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Human-building interaction under various indoor temperatures through neural-signal electroencephalogram (EEG) methods

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ABSTRACT

In this study, potential of neural-signal electroencephalogram (EEG)-based methods for enhancing human-building interaction under various indoor temperatures were explored. Correlations between EEG and subjective perceptions/tasks performance were experimentally investigated. Machine learning-based EEG pattern recognition was further studied. Results showed that the EEG frontal asymmetrical activity related well to the subjective questionnaire and objective tasks performance, which can be used as a more objective metric to corroborate traditional subjective questionnaire-based methods and task-based methods. Machine learning-based EEG pattern recognition with linear discriminant analysis (LDA) classifiers can well classify the different mental states under different thermal conditions. Utilization of the EEG frontal asymmetrical activities and the machine learning-based EEG pattern recognition method as a feedback mechanism of occupants, which can be implemented on a routine basis, has a great potential to enhance the human-building interaction in a more objective and holistic way.

1. Introduction

Human-building interaction is an emerging subject studied by architects and engineers, who have seen digital information elements incorporated into the fabrics of buildings as a way of creating environment that meets the dynamic challenges of future habitation, with the vision of continuing ubiquitous computing embedded in the world around us [1]. The basic idea behind is to apply the human-computer interaction (HCI) concepts and methods to building design and operation, and consequently to improve the human-building interaction. Human-building interaction is essentially a two-way dynamic mechanism, comprising both the impacts of built environment on occupants, and occupants' feedbacks to the built environment. Improving the human-building interaction is also in accordance with the broader definition of sustainable built environment, which places more and more emphasis on human and highlights the collaboration of disciplines including biological, social and physical sciences, and engineering [2,3].

One important aspect of the built environment is the indoor thermal environment, and its impacts on occupants have been studied extensively during the past few decades. Fanger [4] initiated the study of thermal comfort using the questionnaire-based predicted mean vote model, which has been developed subsequently by many researchers undertaking chamber studies and field studies. Based on these studies, ASHRAE Standard 55 [5] provides recommendations to thermally comfortable indoor environment, by considering the combined effects of temperature, humidity, air speed and human factors including clothing and metabolic rate. In addition to thermal comfort, studies also investigated the impacts of thermal environment on other subjective perceptions such as perceived air quality, sick building syndromes and perceived work performance [6–8]. The main conclusions from these studies were that self-perceptions would generally deteriorate when thermal environment is out of thermal comfort zone, especially on the warmer side [9]. Apart from subjective questionnaire-based studies, objective human productivity studies are also extensive. Objective human productivity under different thermal environment has been quantified by performance of lab-based cognitive tasks such as memory and computation tasks [10–12], or field-based observations such as the number of phone calls in call centers [13]. For effects of temperature in particular, the literature review by Seppanen [14] et al. summarized the task performance decrements as a U-shape function of temperature, which showed that performance was relatively worse when the temperature was either too low or too high.

Physiological indices have also been utilized to quantify the impacts

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of thermal environment on occupants, including skin temperature, heart rate, respiration ventilation, blink rate, end-tidal partial CO_2 ($ETCO_2$), arterial blood oxygen saturation (SPO_2), biomarkers in saliva and tear film quality [15,16]. These indices were also used to establish the correlations of physiological measurements with subjective perceptions and objective task performance. Electroencephalogram (EEG) is an electrophysiological method to measure electrical activity of the brain. Yao et al. [17] used bipolar method (one on the right side of the head, another at the center of the forehead, and a third on the earlobe as reference) to investigate impacts of indoor temperature on EEG signal of human subject, and concluded that the power of various EEG frequency ranges were different under various temperatures. Choi et al. [18] used 8 channels EEG headset to monitor brain activities under various combined indoor environment, and concluded that high-beta wave in the temporal lobe can be used to assess the stress. More advanced physiological method such as functional magnetic resonance imaging (fMRI) has also been used to study brain activities for thermal comfort [19].

Despite extensive studies on impact of indoor thermal environment on occupants, mechanisms of occupants' feedback to the building are rather limited. One example to create such feedback mechanism is the development of personalized ventilation (PV) system, which allows occupants to actively adjust their immediate zones [20–22]. For the centrally controlled indoor air conditioning systems, the major feedback mechanisms are still subjective questionnaire-based methods. For instance, some researchers have developed a web-based survey and accompanying online reporting tools to obtain feedbacks from occupants, including IEQ questions such as thermal comfort, indoor air quality, lighting, and acoustics [23]. Jazizadeh et al. [24] further proposed a framework to integrate building occupants into the air conditioning system control loop, which controlled the air conditioning system based on occupants' personalized thermal comfort votes in addition to data collected from various environmental sensors. However, the subjective survey-based methods lack certain objectivity and are prone to perception biases. Furthermore, objective productivity of occupants and its optimization cannot be considered in this approach because traditional methods of task-based evaluations and many physiological measurements mentioned above cannot be incorporated into the human-building interaction loop due to difficulties to be implemented on a routine basis in real-life.

The ultimate goal of this research is to use EEG-based methods as a feedback mechanism of occupants, which is more objective and holistic and is able to be implemented on a routine basis, to improve the human-building interaction (Fig. 1). To achieve this goal, the first step is to study EEG-based methods more thoroughly in the context of indoor environment: different EEG indices and feedback mechanisms should

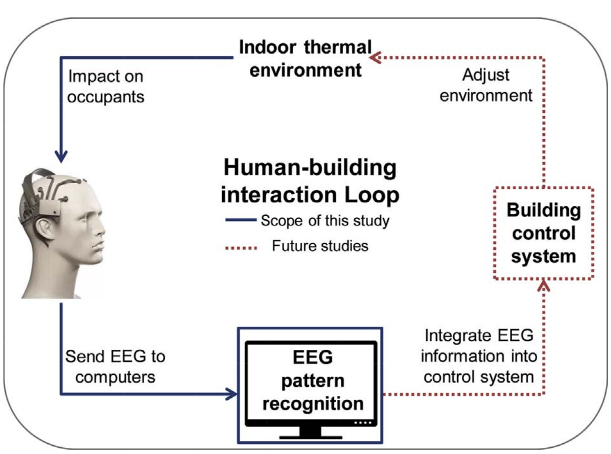


Fig. 1. EEG-based methods as a feedback mechanism of occupants to improve the human-building interaction.

be explored. The next step is to integrate the monitored real-time EEG information into the building control system. The final step is to control the indoor environment based on EEG information and other real-time inputs (such as environmental sensors' data). Through the feedback of EEG information to the building control system which then controls the indoor environment accordingly, the two-way human-building interaction will be improved.

As the first step, this study focused on indoor thermal environment and explored EEG indices and feedback mechanisms (Fig. 1). Correlations between EEG and subjective questionnaire-based results, and between EEG and objective task results under different indoor temperatures were established experimentally. Machine learning-based EEG pattern recognition was explored, which is a widely used human-computer interaction technique adopted by EEG emotion research [25–27] and EEG mental workload/vigilance research [28,29], and can be a potential feedback mechanism for the human-building interaction.

2. Methodology

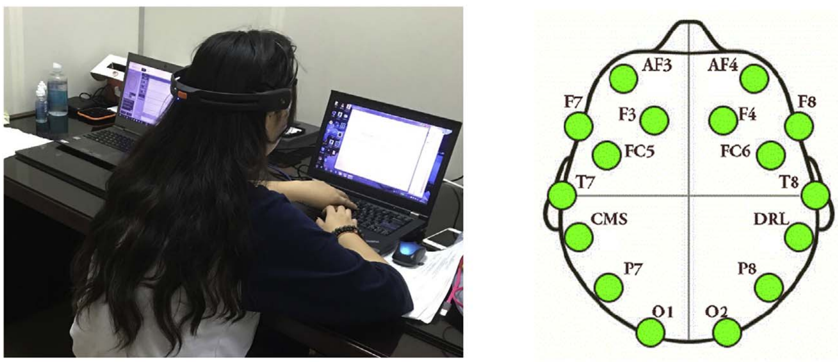
2.1. Experiment

The experiment was conducted in a typical office room in Nanyang Technological University, Singapore. The room is 4.7 m in length, 3.1 m in width, and 2.6 m in height (floor to false ceiling). The air conditioning and mechanical ventilation (ACMV) system of the room is traditional mixing ventilation with cooling coil, and the room air temperature can be controlled by adjusting the valves of the ACMV. A heater was used to adjust the room air temperature. The effect of radiant temperature was considered minimal because the room is not exposed to sunlight and has no windows and no radiant asymmetry exists either. Therefore, operative temperature should equal to air temperature according to ASHRAE Standard 55 [5]. Three room air temperature levels, i.e. 23, 26 and 29 °C, were studied in this experiment and other environmental indices were kept relatively unchanged. The three temperature levels were designed to lead to equally spaced thermal sensations, centered at thermal neutral sensation based on typical dressing code and indoor environment in Singapore's context. While it has been reported previously that occupants' performance is likely to increase towards the cooler conditions (e.g. 19 °C air temperature), indoor air temperature below 20 °C is less common in Singapore's context, and thus cooler conditions were not studied in the current work.

Twenty-two healthy university students (male-to-female ratio of 1.75) were recruited as human subjects. The human subjects were required to wear common local attire (short-sleeve shirt and trousers), which corresponds to a clothing level of 0.57clo according to the ASHRAE Standard 55 [5]. The experiment was within-subject and each human subject experienced all three temperature levels. Before the experiment, they were asked to keep good physical conditions. In each day, there were three timeslots, i.e. 10:30 a.m.-12:30 p.m., 1:00 p.m.-3:00 p.m., and 3:30 p.m.-5:30 p.m. Each human subject participated for three days, and could only choose the same timeslot in each day to minimize other confounding factors. To further ensure the data quality, only one human subject was tested in each timeslot.

Subjective questionnaires were designed to investigate thermal comfort, perceptions of indoor environment, sick building syndrome (SBS), mood and self-perceived performance. Thermal comfort, perceptions of indoor environment and SBS were denoted as Questionnaire-I. Mood and self-perceived performance were denoted as Questionnaire-II. Computerized tasks were designed to evaluate performance, and measures were taken to minimize learning effect, including a) tasks were chosen such that they require very basics abilities; b) a practice session was conducted to help human subjects to be proficient with the tasks before the formal experiment, and c) three parallel sets of questions with similar difficulty but different contents were used in formal experiment. EEG was recorded both in rest condition (no

Fig. 2. Procedure for each timeslot.



(a) (b)

Fig. 3. Emotiv EPOC: (a) setup; (b) channel locations.

tasks) and in task condition (doing computerized tasks). Body temperature was measured twice in each timeslot. The sequence of temperature conditions among human subjects was also balanced to further minimize any sequential effects such as fatigue effects. The experimental procedure in each time slot is shown in Fig. 2.

2.2. Questionnaires, computerized tasks and body temperature data collection and analysis

The questionnaires utilized to investigate subjective perceptions of environment were compiled from ASHRAE Standard 55 [5] and other literatures [30–33]. The questionnaires in this study used 7-point scale to rate different aspects of indoor environment (e.g. thermal and general environment), sick building syndromes, mood and self-perceived performance. For SBS in particular, metrics were head sensation, nose sensation, throat sensation, eyes sensation, ear sensation and breathe sensation. These metrics were tested with a larger population in a previous experiment by reliability test and factor analysis to ensure that affiliated sub-questions for each metric (e.g. stifle, chest tight, anoxia, and breathing difficulty as affiliated sub-questions for the breath sensation metric) have good internal consistency and can be represented by that metric [34]. Therefore, these SBS metrics were used directly in this study and the value of each SBS metric was taken as the average values of its affiliated sub-questions. For all metrics, scale 1 to 7 was used, and thus scale 4 represents the neutral state. In brief summary, a) for thermal sensation, scale 1 refers to cold and scale 7 refers to hot; (b) for thermal acceptability, general environment, SBS, mood and self-perceived performance, scale 1 refers to very unacceptable/very bad, and scale 7 refers to very acceptable/very good.

The computerized tasks used in the experiment were compiled from cognitive psychology, behavioral psychology and neuropsychology. These tasks were commonly used in the previous environmental chamber studies, and were believed to represent essential aspects of mental activities. These tasks were developed into question sets and computerized for better implementation. Representative types that contain different aspects of mental activities are listed below.

- Short term memory: Two types of short term memory tests were used. Pair recall asked human subjects to remember two groups of character pairs each time followed by recalling the missing character in each pair [35]. Words recall asked subjects to remember two groups of words each time followed by recalling the words in each group [36].
- Perception: Visual trace asked human subjects to visually trace each curve and correctly label it [37].

Body temperature was measured by a non-contact clinical thermometer (Visiofocus mod. 06400, TECNIMED SRL). Both the forehead temperature and the finger temperature were measured.

Non-parametric statistical tests were used for all the metrics for consistent comparisons, because distribution of many metrics did not follow the normal distribution and cannot be tested by parametric statistical tests. Related-sample Wilcoxon signed ranks test was used (within-subject). $P < 0.05$ was taken as significant level in the discussion unless stated otherwise, and p-value below significant level implies that significant difference exists and dominates the effect of random error.

2.3. EEG data collection and analysis

2.3.1. Emotiv EPOC based data collection

The Emotiv EPOC is a high resolution, nonintrusive, and portable wireless headset that measures 14 channels of EEG data (EPOC+, Emotiv Inc. USA). The electrodes are located at AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4 according to the International 10–20 system, forming 7 sets of symmetric channels as shown in Fig. 3. Two extra electrodes (CMS/DRL) are used as references. The EPOC internally samples at the frequency of 2048 Hz, and then down-samples to 128 Hz per channel. The data are then sent to a computer via Bluetooth, which utilizes a proprietary USB dongle to communicate using the 2.4 GHz band. Prior to use, all felt pads on top of the sensors need to be fully moistened with saline solution. The Emotiv Software Development Kit (SDK) provides a packet count functionality to ensure no data is lost and real-time sensor contact display to ensure quality of measurements. After the data collection, all data were loaded to Matlab for further processing.

2.3.2. EEGLAB based data pre-processing

The EEG data were pre-processed by the widely used EEGLAB toolbox (version13.4.4b) [38] running under the Matlab environment. The recommended pre-processing procedure by the EEGLAB developers was used in this study. The electrical noise (50/60 Hz) was already removed inside the Emotiv EPOC headset. The continuous data imported into the EEGLAB toolbox were first high-passed at 3 Hz to remove DC offset and low-frequency skin potential artifacts, and then low-passed at 45 Hz to remove high-frequency noises. Non-stereotyped artifacts such as large movement noises were then visually rejected by scrolling the data. The remaining artifacts such as eye blinks and muscle activities were removed by the EEGLAB built-in independent component analysis (ICA) algorithm, which decomposes the EEG signal into maximally independent components and artifact components were then removed.

The artifacts-free continuous data were then segmented into 8-second epochs. Power spectrum analysis was conducted for each 8-second epoch by the EEGLAB's spectopo function, which uses the pwelch function from the Matlab signal processing toolbox. Each epoch was analyzed using a 128-point window with 64-point overlap, i.e. 50% overlap. This power spectrum analysis computed the discrete power densities within the range of 3–45 Hz, which forms the basis for the subsequent analysis.

2.3.3. EEG frontal asymmetrical activities

The EEG metric used for establishing the correlations between EEG and subjective questionnaire-based results, and between EEG and objective task results is the brain asymmetrical activity. Brain asymmetrical activities have been widely studied by various brain measuring techniques including EEG and fMRI, and the results indicated that the left-hemisphere of the brain is more correlated with positive/approach emotion, and the right-hemisphere of the brain is more correlated with negative/withdrawal emotion [39,40].

The brain activities can be quantified by the power densities of different frequency ranges. There are five major brain waves with different frequency ranges [41]. In general, delta wave is within the range of 0.5–4 Hz, which is primarily associated with deep sleep. Theta wave is within the range of 4–8 Hz, which is regarded as consciousness slips towards drowsiness. Alpha wave is within the range of 8–13 Hz, and is the most prominent rhythm in the whole realm of brain activity. Alpha wave is often present in relaxed awareness without attention or concentration, and reduces or disappears by hearing unfamiliar sounds, or by mental concentration or attention. Beta wave is within the range of 13–30 Hz (though in some literature no upper bound is given), which is the usual waking rhythm of the brain associated with active thinking, active attention, focus on the outside world or solving concrete problems. The amplitude of beta is smaller compared with previous three bands. The frequencies above 30 Hz (mainly up to 45 Hz) correspond to the gamma range, and the amplitude of gamma wave is often much smaller.

In this study, the frontal activities were quantified according to the previous literatures [39,42,43] and the discussion above as the mean power of beta range minus the mean power of alpha range, and higher value indicates more active. For a specific condition for each human subject, the mean power was calculated by averaging the power spectrums of data epochs. The frontal asymmetrical score was then calculated as the activity at F3 (left) minus F4 (right), and therefore higher asymmetrical score indicates more positive/approach emotion. Finally all human subjects' asymmetrical scores were averaged to give a final score for each specific thermal condition. Related-sample Wilcoxon signed ranks test was used (within-subject) for pairwise comparison.

2.3.4. Machine learning-based EEG pattern recognition

The machine learning based EEG pattern recognition techniques in previous studies have utilized various machine learning techniques. The essential idea of machine learning is to train a classifier with known data (i.e. the specific classes of different training data are already known), and this classifier will then be used to classify unknown data according to certain rules (i.e. to predict the classes that the unknown data belong to). In this study, the classes are different mental states under various indoor temperatures, and the purpose is to correctly classify these different mental states.

Linear discriminant analysis (LDA) classifier in Matlab statistics toolbox [44] was used for the machine learning based EEG pattern recognition. The LDA models each class as a multivariate normal distribution and assigns the same covariance matrix to each class. To train a LDA classifier, for each class, the parameters of a multivariate normal distribution were estimated with training data. To classify the unknown data, the trained LDA classifier seeks to minimize the expected classification cost in Eqn. (1).

$$\hat{y} = \arg\min_{y=1,\ldots,K} \sum_{k=1}^{K} \hat{P}(k|x)C(y|k) \tag{1}$$

where $\hat{y}$ is the predicted classification; K is the number of classes; $\hat{P}(k|x)$ is the posterior probability of class k for observation x; and $C(y|k)$ is the misclassification cost of classifying an observation as y when its true class is k. In this study, the default values for cost function were used, namely $C(y|k) = 1$ if $y \sim = k$, and $C(y|k) = 0$ if $y = k$. In other words, the cost is 1 for incorrect classification, and 0 for correct classification.

The posterior probability $\hat{P}(k|x)$ that an observation x is of class k is defined in Eqn. (2).

$$\hat{P}(k|x) = \frac{P(x|k)P(k)}{P(x)} \tag{2}$$

where $P(k)$ is the prior probability of class k, which is empirically defined as the number of training samples of class k divided by the total number of training samples in this study; $P(x)$ is a normalization constant, namely the sum over k of $P(x|k)P(k)$; and $P(x|k)$ is the multivariate normal density defined in Eqn. (3).

$$P(x|k) = \frac{1}{(2\pi|\Sigma_k|)^{1/2}} \exp\left\{-\frac{1}{2}(x-\mu_k)^T \Sigma_k^{-1}(x-\mu_k)\right\} \tag{3}$$

where μ_k is the mean; Σ_k is the covariance matrix; $|\Sigma_k|$ is the determinant; and Σ_k^{-1} is the inverse matrix.

Selection of features, i.e. the multi-variables in the LDA, in the current work followed previous studies in EEG emotion recognition or mental vigilance recognition [25,29], where the mean power density in each 1 Hz frequency range was used as the feature. Emotiv EPOC has 14 channels and 42 frequency ranges (within 3–45 Hz range) were considered for each channel in this study. Therefore, the total number of features available was 588.

Individual-based user-dependent classifier, i.e. each human subject has his/her unique classifier, was used in this study. This approach was often used by studies in which the number of human subjects was relatively small [25,27,45], as EEG signal normally has large inter-person differences [46]. On the other hand, user-independent classifier was explored by studies in which the number of human subjects was large, and inter-person differences were therefore able to be adjusted [29,47,48].

The classification procedure was as follow: for each human subject, a) half of the data epochs were randomly selected to train the classifier, while the other half of the data epochs were kept for prediction; b) for the training data, the ANOVA was used to select the user-dependent features with the threshold of significance level $p < 0.05$, i.e. at least one thermal condition is significantly different for a feature to be selected; c) the LDA classifier was trained by the training data with the user-dependent features; and d) the trained LDA classifier was then used to classify the prediction data, and the classification rate was calculated as the percentage of correctly predicted data, i.e. the percentage of data epochs that were correctly predicted. As there are three thermal conditions, the classification rate needs to be sufficiently higher than 1/3, i.e. the random rate of labeling the data correctly.

3. Results and discussion

3.1. Environmental background

Temperature, relative humidity (RH) and air velocity were

Table 1
Environmental background in the vicinity of the human subject.

Targeted	23 °C		26 °C		29 °C	
Monitored	Temp (°C)	RH (%)	Temp (°C)	RH (%)	Temp (°C)	RH (%)
temperature and RH	22.6 ± 0.2	70.1 ± 0.6	25.8 ± 0.1	61.3 ± 0.6	29.1 ± 0.4	50.5 ± 1.1
Monitored CO_2 and air velocity	CO_2 < 1000 ppm; Air-velocity < 0.1 m/s					

Table 2
Results of questionnaire, computerized tasks and body temperature.

Metrics		Cool	Cool-Warm p-value	Warm
Q1. Thermal sensation	Q1	3.09 ± 1.02	< 0.001	5.09 ± 0.68
Q2. Thermal acceptability	Q2	4.64 ± 1.34	0.126	4.14 ± 1.21
Q3. Breath	Q3	6.43 ± 0.84	0.001	5.14 ± 1.70
Q4. Air quality	Q4	4.91 ± 1.48	< 0.001	2.91 ± 1.02
Q5. General environment	Q5	5.27 ± 1.28	0.002	4.32 ± 1.25
Q6. Mood	Q6	5.59 ± 1.10	0.009	4.79 ± 1.27
Q7. Self-perceived performance	Q7	5.19 ± 0.90	0.019	4.38 ± 1.39
T1. Pair recall	T1	14.02 ± 5.02	0.408	13.82 ± 6.57
T2. Word recall	T2	6.45 ± 2.11	0.527	6.86 ± 2.07
T3. Visual trace	T3	27.23 ± 7.80	0.983	27.82 ± 7.29
B1. 40min-finger	B1	35.74 ± 0.75	< 0.001	36.54 ± 0.64
B2. 40min-head	B2	36.73 ± 0.38	0.039	37.00 ± 0.44
B3. 120min-finger	B3	34.92 ± 0.58	< 0.001	36.34 ± 0.64
B4. 120min-head	B4	36.59 ± 0.28	< 0.001	36.93 ± 0.31
Remarks:		**Cool-Neutral p-value**	**Neutral**	**Warm-Neutral p-value**
Q1-Q7, metrics of questionnaire:	Q1	0.001	4.19 ± 0.73	0.002
(1) Thermal sensation: 1 refers to cold, and 7 refers to hot	Q2	0.296	5.09 ± 1.44	0.023
(2) Thermal acceptability, SBS, Environment, Mood and Self-perceived performance: 1 refers to very unacceptable/very bad, and 7 refers to very acceptable/very good	Q3	0.016	5.97 ± 1.30	0.006
	Q4	0.026	4.00 ± 1.69	0.001
	Q5	0.999	5.27 ± 1.42	0.003
	Q6	0.138	5.51 ± 1.22	0.010
	Q7	0.515	5.26 ± 1.23	0.007
T1-T3, metrics of computerized tasks:	T1	0.049	16.59 ± 5.73	0.028
(1) Pair recall and Word recall: accurate answers per minute	T2	0.638	6.81 ± 2.87	0.910
(2) Visual trace: total accurate answers	T3	0.001	31.50 ± 7.13	0.032
B1-B4, body temperature in °C:	B1	< 0.001	36.56 ± 0.59	0.781
(1) 40min-finger and 40min-head: measured at 40min for finger and forehead	B2	0.121	36.85 ± 0.39	0.106
(2) 120min-finger and 120min-dead: measured at the end of the session	B3	< 0.001	36.18 ± 0.55	0.284
	B4	0.002	36.78 ± 0.29	0.018

continuously monitored by air velocity meters (Velocicalc air velocity meter 9545, TSI Inc.) during the experiment. CO_2 was continuously monitored by CO_2 meters (model CM-0018, CO_2 Meter, Inc. USA). All environmental data was collected at seating level in the vicinity of human subjects with a sampling rate of $1/60\ s^{-1}$, i.e. 1-min interval (Table 1). As can be seen, the monitored temperatures in general were close to the targeted values.

3.2. Questionnaire

The results of the subjective questionnaire are shown in Table 2. For thermal sensation, 23 °C condition led to slightly cool sensation, 26 °C led to neutral sensation, and 29 °C led to slightly warm sensation as defined by the 7-point scale, and the pairwise p-values were all significant. This was also in line with the prediction by ASHRAE standard 55 [5]. In the subsequent analysis, the three thermal conditions are denoted as cool, neutral and warm conditions respectively for convenience.

For thermal acceptability, all values were above neutral, which suggested that the three thermal conditions were deemed acceptable in general. Between neutral and warm conditions, neutral condition was considered more acceptable than warm condition, and the difference was significant. Between neutral and cool conditions, though the difference did not reach significance level, neutral condition still had higher value than cool condition, which suggested neutral condition was slightly more acceptable than cool condition. The p-value was not significant may be attributed to larger standard deviations. Between cool and warm condition, cool condition again had higher value, though the p-value was not significant possibly due to the same reason.

For breath sensation, all values were above neutral, which suggested that three conditions were generally deemed good. Cool condition led to the best sensation, neutral condition was in the middle, and warm condition was the worst. All pairwise p-values were significant. For air quality perception, the trend was similar to that of breath sensation, with the exception that the value of air quality perception under warm condition was below neutral, which suggested that warm condition was deemed as slightly unacceptable for air quality perception metric. Previous chamber studies and field investigations also suggested that in the range of acceptable thermal conditions, perceived air quality generally decreased as temperature increased [6–8,15].

For general environment perception, the values were all above neutral. The values of cool condition and neutral condition were almost the same, which suggested that the general satisfaction for these two conditions were similar. The warm condition had lower value than other two conditions, which suggested that warm condition was relatively less satisfactory for this metric. The pairwise differences of cool-warm and neutral-warm were both significant. For mood and self-perceived performance, the trends were very similar to that of general environment perception, which suggested that human subjects' mood and self-perceived performance were most closely related to their perception of general environment.

3.3. Computerized tasks

The results of the computerized tasks are summarized in Table 2 as well. For short-term memory tasks, values were accurate answers per minute [49]. For visual trace task which cannot be finished within given time, values represented total accurate answers. Because paired (within-subject) statistical test was used for performance analysis, variations of strategies among different human subjects to answer questions did not matter much.

Between cool and warm conditions, there were no significant differences for the three tasks. Between neutral and cool conditions, neutral condition led to better performance for two of the tasks than cool condition, and the differences were significant. Between neutral and warm conditions, neutral conditions again led to better performance for two of the tasks than warm condition, and the differences were significant. This trend was generally in accordance with previous studies. Seppanen et al. [14] conducted a literature review, and summarized from various studies the performance decrements as a U-shape function of temperature, which showed that performance decrements were lowest around 24–26°.

3.4. Body temperature

The results of the body temperature are shown in Table 2. The body temperatures were closely related to the thermal sensation, i.e. lower body temperature leads to lower thermal sensation, and vice versa. The most reliable metric was the forehead temperature measured at the end of each timeslot, as all the pairwise p-values were significant. The main reason might be that forehead temperature is more stable than finger temperature, as human subjects may have different postures and therefore finger temperature has larger standard deviation, which can be seen from the results. Measurements taken at the end was also more reliable than those taken immediately after the acclimatization period, as some of the p-values did not reach significance level for measurements taken at 40 min. Body temperature could be used to correlated with thermal sensation, as previous researchers used finger skin temperature [15] or whole body weighted/unweighted skin temperature [50].

3.5. EEG frontal asymmetrical activities

The results of EEG frontal asymmetrical activities are shown in Fig. 4. As asymmetrical scores were calculated as F3 (left) relative to F4 (right), F4 was the reference and therefore asymmetrical scores were plotted at F3 location.

For rest condition (i.e. not doing any tasks), the asymmetrical scores under cool and warm conditions were around (only minimally above) zero, which suggested that the emotion states under these two conditions did not show apparent positive/approach or negative/withdrawal emotion. For the neutral condition, the asymmetrical score was above zero, which suggested that the emotion state was positive/approach under this condition. The pairwise differences of neutral-cool and neutral-warm were both significant, while the pairwise difference of cool-warm was not significant. The questionnaire-I was an evaluation of the subjective perceptions under rest condition, and it can be seen that rest EEG frontal asymmetrical activities were more closely related to the thermal acceptability, as neutral condition was also subjectively perceived as better and more acceptable than the other two thermal conditions. Other metrics in questionnaire-I, such as perception of air quality or general environment, were not well related to the rest EEG frontal asymmetrical activities, because these subjective metrics indicated that cool condition led to better perception.

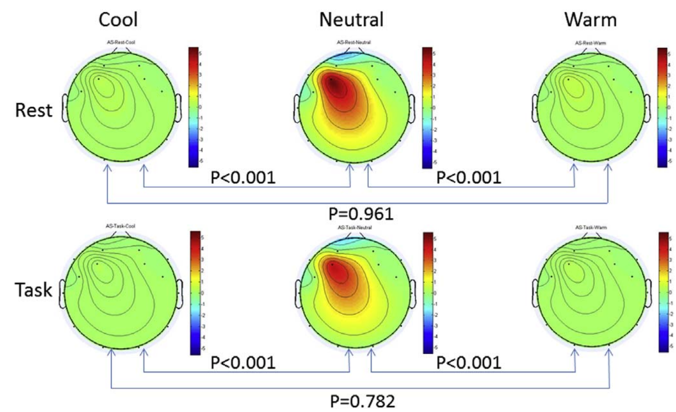


Fig. 4. EEG frontal asymmetrical activities: the asymmetrical scores were plotted at F3 location on a scale of −5 to 5.

For task condition, the EEG frontal asymmetrical activities were similar to those under rest condition. The questionnaire-II was an evaluation of mood and self-perceived performance immediately after the computerized tasks, and it can be seen that the task EEG frontal asymmetrical activities were less related to these two metrics, as these two metrics did not show significant difference between cool and neutral conditions. Rather, the task EEG frontal asymmetrical activities related more closely with the actual performance of computerized tasks, as both the asymmetrical scores under task condition and the performance of computerized tasks indicated that the neutral condition led to the best state, while the other two thermal conditions were similar and led to relatively worse states. This further indicated that self-perceived performance does not necessarily relate to actual performance.

3.6. Machine learning-based EEG pattern recognition

The machine learning-based EEG pattern recognition results for the rest condition and task condition are shown in Fig. 5. The full-set features varied from person to person and were in the range of 400–500. For each human subject, the classification rate of full-set features was first calculated, and then the full-set features were reduced one by one and the corresponding classification rates were calculated. Finally the rates were averaged across human subjects that led to the curves in Fig. 5. The standard deviation bars denote the dispersion among human subjects, and were plotted at 20-feature intervals. The random rate of 1/3 was assigned to classifiers with zero feature case.

As can be seen for rest and task conditions, the classifiers with full-set features led to the best average classification rates of above 95%. For the rest condition, the average classification rate went below 90% and began to diverge significantly after around 200 features, and reached its first low point at around 100 features. The rest average classification rate then increased again until around 50 features, and finally decreased again. For the task condition, the general pattern was similar with slightly different turning points. The task average classification rate reached its first low point at around 150 features, and this low point was higher than that of rest condition. The task average classification rate then increased again until around 80 features, and this peak was flatter and higher than that of rest condition. Finally the task average classification rate decreased again. The results suggested that the LDA classifiers can well classify the different mental states under three thermal conditions for both rest and task conditions in roughly two feature ranges. The first range was from the full-set features to around 200 features, and the second range was around 50–80

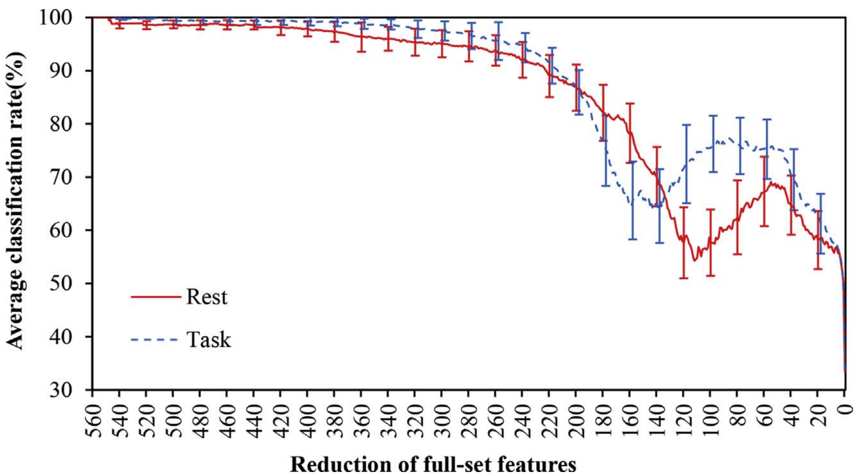


Fig. 5. Machine learning based EEG pattern recognition. For the full-set features averaged across human subjects: a) rest: the average number is 494, and the average classification rate is 98%; b) task: the average number is 489, and the average classification rate is 99%.

features. The classification rates in the first range were higher than that in the second range. Still, for the LDA classifiers, more features did not necessarily guarantee higher classification rate, as there was a low point between these two ranges.

4. Conclusions and outlook

In this study, new EEG-based methods to enhance human-building interaction under various indoor temperatures were experimentally investigated. Correlations between EEG and subjective perceptions, and between EEG and tasks performance were established by the EEG asymmetrical frontal activities. Machine learning based EEG pattern recognition was further explored. Main conclusions from this study include:

- The three temperature levels led to three distinct thermal sensations, which were also closely related to forehead skin temperatures. For the thermal acceptability metric, neutral condition was deemed as the most acceptable. For the breath sensation and perceived air quality, cool condition led to the best sensation, neutral condition was in the middle, and warm condition was the worst. For the general environment perception, mood and self-perceived performance, cool condition and neutral condition were similar, while warm condition was deemed as relatively less satisfactory.
- For the computerized tasks, neutral condition led to the best performance than the other two thermal conditions. Cool and warm conditions led to similar task performance.
- For the EEG frontal asymmetrical activity, trends of rest condition and task condition were similar: neutral thermal condition led to more positive/approach emotion than the other two thermal conditions, while the other two thermal conditions were similar. The EEG rest frontal asymmetrical activity was more related to the thermal acceptability metric in the subjective questionnaire. The EEG task frontal asymmetrical activity also related well to the computerized tasks performance.
- For the machine learning based EEG pattern recognition, full set of user-dependent features rates were the best for both the rest and task conditions (above 95%). The LDA classifiers can well classify the different mental states under three thermal conditions for both rest and task conditions in roughly two feature ranges.

The EEG asymmetrical activities can be used as a more objective metric to corroborate traditional subjective questionnaire-based methods and task-based methods, and as a useful input to improve the human-building interaction. Furthermore, the machine learning based EEG pattern recognition method can be utilized to classify different mental states under various thermal conditions in a more automatic and efficient way for human-building interaction. The current study focused on the user-dependent classifiers, which can achieve very high accuracy as a result of not considering inter-person differences. This approach requires that each individual has to train his/her own classifier, which can then be incorporated into different buildings where each individual normally stays. The potential future study is to build a more general user-independent classifier with a much larger population by considering main differences in gender, age, personality, and occupation, as some of the researchers have already explored in emotion or mental vigilance EEG studies [29,47,48]. Although the classification accuracy might be compromised by using the user-independent classifier, this can make the technique more applicable since it does not require training individual classifiers. Furthermore, as larger sample size can improve the statistical power, more human subjects in future study may also reveal other useful findings. In addition, the tasks and settings in environmental chambers could be quite different from those in actual offices. In future studies other more complicated tasks such as decision makings [51] and longer exposure similar to those in actual offices could also be explored. In future experiments, it would also be interesting to explore the lower range of temperature. In general, the use of EEG indices and machine learning based EEG pattern recognition techniques can help to improve the two-way dynamic human-building interaction in the future.

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