method involved six stages, as depicted in Figure 1: 1) Selecting spaces and 3D simulation, 2) Field experiments and laboratory experiments, 3) Signal processing and emotion recognition, 4) Comparative analysis, 5) Recognizing spatial features, and 6) Generating a corresponding table of spatial emotions and spatial characteristics. These stages are detailed below.

1) Selecting spaces and 3D simulation: Several urban linear spaces are selected. As for path selection, abundant spatial forms, elements, and structures are required to cause a variety of emotional responses. Sketchup, Lumion, and other software will be used to build 3D models of all linear spaces using Google maps as a reference.
2) Experiments: Human biological stimulation instruments, head-wearing mini DV recorders, GPS devices, and computers aided field experiments. Participants wearing sensor devices will walk through each linear space as device sensors record physiological signals, including signals

of EDA, ECG, EMG, and continuous location information. At the end of each experiment, an interview will be conducted and each participant draw a preliminary draft of the emotional response map. Participants' physiological signals in the virtual environment are tested in the laboratory using VR.

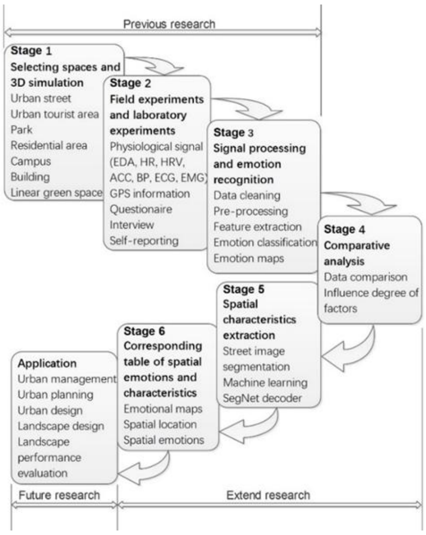

Figure 1: Framework of method.

3) Signal processing and recognition: Online data analysis software is applied to analyze physiological signals obtained from biosensors. Statistical characteristic values are extracted. Subsequently, the emotional recognition model based on selected algorithm is used to conduct training on the feature set, and four basic emotional states will be obtained.
4) Comparative analysis: To verify the accuracy of the experiment, comparisons of emotional maps of field experiments and laboratory experiments are required. Additionally, verified are degrees of influence of crowds, cars, weather, and other accidental factors on emotions. The proportion of influence of spatial characteristics on user emotions will be obtained.
5) Recognizing spatial features: Street image segmentation technology and machine learning technology are applied to identify street characteristics of all linear spaces. DeeplabV3+ technique is used for image segmentation of space photos to identify elements.
6) Generating a corresponding table of spatial emotions and spatial characteristics: After completing spatial emotion recognition and spatial characteristics extraction, emotional responses caused by other spatial factors are identified and removed, and a corresponding table of spatial emotions and spatial characteristics will be drawn. The flowchart of experiment, data analysis and evaluation are shown in the Figure 2 below:

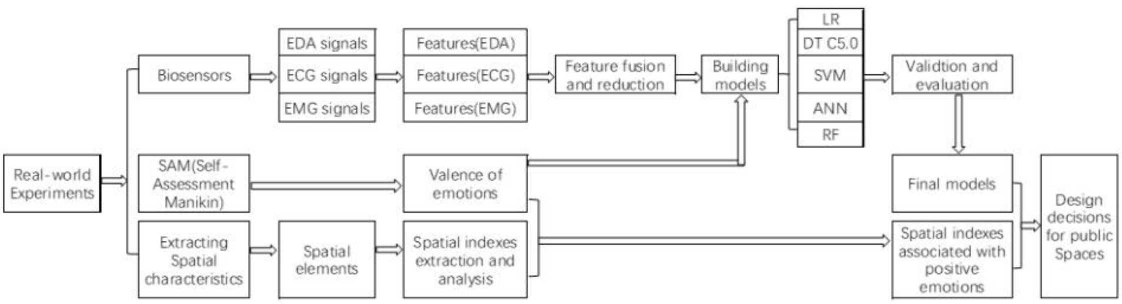

Figure 2: The flowchart of the research process.

4. Conclusions

The user emotional response to the space is an important factor of space quality evaluation. For the built space, in order to avoid too subjective evaluation, the method proposed in this study can be used to obtain the user physiological signals of walking through the space and use the established space. The emotion recognition model of this space provides a quantitative and evidence-based evaluation of the space, and provides a basis for design decisions for the optimization of the built space. For the planned urban public space, the virtual model of the space can be used to extract the spatial characteristics and physiological signals of the participants. Through machine learning, the emotional response evaluation of the space can be finally obtained, and decision-making suggestions for program evaluation and modification can be provided..

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