Master's Thesis

Title

Real-time indoor environmental control method for improving personal thermal comfort using multimodal biometric information

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Abstract

With the widespread adoption of remote work and satellite offices, the diversification of work environments has been progressing. However, the deterioration of the indoor environment has been pointed out as a factor that hinders productivity. When the quality of the indoor environment is not properly maintained, it can lead to increased psychological stress and negative health effects. High temperatures cause uncomfortable conditions, while low temperatures can result in cold-induced uncomfortable feelings and weakened immune function. These effects not only lower short-term productivity but also increase long-term physical and mental health risks. Additionally, thermal comfort perception varies significantly among individuals depending on factors such as age, gender, psychological state, and activity level. Previous studies have shown that individual differences in thermal comfort within thermal environments are statistically significant, particularly among highly sensitive groups such as the elderly and children.

Therefore, when estimating thermal comfort, it is necessary to develop a personalized model that considers individual characteristics. Research utilizing wearable devices has confirmed that biometric information (e.g., electrocardiograms, respiration, and skin electrical activity) can be used to estimate comfort with high accuracy. Based on these technologies, personalized indoor environmental control using actuators has been proposed, and it has been suggested that achieving an optimal thermal environment contributes to improved comfort. However, most existing studies have relied on estimation models created from datasets or actuator operations based on average indicators.

This thiesis aims to provide a comfortable indoor environment tailored to individuals through personalized indoor environmental control. The proposed method measures

multimodal biometric information and utilizes it to estimate human states. Yuragi learning enables estimation while tolerating noise, addressing the issue that biometric data generally contains a significant amount of noise.

Yuragi learning is an approach inspired by decision-making models in the brain. It defines a dynamical model where decision variables possess attractors, allowing them to store information. When an observation is given, the system outputs a confidence value indicating which stored information is being observed. Yuragi learning was applied to estimate individual thermal comfort. Furthermore, we extended Yuragi learning to process multimodal data. A feature selection method was introduced to extract relevant features from multimodal biometric information and select the most useful ones for estimation, enabling the creation of a personalized model for each individual.

By determining actuator operations based on the estimated thermal comfort, the system can provide a comfortable indoor environment tailored to individuals. We implemented a system that measures biometric information, estimates thermal comfort using multimodal Yuragi learning, and controls actuators accordingly. Experiments were conducted to verify the system's effectiveness in mitigating uncomfortable conditions.

In the experiment, different temperature and humidity environments were prepared, and participants moved from one environment to another after spending a certain period in the initial setting. In this situation, it was demonstrated that thermal comfort could be accurately estimated and that appropriate interventions could be performed. Additionally, new insights were obtained, suggesting the necessity of incorporating weighting mechanisms and long-term pre-training to achieve more personalized estimations. Additionally, when performing actuator control, caution is required when both confidence levels are low. Determining the most appropriate control method for improving thermal comfort remains a subject for future research.

Keywords

Biometric information

Feature selection

Multimodal

Thermal comfort

Yuragi learning

Actuator control

Real-time estimation

Personalized model

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1 Introduction

The spread of remote work and satellite offices has diversified people's working environments, drawing increasing attention to the importance of the indoor environment in recent years. However, depending on the environment, it may hinder people's activities, leading to a growing focus on research regarding the quality of the indoor environmental quality (IEQ) and its impact on human cognition [1].

The indoor environment comprises various elements such as the thermal environment, lighting, noise, indoor air quality, and non-visual light factors, which are reported to affect humans both psychologically and physically. Among these, it has been pointed out that when the quality of the indoor environment, such as temperature and humidity, is not properly maintained, people's psychological burden increases, potentially causing adverse health effects [2]. High-temperature environments cause uncomfortable conditions, increase heart rate, and induce fatigue, while low-temperature environments lead to uncomfortable feelings from cold and weakened immune function. These effects can result in reduced productivity in the short term and increased mental and physical health risks in the long term. Even short-term mental stress may accumulate into long-term and persistent burdens, severely impacting health.

To address these issues, it is necessary to estimate thermal comfort. People's sense of being comfortable or uncomfortable varies even in the same environment. These differences are influenced by various factors, such as age, gender, psychological state, and current activity levels. Conventionally, the prediction and evaluation of thermal comfort in indoor environments have been primarily conducted using PMV (predictive mean vote) [3], but the limitations of the PMV model have been analyzed in various studies. In this regard, Ref. [4] emphasizes the importance of individual differences in thermal comfort. This study observes significant variations in subjective comfort levels in thermal environments among numerous participants, demonstrating that these individual differences are statistically significant. Such differences explain why individuals take different heating or cooling actions even within the same office or residence. Furthermore, these individual differences are particularly prominent in sensitive groups, such as the elderly and children, suggesting they have different comfortable temperature ranges from other age groups.

In response to these challenges, many approaches use biometric information to estimate people's psychological states. The authors of [5] investigate the relationship between biometric information and psychological states and demonstrate that physiological data obtained from wearable devices (e.g., electrocardiograms (ECG), respiration (RESP), electrodermal activity (EDA)) can predict stress and emotional states with high accuracy. This study achieved a classification accuracy of up to 80% for distinguishing between neutral, stress, and pleasure states, and up to 93% for distinguishing between stress and non-stress states. Although the study focuses on stress induced by specific tasks, similar estimations are expected for stress caused by impaired thermal comfort.

In the context of thermal comfort, it has also been shown that comfort levels can change rapidly during transient states, such as when moving from one environment to another or when temperature or occupancy density changes within the same environment. For instance, environmental changes (e.g., moving from a quiet to a noisy environment) induce stress responses, increasing psychological and physiological burdens [6]. This indicates that comfort in indoor environments is highly susceptible to changes in the surrounding environment.

In Ref. [7], participants exhibited adaptive behaviors such as turning on fans or opening windows when thermal comfort became uncomfortable. There are also attempts to automate these behaviors using air conditioning devices [8]. This study implements automatic control of HVAC (heating, ventilation, and air conditioning) systems based on preset values set by participants and on thermal sensations estimated from skin temperature and heart rate. The control based on estimation demonstrates timely adjustments to temperature settings and provides a more comfortable thermal environment than control based on preset values. This research highlights the potential to improve individual comfort through interventions tailored to each person.

Therefore, it is essential to maintain thermal comfort to prevent various adverse effects on the human body. Stress levels tend to increase particularly during environmental transitions, highlighting the necessity of targeted interventions at these moments. While research on estimating comfort using biometric information exists, few studies emphasize personalization based on environmental changes and individual differences. Moreover, research integrating actuator control with such estimations remains limited. Thus, a comprehensive approach addressing these aspects is required.

This thesis proposes a method for estimating personal thermal comfort and providing an optimal indoor environment. By utilizing multimodal biometric information for learning and estimation, the system enables the prediction of individual-specific thermal comfort. Based on these estimations, actuators are controlled as needed at appropriate times to intervene in the environment, leading to a comfortable state. Performing these processes in real time ensures the continuous creation of an optimal space where individuals can function comfortably. The proposed method was introduced, and its effectiveness was verified through experiments.

This thesis is structured as follows: Section 2 reviews related studies, while Section 3 describes the proposed method in detail. Section 4 presents the experiments conducted to validate the effectiveness of the method, and Section 5 summarizes the results and discussion. Finally, the conclusion is presented in Section 6.

2 Related Work

2.1 Indoor Thermal Comfort

Thermal comfort is defined as ”the condition in which a person perceives the surrounding thermal environment as comfortable and does not experience an uncomfortable state” [9]. Although this definition is a subjective sensation, ANSI/ASHRAE Standard 55-2017 defines multiple environmental and personal factors to enable its evaluation. This standard classifies the factors affecting thermal comfort into the following six categories:

- **Air Temperature**: The temperature of the air, generally considered comfortable within the range of 22–26°C.
- **Relative Humidity**: The proportion of water vapor in the air, with a comfortable range typically between 30–60%.
- **Mean Radiant Temperature (MRT)**: The average temperature of surrounding objects and surfaces emitting radiant heat, influenced by the surface temperatures of walls, ceilings, etc.
- **Air Velocity**: The speed of air movement; moderate airflow enhances comfort, while excessive airflow causes uncomfortable feelings.
- **Metabolic Rate**: An indicator of human activity levels, where sitting corresponds to 1.0 MET and walking to approximately 2.0 MET.
- **Clothing Insulation**: A numerical representation of the thermal insulation provided by clothing, typically 0.5 clo for light clothing and over 1.0 clo for winter clothing.

To evaluate thermal comfort, the Predicted Mean Vote (PMV) model has been established [3]. PMV represents the predicted mean thermal sensation (e.g., hot, cold) experienced by a large group of individuals under specific environmental conditions. The PMV model was developed using extensive data collected through laboratory experiments and field studies. This data was gathered based on a self-assessment scale where subjects reported their perceived thermal sensation under specific indoor environmental conditions, using a seven-point scale ranging from -3 (cold) to $+3$ (hot) as shown in Table 1. The predictive equation is defined in Eq. (1), where M represents the metabolic rate (W/m^2), and L represents the thermal load (W/m^2) that the human body must dissipate to maintain thermal equilibrium. The thermal load is calculated using various parameters such as metabolic rate (energy generated by the body, W/m^2), water vapor pressure (Pa), air temperature (°C), and clothing area factor (clothing surface area/body surface area).

$$\text{PMV} = \left[0.303e^{-0.036M} + 0.028\right] \cdot L \tag{1}$$

Although PMV provides an average prediction, not everyone perceives comfort in spaces deemed comfortable according to PMV. The Thermal Comfort Vote (TCV) [3] is an index that focuses on individual perceptions of comfort. TCV is widely used to evaluate subjective comfort levels in thermal environments and is represented using a four-level scale (Table 2). This index allows for a more personalized evaluation of environmental comfort.

Table 1: PMV scale and predictive sensation

Scale	**Predictive Sensation**
+3	Hot
+2	Warm
+1	Slightly warm
0	Neutral
-1	Slightly cool
-2	Cool
-3	Cold

Table 2: TCV Scale

TCV Scale	**Definition**
0	Comfortable
-1	Slightly uncomfortable
-2	Uncomfortable
-3	Very uncomfortable

2.2 Thermal Comfort Estimation Using Biometric Information

Recent studies have recognized the relationship between biometric information and human thermal sensation, reporting that thermal comfort can be estimated using sensors [10]. A machine learning-based approach has been proposed to estimate human thermal comfort using a small number of wearable and environmental sensors. As indicators of thermal sensation, both subjective thermal comfort (representing personal thermal perception) and objective thermal comfort (calculated using the PMV equation) are utilized. Correct labels for both types of thermal comfort were obtained through subjective questionnaires and PMV-based calculations.

To build estimation models, data was collected using wearable and environmental sensors. This included biometric data such as skin temperature, clothing surface temperature, and heart rate, as well as environmental data such as air temperature, radiant temperature, humidity, and wind speed. Additionally, individual characteristics such as basal metabolic rate (BMR), metabolic equivalent (MET), and clothing insulation value (Clo) were incorporated into the model's training data to account for individual differences. These individual characteristics are key variables in the PMV model for thermal comfort calculation and contribute to improving the model's accuracy.

Experiments were conducted in a specially designed space (1.5m$\times$1.5m$\times$2.0m) equipped with heaters, air conditioners, humidifiers, and dehumidifiers to control temperature and humidity, allowing participants to experience different environmental conditions. Participants wore sensor-equipped wristbands on their left and right arms and legs, with an additional sensor attached to the right thigh to measure clothing surface temperature. A pulse sensor was placed on the left pinky finger, and environmental sensors such as wind speed sensors, temperature and humidity sensors, and infrared camera modules were also used.

During the experiment, sensor data was collected every 15 minutes while environmental temperature and humidity were adjusted. To assess subjective thermal comfort, participants were asked to answer comfort-related questions. Before starting the experiment, participants were given a break period and were asked to provide personal data such as metabolic rate (MET) and clothing insulation value (Clo).

Using the collected data, three machine learning models—Support Vector Machines (SVM), Neural Networks, and Random Forest—were trained. A five-fold cross-validation approach was used, and data normalization was performed using z-scores. Temporal feature extraction was applied to the sensor data, resulting in 1,605 data sets, of which 1,284 were used for training and 321 for testing.

Among the three machine learning models, the Random Forest model achieved a mean absolute error of 0.73, making it suitable for predicting subjective thermal comfort on a seven-level scale, while the Neural Network model achieved a mean absolute error of 0.47, making it suitable for predicting objective thermal comfort. By altering sensor combinations, the estimation accuracy was analyzed, demonstrating that human thermal comfort can be roughly estimated even with a small number of sensors.

This study highlights the improvement in accuracy achieved through personalization. The existing research created an average model based on biometric information from all participants but did not generate individualized models. Therefore, in this thesis, we propose a method that creates personalized models and extends them to include actuator control following the estimation.

3 Real-time Indoor Environmental Control Method

This thesis proposes a method for estimating personalized thermal comfort and providing a comfortable environment. By utilizing multimodal biometric information for learning and estimation, it becomes possible to predict individual thermal comfort variations. Based on this estimation, actuators are operated at the necessary timing and intensity to intervene in the indoor environment, guiding it toward a comfortable state. Performing these processes in real-time ensures the creation of a space where individuals can consistently operate in comfort.

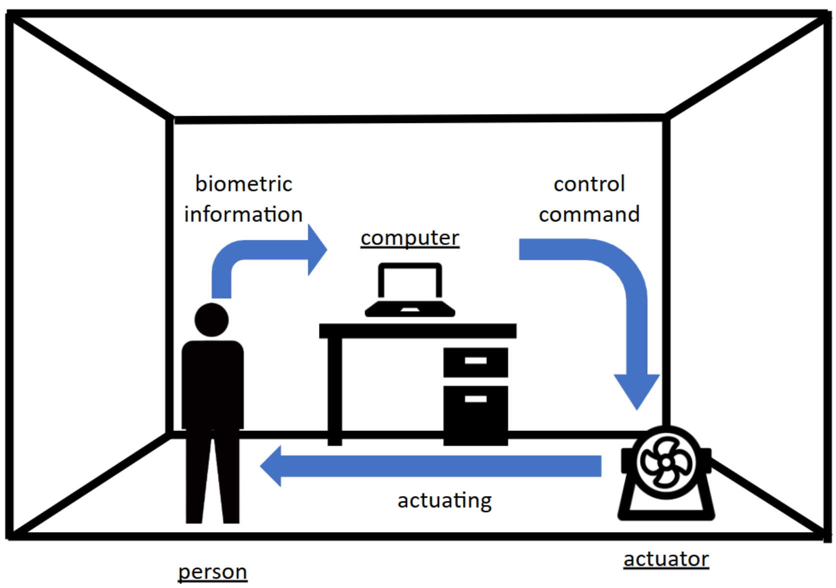

Figure 1: System overview

3.1 Estimation of Personal Thermal Comfort

Wearable sensor data often contain noise, which poses a challenge for real-time situational judgment. To address this issue, our research employs Yuragi learning [11], a method proposed by our research group. Reference [12] applies Yuragi learning to the stress estimation. This method utilizes the Bayesian Attractor Model (BAM) [13], which models human decision-making processes, to estimate stress states based on biometric information.Furthermore, it has been demonstrated that, similarly, by utilizing biometric information, this approach can be applied not only to stress estimation but also to the estimation of thermal comfort. [14].

In [13], the authors formulates decision-making tasks as problems in which multiple choices are available based on observed information. The process leading to decision-making is modeled as a probabilistic framework using Bayesian estimation. To model decision-making in the brain, a decision variable is defined along with a dynamical system containing attractors, where each choice corresponds to one attractor.

It is generally understood that the brain accumulates sensory information over time and makes decisions once sufficient information is gathered. However, the precise mechanisms underlying this accumulation remain an important unresolved issue. For example, sensory processing involves feedback related to ongoing decision-making, and modeling how individuals compute confidence in their decisions is another aspect of this challenge. Furthermore, conventional decision-making models typically consider only a single decision and terminate modeling once the decision is made. BAM was proposed to address these challenges. The following sections describe how Yuragi learning is applied to classify thermal comfort states within the system.

3.1.1 Setting of Attractors

In BAM, information is observed periodically, and Bayesian estimation updates the internal decision variable with each observation. The extent to which the estimated decision variable approaches a particular attractor is defined as confidence. BAM determines the most appropriate choice among predefined options through Bayesian estimation based on external stimuli (observation). BAM maintains a decision state z_t, which is updated by observation x_t. In Bayesian estimation, z_t is not treated as a single fixed point but rather as a probability distribution $P(z_t)$ that reflects uncertainties in observations and brain states. The state space of z contains n attractors $\Phi_1, \ldots, \Phi_n$ corresponding to the number of predefined choices. When z_t sufficiently approaches Φ_i, the system makes a decision to select the i-th option. Because z_t is represented probabilistically, confidence in decision-making is derived from the probability density of $z_t = \Phi_i$.

3.1.2 Feature Selection

In this estimation process, six types of features are extracted from multiple modalities (such as electrodermal activity and skin temperature): mean, standard deviation (std), minimum (min), maximum (max), range, and slope. From these, only the features useful for estimation in each modality will be selected.

At each time step, the wearable sensor captures modality observations o_t, and based on these observations, known features x^{cand} related to stress in each modality can be extracted. Since x^{cand} includes various types of observed values with different ranges, normalization is performed for each feature. The normalization parameters are the mean μ and variance σ of the observed values labeled as a comfortable state. The j-th element of x_t, denoted as $x_{t,j}$, is defined by Equation (2), where x_j^{cand} represents the j-th element of x^{cand}.

$$x_j = \frac{x_j^{\text{cand}} - \mu}{\sigma} \tag{2}$$

Next, for these normalized observations x_j, feature selection is performed for each individual based on their thermal comfort response. The criterion for selection is the extent to which the values differ between uncomfortable and comfortable states. This thesis focuses on the difference between uncomfortable states and comfortable states.

The feature selection process for thermal comfort classification follows the steps below (Figure 2). Here, the set of pre-collected candidate features for training is denoted as X_{train}, and the label L_o indicates whether each feature belongs to a uncomfortable or comfortable state.

1. Calculate the mean value of x_j for the observations labeled as uncomfortable in X_{train}:

$$\bar{x}_j = \frac{\sum_{\{o:o\in O_{\text{train}},L(o)=i\}} x_j}{|\{o : o \in O_{\text{train}}, L(o) = i\}|} \quad (i = \text{uncomfortable}) \tag{3}$$

2. Compare $\bar{x}_j$ with the threshold λ and select or discard the feature:

   - If $\bar{x}_j$ is greater than or equal to λ, select the j-th feature:

$$\bar{x}_j \geq \lambda : x_j \text{ is selected} \tag{4}$$

- If $\bar{x}_j$ is smaller than λ, discard the j-th feature:

$$\bar{x}_j < \lambda : x_j \text{ is removed} \tag{5}$$

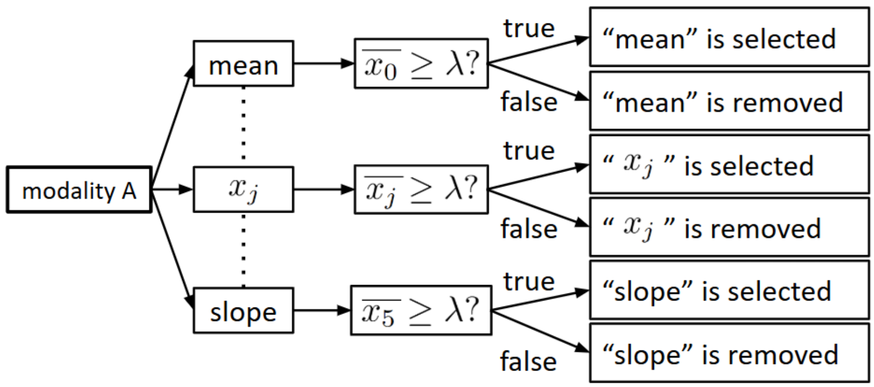

Figure 2: Feature selection flow

The above process is applied individually to each modality. Since biometric responses to environmental changes vary from person to person, this method personalizes the thermal comfort classification model, making it more adaptive to individual differences.

For thermal comfort estimation, biometric information must be measured for a fixed duration $T_{estimate}$. The actuating cycle $T_{control}$ is performed at the interval in which the estimation results are obtained. In this experiment, $T_{control} = T_{estimate}$, and this duration is set to 1 minute. Notably, since no estimation results are available immediately after the experiment starts, the actuator remains in its initial state during $T_{estimate}$.

3.1.3 Multimodal Integration Processing

The confidence scores computed for each modality using the selected features are integrated across modalities to obtain the final confidence score $P(z_t = \Phi_i|\mathbf{x})_{\text{integrated}}$ for label i under the current input x_t. This integration is performed as shown in Eq. (6), where M represents the set of modalities.

$$P(z_t = \Phi_i \mid \mathbf{x})_{\text{integrated}} = \sum_{m \in M} P(z_t = \Phi_i \mid \mathbf{x})_m \tag{6}$$

The state Φ_i with the highest confidence $P(z_t = \Phi_i|\mathbf{x})_{\text{integrated}}$ is selected as the current state.

3.2 Actuator Control for Improving Personal Thermal Comfort

The method for improving personal thermal comfort through actuator control is highly dependent on the operational specifications of each actuator. Various actuators can be used to control indoor thermal comfort, with air conditioners and circulators being commonly found in office environments. These devices can automatically modify the indoor environment by setting appropriate parameters. Determining the optimal settings requires predicting individual comfort levels when the indoor environment changes, which is beyond the scope of this thesis.

Therefore, this thesis assumes that appropriate settings are given in advance and focuses on deciding whether to adjust to those settings. If an uncomfortable state is detected, the settings are changed accordingly, whereas if comfort is maintained, it is necessary to determine whether to continue actuating or not. Since this also depends on the type of actuator, the decision must be made appropriately according to the device specifications.

For the experimental evaluation in this thesis, a circulator is used to verify the improvement of thermal comfort through on-off control. The flowchart of this process is shown in Fig. 3.

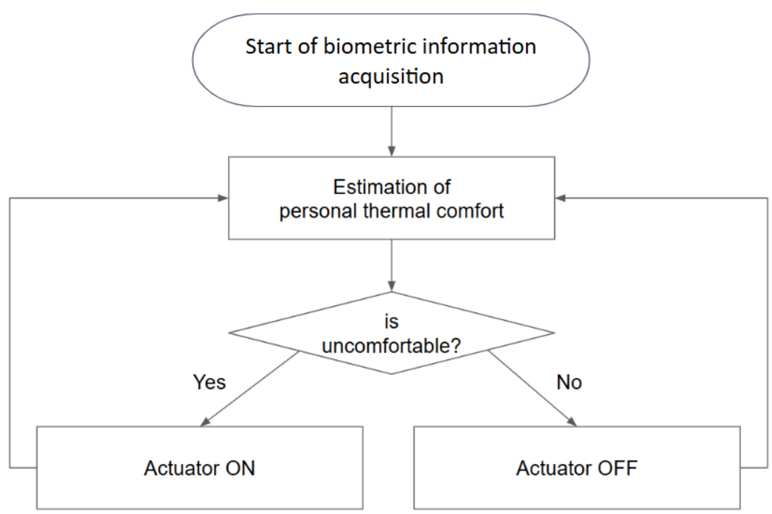

Figure 3: Flowchart of actuator control

4 Experiment

To evaluate the proposed method, an experimental evaluation was conducted. The experiment consists of two main verification points:

1. Whether thermal comfort can be accurately estimated.

2. Whether environmental intervention can effectively actuate.

For the first verification, we examine whether the estimation correctly accounts for individual differences in thermal comfort perception. In this experiment, temperature and humidity in the indoor environment are used as factors influencing comfortable and uncomfortable states. Two rooms are prepared as the experimental environment, with one set as a comfortable environment and the other as an uncomfortable environment. The temperature and humidity in each room are adjusted using air conditioners and heaters to create a personalized environment based on the uncomfortable and comfortable levels of each participant. Initial values are set according to PMV and further adjusted based on participant feedback through questionnaires to personalize the environment (Table 3).

Table 3: Room setting

Room number	**Default**	**Situation**
Room1	$PMV = 0$	Comfort
Room2	$PMV = 2$	Uncomfortable

Table 4: TSV scale

TSV Scale	**Definition**
+3	Hot
+2	Warm
+1	Slightly warm
0	Neutral
-1	Slightly cool
-2	Cool
-3	Cold

The questionnaire used for adjustment is based on the Thermal Comfort Vote (TCV). If the TCV response for Room2, designated as the uncomfortable room, is “Comfortable” or “Slightly uncomfortable,” air conditioning is adjusted, and another questionnaire is conducted.

The second verification examines whether personalized and appropriate environmental intervention effectively eliminates uncomfortable conditions. In this experiment, if the system estimates an uncomfortable state, actuators will be activated to provide airflow until the environment is estimated to be comfortable. The effectiveness of the intervention is evaluated based on participant questionnaire responses, examining whether they perceive the environment as comfortable. The questionnaire is conducted every minute during the experiment, collecting both TCV and Thermal Sensation Vote (TSV) responses (Fig. 4). TSV is represented on the same seven-point scale as PMV (Table 4).

time	Sensation	Comfort
1 min	-3 · -2 · -1 · 0 · 1 · 2 · 3	0 · -1 · -2 · -3
2 min	-3 · -2 · -1 · 0 · 1 · 2 · 3	0 · -1 · -2 · -3
3 min	-3 · -2 · -1 · 0 · 1 · 2 · 3	0 · -1 · -2 · -3
4 min	-3 · -2 · -1 · 0 · 1 · 2 · 3	0 · -1 · -2 · -3
5 min	-3 · -2 · -1 · 0 · 1 · 2 · 3	0 · -1 · -2 · -3
6 min	-3 · -2 · -1 · 0 · 1 · 2 · 3	0 · -1 · -2 · -3
7 min	-3 · -2 · -1 · 0 · 1 · 2 · 3	0 · -1 · -2 · -3
8 min	-3 · -2 · -1 · 0 · 1 · 2 · 3	0 · -1 · -2 · -3
9 min	-3 · -2 · -1 · 0 · 1 · 2 · 3	0 · -1 · -2 · -3
10 min	-3 · -2 · -1 · 0 · 1 · 2 · 3	0 · -1 · -2 · -3
11 min	-3 · -2 · -1 · 0 · 1 · 2 · 3	0 · -1 · -2 · -3
12 min	-3 · -2 · -1 · 0 · 1 · 2 · 3	0 · -1 · -2 · -3
13 min	-3 · -2 · -1 · 0 · 1 · 2 · 3	0 · -1 · -2 · -3
14 min	-3 · -2 · -1 · 0 · 1 · 2 · 3	0 · -1 · -2 · -3
15 min	-3 · -2 · -1 · 0 · 1 · 2 · 3	0 · -1 · -2 · -3
16 min	-3 · -2 · -1 · 0 · 1 · 2 · 3	0 · -1 · -2 · -3
17 min	-3 · -2 · -1 · 0 · 1 · 2 · 3	0 · -1 · -2 · -3
18 min	-3 · -2 · -1 · 0 · 1 · 2 · 3	0 · -1 · -2 · -3
19 min	-3 · -2 · -1 · 0 · 1 · 2 · 3	0 · -1 · -2 · -3
20 min	-3 · -2 · -1 · 0 · 1 · 2 · 3	0 · -1 · -2 · -3

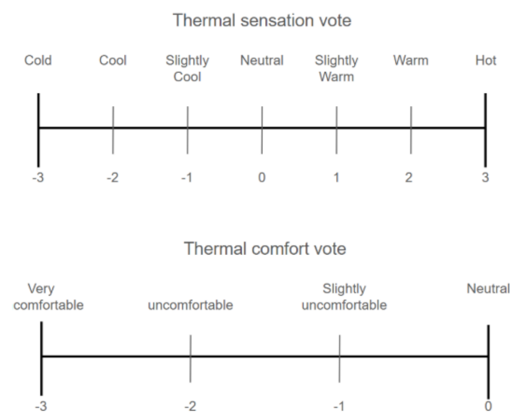

Figure 4: Questionnaire sheet

4.1 Implementation

4.1.1 Real-time Acquisition of Biometric Information

In this thesis, biometric data is obtained using the Empatica E4 wristband (Fig. 5). The E4 wristband can collect various physiological signals, including three-axis acceleration (ACC), blood volume pulse (BVP), electrodermal activity (EDA), interbeat interval (IBI), and skin temperature (TEMP). Among these, four signals (BVP, EDA, IBI, and TEMP), which are highly correlated with psychological states, are acquired in real time. The thesis [15] decomposes the raw EDA signal into three components: phasic EDA, SMNA phasic EDA, and tonic EDA, using all four components for estimation. Phasic EDA represents short-term EDA changes, while tonic EDA reflects long-term trends. SMNA phasic represents sudomotor nerve activity, assuming that phasic EDA is the impulse response result of SMNA input. Since SMNA phasic and phasic EDA exhibit similar tendencies, only phasic EDA is used for estimation. Moreover, as the experimental design involves calculating features from one-minute data segments, tonic EDA is used instead of the raw EDA signal due to its similarity in reflecting long-term changes. Consequently, phasic EDA and tonic EDA are adopted as the two electrodermal activity components for estimation, along with the six modalities listed in Table 5.

Table 5: Description and units of selected modalities

Modality	**Description**	**Unit**
phasicEDA	Short-term electrodermal activity	µSiemens
tonicEDA	Long-term electrodermal activity	µSiemens
TEMP	Skin temperature	℃
BVP	Blood volume pulse	µSiemens
IBI	Interbeat interval	Seconds

Table 6: Sampling rate of modalities

Modality	**Sampling rate**
BVP	64Hz
Others	4Hz

Data transmission is performed using the streaming server provided by Empatica. As shown in Table 6, this server receives biometric data from the E4 wristband via a TCP connection at fixed intervals.

Figure 5: E4 wristband

Figure 6: Daikin assist circulator

4.1.2 Actuator Control

In this thesis, a Daikin assist circulator is used as the actuator (Fig. 6). The circulator is controlled based on the estimated state. It is connected to a Raspberry Pi 3 Model B (RPi3) running Linux via serial communication, allowing control signals to be sent through the RPi3. The overall system communication is illustrated in Fig. 7. The computing device acts as both a server receiving biometric data and an execution unit for the estimation program. It receives biometric data via Bluetooth, transmits estimation results over a network, and sends control commands to the actuator through a wired serial connection.

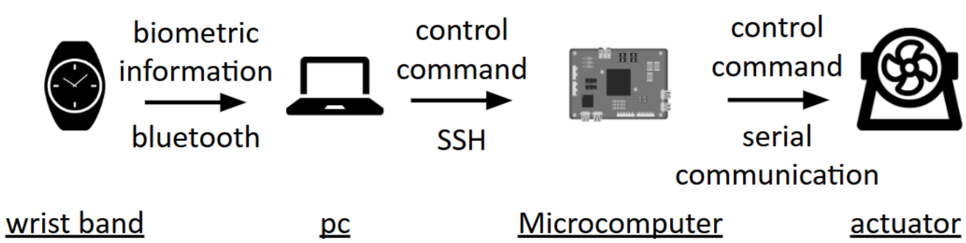

Figure 7: Overview of system connection

4.2 Experiment Flow

The experiment consists of preliminary learning in each room, followed by a control experiment where participants move from the uncomfortable room to the comfortable room while the system intervenes. The experiment follows seven steps (Fig. 8):

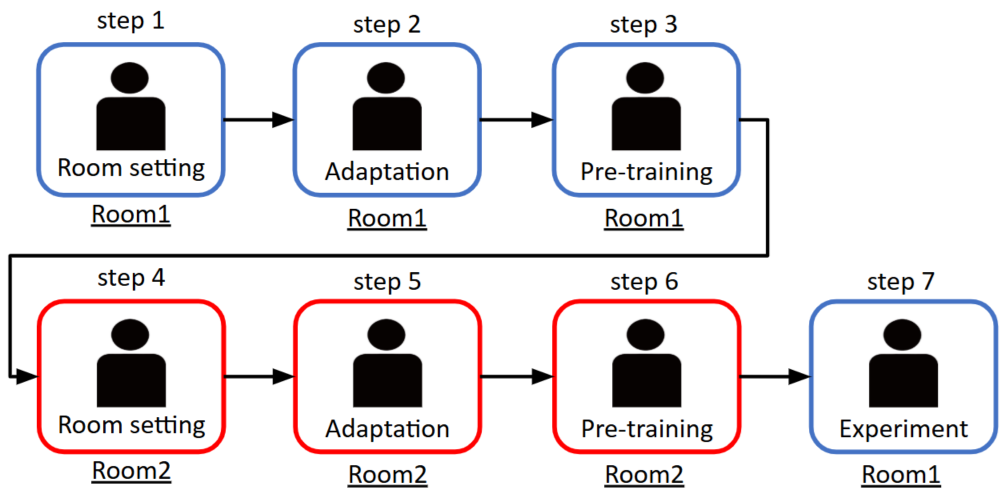

Figure 8: Experiment flow

Additionally, a comparative experiment is conducted by analyzing the case without actuator control in step 7. The estimation is carried out using the same attractor information as in the actuator control case, and by comparing the survey results and the transitions in biometric information, the effects on thermal comfort, biometric responses, and actuator control are analyzed.

5 Evaluation

The experimental result with actuator control is shown in Fig. 9, while the result without actuator control is presented in Fig. 10. The upper section of these figures illustrates the transition of confidence in step 7, where the x-axis represents the elapsed time and the y-axis represents the confidence level. The estimated result is shown in the lower section of the figure, where higher values indicate greater confidence in the estimation. Additionally, the responses from the questionnaire are shown in Fig. 11 and Fig. 12. A detailed description of the results obtained is given in the following sections.

5.1 Estimation of Thermal Comfort

As shown in Fig. 9, between 1 and 10 minutes, the system conducts estimation and outputs "uncomfortable" state. After 10 minutes, it outputs "comfortable" state. According to Fig. 11, the subjective responses indicate a continuously comfortable state. The difference between this subjective response and the biometric-based estimation results between 1 to 10 minutes raises questions. Referring to the TCV responses in the case without actuator control shown in Fig. 11, uncomfortable sensations is reported for up to 4 minutes. This suggests that while the body remains in an uncomfortable state for the first 4 minutes, airflow contributes to achieving a comfortable condition. By capturing this situation, the confidence in the comfortable state is higher with the actuator control compared to the without the actuator control.

The discrepancy between physical comfort and perceived comfort can be attributed to cognitive bias, where individuals tend to perceive relative comfort based on the difference from the previous environment. Even if the body has not fully returned to a comfortable state, respondents may perceive and report comfort. Therefore, this method is considered to capture comfort more accurately than manual control based solely on perception.

5.2 Effectiveness of Actuating

The confidence in the comfortable state increased when the circulator was running. In Fig. 9, after stopping airflow from the circulator, the confidence in an uncomfortable state continues to decrease, while the confidence in comfort increases, indicating that the timing of stopping airflow accurately reflects the physiological response. On the other hand, in the without actuator control case shown in Fig. 10, the confidence in comfort does not increase, and the confidence in an uncomfortable state, which initially stabilized, rises again.

These results indicate that airflow contributes to stabilizing the body in a comfortable state. Moreover, referring to the TCV responses, the system successfully guides the individual to a comfortable state 4 minutes earlier. Based on these findings, it is concluded that the proposed method enables efficient actuator control.

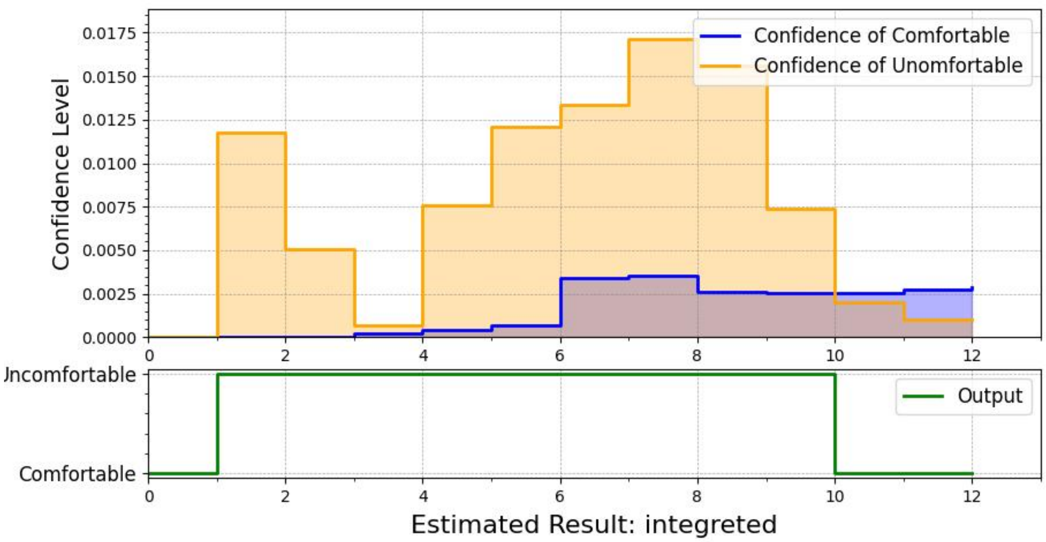

Figure 9: Estimation result: With actuator control

5.3 Discussion

The estimation results for each biometric information are shown in Fig. 13 to Fig. 16, demonstrating that the confidence variations differ across each biometric modality. Additionally, in these figures, the BVP values remain zero, and the estimation results are neutral. This is because no feature was selected for BVP, as shown in Table 7.

Comparing Fig. 9 and Fig. 14, it is shown that TEMP significantly influences the

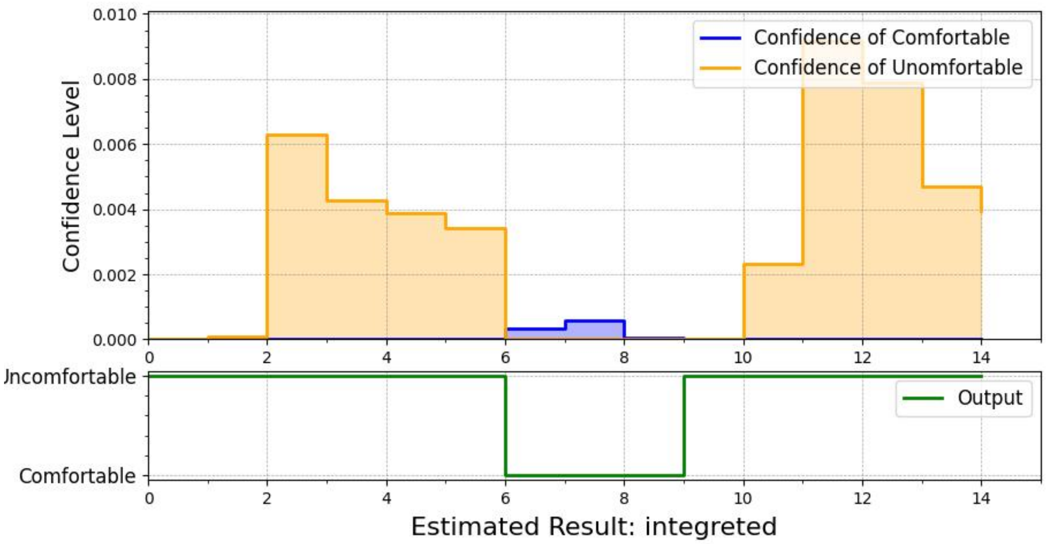

Figure 10: Estimation result: Without actuator control

estimation results between 4 and 10 minutes. However, referring to Fig. 13, the fluctuations in EDA more closely align with the TCV responses. This discrepancy, where the modality contributing most to the estimation differs from the modality that best reflects actual thermal comfort, suggests the need for applying weightings to emphasize more relevant modalities. However, determining which modality best represents thermal comfort depends on various factors, such as the psychological state at the time, and individual physiological differences. Therefore, careful design and consideration are required when assigning these weightings.

In the proposed method, biometric values representing "comfortable" and "uncomfortable" states for Yuragi-learning are determined based on a single measurement value (step 3 and step 6), and a decision is made on which feature values to use. It was confirmed that the values of biometric information and the selected feature values differed among multiple experimental runs.

This suggests that even within the same experimental protocol, the results are influenced by psychological states or activities performed on that day. Therefore, to develop

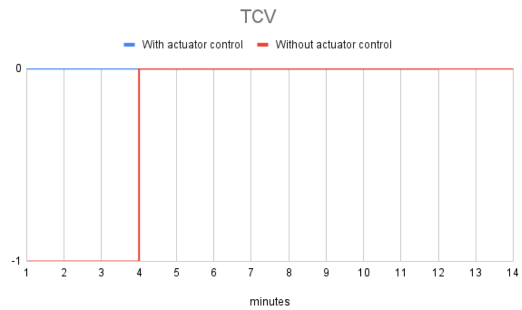

Figure 11: TCV in each experiment

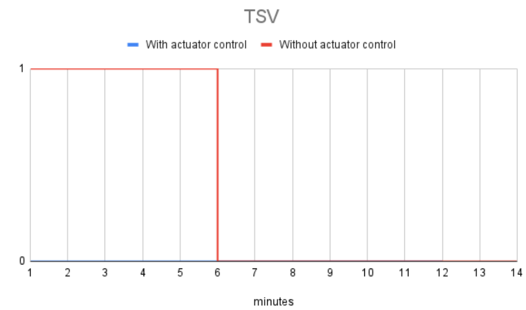

Figure 12: TSV in each experiment

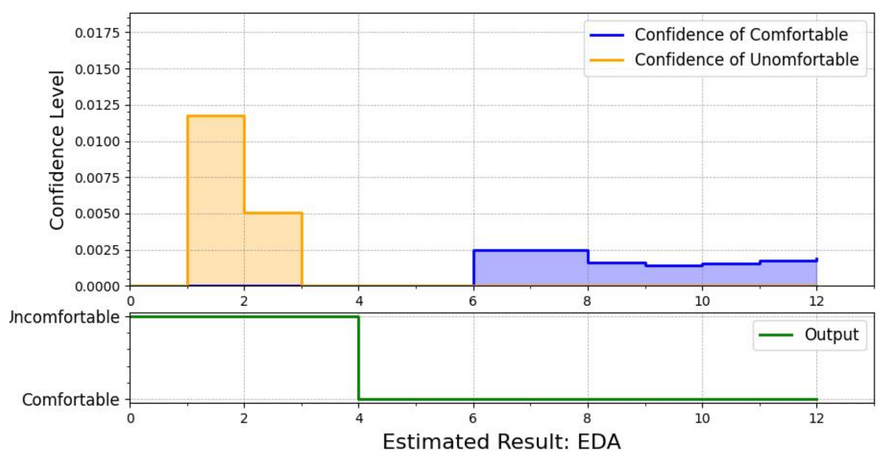

Figure 13: Estimation result of EDA: With actuator control

a more personalized model, further investigation is required regarding multiple iterations of pre-learning and methods for selecting features that adapt to varying conditions. Additionally, when performing actuator control, caution is required when both confidence levels are low. Possible actions include continuing the current operation or reverting to the initial state. Determining the most appropriate control method for improving thermal comfort remains a subject for future research.

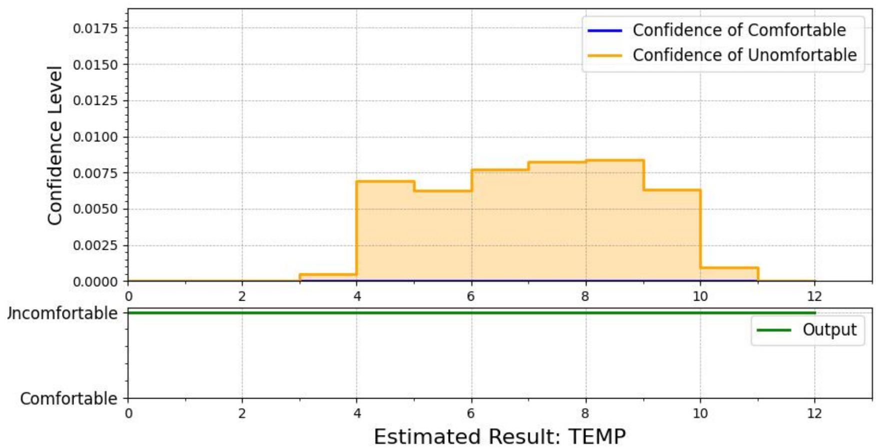

Figure 14: Estimation result of TEMP: With actuator control

Table 7: Selected feature: With actuator control

	mean	std	min	max	range	slope
phasicEDA		✓				
tonicEDA	✓		✓	✓		
temp	✓		✓	✓		✓
bvp						
ibi		✓		✓	✓	

Table 8: Selected feature: Without actuator control

	mean	std	min	max	range	slope
phasicEDA						
tonicEDA	✓		✓	✓		✓
temp	✓		✓	✓		
bvp		✓		✓		
ibi						

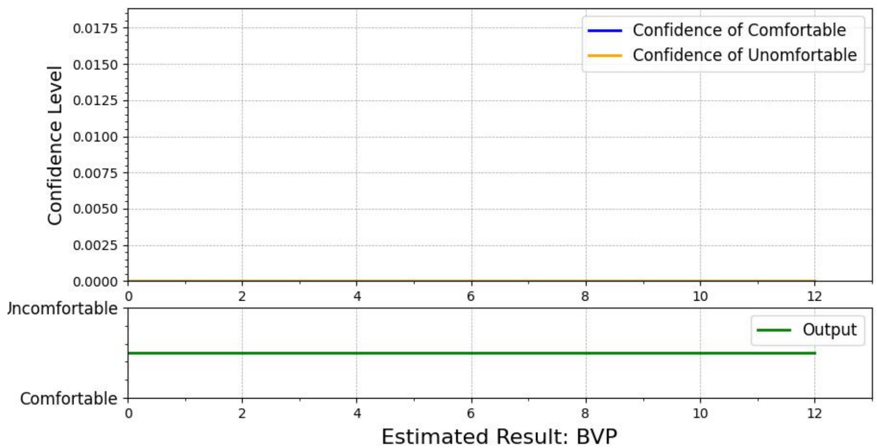

Figure 15: Estimation result of BVP: With actuator control

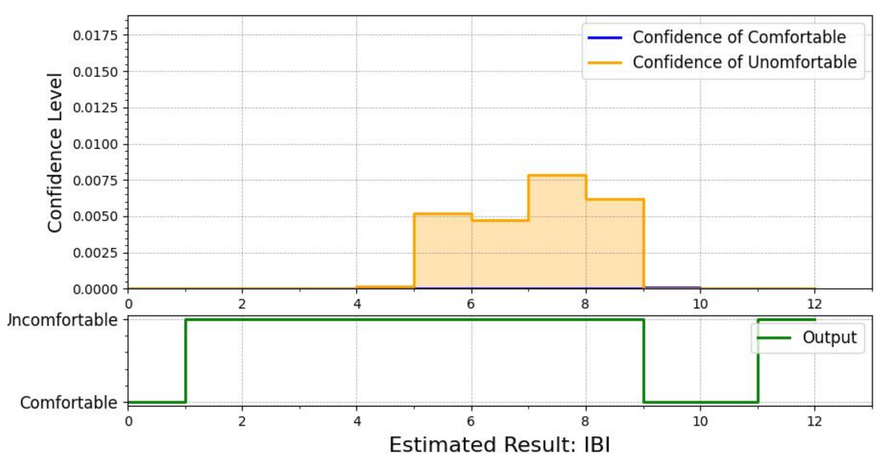

Figure 16: Estimation result of IBI: With actuator control

6 Conclusion

In this thesis, we proposed a method for estimating personal thermal comfort and providing an optimal indoor environment in real-time. By utilizing multimodal biometric information obtained from wearable devices and applying Yuragi learning, we achieved high-accuracy comfort estimation while accounting for noise. Furthermore, based on the estimation results, we controlled actuators at appropriate timings to perform environmental interventions that alleviate uncomfortable conditions.

To verify the effectiveness of the proposed method, we conducted an experiment to evaluate thermal comfort by preparing both comfortable and uncomfortable environments. The experimental results confirmed that the estimation using the proposed method appropriately captured individual differences in comfort. Additionally, it was demonstrated that actuators could be effectively controlled to enhance thermal comfort.

Future challenges include the potential for creating more personalized models. Improving accuracy can be expected by determining which biometric information best reflects an individual's thermal comfort and applying appropriate weighting, as well as increasing the number of pre-training sessions. Additionally, determining the most appropriate control method for improving thermal comfort remains a subject for future research. Furthermore, in the future, it will be necessary to extend the estimation and actuate to a broader range of individuals.

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