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Research Article • DOI: 10.2478/ftee-2023-0021 FTEE • 31(3) • 2023 • 1–8

Temperature and Humidity Data Evaluation of Tight Sportswear During Motion Based on Intelligent Modeling

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Abstract

A neural network structure of Long Short Term Memory (LSTM) is proposed which could be used to predict the temperature and humidity of other key parts from the temperature and humidity data of some parts of the human body when wearing tight sportswear, so as to realize the temperature and humidity data prediction of all key points of the human body. The temperature and humidity of different people wearing tights were collected by DHT sensors. The experimental results show that the LSTM neural network structure proposed has higher prediction accuracy than other algorithms, and the model evaluates the feasibility of temperature and humidity data of tights in a state of motion, which facilitates the study of dynamic thermal and humid comfort and reduces the time cost of analyzing the temperature and humidity distribution and changing the law during human movement. It will effectively promote the study of temperature and humidity changes when people wear sports tights, provide theoretical reference for the study of human skin temperature in the field of sports medicine, and provide practical guidance for the application of human skin temperature changes in sports clothing production, diagnosis and prevention of sports injuries.

Keywords

Motion state, Tight sportswear, Temperature and humidity, Prediction model.

1. Introduction

Sports tights have attracted much attention in recent years, and are no longer limited to professional athletes. For the research of tight sportswear, function and comfort are the main research directions of this kind of clothing. At present, the research of tight-fitting sports clothing focuses on functional research. Just like the above-mentioned sports protection and improving athletes' strength, speed and endurance, the research of comfort is often neglected. However, comfort is also of great research significance for improving sports performance [1-6], that is, tight-fitting sportswear brings inappropriate heat and humidity or pressure or touch to the human body during sports, which is not conducive to the wearer's sports state. For example, for endurance sports such as running, cycling and marathons, thermal physical comfort is particularly important. This kind of high metabolic rate sports can generate 800-1300W of heat, which in turn raises the core temperature of the body and eventually leads to the increase of the average skin temperature. This thermal stress may even cause heatstroke. Such an exhausting situation not only affects the sports performance of the wearer, but also threatens their physical and mental health, which can easily lead athletes to quit the sport [7-9]. With the promotion of sports, the comfort of tight-fitting sportswear has attracted more and more attention. In recent years, scholars [10-19] have gradually analyzed the influencing factors of tight-fitting clothing comfort. Scholler et al. used an infrared camera to measure the skin temperature of people wearing cycling clothes during riding [20]. Awais et al. proposed a process for the thermal simulation of sportswear by considering the human thermophysiological model and important thermal properties of fabrics to measure the core body and mean skin temperatures[21]. Fiala et al., built the UTCI-Fiala mathematical model of human temperature regulation to predict the human temperature[22].

The existing research on the prediction of human clothing temperature and humidity information is mostly based on a physical model or geometric model in mathematics. However, this model cannot learn the characteristics of data from temperature and humidity data, and cannot well represent the correlation between heat and humidity data of different parts of the human body.

Data collection in motion is a time-consuming and laborious experiment, and the collected data may be unstable or inaccurate. In order to solve this problem, we imagine that building a model can reduce the number of experiments and save the collection time. In addition, as a whole, there may be some correlation between the temperature and humidity of human parts. In view of this idea, this paper designed a model which only needs to collect the data of one or several parts to predict the data of other parts.

Because the change of body temperature and humidity is a time series when the human body is moving, it changes with time. In view of this, this paper proposes a long-term and short-term memory model based on a particle swarm search, which is based on the temperature and humidity data of different people wearing tight clothes. The model is a time series data-driven model which can understand the relationship between temperature

Tights	Fabric composition	Fabric structure	Weight/ $g \cdot m^{-2}$	Thickness/ mm	Thread density/ longitudinal fabric density/coil number·$(5cm)^{-1}$	Thread density/ horizontal fabric density/coil number·$(5cm)^{-1}$
T1	70%Polyester, 26%Nylon, 4%Spandex	Jersey stitch	230.8	0.66	178.0	93.5
T2	86%Polyester, 14%Spandex	Warp plain stitch	200.6	0.91	100.0	185.0
T3	75%Polyester, 25%Nylon	Warp plain stitch	181.1	0.60	99.0	103.5
T4	91%Polyester, 9%Spandex	Jersey stitch	153.3	0.94	136.5	88.5
T5	72%Polyester, 28%Spandex	1×1 rib stitch	159.1	0.71	83.0	148.0
T6	65% Polyamide, 35% Elastane	Jersey stitch	245.5	0.48	90.5	175.0
T7	81% Polyester, 19% Elastane	1×1 rib stitch	264.7	0.87	121.5	138.0

Table 1. Fabric parameters of tight sportswear

and humidity data of different parts of the human body from the data, and can characterize the information characteristics of the heat and humidity of different parts of the human body. From the sampled temperature and humidity data of different human bodies, we can better explore the relationship between the heat and humidity information data of different parts of the human body, and further explore the useful parts of the heat and humidity information.

1.1. Long Short-Term Memory neural network model

In this paper, the Long Short-Term Memory(LSTM) neural network is used to establish a time series model of temperature and humidity. The LSTM neural network prediction model is a time recursive neural network which can solve the problem of long-term dependence. So far, LSTM has been widely used in transportation, finance and other fields, but not including clothing. We will adopt the LSTM model to predict the temperature and humidity data of different parts of the human body.

The LSTM cell structure consists of the Input Gate, Output Gate, Forget Gate and Cell State. At time t, the LSTM structure is updated as follows.

$$f_t = \sigma(W_f x_t + U_f h_{t-1} + b_f)$$
$$i_t = \sigma(W_i x_t + U_i h_{t-1} + b_i)$$
$$\tilde{c}_t = \tanh(W_c x_t + U_c h_{t-1} + b_c)$$
$$o_t = \sigma(W_o x_t + U_o h_{t-1} + b_o)$$
$$c_t = f_t c_{t-1} + i_t \tilde{c}_t$$
$$h_t = o_t \cdot \tanh(c_t)$$

Where, f_t, i_t, o_t are the outputs of the forgetting gate, input gate and output gate at time t; c_t and $\tilde{c}_t$ are the contents stored in the t time memory unit; x_t and h_t are the input vector and the output of the hidden layer at time t, respectively; σ represents the Sigmoid function; W_f, U_f and b_f are the weight and deviation of the forgetting gate respectively. W_i, U_i and b_i are the weight and deviation of the input door, respectively; W_o, U_o and b_o are the weights and deviations of the output gates, respectively; and W_c, U_c and b_c are the weight and deviation of the contents stored in the memory unit, respectively.

The gating structure in the neural unit structure of the LSTM neural network uses the Sigmoid function and tanh function. Among them, the

Sigmoid function:

$$f(x) = \frac{1}{1+e^{-x}}$$

tanh function:

$$f(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$$

The main difference between the Sigmoid function and tanh function is that the value range of the Sigmoid function is (0,1), while that of the tanh function is (-1,1). Both functions increase with an increase in variable x, and finally realize the function of the gating structure.

2. Experiment

2.1. Experimental instrument

In order to study the thermal and wet comfort of sports tights for the human body, a DHT22 digital temperature and humidity sensor is mainly used in the temperature and humidity data acquisition module. DHT22 is a temperature and humidity composite sensor of low cost and long-term stable operation, with relative humidity and temperature measurement, of quick response, small size, low power consumption, high cost performance, strong anti-interference ability, and with a calibrated digital signal output [23-24].

The acquisition device is mainly embodied in the hardware design and software program design centered on Arduino Nano 33 BLE. It processes, compares, analyzes and comprehensively judges the real-time data collected by the temperature and humidity sensor embedded in the tights, then sends and receives the data through the Bluetooth function, and stores all the data during the exercise.

2.2. Experimental garments

Seven tight sportswear long-sleeved tops were purchased for 3 participants who are male, Their age and body size are as follows, respectively: age: 25±1, height: 175.1±2.0cm, weight: 66.3±3.1kg, bust girth: 91.6±1.9cm, shoulder width: 41.1±0.2. Parameters of the tight sportswear are shown in Table 1.

2.3. Acquisition site

In order to study the thermal and humid comfort of the upper body, the temperature and humidity of the chest, back, waist and abdomen of the upper body were measured, as shown in Figure 1. DHT22 was attached to these four parts, and the temperature and humidity data of these parts were collected during running.

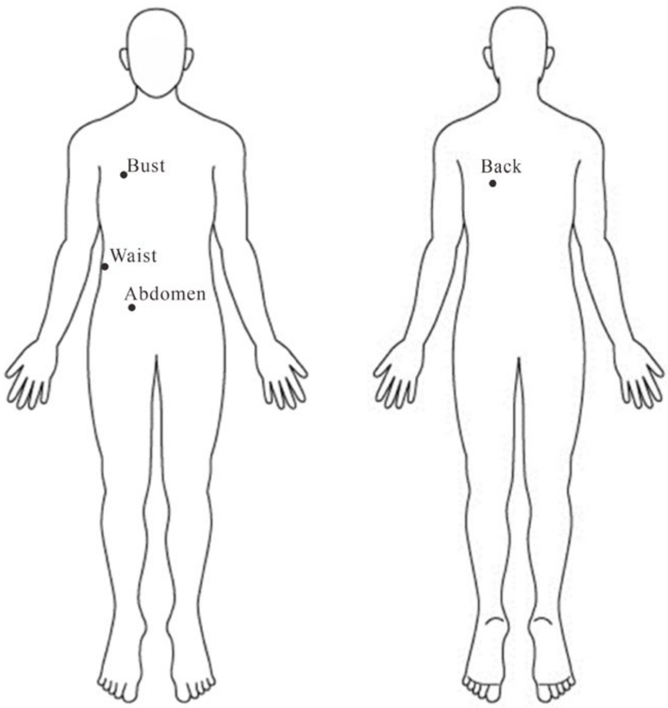

Fig. 1 Measurement points on human body

Fig. 2 Experimental site and data acquisition

2.4. Experiments plan

These participants were requested to run at a speed of 6km/h on a treadmill for 30minutes, as shown in Figure 2. The experiment was conducted in a room with a temperature of (20±2)℃ and relative humidity of (60±5)%. All the subjects wore the same style tight pants.

3. Temperature and humidity data analysis

We used SPSS 23.0 to analyze the Spearman correlation of the collected data, shown in Table 2 and Table 3. From Table 2 and Table 3, it can be seen that there is a high correlation between the humidity of the waist, chest, back and abdomen, thus for humidity data collection, only one part of the data can be used to predict the humidity of other parts through the LSTM model. However, through the analysis of Spearman correlation results, it is found that the temperature correlation between the abdomen and chest is low, as well as that between the back and chest is low, while the correlation between the abdomen, back and waist is high. Therefore, for temperature collection, only the temperature of the chest and waist is needed. The purpose of this paper is only to verify the feasibility of the LSTM model, thus it only analyzes the temperature and humidity of the waist, and then predicts the humidity and temperature of the chest, back and abdomen.

4. Construction of model

In this paper, the LSTM model uses a hidden layer to predict the comfort, and

			Abdomen humidity, %	Back humidity, %	Chest humidity, %	Waist humidity, %
Spearman Rho	Abdomen humidity, %	Correlation coefficient	1.000	0.815**	0.822**	0.962**
		Significance (two-tailed)	.	0.000	0.000	0.000
	Back humidity, %	Correlation coefficient	0.815**	1.000	0.988**	0.813**
		Significance (two-tailed)	0.000	.	0.000	0.000
	Chest humidity, %	Correlation coefficient	0.822**	0.988**	1.000	0.819**
		Significance (two-tailed)	0.000	0.000	.	0.000
	Waist humidity, %	Correlation coefficient	0.962**	0.813**	0.819**	1.000
		Significance (two-tailed)	0.000	0.000	0.000	.

Table 2. Correlation between humidity in different parts

			Abdomen Temperature, ℃	Back temperature, ℃	Chest temperature, ℃	Waist temperature, ℃
Spearman Rho	Abdomen temperature, ℃	Correlation coefficient	1.000	0.838**	0.093	0.502**
		Significance (two-tailed)	.	0.000	0.354	0.000
	Back temperature, ℃	Correlation coefficient	0.838**	1.000	0.084	0.339**
		Significance (two-tailed)	0.000	.	0.401	0.001
	Chest temperature, ℃	Correlation coefficient	0.093	0.084	1.000	0.350**
		Significance (two-tailed)	0.354	0.401	.	0.000
		Correlation coefficient	0.101	0.101	0.101	0.101
	Waist temperature, ℃	Significance (two-tailed)	0.502**	0.339**	0.350**	1.000
		Correlation coefficient	0.000	0.001	0.000	.

Table 3. Correlation between temperature in different parts

takes the comfort and temperature on the waist surface as input variables, and the prediction result is the comfort on the abdominal surface, the temperature on the abdomen surface, the humidity on the back surface, the temperature on the back surface, the humidity on the chest surface, and the temperature on the chest surface. The number of neurons in the input layer and in the output layer is 2 and 6, respectively. The number of neurons in the hidden layer represents the number of nodes used for memory, which is selected as 30. Construct the collected temperature and humidity data into a training set matrix, as follows:

$$TrainData = \{(y^{(1)}_{\text{A-humd}}, y^{(1)}_{\text{B-humd}}, y^{(1)}_{\text{C-humd}}, x^{(1)}_{W-humd}) \\ (y^{(2)}_{\text{A-humd}}, y^{(2)}_{\text{B-humd}}, y^{(2)}_{\text{C-humd}}, x^{(2)}_{W-humd} \cdots, (y^{(m)}_{\text{A-humd}}, \\ y^{(m)}_{\text{B-humd}}, y^{(m)}_{\text{C-humd}}, x^{(m)}_{W-humd})\}$$

$$TrainData = \{(y^{(1)}_{\text{A-temp}}, y^{(1)}_{\text{B-temp}}, y^{(1)}_{\text{C-temp}}, x^{(1)}_{W-temp}) \\ (y^{(2)}_{\text{A-temp}}, y^{(2)}_{\text{B-temp}}, y^{(2)}_{\text{C-temp}}, x^{(2)}_{W-temp}), \ldots, (y^{(m)}_{\text{A-temp}}, \\ y^{(m)}_{\text{B-temp}}, y^{(m)}_{\text{C-temp}}, x^{(m)}_{W-temp})\}$$

where, A-humd means the humidity on the abdomen surface. A-temp the temperature on the abdomen surface, B-humd the humidity on the back surface, B-temp the temperature on the back surface, C-humd the humidity on the chest surface, C-temp the temperature on the chest surface, W-humd the humidity on the waist surface, and W-temp means the temperature on the waist surface.

The specific process is as shown in Figure3.

The artificial neural network library Keras in Python is used to model the LSTM neural network, the key parts of which are introduced below.

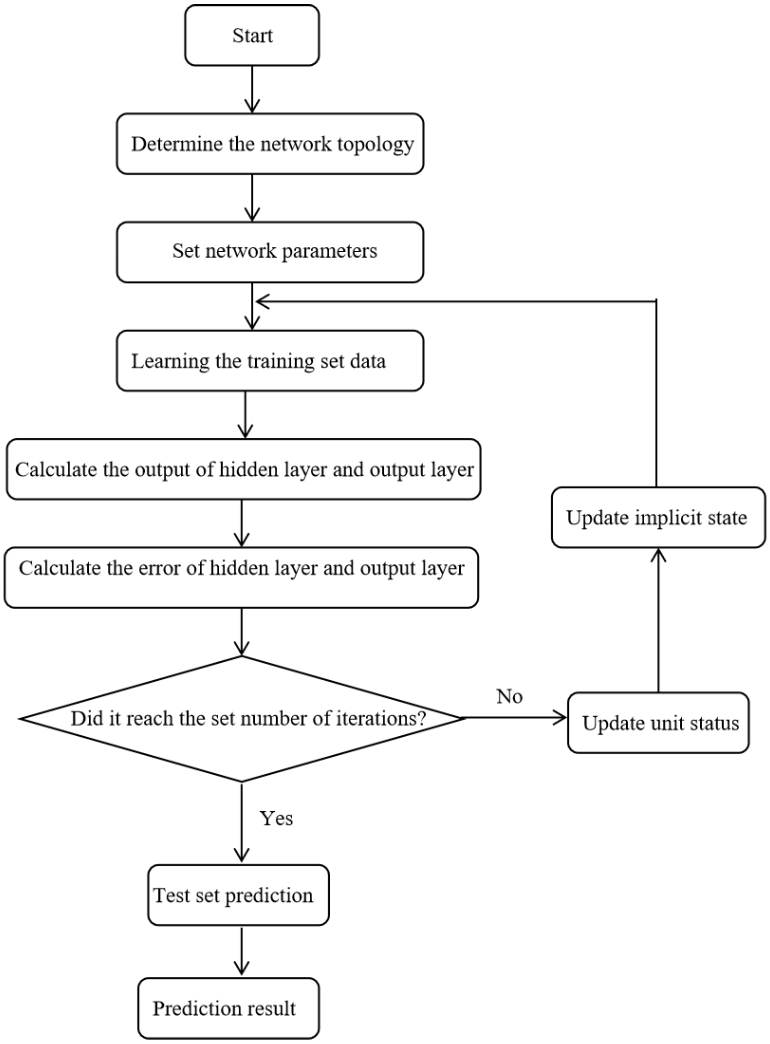

Fig. 3 Flow chart of LSTM model

The Min Max Scaler is used to normalize the training data and test data:

scaler = Min Max Scaler()
train X = scaler.fit_transform(train X)
train Y = scaler.fit_transform(train Y)
test X = scaler.transform(test X)

Use the Input in Keras to establish the input layer, LSTM the LSTM layer and Dense the output layer. An LSTM neural network model with a structure of 2-30-6 and a time step of 10 is created by using the Model. The activation function is the ReLU function, the learning algorithm - the Adam algorithm, the loss function - the mean square error, and the initial learning rate is 0.0001.

input_dim =2
output_dim = 6
lstm_units = 64
timesteps = 10
Input_layer = Input(shape=(timesteps, input_dim))
lstm_input = Reshape(target_ shape=(timesteps, lstm_units))(Input_layer)
lstm_output = LSTM(lstm_units, activation='relu')(lstm_input)
Output_layer = Dense(output_dim) (lstm_output)
model = Model(inputs= Input_layer, outputs= Output_layer)

Compile the model for training with model.compile:

model.compile(optimizer='adam', loss='mse')

Use model.fit to learn the data of the training set, with a number of iterations of 300: *history = model. fit (trainx, trainy, epochs = 300)*.

Use the model.predict to predict the test set data:

lstmt = model.predict(test X)

Inverse normalization is performed on the prediction result to obtain the final result:

lstm_predict = scaler.inverse_ transform(lstmt)

The mean absolute error (MAE), mean absolute percentage error (MAPE) and root mean square error (RMSE) are used to measure the performance of the model in predicting temperature and humidity. MAE can well reflect the error of the predicted value; MAPE is a percentage value, indicating the average deviation degree of the predicted value from the real value; RMSE represents the deviation between the predicted value and the real value, which is often used as an evaluation index for time series prediction problems. Their calculation formula is as follows.

$$\mathrm{MAE}=\frac{1}{\mathrm{N}}\sum_{i=1}^{\mathrm{N}}|x_i-t_i|$$

$$\mathrm{MAPE}=\frac{100\%}{\mathrm{N}}\sum_{i=1}^{\mathrm{N}}\frac{|x_i-t_i|}{t_i}$$

$$\mathrm{RMSE}=\sqrt{\frac{1}{\mathrm{N}}\sum_{i=1}^{\mathrm{N}}(x_i-t_i)^2}$$

Where, x_i and t_i represent the predicted value and actual value of the i-th sample, respectively, and n represents the number of samples. The lower the values of these three indicators, the higher the prediction accuracy and the better the performance of the model.

5. Results and discussion

Take T5 as the test sample, that is, the test set, and the amount data of other samples as the training set. Figure 4 presents the prediction results.

As can be seen from Figure 4, the predicted results of the LSTM model for temperature and humidity are close to the actual values, respectively. In order to verify the reliability of this model,

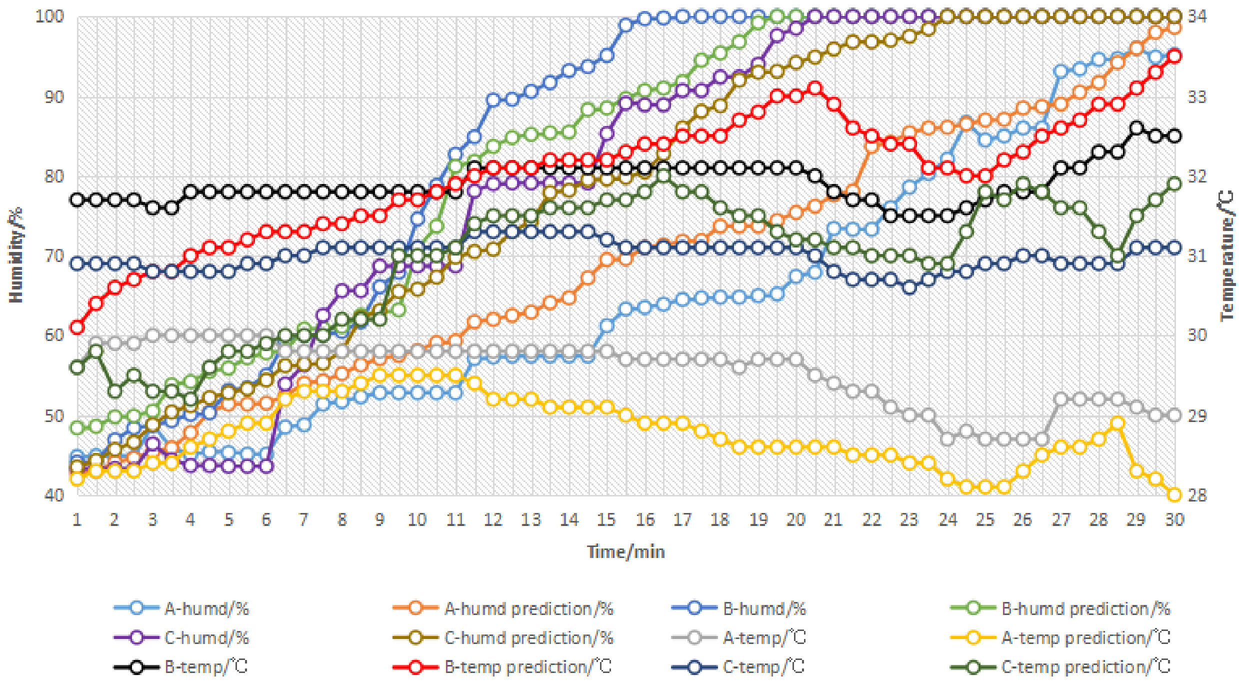

Fig. 4. LSTM model prediction results

Comfort sense	Prediction model	MAE	MAPE	RMSE
A-humd	BP neural network	7.2682	0.3364	8.2078
	RNN	5.6314	0.1876	7.1911
	LSTM	4.9695	0.0814	5.6164
A-temp	BP neural network	6.3590	0.2838	7.5956
	RNN	5.1719	0.1123	6.0645
	LSTM	0.7881	0.0266	0.8719
B-humd	BP neural network	6.9588	0.3138	7.9893
	RNN	6.8672	0.3072	7.9201
	LSTM	2.6220	0.0353	3.8243
B-temp	BP neural network	3.2595	0.0517	4.4136
	RNN	1.9904	0.0301	0.7382
	LSTM	0.5424	0.0170	0.6483
C-humd	BP neural network	7.2777	0.3414	8.2873
	RNN	5.6293	0.1793	6.8152
	LSTM	3.3424	0.0520	4.5567
C-temp	BP neural network	4.0872	0.0713	5.2473
	RNN	2.7166	0.0369	3.9719
	LSTM	0.6356	0.0205	0.7686

Note: A-humd means the humidity on the abdomen surface, A-temp the temperature on the abdomen surface, B-humd the humidity on the back surface, B-temp the temperature on the back surface, C-humd the humidity on the chest surface, and C-temp the temperature on the chest surface.

Table 4. Comparison of error values of prediction results of three neural network models

the LSTM neural network is compared with the recurrent neural network (RNN) model and BP neural network model, respectively, as shown in Table 4.

It can be seen from Table 4 that the average absolute error, average absolute percentage error and root mean square error of the LSTM neural network model are lower than those of the BP neural network and RNN model respectively, that is, the prediction accuracy of the LSTM neural network model is higher than these two algorithms. Taking the humidity on the abdomen surface as an example, the average absolute error, average absolute percentage error and root mean square error of the LSTM neural network model are reduced by 2.2987, 0.255 and 2.5914, respectively compared with the BP neural network. Compared with the RNN model, the average absolute error, average absolute percentage error and root mean square error of the LSTM neural network model decreased by 0.6619, 0.1062 and 1.5747, respectively. Therefore, the LSTM neural network prediction model is better than the BP neural network model and RNN neural network model for the prediction effect of temperature and humidity in different parts.

6. Conclusion

In this paper, an intelligent model(LSTM neural network structure) is proposed for quickly obtaining comfort data in motion. When people wear tight sportswear, the neural network predicts the temperature and humidity of several other key parts according to the temperature and humidity data of one part of the body. In order to verify the reliability of the proposed model, it is compared with the other two neural network models, and it is found that the LSTM neural network constructed in this paper has higher prediction accuracy, which also shows the feasibility of LSTM in predicting temperature and humidity. However, limited by the number of test samples, the accuracy of the model can get better prediction results and higher accuracy in more sample sizes. In a word, the model reduces the experimental cost, facilitates the study of dynamic thermal and humid comfort to a certain extent, and will improve the efficiency of analyzing the distribution and variation of temperature and humidity during human movement. This study will effectively promote the study of temperature and humidity changes when people wear sports tights, provide theoretical reference for the study of human skin temperature in the field of sports medicine, and provide practical guidance for the application of human skin temperature changes in sports clothing production, diagnosis and prevention of sports injuries.

Acknowledgment

The authors would like to acknowledge the financial support from the International Cooperation Fund of Science and Technology Commission of Shanghai Municipality(Grant NO. 21130750100) and Fujian Province Social Science Planning Project(FJ2020C049).

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