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A Study on Training Data Selection Method for EEG Emotion Analysis Using Artificial Neural Network

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Abstract

The learning of the artificial neural network is performed in the process of modeling using the acquired data set. At this time, the erroneous selection of training data makes it difficult to stabilize the model, leading to a decrease in the recognition rate. In this paper, we investigate how to select the training data to improve the recognition rate in constructing an artificial neural network for emotion classification using DEAP (Database for Emotion Analysis using Physiological Signals). EEG was recorded on two channels of FP1 and FP2 among 32 channels during the viewing of images which cause pleasure, sadness and shock feeling. PSD (Power Spectral Density) values obtained by applying FFT (Fast Fourier Transform) to EEG data were used as feature data of brain waves to be input to the artificial neural network. Finally, emotion classification was performed by modeling artificial neural networks by selecting training data from EEG data based on Valence and Arousal values determined using SAM (Self-Assessment Manikin) method.

Keywords: *Artificial Neural Network, DEAP, EEG, Emotion Analysis, PSD.*

1. Introduction

Electroencephalography (EEG) is a minute current created by signal transmission between the cranial nerves and is recorded by amplifying the signals observed on the electrodes placed along the scalp. EEG measurements use less expensive equipment and have faster response times than other brain activity detection methods such as CT and MRI. Recently, because of the advantage of using non-invasive and light equipment, brain waves are being used as a tool to analyze brain activity in various fields. EEG is used in the study of human emotion [1]recognition [1], and it is used in the field of diseases such as seizure detection [2] and depression diagnosis [3] and BCI. Studies in the field of the disease include studies of degenerative brain diseases such as dementia [4], studies of brain dysfunction with motor impairment, and detection of sleeping disorders [5]. In the BCI field, which allows the user to manipulate the machine by using pre-processed EEG signals, there are researches on robot control using EEG [6-7] and motion control of EIS using EEG [8]. In addition, active research has been conducted in various fields such as analysis of emotional effects of contents, psychotherapy, and so on.

The emotion recognition studies using the EEG related to this paper include studies on a classification algorithm using features obtained by applying FFT (Fast Fourier Transform) algorithm to brain waves [9], on a method of using the linear prediction coefficients as a feature parameter after modeling the EEG as an AR (Autoregressive) model [10].

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In the emotion classification study using EEG data, there is a problem in that there is a difference in the change of the EEG due to the size of emotion felt for the same emotional stimulus according to the personality or disposition of the subjects. Because of this problem, the independent model for the subject is more difficult to classify due to the volatility among the subjects compared to the subject-dependent model [11].

In this paper, we propose a method to select recorded EEG data from subjects with various tendencies when selecting learning data to model the classifier to solve these problems. In the proposed method, Valence and Arousal values measured by SAM (Self-Assessment Manikin) were used to classify data for modeling. The EEG data recorded from the subjects who had seen the same stimulus video were divided into two groups using Valence and arousal values and the learning data was selected and modeled for each group.

The composition of this paper is as follows. In Chapter 2, we describe the DEAP database [12], feature extraction algorithm, and artificial neural network. In Section 3, we show how to select training data for artificial neural network modeling. In Section 4, we verify the performance of neural network models modeled using selected EEG data. Finally, Chapter 5 analyzes the results and concludes them.

2. Experimental data

In this paper, we use DEAP (Database for Emotion Analysis using Physiological Signals), a brain wave data set prepared for emotion classification research at Queen Mary University of London, England. The DEAP database provides information for analyzing human emotions measured from subjects such as EEG data, galvanic skin response (GSR), electro-oculography (EOG), and body temperature.

EEG data provided by the DEAP database were collected using 512 Hz sampling frequency and then downsampled to 128 Hz sampling frequency. The downsampled EEG data is processed through a preprocessing process such as the application of a bandpass filter that passes a 4-45Hz signal and removal of signal noise caused by eye blinking, heart movement, etc. Biological signals were collected from 32 healthy volunteers aged 19 to 37 years. After showing 40 one-minute music video clips that stimulate emotions in the volunteers, the emotional state during watching each video was evaluated using SAM (Self-Assessment Manikins), which is used as a self-diagnostic scale [12]. In this paper, we used data recorded on two channels of FP1 and FP2 among the EEG data generated while viewing three emotion-induced images of pleasure, sadness and shock in the DEAP database.

PSD (Power Spectral Density) values were used to extract feature data for emotion analysis from recorded EEG data. To obtain the PSD value, an algorithm such as Fast Fourier Transform must be used to convert EEG data, which are time domain data, into frequency domain data. Fast Fourier transform is an algorithm designed to quickly perform discrete Fourier transform and its inverse transform that converts a time domain function into a frequency domain function. Assuming that the $x_0, \dots, x_{n-1}$ values are complex numbers, the discrete Fourier transform is defined as follows.

$$\mathrm{X}(f_k) = \sum_{n=0}^{N-1} x_n e^{-j2\pi nk/N} k = 0,1,\cdots,N-1 \tag{1}$$

If the signal function is converted into the frequency domain by Eq. (1), the proportion of the frequency bands of one signal that cannot be confirmed in the time domain can be confirmed. When the EEG signal is converted into a frequency domain value and the spectrum is generated, the components of the EEG signal are divided into delta (1-4 Hz), theta (4-8 Hz), alpha (8-13 Hz), beta (13-30), and gamma (30-45 Hz) bands. After that, the change of EEG due to emotional change can be analyzed using the change of each EEG frequency band by emotion stimulation.

The PSD value can be obtained by applying Eq. (2) to EEG data converted into the frequency domain by applying Eq. (1).

$$P(f_k) = |X(f_k)|^2/N \tag{2}$$

The mean value of the PSD index for each band calculated using Eq. (2) can be used as feature data for EEG analysis.

ANN (Artificial Neural Network) algorithm was used as a classifier for emotion classification using EEG feature data. As the input value of ANN, the PSD (Power Spectral Density) value, which is extracted through frequency analysis of EEG using Fast Fourier Transform Algorithm, is used. And ANN used three nodes to classify three emotions: pleasure, sadness, and shock. To compare the performance according to the number of hidden nodes, experiments were conducted while changing the number of hidden nodes.

3. Proposed method

We propose a method to classify EEG data based on Valence and Arousal values estimated using SAM to model artificial neural networks using EEG data of subjects with various tendencies. The mean and standard deviation of Valence and Arousal values of EEG data recorded while subjects watched the same stimulus is used as the classification criteria. EEG data are divided into two groups: the group with a difference from the mean greater than the standard deviation and the group with a difference from the mean less than the standard deviation. Figure 1 shows the Valence and Arousal values of the EEG data recorded while showing the video clip that elicits the shock emotion to the subjects.

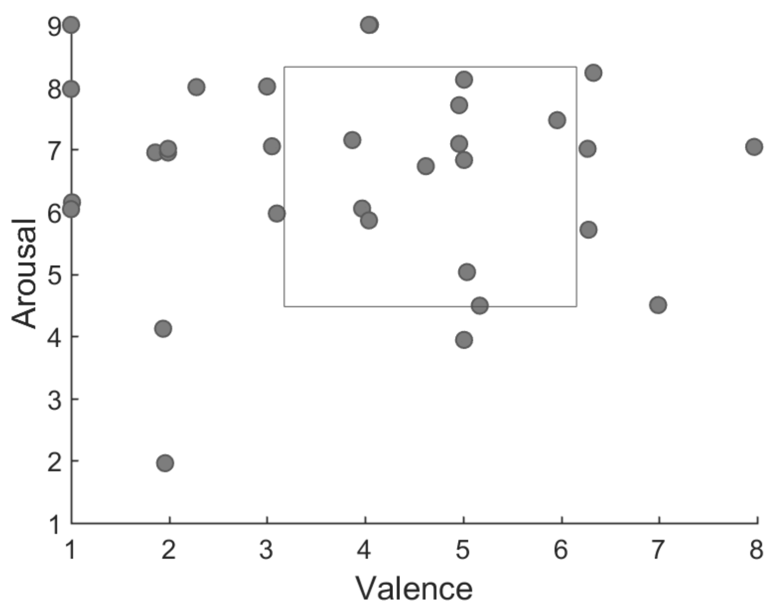

Figure 1. Valence and Arousal values of recorded EEG data while watching shock-induced images

In [Figure 1], the horizontal axis represents the Valence value of each EEG data and the vertical axis represents the Arousal value. The rectangle drawn in the middle of Figure 1 shows the boundary of the EEG data group divided by the mean and standard deviation values of Valence and Arousal of EEG data. When selecting training data for artificial neural network modeling, EEG data of subjects with various tendencies can be used for modeling by equally selecting EEG data of two groups. In the next section, we conduct experiments to confirm the effect of the proposed training data selection method on the modeling results of the artificial neural network model. Experiments were conducted by dividing experimental data into training data groups and test data groups that were not used for modeling but used for verification only.

4. Result

To compare and analyze the performance of the artificial neural network modeled using training data selected with the proposed method, we constructed a total of three training data sets. In the first data set, only EEG data that the Valence and Arousal values are inside the boundaries of the two groups classified by the proposed method were selected, and in the second data set, EEG data with Valence and Arousal values outside the boundary was selected. Finally, in the third data set, the training data was composed by equally selecting data from the two groups. Then, the frequency conversion using Eq. (1) and the calculation of the PSD value using Eq. (2) are performed on the data of each group. In this experiment, we use two channels of FP1 and FP2, so a total of eight input values are generated. Figure 2 shows a graph showing the performance of the artificial neural network model according to the training data sets and the number of hidden nodes with accuracy.

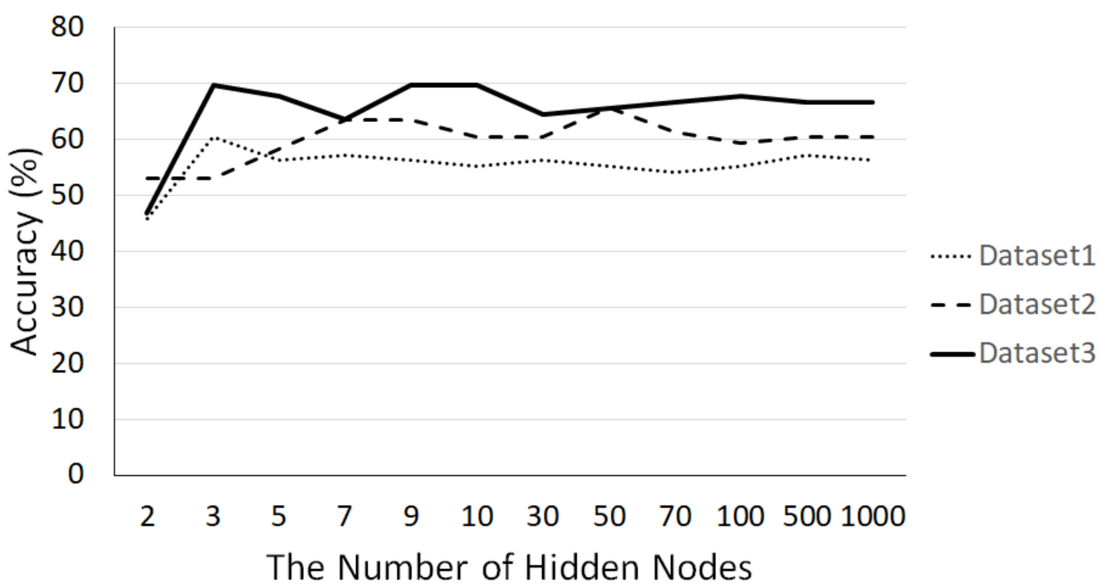

Figure 2. Accuracy based on learning data and number of hidden nodes

In [Figure 2], the horizontal axis of the graph represents the number of hidden nodes of each artificial neural network model, and the vertical axis represents the accuracy of each model. The accuracy graph of the neural network model modeled using each dataset is shown in different lines. Experimental results When the training data of the neural network model is constructed using the third data set consisting of EEG data of subjects with various tendencies, it can be seen that the accuracy is higher than the model using other data sets. From the experimental results, it can be seen that the performance of fitting the untrained data of the neural network model can be improved when the data of various characteristics are selected as the training data by using the criteria proposed in this paper.

5. Conclusion

In this paper, we classify the EEG data into two groups, near from mean, and far from mean by using Valence and Arousal values of EEG data obtained by the SAM method. Then, by selecting the data equally in the two groups, EEG data recorded from subjects with various tendencies were selected as the training data of the neural network. The mean PSD value of each frequency band of EEG was used as a feature to use the selected learning data for modeling the artificial neural network model. The EEG data used for the experiment were recorded in two EEG channels of FP1 and FP2, and four bands of theta, alpha, beta and gamma were used. Since four features are extracted for each channel, a total of eight values are generated as input values of the neural network model.

Then, Experiments were conducted to compare the accuracy of the neural network models modeled using the training data selected using the proposed method and the modeled models using EEG data of the subjects with specific tendencies as training data. Experimental results show that it is better to construct training data by using EEG data of subjects with various tendencies rather than constructing training data by using EEG data of subjects with specific tendencies.

However, the method presented in this paper has disadvantages in that the EEG data provided by the subjects who elicited emotion by the same stimulus do not show any significant change, or when the persons with similar tendencies are set as subjects, the improvement effect is small.

However, if the experimental data group does not belong to this case and the data amount is small and the results greatly vary according to the training data selected for neural network modeling, the proposed method can be useful as a method for improving the model performance.

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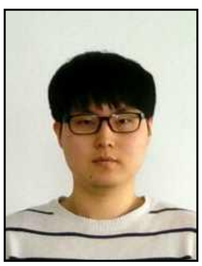

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