Proceedings of the
8th Graz Brain-Computer Interface Conference 2019 DOI: 10.3217/978-3-85125-682-6-64

MOVEMENT RELATED CORTICAL POTENTIALS DURING HAND OPENING AND CLOSING IN ALS PATIENTS

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ABSTRACT: Amyotrophic lateral sclerosis (ALS) is a neurodegenerative disease, which leads to the progressive loss of muscle control. In Denmark, approximately 150 people are diagnosed with ALS each year. The ensuing burden on related health care costs increases substantially as patients lose the ability to perform tasks of everyday living. Brain-computer interface (BCI) systems provide an approach to allow these patients some interaction with their environment. In this ongoing study we investigate whether the movement-related cortical potential (MRCP) extracted from electroencephalography (EEG) signals can be used for BCI control of an assistive glove in ALS patients. To this aim, the BCI needs to detect the intention of the subject to open and close the hand. The MRCP is a slow negative drift that commences 2 seconds prior to movement onset and contains features that differ between different types of movement, making it an ideal signal modality for multi-dimensional BCI control. Preliminary analysis from three ALS patients reveal a classification accuracy above 85% for the best channel between movement and rest conditions. However, classification accuracy between movement types (hand opening/closing), was lower (>65% for the best channel). Combining MRCP detection, with methods that allow using a single input (brain switch) to select multiple commands, may thus be a viable solution for this patient group.

INTRODUCTION

Amyotrophic lateral sclerosis (ALS) is a debilitating progressive neurological disease. In Denmark, more than 150 new ALS patients are diagnosed per year. Symptoms vary from patient to patient, but may be manifested by reduced muscle strength, muscle wasting, fatigue, increased muscle tension, convulsions, muscle soreness, dysfunction, speech impairment, and difficulty breathing; several patients also present with behavioral changes and Frontotemporal Dementia. In Denmark, approximately 20% of ALS patients end up with respiratory therapy due to respiratory problems [1]. ALS has both personal as well as societal consequences. The economic impact of ALS at the community level is high [2], a large proportion being due to the care costs when patients can no longer perform everyday activities like personal care due to muscle weakness [3]. Therefore, it is of great interest to provide these patients with assistive systems that would facilitate and/or prolong functional independence, and thereby decrease the need for constant care.

The focus of the present study is on the assistance of hand grasping function. Several methods can be used to assist grasping function in paralyzed patients (e.g., functional electrical stimulation – FES and exoskeletons) [4]. For example, rigid exoskeletons are efficient in restoring movements but they are also bulky and esthetically unappealing. FES can be delivered using a compact hardware but the movements are difficult to control precisely and selectively. Recently, a number of soft exoskeletons have been proposed [5], [6]. A typical solution comprises a textile glove that is actuated using a network of tendons pulled by a motor placed somewhere on the body (e.g., around the waist). These systems combine good controllability and compact design, and therefore, represent an attractive solution to assist highly disabled patients.

The overall aim of the present project is to develop a brain-computer interface (BCI) [7], [8] that can be used to control a soft hand exoskeleton in ALS patients. The envisioned BCI will be based on detection and classification of movement related cortical potentials (MRCPs) [9]. The MRCP is a characteristic modulation of brain potentials comprising a negative deflection that anticipates the movement, followed by a positive rebound. The MRCP has been selected because it does not require training, it is present during motor execution and imagination, and it has been successfully detected in different patient populations [10], [11], including ALS [12]. In order to control a soft glove, the user should be able to generate opening and closing commands via BCI (Fig. 1). Previously, the MRCPs related to foot dorsiflexion were successfully detected and used for online control of a foot orthosis [13]. In addition, several studies have used MRCPs to detect and classify hand motions, including different grasp types [14], and movement speed and force [15]. In a recent study [16], low-frequency time domain features within the bandwidth of the MRCP were used to detect and classify natural reach-to-grasp movements. However, these studies were performed in healthy subjects, except [15] which was conducted in stroke patients.

In the present study, electroencephalography (EEG) signals during hand opening and closing were recorded

 DOI: 10.3217/978-3-85125-682-6-64

in three patients suffering from ALS. The patients were recruited at different stages of ALS, as assessed by the ALS functional rating scale [17]. The aim was to preliminarily assess the feasibility of detecting the patient intention to perform the two hand movements (closing vs. rest, opening vs. rest) as well as to discriminate between them (closing vs. opening).

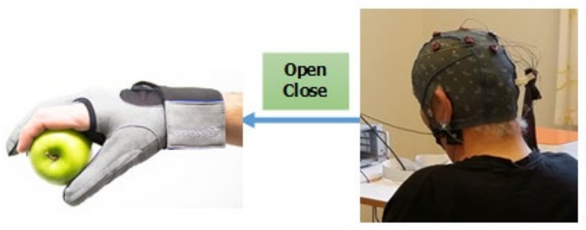

Figure 1: The envisioned BCI system for restoring grasping using a soft exoskeleton glove

MATERIALS AND METHODS

Patients

Three patients with ALS participated to the recording. All signed an informed consent form approved by the local ethical committee. The patients were recruited by a neurologist, who also determined the functional score using the ALS functional rating scale [18]. The scores for the patients numbered 13, 14 and 23 were 0, 0, and 3.6, respectively. All recordings were performed at the patient's home.

Signal acquisition

Non-invasive electroencephalographic (EEG) recordings were obtained using the g.USBamp (g.tec, AU) and g.GAMMAcap equipped with nine active electrodes (g.LADYbird). The electrodes were arranged according to the standard 10-20 system over the motor area of the arm/hand (channels: F3, FC1, FC5, Cz, C3, C7, CP1, CP5, P3) contralaterally to the dominant hand of the patient. Electromyography (EMG) was recorded from the hand flexor and extensor muscles using a bipolar configuration (Ag/AgCl electrodes (AMBU Neuroline, US)). The ground for the EMG recording was separate from the EEG ground. The sampling frequency was set to 1200 Hz for all signals and no filtering was activated in the amplifier.

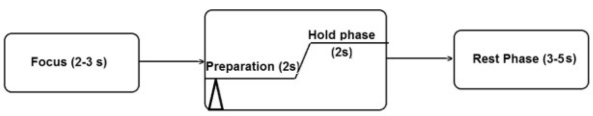

Figure 2: The cue-based data collection paradigm comprising focus, preparation, hold and rest phase. The protocol is explained in the text.

The patients were seated in a chair in front of a table. Since two of the patients had no residual hand function, EMG could not be implemented to indicate movement

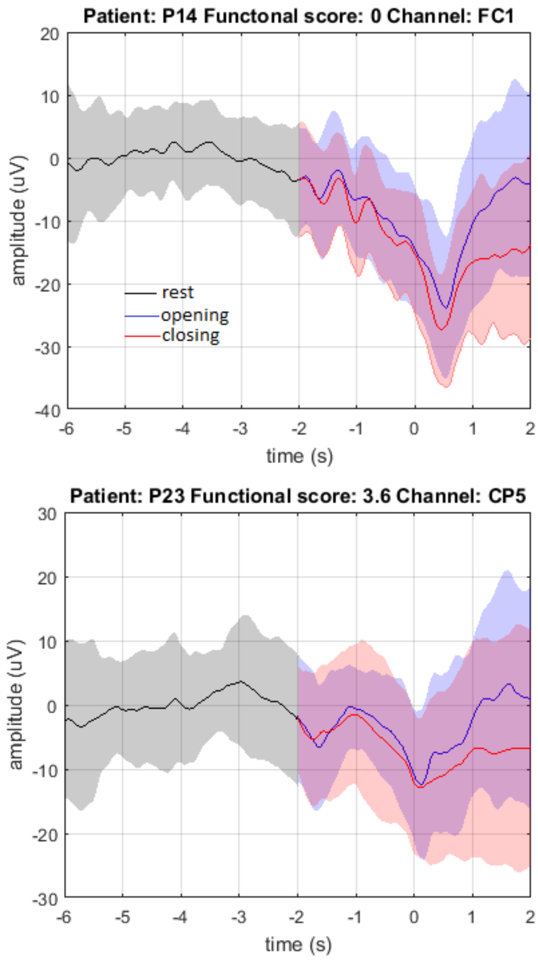

Figure 3: The traces (mean ± standard deviation) for rest (black line), MRCP during closing (red line) and opening (blue line) for patient P14 (top) and P23 (bottom). Movement onset is at 0 s. Two representative channels are depicted (FC1 and CP5).

onset and thus to extract the MRCP of each trial. Patients were thus presented with a visual cue that was displayed on a computer screen following a predefined experimental paradigm (Fig. 2). In the focus phase, the patient was asked to focus on the middle of the screen. In the preparation phase, the movement to be executed was indicated by a text message (open/close) and a triangular cursor started moving across the screen. When the cursor arrived at the middle of the screen, it instantly jumped, indicating the moment when the patient should perform the movement. The patient was instructed to hold the movement, until the cursor disappeared from the screen (hold phase). This was followed by a resting phase. In each recording block, 15 hand opening and 15 hand closing movements were collected in randomized order, and two blocks were recorded in the experimental session, hence 30 movements in total in each class.

Signal processing

The EMG signals were bandpass filtered using a second order Butterworth filter with a cut off frequency at 10 Hz (movement artifacts) and 3 Hz (linear envelope). The

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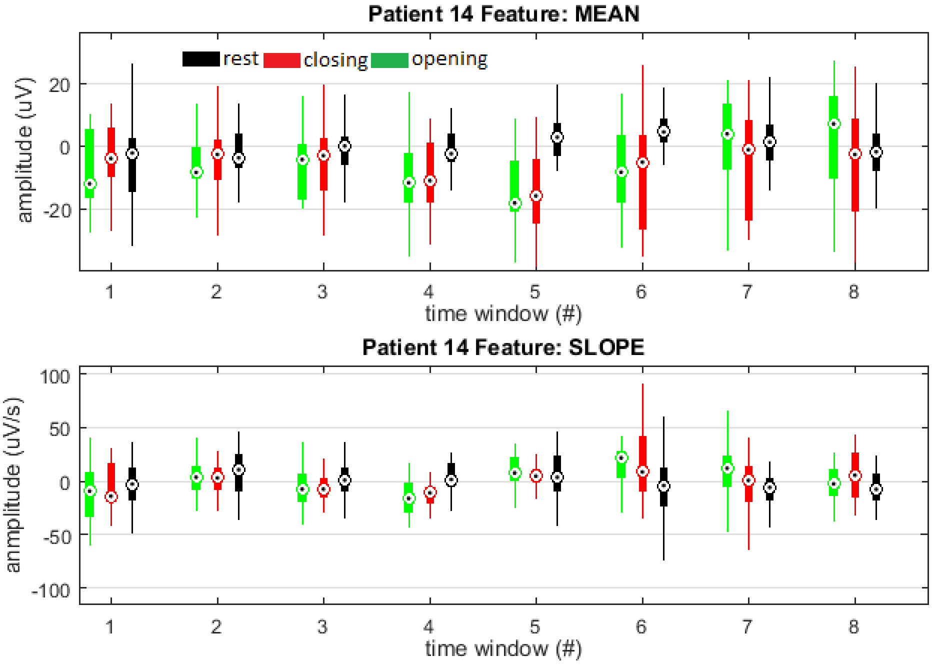

Figure 4: Distribution of time domain features extracted from the epochs shown in Fig. 3 (Patient 14). The boxplots indicate median, interquartile range and min/max values for mean (top) and slope (bottom) in each time window for rest (black), closing (red) and opening (green).

EEG signals were bandpass filtered between 0.01 and 3 Hz (zero-phase Butterworth 2nd order) which is the bandwidth of the MRCP. Segmenting the epochs was challenging due to noise from the electrical/medical equipment (e.g., patient respirator) and low signal levels (e.g., weak or no EMG). Therefore, a custom-made Matlab application was developed and used to manually inspect each trial and to discard those that were corrupted. In all patients, there was at least 20 good trials in each movement class. The onset of the trial was identified either manually based on the recorded EMG or based on the cue to move.

The selected "good" trials were then segmented to extract the MRCP and rest. The interval from -2 s to 2 s, with respect to the movement onset (0 s), was considered as an MRCP and the interval between -6 s and -2 s was assumed to be the resting state. The MRCPs were baseline corrected by subtracting the mean of the resting state.

Classification

For the purpose of classification, the time domain features were computed from the epochs (MRCP and rest). Most studies that rely on MRCP consider only the phase preceding the movement (negative deflection). This is done to minimize the detection delay and provide timely feedback using electrical stimulation following the paradigm of Hebbian learning [19]. In the context of the present project, however (Fig. 1), the overall reliability of detection and classification is more important than the delay since the focus is on robust control. Therefore, the entire epoch was considered, including both pre and post movement phases (i.e., deflection and rebound of the MRCP).

Each epoch was divided in windows (500 ms) and the mean and the slope of the signal were computed within each window, resulting in 16 features per epoch. Linear discriminant analysis was used for classification between the pairs of classes (open vs. rest, close vs. rest, and open vs. close). The classification was tested for each individual channel. Due to the low number of trials, the classifier was validated using the leave-one out cross validation scheme. The classification accuracy was adopted as the outcome measure.

RESULTS

The average traces of the rest and MRCP epochs recorded in two patients with substantially different functional scores are shown in Fig. 3. In both cases, the MRCP is prominent for both movements, and there is a difference between the two MRCPs, particularly during the rebound phase. However, there is also a significant variability and overlap between the MRCPs corresponding to opening and closing.

The distribution of the time domain features for the same data as in Fig. 3 top (patient 14, channel FC1) is depicted in Fig. 4. Both mean and slope features exhibit clear differences between movement and rest, and this reflects the morphology of the MRCP. The mean in the windows 4, 5 and 6 indicate the negative deflection of the MRCP. The slope in the windows 4 and 6 exhibit the change in the sign, which corresponds to the downward (negative slope) and then upward (positive slope) trend of the MRCP. The difference in the features between the two

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Table 1. Classification results

Subject	Classes	Classification accuracy (%)								
		F3	FC1	FC5	Cz	C3	C7	CP1	CP5	P3
Patient 14	O/C	67	76	43	74	44	48	53	49	59
	O/R	90	91	73	94	90	83	86	80	79
	C/R	93	99	75	97	91	82	88	79	84
Patient 13	O/C	65	51	65	47	51	49	47	49	51
	O/R	88	88	77	78	85	78	88	83	77
	C/R	78	77	75	86	89	69	80	75	80
Patient 23	O/C	59	53	46	50	49	54	60	72	51
	O/R	78	77	78	84	86	83	81	78	86
	C/R	78	81	73	89	86	84	95	80	78

C, O and R stand for closing, opening and rest

movements is however less visible, i.e., nevertheless, there seems to be a difference in the mean in time windows 7 and 8 and in the slope in time windows 6 and 7, reflecting the faster and stronger rebound of the MRCP associated to hand opening (see also Fig. 3).
The channel-wise classification success rates obtained using the leave one out cross validation scheme are shown in Table 1. The grayed cells indicate the channels with the highest classification success rate.

DISCUSSION

In the present study, EEG data were collected during hand opening and closing movements from three ALS patients, and the MRCP profiles were extracted. An important conclusion from the collected profiles is that a pronounced MRCP can be observed even in highly disabled ALS patients (patient 13 and 14). The profiles resemble, in shape as well as in depth, those that were collected in a more functioning patient (patient 23). This is in line with the results reported in [12] where they compared the MRCPs of ALS patients to those of healthy subjects and found no significant difference in the peak negativity.
A preliminary classification of the collected patterns has demonstrated that they have sufficient discriminative information to be correctly classified. Both opening and closing could be differentiated from rest with high accuracy. Classifying between opening and closing was however a substantially more challenging task, as can be seen from the low classification accuracies for many channels (O/C in Table 1). An important insight is that the classification should likely consider the post movement period, since this is the phase where the two profiles somewhat diverge (Fig 3).
The present test is a first and simple evaluation of the feasibility of discriminating between the patterns. The next step is to implement classification using a sliding window during pseudo online (offline data) and online applications. This represents a more difficult task and it is to be expected that the accuracies will be lower than those reported here (Table 1). In addition, instead of classifying on each channel individually, they could be combined using a spatial filter [20] and classification could be performed on the surrogate channel. Finally, for the offline analysis in the present study, the corrupted trials were eliminated manually. During an online application, an automatic artifact rejection scheme needs to be implemented [21], [22].
Nevertheless, the obtained results are encouraging for detection (movement versus rest), which is the most important command for the online system. Even if direct classification (closing versus opening) is revealed insufficiently reliable, the lack of this input can be circumvented using state machine and/or recently presented electrotactile menus [15]. Both of these methods allow using a single input (brain switch) to select multiple commands.

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