Study on evaluation model of soundscape in urban park based on Radial Basis Function Neural Network: A case study of Shiba Park and Kamogawa Park, Japan

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Abstract. In order to explore whether artificial neural network can simulate and predict the subjective and objective data of soundscape in urban environment, this study developed the subjective and objective transformation model of soundscape in urban park based on radial basis function neural network. The test was conducted based on the soundscape survey data of Shiba Park and Kamogawa Park in Japan. The results showed that the subjective and objective evaluation model of soundscape constructed by radial basis function neural network could predict more accurate subjective evaluation value, the average prediction accuracy rate was 91.23%. In addition, the soundscape in the higher loudness, loudness level and sound pressure level, and the lower sharpness got a higher accuracy, which is beneficial to simulating the tourists' psychological state of the soundscape. The study proved that the artificial neural network model can provide an effective method for further and more comprehensive acoustical environment research in the future.

1. Introduction
As an important sensory landscape, soundscape affects people's life and recreation [1]. In high-density cities, urban parks provide places for citizens to relax and rest, and improve the quality of their life [2]. In recent years, the research of soundscape in urban park has also become a hot topic in the field of urban environment [3, 4, 5]. In the aspect of soundscape research, the soundscape walking method can distinguish the characteristics of different soundscape elements and transform them into corresponding perception [6]. For the non-semantic sound with the same semantic sound and physical characteristics, there are obvious differences in human subjective evaluation [7]. Davies’ research [8] shows that soundscape is divided into three semantic levels: sound source, sound descriptor and soundscape descriptor. Kerrick [9] puts forward semantic differential classification technology, and Cain [10] divides the sound evaluation into two principal components: calm and active, and the soundscape can be well distinguished by the two principal components. The law of psychological physics has a good fit for the subjective and objective data of soundscape [11, 12]. Through exploration, scholars have enriched the study of soundscape, but the research on subjective and objective evaluation of soundscape in urban park by artificial neural network is still rarely reported.
Radial basis function (RBF) neural network is a forward neural network proposed by Powell M. J. D [13]. The RBF has all the advantages of the general neural network, and can determine the corresponding network topology structure according to the specific problems. It has the function of self-learning, self-organizing and adaptive. In addition, the neuron transformation function in the RBF’s hidden layer is a local response function, which has the ability of local learning and can perform high-speed and large-scale data fusion [14]. The RBF is different from the general feedforward network in that the input layer to the hidden layer is nonlinear, the hidden layer to the output layer is linear, so it is suitable for the psychoacoustics problem, and the accuracy is obtained. The accuracy and calculation speed are better than the multivariate linear regression model, the BP neural network model etc. Therefore, RBF neural network was used to explore the subjective and objective evaluation model of soundscape in urban parks, and an empirical study was carried out with the examples of Shiba Park in Tokyo, Japan and Kamogawa Park in Kyoto. In the application of landscape planning in the future, the objective data of soundscape in the city park can be transformed into corresponding subjective evaluation scores by the neural network, and then the psychological state of tourists in the corresponding position can be simulated. It provides the theoretical basis and effective method for the further and comprehensive soundscape research in the future.

2. Method

2.1. Study area

2.1.1. Shiba Park. Shiba Park, one of the oldest parks in Japan, is located in Tokyo, Japan. Its geographical coordinates are 139 °45 °E and 35 °39 °N, covering an area of 12.25 hectares. Opened the garden after the first. Originally, it was a vast park, but because of the separation of church and state, some of the area was excluded, so it became a ring park. The park has a long history of park atmosphere, camphor trees, beech trees, plum flowers, Japanese cherry blossoms and ginkgo, etc [15].

2.1.2. Kamogawa Park. Kamogawa Park is located in Tokyo, Japan. Its geographical coordinates are 135 °46N and 35 °02N, covering an area of 34.8 hectares. Built in 1970, it is a park running through the Aichuan River bed in the heart of Beijing. Aichuan Park's border is across the river north-south stretch of waterfront green, including sports squares, trails and other infrastructure. The main vegetation in Akagawa Park is Park Tree, Japanese Red Pine, rough Leaf Tree and Japanese Cherry Blossom, etc.

2.2. Model of RBF neural network

Input layer: the input sample vector is 5 dimensional (A1, A2... A7), which are psychoacoustic parameters selected by correlation demonstration and pre-experiment to influence the subjective perception of soundscape: Loudness (unit sone), Loudness level (unit phon), sharpness (unit acum), sound pressure level (unit dBA) and linear sound pressure level (unit dB).

Hidden layer: the hidden layer consists of K radial basis functions (Φ1(x), Φ2(x)... Φk(x)) and takes Gaussian function as kernel function.

Output layer: the output layer is an evaluation of soundscape preference with an output vector of 1 dimension.

2.3. Data collection

For the objective data, the soundscape samples were recorded by SONY PCM-D100. They were gathered at 6:00-10:00, 11:00-15:00 and 16:00-20:00, respectively. A total of 48 soundscape samples were collected in Shiba Park in Tokyo and Kamogawa Park in Kyoto. Two samples were seriously disturbed by events, so these samples were removed and 46 samples of soundscape in urban parks were obtained.

For subjective data, previous research on subjective evaluation of soundscape shows that more than 7 reviewers can get more accurate results [6]. The 12 reviewers were selected and trained together,
reducing the difference of subjective evaluation among different individuals. In addition, while the objective data was collected, the values of soundscape preference was obtained by reviewers through the 5 points method. Then the values were dimensionless thought Max-min normalization.

3. Results

3.1. Subjective and objective data parameters
The psychoacoustic parameters of the soundscape samples were obtained by ArteiS. Table 1 shows some of the subjective and objective parameters.

3.2. RBF training
The code program of RBF neural network was compiled by Matlab, and the neural network was established by training data and training target. The subjective and objective data of 1-40 soundscape samples were respectively substituted into the input data and the output data for RBF training. Then the subjective target data were obtained by inputting the objective data of the 41-46 soundscape sample to test the error of the trained network in the research. The simulation results and accuracy are shown in Table 2.

The results show that the prediction accuracy of the subjective and objective model based on REF neural network is between 84.13% and 98.42%, and the average accuracy is 91.23%. The accuracy of the network is the same as that of the application of Fechner's law in psychophysics, and is close to the prediction accuracy of Stevens' law [11, 12]. However, the prediction accuracy was fluctuant, so the factors affecting prediction accuracy were further analyzed.

| Sample | Objective parameter | Subjective parameter |
|--------|---------------------|----------------------|
|        | Loudness (sone)     | Loudness level (phon)| Sharpness(acum)| dBA | dB | Value |
| 1      | 26.08               | 87.05                | 2.40           | 71.18 | 72.90 | 0.48  |
| 2      | 26.49               | 87.27                | 2.30           | 70.65 | 73.85 | 0.46  |
| 3      | 27.53               | 87.83                | 2.27           | 71.29 | 73.02 | 0.30  |
| 4      | 27.71               | 87.92                | 2.33           | 71.65 | 73.35 | 0.30  |
| 5      | 26.81               | 87.45                | 2.33           | 71.22 | 73.83 | 0.23  |
| 6      | 25.52               | 86.74                | 2.35           | 70.58 | 72.88 | 0.23  |
| 7      | 29.51               | 88.83                | 2.07           | 70.90 | 75.16 | 0.43  |
| 8      | 29.14               | 88.65                | 1.99           | 70.95 | 74.58 | 0.57  |
| 9      | 29.30               | 88.73                | 2.03           | 71.03 | 73.62 | 0.57  |
| 10     | 28.91               | 88.53                | 1.99           | 70.80 | 74.19 | 0.63  |
| 11     | 23.84               | 85.75                | 2.09           | 68.13 | 72.20 | 0.54  |
| 12     | 25.25               | 86.58                | 2.13           | 69.02 | 72.70 | 0.43  |
| 13     | 21.17               | 84.04                | 2.32           | 68.11 | 72.09 | 0.23  |
| 14     | 24.24               | 85.99                | 2.22           | 69.09 | 73.22 | 0.46  |
| 15     | 25.32               | 86.62                | 2.16           | 69.12 | 74.00 | 0.48  |
| 16     | 34.09               | 90.91                | 1.47           | 74.04 | 78.43 | 0.77  |
| 17     | 38.70               | 92.74                | 1.60           | 76.12 | 79.78 | 0.65  |
| 18     | 22.44               | 84.88                | 2.36           | 69.18 | 71.87 | 0.23  |
| …      | …                   | …                    | …              | …     | …     | …     |
| 41     | 31.64               | 89.84                | 1.82           | 71.50 | 76.70 | 0.57  |
| 42     | 39.69               | 93.11                | 1.75           | 75.68 | 80.31 | 0.63  |
| 43     | 29.32               | 88.74                | 2.12           | 70.80 | 75.33 | 0.57  |
| 44     | 38.03               | 92.49                | 1.94           | 74.65 | 79.11 | 0.60  |
| 45     | 43.48               | 94.42                | 1.82           | 78.07 | 80.44 | 0.54  |
| 46     | 29.52               | 88.84                | 2.05           | 71.33 | 73.55 | 0.63  |
Table 2. Simulation results and error Analysis

| Soundscape sample | 41  | 42  | 43  | 44  | 45  | 46  |
|-------------------|-----|-----|-----|-----|-----|-----|
| Actual values     | 0.57| 0.63| 0.57| 0.60| 0.54| 0.63|
| Predicted values  | 0.65| 0.62| 0.52| 0.56| 0.57| 0.73|
| Prediction accuracy (%) | 85.88| 98.42| 91.18| 93.33| 94.49| 84.13|

By regression analysis of the loudness, loudness level, sharpness, dBA, dB and the prediction accuracy obtained from the simulation results, the index relations affecting the prediction accuracy were obtained, as shown in figure 3. With the increase of loudness, dBA and dB, the accuracy of prediction increases, which is attributed to that the clearer and brighter the sound, the better the recognition and discrimination of the sound signal [16]. The higher sharpness leads to the decrease of prediction accuracy, which is due to the fact that sharpness is an indicator that affects negative sound perception, especially the accuracy of subjective evaluation can be reduced by eventful high sharpness sound signals.

![Figure 1. Relationship between objective Index and Prediction accuracy](image1)

4. Conclusion

Artificial intelligence is a new field of development. Under the background of "man-machine symbiosis" advocated in recent years, this paper constructs the subjective and objective transformation model of soundscape in urban parks by REF neural network. In order to predict and simulate the subjective and objective data by artificial neural network model, the main conclusions are as follows: (1) REF neural network was used to train and study the indexes of loudness, sharpness, dBA, dB and subjective preference evaluation of soundscape. The prediction accuracy of the model is between 84.13% and 98.42%, and the average accuracy is 91.23%, which achieves the accuracy of applying the law of psychophysics in soundscape. (2) Among the indexes that affect the prediction accuracy of the network, the loudness, loudness level, dBA and dB have a positive correlation with the prediction accuracy, and the sharpness has a negative correlation with the prediction accuracy.

Quantitative evaluation of soundscape in urban parks is the application trend of soundscape protection, utilization and development in the future. Artificial neural network can train, study and analyze the subjective and objective data more accurately. This study proves that the artificial neural network model can provide an effective method for the further and comprehensive soundscape research in the future, in order to provide a reference for the deeper planning of the soundscape and the improvement of the environment in urban parks.
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