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Efficient Channel Selection Approach for Motor Imaginary Classification based on Convolutional Neural Network

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Abstract— Brain Computer Interface (BCI) may be the only way to communicate and control for disabled people. Someone's intention can be decoded from their brainwaves during motor imagery action. This can be used to help them control their environment without making any physical movement. To decode someone's intention from brainwaves during motor imagery activities, machine learning models trained on features extracted from the acquired EEG signals have been used. Although the technique has been successful, it has encountered several limitations and difficulties especially during feature extraction. Moreover, many current BCI systems rely on a large number of channels (e.g. 64) to capture spatial information which are necessary during training a machine learning model.

In this study, Convolutional Neural Network (CNN) is used to decode five motor imagery intentions from EEG signals obtained from four subjects using 64 channels EEG device. A CNN model trained on raw EEG data managed to achieve a mean classification accuracy of 99.7%. Channel selection based on learned weights extracted from a trained CNN model has been performed with subsequent models trained on only two selected channels with higher weights attained a high accuracy (average of 98%) among three participants out of four.

Index terms: Convolutional Neural Network (CNN), machine learning, Electroencephalography (EEG), brain-computer interface (BCI), feature maps.

I. INTRODUCTION

Brain Computer Interface (BCI) is a direct communication pathway between human brain and an external device [1]. The development of a BCI system involves series of steps such as brain signal acquisition, preprocessing, feature extraction, classification, and the control interface implementation [2]. In recent years, BCI related researches especially in the field of healthcare/rehabilitation, have attracted a lot of attention in academia and industry. Some BCI decoding Brain Computer Interface (BCI) is a direct communication pathway between human brain and an external device [1]. The development of a BCI system involves series of steps such as brain signal acquisition, preprocessing, feature extraction, classification, and the control interface implementation [2]. In recent years, BCI related researches especially in the field of healthcare/rehabilitation, have attracted a lot of attention in academia and industry. Some BCI decoding Machine learning have been widely used to perform classification of acquired EEG signal for BCI applications [6]. Wang et al. used machine learning algorithms including FLD (Fisher Linear Discriminant) and SVM (Support Vector Machine), to decode and classify motor imagination based on EEG signals to control a humanoid robot [7]. To perform classification using conventional machine learning algorithms, necessary features must be manually extracted from EEG recordings for training of the machine learning model, which is a challenging task to date. Factors such as motion artifacts [8], electrooculography noise [9], and electromyogram interference inherent in EEG recordings also makes it difficult to extract accurate and robust set of features in the conventional machine learning systems. In motor imaginary classification tasks, the imagined movement is often lost in this mixture of signals [10]. In addition, the choice of good discriminative features to train a conventional machine-learning model is time consuming, difficult and requires the knowledge of an expert, and if feature extraction process is not performed well it may result to low classification accuracy [11]. The performance of a BCI system using motor imagery is greatly depending on how features are extracted [12]. These limitations of the conventional machine learning based BCI systems, necessitate the need for an alternative approach to developing EEG driven BCI systems especially in the field of rehabilitation.

Recent development in deep learning has offered a viable approach to extract features automatically through a deep layer of hidden units, which can address the drawbacks of conventional machine learning. Deep learning has been reported to have capabilities of detecting necessary features even in the presence of interferences/noise [13]. This makes it a promising technique for processing highly contaminated EEG recordings unlike the conventional machine learning approach. Furthermore, the recent possibility of running a pre-

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trained deep learning model on smart devices makes deep learning even more practical for real time application in real life.

In this study, a Convolutional Neural Network (CNN) based model was used for decoding multiple classes of imagined upper limb movement on raw EEG signals obtained from transhumeral amputees. By examining the performance of the built CNN model across different window sizes, we investigated the possibility of applying deep-learning based model in real time application. Further, channels selection using CNN is being proposed.

II. METHODS

A. Subjects

A total of four male transhumeral amputees aged 41.50±7.05 years with mean residual limb of 25.50±4.20 cm as measured from the shoulder blade downwards participated in the study. The participants willingly gave permission for the publication of their photographs/data for scientific and educational purposes in a written approval. Before the experiment, the Institutional Review Board of Shenzhen Institutes of Advanced Technology, Chinese Academy of Sciences, China, approved all the protocols.

B. Equipment setup and data acquisition

For the data collection, we used a commercial EEG recording system (EasyCap, Herrsching, Germany) that integrates the Neuroscan software (version 4.3). The acquisition system consists of 64 electrode channels made of Al-AgCl. The Al-AgCl electrodes were placed over the scalp of each subject with respect to the 10-20 system standard. Before the electrode placement, each subject's hair was cleaned to ensure that high quality signals are obtained. Also, the impedance between each Al-AgCl electrode channel and the subject's scalp was kept as low as 10 kΩ or even lower in some certain situation. After setting up the EEG acquisition system, the subjects were instructed to sit straight facing a computer screen where five different motor imagery (MI) tasks were displayed one after the other. The MI tasks are hand open (HO), hand close (HC), wrist supination (WS), wrist pronation (WP), and no motion (NM). Each task was displayed for a period of approximately 5s on the screen. To minimize the occurrence of mental fatigue, that main affect EEG recordings, a rest period of about 5s was observed in between two consecutive tasks. To obtain sufficient amount of dataset needed to train, validate, and test the proposed CNN based model, each participant completed five trials. In each trial, each task was repeated ten times leading to a total of 50s data recordings per MI task in a trial. Fig. 1 shows the experiment setup.

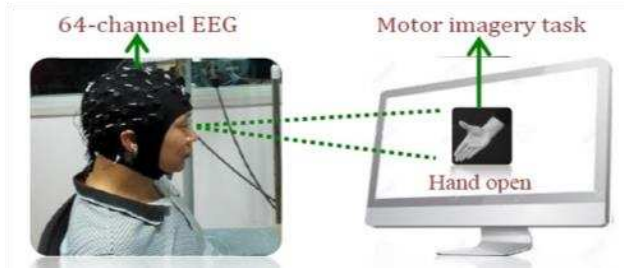

Fig. 1. Experimental settings for EEG recordings

C. Data preprocessing

For each subject's data, a moving window (non-overlapping) was used to slice the input data in time domain. Different window length W_l were used and tested to imitate the possibilities of using the CNN model in real time classification. The 64 widths were left to keep the number of channels; hence our data set was sliced, resulting into samples of dimension (W_l, 64), 2-D image like, were the width represents the spatial structure whilst the height represents the temporal structure [15]. Each sample was normalized using min-max normalization to keep zero mean and unit variance. 80 % of the entire dataset per participant was used for training and 20% for testing.

D. CNN architecture

The CNN model used in the current study has two main parts, the feature extractor part and the trainable part. The feature extractor part contains multiple layers of convolution and pooling. The convolution layer is able to learn and extract features from the raw data automatically and the pooling layer is used for down sampling task. The trainable part contains fully connected multilayer perceptron, which perform classification based on the features extracted in the feature extractor part [16]. The CNN was trained, validated and tested with each participant's data separately. The network had two convolutional layers, first layer with 32 filters and second layer with 64 filters. Each layer had filters size of (5, 5). These filters are aimed to capture different local spatial, spectral and temporal patterns features related to imagined motor activity [17]. ReLu activation function was applied after each convolution layer. Let W_k represent weight of filter k, werek $= 1, \dots .32$ for first convolution layer and k $= 1, \dots .64$ for second convolution layer. Let $V \epsilon P^{M*1}$ denote a vector input with $M = 100 * 64$. W is a hyper-parameter to be learned [18]. The feature map output in convolution layer two is:

$$Convolution(V)_k = RELU(W_k V_k) \quad \text{for } k = 1, \dots \dots 64 \tag{1}$$

max pooling was used after each convolution as it considered to improve network performance [17]. Fig.2 shows the architecture of the developed CNN model

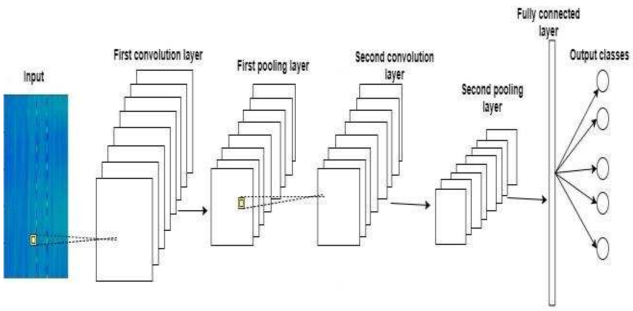

Fig.2. Architecture of the used CNN model for MI classification

III. Results

A. Classification Performance

An average classification accuracy of 99.7% was achieved with a 0.1s window. We also examined the performance of the CNN mode across different window sizes. 0.1 second and 1.0 second windows are presented in Tables 1 and 2, respectively. It can be observed that the model maintained high classification accuracy for both windows with lower optimization speed as the window size increases. This is because larger windows contain more information for learning.

Table 1. 0.1-Seconds window performance metric

Participants	P1	P2	P3	P4
Accuracy	1.0	0.99	0.99	0.99
Precision	1.0	1.0	0.99	1.0
Recall	1.0	1.0	1.0	1.0
F1_Score	1.0	1.0	0.99	1.0

Table 2. 1-Second window performance metric

Participants	P1	P2	P3	P4
Accuracy	1.0	0.99	0.99	1.0
Precision	1.0	0.98	0.97	1.0
Recall	1.0	0.99	1.0	0.99
F1_Score	1.0	1.0	0.99	1.0

The learning curves for 0.1 Second and 1 Second window sizes are shown in Fig. 3 and 4, respectively.

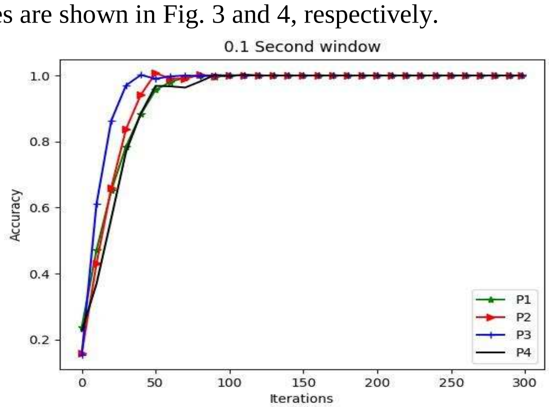

Fig 3. learning curve for 0.1 Second window

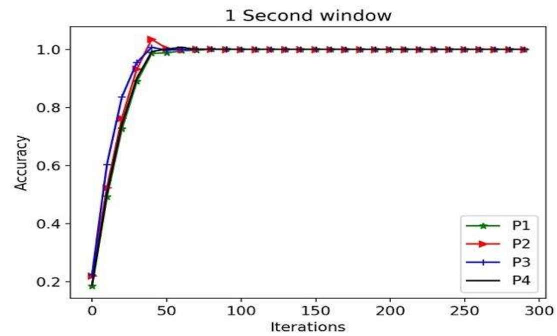

Fig 4. learning curve for 1 Second window

Table 3. Shows the performance of the conventional machine learning models as reported on the previous work on the same dataset [5], in which spectral domain features extracted from the EEG recordings in frequency domain were used to train conventional machine learning classifiers, the linear discriminant analysis (LDA), artificial neural network (ANN) and k-nearest neighbors (kNN).

Table 3. Accuracies based on extracted features

	LDA	ANN	KNN
Av.accuracy (%)	97.81	96.44	96.92

B. Channel reduction

Channel selection were performed based on the weights learned by each channel. We extracted weights from the feature maps formed in the first convolution layer. The weights were calculated using the formula in (2). w_l stands for window length, which is 100 for this study

$$W_P = \sum_{q=0}^{q=W_l} W_{(p,q)}, \qquad (2)$$

Where $0 \leq p < 64$ and $0 \leq q < W_l$

To perform channel reduction, the first twenty (20) channels with highest weights were selected for each participant. Reducing the number of channels up to two (2) in ascending order of the weights was performed and the performance of the models across all four participants was observed and recorded as seen in tables 3,4,5 and 6. More iterations are required to train a model with fewer channels because the models learn from less but significant channel information. The third participant reported phantom limb pain (PLP) during data collection. Amputee with PLP has worse motor control over their phantom hand [4].

Table 3. First Participant channel reduction

Iterations	Number of channels				
	64	20	12	4	2
300	0.99	1.0	0.97	0.95	0.86
500	1.0	1.0	0.98	0.96	0.90
2500	1.0	1.0	1.0	0.96	0.94
5000	1.0	1.0	1.0	1.0	0.98

Table 4. Second Participant channel reduction

Iteration	Number of channels				
	64	20	12	4	2
300	1.0	0.99	0.98	0.66	0.47
500	1.0	1.0	0.99	0.92	0.78
2500	1.0	1.0	1.0	0.96	0.93
5000	1.0	1.0	1.0	1.0	0.98

Table 5. Third participant channel reduction

Iteration	Number of channels				
	64	20	12	4	2
300	0.99	0.98	0.95	0.69	0.44
500	1.0	0.99	0.97	0.94	0.58
2500	1.0	0.99	0.98	0.94	0.63
5000	1.0	1.0	1.0	0.99	0.67

Table 6: Fourth participant channel reduction

Iterations	Number of channels				
	64	20	12	4	2
300	0.99	0.98	0.95	0.69	0.62
500	1.0	0.99	0.97	0.94	0.89
2500	1.0	0.99	0.98	0.94	0.91
5000	1.0	1.0	1.0	0.99	0.98

Conclusion

In this study, we propose the use of convolution neural network for decoding of motor imaginary activities from raw EEG recordings as it avoids some of the drawbacks found in the conventional machine learning approaches. The size of the proposed CNN model is small and simple, with few parameters to learn. This makes it easy for a pre-trained model to be exported and embedded on smart devices for real time applications. Furthermore, as our model maintained high classification accuracy with fewer channels, the channel reduction demonstrated that it is possible to use fewer channel portable EEG devices which can reduce the cost of such device and still achieve high classification accuracy. Also, the method of channel selection can be used to locate the important/significant region on a human scalp for a particular activity hence save time during electrode placement for EEG devices.

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