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PERSONAL THERMAL COMFORT PREDICTION BASED ON EEG SIGNAL

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Abstract

Quantitative measurements of thermal comfort conditions are required for a more valid measurement result than using a questionnaire only. This research aims to conduct a preliminary study using electroencephalography (EEG) signals to predict personal thermal comfort in an indoor environment. The individual's satisfaction or dissatisfaction describes personal thermal comfort to the thermal condition exposure. The applied classification method in this research is the k-Nearest Neighbor classification. The obtained results show that the brain's occipital lobe (represented by the O2 channel) and the frontal lobe (represented by the FC5 channel) were suspected can quantizing personal thermal comfort. The quantization was generated in the delta (0-4 Hz) and theta (4-8 Hz) frequency ribbon in the O2 channel, as well as the beta (13-30 Hz) frequency ribbon in the FC5 channel. With its accuracy of 85%, the k-Nearest Neighbor algorithm was suitable to predict personal thermal comfort.

Keywords: Brain signal, k-Nearest Neighbor algorithm, Physiological signal, Power spectral density, Thermal comfort.

1. Introduction

Thermal comfort is one of the building parameters to indicate the indoor environmental quality. It is an essential factor that can affect a person's work productivity. Several previous experiments have proven the relationship between comfort and productivity. It is said that the more uncomfortable an indoor environment then the more likely a person's productivity will decrease [1]. Data shows that the most significant amount of electrical energy in Indonesia's buildings is required to fulfil that building's thermal comfort [2, 3]. The high energy use is caused by inefficient air conditioner (AC) usage when it is set incorrectly and does not fit with the occupants' needs [4]. Observation of occupant's thermal comfort is required to determine the air conditioner's correct setting for more energy-efficient use of the system.

Thermal comfort is a response of the human body that will provide physiological and psychological responses towards the surrounding thermal environment. A physiological response appears in the form of feeling hot or cold. It was known as thermal sensation, and it correlates to the process of heat exchange when the human body attempts to maintain its core temperature. Meanwhile, according to the ANSI/ASHRAE Standard 55 [5], thermal comfort is a state of a person's mind that expresses satisfaction towards the thermal environment and can be assessed through subjective evaluation. It can be seen that thermal comfort leans more on the psychological response of the body. The body's response concerning its thermal comfort includes sensations and the body's perception, which was where the psychology works.

A person's thermal comfort in a room can be assessed using questionnaires. Questionnaires are a method to measure an excellent thermal comfort, but it poses the challenge of quantifying perception (qualitative value) into numbers (quantitative value). Another method and measuring tool are required to obtain a more valid measurement result of thermal comfort condition. Several prior experiments used physiological signals such as skin temperature [6-9], body temperature [10], blood flow [6], amount of sweat [6], heart rate [7], blood pressure [8], and heat released from the skin [7] as parameters from the process of heat transfers that can represent thermal sensation.

A few research types have also discovered that brain wave detected using electroencephalography (EEG) technology can be utilized to observe thermal sensation [11-13]. Brain waves from the EEG are a physiological sign from the body that represents something in the person's thoughts due to a certain stimulant. This signal can illustrate the brain’s activity [14], the level of concentration/attention [14], emotional level [14-16], pleasant/unpleasant [11], and level of relaxation [16]. It indicates that EEG signals can predict personal thermal comfort through psychological analysis by stating whether it shows "satisfaction" or "dissatisfaction" towards a certain thermal environment. So far, no studies have been found to detect brain signal by EEG to predict personal thermal comfort.

Represented brain waves by EEG require a classification algorithm to predict the tested qualitative value. Implemented features in the EEG signal classification consist of power spectral density, the average value of raw data, the standard deviation of raw data, and others. The features obtained from EEG signals only have quantitative value. However, the meaning of the quantitative value is unknown. Therefore, a classification method for EEG signal features is required to correlate the quantitative value with qualitative value, such as thermal comfort, pain, hand motions, etc. Several methods of classification have been used in prior research, including the Support Vector Machine (SVM) method [17], [18], k-Nearest Neighbor (kNN) [17, 18], Artificial Neural Network [17], Linear Discriminant Analysis (LDA) [13, 17], Quadratic Discriminant Analysis (QDA) [17], Logistic Regression [18], and Naive Bayesian [18].

This research aims to conduct a preliminary study using EEG signals to predict personal thermal comfort in an indoor environment. The individual's satisfaction or dissatisfaction describes personal thermal comfort to the thermal condition exposure. The classification method used in this research is the k-Nearest Neighbor (kNN) classification.

2. Methods

The phases of this research are illustrated in Fig. 1. To predict personal thermal comfort, the k-Nearest Neighbor (kNN) classification algorithm was connected to the output data of thermal comfort with the brain signals' input data from the EEG signals based on the environmental and personal condition when the measurement was taken, as seen in Fig. 2.

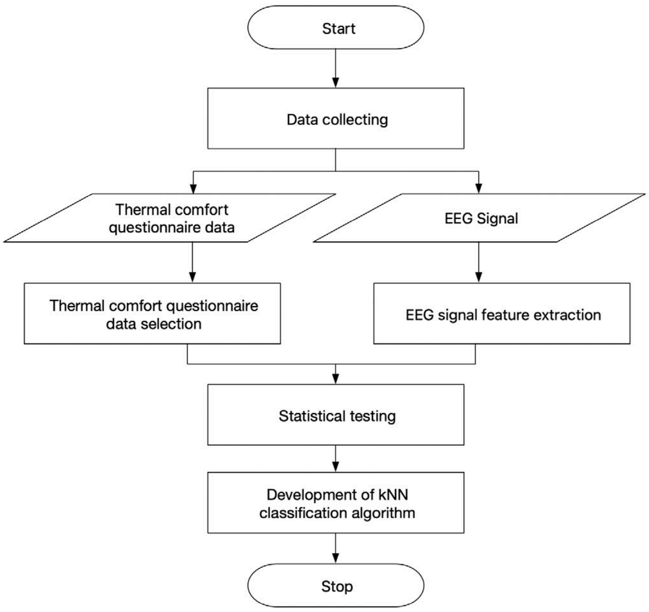


Fig. 1. The phase of the research.

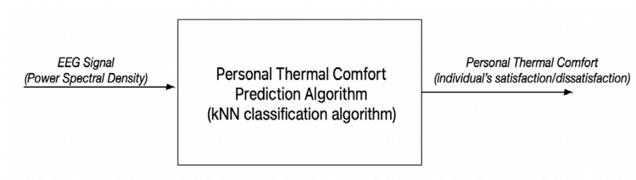


Fig. 2. Algorithm block diagram of personal thermal comfort prediction.

2.1. Data collecting

Thermal comfort is affected by environment and human factors [19]. Several research types have varied the physical parameters of an environment [12, 20] with personal parameters [21, 22]. The measurement time varies from 15 minutes [20] to 120 minutes [22], depending on the aim and the parameter variation used in the measurement. In this research, the thermal comfort level was conditioned by varying the respondents' body metabolism with different activities. Each respondent was asked to undertake two different activities, namely an office activity (1.0 met) and a physical activity (3.0 - 4.0 met). Both activities were performed in the PSoC (Programmable System on Chip) Room, Laboratory of Sensor and Telecontrol System, Department of Nuclear Engineering and Engineering Physics, Faculty of Engineering, Universitas Gadjah Mada, with an adjusted room air temperature that corresponds to the National Standard of Indonesia (SNI 6390:2011) [23]. The testing was carried out for 40 minutes, with the details of the data retrieval shown in Fig. 3. The data taken from this testing was the EEG signal data and the questionnaire data.

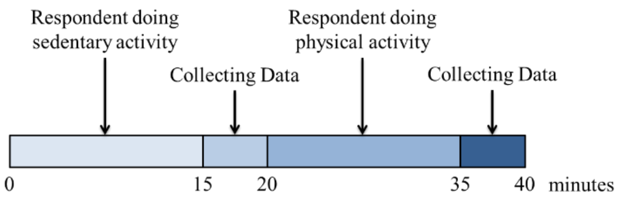


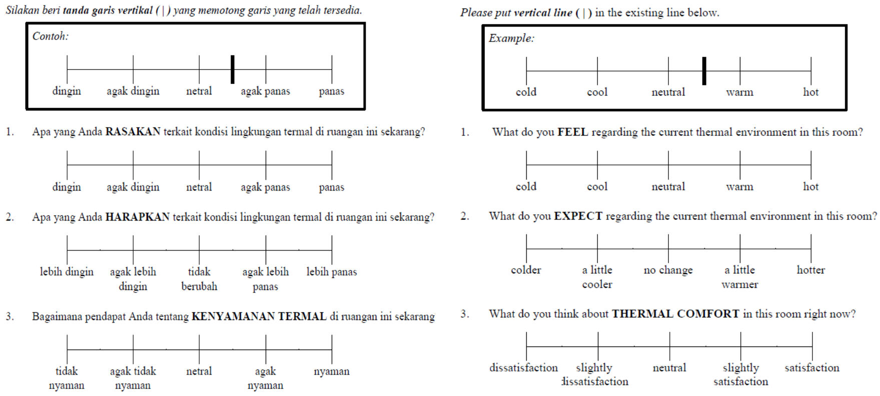
Fig. 3. Detail scheme of data acquisition.

2.1.1. Thermal comfort questionnaire data

The questionnaire used in this research was made in Bahasa Indonesia. The questionnaire was divided into three questions about thermal sensation, thermal preference, and thermal comfort in the order of question numbers 1, 2, and 3, respectively, as can be seen in Fig. 4. The question of thermal comfort was used to conduct an assessment of whether an individual felt satisfaction or dissatisfaction in the thermal environment. The results of this questionnaire were the output data to develop the k-Nearest Neighbor classification algorithm. The question on thermal sensation and preference was used to conduct data selection in order to know which data was correctly answered by the respondent. The questionnaire data selection utilized a premise test by summing the score of the answers from the thermal sensation with the thermal preference. Because the thermal sensation questionnaire was provided on a five scale, the score offered was at a range of -2 to +2. The sum of the scores for thermal sensation and thermal preference must not exceed that range. If so, the actual data, both questionnaires and EEG data, will be thrown away.

2.1.2. EEG signal

The EEG signal was recorded using consumer-grade Emotiv EPOC, which has 14 channels (F3, F4, FC5, FC6, F7, F8, T7, T8, P7, P8, O1, O2, AF3, AF4), with the placement of the electrodes pictured in Fig. 5. The EEG signal recording results were saved in a file with a Comma Separated Value (CSV) format. The following feature extraction processes were done to acquire the EEG signal features of this research. The features implemented were the power spectral density value for delta, theta, alpha, beta, and gamma ribbon frequency of 14 channels. The extraction process comprises four separate processes as follows: artifact rejection process, filtering using the band-pass filter, calculating power spectral density, and feature normalization process.



(a) Version Bahasa Indonesia **(b) English Version**

Fig. 4. The questionnaire used in this research.

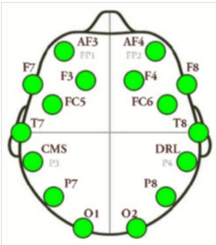


Fig. 5. Electrode placement for Emotiv EPOC [24].

2.2. Statistical testing

A statistical test was conducted to ensure that the questionnaire's data represents the changes in activity stimulant. Data analysis was completed according to the schematic in Fig. 6. The T pairs testing with a 95% accuracy level ensures that the stimulants' changes (activity conditions) produce different responses from both the questionnaire's respondents and EEG signal's respondents.

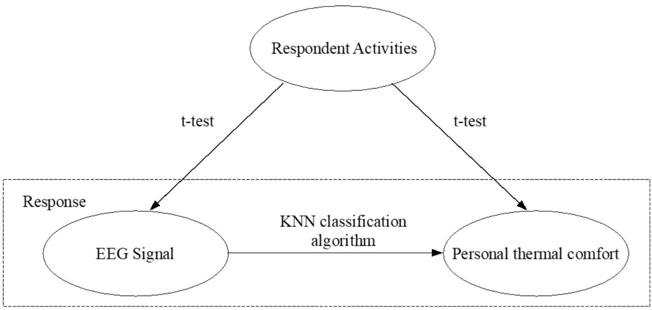


Fig. 6. Data analysis scheme.

2.3. Development of kNN algorithm classification

The k-Nearest Neighbor (kNN) is a machine learning classification algorithm based on the distance of a data with a group of train data sets taken from k nearest neighbors. Two factors that influence the performance of kNN are, first, the method for calculating the distance between the new data with the data of learning into its neighbor, and the last is the number of nearest neighbors. Based on these two factors, there are several types of kNN algorithms [25], which are listed below.

- Fine-kNN. The number of neighbor is one, the distance is Euclidean. The Euclidean distance is given by Eq. (1) where x and y are subjects to compared with n characteristics.

$$P(x, y) = \sqrt{(x_1 - y_1)^2 + (x_2 - y_2)^2 + \cdots + (x_n - y_n)^2} \quad (1)$$

- Medium-kNN. The number of neighbor is ten, the distance is Euclidean.
- Coarse-kNN. The number of neighbor is 100, the distance is Euclidean.
- Cosine-kNN. The number of neighbor is ten, the distance is cosine. The Cosine distance from vector u and v is calculated by Eq. (2).

$$Distance = 1 - \frac{u.v}{|u|.|v|} \quad (2)$$

- Cubic-kNN. The number of neighbor is ten and the distance is cubic. The Cubic distance from two vector n-dimensional u and v is calculated by Eq. (3).

$$Distance = \sqrt[3]{\sum_{i=1}^{n} |u_i - v_i|^3} \quad (3)$$

- Weighted-kNN. The number of neighbor is ten, the distance is weighted. The Weighted Euclidean distance from vector u and v is calculated by Eq. (4), where $0 < w_1 < 1$ and $\sum_{i=1}^{n} w_i = 1$.

$$Distance = \sqrt{\sum_{i=1}^{n} w_1 (u_i - v_i)^2} \quad (4)$$

The k-Nearest Neighbor (kNN) classification algorithm was developed if the data spread could explain that the research data could be differentiated. To attain a high accuracy from the classifier that was created, this development process was made up of several analysis phases and optimization. The steps to develop the kNN classification algorithm were as follows:

- It determined the type of kNN classification algorithm by comparing each type of algorithm's accuracy, which was the Fine-kNN, Medium-kNN, Coarse-kNN, Cosine-kNN, Cubic-kNN, and Weighted-kNN algorithm.
- Optimization of the frequency ribbon combination aims to discern the most dominant frequency ribbon to state the stimulant changes.
- Optimization of the kNN algorithm performance, which aims to determine the algorithm parameters, generated the highest accuracy, in this case, the value of k in the k-Cross-Validation.
- Optimization of feature combination per channel aims to discover the most dominant feature and discern the part of the brain that mirrors thermal comfort.

3. Results and Discussion

3.1. Data analysis of the thermal environment parameters

The parameters of a thermal environment (temperature, humidity, and wind speed) significantly impact personal thermal comfort. During this research's data acquisition process, the thermal environment parameters were maintained in the SNI 6390:2011 safe range and explained the energy conservation of a building's airflow system. The standards state that in order to provide a comfortable environment, the dry-bulb temperature and humidity must be 24°C, - 27°C or 25°C ± 1.5°C and 60% ± 5% RH, respectively [23].

The data acquisition process results state that the temperature and relative humidity were 25 ± 1 °C and 55 ± 5% RH, respectively. It fits the standards' requirements, confirming that the temperature and relative air humidity of the room during the process could represent personal thermal comfort.

3.2. Data selection

The data selection results show that from the 21 questionnaire respondents, there was one who was invalid, and the details can be seen in Table 1.

Table 1. Invalid data from the questionnaire.

Condition	Thermal Sensation	Thermal Preference	Total	Result
Sedentary activity	-1.917	-1.292	-3.208	Rejected
Physical activity	1.063	0.729	1.792	Accepted

Based on Table 1, there was one condition that did not pass the preliminary test. Therefore, it was a questionnaire; none of the conditions could be used. The data selection process obtained 40 sets of questionnaire data for office and physical activity conditions that could be processed when testing the data distribution.

3.3. Data spread analysis based on respondent's activities

A statistical test was conducted in order to ensure that the data from the questionnaire represents the changes in activity stimulants. The process utilized the T-paired test with an accuracy of 95% since each respondent participated in two separate measurements of different conditions. The test was based on the following hypotheses:

- The null hypothesis (H_0): $\mu 1 = \mu 2$ (there was no difference between the respondent's questionnaire value when partaking in an office activity and physical activity)
- The alternative hypothesis (H_1): $\mu 1 \neq \mu 2$ (there was a difference between the respondent's questionnaire value when partaking in an office activity and physical activity)

A *p*-Value determined the chosen hypothesis yielded from the experiment. If *p*-Value > 0.05, then H_0 was received, and H_1 was rejected. If *p*-Value < 0.05, then H_0 was rejected, and H_1 was received.

The results show that the average scale of thermal comfort during office activities was as big as 1.007, while physical activities were as big as -0.256. It indicates that office activities and physical activities can be differentiated through the results of the questionnaire. To better describe the questionnaire data spread, the data has been depicted inside a boxplot in Fig. 7.

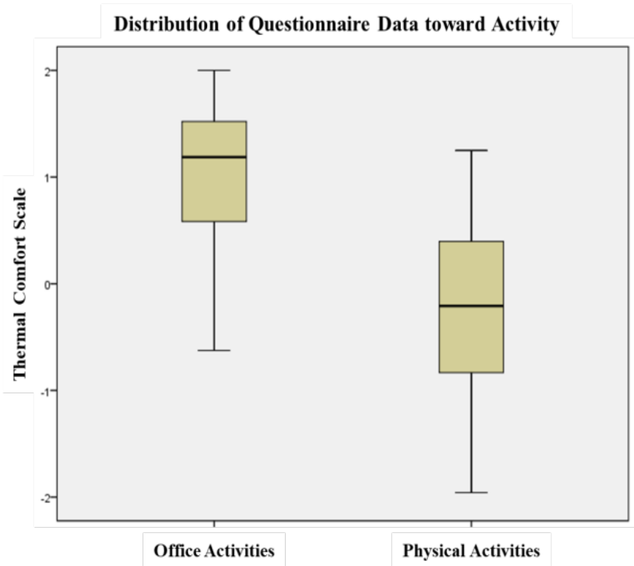


Fig. 7. Data spread of the questionnaire on the respondent's activities.

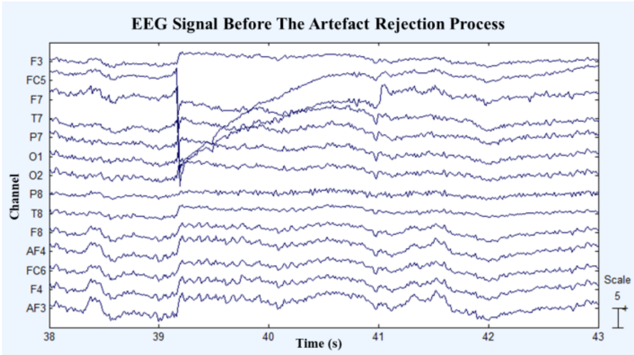
3.4. Data spread analysis based on respondent's activities

Feature extraction can be conducted through 4 phases: artifact rejection process, signal filtering process, calculating the power spectral density value, and feature normalization.

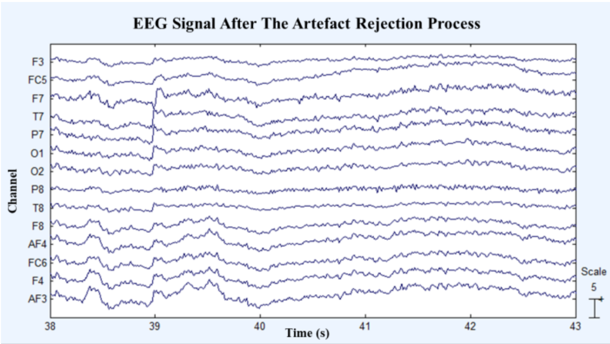
3.4.1. Artefact rejection

An artifact, which was a form of noise inside EEG signals, was monitored through EEG Lab installed in the MATLAB software. By monitoring the time where the noise appeared, it can be discarded from the CSV formatted file's raw data. The discarded artifacts were artifacts originating from the physiological process and the environmental factors. The comparison between the EEG signal before and after the artifact rejection process was pictured in Fig. 8.

Based on Fig. 8, by utilizing the Artefact Rejection function in EEG Lab, the noises found in the EEG signal become visible and can be erased. Hence what was left was a cleansed raw data of the EEG signal. It can be summed that erasing the artifact from the raw data in the CSV file produced a cleansed data.



(a) EEG signal before artefact rejection process.



(b) EEG signal after artefact rejection process.

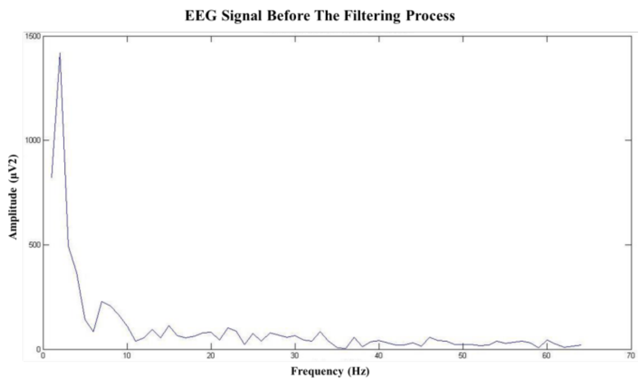
Fig. 8. Time artifact was detected.

3.4.2. Signal filtering

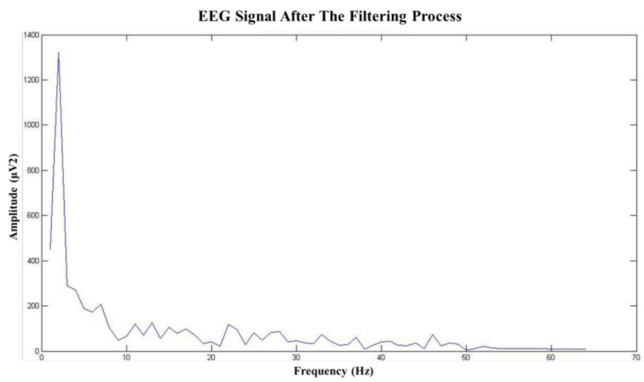
The EEG signal cleansed of artifacts will then go through a filtering process. In this process, the filter was the band-pass filter, which was tested through a frequency from 0.1 Hz to 50 Hz. The results from the signal filtering process were shown in the following Fig. 9. Based on Fig. 9, if we were to overpass a frequency of 50 Hz, a signal that at first has considerable power will weaken until it reaches a value nearing 0 μV2. It indicates that the filter worked; thus, the EEG signal that will be processed afterwards will genuinely be clean and within the required range (0 Hz was the bottom border of the delta ribbon frequency, while 50 Hz was the upper border from the gamma ribbon frequency).

3.4.3. Calculate Power Spectral Density (PSD) value

Calculating the power spectral density (PSD) value that becomes a feature in this research was done utilizing the MATLAB software. The calculation was done using the Pwelch periodogram function. An example of the data spread from the power spectral density calculation for channel FC5 was shown in Fig. 10. It was shown in Fig. 10 that the PSD value obtained from the calculation has an extensive range, with many outliers from those conditions, specifically for the delta ribbon frequency. That extensive range must be anticipated, and one way was through normalization.



(a) The EEG signal before filtering process.



(b) The EEG signal after filtering process

Fig. 9. Frequency of EEG signal before and after filtering process.

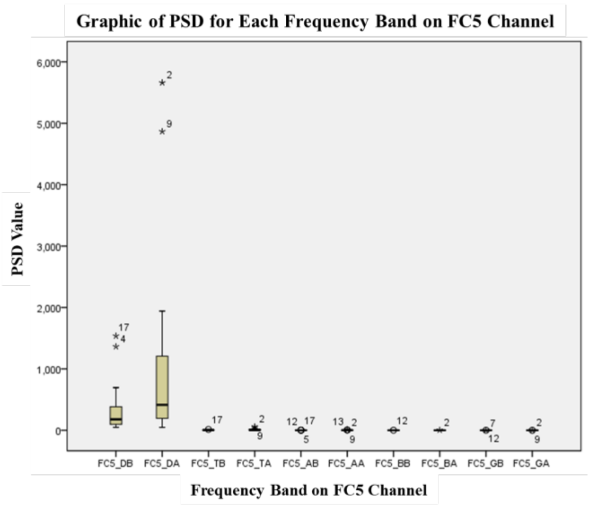


Fig. 10. PSD data spread for each ribbon frequency in channel FC5.

3.4.4. Feature normalization

Feature normalization was done to decrease the wide range between the PSD values and reduce the number of outliers from the obtained feature value. The results of the feature normalization can be seen in Fig. 11. It was shown in Fig. 11 that the range from each feature in the ribbon frequency becomes narrower than before normalization. The outlier inside the data also disappears after conducting normalization. The normalized data will then be used to develop the k-Nearest Neighbor classifiers algorithm.

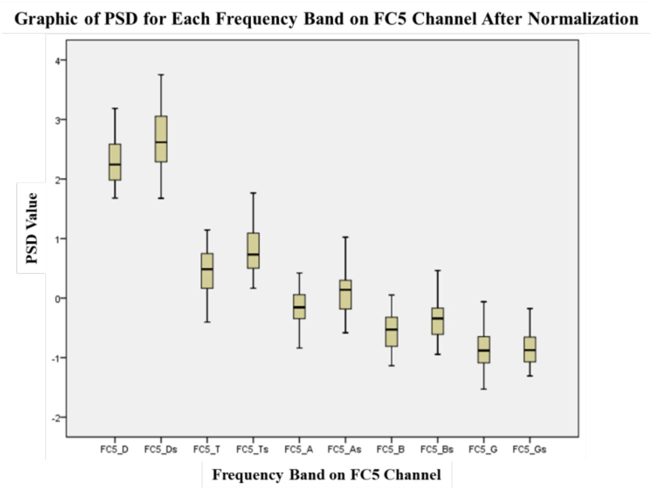


Fig. 11. PSD data spread of each ribbon frequency in channel FC5 after normalization.

3.5. Data spread analysis of the EEG signal based on the respondents' activities

A data spread analysis was conducted to ensure there was a change of EEG signal due to a change stimulated from the respondents' activities. This analysis was done using the T-test paired with a 90% level of accuracy. The matrix from the statistical test results of the EEG signal's data spread towards the respondents' activities was shown in Fig. 12. Based on the matrix, the green-coloured cells showed that the PSD value in that channel could be used to differentiate the respondents' activities. In contrast, the yellow-coloured cells show the PSD value in that channel that cannot be used to differentiate the respondents' activities. The matrix indicates that low frequencies, such as delta and theta, were sensitive enough to detect the different activities. However, for waves with a higher frequency, such as alpha, beta, and gamma, the different activities showed no significant results in the Power Spectral Density value.

3.6. Developing the k-Nearest Neighbor classifiers algorithm

The k-Nearest Neighbor classifiers algorithm was created using MATLAB software. Developing the classifiers algorithm was to classify the EEG signal used on the questionnaire as a physiological response.

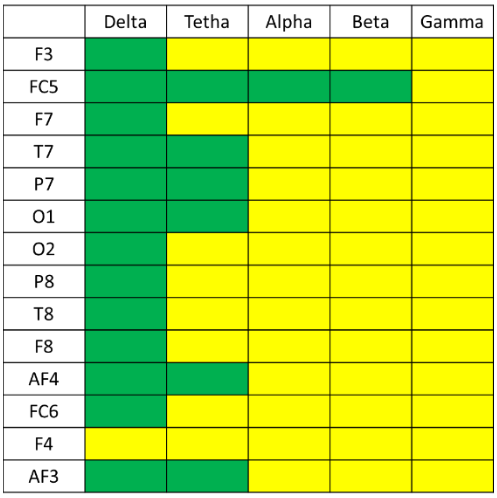


Fig. 12. Matrix of the statistical test for EEG signal data spread of the respondents' activities.

3.6.1. Determining the kNN type of algorithm

The first step in optimizing the ribbon combination frequency was determining the k-Nearest Neighbor classifiers algorithm in MATLAB software. The algorithms were the Fine-kNN, Medium-kNN, Coarse-kNN, Cosine-kNN, Cubic-kNN, and the Weighted-kNN. Those six types of kNN were tested using all the features in order to produce accuracy. The kNN type with the highest accuracy will be the algorithm that was used and optimized. The accuracy test results of all six kNN algorithm types can be seen in Fig. 13, with the highest accuracy in the Fine kNN algorithm of 82.5 %. Based on that result, the Fine-kNN algorithm was put through an optimization process.

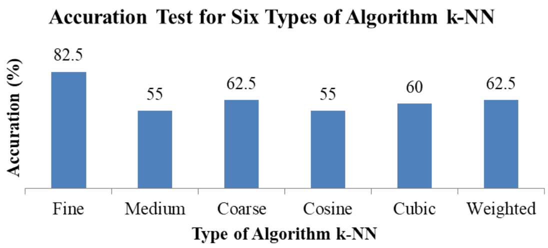


Fig. 13. Results of the accuracy-test for six types of k-NN algorithms.

3.6.2. Optimization ribbon frequency combination

Optimizing the ribbon frequency combination begins with inserting all the features into the algorithm, then the ribbon frequencies were erased one by one from the combination. The results of the optimization of the ribbon frequency combination were depicted in Fig. 14. The ribbon frequency combination consists of the delta, theta, and beta ribbons, which were capable of producing an 85% accuracy, which was more than when using all the features, which only gives an accuracy of 82.5%.

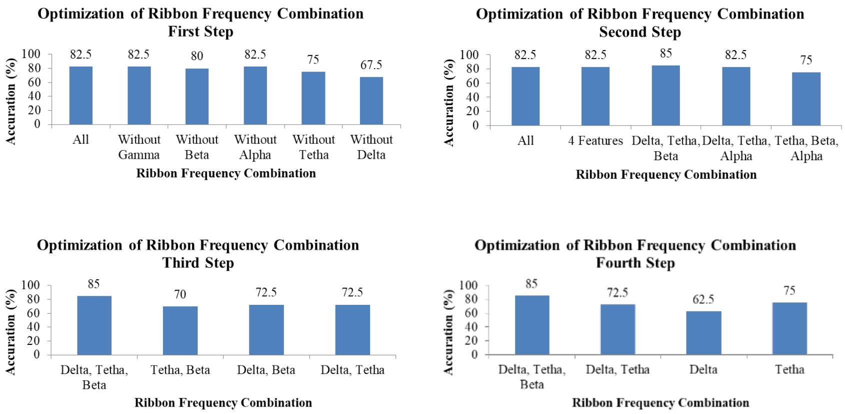


Fig. 14. Results of the accuracy-test of the first ribbon frequency combination.

3.6.3. Optimization

Using the ribbon frequency combination in step 2, the k-Nearest Neighbor classification algorithm's performance can be optimized by varying the value of k in the k-Cross-Validation. The results were shown in the following Fig. 15. Based on Fig. 15, it can be concluded that the highest accuracy of classification was when $k = 9$, $k = 10$, and $k = 11$, which is as big as 85%.

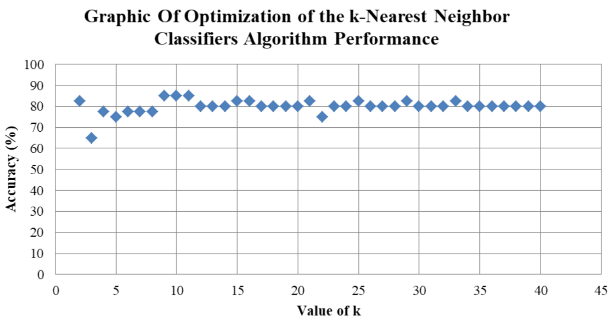
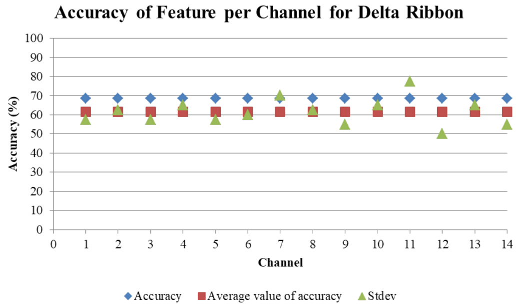


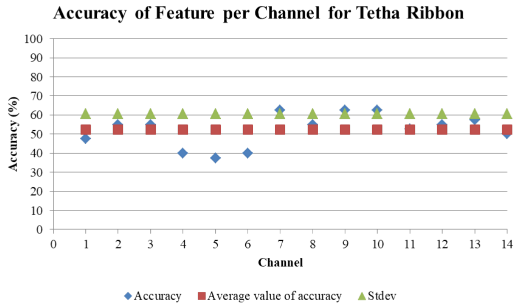
Fig. 15. Results of the Optimization of the k-Nearest Neighbor classifiers algorithm performance.

3.6.4. Optimization of feature combination per channel

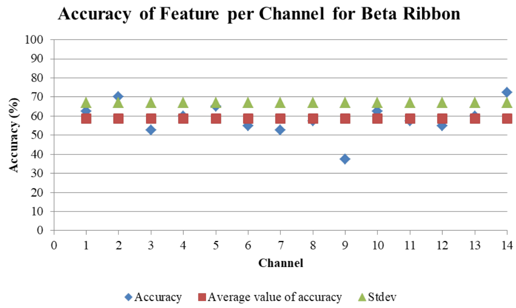
The final optimization was the optimization of the feature combination per channel. Its purpose was to determine which feature has the most effective and which part of the brain that mirrors thermal comfort. The ribbon frequencies used in this optimization were the delta, theta, and beta ribbons that have the highest accuracy and validated with a value of $k = 10$ in the k-Cross-Validation. The features per channel were tested one by one in order to know what accuracy can be produced using only one feature. After all, the features were tested, continued by finding the average value and the standard deviation of the accuracy in order to get the accuracy range (average standard deviation (%) from each ribbon frequency. The features that will be combined were the features that have the highest level of accuracy above the measured range. After determining the feature combination, like ribbon frequency combination optimization, the features were eliminated one by one in order to know which feature can be felt when describing a personal thermal comfort. The results of this process were shown in Fig. 16.



(a) Delta ribbon.



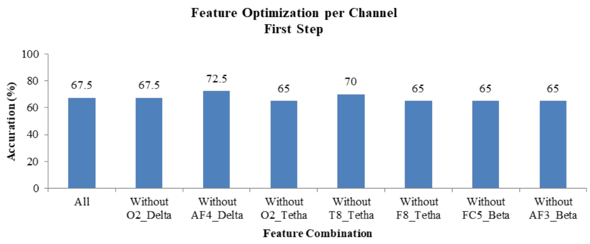
(b) Theta ribbon.



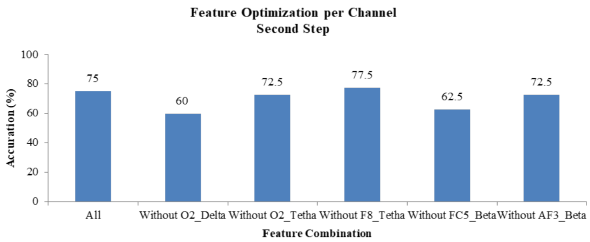
(c) Beta ribbon.

Fig. 16. Feature accuracy per channel.

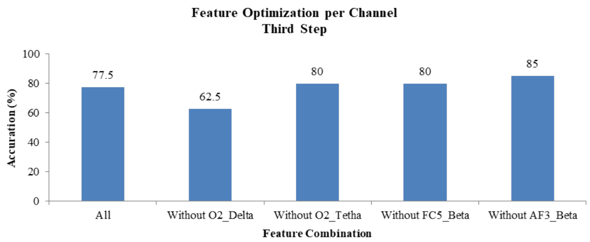
Based on Fig. 16, the features that will be combined were channel 7 (O2) and channel 11 (AF4) delta, channel 7 (O2), channel 9 (T8), and channel 10 (F8) theta, as well as channel 2 (FC5) and channel 14 (AF3) beta. The optimization results from combining the features can be seen in Fig.17.



(a) First step.



(b) Second step.



(c) Third step.

Fig. 17. Results of feature optimization per channel.

Based on Fig. 17(a) depicts the first step in this optimization. When the AF4_Delta and T8_Theta features were erased, the accuracy increases. It indicates that the effects of both channels were insignificant. Thus, both channels were eliminated in the second step. While in Fig. 17(b), it was a picture of step two, whereby erasing F8_Theta, the accuracy, which before was only 75%, increases to become 77.5%. Therefore, the F8_Theta feature was also erased on the third step. In Fig. 17(c), it was shown that the third step from the optimization process. After all the features were used, the accuracy was as big as 77.5%. Furthermore, after eliminating feature AF3_Beta, the value increased to 85%, which was the same value we would receive if all the channels were used. Thus, it can be seen that the features which produce the most optimal accuracy were the O2_delta feature, O2_theta, and FC5_beta, with the value of *k* in the k-Cross-Validation as big as 10.

4. Conclusions

This research concluded that the sense of personal thermal comfort and thermal inconvenience could be predicted using brain waves represented by EEG signals. In order to obtain that prediction, the k-Nearest Neighbor classification algorithm method can be used as a classifier when correlating the EEG signal with the thermal comfort of an individual.

By utilizing feature combination optimization, information can be obtained that the occipital lobe of the brain represented by the O2 channel, and the frontal lobe represented by the FC5 channel, was able to quantize personal thermal comfort. The quantization was generated in the delta (0-4 Hz) and theta (4-8 Hz) frequency ribbon in the O2 channel, as well as beta (13-30 Hz) frequency ribbon in the FC5 channel.

Relating to the prediction of the thermal comfort value using the EEG signal, it was possible to use the Fine k-Nearest Neighbor classifiers algorithm with O2_delta, O2_theta, and FC5_beta features and the value of *k* being 10 in the k-Cross-Validation. With an accuracy of 85%, a k-Nearest Neighbor algorithm can be used to predict personal thermal comfort.

Furthermore, to improve the accuracy of predictions, several things can be improved for further research. In this study, the normalization process was carried out on the resulting feature values. The normalization process can be carried out at the beginning of the EEG signal processing. In this way, the uniqueness of each feature will be more observable. In addition, increasing the number of features using different feature types will provide the possibility to increase the accuracy of predictions.

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Nomenclatures

H_0	Null hypothesis
H_1	Alternative hypothesis
n	Number of characteristics in Eq. (1)
p-Value	The chosen hypothesis yielded from the experiment
u, v	Vectors in Eq. (2), (3) and (4)
w_1	Weight in Eq. (4)
x, y	Subject to compared with *n* characteristic

Greek Symbols

μ_1	Respondent's questionnaire value when partaking in an office activity
μ_2	Respondent's questionnaire value when partaking in a physical activity
$\mu V2$	Amplitude (Fig. 9)

Abbreviations

AC	Air Conditioner
ASHRAE	American Society of Heating, Refrigerating and Air-Conditioning Engineers
CSV	Comma Separated Value
EEG	Electroencephalography
kNN	k-Nearest Neighbor
PSD	Power Spectral Density
PSoC	Programmable System on Chip
SNI	Standar Nasional Indonesia (National Standard of Indonesia)

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