A Thermal Comfort Estimation Method by Wearable Sensors

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ABSTRACT

Realizing an environment that could automatically modify temperature and humidity according to human thermal comfort using an air conditioning system, it is necessary to measure the quantified changes of human thermal comfort continually. While quantifying thermal comfort, human biometric data and environmental data from various environments are needed. Therefore, we proposed a method to estimate human thermal comfort through regression analysis with human biometric data acquired by wearable sensors. Since the PMV model is generally used to evaluate human thermal comfort, the PMV value as the correct thermal comfort could be calculated from the PMV formula. We constructed an experiment environment for acquiring the subject's biometric data and gained the subjects' METs and clo value for calculating the PMV value. The biometric data were analyzed in three regression models to predict PMV value, and MAE and RMSE evaluated each regression model. The fewest number of wearable sensors could be confirmed by gradually reducing the feature values of input data of the regression model. As a result, we acknowledged that the human thermal comfort in an indoor environment could be estimated by heart rate data and left-arm temperature data while applying the proposed method to a daily environment.

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CCS CONCEPTS

• **Human-centered computing** → *Ubiquitous and mobile computing*; *Ubiquitous and mobile computing design and evaluation methods*;

KEYWORDS

PMV, Thermal Comfort, Wearable Sensor, Regression Analysis, Machine Learning

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1 INTRODUCTION

People like to put themselves in a comfortable environment. For example, people tend to spend in the shade and other cool spaces to avoid the heat in summer, and they tend to spend in warm places or under sunshine to avoid the cold in winter [1]. Based on this characteristic of human beings, some environments or devices that could self-adjust indoor temperature and humidity have been developed [2, 3]. Human comfort is affected by people's perceptions and mental state, and human body status' changes or external conditions would lead to changes in humans' current comfort level. Human comfort includes many aspects, but most of them are difficult to measure or evaluate, such as behavioral comfort, emotional comfort [4], and psychological comfort [5]. Generally speaking, comfort is difficult to define and quantify, especially at the engineering level; nevertheless, thermal comfort is an exception. People are more sensitive to thermal sensation in an indoor environment than other sensations [6], such as light sensation and noise sensation, so evaluating thermal comfort is urgently needed.

When constructing a thermal comfort environment, we would use some equipment to control environmental features, such as air conditioners or humidifiers. If the current environment cannot satisfy the people's needs, it is essential to adjust the environmental features. Because human thermal comfort could unify the environmental features related to heat, we could only consult with human thermal comfort when adjusting the environment. The premise is that human thermal comfort can be quantified. And this might be achieved by reconstructing the human thermal model [7, 8], though it is not easy to do complex mathematical works in the biological model. Nevertheless, we considered machine learning to simplify the approach by finding relationships between human thermal comfort and human biometric data.

If thermal comfort could be quantified, it is possible to monitor human thermal comfort variations in real-time. We need a large amount of human biometric data and environmental data from an environment under different conditions. Also, wearable sensors and environmental sensors could acquire these data. In fact, temperature adaptive rooms based on temperature sensors have been applied to some buildings. However, whether such an environment or system could be satisfying the human's thermal sensation is still unknown. Therefore, this paper proposes a method to estimate thermal comfort through the regression analysis of wearable sensor data.

2 RELATED RESEARCH

2.1 PMV Model

Human thermal comfort is defined as a human's psychological satisfaction to the current thermal environment [9]. This satisfaction could be evaluated with a PMV model in an indoor environment [10]. The PMV model divides the human thermal sensation into seven levels from -3 to 3, as shown in Table 1. The PMV value could also be calculated with six variables: the metabolic rate, the clothing insulation, the mean radiation temperature, the environmental temperature, the relative environmental humidity, and the airflow [11]. The meaning of each variable in the PMV model is as follows:

- The metabolic rate is the amount of heat produced by the human's behavior or activity. Since the sensible temperature variations when human working or exercising, the amount of activity is 1 Met per unit of human metabolism while sitting on a chair at rest [12]. In the case of multiple, it is expressed as Mets.
- The clothing insulation is expressed as a quantified value of the heat retention capacity of clothes. It is a unit of the thermal resistance value of clothes, usually called clo value.
- The mean radiation or thermal radiation means that every object continues to radiate its heat as electromagnetic waves. The unit is the same as the temperature.
- The environmental temperature is considered to be equivalent to the air temperature of the room.
- The relative environmental humidity is a percent of moisture in the air.
- The airflow is represented by the average wind speed.

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

2.2 Thermal comfort estimation method

Predicting human thermal comfort through biometric data could first be found in the research of thermal manikin. The thermal manikin was developed to study the relationship between human thermal comfort and the environment [13]. When the environmental conditions are modified, the manikin's thermal resistance will change, so manikin's thermal comfort level could be estimated. Nowadays, with the development of image recognition technology, the non-contact measurement method is being proposed. Ghahramani et al. has estimated individuals thermal comfort by real-time monitoring of face thermography [14]. On the contrary, Burzo et al. used infrared thermography and some biosensors to detect humans' discomfort in the building [15]. Among the six variables of the PMV model, the clothing insulation is the most difficult to measure. However, we have just found research on the classification of clothes through the HOG algorithm [16]. It has not been applied to the prediction of thermal comfort yet.

2.3 Sensing of human biometric data with wearable sensor

Because wearable sensors are small, simple enough, and easy to be operated, people have usually used wearable sensors to measure human biometric data. Due to the development of machine learning in recent years, the approach of classification or regression using wearable sensor data to predict a specific feature or variable is applied to many studies. 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 [17]. Ozdemir et al. developed a system for detecting falls by classifying the data from accelerometer, gyroscope, and magnetometer [18]. Besides, since wearable sensors are relatively inexpensive, it is easy to decrease development costs in constructing a system. In fact, the use of wearable sensors to estimate the thermal comfort of a single individual has been tried [19].

3 PROPOSED METHOD

In order to perform regression analysis, the input data of the sensors and the correct data of the PMV value are required. The input data of PMV value could be obtained by formula or questionnaire. The continuous value obtained by the formula could be subjected to regression analysis. The discrete values obtained from the questionnaire can be used for classifying the PMV level.

3.1 Creating learning data

Formula 1 could calculate PMV value (human thermal comfort) and Formula from 2 to 5 could calculate variables of the PMV model, where M is the metabolic heat production, W is the external mechanical work of the person, P_a is the atmospheric pressure, t_a is the environmental temperature, RH is the relative environmental humidity, f_{cl} is the clothing area factor, I_{cl} is the insulation of the clothing ensemble, h_c is the convective heat transfer coefficient, v_{ar} is the mean air velocity, t_r is the mean radiation temperature, and t_{cl} is the surface temperature of clothing. In this paper, we did not consider the influence of wind speed, so we assume that the wind speed is 0. Besides, although the surface temperature of the clothes can be obtained by the one-variable quartic equation after the variables are introduced into formula 2, we directly measured the surface temperature of the clothing with a temperature sensor.

On the other hand, although the questionnaire can directly ask the level of human thermal sensation, the amount of data obtained in this way is extremely limited without a large number of experimental subjects. Though we investigated the experiment subjects' thermal comfort, it was only used in comparison with the calculated results, not in machine learning.

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

$$\begin{aligned} t_{cl} = & 35.7 - 0.028 * M - I_{cl} * [3.96 * 10^{-8} f_{cl}[(t_{cl} \\ & +273)^4 - (t_r+273)^4] - f_{cl}h_c(t_{cl} - t_a)]] \end{aligned} \tag{2}$$

$$h_c = \begin{cases} 2.38 * (t_{cl} - t_a)^{0.25} \\ (2.38 * (t_{cl} - t_a)^{0.25} > 12.1(v_{ar})^{0.5}) \\ 12.1(v_{ar})^{0.5} * v_{ar} \\ (2.38 * (t_{cl} - t_a)^{0.25} < 12.1(v_{ar})^{0.5}) \end{cases} \tag{3}$$

$$\begin{aligned} f_{cl} &= 1.00 + 1.29 * I_{cl} for (I_{cl} \leq 0.078 m^2 k/w) \\ f_{cl} &= 1.05 + 0.645 * I_{cl} for (I_{cl} > 0.078 m^2 k/w) \end{aligned} \tag{4}$$

$$P_a = (RH/100 * e^{-(18.6686 - 4030.18/(t_a + 235))}) \tag{5}$$

3.2 Acquisition of human biometric data

Although each variable of the PMV model could be measured from commercially available instruments such as infrared thermometers, hygrometers, and wind speed meters, it is not easy to match the data and use them for environmental control systems. Thus, we used wearable sensors such as NTC thermistors, GSR sensor, and heart rate sensor and environmental sensors and infrared temperature sensors to obtain skin surface temperature (5 locations), skin surface potential, heart rate, room temperature, and room humidity, the human radiation temperature. Considering the influence of individual differences, the BMR (Basal Metabolic Rate), including weight, height, age, sex, the four individual differences, was calculated from Formula 6 and Formula 7, and we added the BMR to the input data set. Also, we asked the thermal sensation with a questionnaire at the same time.

Although there have been related studies on inferring thermal comfort by thermal imaging technology, it is not easy to measure all variables with only one kind of camera. The mean radiation temperature requires thermal cameras, and the metabolic rate and clothing insulation need the RGB cameras with doing image processing. Additionally, air temperature, air humidity, and airflow cannot be measured with cameras. Therefore, a hybrid system is required when using cameras to estimate thermal comfort.

$$\begin{aligned} BMR(Male) = & 13.397 * Weight + 4.799 * Height \\ & -5.677 * Age + 88.362 \end{aligned} \tag{6}$$

$$\begin{aligned} BMR(Female) = & 9.247 * Weight + 3.098 * Height \\ & -4.33 * Age + 447.593 \end{aligned} \tag{7}$$

4 EXPERIMENT

4.1 Experiment Environment

In order to acquire the amount of learning data, it is necessary to obtain the wearable sensor data of the subjects while changing the environmental conditions. Therefore, we constructed a pipe-type booth as our experiment environment with two heaters, one cooler, one humidifier, and one dehumidifier for controlling indoor temperature and humidity. Figure 1 shows the appearance of the booth. The subjects were asked to stay in the booth with NTC thermistors attached to 5 parts of the body (left arm, right arm, left leg, right leg, chest), and GSR (Galvanic Skin Response) sensor and heart rate sensor attached to the fingers. Correspondence between sensors and data is shown by Table 2. The subjects' wearing position of the sensors is showing in Figure 2. After starting the experiment, we switched on or off the heater, cooler, humidifier, and dehumidifier. However, there were four output control patterns in our experiment: simultaneous open of heater and humidifier, simultaneous open of heater and dehumidifier, simultaneous open of cooler and humidifier, and simultaneous open of cooler and dehumidifier. We obtained the subjects' biometric data for each pattern, but we did not allow the experimental subjects to change their current activity and clothing before the next pattern. The subjects were also requested to report their height, weight, age, sex, activities, and clothing after each pattern with an interface shown in Figure 3. At the time of reporting, the subjects could refer to the energy expenditure of the activities table and the guideline for clo value [20–23]. For example, if a subject did the typing work during the experiment, he or she would have entered 1.5 in the metabolic rate field of the interface. Also, if a subject were wearing a short-sleeved shirt, thin long-sleeved blouse, thick jacket, thick trousers, shorts, and sports socks, he or she would have entered 1.12 in the clothing insulation field of the interface because the clo values corresponded to 0.08,

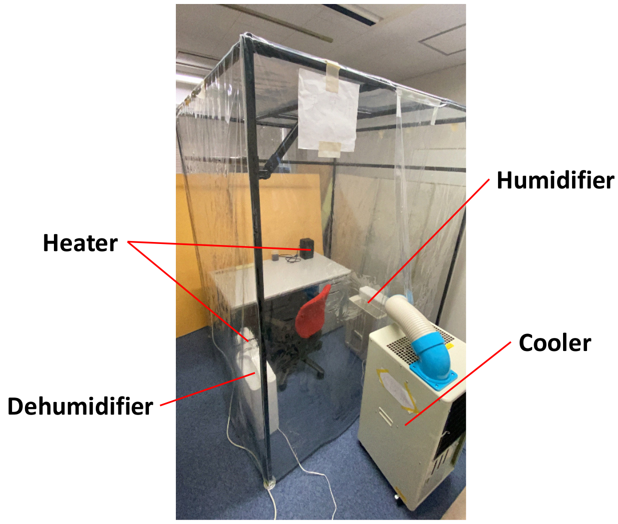

Figure 1: Experiment Environment

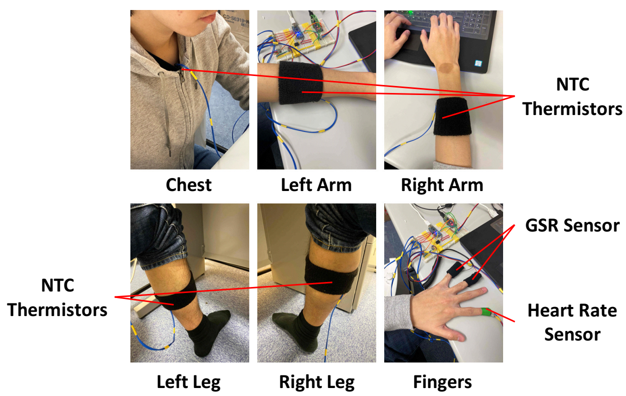

Figure 2: Implementation of Sensors

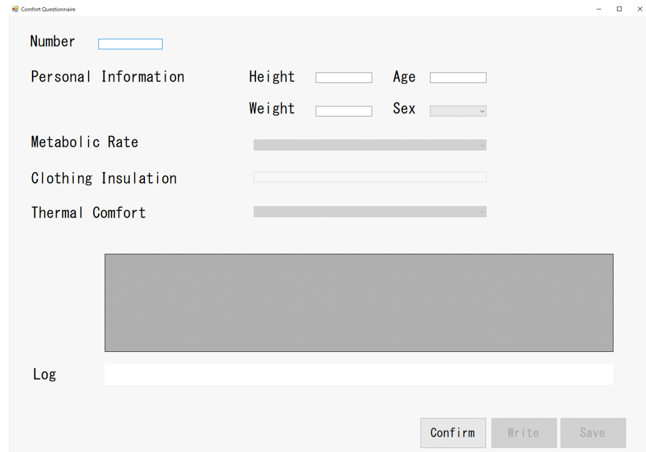

Figure 3: Comfort Questionnaire

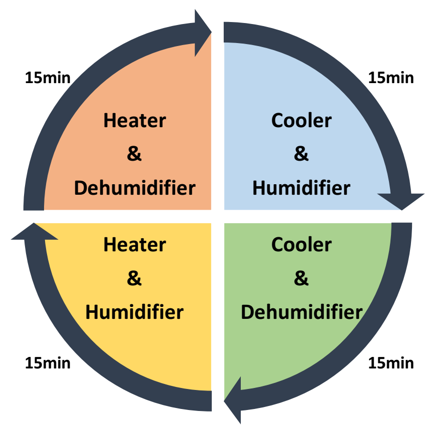

Figure 4: The Relationship between the Use of Environmental Control Equipment And the Measurement Time

0.18, 0.54, 0.24, 0.06, 0.02, respectively. Moreover, the subjects could check the input information in the gray part of the interface.

4.2 Experiment Contents

Since it takes time for the booth's temperature and humidity to stabilize, the measurement time for each pattern was 15 minutes, and sensor data was acquired at 20-second intervals during that time. Figure 4 is showing the relationship between the use of environmental control equipment and the measurement time for one subject. Above all, it would take one and a half hours for each subject if adding the experiment description time and resting time. We obtained data from 7 subjects in this paper. After the measurement, the outliers and the other sensor data simultaneously with the outlier were removed from the acquired data set.

4.3 Evaluation Method of Regression Models

The radiation temperature, clothing surface temperature, environment temperature, environment humidity obtained from the wearable sensor, and the METs and clothing insulation obtained from the interface was used to calculate the PMV value. Left arm temperature, right arm temperature, left leg temperature, right leg temperature, chest temperature, skin surface potential, heart rate, environmental temperature, environmental humidity, metabolic rate, clothing insulation, and BMR were inputted to regression models to predict PMV value. When training the model, we used 5-fold cross-validation and a time series split validation with a default value of 5. Moreover, SVM, Neural Network, and Random Forest were used to regression models, and MAE and RMSE evaluated each model. The MAE here is the average of the absolute values of the difference between the calculated PMV value and the estimated PMV value. Each regression model was created using Scikit-learn [24], and the SVM penalty function was set to 1.0. The activation function of the neural network was set as ReLU, and the optimizer was set as ADAM [25].

Table 2: Correspondence between sensors and data

Sensor Type	Sensor Name	Data Name
Wearable Sensors	NTC Thermistors	Left arm temperature, Right arm temperature, Left leg temperature, Right leg temperature, Chest temperature
	GSR Sensor	Skin Surface Potential
	Heart Rate Sensor	Heart Rate
Environmental Sensors	Thermo-hygrometer	Environmental temperature, Environmental Humidify

Besides, because the magnitude difference between the input data and output data of the regression models might cause large errors in the prediction results, we normalized the input data. Since we used many different kinds of wearable sensors, we hope to reduce the influence of physical quantities while training the model. Therefore, among the normalization methods, we chose z-score normalization, which is shown by Formula 8 [26], where X is raw data, μ is the mean of raw data, and σ is the variance of raw data.

$$Z = \frac{X - \mu}{\sigma} \tag{8}$$

4.4 Feature Expansion

The number of wearable sensors should be as few as possible so that it is essential to avoid inconvenience in predicting a person's thermal comfort in a daily environment. However, if we directly cut some feature values down, the prediction accuracy might be significantly decreasing. Therefore, we expanded the eigenvalues of input data of the regression model. Because it could be assuming that each feature value is related to time, we added the mean value 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 which are not related to time cannot be expanded. As a result, the input data set was increased from 12 dimensions to 30 dimensions.

5 RESULT

5.1 Regression Result of Thermal Comfort

The regression results of the 5-fold cross-validation are shown in Table 3, and the curve of calculated PMV value and the regression curve of each model are shown in Figure 5. The regression curve is extracted from 100 sets of the estimated PMV values for each model. Though 5-fold cross-validation obtained five regression curves, we just showed the fifth curve due to the mechanism of scikit-learn, which is the same as the regression curves in time series split validation. Although the regression results of the three models are not very different, we could still see that the SVM has the smallest prediction error, its regression curve is relatively smooth, and the fluctuation is the smallest. However, due to the characteristics of SVM prone to overfitting, we cannot say that SVM is most suitable for predicting human thermal comfort. The regression results of the time series split validation are shown in Table 4, and the curve of calculated PMV value and the regression curve of each model are shown in Figure 6. Both of the two validation methods, the MAE of Random Forest is the highest, so it is speculated that RF

Table 3: 5-fold Cross Validation Regression Result

Model	MAE	RMSE
SVM	3.12	4.35
Neural Network	3.74	4.94
Random Forest	3.53	4.73

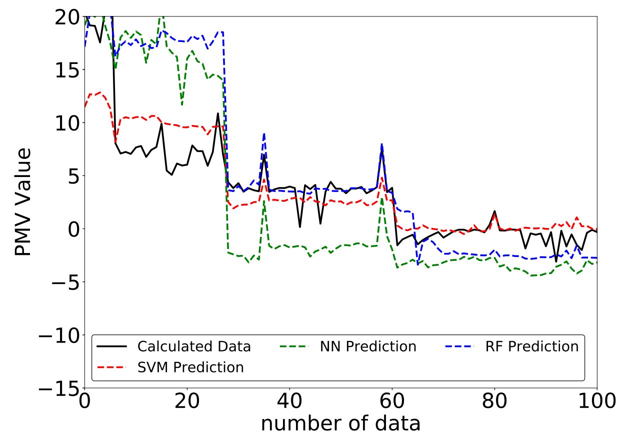

Figure 5: Calculated PMV Curve and Regression Curve in case of 5-fold Cross Validation

might not be suitable for regression analysis. Because the number of data used each time is different in time series split validation, we had thought that as the number of verifications was increasing, the MAE and RMSE would gradually be decreasing. However, in fact, there is no such situation from Table 4. In addition, the results of time series split validation are generally inferior to the results of 5-fold cross-validation. Therefore, we believe that the data in this paper does not have an intense time continuity.

5.2 Feature Squeezing

As mentioned in Section 4.4, it is best to use the fewest wearable sensors in using the estimation method in a daily environment. Although we could reduce the feature values by determining the linear correlation between the eigenvalues using PCA, we cannot guarantee that the eigenvalue with the highest linear correlation is the most appropriate. However, there are too many patterns to compare while reducing the eigenvalues in succession. Therefore,

Table 4: Time Series Split Regression Result

Model	Number of times	MAE	RMSE
SVM	1st	3.51	5.19
	2nd	3.11	3.89
	3rd	3.67	4.79
	4th	4.83	7.57
	5th	1.32	1.66
	mean	3.29	4.62
Neural Network	1st	3.19	4.97
	2nd	2.65	4.30
	3rd	4.23	5.70
	4th	4.74	7.72
	5th	2.20	2.60
	mean	3.40	5.06
Random Forest	1st	4.16	5.59
	2nd	1.52	2.13
	3rd	3.51	5.21
	4th	6.96	8.87
	5th	3.50	4.55
	mean	3.93	5.27

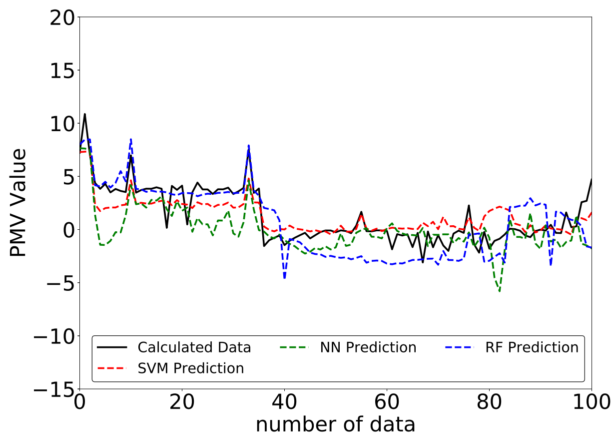

Figure 6: Calculated PMV Curve and Regression Curve in case of Time Series Split

we reduced the wearable sensor one by one according to the regression results. The feature squeezing patterns were set from pattern 2 to pattern 8 as below. The data used in each pattern is shown in Figure 7.

- Pattern 1: All data.
- Pattern 2: Exclude METs and clo value from all data.
- Pattern 3: Exclude environmental temperature and environmental humidity from all data.
- Pattern 4: Exclude METs, clo value, environmental temperature, and environmental humidity from all data.
- Pattern 5: Excludes right arm temperature and right leg temperature based on pattern 4 data.
- Pattern 6: Excluding left arm temperature and left leg temperature based on pattern 4 data.

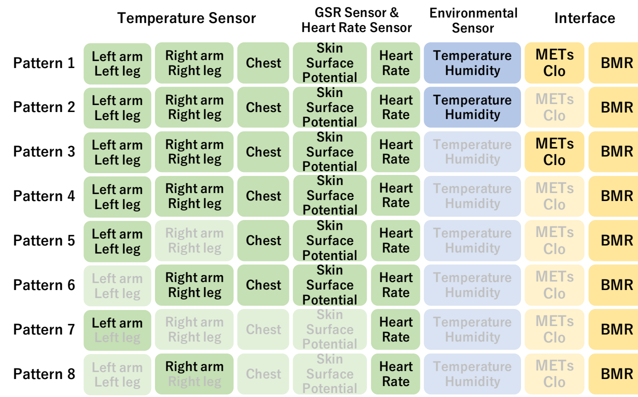

Figure 7: Data used in each pattern

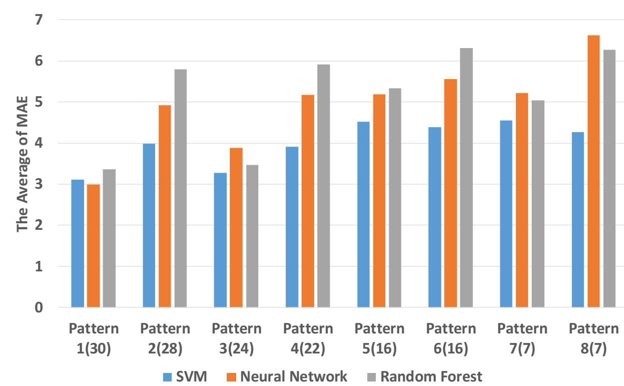

Figure 8: MAE value for each pattern in each regression model

- Pattern 7: Excluding left leg temperature, chest temperature, and skin potential based on pattern 5 data.
- Pattern 8: Excluding right leg temperature, chest temperature, and skin potential based on pattern 6 data.

The squeezing result is shown in Figure 8. We could see that the MAE of Random Forest is relatively large in all patterns, while the MAE of SVM is relatively small. And MAE is roughly on the rise among the 8 patterns. Although the number of eigenvalues used between Pattern 5 and Pattern 6, and between Pattern 7 and Pattern 8 are the same, we could still see that Pattern 5 is better than 6, and Pattern 7 is better than 8. In other words, when using the temperature data of the left half human body, the regression results would be better. Consequently, although we have reduced the number of sensors to two kinds, we still need to improve the prediction accuracy when using a few wearable sensors.

5.3 Limited PMV regression results

In the regression curve shown in Section 5.1, we could see that the calculated PMV value have reached 20, which does not conform to the definition of PMV, that is, the range of PMV cannot exceed -3 to 3. The wearable sensor data might cause this error, but because

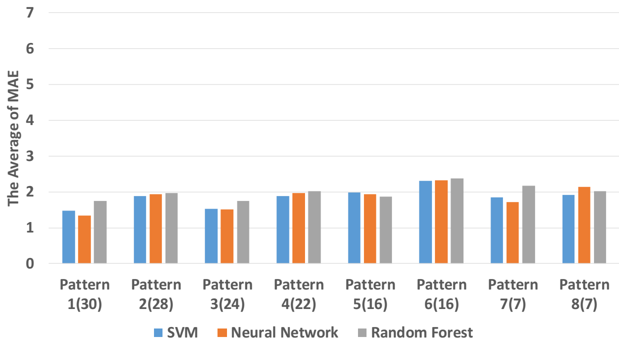

Figure 9: Limited Comfort Regression Results at Timing 1

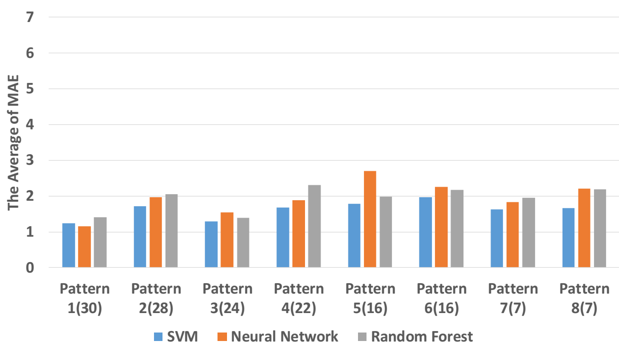

Figure 10: Limited Comfort Regression Results at Timing 2

of the unexpected situation of the sensors during the measurement process, we cannot make up the error for now. Excluding the calculated values with large deviations, the remaining calculated values are not within the normal range. However, we compared the calculated PMV value with environmental conditions. Although there is a large error in the value, the trend of both is consistent. Here, we can limit the PMV calculation value; specifically, the results below -3 are all changed to -3, and the results above 3 are all changed to 3. This restriction can be set at the following two timings.

- Timing 1: Limit the calculated PMV value before regression analysis.
- Timing 2: Limit the estimated PMV value after regression analysis, and the calculated PMV value when comparing with the estimated value.

The restricted results at the two timings are shown in Figure 9 and Figure 10. We found that under the condition of limiting the range of calculated PMV value, MAE is indeed greatly reduced compared to section 5.2, but it is still high. We hope that MAE could be suppressed below 0.5. In addition, the variation of MAE from pattern 1 to pattern 8 is not obvious. Finally, we did not see the difference in the results under the two timings.

6 CONSIDERATIONS

6.1 Discussion on Mets

Although METs could be acquired by referring to the energy expenditure table of activities, we could also calculate by the following Formula from 9 to 13. The energy consumption at rest in Formula 12 is equivalent to energy consumption when the exercise intensity is 1. Because the BMR contained in the numerator and denominator could be reduced when calculating RMR (Resting Metabolic Rate), the calculated METs not include individual differences except age. In other words, the thermal comfort of the human calculated by the PMV model does not consider the impact of individual differences. In this paper, the Karvonen Formula was used, but the expression of exercise intensity has nothing to do with the elimination of individual differences [27].

$$\text{Maximum Heart Rate} = 220 - \text{Age} \tag{9}$$

$$\text{Exercise Intensity} = \frac{(\text{Heart Rate} - \text{Resting Heart Rate}) * 100}{\text{Maximum Heart Rate} - \text{Resting Heart Rate}} \tag{10}$$

$$\text{Energy Consumption} = BMR * \text{Exercise Intensity} * \text{Time} \tag{11}$$

$$RMR = \frac{\text{Energy Consumption} - \text{Resting Energy Consumption}}{BMR} \tag{12}$$

$$RMR = 1.2 * (METs - 1) \tag{13}$$

6.2 Errors resulting from PMV model parameters

In this paper, we used the calculated PMV value as the correct data of thermal comfort. However, because each variable of the PMV model has a certain applicable range, if the variables exceed their applicable range, the calculated PMV value will become extremely inaccurate. The applicable range of each variable of the PMV model is shown in Table 5. According to the measured values acquired from the experiment, we can find that some of the data are indeed out of the range. In addition, when obtaining the clo value, the clo value entered might be different from the actual value due to the different understanding of the subject. Finally, since we could not get the wind speed sensor, we have assumed that the wind speed is zero in the experiment. Therefore, the convective heat transfer coefficient cannot be calculated correctly. In fact, according to the experimenter's feedback, they had slightly felt the airflow during the experiment. And this might also lead to errors in calculating PMV.

6.3 Precautions for the questionnaire

In the PMV model, the expression of words for human thermal comfort is slightly different from the definition in English, so there is a little difference in asking thermal sensation to the subjects. In Japanese, words such as "warm" and "cool" tend to give the subject

Table 5: 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

a positive image. However, all non-neutral scales in the definition of PMV scale are negative expressions. Thus, it is considered more appropriate to ask the subject, "How many degrees do you want the temperature to rise or fall?" rather than asking the subject about the feeling of thermal sensation.

7 CONCLUSIONS

In this paper, we proposed a method of estimating human thermal comfort in an indoor environment using wearable sensors. In the proposed method, we acquired biometric data such as skin surface temperature, skin surface potential, heart rate, metabolic rate, and clothing insulation and environmental data such as environmental temperature and environmental humidity. We performed regression analysis results by three regression models. In evaluating the regression model, SVM had the best result under 5-fold cross-validation and time series split validation. As a result of dimensionality reduction to wearable sensor data, it was confirmed that the PMV value could be estimated from the 7-dimensional data set acquired from the left arm temperature sensor and heart rate sensor. Besides, MAE was further reduced by limiting the PMV calculated value, but this result is necessary to be verified in a daily environment.

One of the future tasks is to perform classification results using the answered thermal sensation by the subjects as correct thermal comfort data, and we need to compare the regression results with classification results to verify whether the calculated PMV value is trustworthy. Since it is difficult to improve the comfort estimation result only by wearable sensors, it is conceivable to use multiple cameras and wearable sensors in performing regression analysis with the CNN model.

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