# Experiments on Classification of Electroencephalography (EEG) Signals in Imagination of Direction using Stacked Autoencoder

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# Experiments on classification of electroencephalography (EEG) signals in imagination of direction using Stacked Autoencoder

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**Abstract**

This paper presents classification methods for electroencephalography (EEG) signals in imagination of direction measured by a portable EEG headset. In the authors' previous studies, principal component analysis extracted significant features from EEG signals to construct neural network classifiers. To improve the performance, the authors have implemented a Stacked Autoencoder (SAE) for the classification. The SAE carries out feature extraction and classification in a form of multi-layered neural network. Experimental results showed that the SAE outperformed the previous classifiers.

*Keywords*: electroencephalography, stacked autoencoder, neural network, portable EEG headset, imagination of direction

## 1. Introduction

Electroencephalography (EEG) is a non-invasive way for measuring human brain activity. A lot of studies on Brain Machine Interface (BMI) have make use of EEG because of its greater availability than invasive ways. In addition, portable and low-cost EEG devices have been developed and readily accessible nowadays. Having said that, there are unclear points in the accuracy of those portable EEG devices,[1,2] hence the potential of applications using them should be explored.

Seto et al. had studied on classification of EEG signals in imagination of direction measured by a medical EEG device.[3] Following their study, we employed a portable EEG headset to record EEG signals in imagination of direction, and implemented feature extraction with Principal Component Analysis (PCA) and several neural networks for the classification.[4,5] We validated the classification performance and confirmed that the best classification rate of the method using the medical EEG device was still better than those of our methods.

To achieve higher classification rate, we have implemented a Stacked Autoencoder (SAE) for feature extraction and classification of EEG signals in imagination of direction measured by the portable EEG device. G. E. Hinton et al. said that deep autoencoder networks can reduce the dimensionality of data much better than PCA.[6] Therefore, we introduced a SAE to our study. Here we describe the SAE implemented for EEG signal classification and show results of comparative experiments that validate its effectiveness.

## 2. EEG Data Acquisition and Preprocessing

Fig. 1 shows a wireless portable EEG headset developed by Emotiv Inc., named EPOC.[7] We used the headset for EEG data acquisition in our preceding study.[4,5] EPOC has 14 electrodes and two reference electrodes, recording EEG signals at a sampling rate of 128 Hz. The electrodes are placed on the scalp according to an extended 10-20 system for EEG measurement as shown in Fig. 2.

Fig. 1. Emotiv EPOC (wireless portable EEG headset)

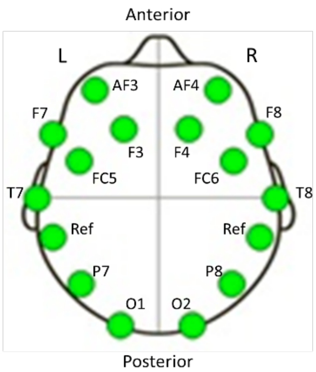


Fig. 2. Electrode placement of EPOC

Nine male university students participated in experiments as subjects for EEG data acquisition. Their average age was 21.9 years. Fig. 3 shows the experimental environment. During the experiments, a subject imagined one figure of arrows shown in Fig. 4. The obtained EEG signals were preprocessed to produce input vectors to a classifier. Fig. 5 is a flowchart of the preprocessing. The input vectors are composed of 23 elements. See Refs. 4 and 5 for more details about the EEG data acquisition and preprocessing.

Fig. 3. Experimental environment

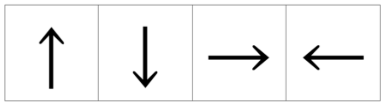

Fig. 4. Arrows indicating directions (up, down, right, and left)

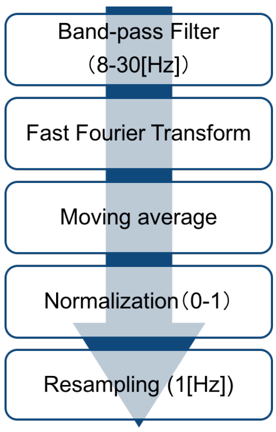


Fig. 5. Flowchart of preprocessing

## 3. Classification with Stacked Autoencoder

In our previous studies,[4,5] we applied PCA to the preprocessed EEG data for reducing the dimension, and trained three-layered neural networks using the data as feature vectors. This classification method is called "PCA-NN" in this paper.

We introduced deep neural networks in order to achieve better classification performance. Although training a deep neural network was difficult for backpropagation due to vanishing gradient problem, pretraining weights between nodes of a deep neural network can be a solution to the problem.

Stacked Autoencoder (SAE) is a way of constructing a deep neural network, in which deep architectures are initialized by stacking pretrained autoencoders. Fig. 6 illustrates a typical autoencoder that is an hourglass-shaped three-layered neural network. This neural network has the same number of nodes in the input and output layers, and it is trained so that it can yield output values equal to given input ones by backpropagation. As mentioned above, autoencoders can be used for dimensionality reduction. The anterior part between the input and hidden layers of autoencoder works as an encoder, compressing input signals and extracting important information from them. The encoder parts of pretrained autoencoders are stacked for initializing a deep neural network. We trained the autoencoders with the preprocessed EEG data for 1000 epochs.

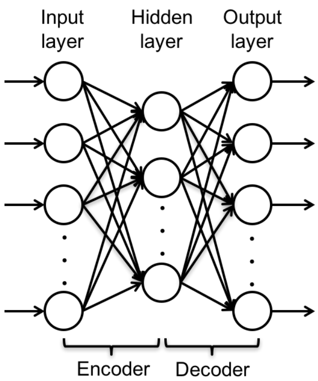


Fig. 6. Autoencoder

We constructed initial SAEs with the pretrained autoencoders and then performed fine-tuning for 1000 or 10000 epochs. Fig. 7 shows the architecture. The SAE has an input layer, two hidden layers, and an output layer. Input vectors to the SAE are composed of 23 elements produced from the EEG signals obtained through the preprocessing shown in Fig. 5. The output layer has four nodes in order to classify given EEG signals into the four directions: up, down, right, and left. The number of nodes of the first and second hidden layers were tentatively set to 20 and 10, respectively. Searching the optimum number of hidden layers and their nodes is a future work.

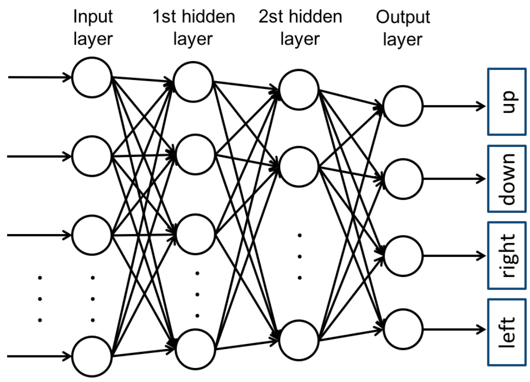


Fig. 7. Stacked Autoencoder with two hidden layers

## 4. Results and Discussion

The classification rates of the classifiers were evaluated with 5-fold cross validation. Table 1 and Table 2 show the evaluation results for the EEG signals obtained from one of the subjects. In the PCA-NNs, the PCA kept features with a 90% cumulative contribution ratio, and trimmed off the others. In the result, 17-dimensional feature vectors were produced. Therefore, the NNs of the PCA-NN were composed of 17-17-4 nodes in the input, hidden, and output layers. On the other hand, the structure of the SAEs were 23-20-10-4; the number of the input nodes is 23 that is equal to the dimension of the preprocessed input vector.

As shown in Table 1, the maximum classification rate by the PCA-NNs was 35.0% at FC5 electrode. It appears that overfitting caused the poor performance in some of the PCA-NNs trained for 10000 epochs.

Table 2 shows the classification rates of the SAEs. It clarified that the SAEs achieved better classification performance than the PCA-NNs. One of the SAEs realized 61.7% classification rate at FC5 electrode. Nevertheless, the work by Seto et al. using a medical EEG device[3] is still better than the results obtained in this study.

It would be expected for improvement that a deeper SAE could provide superior performance than the SAEs with only two hidden layer used in this study. In addition, we will use denoising autoencoders[8,9] to extract more relevant features for the classification of EEG signals.

Table 1. Classification rate percentages of PCA-NN

| Electrode | Epoch 1000 | Epoch 10000 |
|---|---|---|
| AF3 | 25.8 | 25.8 |
| F7 | 29.2 | 26.7 |
| F3 | 26.7 | 29.2 |
| FC5 | 35.0 | 25.8 |
| T7 | 33.3 | 26.7 |
| P7 | 31.7 | 27.5 |
| O1 | 25.0 | 25.8 |
| O2 | 25.0 | 25.0 |
| P8 | 34.2 | 28.3 |
| T8 | 30.0 | 25.8 |
| FC6 | 25.8 | 26.7 |
| F4 | 27.5 | 24.2 |
| F8 | 24.2 | 24.2 |
| AF4 | 26.7 | 23.3 |

Table 2. Classification rate percentages of SAE

| Electrode | Epoch 1000 | Epoch 10000 |
|---|---|---|
| AF3 | 35.8 | 34.2 |
| F7 | 56.7 | 49.2 |
| F3 | 41.7 | 40.0 |
| FC5 | 55.8 | 61.7 |
| T7 | 40.8 | 40.8 |
| P7 | 37.5 | 41.7 |
| O1 | 30.0 | 33.3 |
| O2 | 28.3 | 30.8 |
| P8 | 24.2 | 29.2 |
| T8 | 45.0 | 32.5 |
| FC6 | 39.2 | 34.2 |
| F4 | 34.2 | 33.3 |
| F8 | 35.0 | 32.5 |
| AF4 | 36.7 | 35.0 |

## 5. Conclusion

We implemented the SAEs for classification of EEG signals in imagination of direction, and compared the performance with those of the NNs trained using the feature vectors extracted by PCA. The results demonstrated that the SAEs achieved the improvement, however the achievement of the preceding study using a medical EEG device is still better than ours using the portable EEG headset. There remains much to explore a way to select the number of layers in the SAEs and to adopt denoising autoencoders as future work.

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