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Detecting and classifying movement-related cortical potentials associated with hand movements in healthy subjects and stroke patients from single-electrode, single-trial EEG

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Abstract

Objective. To detect movement intention from executed and imaginary palmar grasps in healthy subjects and attempted executions in stroke patients using one EEG channel. Moreover, movement force and speed were also decoded. *Approach*. Fifteen healthy subjects performed motor execution and imagination of four types of palmar grasps. In addition, five stroke patients attempted to perform the same movements. The movements were detected from the continuous EEG using a single electrode/channel overlying the cortical representation of the hand. Four features were extracted from the EEG signal and classified with a support vector machine to decode the level of force and speed associated with the movement. The system performance was evaluated based on both detection and classification. *Results*. ~75% of all movements (executed, imaginary and attempted) were detected 100 ms before the onset of the movement. ~60% of the movements were correctly classified according to the intended level of force and speed. When detection and classification were combined, ~45% of the movements were correctly detected and classified in both the healthy and stroke subjects, although the performance was slightly better in healthy subjects. *Significance*. The results indicate that it is possible to use a single EEG channel for detecting movement intentions that may be combined with assistive technologies. The simple setup may lead to a smoother transition from laboratory tests to the clinic.

Keywords: Movement-related cortical potentials, movement intention, brain-computer interface, movement kinetics, EEG, signal processing.

1. Introduction

Brain-computer interfaces (BCIs) have been used for several years as a means for communication and control [1], but more recently has been extended to neurological rehabilitation (for inducing cortical plasticity) [2]. The induction of plasticity has been shown to correlate with motor learning [3]; therefore, it seems reasonable to propose the use of BCIs for rehabilitation where lost motor skills (including grasping [4]) must be relearned, for example after stroke [5, 6]. Recently, a protocol was proposed to induce long-term potentiation-like plasticity, a proposed mechanism for declarative and procedural memory [7], where motor cortical activation is paired with somatosensory feedback from peripheral electrical stimulation in a similar way as paired associative stimulation [8]. This approach has been tested when targeting the lower extremities in healthy subjects and stroke patients [9-11]. The procedure includes cortical activation through kinaesthetic motor imagination (MI) of a contraction of the target muscle, and somatosensory feedback provided by stimulating the nerve innervating that muscle [9]. Plastic changes were observed when the afferent feedback reached the cortex during the execution phase of MI. Therefore, the imaginary movement onset must be predicted (due to the propagation time of the afferent feedback) for triggering the electrical stimulator, so that the afferent feedback reaches the cortex at the correct time.

It has been shown that in both imagined and real movements there is a slow depression in the EEG up to 2 s prior the onset of the imagined or real movement. This property allows for early detection of movement onset [10, 12]. This negative brain potential in the low frequency band (<1 Hz) is known as the movement-related cortical potential (MRCP), and it can be further divided into the bereitschaftspotential [13] and contingent negative variation [14] if the movements are self-paced or cued, respectively. The MRCP consists of an initial negative phase which is associated with the movement preparation or intention and a movement-monitoring positive phase [15]. The movement intention is observed prior the onset of the movement (executed or imaginary) and the movement-monitoring phase after the onset of the movement. The movement intention is modulated by various factors, such as fatigue, level of intention and movement selection [16]. Kinetic information such as the level of force and speed of the movement is encoded in the movement intention for plantar- [15] and dorsiflexion of the ankle joint [17]. This information has been decoded from single-trial MRCPs for both the lower extremities and wrist movements in previous studies [17-23].

Before movement kinetics can be classified for useful BCI purposes, the movements themselves must be detected. Several approaches have been used to discriminate movements from the idle state for finger, arm and foot movements [10, 12, 23-31]. However, the detection of movement intention and decoding of kinetic information from MRCPs associated with functional movements such as palmar grasps from healthy subjects and stroke patients have not yet been fully investigated. By detecting and classifying movement intentions associated with different levels of force and speed, it is possible to provide afferent feedback from electrical stimulation or rehabilitation robots, in such a way that the afferent feedback matches the efferent activity from the motor cortex. Furthermore, the classification of movement-related parameters would allow for control of multiple degrees of freedom.

The aim of this study was two-fold: 1) to detect MRCPs from a single EEG channel during palmar grasping tasks in healthy and stroke subjects, and 2) to classify two levels of force and speed from the MRCP using a single EEG channel. The performance obtained using a single EEG channel was compared to that using a Laplacian channel. This is a spatial filter which is state-of-the-art for MRCP detection [10, 12, 23, 25, 26, 31-34], derived from nine EEG channels to provide evidence for an easier setup that may assist in the technology transfer from the laboratory to the clinic.

2. Methods

2.1. Subjects

15 healthy subjects (3 men and 12 women: 27±11 years of age) and five stroke patients (see table 1) participated in this study. All patients had residual movement and were able to perform palmar grasps. The score from an Action Research Arm Test is reported in table 1. The test is an observational test to determine upper limb

function; it is divided into 19 items grouped in subtests for grasp, grip, pinch and gross movement. The performance of each item is rated from 0 to 3 (normal movement). All subjects understood the instructions and the tasks to perform. None of the participants had any prior BCI experience. All subjects and patients gave their written informed consent (N-20130081). All procedures were approved by the local ethical committee in accordance with the Declaration of Helsinki.

Patient	Diagnosis	Affected side (limb)	Gender	Age	Days since event	ARAT
1	Infarction	Left	Female	59	35	11
2	Hemorrhage	Left	Female	57	65	31
3	Hemorrhage	Left	Male	72	43	24
4	Infarction	Right	Male	51	62	-
5	Infarction	Right	Female	58	46	47

Table 1: Patient data. The total score (maximum is 57) from an Action Research Arm Test (ARAT) was available for four of the patients. There is great variability in the scores which shows that the group is rather heterogeneous in terms of level of functionality.

2.2. *Experimental protocol*

The subjects were seated in a comfortable chair with their right forearm (Patient 1-3 used the left hand; the affected side) placed on a table while holding a handgrip dynamometer (Noraxon USA, INC., Scottsdale, Arizona). The healthy subjects were asked to execute and imagine four isometric palmar grasp tasks. The stroke subjects were asked to perform each grasp as well as possible; this will be referred to as attempted motor execution in the following text. At the beginning of the experiment, the maximum voluntary contraction (MVC) was determined followed by 40 externally cued repetitions of each of the four grasp tasks. The four grasp tasks were as follows: 1) 0.5 s to reach 20% MVC, 2) 0.5 s to reach 60% MVC, 3) 3 s to reach 20% MVC and 4) 3 s to reach 60% MVC. To assist the subjects in performing the movements with the correct percentage of MVC and time to reach that level (except for the imagined movements), the movements were visually cued (see figure 1). Force from the dynamometer was used as input to a custom made program (SMI, Aalborg University) where the subjects were asked to produce force (gray line in figure 1) to match a template (black line in figure 1). The entire template was shown while a moving cursor (the force that was produced) indicated when to initiate the movement. The same template was used by the healthy and stroke subjects. The subjects were given 2 min to practice each grasp task; the stroke patients were allowed to practice the movements with their less affected hand before the recording started. For the healthy subjects and stroke patients, breaks were allowed when needed. The order of the tasks was randomized in blocks.

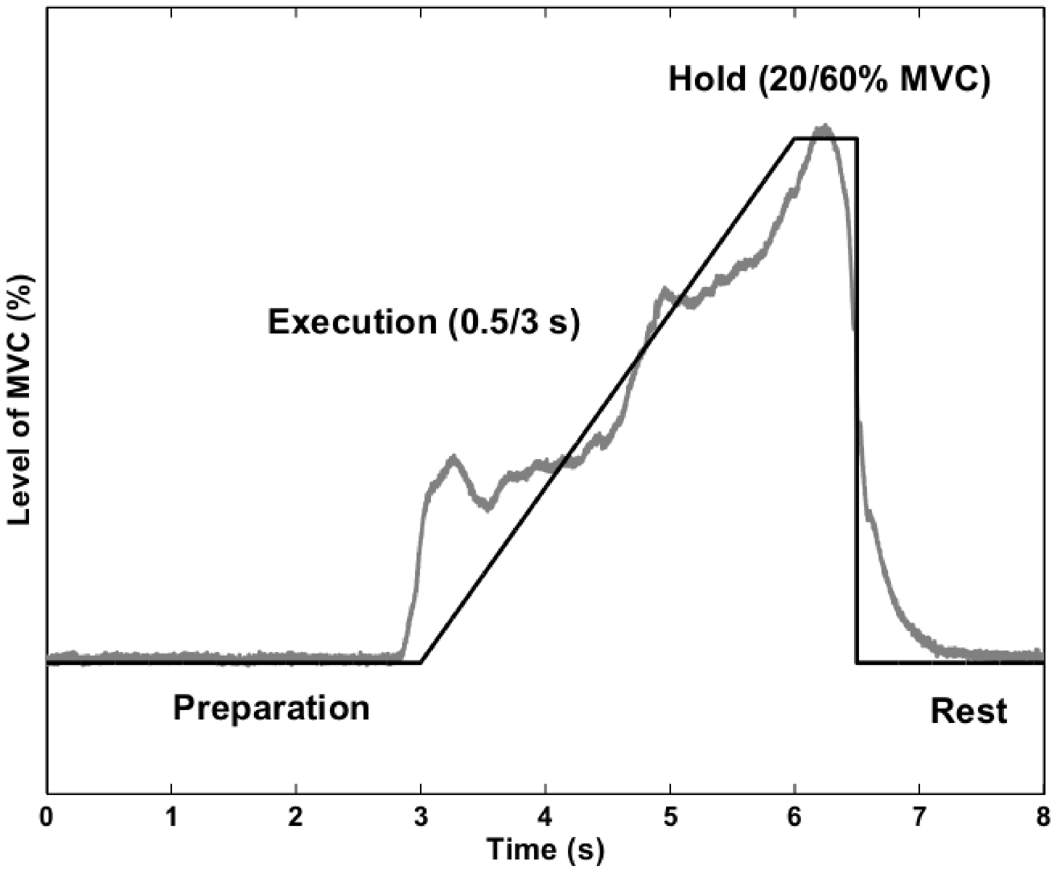

Figure 1. The black line is the visual trace that was presented to the subject. The grey trace is the force produced by a representative stroke patient. The subjects prepared for 3 s followed by the execution phase. The contraction was maintained for 0.5 s after which a rest period was given (between 4-5 s). The task onset is at 3 s.

2.3. Signal acquisition

2.3.1. EEG

Continuous monopolar EEG was recorded from nine channels (EEG amplifiers, Nuamps Express, Neuroscan) using Ag/AgCl cup electrodes. The EEG from the healthy subjects and the stroke patients with right hemiparesis (patient 4 and 5 in table 1) was recorded from F7, F3, Fz, T7, C3, Cz, P7, P3 and Pz. The EEG from the stroke patients with left hemiparesis (patient 1-3 in table 1) was recorded from Fz, F4, F6, Cz, C4, T8, Pz, P4 and P8. Electroencephalography (EOG) was recorded from Fp1. The EEG and EOG were sampled with 500 Hz and analog to digital converted with 32 bits accuracy. All channels were referenced to the right earlobe and grounded at nasion. During the experiment, the impedance of all electrodes was kept below 5 kΩ. To synchronize all trials, a trigger was sent from the visual cueing program to the EEG amplifier at the beginning of each trial (at 0 s in figure 1).

2.3.2.Force and MVC

Force was recorded using a handgrip dynamometer and used as input to the visual cueing program to provide feedback to the subject. The force was recorded with a sampling rate of 2000 Hz. The MVC was determined at the beginning of the experiment as the maximum of three trials of maximal force performed with 1 min of rest in between each movement. Besides the trigger sent to the EEG amplifier, force was used to determine movement onset for the executed tasks. Specifically, the onset was defined as the initial time instant of the first 200-ms window for which all samples had force values above the baseline [23]. The baseline was defined as the mean value of the force signal during the resting phase and the first second of the preparation phase (see figure 1). All movement onsets were visually inspected.

2.4. Detection

The EEG signals were bandpass filtered from 0.05-10 Hz in the reverse and forward direction with a digital 2nd order Butterworth filter. The movements were detected in two scenarios: using a single channel (C3 or C4) or using a Laplacian channel (linear combination of nine channels). The Laplacian channel was obtained as C3-(F7+F3+Fz+T7+Cz+P7+P3+Pz)/8 for right hand movements. For left hand movements, it was computed in the same way but with centre electrode C4 instead of C3.

The methodology for detecting cued and self-paced movements has been described previously [10, 12, 23], but will be outlined in the following paragraph. The procedure for estimating the online performance of a BCI based on executed, imagined and attempted movements is similar.

The four pre-processed continuous recordings (one for each of the four grasp types) were concatenated to one continuous recording (~30 min). The recording was divided randomly into four parts: three parts for training and one part for testing, with a similar number of the four movement types in each part. Moreover, an additional simulation was performed where the first half of each of the four pre-processed recordings was concatenated into one continuous training recording (~15 min), and the other halves were concatenated into one continuous testing recording (~15 min). This simulation was used to indicate the performance of the system in a real-world application where data are collected first to calibrate the system.

From the training data, a template of the initial negative phase of the MRCP was extracted from an average of all the training trials from the peak of maximum negativity and 2 s prior to this point (see figure 2). After the template was extracted, the detection threshold was determined by using a receiver operating characteristics (ROC) curve that was obtained through three-fold cross-validation on the training set. The detection threshold was selected at the upward convex part of the ROC curve to obtain a trade-off between the true positive rate (TPR) and the number of false positive detections. The detector decisions were based on the likelihood ratio (Neyman Pearson lemma) calculated between the template and the signal from the testing set (single or Laplacian channel) using a 2 s window with a 200 ms shift. Detections occurred when two out of three consecutive windows exceeded the detection threshold, and the EOG amplitude in Fp1 was below 125μV peak-to-peak. To quantify the performance of the detector, the TPR, number of false positives (FPs) per minute (FPs/min) and the detection latency were calculated. The detection latency was defined as the point of detection with respect to the onset of the movement (or task onset for imagined movement).

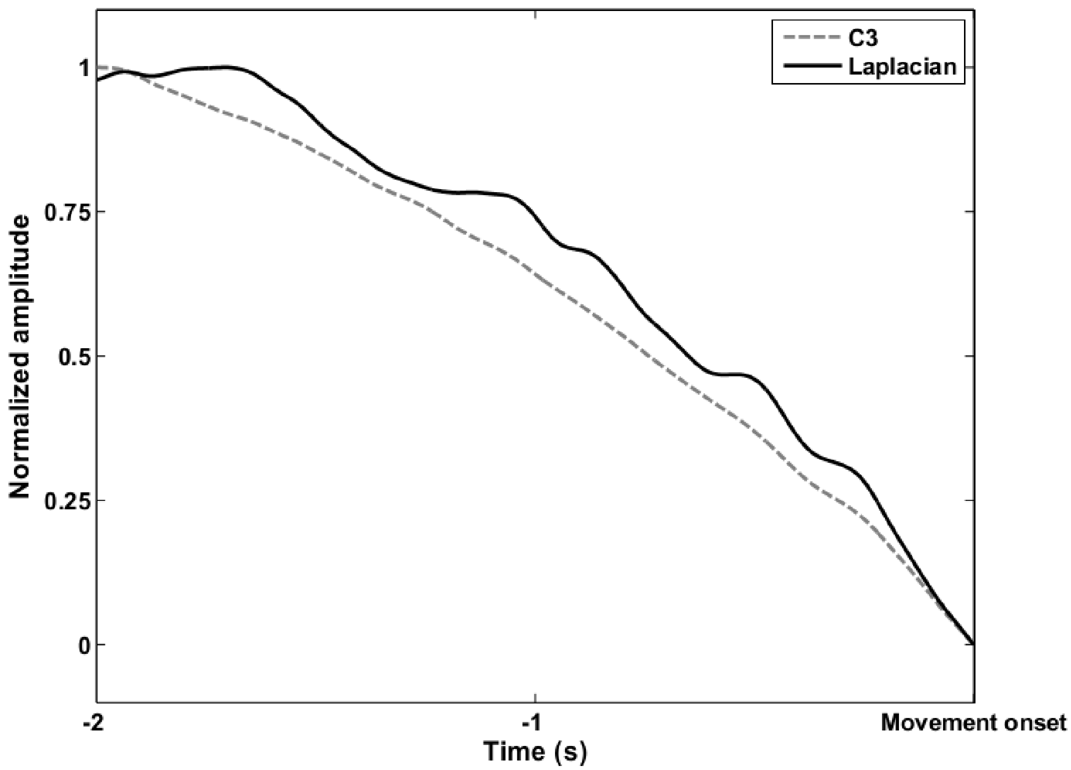

Figure 2. The detection template for the single (dashed grey line) and Laplacian (solid black line) channel is shown for a representative stroke patient.

2.5. Feature extraction and classification

2.5.1.Feature extraction

Four features were extracted from the 2 s data window from the averaged point of detection and 2 s prior to this point for each epoch. The following features were extracted: i) peak of maximum negativity, ii) mean amplitude, iii) slope of a linear regression fitted to the data window and iv) the average power in the interval from 0-5 Hz. The average power was calculated using the power spectral density which was calculated using a Hamming window with a width of 250 samples and 125 samples overlap. Epochs were rejected when the EOG amplitude in Fp1 exceeded 125μV peak-to-peak.

2.5.2. Movement classification

The classification of movements was divided into two categories: 2-class and 4-class problems. In the 2-class problem, all pairwise comparisons (0.5 s to reach 20% MVC versus 0.5 s to reach 60% MVC, etc.) were calculated. The features were classified using a support vector machine (SVM) with a linear kernel, and the classification accuracies were obtained using leave-one-out cross-validation. For the 4-class problem, the binary SVM classification was extended to four classes using the 'one-versus-one' scheme. A classifier was constructed for each task pair, and a test sample was classified by all classifiers; the label to the test sample was given based on the class with most votes.

2.6. System performance

The detection and classification were performed separately, but it was assumed that the two events are independent. Given this assumption, the estimated system performance of a BCI that can detect and classify the movement type can be calculated using the following formula:

$$Performance = \frac{\mathrm{CA}(1,2) * [\mathrm{TPR}(1) + \mathrm{TPR}(2)]}{2}$$

CA(1,2) is the classification accuracy of the task pair (2-class system) of task 1 and 2 while TPR(1) is the TPR for task 1. To estimate the performance of a 4-class system, the classification accuracy of the specific task is multiplied with the corresponding TPR.

2.7. Statistics

Three 2-way analysis of variance (ANOVA) tests were performed to find differences between: the TPRs (average across tasks), detection latencies and number of FPs/min. The two factors were: 'movement type' and 'channel'. The factor 'movement type' had three levels: ME, MI and attempted ME, while 'channel' had two levels: single channel and Laplacian channel. Also, three similar 2-way ANOVAs were performed with 'movement type' and 'simulation' as factors. 'Simulation' had two levels: cross-validation and 50/50 training and testing. Two 3-way ANOVA tests were performed for the classification accuracies and system performance (average across task pairs and tasks in the 2-class and 4-class problem, respectively). The two factors were the same as above, and the third factor was ‘number of classes’ which had two levels: 2 and 4. Two similar 3-way ANOVAs were performed where ‘channel’ was substituted with ‘simulation’. Significant test statistics were followed up with post hoc analysis with Tukey’s correction for multiple comparisons. Statistical significance was assumed when the p-value < 0.05.

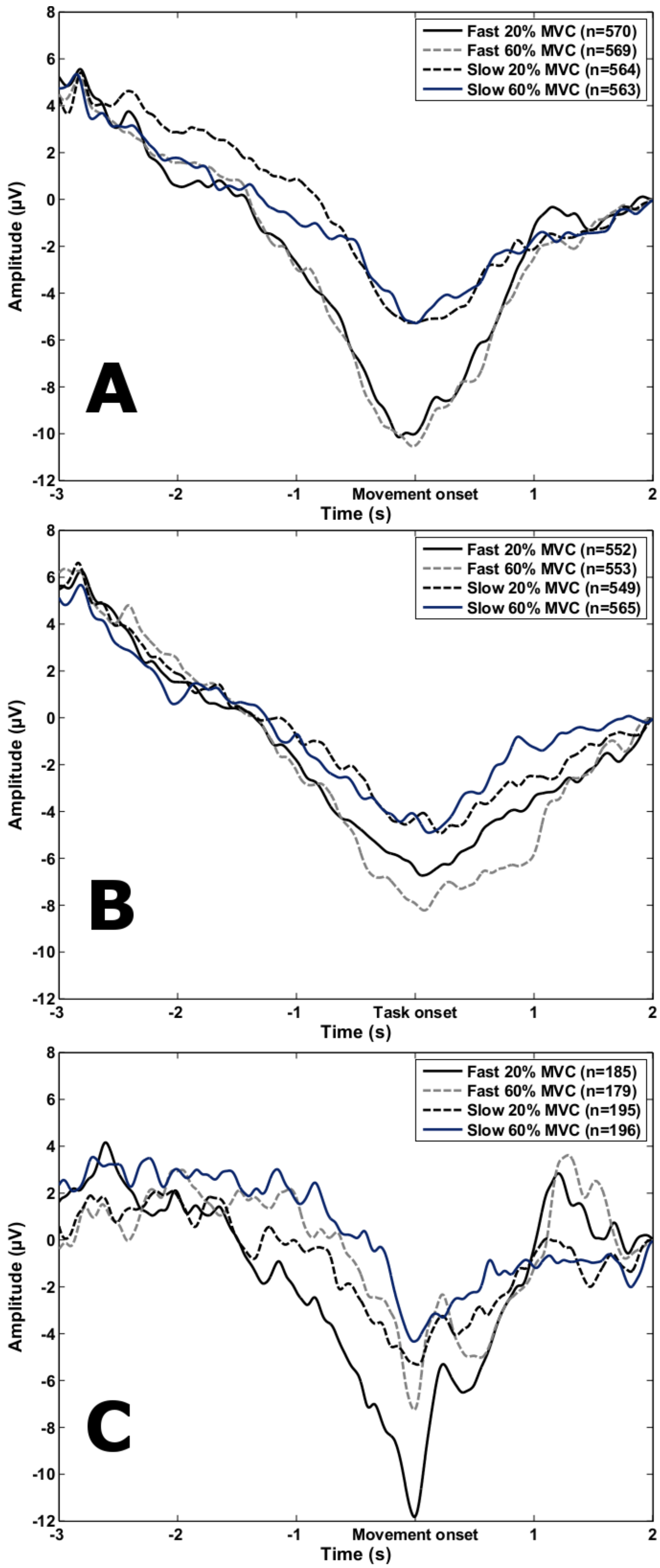
Fast 20% MVC (n=570)
Fast 60% MVC (n=569)
Slow 20% MVC (n=564)
Slow 60% MVC (n=563)
A
Amplitude (µV)
Movement onset
Time (s)
Fast 20% MVC (n=552)
Fast 60% MVC (n=553)
Slow 20% MVC (n=549)
Slow 60% MVC (n=565)
B
Amplitude (µV)
Task onset
Time (s)
Fast 20% MVC (n=185)
Fast 60% MVC (n=179)
Slow 20% MVC (n=195)
Slow 60% MVC (n=196)
C
Amplitude (µV)
Movement onset
Time (s)

Figure 3. The grand averages of the epochs for the four palmar grasp tasks using a single channel are plotted for executed (A), imaginary (B) and attempted (C) movements. 'Fast' refers to 0.5 to reach the desired level of MVC, and 'slow' refers to 3 s to reach that level. Epochs for imaginary movements are aligned to the task onset (t = 3 s in figure 1) since no force was produced to determine the onset of the imaginary movement.

3. Results

The results are summarized in tables 2-7 for detection, classification and system performance, respectively.

3.1. Detection

The performance of the detector (table 2) was similar when using a single channel or the Laplacian filtered channels. On average (across tasks), ~75% of all movements were correctly detected with similar TPRs for the executed, imaginary and attempted movements. The difference in the TPRs was not significant when using the two approaches ($F_{(1,64)}$=0.23; P=0.64), and no significant differences were observed between the movement types ($F_{(2,64)}$=0.18; P=0.84). The interaction between the factors 'channel' and 'movement type' was not significant ($F_{(2,64)}$=1.05; P=0.36). In general, the highest TPRs were observed for fast movements when the movements were executed. Conversely, the greatest TPRs were obtained for slow movements in MI. The movements were detected with similar latencies with respect to the movement onset for the three movement types and the two channels. The interaction between the two factors was not significant ($F_{(2,64)}$=0.061; P=0.94); nor was the effect of 'channel' ($F_{(2,64)}$=0.68; P=0.41) and 'movement type' ($F_{(2,64)}$=1.09; P=0.34). Lastly, the number of FPs/min was similar when comparing the single channel with the Laplacian derivation ($F_{(1,64)}$=0.23; P=0.63), but more FPs were observed per minute for the stroke patients ($F_{(2,64)}$=11.85; P=0.000042) compared to the executed and imaginary movements from the healthy subjects.

Task	**ME** **C3 / Laplacian**	**MI** **C3 / Laplacian**	**Attempted ME** **C3-4 / Laplacian**
Fast 20% MVC	73/71±12 / 67/68±8	68/70±10 / 70/72±9	82/78±8 / 76/80±10
Fast 60% MVC	76/77±8 / 74/74±10	74/72±10 / 73/74±8	78/78±6 / 78/82±8
Slow 20% MVC	78/75±16 / 73/73±8	73/75±9 / 78/80±11	64/63±3 / 74/71±11
Slow 60% MVC	77/74±11 / 76/76±11	74/73±9 / 76/78±8	74/75±12 / 66/63±9

Median/Mean across tasks	76/74±12 / 73/73±10	73/73±10 / 75/76±10	73/74±10 / 75/74±12
FPs/min	1.6/1.5±0.7 / 1.8/1.7±0.5	1.5/1.5±0.6 / 1.7/1.6±0.5	2.6/2.7±1.0 / 3.0/2.7±1.0
Detection latency [ms]	-117/-126±80 / -152/-148±72	-78/-102±77 / -87/-111±68	-82/-114±94 / -154/-138±85
	Median/Mean±SD	**Median/Mean±SD**	**Median/Mean±SD**

Table 2. The performance of the detector is presented for executed and imaginary movements from healthy subjects and executed movements from stroke patients (rightmost column). The duration of the recordings was ~30 min.

The simulation, where the first half of the data was used (table 3), was not significantly different from the simulation where cross-validation was used in terms of TPR ($F_{(1,64)}$=1.83; P=0.18), detection latencies ($F_{(1,64)}$=3.94; P=0.051) and FPs/min ($F_{(1,64)}$=0.008; P=0.93).

Task	**ME**	**MI**	**Attempted ME**
Fast 20% MVC	65/65±10	70/71±12	76/76±5
Fast 60% MVC	72/72±10	71/70±9	73/73±5
Slow 20% MVC	75/71±14	78/77±11	63/64±11
Slow 60% MVC	75/73±15	73/74±10	65/70±11
Median/Mean across tasks	69/70±13	73/73±11	71/71±10
FPs/min	1.4/1.4±0.5	1.6/1.7±0.8	2.9/2.5±0.9
Detection latency [ms]	-53/-64±87	-69/-90±69	-57/-47±125
	Median/Mean±SD	**Median/Mean±SD**	**Median/Mean±SD**

Table 3. The performance of the detector is presented for executed and imaginary movements from healthy subjects and executed movements from stroke patients (rightmost column) when using the first half of the data for training and the other half for testing. The values were calculated using C3 (or C4). The duration of the recordings for testing was ~15 min.

3.2. Classification

On average 4±4, 4±4 and 6±8 epochs were rejected per subject for executed, imaginary and attempted movements, respectively. The classification accuracies (table 4 and 5) were calculated for each task pair (2-class) and each task (4-class). In general, the highest classification accuracies for the task pairs were obtained when speed was varied. On average, the classification accuracies were 57-64% for the 2-class problem and 32-40% for the 4-class problem. In figure 4, the variability of the MRCP can be seen for a single task (Fast 20% MVC).

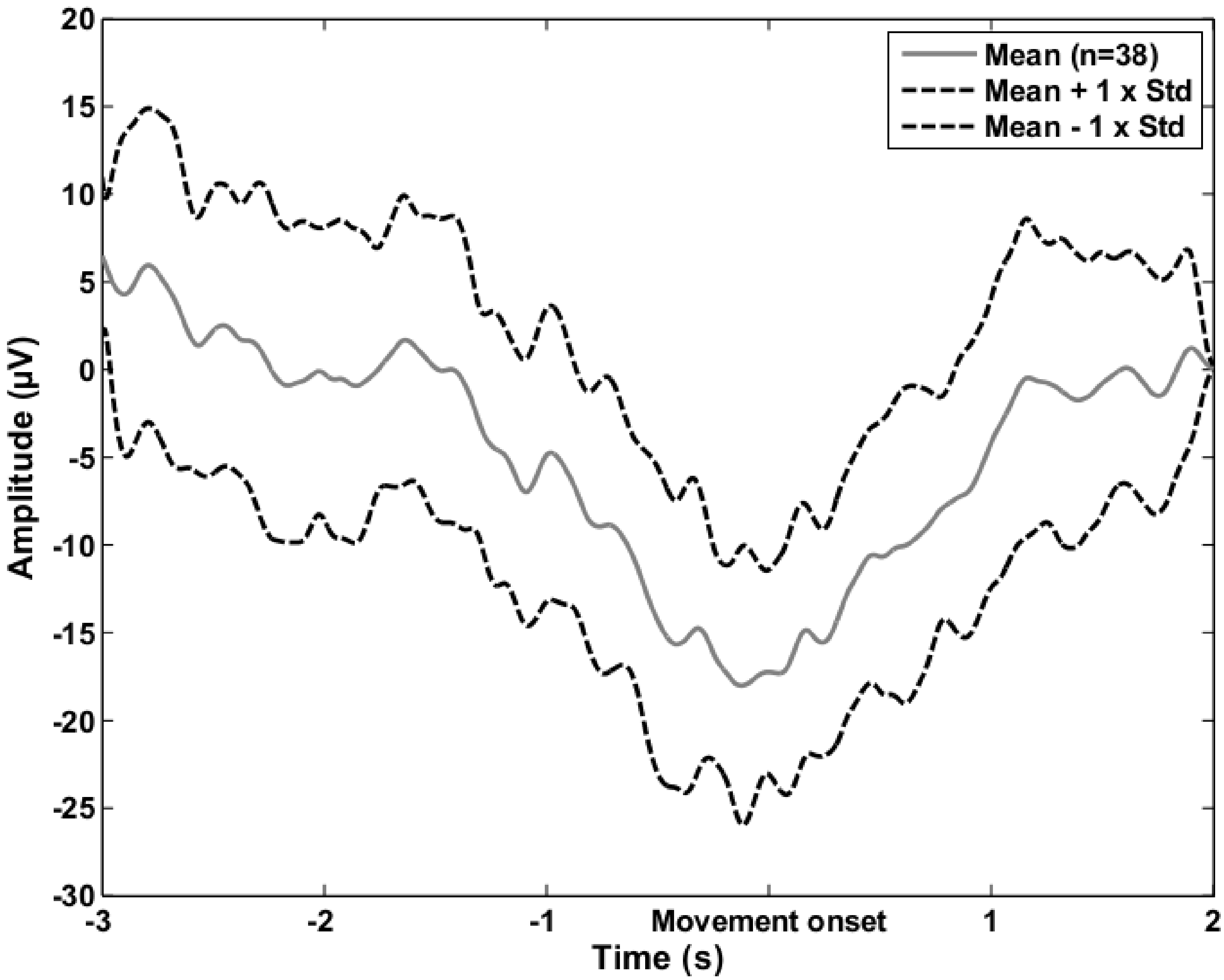

Figure 4. Averaged MRCP for a representative healthy subject performing fast movements at 20% MVC. The mean value is shown as well as the standard deviation at each time point across epochs.

The classification accuracies were similar across the movement types, but with slightly higher performance for ME and attempted ME, compared to MI. For the classification accuracies, the ANOVA revealed no significant interaction between the three factors: 'channel', 'movement type' and 'number of classes' ($F_{(2,128)}$=0.17; P=0.85), but significant effects of 'channel' ($F_{(1,128)}$=6.23; P=0.014), 'movement type' ($F_{(2,128)}$=11.62; P=0.000023) and 'number of classes' ($F_{(1,128)}$=514.37; P=0.11*10^{-47}) were observed. The classification accuracies were significantly higher when the large Laplacian filter was applied, and the post hoc analysis revealed larger classification accuracies for ME compared to MI. As expected, the highest classification accuracies were obtained for the 2-class problem compared to the 4-class problem.

Task pair / task	**ME** **C3 / Laplacian**	**MI** **C3 / Laplacian**	**Attempted ME** **C3-4 / Laplacian**
Fast 20 vs. Fast 60	59/57±9 / 55/57±9	53/53±9 / 59/59±7	55/53±5 / 56/56±5
Fast 20 vs. Slow 20	62/61±10 / 60/59±12	60/59±7 / 65/64±9	67/67±4 / 62/62±5
Fast 20 vs. Slow 60	64/64±10 / 71/71±7	53/57±8 / 58/58±9	65/66±9 / 71/69±5
Fast 60 vs. Slow 20	61/63±9 / 72/68±8	62/59±9 / 54/55±8	62/56±14 / 66/64±5
Fast 60 vs. Slow 60	63/66±12 / 68/70±8	56/58±10 / 57/57±9	62/56±11 / 72/72±6
Slow 20 vs. Slow 60	59/59±7 / 62/59±13	58/55±8 / 55/57±11	61/59±4 / 63/61±4
Median/Mean across task pairs	61/62±10 / 65/64±11	57/57±9 / 58/58±9	61/60±10 / 65/64±7
Fast 20	38/42±17 / 39/39±13	35/33±14 / 43/39±14	38/42±18 / 26/32±10
Fast 60	27/33±21 / 34/35±13	29/27±18 / 29/26±16	13/15±15 / 38/37±14
Slow 20	26/31±18 / 25/29±22	37/31±14 / 37/40±20	24/32±17 / 34/31±16
Slow 60	43/40±17 / 48/46±18	36/35±15 / 28/28±20	46/45±22 / 54/60±19
Mean across tasks	33/37±19 / 38/37±18	34/32±16 / 35/33±19	31/34±22 / 37/40±19
	Median/Mean±SD	**Median/Mean±SD**	**Median/Mean±SD**

Table 4. The performance of the classifier is presented for all pairwise combinations of the four tasks (2-class problem) and for all tasks together (4-class problem). The performance is presented when using a single channel and a Laplacian channel for ME, MI and attempted ME.

The classification accuracies associated with the simulation, where the first half of the data was used (table 5), was not significantly different from the simulation where cross-validation was used ($F_{(1,128)}$=3.49; P=0.064).

Task pair / task	ME	MI	Attempted ME
Fast 20 vs. Fast 60	58/57±9	52/50±8	54/53±3
Fast 20 vs. Slow 20	56/58±10	55/55±8	62/61±5
Fast 20 vs. Slow 60	59/61±13	48/51±8	68/66±8
Fast 60 vs. Slow 20	58/61±11	56/55±10	57/56±11
Fast 60 vs. Slow 60	65/65±12	51/553±13	58/57±11
Slow 20 vs. Slow 60	56/56±11	58/57±9	58/57±6
Median/Mean across task pairs	58/60±11	53/54±10	58/58±9
Fast 20	35/35±13	40/37±15	30/38±11
Fast 60	28/34±20	20/26±20	13/13±12
Slow 20	32/31±15	29/28±16	20/24±18
Slow 60	33/32±20	17/22±17	60/59±21
Mean across tasks	33/33±17	26/28±18	29/34±24
	Median/Mean±SD	**Median/Mean±SD**	**Median/Mean±SD**

Table 5. The performance of the classifier is presented for all pairwise combinations of the four tasks (2-class problem) and for all tasks together (4-class problem) when using the first half of the data for training and the other half for testing. The values were calculated using C3 (or C4).

3.3. System performance

The performance of the 2- and 4-class systems is presented in table 6 and 7; it was calculated with the assumption that detection and classification were independent of each other. For the 2-class system 41-47% of all movements (ME, MI and attempted ME) were correctly detected and classified while 23-29% of all movements were correctly detected and classified in the 4-class system. There was no significant interaction between 'channel', 'movement type' and 'number of classes' ($F_{(2,139)}$=0.048; P=0.95). The ANOVA revealed differences in the classification accuracies between the factor 'channel' ($F_{(1,139)}$=4.32; P=0.04), 'movement type' ($F_{(2,139)}$=5.16; P=0.007) and 'number of classes' ($F_{(1,139)}$=311.94; P=$0.40*10^{-37}$).

Task pair / task	ME	MI	Attempted ME

	[TPR*CA] C3 / Laplacian	[TPR*CA] C3 / Laplacian	[TPR*CA] C3-4 / Laplacian
Fast 20 vs. Fast 60	40/43±7 / 39/41±11	40/38±7 / 44/43±8	42/41±9 / 41/46±8
Fast 20 vs. Slow 20	43/45±8 / 44/42±10	42/43±7 / 48/49±8	48/47±9 / 46/46±7
Fast 20 vs. Slow 60	45/47±8 / 48/51±10	41/41±6 / 43/43±8	52/51±10 / 53/50±8
Fast 60 vs. Slow 20	47/48±8 / 49/50±13	45/43±7 / 41/42±12	39/40±8 / 47/49±9
Fast 60 vs. Slow 60	48/50±10 / 52/53±16	40/42±7 / 43/43±14	47/44±10 / 51/53±10
Slow 20 vs. Slow 60	43/44±10 / 44/43±13	41/41±7 / 45/45±12	42/41±9 / 42/41±8
Median/Mean across task pairs	45/46±10 / 46/47±10	41/41±8 / 44/44±8	43/44±9 / 46/47±8
Fast 20	24/30±12 / 29/26±15	22/23±10 / 29/28±10	33/33±14 / 23/25±7
Fast 60	19/26±17 / 23/26±16	19/20±14 / 25/19±12	10/12±12 / 28/31±14
Slow 20	21/21±10 / 15/21±20	26/23±10 / 29/31±14	16/20±10 / 25/21±9
Slow 60	31/29±8 / 33/35±16	25/25±11 / 25/22±14	34/34±19 / 36/37±11
Mean across tasks	23/27±14 / 29/27±14	25/23±11 / 27/25±13	21/25±17 / 27/29±12
	Median/Mean±SD	**Median/Mean±SD**	**Median/Mean±SD**

Table 6. The system performance (% correctly detected and classified movements) is presented for all 2-class systems (pairwise combination of tasks) and the 4-class system. The performance is presented when using a single channel and a Laplacian channel for ME, MI and attempted ME.

The system performance associated with the simulation, where the first half of the data was used (table 7), was lower compared to the simulation where cross-validation was used ($F_{(1,128)}$=4.3; P=0.04).

Task pair / task	ME [TPR*CA]	MI [TPR*CA]	Attempted ME [TPR*CA]
Fast 20 vs. Fast 60	41/39±8	34/35±8	41/42±2
Fast 20 vs. Slow 20	38/40±10	40/41±7	42/42±5
Fast 20 vs. Slow 60	42/42±10	33/37±7	47/48±9
Fast 60 vs. Slow 20	41/44±13	41/40±7	37/38±5
Fast 60 vs. Slow 60	43/48±12	34/38±11	40/41±9
Slow 20 vs. Slow 60	40/40±13	47/43±9	37/38±8
Median/Mean across task pairs	41/42±12	38/39±9	40/41±8
Fast 20	22/23±9	12/18±14	10/9±8
Fast 60	19/25±15	21/22±13	13/14±11
Slow 20	23/22±12	13/17±14	44/41±14
Slow 60	25/24±17	19/21±4	23/23±4

Mean across tasks	22/24±14	18/19±12	20/22±16
	Median/Mean±SD	**Median/Mean±SD**	**Median/Mean±SD**

Table 7. The system performance (% correctly detected and classified movements) is presented for all 2-class systems (pairwise combination of tasks) and the 4-class system when using the first half of the data for training and the other half for testing. The values were calculated using C3 (or C4).

4. Discussion

Four hand movement types were detected from the continuous EEG using a single channel, and the levels of force and speed were classified. Approximately 75% of the movements (ME, MI and attempted ME) were detected ~100 ms before the onset of the movement/task, with 1.5 and 2.7 FPs/min for healthy subjects and stroke patients, respectively. When the level of force and speed was decoded, 57-62% of the movement intentions was correctly decoded with slightly lower classification accuracies for MI and attempted ME. With combined detection and classification, 41-46% of the movements were correctly detected and classified. This indicates that it may be possible to detect movements using only one EEG channel in a BCI that can activate assistive technologies for providing afferent feedback.

4.1. Detection

In general, the TPRs were similar when comparing the mean across tasks for healthy subjects and stroke patients which is also reflected in a similar signal-to-noise ratio for healthy subjects and stroke patients (see figure 3). The MRCP had similar amplitude in stroke patients and healthy subjects despite the neural injury which may be due to better motivation, or the fact that less mental effort and shorter planning is needed [35, 36]. It should be noted that the number of FPs/min was 2.7 for the patients, compared to 1.5 for the healthy subjects. This may indicate that the stroke patients had difficulties in resting between the movements, which may have triggered the detector. The detector threshold was based on a trade-off between the number of FPs and TPR; thus, a reduction in the number of FPs/min would lead to lower TPRs. In addition, more epochs were removed from the analysis for the stroke patients due to EOG; this indicates that the detector was disabled during the movements due to the EOG threshold. In general, the detector is relatively resistant to movement and EMG artefacts that do not have overlapping frequency ranges with the MRCP; this is in contrast with EOG, wherein the detector needs to be disabled. Despite this, there are still some FPs/min, which could be a result of the inherent variability in the EEG. To account for this and reduce the number of FPs, the system could potentially be implemented as a synchronous BCI whereby the detector is only active when the subjects are supposed to perform the movements.

The tasks that were easiest to discriminate from the idle state varied for ME, MI and attempted ME, although the performance was quite similar. It was expected to see greater TPRs for the fast movements due to the highest signal-to-noise ratio; this was also the case for the patients, but not for the healthy subjects performing ME and MI, on the contrary to the findings from foot movements [23]. The TPRs for hand movements, when using a single channel and a Laplacian channel, were slightly lower for ME compared to previous studies where foot movements were detected, on the contrary to MI and attempted ME that showed higher TPRs [10, 12, 23, 32, 37]. The lower TPRs for healthy subjects performing ME are surprising since the motor cortical representation of the hand is more superficial, and therefore closer to the recording electrode, than the representation of the foot, which will lead to a greater signal-to-noise ratio. Small adjustments of the hand in the rest period could potentially increase the detection threshold (a trade-off between the TPR and FPs) to avoid many FP detections; this will decrease the TPR. The size of the cortical representation of the hand, and the fact that only nine recording sites were used, may be an explanation for the similar performance when using a single electrode instead of nine. This suggests that enhancing the activity of a particular spatial location (e.g. C3) through spatial filtering does not improve the performance significantly since a large area of the cortex contribute to the generation of a hand movement, and the electrode that captures the greatest movement-related activity change during the movement preparation.

4.2. Feature extraction and classification

The classification of the movement intentions was performed with two and four classes. The classification accuracies for the 2-class problem were in the range of 57-62% when using one EEG channel and 58-64% for the Laplacian channel. The statistical analysis revealed that the performance was improved when the spatial filter was applied. The application of a spatial filter has been shown to improve single trial analysis by improving the signal-to-noise ratio [38]; this will make it easier to detect the small differences in the MRCP morphology associated with different levels of force and speed [15].

The best classification accuracies, although they were similar, were obtained for ME and attempted ME compared to MI; this is due to greater separation between the movement types (see figure 3). The classification accuracies are on average lower compared to previous studies where decoding of movement kinetics for the foot and wrist was investigated [18-20, 22, 23]. The task pairs associated with the greatest classification accuracies are similar to previous findings where movements performed with different levels of speed are easier to discriminate [23]. The averaged classification accuracies for the 2-class and 4-class problems were at chance level calculated with a confidence interval (α=0.05) [39].

The classification accuracies could potentially be improved by identifying discriminative physiological meaningful features. This could be obtained through recordings with an increased density of electrodes over the cortical representation of the hand and performing e.g. time-frequency representations of the different movement types to identify where and at what time instances the tasks differ. Moreover, with an increased density of electrodes the classification accuracies could potentially be improved by performing feature extraction on each channel instead of a single EEG channel or surrogate channel. This would lead to a large feature vector, where discriminative features can be identified through feature selection techniques. In this way, the simple EEG electrode setup is lost, but with more electrodes to choose from, the heterogeneity of stroke patients may be accounted for by selecting features from potentially more optimal sites than a fixed spatial location (e.g. C3). In this scenario, subject-dependent features will be used instead of subject-independent features as in this study.

4.3. Implications

It is not known which level of system performance is needed to induce plasticity [2]. System performance (only discrimination between imaginary movements and the idle state) of ~60-70% was sufficient to induce a significant increase in the cortical projections of the target muscle when combined with correctly timed electrical stimulation [10, 25]. The system performance for a 2-class system in this study was 41-46%, which was reduced mainly due to many cases of incorrect classification of correctly detected movements. The performance of the detector (73-76%) was in the range of what has been reported to induce plasticity by combining it with assistive technologies such as functional electrical stimulation or rehabilitation robotics. A question that should be addressed is if it is needed to provide sensory feedback that matches the exact efferent signal kinetics which may be difficult if the performance of the classifier is impeding the system performance.

The results indicated that the system could work with a single EEG channel. The use of only one electrode will reduce the time spent on preparation in a clinical setting, so that the patient can spend more time on training. It may make it easier for the clinic personnel to utilize the technology, and it is a step towards moving the BCI from the lab to the clinic. From the patient's point of view, not just stroke patients but also permanent users of BCIs such as those suffering from spinal cord injury and amyotrophic lateral sclerosis, a lower number of electrodes is desirable e.g. washing the hair every day is an annoying task for many patients and wearing many electrodes can be uncomfortable [40, 41]. For BCI technology to be used on a daily basis in rehabilitation clinics, several issues still need to be addressed. From a physiological point of view, clinical effects of BCI-based rehabilitation must be documented, and the design of rehabilitation protocols still needs to be optimised e.g. by the use of various feedback modalities and methods to maintain the attention and motivation of the patients. From a technical point of view, the system should be reliable, as well as fast and easy to calibrate, or their use will not be taken up by clinicians and patients alike.

4.4. Limitations

In this study, the data were processed offline but simulated as an online system by detecting the movements in the continuous EEG through cross-validation. Also, a real-world setting was simulated where the first half of the data was used to calibrate the system (training session), and the other was used to test the system (feedback session). The performance of the detector in both scenarios was similar, but it was slightly lower for the classification. This indicates that more training data improve the performance of the classifier, which will prolong the training session since more movements must be performed. It is expected that similar detection performance would be obtained for an online system, as it has been shown previously using the same methodology for detecting movement intentions from foot movements [10, 12]. In the current study a zero-phase shift filter was applied, which potentially could lead to later detections in an online system when data are imported in blocks (all samples are needed to perform the forward and reverse direction filtering). The delay could be reduced by decreasing the number of samples in each block; however, there is a risk of edge effects from the filtering. Another approach is to use a causal filter, which also will induce a delay when data are streamed continuously, but the magnitude of this delay is determined by the order of the filter. With the template matching approach it was shown that movements could be detected 100-150 ms before the movement onset. It means that a delay from the filtering is acceptable to fulfil the temporal association for induction of long-term potentiation-like plasticity [9]. The detection and classification were performed separately, and there is a possibility that the classification accuracies may vary in an online system since the point of detection will vary. If the movements are detected earlier less discriminative information is available for feature extraction and classification, which will lead to lower classification accuracies. However, if the movements are detected later, more discriminative information is available [23]. There is still a constraint that the movements must be detected with limited detection latencies, so there is a trade-off on how much discriminative information can be obtained for the BCI to be functional for inducing plasticity [9]. A way to control the detection latency and obtaining shorter latencies with respect to the onset of the movement is to increase the detection threshold. This will come on an expense of reducing the TPR or increasing the number of FPs/min since the threshold is obtained as a trade-off between these two parameters.

5. Conclusion

Executed and imaginary movements by healthy subjects, as well as attempted movements by stroke patients, can be detected from the continuous EEG using a single channel. This may be useful for the technology transfer of

BCIs from the laboratory to the clinic. Force and speed can be decoded from the movement intention. This property is relevant for BCIs that can be combined with assistive technologies in neurological rehabilitation where the afferent feedback can be provided according to the efferent activity from the motor cortex.

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