# Using passive BCI to online control the air conditioner for obtaining the individual specific thermal comfort *

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*Abstract*— **Thermal comfort has an important impact on human health and work efficiency, which has attracted more attention in recent years. Although electroencephalogram (EEG) has been used to evaluate thermal comfort, it has not been reported to be used in controlling the air conditioner. This paper attempted to construct a passive EEG based brain-computer interface (BCI) system to regulate the room temperature. During the experiment, EEG signals in two conditions, thermal comfort and hot discomfort, were collected to build a discriminant model. And then, an online experiment was conducted to verify the thermal comfort effect of the BCI temperature control. Results showed that all the five subjects could obtain a better thermal sensation under the BCI control in an overheated environment. This study indicated the feasibility of indoor temperature control technology based on physiological signals. It can provide a new way to obtain personalized thermal comfort.**

***Keywords*— thermal comfort; individual EEG-based discriminant model; passive brain-computer interface (BCI); online temperature control.**

## I. Introduction

Thermal comfort is a mind state that can express satisfaction with the thermal environment, which involves environmental, physiological and psychological aspects [1]. Related researches have stated the influence of thermal comfort on health and work efficiency [2,3]. Human spend most time indoors. If in a poor thermal environment for long time, uncomfortable symptoms such as pain, headache occur; meanwhile work efficiency decreases. Therefore, thermal comfort has been more popular in fields of building, energy conservation and neuroergonomics.

The one important issue is to evaluate thermal comfort. The main evaluation methods include subjective and objective methods. Subjective methods require subjects to answer some questions about thermal environment such as thermal sensation, acceptability, satisfaction and comfort [4]. Bedford proposed a 7–scale evaluation index including thermal comfort and sensation [5]. Thermal sensation has been widely used, which is distributed on 7 discrete scales from cold to hot [6]. Subjective methods can directly express subjects' current thermal comfort, but it takes time to fill in the questionnaire, which interrupts subjects' original state.

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Therefore, many scholars have proposed the objective methods to evaluate thermal comfort uninterruptedly. Relevant physiological parameters have been used to express thermal comfort objectively. Electroencephalogram (EEG) is one of sensitive parameters which can evaluate thermal comfort. Some characteristics of EEG have been found to be related to thermal comfort. For example, power of frequency bands changes under different thermal comfort levels [7]. α band dominates under neutral and slightly cool thermal sensations, while β band dominates under the other thermal sensations. During local cooling, power spectrum in δ band increases at frontal area, α activity decreases at the posterior part, and β activity increases in bilateral fronto-temporal areas [8]. Local cooling also leads to the change of EEG waveform called cold-evoked potentials [9].

However, there are individual differences in thermal comfort, mainly including age, gender, thermal history and economic level [10,11]. In the same thermal environment, the thermal sensation of different subjects may be different because of individual differences. The automatic temperature control system based on thermal comfort models generally ensures thermal comfort of most people, which ignores individual differences. Individual thermal comfort control system ensures personalized thermal comfort but requires self-feedback to the environment.

Therefore, we attempt to construct an automatic indoor temperature control system aimed at individuals, so that human can feel comfortable in an overheated environment. Passive brain-computer interface (BCI) can provide a personalized control method without self-feedback, which uses objective parameters like EEG to monitor human state for controlling external devices [12]. For example, passive BCI system can be used to monitor driving fatigue, whose aim is to improve people's performance and reduce human error. If individual thermal comfort can be monitored and controlled by passive BCI, indoor environments can meet individual comfortable requirements. In this paper, using passive BCI, we monitor thermal comfort in real time and control indoor temperature without manual operations, which have been little discussed until now.

## II. Materials and Methods

### *A. Procedure of Experiment*

Five healthy subjects (22–25 years old) participated in the experiment and signed the written consent. The experimental design included the establishment of individual discriminant model, online control based on passive BCI and the evaluation method of thermal comfort. In this experiment, we simulated a summer overheated environment and expected to control the indoor temperature to the thermal comfort range. Using EEG signals under the comfortable and hot environment, we built a discriminant model to classify comfort and hot discomfort. In the online control experiment, subjects were exposed to an overheated condition, and individual thermal comfort was maintained by a passive BCI system.

The experiment included 5 sessions as shown in Figure 1. All sessions were conducted in a 2m×2m×2.5m room. Session 1–4 were offline experiments to establish an individual thermal comfort discriminant model. In these sessions, subjects adapted to the comfortable or hot environment. Comfortable environment (session1, 3) was built by the air conditioner based on individual comfortable temperature (25-27 °C). The hot offline environment (session 2, 4) was also built by the air conditioner whose temperature was set at 30 °C. When the subjects felt comfortable or hot, the offline experiment began. They were required to stay in the condition for 20 min. By offline experiments, the discriminant model was built and used in the online control experiment.

Session 5 was the online control experiment to test the feasibility of the passive BCI system. In this session, subjects were exposed to a hot environment built by an electric heater for 20–35 min. Based on the discriminant model, thermal comfort could be monitored in real time. The air conditioner was controlled by the EEG discriminant results and the control strategy (see II. B for details).

After each session, subjects evaluated thermal comfort according to the questionnaire in Table I. Table I investigated three important responses including thermal comfort, sensation and acceptability to comprehensively evaluate subjective feeling [13]. The scores were divided into 6 discrete levels. If the score was –0.5, 0, +0.5, it meant comfort. +1 meant slightly hot discomfort but acceptable. +2 meant moderate discomfort but also acceptable. +3 meant much hot discomfort and unacceptable.

In all sessions, EEG signals were recorded by 8-lead wireless EEG device (Neuracle) at a 1000Hz sampling rate. The electrodes were placed at F3, F4, T3, T4, P3, P4, O1, O2 according to the international 10–20 system. Room temperature was recorded per minute by a thermometer placed about 1.2m above the ground. The accuracy of thermometer was ±0.2 °C.

TABLE I. 6-SCALE THERMAL COMFORT SCORE

| | | | | hot discomfort | | |
|---|---|---|---|---|---|---|
| **thermal comfort** | comfort | | | slight | moderate | very much |
| **thermal sensation** | slightly cool | neutral | slightly hot | a little hot | hot | much hot |
| **thermal accepta-bility** | acceptable | | | | | not accep-table |
| **score** | –0.5 | 0 | +0.5 | +1 | +2 | +3 |

### *B. EEG-based thermal comfort discriminant model and online BCI control strategy of air conditioner*

Figure 2(a) showed the establishment of the individual thermal comfort discriminant model. EEG data of session 1–4 composed an offline EEG data set. After 0.5–35Hz filtering, the preprocessed data set was divided into 1 s epoch without overlap. In feature extraction, power spectrum density (PSD) of each epoch was calculated, which converted EEG into frequency domain data in four frequency bands (δ: 0.5–4Hz; θ: 4–8Hz; α: 8–13Hz; β: 13–30Hz) [14]. PSD () represented the PSD of a certain frequency band. For example, PSD (δ) meant the PSD of δ band. We chose the PSD ratio of each low-frequency band and the total high-frequency bands as the feature set, i.e. PSD (δ)/ (PSD (α)+PSD (β)), PSD (θ)/ (PSD (α)+PSD (β)). The dimension of the feature set was 16. We used supported vector machine to establish a thermal comfort discriminant model which could classify comfort and hot discomfort.

Figure 2(b) showed the real-time process of online EEG in each detection window. In the online control experiment, the detection window was chosen 1 min, which contained 1-min length of EEG data. Each 1-min EEG data were sent to the passive BCI system and discriminated in real time. In this process, an integrated discriminant method was used to obtain the decision value of EEG in each detection window. The 1-min EEG data were divided into 1 s epoch without overlap. The features of each epoch were extracted, which were consistent with those of the discriminant model. Through the model, the decision value of each epoch was obtained. These decision values were averaged as the output result of EEG in the detection window. If the output result < 0, it meant hot discomfort; and if the output result > 0, it meant comfort. A simple control strategy was used to control indoor temperature. This control strategy synthesized output results of three consecutive detection windows which overlapped two windows. If two results of the three detection windows were hot discomfort, the air conditioner was opened and kept refrigeration for 5 min. The time interval of two consecutive opening of air conditioner was more than 3 min.

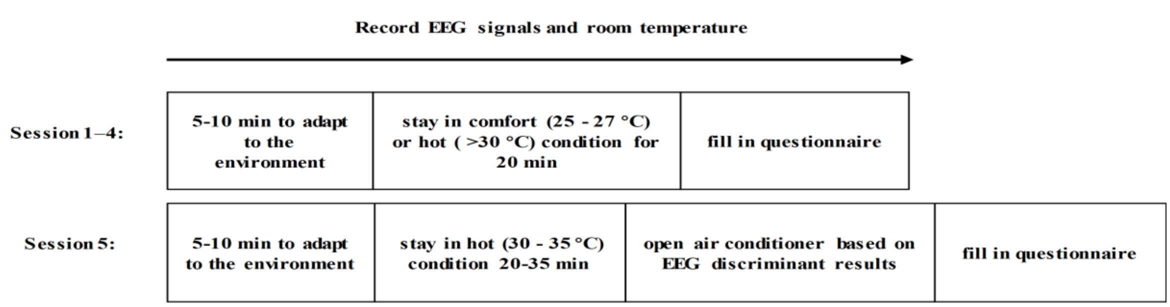


Figure 1. Experiment procedure.

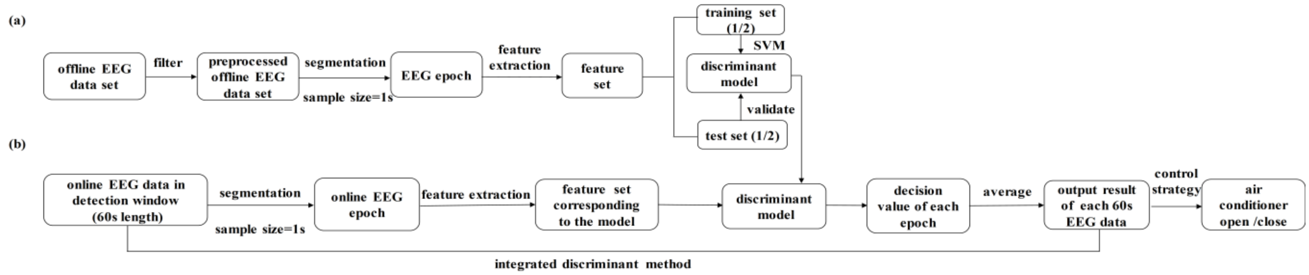


Figure 2 (a) Discriminant model establishment. (b) Real-time process of online EEG data in each detection window.

# III. Results

## A. Offline discriminant result

Using the integrated discriminant method with 1 s sample size, we chose different lengths of detection window to discriminate thermal comfort in offline experiments. Figure 3 showed the offline discriminant results of 10–fold cross–validation of each subject under different lengths of detection window. The length of the detection window determined the time accuracy. The longer the length was, the worse the time accuracy was. As can be seen from Figure 3, even if the length of detection window was 1 s, the discriminant accuracy was obviously higher than random guessing, whose mean value was 60.2%. With the increase of the window length, the classification accuracy also increased. When the length was 60 s, the mean accuracy was highest, which was 74.4%. These results showed the feasibility to classify comfort and hot discomfort by the EEG model. Based on these results, the length of EEG epoch was chosen 1 s to build the thermal comfort discriminant model; and considering the slow change of thermal comfort, the length of online detection window was chosen 60 s to monitor thermal comfort.

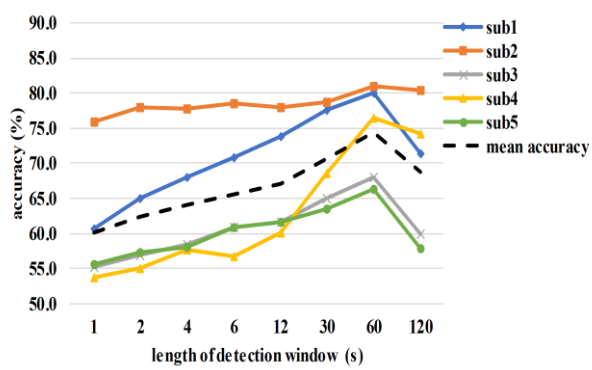


Figure 3. The offline discriminant accuracy of each subject based on the individual model under different lengths of detection window.

## B. Online real-time output results

Figure 4 showed the two typical subjects' output results in the online experiment, including the changes of decision values and room temperature. As shown in Figure 4, each subject's online BCI was successfully driven to control the air conditioner several times. The control process was conducted without room temperature feedback or manual operations. In addition, subjects could keep original state without interruption. Thermal comfort scores were all within thermal comfort acceptable range in the online experiment. The results showed that the BCI control system could meet the requirements of adjusting personalized thermal comfort.

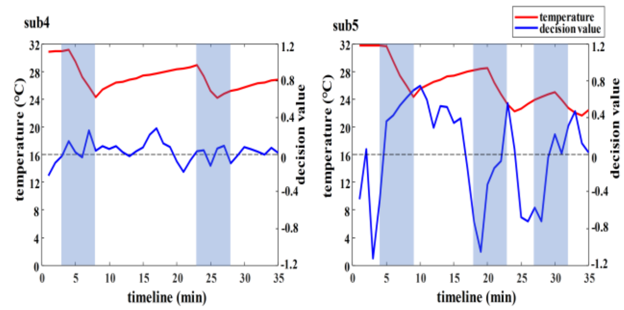


Figure 4. Real-time decision values and indoor temperature of two typical subjects in the online experiment. The red line was the room temperature curve, the blue line was the real-time output decision value of each detection window. The black dotted line represented that decision value was 0. Decision value > 0, the output result meant comfort; decision value < 0, the output result meant hot discomfort. The shaded area meant that the air conditioner was opened and kept refrigeration in the zone.

However, in the online control experiment, current thermal comfort of each epoch was not clear because of no feedback. To examine the reliability of the thermal comfort discriminant model, we compared the EEG features of the two environments in the online experiment with those in offline experiments. Figure 5 showed the offline and online mean feature values of all subjects and all leads under comfortable and hot environment. In the online experiment, PSD ratios in the comfortable environment were all lower than those in the hot environment, which were consistent with feature differences in the offline experiment. The results showed that the thermal comfort discriminant model was reliable to classify comfort and hot discomfort online.

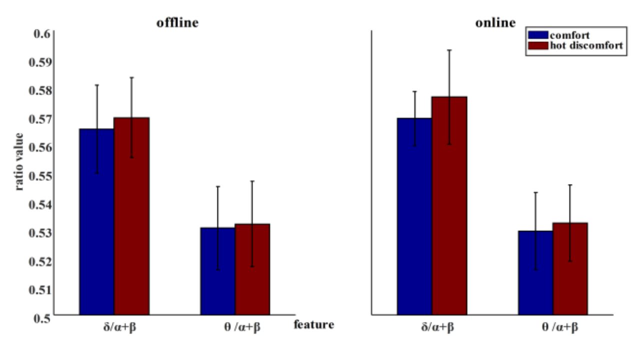


Figure 5. Comparison of mean features under the offline and online experiment.

### C. *Comparison of mean room temperature and thermal comfort score under the offline and online experiment*

Table II showed the mean indoor temperature and thermal comfort score of each subject in offline and online experiments. As can be seen in Table II, in the online control experiment, the maximum difference of mean indoor temperature was close to 3 °C. In addition, in the online experiment of subject 2 and 5, the difference of mean temperature was 2.2 °C, but their thermal comfort scores were the same. These results showed that there were obvious individual differences in thermal comfort. For subject 5, he felt slightly hot discomfort in the online experiment. However, the mean temperature in the online experiment was lower than that in the offline comfortable experiment. It might be caused by the two reasons as follows. The accuracy of the thermal comfort discriminant model was not high. Moreover, the control strategy of air conditioner was relatively simple. The two aspects should be improved in further researches.

In Table II, all final thermal comfort scores in the online experiment were lower than that before the online experiment, which were within the thermal comfort acceptable range. It showed that the passive BCI control could improve personalized thermal comfort in an overheated condition. This automatic temperature control technology based on passive EEG-BCI might help in reducing energy consumption of buildings without sacrificing individual thermal comfort. In this paper, we only discuss the online results of the 5 subjects. It is difficult to get a statistical analysis due to the small number of subjects, which needs to be further discussed in future studies.

TABLE II. MEAN ROOM TEMPERATURE AND THERMAL COMFORT SCORE IN OFFLINE AND ONLINE EXPERIMENT

| experiment / subject | Offline | | | | Online | | |
|---|---|---|---|---|---|---|---|
| | *comfort* | | *hot discomfort* | | | *score* | |
| | *temperature (°C)* | *score* | *temperature (°C)* | *score* | *temperature (°C)* | *before* | *after* |
| sub1 | 27.2 | 0 | 32.8 | 2 | 27.8 | 2 | -0.5 |
| sub2 | 25.7 | 0 | 31.8 | 2 | 28.5 | 2 | 1 |
| sub3 | 26.4 | 0 | 32.0 | 2 | 25.8 | 2 | 0.5 |
| sub4 | 27.0 | 0 | 32.0 | 1 | 27.2 | 1 | 0 |
| sub5 | 27.4 | 0 | 32.0 | 2 | 26.3 | 2 | 1 |
| mean | 26.7 | -- | 32.1 | -- | 27.1 | -- | -- |

## IV. CONCLUSION

In this paper, we built an EEG-based discriminant model to classify individual comfort and hot discomfort. Based on this model, the passive BCI system could control the air conditioner to regulate indoor temperature without any feedback. The final mean indoor temperature was controlled in the comfortable range. Moreover, thermal comfort of all subjects was improved and maintained in the acceptable range. This paper indicated the feasibility of using passive BCI system to control indoor temperature. It can provide a new way to obtain personalized thermal comfort.

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