Classification of EEG Motor Imagery Using Support Vector Machine and Convolutional Neural Network

Yu-Te Wu[1], Tzu Hsuan Huang[1], Chun Yi Lin[1], Sheng Jia Tsai[1], and Po-Shan Wang[1,2]

[1]Institute of Biophotonics, National Yang-Ming University, Taipei, 112 Taiwan.

[2]Dept. of Neurology, Taipei Municipal Gan-Dau Hospital, Taipei, 112 Taiwan.

Abstract- In this study, we used two machine learning algorithms, namely, linear support vector machine (SVM) and convolutional neural network (CNN), to classify the BCI (Brain Computer interface) competition IV-2a 2-class MI (motor imagery) data set which consists of EEG data from 9 subjects. For each subject, 5 sessions of signals from three electrodes (C3, Cz, and C4) were recorded with sampling rate 250Hz. The training data, which consisted of the first 3 sessions, included 400 trials. The evaluation data, which consisted of the last 2 sessions, included 320 trials. Each trial started with gazing at fix cross on screen for 3 seconds followed by a one-second visual cue pointing either to the left or right to instruct the subject for left or right motor imagery over a period of 4 seconds, and then followed by a short break of at least 1.5 seconds. Features were extracted from the 0.5 to 2.5 second signals after the cue for each trial from C3 and C4. Each EEG trial was band pass filtered into different frequency bands, namely, delta (0.5-3Hz), theta (4-8Hz), alpha (8-12Hz), beta bands (13-30Hz), gamma bands (31-60Hz). Those filtered signals were then used as the input data for training the linear SVM. In addition, we generated a 2 by 500 matrix by down sampling the training data from each trial. There are 5760 such matrices in total generated from all subjects and serve as the input data for training CNN and the trained model was evaluated by another 340 matrices from each subject. Our CNN architecture consisted of 2 convolution layer and 2 fully connect layers, and there was a batch normalization layer before the activated layer and a dropout layer with a probability of 50% after the activated layer. The classification accuracies evaluated by averaged kappa values obtained from linear SVM and CNN are 0.5 and 0.621, respectively, suggesting the deep learning CNN method is superior to the classical linear SVM on the EEG classification.

Keyword: Brain Computer Interface (BCI),* Motor Imagery (MI), *Electroencephalography (EEG), Signal Processing, Machine Learning (ML), Support Vector Machine (SVM), Convolution Neural Networks (CNN).

Y.T. Wu is with the Institute of Biophotonics, National Yang-Ming University, Taipei, 112 Taiwan (phone: 886-2-2826-7000; e-mail: yute.wu@msa.hinet.net).

T.H. Huang is with the Institute of Biophotonics, National Yang-Ming University, Taipei, 112 Taiwan (e-mail: kenhts790815@gmail.com)

C.Y. Lin is with the Institute of Biophotonics, National Yang-Ming University, Taipei, 112 Taiwan (e-mail: sifter7380@gmail.com)

S.J. Tsai is with the Institute of Biophotonics, National Yang-Ming University, Taipei, 112 Taiwan (e-mail: tesciph1995@gmail.com)

P.W. Wang is with the Taipei Municipal Gan-Dau Hospital, Taipei, 112 Taiwan (phone:886-2-28587000; e-mail: b8001071@gmail.com)

I. Introduction

A. Brain Computer Interface

The brain computer interface (BCI) is a system to communicate machine and human body commands only through brain wave. A BCI consists of three parts: signal acquisition, signal processing, and controlling of applications [1]. Some of BCIs also include an additional biofeedback to users for self-examination. To control a BCI, we need a biosignal that would change due to the human emotion or behavior. The EEG detection is an appropriate method because of the convenience and low cost. We extracted the signal features to discriminate different human statuses, and translated the features into commands to control devices (see Figure 1).

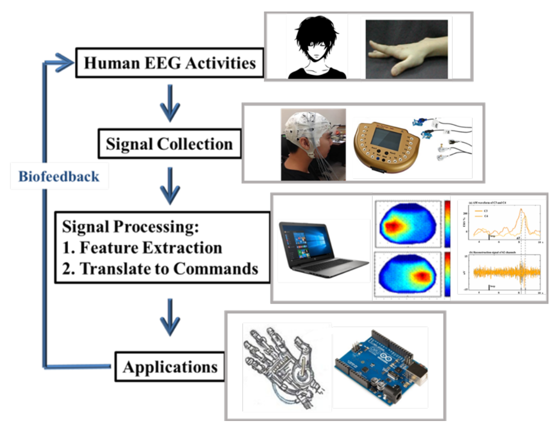


Fig 1. Basic concepts of a brain computer interface. EEG signals are acquired by electrode and processed to extract the features which reflected user's physiological statuses. The features would be translated to external commands depending on application requirements.

B. Analysis of Motor Imagery EEG

There are many EEG signals that can be used to construct a BCI system. In this study, we focused on the motor imagery EEG. Motor imagery (MI) is a mental process by which an individual simulates an action [2]. During a MI task it would produce similar ERD/ERS patterns as during physical movements [3]. By conducting different kinds of MI tasks, different patterns of brain wave can be induced and differentiated in various EEG channels and frequency bands. For example, when an individual imagines moving his right arm, there will be a synchronized neural activities in the primary motor cortex of the left brain. These events related synchronization (ERS) or desynchronization (ERD) in the EEG signal can be seen as a conversion from a resting state to an activated state (see Figure 2). However, the characteristics of brain activities such as the spatial location, temporal onset, and amplitude of power changing are all different from person to person, which makes it a challenge to design a general framework to effectively detect the changes in the motor imagery EEG.

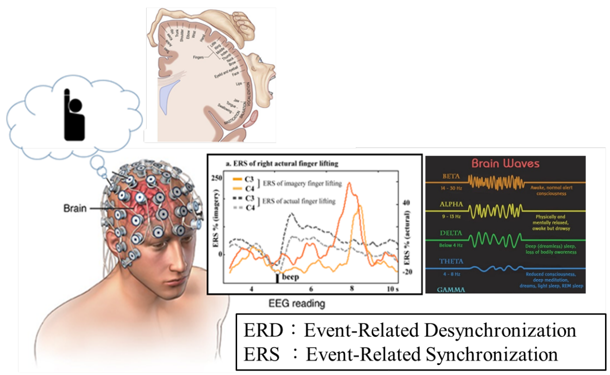


Fig 2. During a motor imagery task, it produces similar ERD/ERS patterns as during an actual physical movement. Depend on the tasks, patterns exhibit at different channels and frequency bands [3].

C. *Deep learning*

In this study, we use a supervised "shallow" classifier and a deep learning method to predict the motor imagery task. Deep learning methods, which is a subcomponent of machine learning field, has been the state-of-the-art classification algorithms for computer vision and natural language processing problems [4]. The neural network imitates the mechanism of the neurons' association in the brain as Figure 3 shown. Briefly, deep learning is a machine learning technique that employs the deep neural network (see figure 4). As the brain is composed of connections of numerous neurons, the neural network is constructed with connections of nodes, which are elements that correspond to the neurons of the brain [5][6][7].

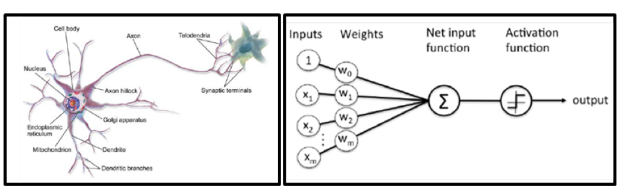


Fig 3. The neural network imitated mechanism of brains. A neural network is constructed with connections of nodes, which are elements correspond to the neurons [6][7].

However, the applications of these deep learning methods in BCI are still limited. The high dimensionality of EEG data encompassing multichannel signals, high sampling rate, and presence of artifacts noise makes it difficult to design an effective deep learning algorithm for EEG classification. The extraction of meaningful EEG features are crucial for implementing a deep learning framework.

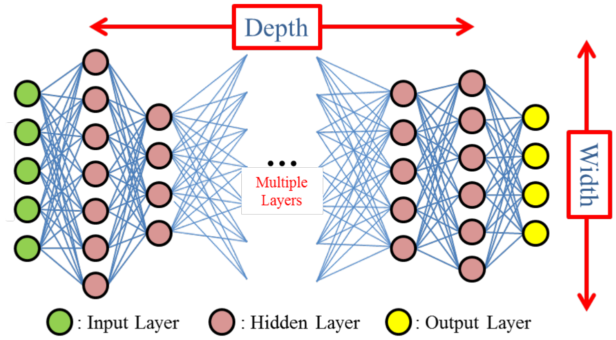


Fig 4. A deep neural network might consist of multiple hidden layers.

II. Data and Algorithms

A. *BCI Competition IV Data set 2b*

In this paper, we use the 2008 BCI competition IV-2a EEG data set 2b [8] to evaluate the designed SVM and CNN classifiers, which is a two-class (left hand and right hand) motor imagery data set recorded at three electrodes (C3, Cz, C4) from 9 subjects with 250-Hz sampling rate. For each subject 5 sessions are provided, in which the first two sessions were recorded without feedback (screening session) and the last three sessions with feedback (smiley feedback session). The timing scheme of a screening session consists of a fixation of 3 s, cue time of 1.25 s, followed by a period of a motor imagery of 4 s. Each screening session contained 120 trials. The timing scheme of a smiley feedback session consists of a fixation of 3 s, followed by a period of a motor imagery of 4.5 s with cue and smiley feedback. Each smiley feedback session consisted of 160 trials.

The training data, which included 2 screening sessions and one smiley feedback session (referred to as 01T, 02T and 03T hereafter), comprised a total of 400 trials. The evaluation data, which included the 2 smiley sessions (referred to as 04E and 05E hereafter), comprised a total of 320 trials. Features are extracted from the 0.5 to 4.5 s after the cue.

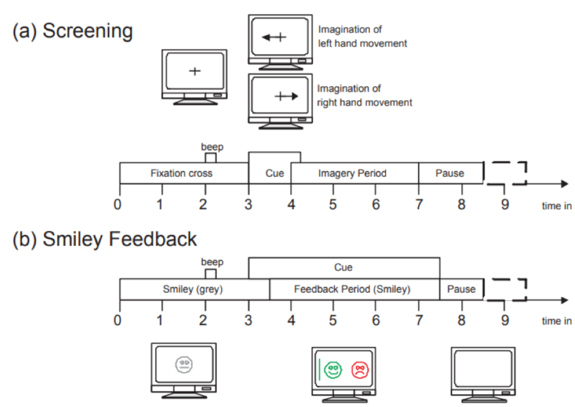


Fig 5. Timing scheme of the screening and smiley feedback sessions [8].

B. Support Vector Machine (SVM)

Classification is a common task in machine learning. Suppose there are two classes of data, the goal is to decide a new data point belonging to which class. Given a set of training samples, a SVM algorithm builds a model that assigns each sample to one category or the other so that the samples of two different categories are separated by a clear gap that is as wide as possible. New samples are then predicted based on which side they fall.

Specifically, in support vector machines, a data point is viewed as a n-dimensional vector. The linear SVM is to separate such points with a (n-1)-dimensional hyperplane. In the processing, we can select two parallel hyperplanes that separate the two classes of data, so that the distance between them is as large as possible. The region bounded by these two hyperplanes is called the margin. There are many hyperplanes that might separate the data, and the best hyperplane must be the one that produces the maximum margin between the two classes. In other words, we choose the hyperplane so that the distance to the nearest data point on each side is maximized. Once the max-margin hyperplane is determined, the samples on the margin are called the support vectors [9].

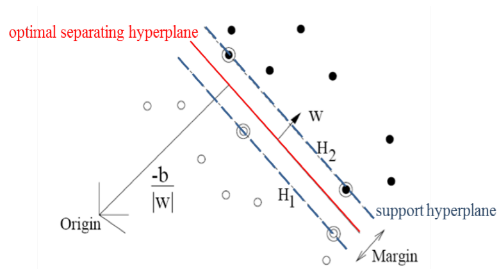


Fig 6. The optimal separating hyperplane and the support vectors [9].

C. Convolutional Neural Networks (CNN)

Convolutional Neural Networks (CNN) is not just a deep neural network that has many hidden layers. It is a deep network that imitates how the visual cortex of the brain processes and recognizes images [5]. CNN includes the feature extractor in the training process rather than designing it manually. The feature extractor is composed of special kinds of neural networks, of which the weights are determined via the training process, and turned the manual feature extraction design into the automated process. The CNN algorithm used convolution in place of matrix multiplication in at least one of the layers of neural networks. It scales up neural networks to process very large data, and it is suitable for processing data that has grid-like topology.

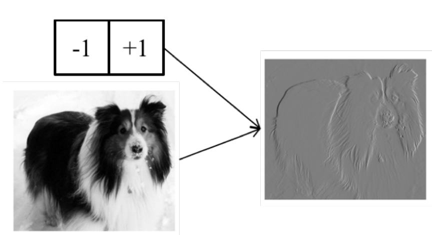


Fig 7. The vertical edge features of a photo are extracted by applying (-1, +1) kernel on it. Likewise, with different kernels, we can extract lots kind of data features [6].

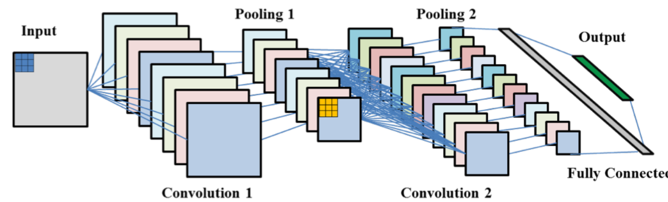


Fig 8. An example of CNN architecture with 2 convolutional layers and 1 fully connected layer. There is an activation layers after each convolution layer which helps the feature extraction.

III. Result

In this study, the linear SVM and CNN were used to classify left or right motor imagery EEG trials. We divided our results into three parts. In the following, the data preprocessing and SVM and CNN results are presented, respectively. In addition, we compare our SVM and CNN results with that obtained from the filter bank common spatial pattern (FBCSP) algorithm [10].

A. Data preprocessing and Performance using SVM

In the data set 2b of BCI competition, the time segment in each trial from channel C3 and C4 was filtered by a 6-order Butterworth band-pass filter and zero phase digital filter to obtain signals of different frequency bands: delta band (1-4Hz), theta band (4-8Hz), alpha band (8-13Hz), beta band (13-30Hz), and gamma band (30-45Hz). After filtering, we selected the 4 seconds of motor imagery period in each trial for the following feature extraction.

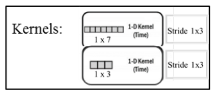
We select 14 features for classification: spectral power of delta ,theta ,alpha ,beta, and gamma bands, ratio of beta-band power to alpha-band power, ratio of power of alpha + beta band to power of delta + theta band from C3 and C4, respectively. For each subject, an individual SVM model was implemented. The selected features from session 01T, 02T, 03T of each subject respective is selected as training data to build a linear Support Vector Machine model, and a 10 fold cross-validation is executed to prevent overfitting. The resultant model was evaluated by the data in predicting session 04E and 05E of each subject, and achieved 0.515 of Cohen's kappa averaged from 9 subjects.

B. Preprocessing Methods and Performance using CNN

We also applied the CNN method to classify the left and right motor imagery EEG. Before applying CNN classifier, the time segment in each trial from channel C3 and C4 was filtered into delta, theta, alpha, beta, and gamma bands as in the data preprocessing for SVM model. The signals were down sampled to 125Hz after filtering, and the 4-second signals of motor imagery period were fed into our CNN architecture to train the classification model. Instead of designing a SVM classifier for each subject, here we construct a general CNN model for all subjects. The training data included the whole processed data from session 01T, 02T, and 03T of all subjects, and the CNN model was evaluated by the data in session 04E and 05E, respectively, from each subject.

In this framework, we used the one-dimensional kernel along the time direction to achieve temporal feature extraction, and 2 fully connected layers were used to integrate the feature output. The model was trained by optimizing the cross entropy using stochastic gradient descend method (Figures 8 and 9, and Table 1). To avoid overfitting, we insert a batch normalization layer before the activation layer and a dropout layer after the activation with a probability of 50%. The average accuracy from 9 subjects of this architecture is 0.613 in Cohen's kappa.

a. Optimization method : SGD
b. Optimization criterion : Cross entropy.
c. A batch normalization layer before the activation layer.
d. Dropout layers after the activation with a probability of 50%.



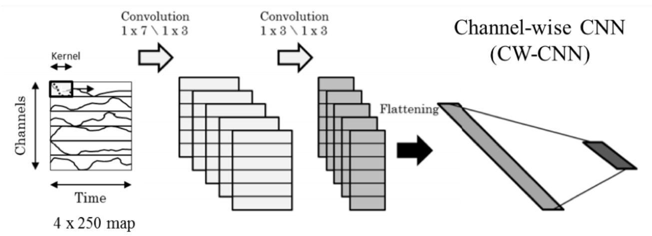


Fig 9. Visualization of CNN architecture

Layer Type	Patch size / Stride	Input Size	Hidden Unit
Convolution	1 x 7 / 1 x 3	2 x 500	32
ReLU	-	2 x 165	-
Convolution	1 x 3 / 1 x 3	2 x 165	32
ReLU	-	2 x 55	-
Linear	-	3520	512
ReLU	-	512	-
Linear	-	512	2
LogSoftMax	-	2	2

Table 1. The Architecture of CNN in this study

C. Evaluation of Each Algorithm

We use the Cohen's kappa value to evaluate the SVM and CNN classifiers. Our SVM and CNN results were compared with that of the FBCSP method which used the naive Bayes Parzen window classifier [10]. Table 2 presents the classification accuracies in Cohen's kappa value obtained from FBCSP, linear SVM and CNN, respectively, on the motor imagery EEG signals from BCI competition IV 2b. The results indicated that the deep learning CNN method outperform to the linear SVM and FBCSP.

	FBCSP	SVM	CNN
Subject 1	0.400	0.492	0.384
Subject 2	0.207	0.250	0.232
Subject 3	0.219	0.103	0.554
Subject 4	0.950	0.811	0.785
Subject 5	0.856	0.708	0.941
Subject 6	0.613	0.570	0.522
Subject 7	0.550	0.441	0.793
Subject 8	0.850	0.800	0.870
Subject 9	0.744	0.460	0.436
Average	0.599	0.515	**0.613**

Table 2. Cohen's kappa values obtained from FBCSP, SVM, and CNN.

IV. Discussion

Deep learning is a powerful tool for the EEG classification. The classification with features selected automatically by CNN outperforms the linear SVM and FBCSP methods using features extracted manually. However, the problem of deep learning is the ineffectivness of a small number of training samples. Although regularization methods such as adding dropout layers or batch normalization can alleviate this problem, there might be an overfitting problem while constructing the model if the dataset is not abundant enough. Also, in BCI systems, it is desired to reduce for recording data which may reduce the number of training samples. Pretraining the network via generative strategies like autoencoder or from collection of different datasets may lead to a better learning result [10]. Overall, out results demonstrate that the deep learning method can be applied to EEG classification and superior to classical SVM method.

In regard to the motor imagery EEG experiment, it's difficult for people to conduct the spontaneous motor imagery successfully. In the future, we will design a biofeedback which can be helpful on self-training [12]. By raising the ability to self-control the motor imagery, we can record more successful trials to optimize the classification models.

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