Neural network-based thermal comfort prediction for the elderly

JinJin Zhang¹, Hong Liu²*, YuXin Wu¹, Shan Zhou¹, MengJia Liu¹

¹ Joint International Research Laboratory of Green Buildings and Built Environments (Ministry of Education), Chongqing University, Chongqing, China 40004
² National Centre for International Research of Low-carbon and Green Buildings (Ministry of Science and Technology), Chongqing University, Chongqing, China 400045

Abstract. Machine learning technology has become a hot topic and is being applied in many fields. However, in the prediction of thermal sensation in the elderly, there is not enough research on the neural network to predict the effect of human thermal comfort. In this paper, two neural network algorithms were used to predict the thermal expectation of the elderly, and the accuracy of the two algorithms was compared to find a suitable neural network algorithm to predict human thermal comfort. The dataset was collected from the laboratory study and included 10 local skin temperatures of the subjects, thermal perception voted at three temperatures (28/30/32°C), different wind speeds, and two forms of wind. Thirteen subjects with an average age of 63.5 years old were recruited for the subjective survey. These subjects sat for long periods of summer working conditions, wore uniform thermal resistance clothing, and collected votes on thermal sensation, as well as skin temperature. The results showed that the prediction accuracy of the two algorithms was related to the added influence factors, and the RBF neural network algorithm was the most accurate in predicting thermal sensation of the elderly. The main influencing factors were average skin temperature, wind speed and body fat rate.

1 Introduction

With the development of computer and artificial intelligence, data acquisition is becoming more and more easy due to the large number of data monitoring systems and acquisition platforms, and the application of machine learning algorithms in the field of thermal comfort is also attracting more and more attention. Due to the complex correlation between thermal comfort, behavior habits, thermal environment and energy consumption, it is difficult to find the inherent law, so the traditional thermal comfort evaluation methods or models are increasingly challenged in application and prediction accuracy. In contrast, machine learning algorithms have attracted more and more attention because they can extract the implicit unknown, valuable or regular knowledge from a large amount of data.

At the same time, some scholars have compared the subjective and physiological responses of young and old people to different thermal environments and found that different groups had different responses to the same thermal environment. For example, some scholars found that older people had higher perceptual thresholds and lower sensitivity to cold and warm environment than younger people[1]. Some people found that in warm and cold environments, older people typically had a thermal sensation 0.5 units lower than younger people[2]. This suggested that older people respond differently to thermal stimuli. Based on the above literature, there may be differences between the elderly and the young in thermal comfort, but so far, we have not found an appropriate thermoregulation model that can reflect the physiological and physiological characteristics of the elderly, so we cannot accurately predict human thermal comfort through the existing model [3]. In order to fill this gap, the goal of this paper is to use neural network to build a thermal sensation model for the elderly to predict their thermal responses under different thermal conditions.

2 Methodology

2.1 The experiment

This experiment was conducted in an artificial climate chamber in summer. Experimental data collection included thermal environment, measurement of human physiological parameters and subjective questionnaire. The thermal environment data includes indoor dry-wet bulb temperature, wind speed, black-bulb temperature, relative humidity, etc. Human physiological parameters includes skin temperature of ten parts (forehead, upper arm, lower arm, back of hand, chest, back, thigh, calf, abdomen and instep). Recording instrument of temperature and humidity test using contact temperature (temperature range of 0 to 50°C, the error of plus or minus 0.5°C, the appropriate measurement range of 10-90% RH, error of plus or minus 2.5% RH, black ball...
temperature range: 100-400°C, the error of plus or minus 0.3°C), the wind speed test using a handheld hot wire anemometer (measuring range: 0~20 m/s, precision: plus or minus 5% (0.03 m/s + measurements)), and the skin temperature test using HOBO tester (temperature range: -40~70 °C , precision: plus or minus 0.21 °C ). Test instruments and methods shall be used in accordance with relevant ASHRAE55-2013 regulations.

Under different indoor dry bulb temperatures (28/30/32°C), different wind speeds (face wind speeds of 0.6, 1.4, 2.2 m/s) and different wind forms (direct and sinusoidal winds), thermal perception polls were conducted under different indoor dry bulb temperatures (28/30/32°C). Subjects were recruited for a subjective survey in which they sat for a long time, wearing a uniform thermal resistance of 0.5 clo to collect thermal sensation votes, and skin temperatures in ten body parts.

Data collection was conducted at the same time as the subject questionnaire survey, including the thermal sensation vote, thermal expectation, etc. Subjects' background information includes whether they suffer from diseases, living habits, etc. The statistical table of physiological information of the subjects is shown in Table 1. After screening, the effective sample size meeting the requirements was: 443 for men, 522 for women, and 964 for the total sample size.

Table 1. Subject anthropometric information.

| Age(years) | Height(cm) | Weight(kg) |
|-----------|------------|------------|
| Mean±S.D. | Mean±S.D.  | Mean±S.D.  |
| 63.5±7.2  | 160.2±8.7  | 63.2±10.2  |

3 Model

3.1. Selection of neural network types

Artificial neural network (ANN), commonly referred to as neural network, is an information processing system based on the structure and function of the human brain. Common neural network models include perceptron, feedforward network, radial basis (RBF), regression neuron network (Hopfield), etc. BP and RBF neural networks belong to feedforward neural network. BP and RBF neural networks are the most widely used neural networks at present, and their algorithms and models are relatively mature. Moreover, existing research results have proved that BP and RBF neural networks not only have good prediction accuracy for large samples, but also have good prediction effect for small samples. Therefore, BP and RBF neural networks are selected to establish human thermal comfort prediction model.

3.1.1 BP neural network

BP network is a kind of multilayer forward of one-way transmission network, layered neurons of the input layer, hidden layer and output layer, each layer of neurons only accept input from a layer of neurons before, input model is based on the progressive transformation of each layer by the output layer after final output, there is no feedback between neurons, each neuron in single internal connection and order delivery.

The learning process of BP network: is divided into two process forward and reverse transmission, when the spread of the positive input of the sample data from the first starting from the input layer, then the implicit layer through layer upon layer processing, finally comes out, so that each layer of neurons state affects only the adjacent layer neurons, when in the output layer can't get output when it changes direction into a back propagation, using gradient search technique to make the neural network's actual and desired output error of the mean square value to a minimum. The network structure is shown in Figure 1. In the case of forward propagation, the input value is from left to right, and the output value of the network is calculated layer by layer by combining the weight and excitation function. In the case of back propagation, parameters such as network weights are adjusted reversely according to the defined error function, so that the error decreases gradually.

Fig. 1. BP neural network structure

When designing BP network, consideration should be given to the number of layers, number of neurons at each layer, initial value, activation function and learning rate.

Firstly, the number of layers of the network is analyzed. It is proved theoretically that the network with bias and at least one hidden layer plus one linear output layer can approximate any function. Increasing the number of layers can reduce the error and improve the accuracy, but also complicate the network. Therefore, a three-layer multi-input single-output network prediction model with a hidden layer is adopted. At present, there is no clear formula for the determination of the number of neurons in the hidden layer, only the empirical formula, and the final determination of the number of neurons should be determined according to experience and experiment. In this paper, the number of hidden layer neurons is selected with reference to empirical formula 1:

\[ l = \sqrt{m + n + a} \]  

(1)

n: Number of input layer neurons
m: Number of output layer neurons
a: Constants greater than 1 and less than 10

According to the above formula, the number of neurons is between 2 and 12. The number of hidden layer neurons was selected as 6. Secondly, the initial weight of BP neural network is analyzed and selected. Generally, the initial weight is selected between -1 and 1.
When the selection of learning rate of BP network is considered, it is generally selected between 0.01 and 0.8.

3.1.2 RBF neural network

The radial basis neural network (RBF neural network) is a feedforward back-propagation neural network. The structure of radial basis neural network is similar to that of forward network, as shown in Figure 2. There are three network layers. From left to right, there are input layer, hidden layer and output layer. The function of the hidden layer is radially symmetric with its origin. RBF network is a local approximation network, and only a small part of the values are modified, so the training time is short. The radial basis neural network has a nonlinear relation from the input layer to the hidden layer, and a linear relation from the hidden layer to the output layer. The hidden layer node of RBF neural network uses the distance between the input mode and the origin vector as the independent variable and the Gaussian function as the activation function. The further away the input layer neuron is from the origin of the function of the radial basis, the lower its activation degree will be.

Fig. 2. RBF neural network structure

There are three unknown parameters in the training method of RBF network: the center point of the radial basis function, the variance and the weight between the hidden layer and the output layer. RBF is a process of repeated experiments by the computer. In the establishment process, there is no need to set the number of hidden layer neurons, and the computer automatically adds the number of hidden layer neurons until the output error of the radial basis neural network reaches the preset requirement.

3.2. Thermal comfort prediction model based on neural network

Although through preliminary data screening, selected the 13 factors affecting thermal sensation, including ten parts of the skin temperature with the average arithmetic average skin temperature, said but in the actual model, introducing the more variables, the interpretation of the results, the more difficult, model application is also more difficult, in principle, should as far as possible to introduce less variable to maximize explain the results. Therefore, the 13 selected variables need to be further analyzed to identify the most important variables used to predict the results and introduce the model. Through feature selection, 13 predictive variables were selected, including gender, age, body fat rate, wind speed, blowing state, duration of blowing, duration of no wind, temperature condition, indoor dry bulb temperature, indoor relative humidity, indoor black bulb temperature, filling time of questionnaire, and average skin temperature. Due to the mutual influence between some factors, or some variables with strong correlation, such as the correlation between indoor temperature and humidity, indoor black-bulb temperature, etc., it needs to be further simplified. Table 1 shows the correlation analysis of some factors. It can be seen that indoor relative humidity, dry bulb temperature and black bulb temperature are strongly correlated with each other, and the correlation values are relatively large. Moreover, their influence on thermal sensation can be largely reflected by $T_{am}$ parameters. In addition, the subjects' body fat rate is highly correlated with gender and age, so the factor of body fat rate can also explain the factors of age and gender to some extent. The duration of wind blowing was also correlated with the duration of no wind. Comprehensive analysis, the model to cut out the gender, age, duration, there is no wind temperature, relative humidity, black ball temperature variables, model choice variables for body fat rate, wind speed, wind speed, wind length, dry bulb temperature and average temperature and so on six skin as the input variables of neural network model, the subjects at this time of thermal sensation as output variables of the model.

4 Results analysis

4.1. Distribution of human thermal sensation

By sorting the experimental data, the average skin temperature of the subjects and the corresponding thermal sensation were plotted as Figure 3. Figure in white dots represent the median, the subjects in thermal sensation vote in feel cold, neutral, hot, median average skin temperature, respectively is 32.89, 33.25, 33.78°C, the skin temperature can be obtained, the higher the participants feel more warm, and each group of data is normally distributed, can also prove the effectiveness of the experimental data.

Fig. 3. Thermal sensation distribution of subject
4.2. Prediction of thermal sensation and analysis of influencing factors

4.2.1 Analysis of influencing factors

In order to obtain the influence degree of each influencing factor on the thermal sensation of the experimenter, and rank the influencing factors according to the importance degree. In this paper, the variables included in the prediction model in the experimental data were analyzed by MATLAB, and the result was drawn as Figure 4. The order of influence degree was: Body fat rate = Skin temperature = Wind regime > Wind speed > Blowing duration > Indoor dry bulb temperature.

Fig. 4. Distribution of factors affecting thermal sensation

4.2.2 Prediction accuracy comparison

In order to evaluate the predictive performance of the model, the samples were partitioned before modeling, 80% of which were used for training the model, and 20% for prediction and verification. In this paper, BP and RBF artificial neural network prediction programs were first written to train and predict human thermal sensation votes respectively, and the prediction results were obtained. Finally, 200 samples were selected to verify the prediction results, as shown in Figure 5, 6 and Table 2. It can be seen from Table 2 that the prediction result of RBF neural network is slightly more accurate than that of BP neural network. The average accuracy of the RBF neural network is about 10 percent higher than that of the BP network.

| Network model       | Prediction accuracy (%) |
|---------------------|-------------------------|
| BP neural network   | 77.33                   |
| RBF neural network  | 87.82                   |

Table 2. Subject’s anthropometric information.

As can be seen from Figure 5, the model established by BP neural network is more accurate in the comfort zone of human body, while in the extreme environment, the prediction accuracy of BP network decreases significantly. However, the prediction accuracy of the RBF neural network model decreased even under extreme circumstances.

Fig. 5. Comparison of BP network prediction results

Fig. 6. Comparison of RBF network prediction results

5 Conclusions

Through the evaluation of the accuracy of the established thermal sensation models, we found that the accuracy of RBF model is higher than BP model. It also can be seen that through the analysis of the predicted value of the model and the value of thermal sensation, it is found that both models have high error rate when the predicted thermal sensation outside the range of [-1, 1]. Combined with the thermal sensation distribution in Figure 5 and 6, the majority of the thermal sensation votes in the experimental data are within the range of [-1, 1], but the sample outside the range is small, which may also make the model fail to fully train and learn and master the data features and results in a large prediction error rate.
Funding

Graduate Scientific Research and Innovation Foundation of Chongqing, China, Grant/Award Number: CYS20024.

Acknowledgments

This work was supported by the Graduate Scientific Research and Innovation Foundation of Chongqing, China (Grant No. CYS20024).

Appendix 1. Correlation analysis of different variables

|      | v2   | v3   | v4   | v5   | v6   | v7   |
|------|------|------|------|------|------|------|
| v1 Age | 0.242** |    |      |      |      |      |
| v2 Gender | -0.802** | 0.013 |      |      |      |      |
| v3 Body fate rate | -0.416** | 0.016 | -0.005 |      |      |      |
| v4 Experimental condition | -0.016 | 0.014 | -0.014 | 0.008 |      |      |
| v5 Wind speed | 0.009 | 0.343** | -0.006 | 0.008 |      |      |
| v6 Wind regime |      | 0.490** | 0.342** |      |      |      |
| v7 Blowing duration |      |      |      |      |      | 0.552** |
| v8 No blowing duration |      |      |      |      |      |      |
| v9 Temperature condition |      |      |      |      |      |      |
| v10 Tair |      |      |      |      |      |      |
| v11 Tglob |      |      |      |      |      |      |
| v12 RH% |      |      |      |      |      |      |
| v13 Mean skin temperature |      |      |      |      |      |      |

Annotation:** means the significance level is greater than 0.01;* means the significance level is greater than 0.05.

References

1. Stevens J C, Choo K K, Temperature sensitivity of the body surface over the life span. Somatosensory & motor research 15(1), pp 13-28(1998).
2. Schellen L, van Marken Lichtenbelt W D, Loomans M G L C, et al, Differences between young adults and elderly in thermal comfort, productivity, and thermal physiology in response to a moderate temperature drift and a steady-state condition. Indoor air 20(4), pp 273-283(2010).
3. Wang Z, Yu H, Luo M, et al, Predicting older people's thermal sensation in building environment through a machine learning approach: Modelling, interpretation, and application. Building and Environment, pp 106231(2019)