A Natural EEG-based Brain-computer interface for hand grasp control: the role of mental practice and concentration

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Introduction

Recently, many attempts have been made to use the EEG as a new communication channel between the human brain and a computer [1]-[7]. In [1], 56-channel EEG signals have been used to detect three kinds of movement, left and right index finger, and right foot movement. By Laplace filtering the 56-channel EEG, 30-channel EEG data were obtained. For each of the 30 channels, a feedforward neural network was trained with back-propagation learning algorithm. In [2], the separability of the EEG signals during right and left motor imagery was investigated by using the parameters of an autoregressive model of order 6 as the feature vector. The EEG signals were recorded by using two bipolar leads over the right and left central areas and visually inspected for artifact suppression. In [3], a spatial filter is used to maximize the difference between the two populations. One population consists of EEG signals recorded during left-hand movement imagery and the second population consists of right-hand movement imagery. In [4], an EEG-based brain-computer interface based on the classification of five different mental tasks (four different motor imageries and one mental calculation) was proposed.

All of the works described above involves the classification of EEG patterns associated with the different motor imageries and cognitive tasks. However, the most important factor in designing an EEG-based BCI - recognizing the resting state with eyes open and the imagined movement - has been disregarded in the research area of BCI. The design of a BCI depends on the application for which it was intended. This work concerns with the development of a natural EEG-based BCI for hand grasp control. It is natural in the sense that the desired movement is what the subject intends to do. The motor tasks to be intended are the imagination of hand grasping and opening. For prosthetic hand grasp control, recognizing the resting state with eyes open and the imagined voluntary movement is important but has been disregarded in the research area of BCI. This work provides a design for recognizing the resting state and the motor task imagery.

One of the major problems in developing a real-time BCI is the eye blink artifacts. The traditional method of eye blink suppression is the removal of the segment of EEG data in which eye blinks occur. This scheme is rigid and does not lend itself to adaptation. Moreover, a great number of data is lost. To overcome these problems and to shorten the experimental session, we have already developed neural adaptive filter for real-time ocular artifact suppression [6].

Another important issue in developing a practical BCI is the training scheme. It should be easy and must not require special attention. Due to the fact that individuals can learn how to change and control their own brain wave activity if they are given immediate feedback in an understandable format, some researchers have investigated the role of feedback and response verification on EEG control [7]. It was reported that the feedback can have inhibitory as well as facilitory effects on the EEG control [7]. The present study examined the role of mental practice and concentration on the EEG control.
Training Scheme

Mental practice refers to repeating a physical skill in the mind, without any physical movement of the body, with the intent of learning or refinement. There are strong evidences that mental practice has a moderate but extremely reliable effect on performance. Not only can mental imagery improve specific motor skills but it also seems to enhance motivation, mental toughness, and controlling arousal. It was suggested that the mental rehearsal duplicates the actual motor pattern that is being rehearsed. In this work, we evaluate the effects of mental rehearsal on the EEG control.

Another issue that must be dealt with developing a BCI for neuroprosthetic control is the recognition of the EEG patterns associated to the resting state with the eyes open and the imagined hand movements. The EEG patterns during the resting state are contaminated by brain potentials caused by unpredictable endogenous factors. Our minds race from one thing to another. This degrades the detection of the EEG patterns. To deal with such times, we need to learn and practice concentration skills and strategies. To concentrate, we have to learn a skill, and as with any skill this means practice repeated day after day until we achieve enough improvement to feel that we can concentrate when we need to. In this work, we use the art or practice of concentration to eliminate distraction and focus on the task at hand. The training procedure used in this work is summarized as follows:

1. Sit quietly in a comfortable position.
2. Close your eyes and focus on your breathing. For the next 2-3 minutes, remain focused on the rise and fall of your chest. Notice that your breathing is calm and steady.
3. Deeply relax all your muscles, beginning at your feet and progressing up to your face. Keep them relaxed. Continue this step for 10 to 20 minutes.
4. There are many different types of imagery and methods of conducting it, with some being far more effective than others. We used a video based method where the subject watched him/herself performing closing/opening the hand while undertaking imagery. The visualization needs to be as meaningful and personal. For this purpose, details should be added which make the images come alive so that it can be really re-lived in the mind. This step is repeated for several times.

Experiments

The EEG data of normal subjects were recorded at a sampling rate of 256Hz by Ag/AgCl scalp electrodes. The eye blinks were recorded by placing an electrode on the forehead above the left brow line. During each trial experiment, one task was performed without any warning tone. Depending on the cue visual stimuli which appears on the computer monitor at 2 s, the subject imagines the hand grasping or opening. If the visual stimulus is not present, the subject does not perform a specific task. Data were recorded for 5 s during each trial experiment and each trial was repeated 50 times for each task. Two experiments were conducted on each subject before and after the mental and concentration practice. We employed neural adaptive noise canceller [6] for eye blink suppression without any visual inspection. This is a concern in real-time applications.

EEG Classification

The features were formed from the 2-s interval of single-channel EEG data, in the time period 2.2-4.2 s, during each trial of experiment. The mean absolute value (MAV), variance, the relative power of beta band to alpha band, the relative power of theta band to alpha band, the relative power of beta band to the total power, the relative power of theta band to the total power, the relative power of alpha band to the total power, 1 Hz-spectral components at different frequency band, and samples of the artifact-free EEG constitute the features. Various feature vectors were formed and were fed into the neural network classifier. The multilayer perceptron (MLP) with back-propagation learning rule was used. The MLP network considered in this study consists of two hidden layers each containing hyperbolic tangent units and two output nodes. The networks were trained with data obtained during 50% of the experimental trials and were validated with data obtained during the subsequent
trials. During the training, the feature vector was randomly selected from the training sets and then fed into the network. The learning process is stopped when it is apparent that the generalization performance has peaked. To assess the robustness of the proposed scheme in EEG classification, two different data sets were created for training and evaluating the network. For each of the two data sets obtained during each experiment day, a neural network was trained and evaluated. The results were then averaged.

Results

The cortical potentials obtained by ensemble averaging 50 trial artifact-free EEG data during imagined hand grasping, hand releasing, and during a resting state are shown in Fig. 1 (a)-(c), respectively. The event-related potentials associated with motor imagery is quit evident. The corresponding time evolution of the mean absolute value (MAV), variance, the alpha and the beta power is also shown in this figure. It is observed that the changes in the parameters closely track the changes in the mental state during motor imagination. Nevertheless, these parameters do not clearly indicate the intent of motor imagination during a single trial experiment [Fig. 1 (d)-(f)]. The motor imagery potentials obtained by ensemble averaging 50 trial artifact-free EEG data during imagined hand grasping and during a resting state are shown in Fig. 1. The event-related potentials associated with motor imagery are quite evident. An interesting observation is that the motor imagery potentials associated with the hand grasping and opening generate different characteristics.

Table I summarizes the results of the single-channel EEG classification during imagination hand grasping, hand opening, and during a resting state by using MLP networks, for different feature vectors and different subjects. The results can be summarized as follows:

- The results show that mental and concentration practice can generally increase the classification accuracy of the EEG patterns.
- It is also of interest to note that at the best case with mental practice an improvement to about 84%, 48%, 32%, and 92%, are obtained by subject BM, EA, FI, and ME, respectively.
- With mental practice, an accuracy as high as 99% is achieved in subject ME, 90% in BM, 88% in EA, and 79% in subject FI.
- The results indicate that the imaginative power of individuals is different which is a intrinsic personality feature.
- In subjects ME, BM, and EA, the effect of mental practice at the motor cortex region is more than that at other areas. This supports the hypothesis that mental practice is an effective method for performance enhancement and motor skill learning.
- It was found that reducing the widow length from 2 s to 1 s, decreases the accuracy.
- The results of this work indicate that the development of a BCI is severely subject-specific.
- The performance of BCI is affected by the cortex area which EEG data is collected, window length, feature set, classification algorithm, and mental rehearsal. There is no specific way to implement the mental imagery. It is up to individual preferences and the present circumstances. It can be done within a very short or a long duration.

References


Table 1: Average Classification Accuracies of the EEG Patterns During Imagined Hand Movement and During a Resting State Before (BT) and After (AP) Mental Practice

<table>
<thead>
<tr>
<th>EEG Channel</th>
<th>F3</th>
<th>T6</th>
<th>T5</th>
<th>Pz</th>
<th>F4</th>
<th>Fz</th>
<th>C3</th>
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<tbody>
<tr>
<td>MAV ,Var ,Pα</td>
<td>51</td>
<td>77</td>
<td>67</td>
<td>79</td>
<td>54</td>
<td>72</td>
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<tr>
<td>MAV ,Var ,Pα</td>
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<td>80</td>
<td>60</td>
<td>83</td>
<td>62</td>
<td>73</td>
<td>55</td>
</tr>
</tbody>
</table>

| Subject EA | MAV ,Var ,Pα | 57 | 84 | 52 | 82 | 52 | 76 | 64 | 82 | 81 | 89 | 69 | 83 | 71 | 85 |
| MAV ,Var ,Pα | 69 | 83 | 68 | 80 | 73 | 79 | 77 | 84 | 79 | 84 | 74 | 83 | 76 | 84 |
| MAV ,Var ,Pα | 68 | 84 | 67 | 82 | 75 | 81 | 79 | 84 | 86 | 86 | 71 | 81 | 75 | 88 |

| Subject FA | MAV ,Var ,Pα | 52 | 53 | 44 | 71 | 54 | 75 | 59 | 55 | 49 | 65 | 52 | 66 | 54 | 50 |
| MAV ,Var ,Pα | 58 | 54 | 64 | 69 | 61 | 78 | 58 | 57 | 58 | 55 | 52 | 59 | 54 | 47 |
| MAV ,Var ,Pα | 54 | 55 | 57 | 70 | 60 | 79 | 58 | 60 | 47 | 65 | 51 | 67 | 55 | 50 |

| Subject ME | MAV ,Var ,Pα | 51 | 65 | 63 | 62 | 53 | 71 | 64 | 69 | 54 | 68 | 47 | 51 | 51 | 98 |
| MAV ,Var ,Pα | 51 | 64 | 73 | 66 | 51 | 69 | 59 | 55 | 62 | 62 | 52 | 65 | 52 | 83 |
| MAV ,Var ,Pα | 53 | 63 | 74 | 75 | 52 | 79 | 61 | 77 | 62 | 86 | 59 | 61 | 62 | 99 |
Fig. 1. The cortical potentials during imagination of hand grasping, opening, and during a resting state: (a)-(c) ensemble averaging of 50 trial artifact-free EEG data; (d)-(f) single trial EEG data.