



Skin Electrical Signal Feature Extraction Based on Wavelet Packet and Establishment of Human Thermal Comfort Model

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Human thermal comfort model is of great significance for improving the thermal comfort of the building's environment indoors. Physiological parameters can reflect the change of human thermal comfort directly and effectively, which are crucial to establish thermal comfort model of human body. Skin electrical signal is one of the most important physiological parameters to reflect the human thermal response, so it's completely useful for the model. Feature extraction directly affects the model's accuracy when the feature vector is used as a part of the model input and the thermal comfort value of human body serves as the model's output. Based on the wavelet packet transform, a new method about extracting features is studied for human thermal comfort model in this paper. The correctness of the method is proved to be effective by experiments; at meanwhile, the experimental results show that the skin electrical signal can reflect the thermal comfort of human body and its features can be used as a condition for the identification of human thermal comfort.

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1.Introduction

Throughout the development of buildings, all of buildings include the element of use, which directly reflects the nature of buildings. With the social development, people's pursuit of the nature has become much higher, not only to satisfy basic living conditions, but provide a healthy and comfortable environment indoors. The air conditioning is indispensable to improve the indoor thermal and humidity environment by regulating the set value of temperature, humidity and air velocity so as to realize the regulation and control of indoor environment parameters and then change the human thermal comfort; but these parameters that users set are usually not of thermal comfort. It often requires user to manually adjust the same repeatedly. Most importantly, it can not find an optimal combination of environmental parameters in a short time to make human body in the most comfortable environment.

Recently, researchers have introduced the physiological theory into the thermal comfort field to establish a human thermal comfort model from a physiological point of view [1]. Skin electrical signal is one of the basic physiological signals that reflect human thermal comfort deeply. The skin electrical activity will be higher when the skin is sweating; otherwise it's fairly low; therefore, the skin electrical signals can reflect the change of human thermal comfort to a large extent and it's suitable to the establishment of thermal comfort model [2]. The selection of feature vector of skin electrical signal is related to the accuracy of thermal comfort model classification[3], and the selection of thermal comfort is more favorable to the classification of thermal comfort. Wavelet packet transform can be used to decompose the low frequency approximation signal and the high frequency signal in full bands, and it is suitable for the feature extraction of skin electric signal in this paper.

2. Wavelet Packet Transform

At present, the most commonly-used methods of extracting physiological signal features include the time domain analysis, the frequency domain analysis and the wavelet transform. The wavelet transform is a new signal analysis method that better highlights local signal characteristics and has characteristics of multi-resolution analysis; but it is only used to decompose the low frequency signal rather than high frequency part. The wavelet packet not only decomposes the low frequency part of the signal step by step, but also decomposes high frequency part of the signal gradually. Besides, the wavelet packet transform can adaptively select the corresponding band to match with the signal spectrum according to the signal feature as decomposed. Thus more detailed and flexible physiological signals feature information can be obtained.

The signals are decomposed into some separate bands without redundant signal and omissions and the decomposed bands all have a certain amount of energy, which reflects the running state of skin electrical signal; therefore, it's reasonable to use the method of wavelet packet energy detection to detect the change of the proportion of energy in corresponding frequency band[4-5].

According to $L^2(R) = \bigoplus W_j$, $j \in z$, the decomposition relationship in wavelet subspace W_{j+1}^n is obtained:

$$W_{j+1}^{n} = U_{j+1}^{n} = U_{j}^{2n} \oplus U_{j}^{2n+1}, j \in \mathbb{Z}$$
(2.1)

General expression of wavelet packet transform can be abbreviated as:

$$W_{j} = \frac{2^{k} - 1}{\bigoplus_{m=0}^{\oplus}} U_{j-k}^{2^{k} + m}, j, k, m \in \mathbb{Z}$$
(2.2)

Since wavelet packet transform is orthogonal, the signals of full decomposition bands are independent from each other, so wavelet packet transform follows conservation of energy. The formula is as follows:

$$E_n(x(t)) = \sum_{m=0}^{2^k - 1} E_n(U_{j-k}^{2^k + m}) = \sum_{m=0}^{2^k - 1} E_n(x^{k,m}(i))$$
(2.3)

En(•) is the energy of signal. Assuming that the data length of discrete signal $x^{k,m}(i)$ is N, its energy can be expressed as follows:

$$E_n(x^{k,m}(i)) = \sum_{i=1}^N (x^{k,m}(i)) / N - 1$$
(2.4)

Commonly, we can make energy normalized by calculating the percentage of decomposed signal band. The relative energy in band m is calculated by formula:

$$E_{n}(m) = E_{n}(x^{k,m}(i)) / E_{n}(x(t))$$
(2.5)

According to conservation of energy, apparently there is:

$$\sum_{m=0}^{2^{\kappa}-1} E_n(m) = 1$$
 (2.6)

3. Feature Extraction

The feature extraction is to seek the most effective features from original features, which will directly affect the thermal comfort properties of the model. Different feature extraction differs hugely in the classification results; therefore, the feature extraction is also worthy of our discussion.

This article selects energy, standard deviation and norm in each decomposed band as features [6]. Theoretically, the wavelet packet decomposition coefficients can be used as its feature, but the wavelet packet coefficients will make a large difference because of its shift invariance and phase difference; therefore, it is not suitable for the features directly, which has resulted in the large amount of classifier calculation and the classification uncertainty in case of a very large number of coefficients of the wavelet packet after multilevel wavelet packet decomposition. In this sense, the more convenient way is to calculate the energy of different nodes at each frequency scale, which cannot only reduce the dimension, but also enhance the robustness of classifier. Compared with wavelet decomposition, the wavelet packet decomposition is more refined, thus it can reflect the changes of signal in more details.

The formula to calculate the signal energy in each frequency band is as follows:

$$E_{j} = \sum_{k=1}^{n} d_{jk}^{2}$$
(3.1)

The norm extracted in this experiment is two norm of vector. For wavelet packet decomposition, the square of two norms is equal to the energy of original signal to some degree. The formula is as follows:

$$x^{2} = (x_{1}^{2} + x_{2}^{2} + \dots + x_{n}^{2})^{1/2}$$
(3.2)

4. Experiment

This experiment has conducted over the past year. Climate chamber is in the range of 8.4m*6.1m *2.4m and the range of window is1.2m*1.2m*0.3m. The indoor environment parameters are controlled by HAIRF precision air HADC0191 and humidifier. The controlled accuracy of temperature is 0.3 °C, the relative humidity accuracy is 2%RH and the average speed of background airflow is less than or equal to 0.3m/s. Italy LSI environmental monitoring system is used to monitor the parameters, including temperature, relative humidity, wet bulb globe temperature and air velocity.

4.1 Acquisition and Processing

Three variable environmental parameters of the thermal comfort model are obtained by the real-time monitoring of the sensor, and the wet bulb globe temperature can be calculated by calculating some parameters, such as the indoor area. During the experiment, the subjects were kept in meditation, the metabolic rate was 1.2met and remained unchanged, and the dress of the subjects was investigated to calculate clothing thermal resistance. Now, the six factors that affect the thermal comfort can be obtained.

The skin electrical signal is acquired by PowerLab in different thermal environment as created artificially. A total of 70 groups have been acquired and 67 groups thereof are as the experimental data with invalid data rejected. Research has found that the effective frequency range of skin electrical signal is about 0.02~0.2Hz. According to Nyquist criterion, the sampling frequency can be set as 10Hz, considering that the experimental procedure is easy to be interfered by other factors, so it is effective to deal with signals and enhance the useful information. Here we use two-order Butterworth filter to deal with the signal and the cutoff frequency is set as 0.3Hz [7].

The Galvanic skin response varies greatly among individuals, so it is necessary to remove differences and standardize it. The formula is as follows:

$$G = G_T - G_M \tag{4.1}$$

G is the standardized signal, G_T is the original signal, and G_M is the signal in thermal neutral environment. The skin electrical signal is decomposed into three layers when decomposed, which can thus produce eight bands, namely, theextract energy, the standard deviation and the norm in each band. We'll get 24 signal features. These features are used as inputs of the model, Outputs of the model those are five level of thermal comfort, which consist of 000,001,010,011,100. They represent respectively the thermal comfort level of cold, cool, moderate, warm and hot.

4.2 Establishment of the Model

BP network is a feedforward neural network practiced by back propagation algorithm, which is one of neural network modes applied widely[8-9]. The network can learn and store a large number of input and output mode mapping relationships without knowing prior mathematical equations. Given the mapping relationships between physiological signals and thermal comfort, this paper selects BP neural network to build the thermal comfort model. The network consists of three layers of neurons, namely, the input layer, the hidden layer and the output layer. Supposing that the input layer has n neurons and the output layer has m neurons.

How to choose a appropriate number of hidden layer is a very complicated problem. In general, there are two kinds of empirical formulas to estimate the number of hidden layer nodes:

$$y = \log_2(n) \tag{4.2}$$

$$y = \sqrt{n+m} + a, a \in [1,10]$$
 (4.3)

From above, we can get the approximate range of y. Ultimately, we can confirm the most suitable number of hidden layer is 7 through multiple experiments.

Using MATLAB neural network toolbox to construct thermal comfort model based on human skin electrical signal. There are 67 groups data in this experiment, 55 groups thereof as the training samples and 12 groups thereof as the test samples. The recognition rate of thermal comfort model is up to 83.34% and the predictive values are in good agreement with the actual values, which can better predict the thermal comfort of human body. The training time of the network is 52 seconds.





It is shown that the thermal comfort model has a high recognition rate for more thermal condition, also it can easily distinguish the comfort thermal condition from the discomfort thermal condition. Thus this experiment show that the model using wavelet packet to extract energy features of skin electrical signal can accurately reflect the thermal comfort of human body. At the same time, the recognition rate is up to 83.34%, which reveals that the mapping

relationship between skin electrical signal and thermal comfort of human body is obvious; besides, it also demonstrate that the method in this paper is feasible.

5. Conclusion

In this paper, the mapping relationships between thermal comfort and skin electrical signal of human body are studied by a large number of physiological experiments. Finally, we establish a thermal comfort model based on the skin electrical signal to predict the human thermal comfort value. For the thermal comfort model, the energy features of skin electrical signal decomposed by the wavelet packet are used as the model inputs. The thermal comfort values are used as model outputs. Test results of the model show that the model's recognition rate is up to 83.34% and it can better predict the thermal comfort value of human body; at meanwhile, the training time of model just is 52 seconds in dealing with enormous data. For shortening the training time and enhancing the accuracy of predicted thermal value, we can reduce dimensions of the extracted features to reduce the amount of computation. In summary, the thermal comfort model based on the skin electrical signal is efficient to reflect the human thermal comfort and it can be adopted as a guidance to improve the comfort of environment indoors.

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