Classification of Left/Right Hand Movement EEG Signals Using Event Related Potentials and Advanced Features

Nguyen Thi Minh Huong, Huynh Quang Linh, and Le Quoc Khai

Abstract

An event-related potentials (ERPs) is the measured brain response that is the direct result of a specific sensory, cognitive, or motor event. Brain-Computer Interface (BCI) is a device that enables the use of the brain's neural activity to communicate with others or to control machines, artificial limbs, or robots without direct physical movements. In this paper, event-related potential (ERP) components of P300 and the advanced features combined an artificial neural network (ANN) were used to classify the electroencephalogram (EEG) signals associated with left and right hand movements. The EEG dataset used in this research was obtained from PhysioNet. Data was preprocessed using the EEGLAB MATLAB toolbox and then was epoched on the stimulation time for P300 and the basis of Event-Related (De) Synchronization (ERD/ERS) and movement-related cortical potentials (MRCP) features. Mu/beta rhythms were isolated for the ERD/ERS analysis and delta rhythms were isolated for the MRCP analysis. The final feature vector included the P300, ERD, ERS, and MRCP features in addition to the mean, power and energy of the activations of the epoched feature datasets. The datasets were inputted into ANN. The results of classification is quite good and it is promised to be used in a BCI context to mentally control a computer or machine.

Keywords

EEG • BCI • MRCP • ERD/ERS • ANN

1 Introduction

Brain-computer interfaces (BCIs) can provide a direct communication and control channel between the brain and external devices, independent of the brain's normal output pathways of peripheral nerves and muscles [1]. Non-invasive BCIs work by detecting and translating electroencephalography (EEG) signals into machine commands. There are two main types of EEG signals used in BCI: spontaneous signals generated by mental tasks and evoked signals resulting from stereotyped sensory stimulation [2]. Motor imagery (MI) related sensorimotor rhythms fall into the former type [3], while P300 event-related potential and steady-state visual evoked potential (ssVEP) belong to the latter ([4]). Recent research tends to combine virtual reality (VR) with BCI systems. VR can provide safe, complex, and controllable experimental environments for BCI training and testing [5]. Several EEG controlled navigation paradigms in virtual environments by MI have been developed. Early navigation was realized by mapping imagination of hand/foot movements to stop/forward commands in one direction [6]. Later, a self-paced paradigm was proposed [7], and three-class MI-based BCIs with self-paced operations were further developed, where the system could detect MI-related brain activities and discriminate amongst different MI tasks [8, 9]. However, due to the complex dynamics

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T. Vo Van et al. (eds.), *6th International Conference on the Development of Biomedical Engineering in Vietnam (BME6)*, IFMBE Proceedings 63, https://doi.org/10.1007/978-981-10-4361-1_35

of sensorimotor rhythms related to hand/foot movements and other mental tasks, several studies have reported that the best classification accuracy is achieved when only two tasks are discriminated [10, 11]. Recently, a system allowing subjects to move freely in three directions by the use of only one mental task was developed [12, 13]. Nevertheless, commands were selected by controlling a rotating bar, which is not a natural and direct way. Since MI-based BCIs provide relatively low degrees of freedom, in applications with a large number of discrete commands such as spelling or remote control, P300-based BCIs are more efficient. Chen et al. [14] used the P300 to select different movements of a virtual hand. Another hybrid BCI system detects P300 and MI signals simultaneously and independently to control a 2D cursor [14]. With the use of two or more source signals, hybrid BCIs should achieve specific goals better than the conventional BCI systems [15].

In [16], the authors recorded EEG signals for three subjects while imagining either right or left hand movement based on a visual cue stimulus. They were able to classify EEG signals into right and left hand movements using a neural network classifier with an accuracy of 80% and concluded that this accuracy did not improve with increasing number of sessions.

The author of [17] used features produced by Motor Imagery (MI) to control a robot arm. Features such as the band power in specific frequency bands (alpha: 8–12 Hz and beta: 1330 Hz) were mapped into right and left limb movements. In addition, they used similar features with MI, which are the Event Related Desynchronization and Synchronization (ERD/ERS) comparing the signal's energy in specific frequency bands with respect to the mentally relaxed state. It was shown in [18] that the combination of ERD/ERS and Movement-Related Cortical Potentials (MRCP) improves EEG classification as this offers an independent and complimentary information. In [19], a hybrid BCI control strategy is presented. The authors expanded the control functions of a P300 potential based BCI for virtual devices and MI related sensorimotor rhythms to navigate in a virtual environment. Imagined left/right hand movements were translated into movement commands in a virtual apartment and an extremely high testing accuracy results were reached. A three-class BCI system was presented in [20] for the translation of imagined left/right hands and foot movements into commands that operates a wheelchair. This work uses many spatial patterns of ERD on mu rhythms along the sensory-motor cortex and the resulting classification accuracy for online and offline tests was 79.48% and 85.00%, respectively. The authors of [21] proposed an EEG-based BCI system that controls hand prosthesis of paralyzed people by movement thoughts of left and right hands. They reported an accuracy of about 90%.

A single trial right/left hand movement classification is reported in [22]. The authors analyzed both executed and imagined hand movement EEG signals and created a feature vector consisting of the ERD/ERS patterns of the mu and beta rhythms and the coefficients of the autoregressive model. Artificial Neural Networks (ANNs) is applied to two kinds of testing datasets and an average recognition rate of 93% is achieved.

2 The Physionet EEG Data

2.1 Description of the Dataset

We have used the EEG Motor Movement/Imagery Dataset recorded using BCI2000 [23] instrumentation system available through Physionet [24]. The dataset consists of more than 1500 EEG records, with different durations (one or two minutes per record), obtained from 109 healthy subjects. Subjects were asked to perform different motor/imagery tasks while EEG signals were recorded from 64 electrodes along the surface of the scalp. Each subject performed 14 experimental runs:

- A one-minute baseline runs (with eyes open)
- A one-minute baseline runs (with eyes closed)
- Three two-minute runs of each of the four following tasks:
  - The left or right side of the screen shows a target. The subject keeps opening and closing the corresponding fist until the target disappears. Then he relaxes.
  - The left or right side of the screen shows a target. The subject imagines opening and closing the corresponding fist until the target disappears. Then he relaxes.
  - The top or bottom of the screen. A target appears on either. The subject keeps opening and closing either both fists (in case of a top-target) or both feet (in case of a bottom-target) until the target disappears. Then he relaxes.
  - The top or bottom of the screen A target appears on either. The subject imagines opening and closing either both fists (in case of a top-target) or both feet (in case of a bottom-target) until the target disappears. Then he relaxes.

The 64-channels EEG signals were recorded according to the international 10–20 system (excluding some electrodes) as seen in Fig. 1.

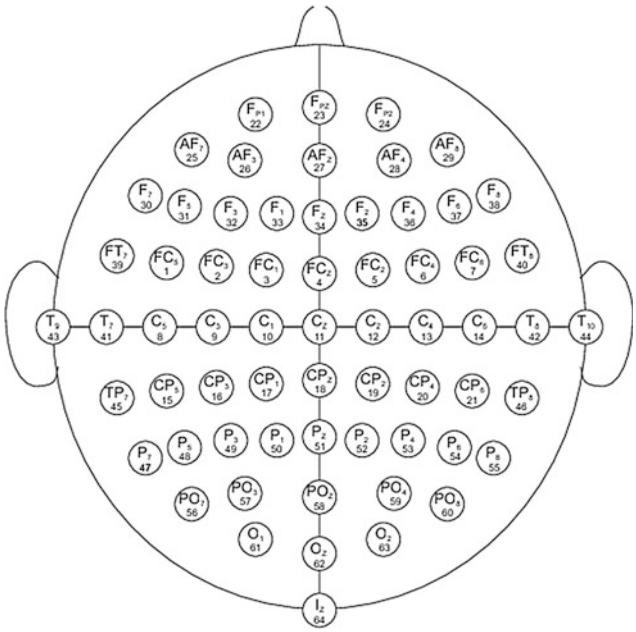

Fig. 1 Electrodes of the International 10–20 system for EEG

3 Methods

3.1 Channel Selection

According to [25], many of the EEG channels appeared to represent redundant information. It is shown in [26, 27] that the neural activity that is correlated to the executed left and right hand movements is almost exclusively contained within the channels C3, C4, and CZ (channels 9, 11, 13 respectively) of the EEG channels. This means that there is no need to analyze all 64 channels of data.

On the other hand, only eight electrode locations are commonly used for MRCP analysis covering the regions between frontal and central sites (FC3, FCZ, FC4, C3, C1, CZ, C2, and C4) [28].

3.2 Filtering

Because EEG signals are known to be noisy and nonstationary, filtering the data is an important step to get rid of unnecessary information from the raw signals. EEGLAB [29], which is an interactive MATLAB toolbox, was used to filter EEG signals. A band pass filter from 0.5 to 90 Hz was applied to remove the DC (direct current) shifts and to minimize the presence of filtering artifacts at epoch boundaries. A Notch filter was also applied to remove the 50 Hz line noise.

3.3 Automatic Artifact Removal (AAR)

The EEG data of significance is usually mixed with huge amounts of useless data produced by physiological artifacts that masks the EEG signals. These artifacts include eye and muscle movements and they constitute a challenge in the field of BCI research. AAR automatically removes artifacts from EEG data based on blind source separation and other various algorithms. The AAR toolbox [30] was implemented as an EEGLAB plug-in in MATLAB and was used to process our EEG data subset on two stages: Electrooculography (EOG) removal using the Blind Source Separation (BSS) algorithm then Electromyography (EMG) Removal using the same algorithm.

3.4 Epoch Extraction (Splitting)

After the AAR process, the continuous EEG data were epoched by extracting data epochs that are time locked to specific event types.

When no sensory inputs or motor outputs are being processed, the mu (8–12 Hz) and beta (13–30 Hz) rhythms are said to be synchronized [31]. These rhythms are electrophysiological features that are associated with the brain's normal motor output channels. While preparing for a movement or executing a movement, a desynchronization of the mu and beta rhythms occurs which is referred to as ERD and it can be extracted 1–2 s before onset of movement. Later, these rhythms synchronize again within 1–2 s after movement, and this is referred to as ERS. On the other hand, delta rhythms can be extracted from the motor cortex, within the pre-movement stage, and this is referred to MRCP. The slow (less than 3 Hz) MRCP is associated with an event-related negativity that occurs 1–2 s before the onset of movement [32, 33]. In our experiments, we extracted time-locking events with type = 3 (left hand) or type = 4 (right hand) with different epoch limits and types of analysis:

- ERD analysis: epoch limits from −2 to 0 s.
- ERS analysis: epoch limits from 4.1 to 5.1 s.
- MRCP analysis: epoch limits from −2 to 0 s.

3.5 Rhythm Isolation

A short IIR band pass filter from 8 to 30 Hz was applied on the ERD/ERS epoched datasets of the experiment for the purpose of isolating mu/beta rhythms. Another short IIR

Table 1 Results for experiments

Features	Accuracy (%)	Hidden layer
All	68	3
P, X	62	15
M, X	62	11
E, X	60	11

The testing results of NNs can provide an accuracy of 68% if all features are used. This result is quite good and it clearly show that the use of advanced feature extraction techniques provides good and clear properties that can be translated using machine learning into machine commands

lowpass filter of 3 Hz was applied on MRCP epoched datasets for isolating delta rhythms. The result of this was 6 files for each run: ERD/ERS and MRCP for both left and right hand movements for each subject

3.6 Feature Vectors Construction and Numerical Representation

After the EEG datasets were analyzed as described in the previous section, the activation vectors were calculated for each of the resulted epochs'. Then, the mean, power, and energy of the activations were calculated to construct the feature vectors. For each subject's single run, 6 feature vectors were extracted as <Power (8 features), Mean (8 features), Energy (8 features), Type (1 feature: ERS/ERD/MRCP), Side (1 target: Left/Right)> resulting in a 108×26 feature matrix. The constructed features were represented in a numerical format that is suitable for use with Neural Networks.

3.7 Neural Networks (NNs)

The MATLAB neural networks toolbox was used for all NN experiments. The number of input features (25 features) determined the number of input nodes for NN and the number of different target functions (1 output: left or right) determined the number of output nodes. Training was handled with the aid of the back-propagation learning algorithm.

4 Results

4.1 The advanced features

For each experiment, the number of hidden nodes for NN varied from 1 to 20. The mean of the accuracy was calculated for each ten training-testing pairs. The features that were used as inputs to NN is symbolized as follows:

- P: the power.
- M: the mean.
- E: the energy.
- X: the sample type (ERS/ERD/MRCP). The results of the experiment are summarized in the Table 1

4.2 Event Related Potentials

After the AAR process, the continuous EEG data were epoched by extracting data epochs that are time locked to specific event types. Analysis window for each response was set to every 1200 ms ranging from 600 ms before to 600 ms after the onset of each stimulus presentation to analysis Event Related Potentials—ERPs. ERPs of a typical subject are plotted with channels 9, 11, 13 as previous Channel Selection in Fig. 2. For each channel, ERPs of left hand movement signals are above figure and ERPs of right hand movement signals are bottom figure. It is clear that waves of ERPs of left/hand movements are different. So, we classify

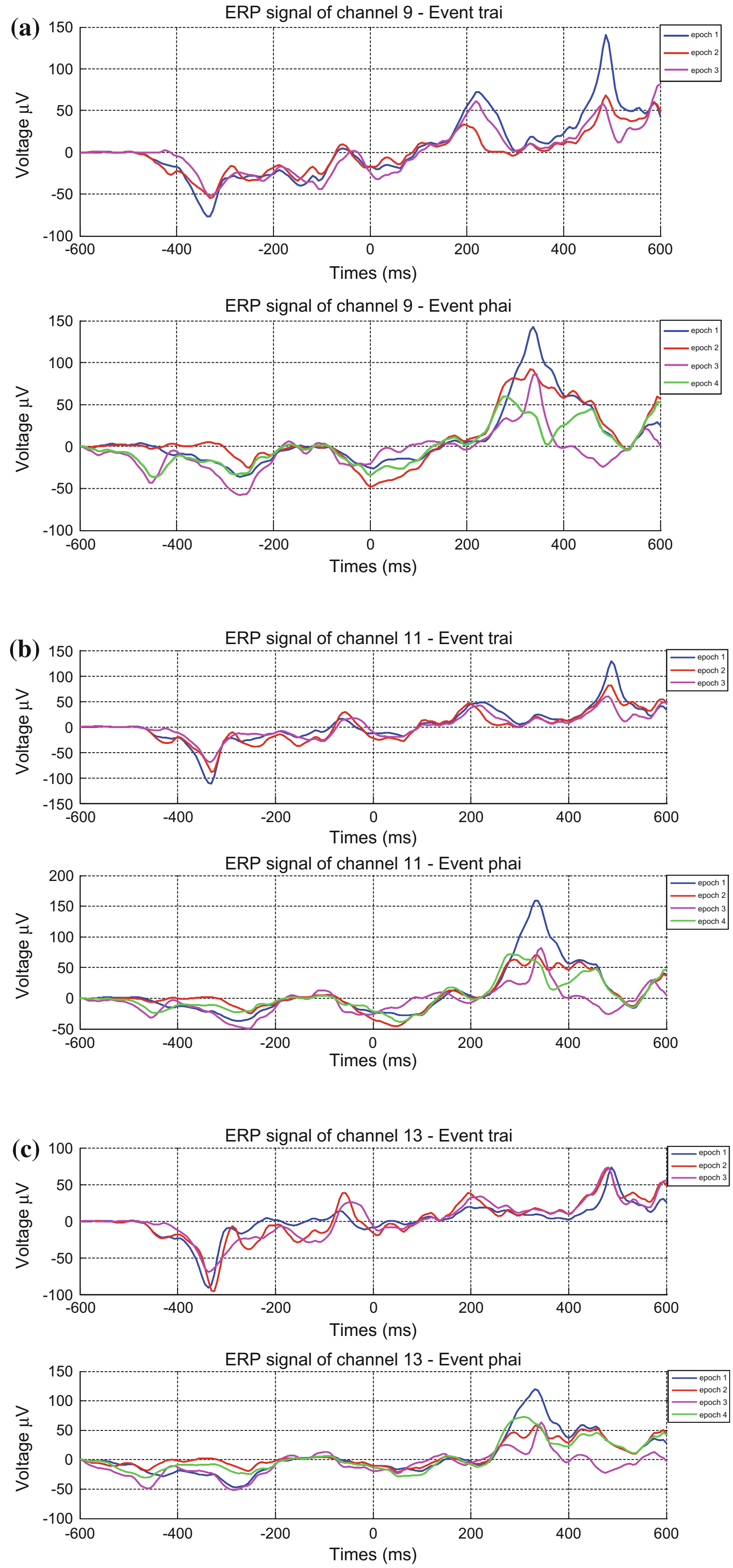

Fig. 2 ERPs of a typical subject. For each channel, ERPs of left hand movement signals are *above figure* and ERPs of right hand movement signals are *bottom figure*. **a** ERPs of channel 9, **b** ERPs of channel 11, **c** ERPs of channel 13

signals of left/right hand movements based on single trials of each subject. Results obtained for all epochs of each subject is 67%. This result show that the using ERP and ANN of EEG signals to perform classification of left and right hand movements is effective. This result can be acceptable for BCI in control.

5 Conclusions

This paper focuses on the classification of EEG signals for right and left hand movements based on a specific set of features. The results of classification is about 65%. It is promised to be used in a BCI context to mentally control a computer or machine. However, these results aren't very good. So, we will find features which might promise a better removal of redundant information from the EEG signal channels and other algorithms to classify signals of left/right hand movements better in future.

Acknowledgements I want to thank developers of the BCI2000 [23] instrumentation system for data. I get in PhysioNet [24].

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