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CLASSIFICATION OF SOUND SOURCE TYPES IN URBAN PUBLIC OPEN SPACES BASED ON PHYSIOLOGICAL MEASUREMENT

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The perception of soundscape is complex and difficult to be described accurately. Although the use of physiological measurement in soundscape research is gradually increasing, most of them focused on proving the existence of the physiological effect, rather than construct the linear relationship between physiological indicators and soundscape perception. In this study, physiological indicators were used to classify sound source types, in order to provide physiological basis for sound source classification, and then the feasibility of using physiological indicators to evaluate soundscape quality was discussed. 20 scenarios of typical sound sources in urban public open spaces were presented in the form of audio-visual interaction in the laboratory, and 9 physiological indicators of 62 participants in these scenarios were measured. The dimensions of physiological indicators were reduced by categorical principal components analysis in order to study the distribution of different types of sound sources in physiological indicators. The results show that when using two dimensions to construct the physiological evaluation system, dimension 1 could well distinguish the difference between natural sound and human noise, however the meaning of dimension 2 was not clear, which means that the types of physiological indicators still need to be tested and adjusted, and also suggest that physiological indicators may be used to evaluate dimensions that are subjectively difficult to evaluate.

Keywords: soundscape, sound source types, physiological measurement, classification

1. Introduction

Since Schafer put forward the concept of "soundscape", researchers have been trying to understand how the sound environment affects people's perception of the city, and how to apply soundscape to urban planning and design [1]. The existing methods for evaluating and predicting soundscape are mainly to study people's subjective evaluation in the environment in the form of questionnaires and interviews, and less to obtain people's perceptions through objective physiological measurement. Unlike traditional noise control, soundscape studies pay more attention to the positive effects of sound, such as triggering pleasant memories of previous experiences or prompting people to relax and recover more quickly [2-4]. For this reason, the research on soundscape not only explores the physical attributes of sound, but also considers the meaning behind sound, which requires the classification of sound sources. When asked to evaluate the urban sound environment, people usually describe the audible sound and its source, and associate the environmental quality with the meaning given by these sounds [5]. The physiological signal may be the medium between physical attributes of sound and subjective perception, so it is necessary to study the sound source classification of urban public open spaces from the perspective of physiological response.

Considering the importance of soundscape perception, a variety of methods for urban sound source classification have been proposed [6,7], and some studies have analysed the correlation between sound source types and their physical parameters. However, we still need to explore whether there is a correlation between the type of sound source and physiological response. Therefore, in this study, the sound sources were classified according to the physiological indicators, and the feasibility of using physiological indicators to evaluate the soundscape quality was discussed by comparing the difference between the physiological data and the traditional classification method.

2. Method

2.1 Participants

A total of 62 unpaid participants were recruited with an average age of 23.29 (SD=5.223; min=16; max=40), including 33 males and 29 females. All the participants had normal hearing and did not take psychotropic drugs, and there was no strenuous exercise and no obvious fatigue in the two hours before the experiment.

2.2 Stimuli

The soundscapes were recorded by the combination of video and audio. According to the previous studies, the typical sound sources and scenarios in 20 urban public open spaces were selected as the stimuli of the experiment. The soundscapes were divided into four main categories: biological sound, geophysical sound, human sound and mechanical sound. The scenarios and the main sound sources are shown in Table 1.

Table 1: Evaluation structure of soundscape

sound category	scenario	sound source	code
biological sound (Bio)	grove 1	birdsong	BS
	grove 2	cicadas chirping	CC
	empty street	birdsong and insects sound	ES
geophysical sound (Geo)	ocean wave	wave sound	OW
	fountain	water sound and conversation sound	FT
	grove 3	leaves rustling	LR
	small waterfall	water sound	SW
	rain	rain sound	RN
	traditional architecture	wind chimes sound	WC
human sound (Hum)	noisy street	conversation sound and advertising sound	NS
	chorus	chorus and music	CH
	square dance	loud music and exercising sound	SD
	basketball court	exercising sound and conversation sound	BC
	playground	children shouting	PC
	food market	peddling and conversation sound	FM
mechanical sound (Mech)	road cleaning	mechanical noise	RC
	highway	vehicle noise	HW
	crossroad	vehicle noise and honk	CR
	road maintenance	pile driver sound	RM
	ventilation	fan sound	VL

2.3 Physiological measurements

Physiological signals were collected by BIOPAC MP160 system, and the physiological indicators included ECG, EEG, EOG, respiratory wave and skin resistance. Through the calculation of the collected physiological signals, 9 physiological indicators including heart rate (HR), R wave amplitude (ΔR), heart rate variability (HRV), low frequency band in HRV power spectrum (LF), α-EEG, β-EEG, respiratory rate (RR), respiratory depth (RD) and skin conductivity level (SCL) were obtained.

2.4 Research procedure

The experiment was conducted in the audiometry room, and the participants were first asked to sit comfortably 1.5 meters in front of the screen. After they understood the experimental procedure, the researcher calibrated the instrument and left the room. The participants were required to fully relax in the first 5 minutes and the resting state of each physiological data was recorded, then the experiment was carried out automatically. Twenty scenarios were presented randomly, and the physiological data of the participants were recorded at the same time. After the end of each scenario, the participants were prompted to relax for 90 seconds. After 10 scenarios were randomly presented, the system prompted that the experiment was over, and the researcher re-entered the audiometry room, removed the headphones and electrodes, and ended the experiment.

3. Results

First of all, the physiological data was normalized according to the resting state of each participant in order to get the relative value of the physiological responses. The dimension of the physiological indicators was reduced, and the distribution of different sound sources in the physiological indicators was analysed by categorical principal components analysis (CATPCA). This was not only possible to understand the degree of relationship between different sound sources when using physiological indicators as a means of observation, but also showed the relationship between the various physiological indicators. Fig. 1 shows the weight of each physiological indicators in two dimensions after reducing the dimension of physiological indicator, and Fig. 2 shows the distribution of the average value of 20 scenario of sound sources in two physiological dimensions. Among them, mechanical sounds are red, human sounds are yellow, geophysical sounds are blue, and biological sounds are green.

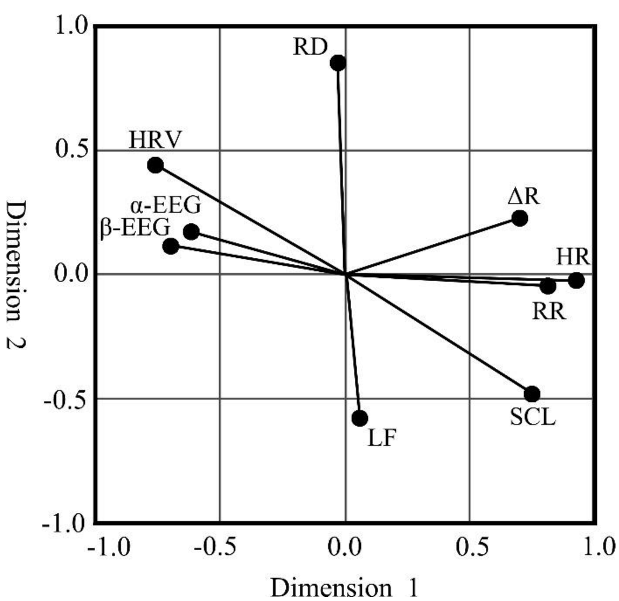

Figure 1: Spatial distribution of 9 physiological indicators.

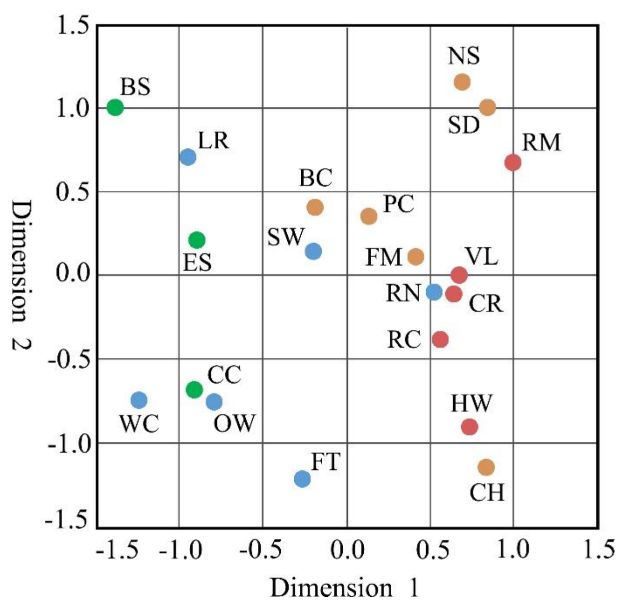

Figure 2: Projection of typical sound source types in principal components.

As can be seen from Fig. 1, the physiological indicators in dimension 1 were mainly composed of α-EEG, HRV, SCL, RR, HR and ΔR, and the main components in dimension 2 were LF and RD. As can be seen from Fig. 2, in dimension 1, biological sounds and geophysical sounds were mainly distributed on the negative axis, while mechanical sounds and human sounds were mainly distributed on the positive axis, which showed that the difference between natural sound and noise can be roughly distinguished by dimension 1. The rain sound was the exception, although it belonged to the geophysical sound, its physiological indictors were closer to the mechanical noise. In dimension 2, the meaning represented was relatively vague, in which noisy street and road maintenance were the lowest, ocean waves and chorus were the highest. This suggested that dimension 2 might be related to the regularity or predictability of the soundscape. Because on the negative axis of dimension 2, the sounds gradually became more chaotic and unpredictable, while on the positive axis, the sounds were more regular and could predict the rhythm of the whole sound environment. In addition, the value of biological sounds were lower than that of geophysical sounds in dimension 2, which also implied that biological sounds were relatively irregular.

4. Conclusions

In this study, the categorical principal components analysis was used to reduce the dimension of physiological indicators, and the distribution of different types of sound sources in physiological indicators was analysed. The results showed that when using the two dimensions to construct the quantitative standard of physiological indicators, dimension 1 could well distinguish the difference between natural sounds and noises, but the meaning of dimension 2 was not clear, which might be the regularity or predictability of sounds. This suggests that physiological indicators may be used to evaluate dimensions that are difficult to explain by subjective data.

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