Offline Decoding of Hand Movement Directions from Non-Invasive EEG

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Abstract. Neuroprostheses can enable motor activities that would otherwise be impossible for some disabled users, thus expanding their capabilities of daily activities. In the present experiment, healthy subjects performed a center out reaching task. Our goal was to detect their hand/arm direction from non-invasive EEG measures. Preliminary, we found that the hand direction can be successfully inferred from the raw EEG.

Keywords: Brain-Computer Interface, Electroencephalogramm, Human Motor Control, Center-out Movement Paradigm

1. Introduction
For disabled people, communication and interaction with their environment are key objectives. While improving communication capabilities has been widely studied, motor control and motor substitution using non-invasive techniques have only recently been studied, thanks to the emergence of powerful algorithms. This study aims at decoding hand movement directions from raw EEG signals, in order to enable new applications for Brain-Computer Interfaces, more precisely the control of arm neuroprosthetics in spinal cord injured persons.

2. Material and Methods
2.1. Experimental setup
Four naïve right handed subjects, (avg. score 13±5%), aged 22±2 were asked to move an extended joystick until reaching one of the 8 targets which were displayed on a screen, and then to come back to central position. The experiment consisted in 8 runs of 64 trials each, which gave 64 trials per class. After a resting period of 2 s, one target (originally) red would turn green, and then the participant has a window of 4 s to reach the target and to return to the original position. A break of 1.5 s to 2.5 s was inserted between the trials.

The montage consisted of 31 electrodes spread over the 10-20 system cap, with an emphasis on the motor cortex. The signal was recorded using 2 g.USBamp (g.tec, Graz Austria), with a sample frequency of 512 Hz. The joystick used was a Thrustmaster T.Flight Stick X coded on 8 bits, with the control column extended to 40 cm, so as to increase the hand stroke.

2.2. Signal processing
The collected EEG signals were visually inspected, and all trials contaminated by artifacts were removed. Then, since each movement can be considered as a combination of the other classes (e.g., upper right diagonal movement is a combination of right and up during the way forth and a combination of left and down during the way back), the forth movement was extracted from each trial, and only orthogonal classes were classified.

Since the 1-dimensional movements (up/down, left/right) were executed faster than the 2-dimensional movements (diagonals), the trials were synchronized with the target reached corresponding to 0 s, and the beginning of the movement happening beforehand.

Features were extracted from the preprocessed EEG using a 4th order Butterworth filter between 5Hz and 30Hz, followed by a spatial filtering using Common Spatial Pattern algorithm (Ramoser et al. 2000). Finally, the normalized variances were computed over a time window of .25s and served as features to compute a classifier using Fisher’s linear discriminant and 10x10 cross validation.
Figure 1. (a) All executed joystick movements for subject S3, (b) an example of CSP output (spatial filters and spatial patterns) and (c) its corresponding classifier accuracy. (note subject S3 has ipsi-lateral activation)

3. Results

As it can be seen in Table 1, the average classification accuracy is around 71% for one class against another one, which is above the confidence limit of 63.4% (for an average of 40 trials per class, with a significance level of 5%) (Müller-Putz et al. 2008).

Table 1. Maximum accuracy [percentage] at the beginning of the movement, for each subject, and for each pair of orthogonal classes

<table>
<thead>
<tr>
<th>Class vs subject</th>
<th>1 - 3</th>
<th>2 - 4</th>
<th>3 - 5</th>
<th>4 - 6</th>
<th>5 - 7</th>
<th>6 - 8</th>
<th>7 - 1</th>
<th>8 - 2</th>
<th>Mean</th>
<th>Trials</th>
</tr>
</thead>
<tbody>
<tr>
<td>S1</td>
<td>74.1</td>
<td>72.2</td>
<td>68.6</td>
<td>69.8</td>
<td>74.1</td>
<td>72.4</td>
<td>73.1</td>
<td>74.3</td>
<td>72.3±2.1</td>
<td>32</td>
</tr>
<tr>
<td>S2</td>
<td>73.2</td>
<td>72.3</td>
<td>79.8</td>
<td>72.5</td>
<td>67.5</td>
<td>66.4</td>
<td>73.9</td>
<td>70.4</td>
<td>72.0±4.1</td>
<td>46</td>
</tr>
<tr>
<td>S3</td>
<td>67.1</td>
<td>69.8</td>
<td>70.7</td>
<td>67.1</td>
<td>71.0</td>
<td>69.3</td>
<td>67.9</td>
<td>76.6</td>
<td>69.9±3.1</td>
<td>50</td>
</tr>
<tr>
<td>S4</td>
<td>71.2</td>
<td>80.2</td>
<td>81.0</td>
<td>61.8</td>
<td>71.3</td>
<td>70.3</td>
<td>63.9</td>
<td>74.8</td>
<td>71.8±6.9</td>
<td>32</td>
</tr>
<tr>
<td>Mean</td>
<td>71.4±2.3</td>
<td>73.6±4.5</td>
<td>75.0±6.3</td>
<td>67.8±4.5</td>
<td>71.0±2.7</td>
<td>69.6±2.5</td>
<td>69.7±4.7</td>
<td>74.0±2.6</td>
<td>71.5±1.0</td>
<td>40</td>
</tr>
</tbody>
</table>

4. Discussion

As explained above, each trial includes a movement followed by the opposite movement. Moreover, one single movement begins with an acceleration, and ends with a deceleration. This could explain that after an initial peak (the sought hand direction), the classification accuracy degrades when closing on the target (as shown in Fig.1 panel (b) ).

These results may be also explained by the nature of the task. During the early phase of the cursor movement, the subject can move freely because he/she is not concerned with overshooting the target. However, as the cursor approaches the target, finer control adjustments are necessary, which may entail different cognitive processes and EEG measures. Future research could explore different tasks and parameters that could produce larger and more consistent EEG patterns.

Our preliminary analyses suggested that hand direction can be decoded from the EEG, but more work is necessary before widespread practical application. In future work, we will employ and evaluate more sophisticated signal processing methods such as Independent Component Analysis and source localization to track more precisely the hand movements.

Acknowledgements

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References
