Aalborg Universitet

Movement intention detection in adolescents with cerebral palsy from single-trial EEG

Jochumsen, Mads; Shafique, Muhammad; Hassan, Ali; Niazi, Imran Khan

Published in:
Journal of Neural Engineering

DOI (link to publication from Publisher):
10.1088/1741-2552/aae4b8

Publication date:
2018

Document Version
Accepted author manuscript, peer reviewed version

Link to publication from Aalborg University

Citation for published version (APA):
Jochumsen, M., Shafique, M., Hassan, A., & Niazi, I. K. (2018). Movement intention detection in adolescents with cerebral palsy from single-trial EEG. *Journal of Neural Engineering*, *15*(6), Article 066030. Advance online publication. https://doi.org/10.1088/1741-2552/aae4b8

General rights
Copyright and moral rights for the publications made accessible in the public portal are retained by the authors and/or other copyright owners and it is a condition of accessing publications that users recognise and abide by the legal requirements associated with these rights.

- Users may download and print one copy of any publication from the public portal for the purpose of private study or research.
- You may not further distribute the material or use it for any profit-making activity or commercial gain
- You may freely distribute the URL identifying the publication in the public portal -

Take down policy
If you believe that this document breaches copyright please contact us at vbn@aub.aau.dk providing details, and we will remove access to the work immediately and investigate your claim.

Downloaded from vbn.aau.dk on: April 29, 2024

Journal of Neural Engineering

ACCEPTED MANUSCRIPT

Movement intention detection in adolescents with cerebral palsy from single-trial EEG

To cite this article before publication: Mads Jochumsen *et al* 2018 *J. Neural Eng.* in press https://doi.org/10.1088/1741-2552/aae4b8

Manuscript version: Accepted Manuscript

Accepted Manuscript is "the version of the article accepted for publication including all changes made as a result of the peer review process, and which may also include the addition to the article by IOP Publishing of a header, an article ID, a cover sheet and/or an 'Accepted Manuscript' watermark, but excluding any other editing, typesetting or other changes made by IOP Publishing and/or its licensors"

This Accepted Manuscript is **© 2018 IOP Publishing Ltd**.

During the embargo period (the 12 month period from the publication of the Version of Record of this article), the Accepted Manuscript is fully protected by copyright and cannot be reused or reposted elsewhere.
As the Version of Record of this article is going to be / has been published on a subscription basis, this Accepted Manuscript is available for reuse under a CC BY-NC-ND 3.0 licence after the 12 month embargo period.

After the embargo period, everyone is permitted to use copy and redistribute this article for non-commercial purposes only, provided that they adhere to all the terms of the licence https://creativecommons.org/licences/by-nc-nd/3.0

Although reasonable endeavours have been taken to obtain all necessary permissions from third parties to include their copyrighted content within this article, their full citation and copyright line may not be present in this Accepted Manuscript version. Before using any content from this article, please refer to the Version of Record on IOPscience once published for full citation and copyright details, as permissions will likely be required. All third party content is fully copyright protected, unless specifically stated otherwise in the figure caption in the Version of Record.

View the article online for updates and enhancements.

This content was downloaded from IP address 130.225.198.224 on 05/10/2018 at 09:36

Movement intention detection in adolescents with cerebral palsy from single-trial EEG

Mads Jochumsen[1], Muhammad Shafique[2], Ali Hassan[3], Imran Khan Niazi[1,4,5§]

[1]SMI, Department of Health Science and Technology, Aalborg University, Aalborg, Denmark

[2]Riphah International University, Islamabad, Pakistan

[3]CEME, National University of Sciences and Technology (NUST), Islamabad, Pakistan

[4] New Zealand College of Chiropractic, Auckland, New Zealand

[5]Health and Rehabilitation Research Institute, AUT University, New Zealand

[§]Corresponding author

Imran Khan Niazi, PhD

New Zealand College of Chiropractic,

6 Harrison Road, Mt Wellington, Auckland, New Zealand

Tel: + 64 95266789

Fax: + 64 95266788

Email addresses:

MJ: mj@hst.aau.dk

MS: muhammad.shafique@riphah.edu.pk

AH: alihassan@ce.ceme.edu.pk

IKN: imran.niazi@nzchiro.co.nz

Accepted Manuscript

Abstract

Objectives: As for stroke rehabilitation, brain-computer interfaces could potentially be used for inducing neural plasticity in patients with cerebral palsy by pairing movement intentions with relevant somatosensory feedback. Therefore, the aim of this study was to investigate if movement intentions from children with cerebral palsy can be detected from single-trial EEG. Moreover, different feature types and electrode setups were evaluated.

Approach: Eight adolescents with cerebral palsy performed self-paced dorsiflexions of the ankle while nine channels of EEG were recorded. The EEG was divided into movement intention epochs and idle epochs. The data were pre-processed and temporal, spectral and template matching features were extracted and classified using a random forest classifier. The classification accuracy of the 2-class problem was used as an estimation of the detection performance. This analysis was repeated using a single EEG channel, a Large Laplacian filtered channel and nine channels.

Results: A classification accuracy of ~70% was obtained using only a single channel. This increased to ~80% for the Laplacian filtered data, while ~75% of the data were correctly classified when using nine channels. In general, the highest accuracies were obtained using temporal features or using all of them combined.

Significance: The results indicate that it is possible to detect movement intentions in patients with cerebral palsy; this may be used in the development of a brain-computer interface for motor rehabilitation of patients with cerebral palsy.

Keywords: Movement intention, Cerebral palsy, Brain-computer interface

Accepted Manuscript

1. Introduction

Cerebral palsy is a condition caused by brain damaged in the early development of the brain which can lead to a variety of different impairments including motor impairments. As for stroke rehabilitation of motor impairments, the rehabilitation of motor impairments associated with cerebral palsy includes physiotherapy, ergo therapy, constraint-induced movement therapy and bimanual therapy as rehabilitation options [1]. Due to the heterogeneity of the injury, there is not a single rehabilitation that fits all patients with cerebral palsy; thus, there is an incentive to investigate new potential rehabilitation techniques. In a recent review [1], it has been discussed if the use of non-invasive brain stimulation can be used for inducing neural plasticity in cerebral palsy as it has been done in stroke populations or healthy participants. One of these techniques is paired associative stimulation where the motor cortex is timely activated through transcranial magnetic stimulation according to somatosensory afferent feedback elicited through electrical stimulation of a peripheral nerve [2]. A disadvantage of the paired associative stimulation is the use of transcranial magnetic stimulation which may be uncomfortable for the user and there is a small risk of inducing a seizure in users that are pre-disposed for epilepsy [3], which cerebral palsy patients are. Natural motor cortical activation is, however, possible to obtain by attempting to perform a movement thus there may not be a need for transcranial magnetic stimulation. In response to the motor cortical activation a movement-related cortical potential (MRCP) or event-related desynchronization/synchronization (ERD/ERS) can be observed in the EEG [4, 5]. To maximize the induction of neural plasticity, and potentially the motor learning effect [6], the somatosensory afferent feedback from electrical stimulation or passive movement (through an exoskeleton or robotic device) must arrive at the cortical level during maximal cortical activation which is immediately prior or during the attempted execution of movement [7-10]. This means that the intention to move must be predicted to allow sufficient time for activating e.g. electrical stimulation and for the somatosensory feedback to reach the cortical level. It is possible to obtain the correct timing for inducing plasticity by detecting either the MRCP or ERD, which has been done in a number of studies previously [11-14]. This is known as brain-computer interface (BCI). Little research has been done in patients with cerebral palsy, and the work that has been done has focused on restoring communication and a pilot randomized controlled trial for rehabilitation [15]. In these studies ERD [16, 17], steady-state visual evoked potentials [16], and P300 have been used [18]. It was shown that patients with cerebral palsy had significant, but limited control of BCIs [16], but it is likely that their performance would increase with training since the use of these control signals require some training [19]. In these studies, the participants were adults with cerebral palsy, so it could be speculated that adolescents may have more difficulty in controlling such BCIs that require training to be functional. In this study, the aim is to investigate if movement intentions can be detected from single-trial EEG with a latency (using only EEG signals prior the movement onset), so it can be used for inducing neural plasticity [7]. Different electrode setups are used: 1) single channel, 2) a linear combination of nine channels, and 3) nine separate channels. Moreover, it is investigated how the detection performance is

Accepted Manuscript

affected by including brain signals after the movement onset. Lastly, the importance of different feature types is estimated to determine whether the MRCP, band power estimates or both contribute to the movement intention detection.

2. Methods

2.1. Participants

Eight adolescents with cerebral palsy were recruited from Railway General Hospital in Rawalpindi, Pakistan. Railway General Hospital is a teaching hospital run by Riphah International University, Islamabad, Pakistan. The patient specifications are summarized in Table 1. All the experimental procedures were in accordance with the Declaration of Helsinki and approved by the local ethical committee of Riphah International University (approval no: ref# Riphah/RCRS/REC/000121/20012016). Apart from the adolescents, permission was obtained from the parents and the caregivers.

Table 1: Specifications of the participants. 'GMFCS': Gross Motor Function Classification System.

Gender	Age	Type	GMFCS
Male	16	Hemiplegia (left side)	Level II
Male	15	Diplegia (both legs)	Level I
Female	11	Diplegia (both legs)	Level II
Male	15	Diplegia (both legs)	Level II
Male	13	Diplegia (both legs)	Level III
Male	15	Diplegia (both legs)	Level II
Male	17	Diplegia (both legs)	Level III
Male	16	Diplegia (both legs)	Level V

2.2. Experimental setup

The participant was seated in a comfortable chair and instructed in performing fast dorsiflexions of the ankle joint. During the movements the participant was asked to minimize blinking and sit as still as possible. Each dorsiflexion was separated by ~10 seconds, and the participant performed as many movements as possible within 15 minutes. On average 65±18 (range: 41-93) movements were performed per participant. The participant was free to move at will, but verbal instructions were given to separate two consecutive movements with at least 5 seconds.

2.2.1. EEG

Nine channels of continuous EEG (EEG amplifiers, Nuamps Express, Neuroscan) were recorded from F3, Fz, F4, C3, Cz, C4, P3, Pz, and P4 according to the International 10-20 system (32 Channel Quick-Cap,

Accepted Manuscript

Neuroscan). The EEG was sampled at 1000 Hz and referenced to the right ear lobe and grounded at the forehead. During the experiment the impedance of the electrodes was below 5 kΩ.

2.2.2.Surface EMG

One bipolar channel of EMG was recorded using the same system as for the EEG. Two surface EMG electrodes were placed on the belly of tibialis anterior (AMBU self-adhesive EMG electrodes). The EMG was recorded for synchronization purposes when dividing the continuous EEG into epochs.

2.3. Data analysis

2.3.1.EMG onset detection

The EMG was bandpass filtered from 10-200 Hz and notch filtered from 49-51 Hz with a 4^{th} order Butterworth filter after which it was rectified (see Figure 1). For each participant a threshold corresponding to 10% of the maximal EMG amplitude was plotted to determine the EMG onsets [14]. All EMG onsets were visually inspected to account for potential errors in the EMG onset detection.

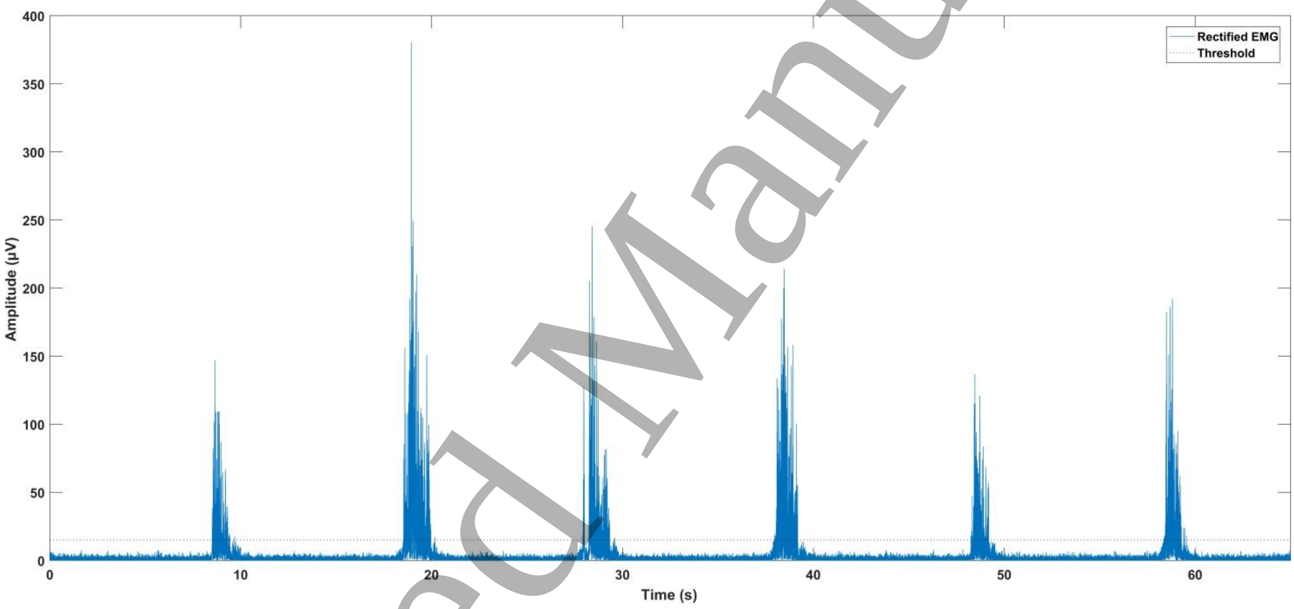

Figure 1: EMG onset detection. The threshold was selected as 10% of the maximal EMG activity.

2.3.2.Pre-processing and feature extraction

Initially, the EEG was bandpass filtered from 0.1-45 Hz with a 4^{th} order zero phase shift Butterworth filter. Based on the extracted EMG onsets the continuous EEG was divided into epochs; 4 seconds prior to 4 second after the EMG onset. All the epochs were baseline corrected using the mean value of data from 4 to 2 seconds prior the EMG onset; this value was subtracted from the entire epoch. The epochs were further divided into two types of epochs: 1) idle activity, and 2) movement preparation/execution. The idle activity was defined as data from 4 to 2 seconds prior the EMG onset, and the movement preparation/execution was defined as 2 seconds prior the EMG onset until the EMG onset and then in 0.25 s increments after the EMG

Accepted Manuscript

onset (until +2 to +4 seconds with respect to the EMG onset). To account for artefact contamination, epochs with amplitudes exceeding 150 μV were rejected from further analysis.

Three types of features were extracted from each channel: 1) mean amplitudes, 2) absolute band power, and 3) template matching. Prior the extraction of the amplitude and template matching features, the epochs were bandpass filtered from 0.1-5 Hz. The mean amplitudes were extracted in four 0.5 second non-overlapping time windows. In the 2 second epoch, the data were bandpass filtered with a 4^{th} order zero phase shift Butterworth filter in 2 Hz non-overlapping bins from 8-30 Hz. The filtered data were squared and the average across the 2 seconds was calculated. A template of the movement epochs was extracted from the averaged epochs for each channel for each participant i.e. up to 9 templates. The template was extracted from -1.5 to 0.5 s with respect to the EMG onset (see e.g. Fig. 2). The template matching feature was obtained by calculating the cross correlation between the template and the epochs without a time lag which led to a maximum of 9 features per epoch.

This processing was repeated in three scenarios: 1) single channel (Cz), 2) Large Laplacian montage around Cz, and 3) nine separate channels.

2.3.3. Classification and feature analysis

Following the feature extraction, a random forest classifier [20] was used to classify the two types of epochs using leave-one-out cross-validation where one epoch was used for testing and the remaining epochs were used for training the classifier. 500 trees were used to train the classifier. The classification was performed on the features extracted from each time window (e.g. -1.75 to 0.25 seconds with respect to the EMG onset). In each time window it was repeated four times using: 1) only amplitude features, 2) absolute band power features, 3) template matching, and 4) all features combined. Thus 4 classifiers were constructed for each of the 17 time windows for each of the channel setup scenarios. All the analyses were performed using MATLAB version 2016b.

2.4. Statistics

The classification accuracies were averaged across the 17 time windows. A 2-way repeated measures analysis of variance was performed on the averaged values with “channel setup” (3 levels: 1 channel, 1 spatially filtered channel, and 9 channels) and “Feature” (4 levels: All features, amplitude, band power, and template) as factors. The Greenhouse-Geisser correction was applied when the assumption of sphericity was violated. Significant test statistics were followed up with a Bonferroni post hoc test to avoid multiple comparisons. Significant test statistics were assumed when $P<0.05$.

3. Results

The results are summarized in Table 2 and Figures 2-6. The participant ID in Table 1 corresponds to the participant ID in Figures 2 and 3.

Accepted Manuscript

Table 2: Representation about data that were recorded from each participant. The number of epochs was the same in all time windows.

Participant	Total number of movements	Number of rejected epochs	Time between movements (s)
1	93	1	10±1
2	66	0	9±2
3	41	19	10±2
4	67	3	11±2
5	90	8	9±2
6	60	0	12±2
7	54	0	11±2
8	52	2	12±3

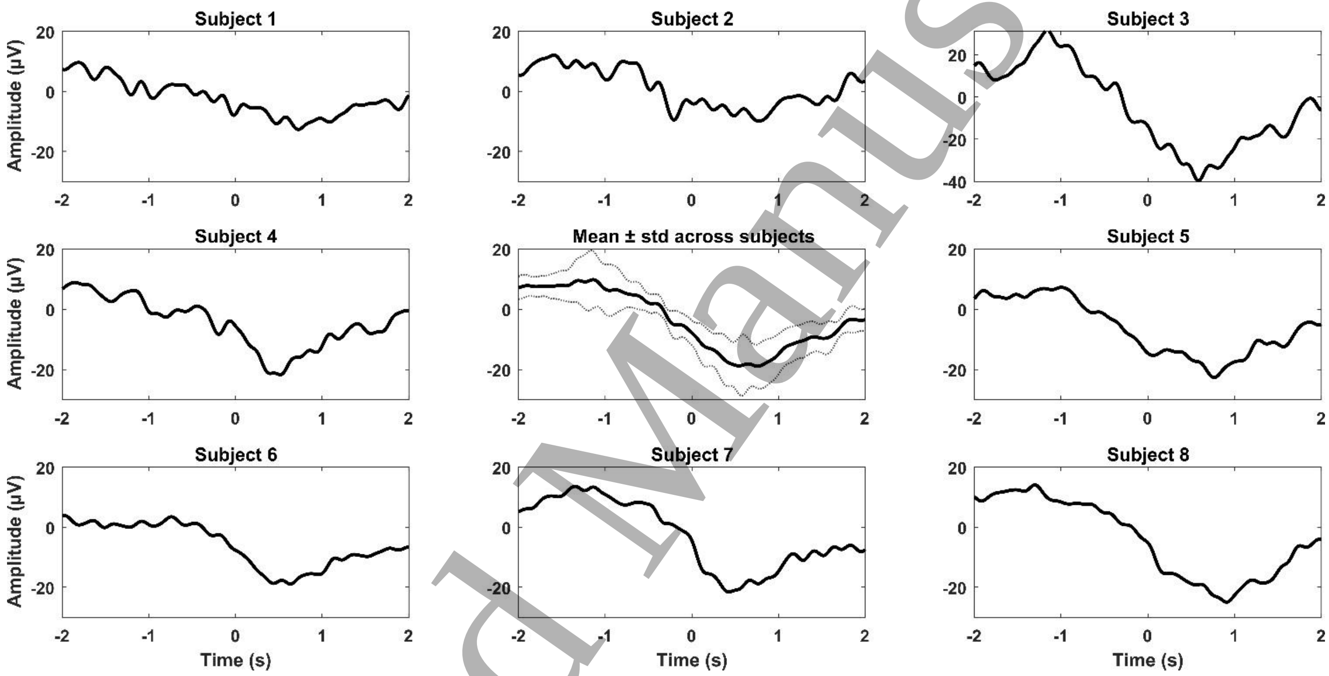

Figure 2: MRCP averages from each participant from Cz. In the middle, the grand average across participants is shown. The EMG onset is at 0 seconds. The scaling of the axes is the same for all graphs except for subject 3.

Accepted Manuscript

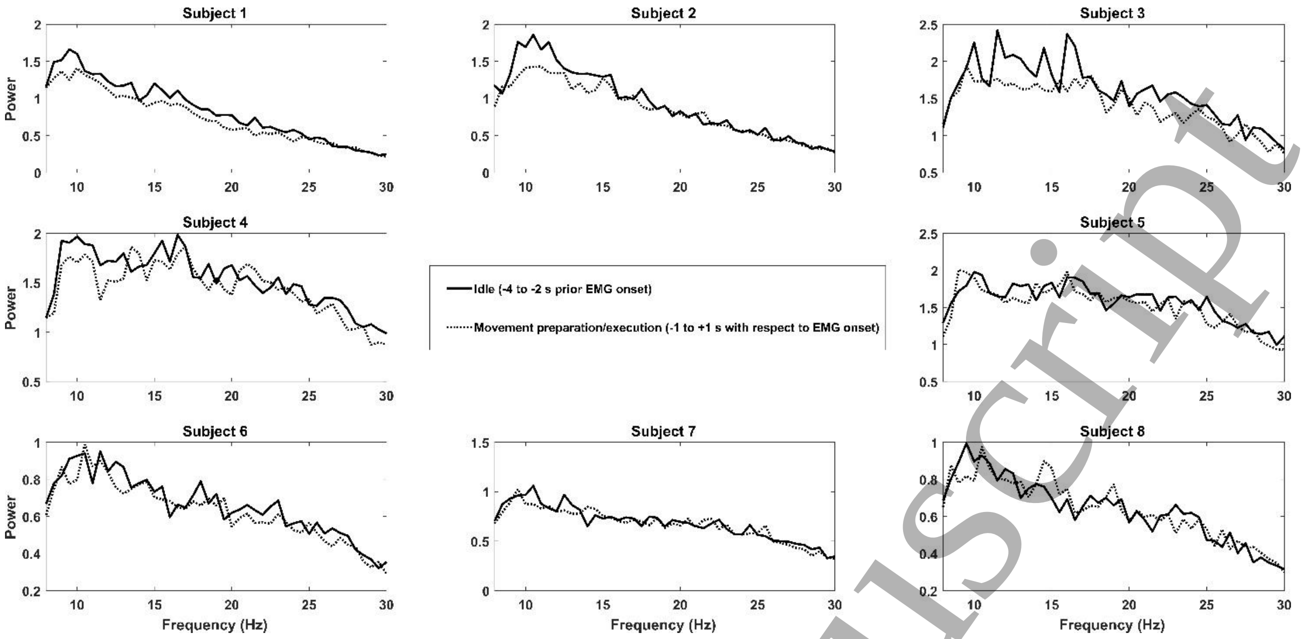

Figure 3: Single-sided amplitude spectrum using fast Fourier transform for each subject using the Cz electrode. This was calculated for each trial and then the average is shown for the mu and beta frequency range.

From Figure 2 it is seen that adolescents with cerebral palsy can produce MRCPs that can be visually observed in the EEG. It should be noted that there are differences in the amplitudes of the peak of maximal negativity, and that the characteristic MRCP shape is not equally prominent in all participants (participant 1 and 2). Moreover, the peak of maximal activity is occurring ~0.5 seconds after the EMG onset. In Figure 3, the power spectral density for each participant is shown. In general, the power was lower for the movement preparation/execution epochs compared to the idle epochs, but there is no peak for specific frequencies for the individual participants.

Using only a single channel (Figure 4) classification accuracies of ~65-75% were obtained when using all the features. It is seen in the figure that the classification accuracies are higher when using the amplitude features compared to the template matching and band power features. It should also be noted that there is no trend of increasing classification accuracies when more data after EMG onset are included in the analysis, except after 3 seconds after the EMG onset where the classification accuracies start to decrease. Also, the standard error is relatively high which indicates that is a considerable amount of inter-subject variability.

Accepted Manuscript

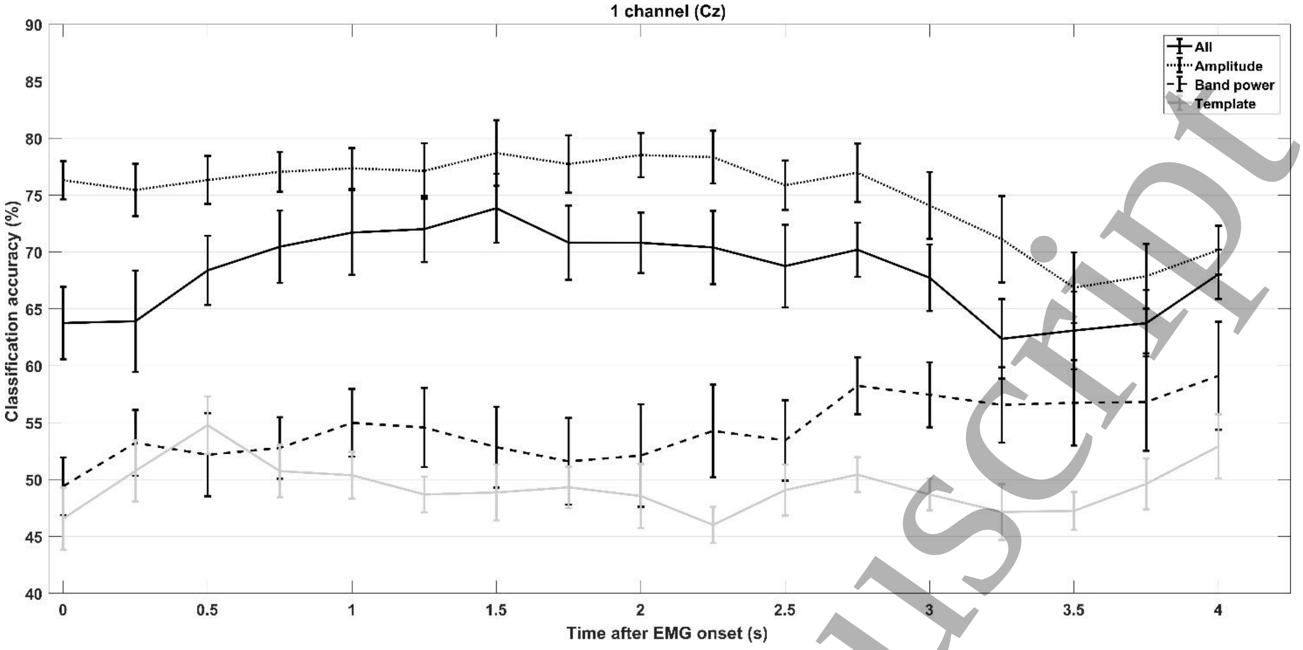

Figure 4: Classification accuracies obtained for a single channel (Cz) when using different types of features extracted from different time segments with respect to the EMG onset. The values are reported as mean ± standard error across participants.

In Figure 5 the results are presented when applying a Large Laplacian montage around Cz. The classification accuracies increased compared to those obtained using a single channel. The classification accuracies increased to 75-80% when using all features or the amplitude features alone. For the template matching and band power features the classification accuracies are around 50-60%. Once again there is no trend of increasing classification accuracies when more data after the EMG onset are included in the analysis, and classification accuracies start to decrease after 1.5 seconds after the EMG onset. The standard error is still relatively high.

Accepted Manuscript

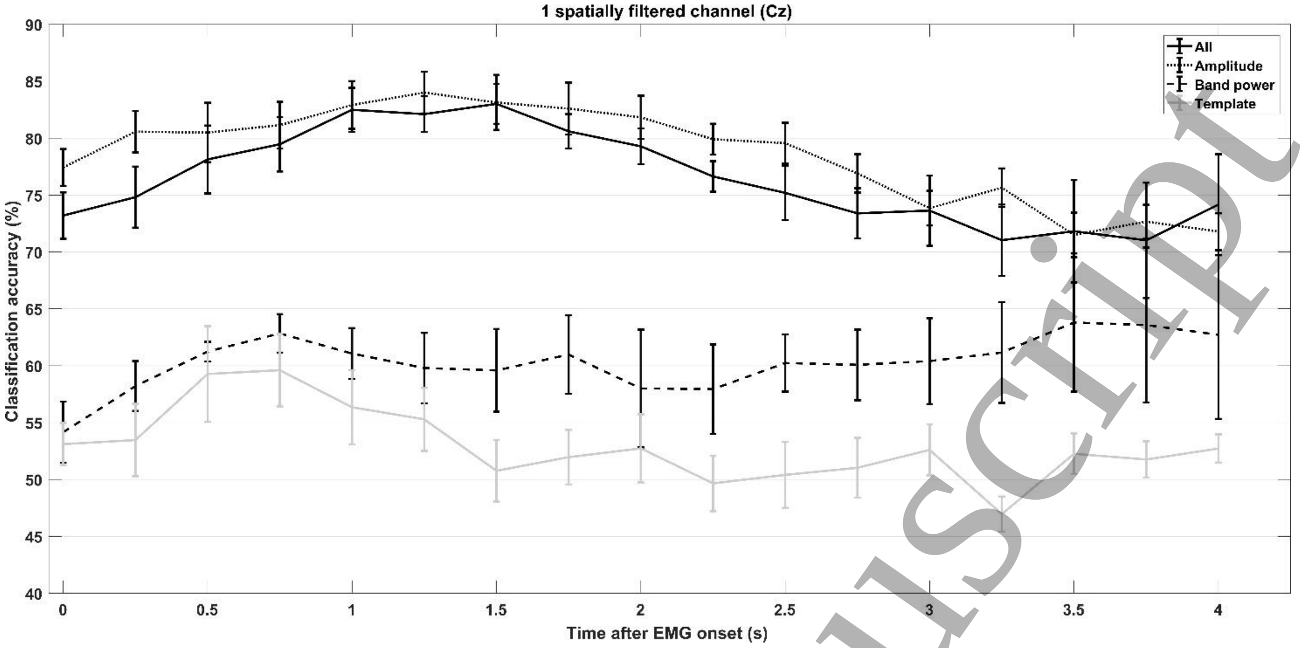

Figure 5: Classification accuracies obtained for a Large Laplacian montage around Cz when using different types of features extracted from different time segments with respect to the EMG onset. The values are reported as mean ± standard error across participants.

Lastly, the classification accuracies were obtained when extracting features from each of the nine channels individually. The results are summarized in Figure 6. The classification accuracies are comparable to those obtained using a Large Laplacian montage. The classification accuracies when using all features and the amplitude features were 75-85%. For the template matching the classification accuracies are higher compared to the two other scenarios with accuracies up to 65%. The band power features are associated with the lowest classification accuracies. Once more there is no trend of increasing classification accuracies when more data after the EMG onset are included in the analysis, at least when using all features or the amplitude features, and the classification accuracies start to decrease 2 seconds after the EMG onset. The standard error is still relatively high. The statistical analysis revealed a significant effect of electrode setup ($F_{(2,14)}$=40.10; P<0.01) and features ($F_{(3,21)}$=186.82.41; P<0.01). There was no interaction between the two factors ($F_{(2.62,18.33)}$=1.41; P=0.27). The post hoc analysis showed that the classification accuracies associated with each feature comparison were different, and that the spatially filtered channel around Cz and all nine electrodes were associated with higher classification accuracies compared to the use of a single channel.

Accepted Manuscript

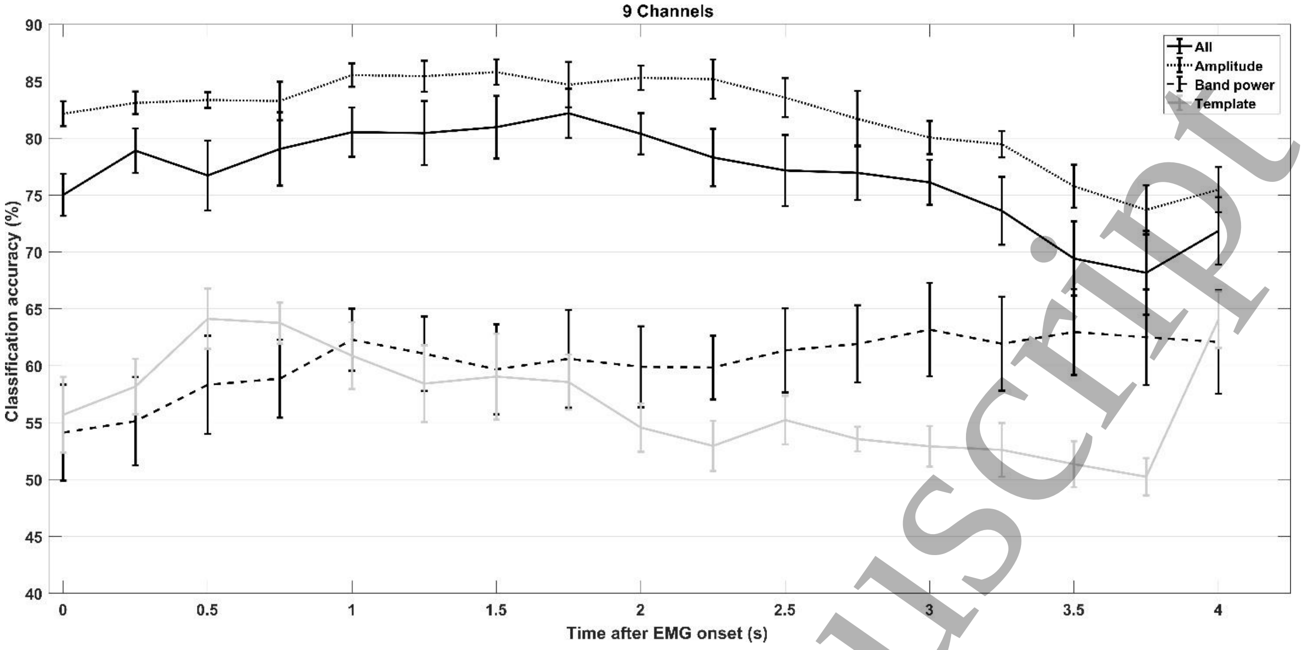

Figure 6: Classification accuracies obtained for nine channels when using different types of features extracted from different time segments with respect to the EMG onset. The values are reported as mean ± standard error across participants.

4. Discussion

Classification accuracies when discriminating between idle activity and movement-related activity were in the range of 75-85%. The highest classification accuracies were obtained when using a Large Laplacian montage around Cz or nine separate channels based on amplitude features or all the features combined. Moreover, no tendencies were observed as more data (up to 2 seconds) after the EMG onset were included in the analysis.

4.1. Movement intention/execution detection

In this study the classification accuracies were used as an estimation of movement intention/execution detection. The performance of the classifier was similar to what has been reported for healthy participants and stroke patients [12, 21], but it should be noted that in the current study the epochs were extracted with a priori knowledge of the EMG onset, which means that it is likely that the online detection performance will decrease. Moreover, the actual chance level was not 50%, but in the range of 60-65% [22]. It was expected that the classification accuracies would decrease a bit more than they did in the analysis windows 2 s after the EMG onset. However, this can be due to a late peak negativity and rebound phase which are included in the 2 second wide analysis windows. It should also be noted that the standard errors are quite high (~5 percentage points). The results showed that spatial filtering could be a useful pre-processing step when detecting movement intentions in this patient group. This has also been indicated previously in healthy participants and stroke patients [21, 23]. One potential explanation of the improved detection performance

Accepted Manuscript

could be that the spatial filter corrects the blurred image of the underlying brain activity due to volume conduction [24]. In future studies it could be relevant to investigate other types of spatial filters or denoising using independent component analysis [23]. However, the Large Laplacian montage has been shown to be a robust choice of spatial filter, and with the fixed coefficients it does not require extensive calibration to determine the filter coefficients [14, 21]. In the results it was seen that it was possible to detect the movement-related activity using only a single electrode. This could have implications for the usability of such a BCI system since the setup time will be extremely short and the user will not require a wash of the hair after each use, but with the improvements in the EEG recording systems and electrode design (e.g. dry electrodes) it may not be necessary to limit the setup to a single electrode overlying Cz (the cortical representation of the foot). Using more electrodes will improve the detection performance which may be an important factor for the use of the system to be taken up by patients and clinicians. By using more electrodes, it will also be possible to account for or individualize the decoder to specific cortical reorganization due to the injury or effect of rehabilitation. Lastly, it was shown that a stable detection performance was obtained despite the inclusion of more data after the EMG onset. This is a bit surprising based on the signal morphology in Figure 2 where more discriminative information can be obtained around the point of maximal negativity (which occurs ~0.5 seconds after the EMG onset), but it has been reported previously that high classification accuracies can be obtained with detection latencies up to 200 ms prior the movement onset [14, 21, 23, 25]. If the use of an MRCP-based BCI is intended for control purposes then it could be relevant to include residual EMG activity to construct a hybrid BCI unless there is too much spasticity [1, 26]. For neuromodulation, by inducing Hebbian-associated plasticity, the movement intentions should be detected using data prior the EMG onset, so it is timely correlated with somatosensory feedback from an assisted movement [7]. It was shown that the detection performance was in the range of what has been reported to induce neural plasticity [9, 10].

4.2. Feature importance

The features based on the mean amplitude were consistently the most discriminative ones compared to spectral features; this was also shown in another study where movement intentions were detected using temporal and spectral features [11]. However, it has also been indicated in a large body of work that spectral features in terms of ERD/ERS are useful for detecting movement-related activity from the EEG [13, 27, 28]. It has also been shown in patients with cerebral palsy that they can produce ERD/ERS patterns [16, 29, 30]. However, this was not reflected in the absolute band power in the current study which is indicated in Figure 3. A potential reason for this could be the fact that real movements were executed, although a modulation of the mu and beta power should be produced, without conscious preparation of the forthcoming movement. By training the participants to carefully plan the executed or imagined movement and maintain the contraction it could be speculated that a stronger modulation of the mu and beta rhythms can be observed. From a signal processing point of view, the discrimination between idle activity and movement-related activity could be

Accepted Manuscript

optimized using other types of spatial filtering such as common spatial pattern spatial filtering which maximizes the variance between two classes. The disadvantages of using this approach is that the morphology of the MRCP may be altered. Moreover, an even finer spectral and spatial (more electrodes) resolution could be used as well, but such an approach could potentially boost the detection performance [13], but the calibration time of the BCI would increase.

4.3. Limitations

A limitation of the current study was that the epochs were extracted with a priori knowledge about the EMG onset; thus, there is a need to validate the findings in an online BCI system to get an indication of its potential use in the rehabilitation of patients with cerebral palsy. It was previously shown that limited BCI control could be obtained in the first BCI session [16], and that the performance likely would increase due to a training effect when the user familiarized with the system [17]. When using an MRCP-based BCI system it is likely that the users do not require any training to use the BCI system since they will be asked to attempt to perform movements and a reasonably high detection performance can be obtained without any prior training of the user or system [31, 32]. All the patients in this study had residual EMG, so the findings should be validated in a larger number of patients with different levels of impairments e.g. patients with a high degree of spasticity or no residual EMG.

5. Conclusion

In this study it was demonstrated that adolescents with cerebral palsy can produce MRCPs and that it is possibly to discriminate between movement intention/execution and idle activity from single-trial EEG. Moreover, it was shown that detection can be performed using a single EEG channel, but spatial filtering is useful for enhancing the detection performance. These results could be relevant for BCI-based rehabilitation of patients with cerebral palsy.

References

1. Reid LB, Rose SE, Boyd RN. Rehabilitation and neuroplasticity in children with unilateral cerebral palsy. Nature Reviews Neurology. 2015;11(7):390.

2. Stefan K, Kunesch E, Cohen LG, Benecke R, Classen J. Induction of plasticity in the human motor cortex by paired associative stimulation. Brain. 2000;123(3):572-84.

3. Rossi S, Hallett M, Rossini PM, Pascual-Leone A. Safety, ethical considerations, and application guidelines for the use of transcranial magnetic stimulation in clinical practice and research. Clinical neurophysiology. 2009;120(12):2008-39.

4. Shibasaki H, Hallett M. What is the Bereitschaftspotential? Clinical Neurophysiology. 2006;117(11):2341-56.

5. Pfurtscheller G, Da Silva FL. Event-related EEG/MEG synchronization and desynchronization: basic principles. Clinical neurophysiology. 1999;110(11):1842-57.

6. Pascual-Leone A, Dang N, Cohen LG, Brasil-Neto JP, Cammarota A, Hallett M. Modulation of muscle responses evoked by transcranial magnetic stimulation during the acquisition of new fine motor skills. J Neurophysiol. 1995;74:1037-45.

Accepted Manuscript

7. Mrachacz-Kersting N, Kristensen SR, Niazi IK, Farina D. Precise temporal association between cortical potentials evoked by motor imagination and afference induces cortical plasticity. J Physiol (Lond). 2012;590(7):1669-82.

8. Mrachacz-Kersting M, Jiang N, Stevenson AJT, Niazi IK, Kostic V, Pavlovic A, et al. Efficient neuroplasticity induction in chronic stroke patients by an associative brain-computer interface. Journal of Neurophysiology. 2016;115(3):1410-21.

9. Xu R, Jiang N, Mrachacz-Kersting N, Lin C, Asin G, Moreno J, et al. A Closed-Loop Brain-Computer Interface Triggering an Active Ankle-Foot Orthosis for Inducing Cortical Neural Plasticity. Biomedical Engineering, IEEE Transactions on. 2014;20(4):2092-101.

10. Niazi IK, Kersting NM, Jiang N, Dremstrup K, Farina D. Peripheral Electrical Stimulation Triggered by Self-Paced Detection of Motor Intention Enhances Motor Evoked Potentials. IEEE transaction on neural systems and rehabilitation engineering. 2012;20(4):595-604.

11. Jochumsen M, Niazi IK, Dremstrup K, Kamavuako EN. Detecting and classifying three different hand movement types through electroencephalography recordings for neurorehabilitation. Med Biol Eng Comput. 2015;54(10):1491-501.

12. Jochumsen M, Niazi IK, Taylor D, Farina D, Dremstrup K. Detecting and classifying movement-related cortical potentials associated with hand movements in healthy subjects and stroke patients from single-electrode, single-trial EEG. Journal of Neural Engineering. 2015;12(5):056013.

13. Ibáñez J, Serrano J, Del Castillo M, Monge-Pereira E, Molina-Rueda F, Alguacil-Diego I, et al. Detection of the onset of upper-limb movements based on the combined analysis of changes in the sensorimotor rhythms and slow cortical potentials. Journal of neural engineering. 2014;11(5):056009.

14. Niazi IK, Jiang N, Tiberghien O, Nielsen JF, Dremstrup K, Farina D. Detection of movement intention from single-trial movement-related cortical potentials. Journal of Neural Engineering. 2011;8(6):066009.

15. Kim T, Lee B. Clinical usefulness of brain-computer interface-controlled functional electrical stimulation for improving brain activity in children with spastic cerebral palsy: a pilot randomized controlled trial. Journal of physical therapy science. 2016;28(9):2491-4.

16. Daly I, Billinger M, Laparra-Hernandez J, Aloise F, Garcia ML, Faller J, et al. On the control of brain-computer interfaces by users with cerebral palsy. Clin Neurophysiol. 2013 Sep;124(9):1787-97.

17. Neuper C, Muller GR, Kubler A, Birbaumer N, Pfurtscheller G. Clinical application of an EEG-based brain-computer interface: a case study in a patient with severe motor impairment. Clin Neurophysiol. 2003 Mar;114(3):399-409.

18. Pires G, Nunes U, Castelo-Branco M. Statistical spatial filtering for a P300-based BCI: tests in able-bodied, and patients with cerebral palsy and amyotrophic lateral sclerosis. J Neurosci Methods. 2011;195(2):270-81.

19. Wolpaw JR, Birbaumer N, McFarland DJ, Pfurtscheller G, Vaughan TM. Brain-computer interfaces for communication and control. Clinical neurophysiology. 2002;113(6):767-91.

20. Breiman L. Random forests. Mach Learning. 2001;45(1):5-32.

21. Jochumsen M, Niazi IK, Mrachacz-Kersting N, Jiang N, Farina D, Dremstrup K. Comparison of spatial filters and features for the detection and classification of movement-related cortical potentials in healthy individuals and stroke patients. Journal of neural engineering. 2015;12(5):056003.

22. Müller-Putz GR, Scherer R, Brunner C, Leeb R, Pfurtscheller G. Better than random? A closer look on BCI results. International Journal of Bioelectromagnetism. 2008;10(1):52-5.

23. Karimi F, Kofman J, Mrachacz-Kersting N, Farina D, Jiang N. Detection of Movement Related Cortical Potentials from EEG Using Constrained ICA for Brain-Computer Interface Applications. Frontiers in neuroscience. 2017;11:356.

24. Blankertz B, Tomioka R, Lemm S, Kawanabe M, Muller K. Optimizing spatial filters for robust EEG single-trial analysis. Signal Processing Magazine, IEEE. 2008;25(1):41-56.

25. Xu R, Jiang N, Lin C, Mrachacz-Kersting N, Dremstrup K, Farina D. Enhanced Low-latency Detection of Motor Intention from EEG for Closed-loop Brain-Computer Interface Applications. Biomedical Engineering, IEEE Transactions on. 2013;61(2):288-96.

Accepted Manuscript

26. Müller-Putz G, Leeb R, Tangermann M, Höhne J, Kübler A, Cincotti F, et al. Towards noninvasive hybrid brain–computer interfaces: framework, practice, clinical application, and beyond. Proc IEEE. 2015;103(6):926-43.

27. Solis-Escalante T, Müller-Putz G, Pfurtscheller G. Overt foot movement detection in one single Laplacian EEG derivation. J Neurosci Methods. 2008;175(1):148-53.

28. Müller-Putz GR, Kaiser V, Solis-Escalante T, Pfurtscheller G. Fast set-up asynchronous brain-switch based on detection of foot motor imagery in 1-channel EEG. Medical and Biological Engineering and Computing. 2010;48(3):229-33.

29. Rigoldi C, Molteni E, Rozbaczylo C, Morante M, Albertini G, Bianchi AM, et al. Movement analysis and EEG recordings in children with hemiplegic cerebral palsy. Experimental brain research. 2012;223(4):517-24.

30. Scherer R, Billinger M, Wagner J, Schwarz A, Hettich DT, Bolinger E, et al. Thought-based row-column scanning communication board for individuals with cerebral palsy. Annals of physical and rehabilitation medicine. 2015;58(1):14-22.

31. Jochumsen M, Niazi IK, Nedergaard RW, Navid MS, Dremstrup K. Effect of subject training on a movement-related cortical potential-based brain-computer interface. Biomedical Signal Processing and Control. 2018;41:63-8.

32. Niazi IK, Jiang N, Jochumsen M, Nielsen JF, Dremstrup K, Farina D. Detection of movement-related cortical potentials based on subject-independent training. Med Biol Eng Comput. 2013;51(5):507-12.

Accepted Manuscript