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Subjective and Objective Thermal Comfort Estimation Using Wearable Sensors and Environmental Sensors

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Abstract: An ideal self-adjusting environment requires adapting human thermal comfort automatically and continuously measuring the changes in human thermal comfort. According to the PMV (Predicted Mean Vote) model, human thermal comfort could be evaluated by human biometric data and environmental data. In this paper, we proposed a method to estimate human thermal comfort through a small number of wearable and environmental sensors based on machine learning. There are two typical definitions of thermal comfort: subjective thermal comfort representing the subjective perception of heat and objective thermal comfort calculated by the PMV formula. We used a subjective questionnaire and PMV formula to obtain the correct label for two kinds of thermal comfort, respectively. Among the three machine learning models, the random forest has 0.73 in MAE, which is suitable for estimating 7-level subjective thermal comfort, and the neural network has 0.47 in MAE, which is suitable for estimating objective thermal comfort. We investigated the estimation accuracy by changing the sensors' combinations. As a result, a small number of sensors could still roughly estimate human thermal comfort.

Keywords: Thermal Comfort, PMV, Wearable Sensor, Machine Learning

1. Introduction

People would like to live in a thermally comfortable environment. For example, people want to make the room cooler with an air conditioner in summer and warmer with a heater in winter. Temperature self-adjusting rooms and houses have been developed to provide a thermally comfortable environment for people and avoid the trouble of manually switching the cooler and heater [1], [2], [3]. However, because people's thermal sensations are different even in the same environment, an automatic environmental temperature adjustment system does not entirely provide a comfortable environment. Self-adjusting rooms or houses require to adjust themselves not only to the environmental temperature but also to human thermal comfort. Therefore, in this study, we focus on human thermal comfort, an essential index for air conditioning control and the realization of a thermally comfortable environment.

In the ASHRAE Standard 55, human thermal comfort is defined as a human's psychological satisfaction with the current thermal environment [4]. This satisfaction could be evaluated with the PMV model in an indoor environment [5]. The PMV model divides the human thermal sensations into a 7-level scale from −3 to 3, as shown in **Table 1**. The positive scale indicates the levels of human discomfort with the heat, and the negative scale indicates the levels of human discomfort with the cold in an indoor environment. The *neutral* level means comfortable. Human thermal comfort has two acquisition ways. Since thermal comfort is defined as a 7-level scale, human thermal comfort could be directly obtained by asking about people's thermal sensations with the current environment. In this paper, we call it subjective thermal comfort. Another one is called objective thermal comfort, which the PMV formula could calculate from the PMV model with six variables: the metabolic rate, the clothing insulation, the mean radiation temperature, the environmental temperature, the relative environmental humidity, and the airflow [6]. The metabolic rate is the amount of heat produced by a human's behavior or activity. According to the sensible temperature variations of human works or exercises, the amount of activity is 1 MET per unit of human metabolism while sitting on a chair at rest [7]. The clothing insulation is expressed as a quantified value of the heat retention capacity of clothes [4]. It is a unit of the thermal resistance value of clothes, usually called the Clo value. The

Table 1 7-level scale of PMV model.

Scale	Meaning
+3	Hot
+2	Warm
+1	Slightly warm
0	Neutral
−1	Slightly cool
−2	Cool
−3	Cold

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mean radiation or thermal radiation means that every object radiates its heat as electromagnetic waves. The unit of mean radiation is the same as the temperature. The environmental temperature is considered equivalent to the air temperature of the room. The relative environmental humidity is a percent of moisture in the air. The airflow mainly refers to the average wind speed. Objective thermal comfort has been used for a long time. If the value of objective thermal comfort is correct and stable, it is straightforward to use the PMV formula directly. However, objective thermal comfort is often calculated outside the range of −3 to 3. There might be some deviations in the PMV formula, but it cannot be said that it is wrong. Therefore, in this study, we attempt to estimate subjective thermal comfort, which is closer to actual human feelings; on the other hand, the estimation of the objective thermal comfort is also tried.

It is noteworthy that adjusting the environment to human thermal comfort is entirely different from adjusting it to environmental temperature. The PMV model points out that six variables, including the environmental temperature, affect human thermal comfort. In other words, five variables are being modified simultaneously except environmental temperature, when we modify human thermal comfort to change an environment. Unfortunately, returning the evaluation results of human thermal comfort obtained from the PMV model to the air conditioning system is not easy. Although Ku et al. proposed a method for calculating PMV based on automatic control and feeding back the calculation results to the air conditioning system, its algorithm is also complicated [8]. Aside from the computation, it is easy to imagine how it is inconvenient for people to wear a large number of sensors while acquiring real-time human biometric data. Remarkably, if it is possible to estimate the evaluation results of human thermal comfort from the PMV model with one or two sensors, it would reduce the inconvenience to people.

The application of machine learning has been continuously developed recently, and machine learning is a series of algorithms that improve performance using experience without being explicitly programmed automatically [9]. Generally speaking, the calculation of the PMV formula requires all variables, that is, a large number of sensors, to obtain data. However, the PMV model does not indicate whether a small number of variables, that is, a small number of sensors, could estimate human thermal comfort. Therefore, this paper proposes a method to estimate human subjective thermal comfort and objective thermal comfort through machine learning using a small number of sensors.

2. Related Research

2.1 PMV Formula

PMV formula is shown as Eq. (1), and Eq. (2) to Eq. (5) could calculate variables affecting human thermal comfort. In this paper, correct labels of objective thermal comfort are calculated by Eq. (1) which is given by ISO 7730 as Ref. [10]:

$$\begin{aligned}PMV = {} & [0.303 * e^{-0.036M} + 0.028][(M - W) \\ & - 3.05 * 10^{-3}[5733 - 6.99(M - W) - P_a] \\ & - 0.42[(M - W) - 58.15] - 1.7 * 10^{-5}M(5867 \\ & - P_a) - 0.0014M(34 - t_a) - 3.96 * 10^{-8} \\ & f_{cl}[(t_{cl} + 273)^4 - (t_r + 273)^4] \\ & - f_{cl}h_c(t_{cl} - t_a)]\end{aligned} \tag{1}$$

where M is the metabolic heat production, W is the external mechanical work by a human (generally 0), P_a is atmospheric pressure, t_a is the indoor environmental temperature, f_{cl} is the clothing area factor, t_{cl} is the surface temperature of clothing, t_r is the mean radiation temperature, and h_c is the thermal convection coefficient. The plural form of unit of M is METs, and 1 MET could be converted to 58.2 W/m^2 heat.

The following is the calculation of each of the variables of Eq. (1). P_a is calculated by Eq. (2):

$$P_a = (RH/100 * e^{-(18.6686 - 4030.18/(t_a + 235))}) \tag{2}$$

where RH is the relative environmental humidity. f_{cl} is given by Eq. (3):

$$f_{cl} = \begin{cases} 1.00 + 1.29 * I_{cl}(\text{if } I_{cl} \leq 0.078\,\mathrm{m^2k/w}) \\ 1.05 + 0.645 * I_{cl}(\text{if } I_{cl} > 0.078\,\mathrm{m^2k/w}) \end{cases} \tag{3}$$

where I_{cl} is the insulation of the clothing ensemble. I_{cl} is generally called as Clo value, and 1 Clo could be converted to 0.0155 m^{2}k/w. t_{cl} is given by Eq. (4):

$$\begin{aligned}t_{cl} = {} & 35.7 - 0.028 * M - I_{cl} * [3.96 * 10^{-8} f_{cl} \\ & [(t_{cl} + 273)^4 - (t_r + 273)^4] - f_{cl}h_c(t_{cl} - t_a)]]\end{aligned} \tag{4}$$

where t_r is the median of the background temperature of the thermography. h_c is given by Eq. (5):

$$h_c = \begin{cases} 2.38 * (t_{cl} - t_a)^{0.25} \\ (\text{if } 2.38 * (t_{cl} - t_a)^{0.25} > 12.1(v_{ar})^{0.5}) \\ 12.1(v_{ar})^{0.5} * v_{ar} \\ (\text{if } 2.38 * (t_{cl} - t_a)^{0.25} < 12.1(v_{ar})^{0.5}) \end{cases} \tag{5}$$

where v_{ar} is the mean wind velocity.

2.2 Human Thermal Comfort Estimation

Early research about human thermal comfort is all based on objective thermal comfort. Due to the PMV formula, there is no need to estimate thermal comfort. Moreover, the human thermal sensation is acquired by many experiments with thermal manikins whose skin surface temperature is under control [11]. Because a thermal manikin could simulate human thermal characteristics when wearing clothes, it has also been widely used to evaluate the thermal environment [12].

As image processing technology evolves, a non-contact measurement method using thermal images was proposed. Ghahramani et al. developed a monitoring system of human thermal comfort with infrared thermography of the face [13]. Tejedor et al. proposed an IRT method for determining older people's thermal comfort using infrared thermography [14]. But these all require thermal imaging cameras. If people are out of range of the thermal camera or are shown in the camera tiny, it is not enough to resolve the estimation issue of human thermal comfort.

Many researchers use machine learning and deep learning to estimate human thermal comfort. Li et al. estimated thermal comfort by allowing Random Forest to learn the combinations of different parts of the human skin temperature collected from thermography [15]. Burzo et al. extracted the features from thermography by k-means and examined the estimation result for a 3-level scale of hot, neutral, and cold in three models of Decision Tree, k-NN, and Naive Bayes [16]. In recent research, Maia et al. built a model of two classifications of comfort and discomfort for estimating horse thermal comfort by image processing [17]. All of the above is based on the estimation of image data. However, there is little research on estimating human thermal comfort based on wearable sensors. We only found that Hasan et al. estimated METs using wearable sensors [18]. Therefore, we fill this gap by presenting a method for estimating thermal comfort using wearable sensors based on machine learning.

2.3 Wearable Sensors in Machine Learning

Wearable sensors are usually used to acquire human biometric data because wearable sensors are small enough and easy to operate. Due to the development of machine learning in recent years, the approach of classification or regression using wearable sensor data for predicting a specific feature or variable is applied to many kinds of research. For example, Lara et al. proposed a method of using acceleration sensor data, GPS sensor data, and heart rate sensor data to predict human behavior [19]. Özdemir et al. developed a system for detecting falls by classifying the data from the accelerometer, gyroscope, and magnetometer [20]. Besides, Düking et al. believe that wearable sensors can provide powerful biofeedback under data mining and machine learning to help athletes optimize their training and health [21]. Since wearable sensors is relatively inexpensive, it is easy to decrease development costs in constructing a system. In this study, we also take advantage of wearable sensors for measuring biological data. And this data is also easy to extract features for training machine learning models.

3. Proposed Method

This study aims to estimate subjective and objective thermal comfort using a small number of sensors. The approach of our proposed method is shown in **Fig. 1**. First, we used wearable and environmental sensors to obtain human biometric and environmental data, and all data are directly or indirectly related to the PMV model. Second, we trained the machine learning model using all sensors; then, we continuously retrained the model reducing the sensors one by one and changing the sensors' combinations. Finally, we compared the estimation results of the different number of used sensors to find the minimum number of sensors and the best sensor combination for estimating human thermal comfort. The content of each subsection of this chapter is as follows: Section 3.1 shows the used sensors and the data types corresponding to the sensors; Section 3.2 describes the acquisition of correct labels of objective thermal comfort; Section 3.3 describes the acquisition of correct labels of subjective thermal comfort.

3.1 Used Sensors and Data Types Corresponding to Sensors

The name of sensors, the acquired data types corresponding to sensors, and the abbreviation of data types are shown in **Table 2**. We used NTC thermistors to obtain skin surface temperature including left arm temperature, right arm temperature, left leg temperature, and right leg temperature. Additionally, we used an NTC thermistor to obtain clothes surface temperature, and we used a pulse sensor to obtain heartbeats. The reason why we obtain heartbeats data is that Green et al. proposed that the heart rate could infer human METs, and METs are directly operated to calculate PMV Value[34]. Furthermore, we used a wind sensor, a lepton module, and DHT22 to obtain wind speed, environmental radiation temperature, and environmental temperature and humidity, respectively. The lepton module is Radiometric Longwave Infrared (LWIR) Camera Module. **Figure 2** shows an example of capturing the front view of a person by the lepton module. The lepton module would give a temperature matrix. We converted the values in the temperature matrix to degrees Celsius according to the following Eq. (6):

$$X_c = \frac{X - 27315}{100} \tag{6}$$

where X is the value in temperature matrix, X_c is the temperature

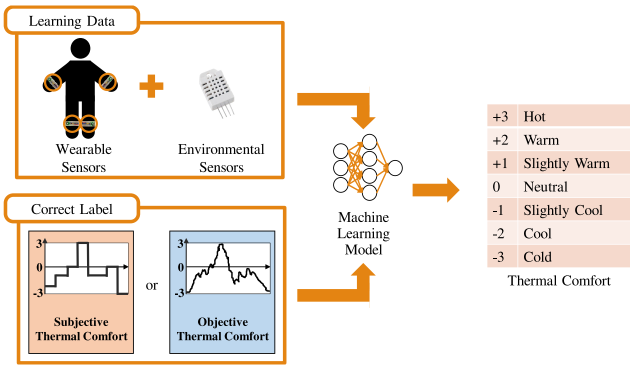

Fig. 1 The approach of the proposed method.

Table 2 Correspondence between sensors and data types.

Sensor Types	Used Sensors	Data Types	Abbreviation
Wearable Sensors	NTC Thermistors	Left Arm Temperature	LAT
		Right Arm Temperature	RAT
		Left Leg Temperature	LLT
		Right Leg Temperature	RLT
		Clothes Surface Temperature	CST
	Pulse Sensor	Heart Beat	HB
Environmental Sensors	Wind Sensor	Wind Speed	WS
	Lepton Module	Environmental Radiation Temperature	ERT
	DHT22	Environmental Temperature	ET
		Environmental Humidify	EH
＼	＼	Individual Difference: METs, Clo Value, BMR	ID

in degrees Celsius after transformation, and −27315 is absolute zero times 100. In this research, we took the median value in the background part of the temperature matrix as the environmental radiation temperature. Besides, considering the influence of individual differences, we gathered not only METs and Clo value but also the BMR (Basal Metabolic Rate). BMR includes four fundamental individual differences: weight, height, age, and sex; they are calculated from Eq. (7) and Eq. (8). We added METs, Clo value, and BMR to the learning data set.

$$BMR(Male) = 13.397 * Weight + 4.799 * Height - 5.677 * Age + 88.362 \quad (7)$$

$$BMR(Female) = 9.247 * Weight + 3.098 * Height - 4.33 * Age + 447.593 \quad (8)$$

3.2 Acquisition of Correct Labels of Objective Thermal Comfort

Correct labels for objective thermal comfort are obtained from the formula in Section 2.1. We could bring the sensor data obtained in Section 3.1 directly into the formulas in Section 2.1 to get the objective thermal comfort value quickly. It is especially worth noting that when we enter the sensor data into Eq. (4), we will get a one-variable quartic equation, t_{cl} is the solution of the equation. To simplify the calculation, we measured t_{cl} which is the clothes surface temperature shown in Table 2 directly from the thigh portion of the pants with an NTC thermistor instead calculating Eq. (4).

3.3 Acquisition of Correct Labels of Subjective Thermal Comfort

Correct labels of the subjective thermal comfort are acquired from the answers to a thermal comfort questionnaire. However, since most people do not understand the meaning of *Human Thermal Comfort,* when asked: "What is your level of human thermal comfort?" it seems a bit difficult to answer. In contrast, "How many degrees do you want to increase or decrease current room temperature?" could be understood even if people do not know the PMV model. By setting seven answer options of the question from −3 to 3, the answer could correspond to the 7-level scale of the PMV model.

In order to better and simply express subjective thermal comfort, we set up 3-level estimation modes of hot, neutral, and cold. The 3-level subjective thermal comfort did not collect the correct data separately. By converting the positive scale of the PMV model to 3 and the negative scale to −3, we could transform the human thermal comfort of the 7-level scale to a 3-level scale. We also tried to estimate 3-level scale subjective thermal comfort by a small number of sensors in this paper.

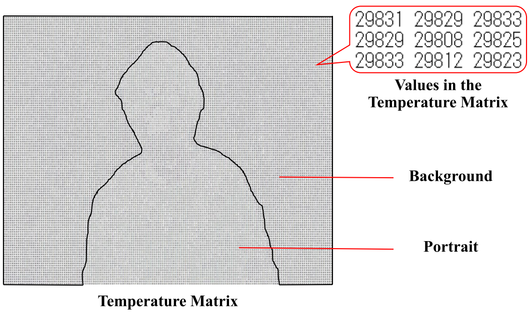

Fig. 2 A temperature matrix captured by the Lepton Module.

4. Experiment

In order to evaluate the estimation results of machine learning models, it is necessary to train and test models by the amount of learning data and correct labels acquired from various environmental conditions. Therefore, we experimented with collecting 11 participants' data in a specially designed space where the temperature and humidity can be regulated.

4.1 Experiment Environment

The specially designed space is a 1.5 m × 1.5 m × 2.0 m pipe-type booth in which two heaters, a cooler, a humidifier, and a dehumidifier were set, as shown in **Fig. 3**.

The lepton module was placed in front of the experiment participant's seat. DHT 22 (a temperature and humidity sensor) and a wind sensor are fixed on the table with curing tape. Experimental participants were asked to put on four wristbands, each attached with an NTC thermistor, on the left arm, right arm, left calf, and right calf. Another NTC thermistor was taped to the surface of the pants on the right thigh, and a pulse sensor was bunched at the left hand's little finger. The location of the cameras, environmental sensors, and wearable sensors are shown in **Fig. 4**. When sensor data was being acquired, the participants would be asked to stay in the booth and do some desk work; meanwhile, the environmental temperature and humidity were constantly changed. After the measurement, the outliers and the other sensor data simultaneously with the outlier were automatically removed from the acquired data set.

A cooler, heater, humidifier, and dehumidifier have only two output modes, respectively: on and off. So the working pattern of environmental controllers in our experiment are roughly divided into four situations: simultaneous turning heater and humidifier on, simultaneous turning heater and dehumidifier on, simultaneous turning cooler and humidifier on, and simultaneous turning cooler and dehumidifier on.

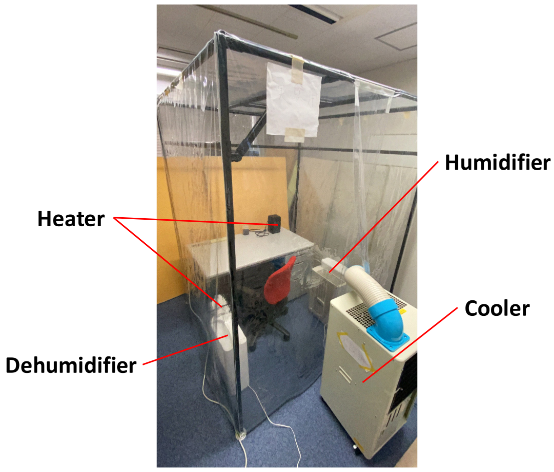

Fig. 3 Experiment environment.

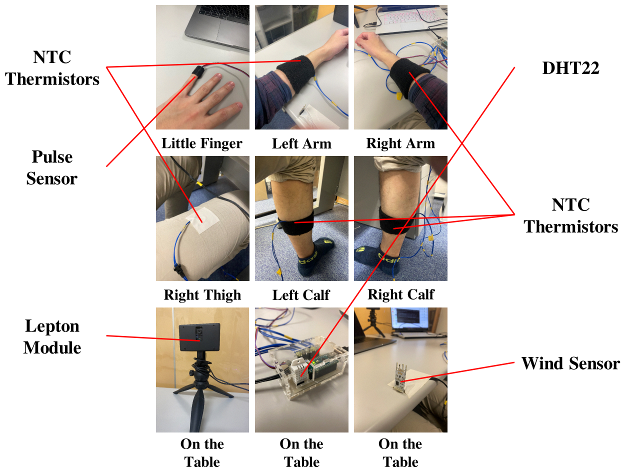

Fig. 4 Implementation of sensors.

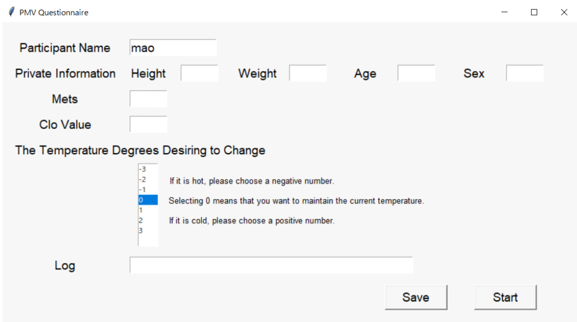

Fig. 5 PMV Questionnaire interface.

4.2 Experiment Description

For collecting the correct labels of subjective thermal comfort, we developed a PMV questionnaire interface with Tkinter [22], a python library, to record people's answers in real-time during the experiment. The screenshot of the interface named *PMV Questionnaire* is shown in **Fig. 5**. The answer concerning subjective thermal comfort could be selected in the check box under *The Temperature Degrees Desiring to Change.*

The participants could rest for 10 minutes before the experiment started, and during this time, they were asked to fill in their name, private information, METs, Clo value, and the degree of temperature desiring to change in the PMV questionnaire interface. METs and Clo value could be referred to the energy expenditure of the activities table and the guideline for Clo value [23], [24], [25], [26]. For example, if a participant wanted to do typing work during the experiment, he or she should have entered 1.5 in the METs field of the interface. Also, if a participant was wearing a short-sleeved shirt, thin long-sleeved blouse, thick jacket, thick trousers, shorts, and sports socks, he or she should have entered 1.12 in the Clo value field of the interface because the Clo value of clothes corresponds to 0.08, 0.18, 0.54, 0.24, 0.06, 0.02, respectively. However, participants were not allowed to change their activities and clothes during the experiment.

Since it took time for the temperature and humidity of the booth to stabilize, the measurement time for each working pattern of environmental controllers was set to 15 minutes, and sensor data was acquired at 20-second intervals during that time.

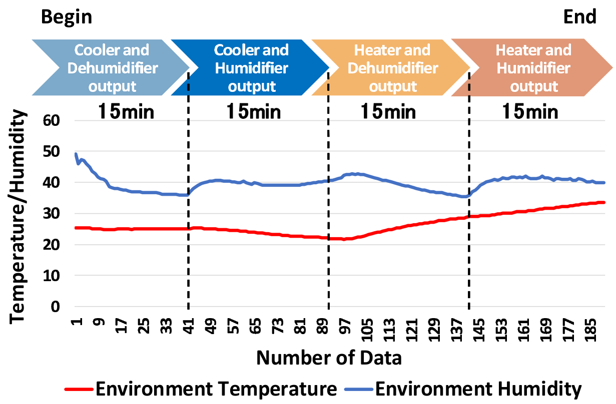

Fig. 6 Environmental temperature and environmental humidity changes during the Experiment from a Participant.

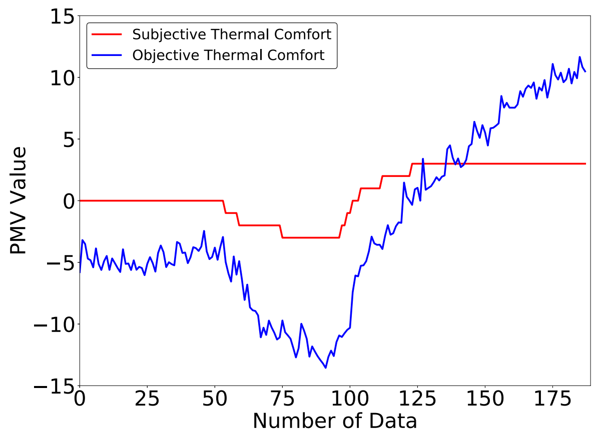

Fig. 7 Subjective thermal comfort and objective thermal comfort changes during the experiment from a participant.

Four measurements were conducted for one participant. **Figure 6** shows the environmental temperature and environmental humidity changes from a participant during the experiment. Each participant usually takes one and a half hours, including resting time, experiment explanation time, and experiment time.

During the experiment, if participants wanted to change the current environmental temperature, they could modify the options in the *The Temperature Degrees Desiring to Change* field, but the environmental temperature would not actually be changed. The descriptions of the experiments for participants in this paper are in Japanese. The Japanese language expression of human thermal comfort is slightly different from the expression of the PMV model. In Japanese, words such as *warm* and *cool* give experiment participants a positive impression. However, in the definition of the PMV model, except for the *neutral* scale, all of the other scales are negative expressions. Since the expression difference might cause the experimental participants to make a deviation in the answered results, when we tried to obtain correct labels of the subjective thermal comfort, we directly asked the experimental participants about the environmental temperature they wanted to change instead of the subjective thermal comfort level. In addition, **Fig. 7** shows the changes of subjective thermal comfort and objective thermal comfort obtained by a participant (the same person in Fig. 6) during the experiment. As discussed in Section 1, the trends in the two kinds of labels are similar, but there is a considerable difference in value.

This research was conducted in accordance with the ethical review rules of the Graduate School of Engineering, Kobe University. The approval number is 03-17.

4.3 Machine Learning and Data Preprocessing

We used SVM, Neural Network, and Random Forest for estimating human thermal comfort under 5-fold cross-validation. In Section 3.3, since subjective thermal comfort is handled as a 7-level scale or a 3-level scale of human thermal sensations, which is an ordinal scale, human thermal sensations are different in scale among all thermal sensation labels from −3 to 3. For example, the scale from 1 (Slightly warm) to 2 (Warm) and the scale from 2 (Warm) to 3 (Hot) are entirely different. In this case, the labels 1, 2, 3, et al. cannot be treated as a group of continuous numbers. Consequently, for 7-level and 3-level subjective thermal comfort, we trained the models in classification. The objective thermal comfort is calculated by the PMV formula, and the calculation results are in the range of −3 to 3, which could be regarded as a group of continuous numbers. Therefore, for objective thermal comfort, we trained the models in regression.

All models have done grid search before the estimation. Grid search is a technique for tuning machine learning models' hyperparameters to optimal values, and it can significantly increase the model estimation accuracy [27]. MAE and F1-score were used to evaluate the estimated results of 7-level and 3-level subjective thermal comfort; MAE and RMSE were used to evaluate the estimated results of objective thermal comfort. The MAE is the mean of the absolute errors of the difference between the correct labels and the estimated thermal comfort values. Each machine learning model was created by Scikit-learn [28]. Besides, because the magnitude difference between the input and output data of the models might cause significant errors in the estimated results, we normalized the input data. Since we used many different kinds of sensors, we hope that the influence of physical quantities could be reduced while training the model. Therefore, we chose z-score normalization among the normalization methods, which is shown by Eq. (9) [29]:

$$X_{norm} = \frac{X - \mu}{\sigma} \tag{9}$$

where X is raw data, μ is the mean of raw data, and σ is the variance of raw data. X_{norm} is normalized data.

The number of sensors should be as few as possible as it is essential to avoid inconvenience in estimating a person's thermal comfort in a daily environment. However, if we directly cut some features of sensors down, the estimation accuracy might significantly decrease. Therefore, we expanded the features of input sensor data while training the models. Because each feature of sensor data is related to time, we added the mean and variance of the ten sets of data (about 3 minutes) before a certain time point of the same feature value to the current moment data set. Some features unrelated to time cannot be expanded, such as METs and Clo value. As a result, the input sensor data set was increased from 12 dimensions to 30 dimensions.

Therefore, after data preprocessing, we obtained 1,605 sets of data from 11 experimental participants, of which 1,284 sets were used for training data and 321 sets were used for testing data.

5. Result

5.1 Estimation Results Using All Sensors

The estimation results of three kinds of correct labels using all sensors are shown in **Table 3**. All MAE, F1-Score, and RMSE are the mean values of 5-fold cross-validation results. The estimated curve of 7-level subjective thermal comfort, 3-level subjective thermal comfort, and objective thermal comfort are shown in **Fig. 8**, **Fig. 9**, and **Fig. 10**, respectively. Abbreviations will represent the name of the machine learning model (e.g., Neural Network: NN, Random Forest: RF) in all the figures. Though we could obtain five estimation curves from 5-fold cross-validation, only the fifth curve of each model is shown in this subsection. In the estimated 7-level subjective thermal comfort results, the random forest has the minimum MAE and highest F1-Score. In the estimated 3-level subjective thermal comfort results, the SVM has

Table 3 Performance metrics of the estimation results.

Types of Correct Label	Model	MAE	F1-Score
7-Level Subjective Thermal Comfort	SVM	0.89	0.40
	NN	0.96	0.33
	RF	0.73	0.47
3-Level Subjective Thermal Comfort	SVM	0.82	0.74
	NN	1.08	0.69
	RF	0.84	0.72
Types of Correct Label	**Model**	**MAE**	**RMSE**
Objective Thermal Comfort	SVM	0.41	1.15
	NN	0.47	0.95
	RF	2.61	3.28

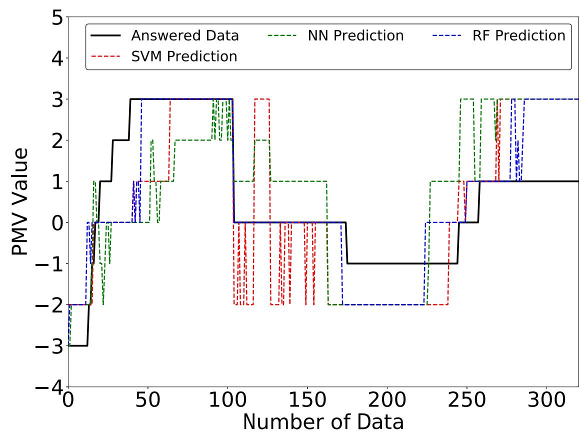

Fig. 8 Estimated curve of 7-level subjective thermal comfort.

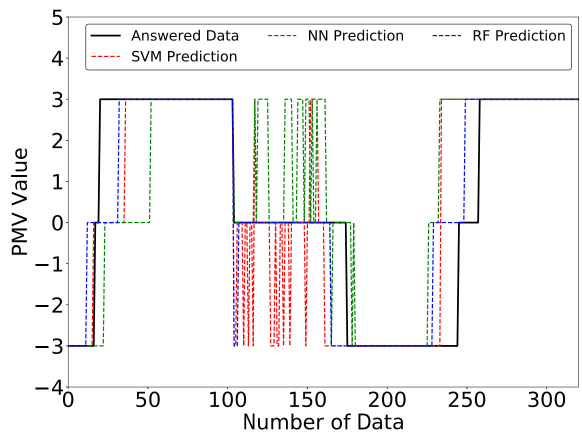

Fig. 9 Estimated curve of 3-level subjective thermal comfort.

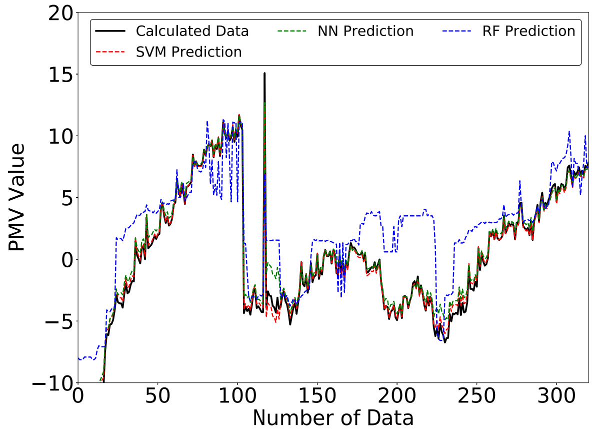

Fig. 10 Estimated curve of objective thermal comfort.

the minimum MAE and highest F1-score. The objective thermal comfort estimation results show that the SVM has the minimum MAE and the neural network has the minimum RMSE. Since the difference between the RMSE and MAE of SVM is larger than the difference between the RMSE and MAE of NN, we could know that there will be more outliers in the estimated value of SVM. Totally for subjective thermal comfort estimation results, the accuracy of the neural network is the worst. For objective thermal comfort estimation results, the accuracy of random forest is the worst.

It could be seen from Fig. 8 and Fig. 9 that many variations show in the estimated curves of SVM and neural network, and the fitness between the estimated curve of Random Forest and correct labels is relatively high. However, in the random forest estimated curve of 7-level subjective thermal comfort, we could see that three misestimation parts appeared in the parts from the 20th data to the 50th data, from the 170th data to the 250th data, and from the 270th data to the last data. On the contrary, very few misestimated parts appeared in the random forest estimated curve of 3-level subjective thermal comfort. Although the performance metrics of SVM are good, the SVM estimated curve of 3-level subjective thermal comfort is very unstable. Consequently, the F1-Score of the estimation results of 3-level subjective thermal comfort is higher than that of 7-level subjective thermal comfort. The fitness of the estimated curves for 3-level subjective thermal comfort is also better.

It could be seen from Fig. 10 that the random forest estimated curve has large deviations, while the SVM and neural network estimated curves have relatively high fitness to the correct labels. Although the MAE of SVM is small enough, the MAE of the neural network is not much different from that, and the neural network estimated curve is much more stable. Overall, the estimation accuracy of the neural network for objective thermal comfort may be the best.

5.2 The Results of the Optimal Sensor Combination

We used the minimum MAE value to search for the best sensor combination when we reduced the used sensors one by one. However, since it is not intuitive to directly reduce the used sensors, we actually reduce the used data type corresponding to sensors. The data types corresponding to sensors have been introduced

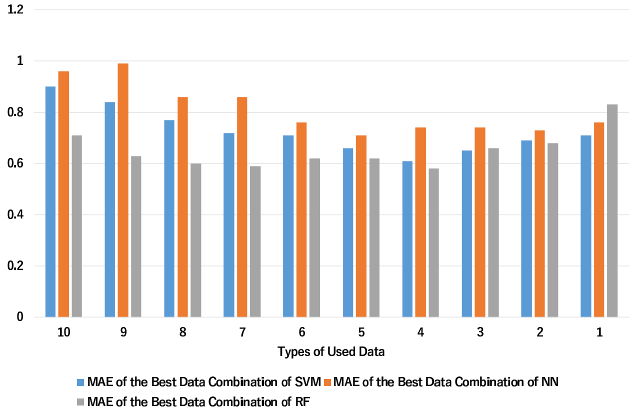

Fig. 11 MAE of the best data type combination results in each number of used data types for 7-level subjective thermal comfort.

Fig. 12 MAE of the best data type combination results in each number of used data types for 3-level subjective thermal comfort.

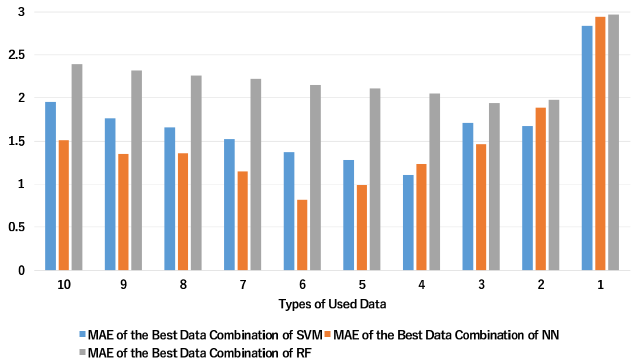

Fig. 13 MAE of the best data type combination results in each number of used data types for objective thermal comfort.

in Section 3.1. The best data type combination for 7-level subjective thermal comfort, 3-level subjective thermal comfort, and objective thermal comfort are shown in **Tables 4**, **5**, and **6**, respectively. The used data types are marked up with a checkmark in these three tables, and the unused data type is blank. The MAE values of each best data combination for 7-level subjective thermal comfort, 3-level subjective thermal comfort, and objective thermal comfort are shown in **Figs. 11**, **12**, and **13**, respectively.

In Fig. 11, we could see that the MAE of the best data type combination of the three machine learning models at 7-level subjective thermal comfort first exhibited a downward trend and then slowly increased. In all the results of the three models, the MAE of the neural network is the largest except for the result using only 1 data type; the MAE of random forest is the smallest from the

Table 4 The best data type combination results in each number of used data types for 7-level subjective thermal comfort.

Number of Used Data Type	Number of Combination	Model	Used Data Type											Performance Metrics	
			Wearable Sensor Data						Environmental Sensor Data				ID		
			Temperature					Other	Temperature		Other				
			LAT	RAT	LLT	RLT	CST	HB	ERT	ET	WS	EH		MAE	F1-Score
10	C_{11}^{10}=10	SVM	✓	✓	✓	✓	✓	✓	✓	✓		✓	✓	0.90	0.35
		NN	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓	0.96	0.34
		RF	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓	0.71	0.47
9	C_{11}^{9}=55	SVM	✓	✓	✓	✓	✓	✓	✓		✓		✓	0.84	0.36
		NN	✓	✓	✓		✓	✓	✓	✓	✓	✓		0.99	0.36
		RF	✓	✓			✓	✓	✓	✓	✓	✓	✓	0.63	0.50
8	C_{11}^{8}=165	SVM	✓	✓	✓		✓	✓	✓			✓	✓	0.77	0.42
		NN		✓	✓	✓	✓		✓		✓	✓	✓	0.86	0.39
		RF	✓	✓			✓	✓	✓		✓	✓	✓	0.60	0.51
7	C_{11}^{7}=330	SVM	✓				✓	✓	✓	✓	✓	✓		0.72	0.45
		NN		✓	✓				✓	✓	✓	✓	✓	0.86	0.38
		RF	✓	✓			✓	✓	✓			✓	✓	0.59	0.52
6	C_{11}^{6}=462	SVM	✓				✓	✓	✓	✓		✓		0.71	0.46
		NN	✓	✓			✓	✓	✓				✓	0.76	0.41
		RF	✓				✓	✓	✓			✓	✓	0.62	0.49
5	C_{11}^{5}=462	SVM		✓			✓	✓	✓	✓				0.66	0.52
		NN	✓					✓	✓	✓			✓	0.71	0.47
		RF	✓						✓		✓	✓	✓	0.62	0.52
4	C_{11}^{4}=330	SVM		✓			✓	✓	✓					0.61	0.55
		NN		✓				✓	✓	✓				0.74	0.46
		RF	✓	✓					✓				✓	0.58	0.54
3	C_{11}^{3}=165	SVM		✓			✓		✓					0.65	0.51
		NN	✓				✓	✓						0.74	0.43
		RF	✓	✓					✓					0.66	0.48
2	C_{11}^{2}=55	SVM					✓		✓					0.69	0.53
		NN	✓							✓				0.73	0.46
		RF	✓						✓					0.68	0.49
1	C_{11}^{1}=10	SVM							✓					0.71	0.50
		NN							✓					0.76	0.47
		RF							✓					0.83	0.41

※ LAT: Left Arm Temperature, RAT: Right Arm Temperature, LLT: Left Leg Temperature, RLT: Right Leg Temperature, CST: Clothing Surface Temperature, HB: Heart Beat, ERT: Environmental Radiation Temperature, ET: Environmental Temperature, WS: Wind Speed, EH: Environmental Humidity, ID: Individual Difference

case of using 10 data types to the case of using 4 data types; the MAE of SVM is the smallest in the other three cases. In Table 4, as the data types decrease, F1-Score for each case is approximately slowly increasing. From this, it can be seen that some types are useless for estimating thermal comfort among all the data types. This trend can also be seen in Table 5. In the cases for 7-level subjective thermal comfort, we could see that the MAE of the best data type combination of random forest reaches the minimum while using four data types, and the F1-Score reaches the maximum. In the result of four data types, though the F1-Score of SVM is the highest all over the results, the MAE of SVM is lower than random forest. The difference between the maximum and the minimum value of the F1-Score is 0.20, and the best data type combination of the F1-Score is only 0.54. It is a low value from the perspective of machine learning classification problems. Besides, the lowest MAE is 0.58. According to the PMV model, this estimation accuracy is relatively high.

In Fig. 12, we could see the same trend as in Fig. 11. Also, in all the results of the three models, the MAE of the neural network is still generally larger; the MAE of random forest is the smallest from the case of using 10 data types to the case of using 5 data types; the MAE of SVM is the smallest in the other four cases. In the cases for 3-level subjective thermal comfort, we could see that the MAE of the best data type combination of random forest reaches the minimum while using 5 data types, and the F1-Score reaches the maximum. The difference between the maximum and the minimum value of F1-Score is 0.08, and the best data type combination of F1-Score is 0.79. In total, the F1-Score is much higher than the results of 7-level subjective thermal comfort. Although the MAE is generally more prominent than 7-level subjective thermal comfort, it is caused by the transformation method (refer to Section 3.3). For 3-level subjective thermal comfort, the evaluation of F1-Score is more critical than the MAE.

In Fig. 13, we could see that the MAE of the best data combination of the three machine learning models at objective thermal comfort first exhibited a slow downward trend and then increased rapidly. In all the results of the three models, the MAE and RMSE of random forest are the largest, and the MAE and RMSE of the neural network are the smallest from the case of using 10 data types to 5 data types and using 3 data types; the MAE of SVM is the smallest in the other three cases. In the cases for objective thermal comfort, we could see that the MAE and RMSE of the best data combination of the neural network reach the minimum while using 6 data types. However, the MAE of each case for objective thermal comfort is much higher than the 7-level and 3-level subjective thermal comfort results.

In summary, the random forest has a relatively high estimation accuracy for 7-level subjective thermal comfort and 3-level subjective thermal comfort, and the neural network has a relatively

Table 5 The best data type combination results in each number of used data types for 3-level subjective thermal comfort.

Number of Used Data Type	Number of Combination	Model	Used Data Type											Performance Metrics	
			Wearable Sensor Data						Environmental Sensor Data				ID		
			Temperature					Other	Temperature		Other				
			LAT	RAT	LLT	RLT	CST	HB	ERT	ET	WS	EH		MAE	F1-Score
10	C_{11}^{10}=10	SVM	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓	0.85	0.73
		NN	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓	0.93	0.71
		RF	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	0.78	0.74
9	C_{11}^{9}=55	SVM	✓		✓	✓	✓	✓	✓	✓	✓		✓	0.81	0.75
		NN	✓	✓	✓			✓	✓	✓	✓	✓	✓	0.92	0.71
		RF	✓	✓	✓	✓		✓	✓		✓	✓	✓	0.69	0.78
8	C_{11}^{8}=165	SVM	✓		✓		✓	✓	✓	✓	✓		✓	0.70	0.78
		NN		✓	✓	✓	✓	✓	✓			✓	✓	0.80	0.76
		RF	✓		✓	✓		✓	✓		✓	✓	✓	0.67	0.78
7	C_{11}^{7}=330	SVM	✓		✓		✓	✓	✓	✓			✓	0.70	0.79
		NN	✓	✓			✓		✓	✓	✓		✓	0.82	0.74
		RF	✓		✓	✓		✓	✓		✓		✓	0.67	0.78
6	C_{11}^{6}=462	SVM	✓				✓	✓	✓	✓			✓	0.66	0.79
		NN	✓		✓		✓		✓	✓			✓	0.76	0.76
		RF	✓	✓					✓		✓	✓	✓	0.66	0.78
5	C_{11}^{5}=462	SVM	✓				✓	✓	✓				✓	0.67	0.78
		NN	✓						✓	✓	✓		✓	0.69	0.78
		RF	✓						✓	✓	✓		✓	0.62	0.79
4	C_{11}^{4}=330	SVM	✓				✓	✓	✓					0.64	0.79
		NN		✓				✓	✓				✓	0.79	0.74
		RF	✓						✓			✓	✓	0.67	0.78
3	C_{11}^{3}=165	SVM					✓	✓	✓					0.68	0.78
		NN							✓	✓			✓	0.77	0.75
		RF	✓						✓				✓	0.72	0.77
2	C_{11}^{2}=55	SVM					✓			✓				0.66	0.78
		NN	✓							✓				0.72	0.77
		RF	✓						✓					0.73	0.77
1	C_{11}^{1}=10	SVM							✓					0.81	0.73
		NN							✓					0.89	0.71
		RF							✓					0.91	0.71

※ LAT: Left Arm Temperature, RAT: Right Arm Temperature, LLT: Left Leg Temperature, RLT: Right Leg Temperature, CST: Clothing Surface Temperature, HB: Heart Beat, ERT: Environmental Radiation Temperature, ET: Environmental Temperature, WS: Wind Speed, EH: Environmental Humidity, ID: Individual Difference

high estimation accuracy for objective thermal comfort; in addition, the fewer the data types we used, the higher the estimation accuracy of the SVM we got.

Furthermore, in this subsection, we did not do the grid search for each model for each number of data types for the above search results. In other words, none of the above machine learning models' hyper-parameters were adjusted before they were trained. This is due to a large number of combinations, and it is extremely time-consuming to adjust hyper-parameters separately. So we unified as the default hyper-parameters in the scikit-learn. However, it is conceivable that the searching results of MAE in Figs. 11, 12, and 13 will be better if the hyper-parameters are tuned for each combination.

5.3 Data Types and Sensors That Have a Major Impact on Thermal Comfort Estimation

The top three important data types for each type of thermal comfort and their corresponding sensors are shown in **Table 7**. We found that environmental radiation temperature is the most frequently used among all the best data type combinations. No matter what kind of thermal comfort is estimated, only the environmental radiation temperature has been retained when the used data type is limited to one. We could know that the environmental radiation temperature is the variable that has the most significant influence on the estimation of thermal comfort. It also means the Lepton module plays a large role in estimating thermal comfort.

When estimating 7-level subjective thermal comfort, left arm temperature and right arm temperature are frequently used; when estimating level 3 thermal comfort, left arm temperature is frequently used; skin surface temperature is not widely used when estimating objective thermal comfort, but the environmental temperature is heavily used. The reason is not yet apparent, and it is preliminarily speculated that this may be caused by the machine learning model characteristic or the experiment environment.

When estimating 3-level subjective thermal comfort and objective thermal comfort, individual differences appear to be particularly important; when estimating 7-level subjective thermal comfort, individual differences are only widely used in the random forest. Because the estimation accuracy of the random forest was the highest when using 5 data types, and from then on, the MAE increased after individual differences were not used, we could notice that individual differences have a significant influence on estimating thermal comfort.

When estimating 7-level subjective thermal comfort and estimating objective thermal comfort, the surface clothes temperature is widely used; when estimating 3-level subjective thermal comfort, the surface clothes temperature is only widely used in SVM. It is caused that different models have different data preferences when estimating thermal comfort.

Table 6 The best data type combination results in each number of used data types for objective thermal comfort.

Number of Used Data Type	Number of Combination	Model	Used Data Type											Performance Metrics	
			Wearable Sensor Data						Environmental Sensor Data				ID		
			Temperature					Other	Temperature		Other				
			LAT	RAT	LLT	RLT	CST	HB	ERT	ET	WS	EH		MAE	RMSE
10	C_{11}^{10}=10	SVM	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓	1.95	2.53
		NN		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	1.51	2.00
		RF	✓	✓	✓	✓	✓	✓	✓		✓	✓	✓	2.39	2.92
9	C_{11}^{9}=55	SVM	✓	✓	✓		✓	✓	✓	✓	✓		✓	1.76	2.34
		NN		✓	✓		✓	✓	✓	✓	✓	✓	✓	1.35	2.06
		RF	✓	✓	✓	✓	✓	✓	✓			✓	✓	2.32	2.86
8	C_{11}^{8}=165	SVM	✓		✓		✓	✓	✓	✓	✓		✓	1.66	2.26
		NN				✓	✓	✓	✓	✓	✓	✓	✓	1.36	1.74
		RF		✓	✓	✓	✓		✓	✓	✓	✓		2.26	2.79
7	C_{11}^{7}=330	SVM			✓		✓	✓	✓	✓	✓		✓	1.52	2.13
		NN				✓	✓		✓	✓	✓	✓	✓	1.15	1.49
		RF		✓	✓	✓	✓		✓	✓		✓		2.22	2.73
6	C_{11}^{6}=462	SVM			✓		✓		✓	✓	✓		✓	1.37	1.94
		NN					✓	✓	✓	✓	✓		✓	0.82	1.30
		RF			✓		✓		✓	✓	✓	✓		2.15	2.63
5	C_{11}^{5}=462	SVM			✓		✓		✓	✓			✓	1.28	1.81
		NN					✓	✓	✓	✓			✓	0.99	1.46
		RF			✓		✓		✓	✓	✓			2.11	2.58
4	C_{11}^{4}=330	SVM					✓		✓	✓			✓	1.11	1.55
		NN					✓		✓	✓			✓	1.23	1.69
		RF					✓		✓	✓	✓			2.05	2.52
3	C_{11}^{3}=165	SVM					✓		✓				✓	1.71	2.10
		NN					✓		✓				✓	1.46	1.88
		RF					✓		✓	✓				1.94	2.40
2	C_{11}^{2}=55	SVM					✓		✓					1.67	2.10
		NN					✓		✓					1.89	2.34
		RF					✓		✓					1.98	2.47
1	C_{11}^{1}=10	SVM							✓					2.84	3.77
		NN							✓					2.94	3.91
		RF							✓					2.97	3.90

※ LAT: Left Arm Temperature, RAT: Right Arm Temperature, LLT: Left Leg Temperature, RLT: Right Leg Temperature, CST: Clothing Surface Temperature, HB: Heart Beat, ERT: Environmental Radiation Temperature, ET: Environmental Temperature, WS: Wind Speed, EH: Environmental Humidity, ID: Individual Difference

Table 7 The top three important data types for each thermal comfort.

Types of Thermal Comfort	Data Types	Sensors
7-Level Subjective Thermal Comfort	Environmental Radiation Temperature	Lepton Module
	Left Arm Temperature	NTC Thermistor
	Clothes Surface Temperature	NTC Thermistor
3-Level Subjective Thermal Comfort	Environmental Radiation Temperature	Lepton Module
	Left Arm Temperature	NTC Thermistor
	Individual Difference	
Objective Thermal Comfort	Environmental Radiation Temperature	Lepton Module
	Clothes Surface Temperature	NTC Thermistor
	Environmental Temperature	DHT22

6. Considerations

6.1 Subjective Thermal Comfort and Objective Thermal Comfort

In theory, the objective thermal comfort should be the correct format of thermal comfort. However, the calculated objective thermal comfort is very different from the range of the PMV model due to unknown reasons. We could know that by comparing the range of changes in the correct labels in Figs. 8, 9, and 10. So we believe that the subjective thermal comfort can reflect the thermal sensation of the human body more accurately, and the deviation of subjective thermal comfort is much smaller than the objective thermal comfort. In addition, the applicable range of the objective thermal comfort is extremely limited. If the variables of the PMV model exceed the applicable range, as shown in **Table 8**, the calculated objective thermal comfort must be inaccurate.

Table 8 Range of PMV variables.

Variables	Range
PMV	−2–2
Metabolic Rate	0.8–4 METs
Clothing Insulation	0–2 Clo
Environmental Temperature	10–30°C
Relative Environmental Humidity	30–70%
Mean Radiation Temperature	10–40°C
Airflow	0–1 m/s

6.2 The Problem of 7-Level Subjective Thermal Comfort

It is doubtful that the answer to “How much do you want to increase or decrease the current room temperature?” can be directly mapped to the 7-level scale of PMV. Perhaps it is not a simple linear correspondence. However, this research focuses on estimation and not on redefining PMV. If we could obtain the PMV value by answering a simple question, it would be better to map the PMV value to the people’s temperature sensation, but it is not easy to achieve. Cheung et al. used the calculated value of the PMV model to estimate the thermal sensations of the human body, and the estimation accuracy was only 34% in the ASHRAE Global Thermal Comfort Database II [30]. Therefore, we additionally used 3-level subjective thermal comfort so that we do not need to consider the correspondence issue of PMV, and we do not need to subdivide thermal comfort in terms of *warm* or *slightly warm.* We think it is meaningful, even if only a few sensors are used to infer how cold or hot a person's temperature feels.

7. Applications

As mentioned at the beginning, the purpose of this paper is that self-adjusting rooms or houses can adjust the environment according to human thermal comfort. Therefore, we present a method for applying the proposed method of estimating human thermal comfort in daily environments using cloud services. Its approach is shown in **Fig. 14**. Specifically, we could deploy a trained model on a virtual machine in the cloud and use MLflow to publish a service that continuously estimates thermal comfort. MLflow is an open-source platform to manage the machine learning lifecycle, including experimentation, reproducibility, deployment, and a central model registry [31]. The services published by MLflow can exchange data between the third-party platform and the cloud virtual machine through the REST API, that is, the third-party platform sends sensor data to the cloud virtual machine, and the cloud virtual machine sends the estimation results to the third-party platform. As follows, we give an example. We used SVM based on scikit-learn trained with left arm temperature, environmental temperature, and the 7-level subjective thermal comfort for the trained model. If a user wants to estimate thermal comfort with higher accuracy, the user can choose more sensor data. If the user is going to be convenient for daily use, then 2 is the minimum. The specific sensor selection can refer to the results in Section 5.2. And, we chose Azure cloud service to set up a virtual machine. As shown in **Fig. 15**, we used M5Stack to control an NTC thermistor and a DHT12 to measure the left arm skin temperature and environmental temperature, and we established communication between M5Stack and the Azure cloud virtual machine through REST API. The M5Stack is a commercially available microcontroller unit [32]. Many microcontroller units or smart wearable devices with network functions could be used in our approach, and the number of sensors can be adjusted according to user needs.

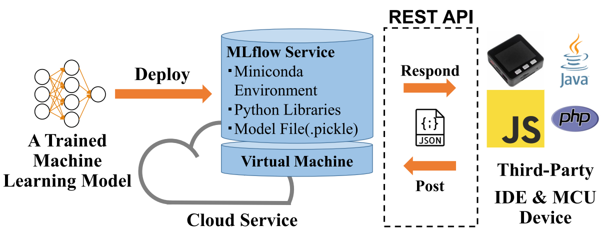

Fig. 14 Approach for applying the estimation system.

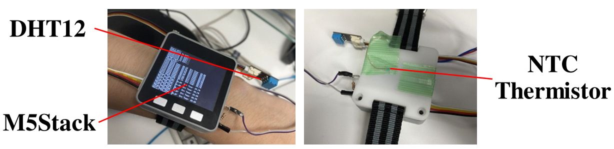

Fig. 15 Implement for applying the estimation system.

Additionally, Fig. 14 only shows the deployment of one machine learning model. By running the MLflow service in a Docker container, we can deploy multiple machine learning models on a virtual machine, such as a model for estimating subjective thermal comfort and a model for objective thermal comfort at the same time. If too many containers are deployed, they can also be managed with Kubernetes [33].

8. Conclusions

In this paper, we proposed a method for estimating the human body's subjective and objective thermal comfort in an indoor environment using wearable and environmental sensors. The proposed method obtained biometric data types such as skin surface temperature, clothes surface temperature, heartbeat, and environmental data types such as environmental radiation temperature, wind speed, environmental temperature, and relative environmental humidity. We estimated the human body's subjective and objective thermal comfort through three machine learning models. The correct labels of subjective thermal comfort are obtained by filling in the PMV questionnaire interface, and the correct labels of objective thermal comfort are calculated by the PMV formula. When using all data types, the random forest has the best accuracy for estimating subjective thermal comfort, and the neural network has the best accuracy for estimating objective thermal comfort. Since the estimation error is relatively large when only 1 data type is used, we have roughly determined that the 2 data types could estimate the thermal comfort within an acceptable range of errors. At this time, the estimation accuracy of SVM is the best. In addition, we presented a method to apply the estimation results of thermal comfort based on cloud services.

One of this research's future works is to redefine the estimated results of subjective thermal comfort. It still requires much experimentation as a basis. We need to consider other questioning methods to obtain the correct labels of PMV precisely. We hope to get some users' feedback on our application system to verify the estimation results in the actual situation. In addition, we would try to estimate thermal comfort in the outdoor environment.

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