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Detection and Classification of Single-Trial Movement-Related Cortical Potentials Associated with Functional Lower Limb Movements

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Abstract

Objectives: Brain-computer interfaces that activate exoskeletons based on decoded movement-related activity have been shown to be useful for stroke rehabilitation. With the advances in the development of exoskeletons it is possible to replicate a number of different functional movements that are relevant to rehabilitate after stroke. In this study, the aim is to detect and classify six different movement tasks of the lower extremities that are used in the activities of daily living.

Approach: Thirteen healthy subjects performed six movement tasks 1) Stand-to-sit, 2) Sit-to-stand, 3) Walking, 4) Step up, 5) Side step, and 6) Back step. Each movement task was performed 50 times while continuous EEG was recorded. The continuous EEG was divided into epochs containing the movement intention associated with the movements, and idle activity was obtained from recordings during rest. Temporal, spectral and template matching features were extracted from the EEG channels covering the motor cortex and classified using Random Forest in two ways: 1) movement intention vs. idle activity (estimate of movement intention detection), and 2) classification of movement types.

Results: The classification accuracies associated with movement intention detection were in the range of 80-90%, while 54±3% of all movement types were classified correctly. The stand-to-sit and sit-to-stand tasks were easiest to classify, while step up often was classified as walking.

Significance: The results indicate that it is possible to detect and classify functional movements of the lower extremities from single-trial EEG. This may be implemented in a brain-computer interface that can control an exoskeleton and be used for neurorehabilitation.

Keywords: Movement intention, Movement-related cortical potential, Brain-computer interface, neurorehabilitation.

1. Introduction

Brain-computer interfaces (BCIs) have over the past years been proposed and tested as a means for induction of neuroplasticity and motor learning/recovery after neurologic injury such as stroke [1-3]. The neuroplasticity, and eventually motor learning [4], is induced by pairing activity in the motor cortex with congruent somatosensory feedback from the affected body part. The idea is similar to paired associative stimulation where the motor cortex is activated using transcranial magnetic stimulation, and electrical stimulation is delivered to a nerve concurrently (e.g. the deep branch of the common peroneal nerve) to elicit the somatosensory feedback [5]. However, the use of transcranial magnetic stimulation in stroke patients may be limited by safety precautions such as seizure induction [6], but the transcranial magnetic stimulation may be substituted by endogenous signals that activate the motor cortex. Two phenomena that are associated with activity in the motor cortex are the movement-related cortical potential (MRCP) and event-related desynchronization/synchronization [7, 8]. The MRCP is a low-frequency potential that starts up to two seconds before self-paced (bereitschaftspotential) [9] and cue-based (contingent negative variation) [10] movements. The major neural generators of the MRCP are the supplementary motor area, premotor cortex and primary motor cortex [7]. The event-related desynchronization/synchronization have similar neural generators, but the activation pattern is hypothesized to be different from the MRCP [7]. Moreover, the event-related desynchronization/synchronization are sensorimotor rhythms observed in the mu and beta frequency range of the EEG [8]. The MRCP and event-related desynchronization are elicited when movements are executed as well as imagined [11, 12]. The MRCP can be further divided into a number of segments [7], but overall it can be divided into 1) readiness potential (RP); this is also called early bereitschaftspotential or contingent negative variation 1, 2) negative slope (NS); this is also called late bereitschaftspotential or contingent negative variation 2, 3) motor potential (MP), and movement-monitoring potential; this is also called reafferent potential. The RP and NS are related to the planning of the movement, while the MP is where the signal is sent from the primary motor cortex to the peripheral nervous system and muscles. The movement-monitoring potential is related to the inflow of afferent feedback. Moreover, it has been shown that the MRCP is modulated by various movement-related parameters such as speed and force of the movement [11]. By detecting the MRCP based on the RP, NS and MP from single-trial EEG, it is possible to predict when movements occur which makes the MRCP useful for BCIs for inducing neuroplasticity where the time difference between movement intention and afferent feedback should mimic the normal motor control loop [13, 14]. It has been speculated that electrical stimulation, exoskeleton or rehabilitation robot should be initiated within 300 ms after the MP [15, 16]. Several studies have been published where it was investigated how to detect movement intentions using different pre-processing, feature extraction and classification techniques (e.g. [12, 17-23]) which roughly lead to classification accuracies in the range of 60-90%. Many studies have reported successful detection/classification of movement intentions in healthy subjects, but it has also been shown feasible to classify movement intentions from patients with motor impairments after stroke [1, 21, 24-28], spinal cord injury [29-32], cerebral palsy [33, 34], amyotrophic lateral sclerosis [35] and tremor [36]. Besides movement intention detection, different movement-related parameters have been extracted such as kinetic and kinematic parameters [21, 25, 37-39], movement direction [40], and various movement types [41, 42]. Many of these studies have focused on isolated movements such as dorsiflexions of the ankle joint, finger movements, hand grasps, wrist and elbow flexion/extension. There are also examples of functional movements that have been decoded involving several joints e.g. for the lower extremities sitting and standing up [43], gait initiation [44], and walking have been decoded [45-47]. For the upper extremities, various movement types have been decoded; these include reaching and other tasks that are performed as activities of daily living (e.g. drinking from a glass and lifting a pot with handles) [48-51].

Rehabilitating isolated movements are highly relevant, but generally, it may be more useful for patients to relearn to perform functional movements, which constitute the majority of the activities of daily living. With the advances in exoskeletons and functional electrical stimulation, it is possible to replicate several functional movements. In this way, it is possible to replicate a number of functional movements and perform them in congruence with the movement intentions if they can be decoded. By decoding several movement types, it is possible to induce task variability in the training, which has been shown to maximize the retention of the trained movement patterns in stroke rehabilitation [52]. Thus in this study, various functional lower limb movements are performed that are used in the activities of daily living. Initially, it will be investigated how these movement types are manifested in the MRCP, and then it will be tested if the movement types can be classified from single-trial EEG recordings.

2. Methods

2.1. Subjects

Thirteen healthy subjects (5 women and 8 men with a mean age of 24 years) participated. The local ethical committee of Region North Jutland (N-20130081) approved the procedures, and all subjects provide their written informed consent prior to participation.

2.2. Experimental Setup

The subjects had to perform six different movement tasks, which were repeated 50 times each. The tasks were: 1) Stand-to-sit; the subject was standing in front of a chair (height of seat: 45 cm) and had to sit on that, 2) Sit-to-stand; the subject was sitting on the chair and had to stand up, 3) Walking; the subject had to walk three strides (starting with the right leg), 4) Step up; the subject had to step up to a plateau (height: 16 cm) starting with the right foot, 5) Side step; the subject took one step to the right side, and 6) Back step; the subject took one step back starting with the right foot. The movements were performed in five runs with breaks in between with subject-dependent durations. Each run consisted of six blocks where each block was 10 movements of the same movement type, i.e. after each run 10 movement trials were performed of each movement type. After each run, a resting recording of two minutes was performed (i.e. five recordings in total) while the subjects were standing relaxed and focused on a point on the wall four meters away. All movements were visually cued; a custom-made program (Knud Larsen, Aalborg University) guided the subject on a monitor four meters away. A clock was counting down for three seconds, and the subject had to initiate the movement task at this point. The movement trials were separated by 15 seconds. The subjects were instructed not to blink or do any facial movements during the 3-second countdown and while the movement task was performed. The experiment was performed in an electrically shielded room, and it lasted approximately three hours. Continuous EEG was recorded during the experiment. Before the recording started, the subjects were instructed in how to perform the movements and they were familiarized with the setup.

2.3. EEG Recording

Continuous EEG was recorded using a 64-channel EEG cap (g.GAMMAcap, G.Tec, Austria) with active electrodes (g.SCARABEO, G.Tec, Austria) and sampled with 1200 Hz (g.HIAMP, G.Tec, Austria). The impedance of the electrodes was kept below 30 kΩ. The signals were recorded using the g.RECORDER software (g.Tec, Austria). The EEG was referenced to the right earlobe. The following channels were used for the analysis: F3, F1, Fz, F2, F4, FC3, FC1, FCz, FC2, FC4, C3, C1, Cz, C2, C4, CP3, CP1, CPz, CP2, CP4, P3, P1, Pz, P2, and P4 (see Figure 1). At the beginning of each trial, a trigger was sent from the visual cueing program (Knud Larsen, Aalborg University) to the amplifier; this was used to divide the data into epochs.

2.4. Pre-processing

All analyses were performed in MATLAB (MathWorks®). Initially, the continuous EEG was bandpass filtered from 0.1-10 Hz using a 4th order zero-phase shift Butterworth filter for the morphological analysis and from 0.1-30 Hz for the movement detection and classification. The filtered EEG signal was divided into epochs from two seconds prior to the movement onset (at time zero indicated by the visual cue) until 0.5 second after. For the movement detection and classification, 50 2-second epochs were extracted from the resting EEG (idle). For each channel, epochs were rejected if they exceeded ±150 µV. The channel was rejected from further analysis if less than 20 epochs were preserved after the rejection.

2.5. Data Analysis – Morphology

The pre-processed epochs were averaged, and the following parameters were extracted as an indicator of the MRCP morphology: 1) RP, 2) NS, and 3) MP. RP was calculated as the mean amplitude in the interval -2 to -0.5 seconds with respect to the movement onset. NS was calculated as the mean amplitude in the interval -0.5 to -0.1 seconds with respect to the movement onset. MP was calculated as the mean amplitude in the interval -0.1 to 0.1 seconds with respect to the movement onset [53]. See Figure 1. The RP, NS and MP were extracted from all channels. Topographical maps of each movement task were constructed based on the average across subjects for the three MRCP segments.

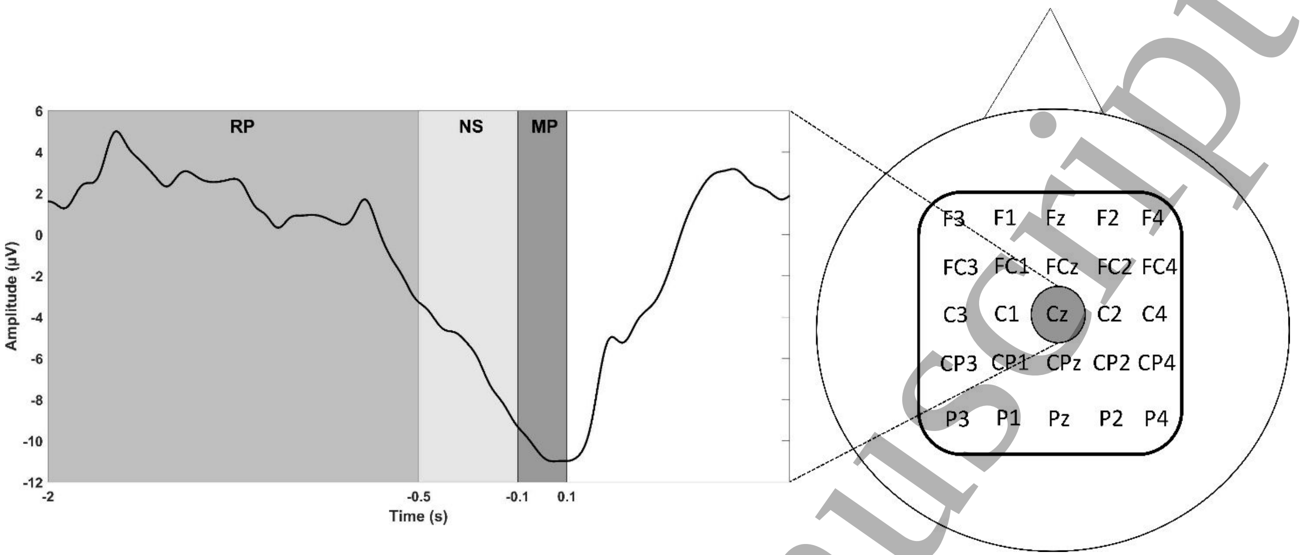

Figure 1: The Readiness Potential (RP), Negative Slope (NS), and Motor Potential (MP) are indicated on the grand average across subjects (n=13) performing the back step movement task. These segments were extracted from each of the channels.

2.6. Data Analysis – Movement Detection and Classification

There were two types of classification scenarios: 1) Movement task vs. Idle, and 2) Movement task vs. Movement task.

2.6.1. Feature Extraction

For the Movement task vs. Idle classification, three feature types were extracted: 1) Template matching, 2) Time-domain, and 3) Frequency-domain. For the Movement task vs. Movement task classification, only time-domain and frequency-domain features were extracted. The features were extracted from all channels. For the template matching feature, an average of the epochs for the specific channel was used, and the cross-correlation was calculated with each epoch. The feature was the cross-correlation with zero time lag. The time-domain features were the mean amplitude of 0.5-second non-overlapping windows i.e. four features were extracted from each channel. The frequency-domain features were power spectral density estimated for the entire epoch in 1 Hz bins from 6-30 Hz. A 1-second Hamming window with 0.5-second overlap was used.

2.6.2. Classification

The features were classified using Random Forest with 512 trees. A leave-one-out cross-validation scheme was used where the classifier was trained on all samples but one, and tested on the remaining sample. A 2-class classification problem was tested for each movement task and the idle activity; this was used as an estimate of the movement intention detection with respect to the idle activity. For the movement task vs.

movement task classification a 6-class problem was tested and a confusion matrix was obtained; this was used as an estimate of movement task discrimination. The classification was based on single-trials and performed on each subject separately.

2.7. Statistics

A 1-way repeated measures analysis of variance (ANOVA) test was performed with 'Movement task' as factor (6 levels: Stand-to-sit, sit-to-stand, walking, step up, back step, and side step) on the classification accuracies associated with movement detection. Moreover, three 1-way repeated measures ANOVA tests were performed with 'Movement task' as factor on the amplitudes of RP, NS and MP. The Greenhouse-Geisser correction was applied if the assumption of sphericity was violated. Significant test statistics were followed up using a posthoc test using Bonferroni correction. The significance level was set to P=0.05. The effect size is also reported (η^2). The statistical analyses were performed in SPSS (IBM).

3. Results

5±7 epochs were rejected from further analysis. The results are summarized in Table 1, 2, and 3, and in Figure 2 and 3.

3.1. Morphology

The grand averages of each movement task are plotted in Figure 2 across subjects. A clear MRCP shape is seen for all of the movement tasks except the walking task that is less prominent. Most of the movement tasks are overlapping while the averaged idle activity is close to 0 μV in amplitude.

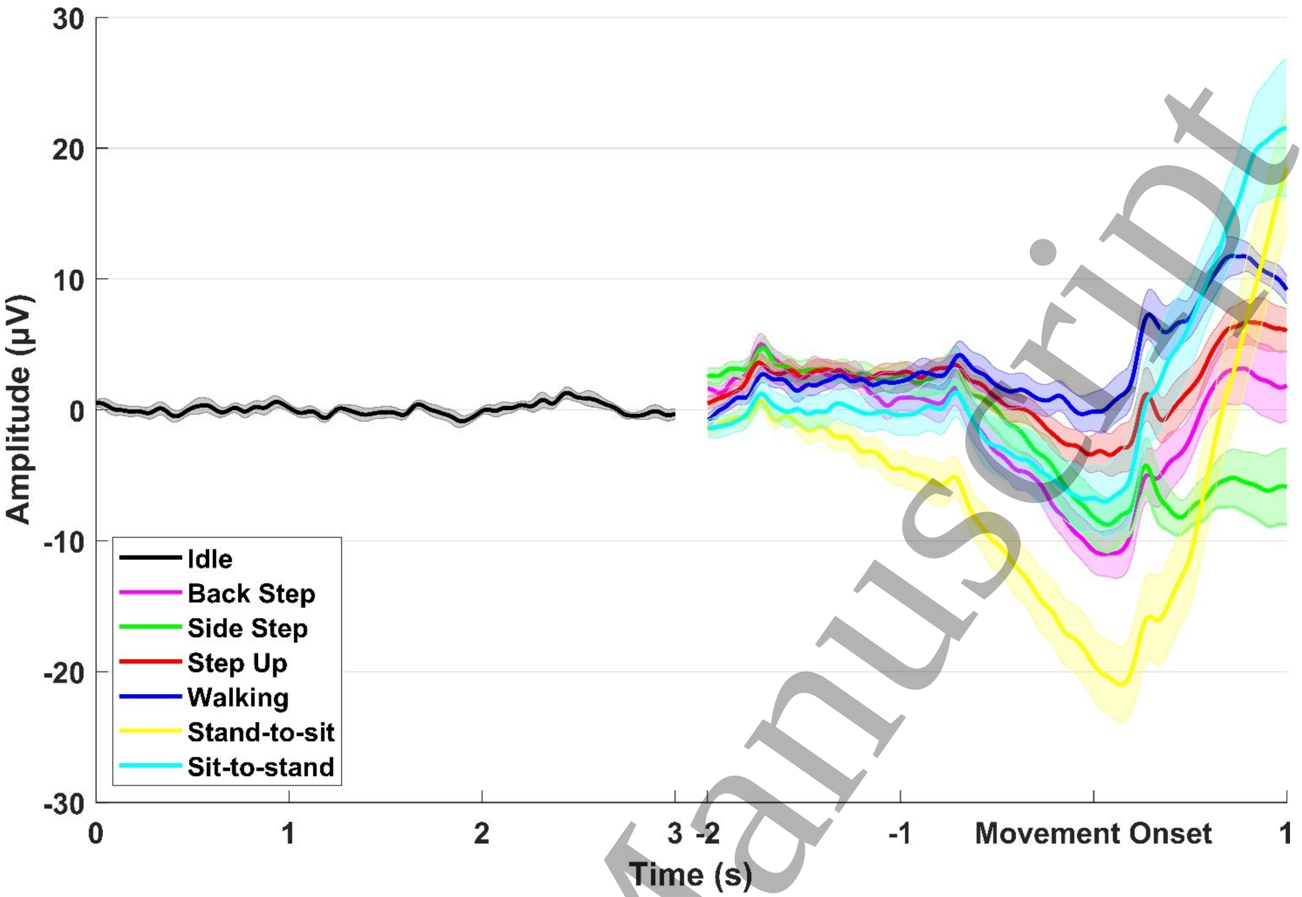

Figure 2: Grand average of the movement tasks and the idle activity across subjects (n=13). The average is shown in the middle of each trace and the shaded areas indicate the standard error.

The RP, NS and MP were extracted from each channel and plotted in a 5x5 grid using MATLABs 'contourf' function. The average across subjects is plotted in Figure 3. There was a clear trend that there was an increase in negativity when moving from the RP to the NS and eventually MP. Regarding the channel location, there was no clear trend of the activation pattern, although the highest amplitudes for the MP are located around the z-line of the electrodes in the FC and C line of the electrodes. As suggested in Figure 2, the amplitudes were lower for the walking and step up compared to the other movement tasks.

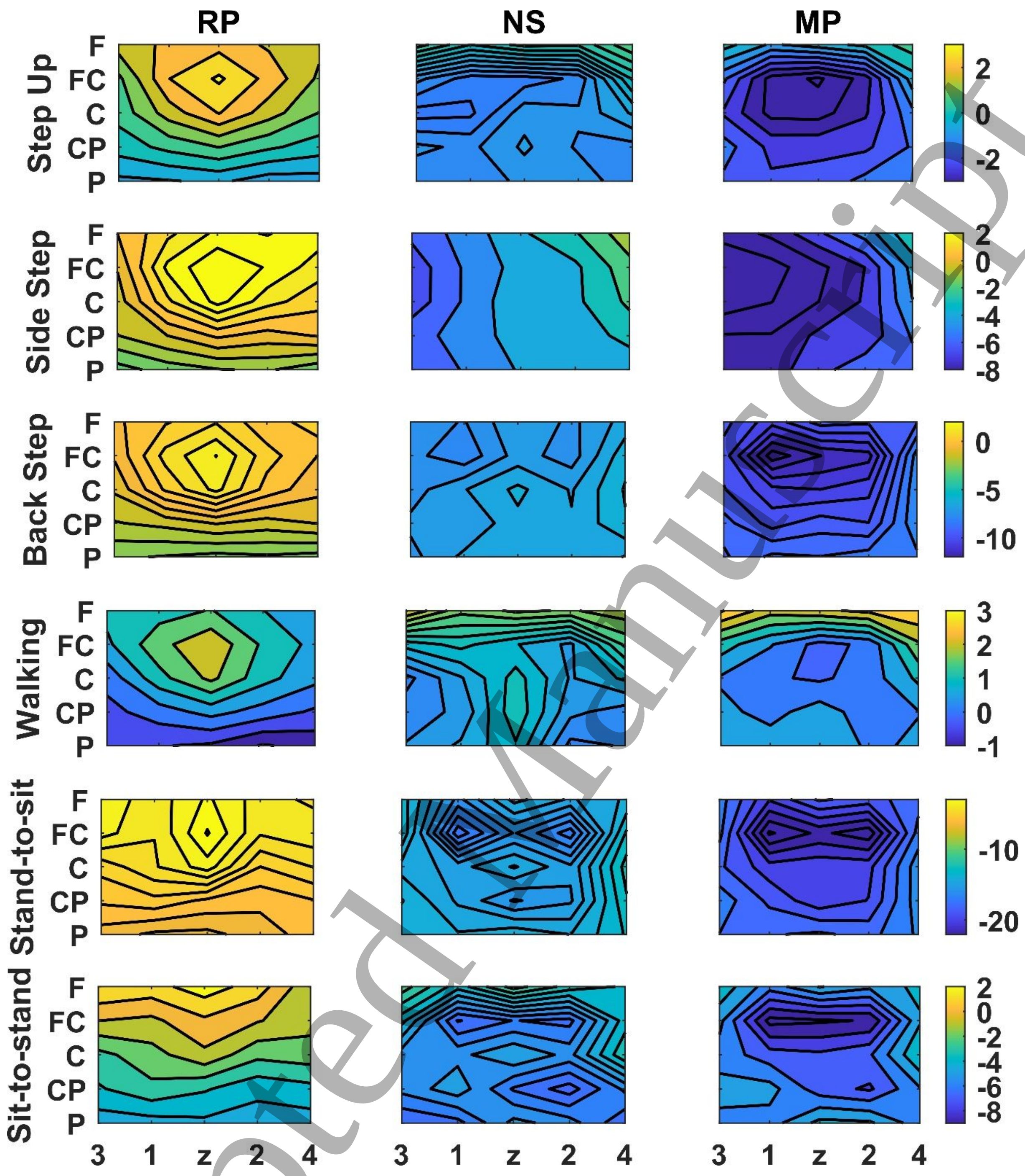

Figure 3: Topographical plot of the mean amplitude of the Readiness Potential (RP), Negative Slope (NS), and Motor Potential (MP) for the different movement tasks. The scaling on the axes is the same for the individual movement task for RP, NS and MP, but it differs across the movement tasks. The values are the averages across subjects (n=13) for the specific channels specified in Figure 1.

The representation of the lower extremities in the primary motor cortex is located at Cz; therefore, the RP, NS, and MP are extracted to show the variability across subjects (Table 1). Again, the walking and step up have lower amplitudes compared to the other tasks, which is consistent across subjects. The statistical analysis revealed a significant effect of movement task for RP ($F_{(2.2,26.3)}$=19.95; P<0.01; η^2= 0.62), NS

($F_{(2.1,24.7)}$=24.47; P<0.01; η^2= 0.67), and MP ($F_{(2.4,28.3)}$=27.28; P<0.01; η^2= 0.70). The posthoc test revealed that the stand-to-sit task had a higher RP amplitude compared to the other movement tasks. The stand-to-sit task had a higher NS and MP amplitude compared to the other movements, and the NS and MP of walking were lower than the other movement tasks except the sit-to-stand movement task. The step up had a lower NS and MP than the back step movement task. Lastly, the side step has a higher MP compared to the step up movement task.

	Amplitude (µV) – Cz		
	RP	NS	MP
Stand-to-sit	-3.2 ± 1.0	-13.9 ± 2.3	-19.3 ± 2.7
Sit-to-stand	-0.2 ± 1.3	-4.5 ± 2.3	-6.8 ± 2.6
Walking	2.1 ± 0.6	1.1 ± 1.2	-0.1 ± 1.5
Back step	1.7 ± 0.9	-5.9 ± 1.4	-10.5 ± 1.7
Side step	2.7 ± 0.8	-3.1 ± 1.7	-8.0 ± 2.0
Step up	2.5 ± 0.6	-0.9 ± 1.1	-3.2 ± 1.4
	Mean ± standard error	Mean ± standard error	Mean ± standard error

Table 1: Overview of the MRCP segments: Readiness Potential (RP), Negative Slope (NS), and Motor Potential (MP) associated with the different movement tasks. All values are presented as mean ± standard error across subjects.

3.2. Movement Detection and Discrimination

The results of the classification accuracies associated with the movement detection estimate are presented in Table 2 as well as the overall classification accuracy of the movement task discrimination. Further exploration of the movement discrimination is outlined in the confusion matrix in Table 3. The classification accuracies of the movement detection were high, between 80-90%. There was a significant effect or movement task ($F_{(5,60)}$=6.13; P<0.01; η^2= 0.34), where the classification accuracy of the step up task was significantly lower compared to the stand-to-sit, sit-to-stand, and side step tasks.

Classification Accuracy (%) – Movement Intention vs. Idle Activity	
Back step vs. Idle activity	85 ± 2
Side step vs. Idle activity	86 ± 2
Sit-to-stand vs. Idle activity	88 ± 2
Stand-to-sit vs. Idle activity	90 ± 2
Step up vs. Idle activity	80 ± 3
Walking vs. Idle activity	83 ± 2
	Mean ± standard error
Classification Accuracy (%) – Movement Task vs. Movement Task	
6-class (all movement types)	54 ± 3
	Mean ± standard error

Table 2: Results of the classification between movement intentions and idle activity, and classification between the six different movement types. The results are presented as mean ± standard error across subjects.

The results of the movement discrimination analysis (Table 3) show that the stand-to-sit tasks was easiest to discriminate followed by the sit-to-stand task. Generally, the discrimination between movement tasks is high

(36-71%), and the values on the diagonal are well-above the theoretical chance level of a 6-class problem (17%). The two least separable movement tasks were the step up and walking tasks.

		Predicted Class					
		Stand-to-sit	Sit-to-stand	Walking	Back step	Side step	Step up
True Class	Stand-to-sit	71 ± 6	10 ± 2	4 ± 2	8 ± 2	5 ± 2	2 ± 1
	Sit-to-stand	9 ± 2	67 ± 5	6 ± 1	6 ± 2	4 ± 1	7 ± 1
	Walking	2 ± 1	6 ± 2	58 ± 4	5 ± 2	9 ± 2	20 ± 2
	Back step	15 ± 2	7 ± 2	10 ± 3	42 ± 6	17 ± 3	9 ± 2
	Side step	7 ± 2	6 ± 2	9 ± 2	16 ± 3	50 ± 4	13 ± 2
	Step up	3 ± 1	9 ± 2	30 ± 3	7 ± 2	15 ± 2	36 ± 5

Table 3: Confusion matrix of the discrimination between the six different movement types. The values are presented as percent, and they are the mean ± standard error across subjects.

4. Discussion

From the EEG recordings, it was shown that MRCPs could be elicited from the functional lower limb movements. The movements could be classified with respect to the idle activity with accuracies in the range of 80-90%. For the movement type discrimination, 54% of the movements were correctly classified with the stand-to-sit and sit-to-stand movements being the most discriminable movement types. The results indicate that it is possible to detect and classify movement intentions associated with functional movements, which may be used in the development of a BCI that introduces task variability in neurorehabilitation.

4.1. MRCP Morphology

MRCPs have been shown to be elicited many times when both single-joint movements and movements across multiple joints are performed. Thus, it was expected to see MRCPs associated with the functional lower limb movements. The amplitudes were in the range of what has been reported previously ~5-30 μV, but there is no indication that movements involving multiple joints lead to higher or lower amplitudes of the MRCP compared to isolated movements; however, a direct comparison was not made in this study. A comparison of the MRCPs associated with these movements have not been performed, but in another study the MRCP associated with gait initiation has been elicited [44], which is similar to walking in the present study. Jiang et al. reported higher MRCP amplitudes (5-25 μV) than the walking task in the current study. Likely reasons for this difference include inter-subject variability and methodological differences in terms of EEG amplifier and signal processing techniques.

The activation pattern of the MRCP has been suggested to start frontally, and then move caudally towards the motor cortex [7], but this is not clearly reflected in the results. This may be due to the type of analysis where averages are calculated across subjects in wide time windows, which may eliminate potential differences or the fact that only a blurred picture of the underlying brain activity is obtained due to volume conduction.

4.2. Detection and Classification

The estimate of movement intention detection was similar (80-90%) to what has been reported in a number of other studies e.g. [23, 44, 54, 55], and the classification between movement types was also significantly higher than chance level (32% - calculated with a significance level of 5% [56]) for most tasks. The step up task was only slightly above chance level although still significant (36%). Many of those movements (30%) were classified as walking which is due to a similar morphology of the MRCP. This could be because the initiation of both movement types are similar (flexion in the hip joint).

The movement intention detection and classification of different movement types were performed separately, so the combined performance (detection + classification) is not obtained. If the two events are considered independent, the classification accuracy for the detection can be multiplied with the classification accuracy for the classification of the different movement tasks [55]. This would lead to a combined accuracy of ~46% (85%*54% - based on the average detection and movement type classification in Table 2). It is not known if this accuracy is enough to induce neuroplasticity, this is an open question yet to answer. The combined accuracy of 46% is probably higher since the two events are likely to be correlated. The combined accuracy would also increase if a subset of different movement tasks were selected since some movement tasks were easier to classify than others. Another alternative could be to only perform movement intention detection, and then decide what movement type to perform. In the latter scenario, it would be the therapists/patient who would need to introduce the task variability by switching between the tasks when the BCI only would detect if there was a movement or not, and not perform any classification between movement types.

The movement intention detection was estimated using classification between movement intentions and idle activity. The epochs were extracted with a priori knowledge of when the movements occurred, thus in a real-time BCI decoder, this information will not be available, and therefore it could be that fewer movements would be detected correctly. The detection algorithm can be modified to become less conservative, but that will increase the likelihood of false-positive detections. A potential way to control this is to construct a cue-based BCI system where the detector is only active in certain time windows.

5. Conclusion

Functional movements of the lower extremities elicit MRCPs that are visible in the EEG. The stand-to-sit task elicited the MRCP with the highest amplitude while walking elicited the MRCP with the lowest amplitude. It was shown that the movements could be detected from the idle activity and the individual movement tasks could be classified. These results suggest that it is possible to develop a BCI that can decode functional movements and be combined with exoskeletons for neurorehabilitation. However, this needs to be validated in future studies.

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References

1. Biasiucci A, Leeb R, Iturrate I, Perdikis S, Al-Khodairy A, Corbet T, et al. Brain-actuated functional electrical stimulation elicits lasting arm motor recovery after stroke. Nature communications. 2018;9(1):2421.

2. Ramos-Murguialday A, Broetz D, Rea M, Läer L, Yilmaz Ö, Brasil F, et al. Brain–machine interface in chronic stroke rehabilitation: a controlled study. Ann Neurol. 2013;74(1):100-8.

3. Cervera MA, Soekadar SR, Ushiba J, Millán JdR, Liu M, Birbaumer N, et al. Brain-computer interfaces for post-stroke motor rehabilitation: a meta-analysis. Annals of clinical and translational neurology. 2018;5(5):651-63.

4. 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.

5. 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.

6. 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.

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

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

9. Kornhuber HH, Deecke L. Hirnpotentialänderrungen bei Willkürbewegungen und passiven Bewegungen des Menschen: Bereitschaftspotential und reafferente Potentiale. Pflügers Arch. ges. Physiol. 1965;284(1):1-17.

10. Walter WG, Cooper R, Aldridge VJ, McCallum WC, Winter AL. Contingent negative variation: An electric sign of sensorimotor association and expectancy in the human brain. Nature (Lond.). 1964;203:380-4.

11. Nascimento OF, Dremstrup Nielsen K, Voigt M. Movement-related parameters modulate cortical activity during imaginary isometric plantar-flexions. Experimental brain research. 2006;171(1):78-90.

12. 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.

13. 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.

14. 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.

15. Grosse-Wentrup M, Mattia D, Oweiss K. Using brain-computer interfaces to induce neural plasticity and restore function. Journal of Neural Engineering. 2011;8(2):025004.

16. 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.

17. Shakeel A, Navid MS, Anwar MN, Mazhar S, Jochumsen M, Niazi IK. A review of techniques for detection of movement intention using movement-related cortical potentials. Computational and Mathematical Methods in Medicine. 2015;2015.

18. Bai O, Lin P, Vorbach S, Li J, Furlani S, Hallett M. Exploration of computational methods for classification of movement intention during human voluntary movement from single trial EEG. Clinical Neurophysiology. 2007;118(12):2637-55.

19. Bai O, Rathi V, Lin P, Huang D, Battapady H, Fei D, et al. Prediction of human voluntary movement before it occurs. Clinical Neurophysiology. 2011;122(2):364-72.

20. Garipelli G, Chavarriaga R, del R Millán J. Single trial analysis of slow cortical potentials: a study on anticipation related potentials. Journal of neural engineering. 2013;10(3):036014.

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. Lew E, Chavarriaga R, Silvoni S, Millán JR. Detection of self-paced reaching movement intention from EEG signals. Frontiers in neuroengineering. 2012;5:13.

23. 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.

24. Jochumsen M, Niazi IK, Navid MS, Anwar MN, Farina D, Dremstrup K. Online multi-class brain-computer interface for detection and classification of lower limb movement intentions and kinetics for stroke rehabilitation. Brain-Computer Interfaces. 2015;2(4):202-10.

25. 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.

26. Antelis JM, Montesano L, Ramos-Murguialday A, Birbaumer N, Minguez J. Continuous decoding of intention to move from contralesional hemisphere brain oscillations in severely affected chronic stroke patients. Engineering in medicine and biology society (EMBC), 2012 annual international conference of the IEEE; ; 2012.

27. Ibanez J, Serrano JI, del Castillo MD, Monge E, Molina F, Rivas FM, et al. Upper-limb muscular electrical stimulation driven by EEG-based detections of the intentions to move: A proposed intervention for patients with stroke. Engineering in medicine and biology society (EMBC), 2014 36th annual international conference of the IEEE; ; 2014.

28. Muralidharan A, Chae J, Taylor DM. Extracting attempted hand movements from EEGs in people with complete hand paralysis following stroke. Frontiers in neuroscience. 2011;5.

29. Lopez-Larraz E, Montesano L, Gil-Agudo A, Minguez J. Continuous decoding of movement intention of upper limb self-initiated analytic movements from pre-movement EEG correlates. J Neuroeng Rehabil. 2014;11:153,0003-11-153.

30. Borisoff JF, Mason SG, Bashashati A, Birch GE. Brain-computer interface design for asynchronous control applications: improvements to the LF-ASD asynchronous brain switch. Biomedical Engineering, IEEE Transactions on. 2004;51(6):985-92.

31. Bashashati A, Mason S, Ward RK, Birch GE. An improved asynchronous brain interface: Making use of the temporal history of the LF-ASD feature vectors. Journal of Neural Engineering. 2006;3(2):87-94.

32. Ofner P, Schwarz A, Pereira J, Wyss D, Wildburger R, Müller-Putz GR. Attempted Arm and Hand Movements can be Decoded from Low-Frequency EEG from Persons with Spinal Cord Injury. Scientific reports. 2019;9(1):7134.

33. 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.

34. Jochumsen M, Shafique M, Hassan A, Niazi IK. Movement intention detection in adolescents with cerebral palsy from single-trial EEG. Journal of neural engineering. 2018;15(6):066030.

35. Gu Y, Farina D, Murguialday AR, Dremstrup K, Montoya P, Birbaumer N. Offline identification of imagined speed of wrist movements in paralyzed ALS patients from single-trial EEG. Frontiers in Neuroscience. 2009;3(62).

36. Ibáñez J, Serrano J, del Castillo M, Gallego J, Rocon E. Online detector of movement intention based on EEG—Application in tremor patients. Biomedical Signal Processing and Control. 2013;8(6):822-9.

37. Gu Y, Nascimento OF, Lucas MF, Farina D. Identification of task parameters from movement-related cortical potentials. Medical biological engineering computing. 2009;47(12):1257-64.

38. Agashe HA, Contreras-Vidal JL. Decoding the evolving grasping gesture from electroencephalographic (EEG) activity. Engineering in Medicine and Biology Society (EMBC), 2013 35th Annual International Conference of the IEEE. 2013:5590-3.

39. Ofner P, Muller-Putz GR. Using a Noninvasive Decoding Method to Classify Rhythmic Movement Imaginations of the Arm in Two Planes. Biomedical Engineering, IEEE Transactions on. 2015;62(3):972-81.

40. Demandt E, Mehring C, Vogt K, Schulze-Bonhage A, Aertsen A, Ball T. Reaching movement onset-and end-related characteristics of EEG spectral power modulations. Frontiers in Neuroscience. 2012;6:00065.

41. Ofner P, Schwarz A, Pereira J, Müller-Putz GR. Upper limb movements can be decoded from the time-domain of low-frequency EEG. PloS one. 2017;12(8):e0182578.

42. 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.

43. Bulea TC, Prasad S, Kilicarslan A, Contreras-Vidal JL. Sitting and standing intention can be decoded from scalp EEG recorded prior to movement execution. Frontiers in neuroscience. 2014;8.

44. Jiang N, Gizzi L, Mrachacz-Kersting N, Dremstrup K, Farina D. A brain–computer interface for single-trial detection of gait initiation from movement related cortical potentials. Clinical Neurophysiology. 2014;126(1):154-9.

45. Presacco A, Goodman R, Forrester L, Contreras-Vidal JL. Neural decoding of treadmill walking from noninvasive electroencephalographic signals. J Neurophysiol. 2011;106(4):1875-87.

46. Presacco A, Forrester LW, Contreras-Vidal JL. Decoding Intra-Limb and Inter-Limb Kinematics During Treadmill Walking From Scalp Electroencephalographic (EEG) Signals. Neural Systems and Rehabilitation Engineering, IEEE Transactions on. 2012;20(2):212-9.

47. Velu PD, de Sa VR. Single-trial classification of gait and point movement preparation from human EEG. Frontiers in neuroscience. 2013;7.

48. Schwarz A, Ofner P, Pereira J, Sburlea AI, Müller-Putz GR. Decoding natural reach-and-grasp actions from human EEG. Journal of neural engineering. 2017;15(1):016005.

49. Schwarz A, Pereira J, Kobler R, Müller-Putz GR. Unimanual and Bimanual Reach-and-Grasp Actions Can Be Decoded From Human EEG. IEEE transactions on biomedical engineering. 2019.

50. Mohseni M, Shalchyan V, Jochumsen M, Niazi IK. Upper limb complex movements decoding from pre-movement EEG signals using wavelet common spatial patterns. Comput Methods Programs Biomed. 2020;183:105076.

51. Pereira J, Ofner P, Schwarz A, Sburlea AI, Müller-Putz GR. EEG neural correlates of goal-directed movement intention. Neuroimage. 2017;149:129-40.

52. Krakauer JW. Motor learning: its relevance to stroke recovery and neurorehabilitation. Curr Opin Neurol. 2006;19(1):84-90.

53. Jochumsen M, Christensen CR, Christensen HR, Cremoux S, Signal N, Allen K, et al. Quantification of movement-related EEG correlates associated with motor training: A study on movement-related cortical potentials and sensorimotor rhythms. Frontiers in Human Neuroscience. 2017;11:1-12.

54. 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.

55. Jochumsen M, Niazi IK, Mrachacz-Kersting N, Farina D, Dremstrup K. Detection and classification of movement-related cortical potentials associated with task force and speed. Journal of neural engineering. 2013;10(5):056015.

56. 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.