Clinical Neurophysiology 126 (2015) 154–159

Contents lists available at ScienceDirect

Clinical Neurophysiology

journal homepage: www.elsevier.com/locate/clinph

A brain–computer interface for single-trial detection of gait initiation from movement related cortical potentials

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ARTICLE INFO

Article history:
Accepted 6 May 2014
Available online 20 May 2014

Keywords:
Brain–computer interface
Gait initiation
Movement related cortical potential
Independent component analysis

HIGHLIGHTS

- Accurate single trial detection of the intention of step initiation from scalp EEG.
- Independent component analysis (ICA) preprocessing helps to automatically remove EEG artifacts and enhances detection performance.
- All participating subjects were BCI/EEG naïve subjects, implying general applicability of the proposed approach.

ABSTRACT

Objective: Applications of brain–computer interfacing (BCI) in neurorehabilitation have received increasing attention. The intention to perform a motor task can be detected from scalp EEG and used to control rehabilitation devices, resulting in a patient-driven rehabilitation paradigm. In this study, we present and validate a BCI system for detection of gait initiation using movement related cortical potentials (MRCP).
Methods: The templates of MRCP were extracted from 9-channel scalp EEG during gait initiation in 9 healthy subjects. Independent component analysis (ICA) was used to remove artifacts, and the Laplacian spatial filter was applied to enhance the signal-to-noise ratio of MRCP. Following these pre-processing steps, a matched filter was used to perform single-trial detection of gait initiation.
Results: ICA preprocessing was shown to significantly improve the detection performance. With ICA preprocessing, across all subjects, the true positive rate (TPR) of the detection was 76.9 ± 8.97%, and the false positive rate was 2.93 ± 1.09 per minute.
Conclusion: The results demonstrate the feasibility of detecting the intention of gait initiation from EEG signals, on a single trial basis.
Significance: The results are important for the development of new gait rehabilitation strategies, either for recovery/replacement of function or for neuromodulation.

1. Introduction

Neurological conditions, such as stroke, spinal cord injury or Parkinson's disease, often result in impaired motor control and consequent difficulty of the patient to perform activities of daily living. One of the goals of rehabilitation is to promote the patient's independency with the aim of restoring the loss of movement ability.

Conventional approaches of rehabilitation promote motor recovery through a "bottom-up" approach, focused on peripheral training, often with robotic trainers. Robotic training has several advantages (a reduction of the effort of physical therapists per patient, the possibility to objectively quantify rehabilitation parameters and training output) (Pennycott et al., 2012) and allows for peripheral activity compatible with unconstrained tasks (Gizzi

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http://dx.doi.org/10.1016/j.clinph.2014.05.003
1388-2457/

et al., 2012). However its effectiveness may also be reduced by the autonomous ability of the robot to complete the movement without the need for patient involvement. Active participation of the patient has been demonstrated to be crucial in improving the outcome of rehabilitation (Pennycott et al., 2012; Duff et al., 2013).

As a complementary and promising branch within motor rehabilitation and assistance are brain–computer interfaces (BCI). BCI technologies provide the means for conveying control commands directly from the brain and can be used either for directly controlling rehabilitation devices (function recovery or replacement) or to provide feedback to the patient based on his/her brain activity (neuromodulation). In the latter case, the patient is actively involved in the rehabilitation process. The feedback is provided by the action of rehabilitation devices (e.g., the movement of an orthotics system) triggered by the brain activity (brain switch).

When the brain activation related to motor intention is measured using non-invasive EEG, the information carried in different frequency bands may be extracted, interpreted and used as the command signal to external devices. These strategies include sensory motor rhythms (SMR), on which most past studies on BCI for neuromodulation have focused (Neuper et al., 2006; Kaiser et al., 2011; Ramos-Murguialday et al., 2013). A disadvantage of this approach, however, is the need for numerous training sessions until the user is able to control the signal adequately. Alternatively, movement related cortical potentials (MRCP) have also been proposed for detecting motor intention from EEG. MRCP is a slow cortical potential that occurs naturally as a person commences or imagines the start of a movement (Gangadhar et al., 2009; Niazi et al., 2011; Garipelli et al., 2013; Xu et al., 2014). The advantage of this approach is that no extensive prior training of the user is required. Moreover, MRCPs can also be used to discriminate between different types of tasks as well as the way a task is executed (Do Nascimento et al., 2008; Gu et al., 2009). One potential confounding factor is that the size of the MRCP is relatively small ($\sim$10 μV) and is prone to many movement artifacts that influence the EEG measures.

MRCPs have been studied during gait initiation, with focus on Parkinsonian patients (Vidailhet et al., 1995; Shoushtarian et al., 2011). Moreover, the study by Do Nascimento et al. (2005) on healthy subjects demonstrated that MRCPs contain rich information regarding gait initiation, which made a strong case for utilizing MRCPs for detecting the intention of gait initiation. However, the ability to detect MRCPs depends on the signal quality and the presence of artifacts, such as due to eye movements or to facial muscle contractions that can significantly affect the performance and robustness of a BCI detection system. This study aims at investigating the possibility of detecting the intention of gait initiation from MRCPs after artifacts were removed in a semi-automatic way. We focused on the step initiation in the forward direction, as it is most relevant for the targeted application. The main objective is to develop and test a brain switch based on the intention to initiate locomotion and, in future developments, to integrate this brain switch into non-ambulatory robotic systems for rehabilitation of walking to promote plasticity in stroke patients (Belda-Lois et al., 2011).

2. Methods

2.1. Subjects

Nine subjects (M6, F3, 21–38 yrs), denoted by SUB1–SUB9, participated in the experiment. No subject had any known neurological disorders. Except for SUB5, all other subjects had no prior experience with BCI systems before the experiment, and were thus considered as naïve BCI subjects. The experiment protocol was approved by the research ethics committee of the University Medical Center Göttingen.

2.2. Experimental protocol

An active EEG electrode system (activCap, Brainproducts GmbH) was used in all the experiments. The EEG electrodes were placed at the International 10–20 system locations Fz, FC1, FC2, C3, Cz, C4, CP1, CP2, Pz, T7, T8 and Fp2. The right ear lobe was used as the reference, and the nasion was used as the ground. The activCap system was connected to a 16-channel gUSBamp EEG amplifier (Guger Technologies OG). The EEG was sampled at 1200 Hz with 50 Hz notch filter enabled. The acquired EEG was then sent to a custom-built Matlab program on a PC through the gUSBamp Matlab API. This Matlab program would display the raw EEG data for the experimenter and store the data for offline processing. Two 6-axial force plates, connected to a Qualisys motion capture system, were also used. The two plates were placed on the ground such that the subjects would be able to step from one plate to the other at their normal strides. The ground reaction forces during the experimental session of the two force plates were recorded by the Qualisys system. To synchronize the EEG recordings and the force recordings, one of the force channels was also connected to the last channel of the gUSBamp system, via a custom-made optical isolator.

During an experimental session, the subjects were asked to perform three recording runs. At the beginning of each recording run, the subject stood on the force plate A. Following a vocal prompt 'BEGIN' by the experimenter, the subjects would step from the force plate A to the second plate (force plate B), and remain standing on plate B until stepping back to plate A. The pace at which the steps were taken was completely controlled by the subjects, without any external cues. The only external command the subject received was the 'BEGIN' prompt at the beginning of the run. This protocol is a completely self-paced BCI protocol. The only restriction was that the standing time on each plate between the forward and backward steps should exceed 4 s. Each run finished when the subjects completed 20 forward steps. The duration for each run usually lasted 6–7 min. This means that the average forward–backward trial interval was approximately 20 s. The subjects took a rest (3–5 min) between the runs.

2.3. Data analysis

The data from the three runs was used for a three-fold cross-validation. For each fold, the MRCP template was first extracted from one of the runs (training run), and the matched filter detection was done using the template on the other two runs (testing runs). The detailed processing procedure is described below.

2.4. Artifact rejection

In previous studies on MRCPs, the data contaminated by artifacts, such as motion artifacts, eye movements etc., was discarded during off-line processing. In this study, the fixed-point independent component analysis (ICA) (Hyvärinen, 1999) was used for semi-automatic artifact rejection for multi-channel EEG. The independent components (ICs) and the mixing matrix were estimated from the training run, and the ICs with artifacts were identified by visual inspection based on both the time course and the scalp maps of the ICs. Subsequently, the raw EEG data were transformed using the ICA mixing matrix, and the identified artifact ICs were rejected automatically, without further inspection. The remaining ICs were then projected back onto the original scalp channels, resulting in 'cleaned' EEG for further processing.

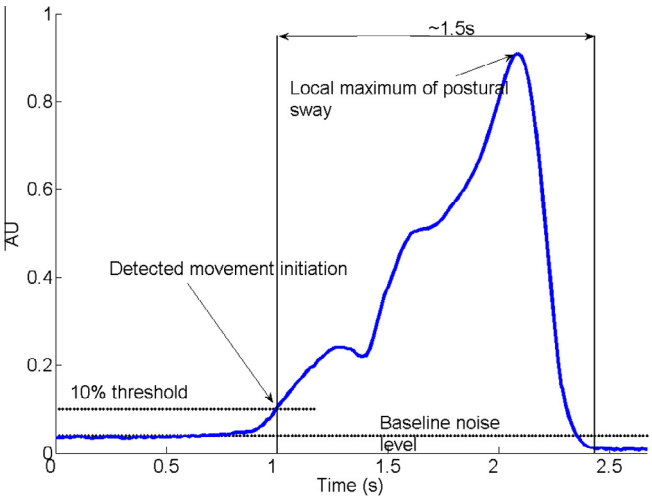

Fig. 1. Illustration of the detection of initiation of movement from the postural sway. The absolute values of antero-posterior and medio-lateral components of the stance force plate are summed and normalized to the local maximum. A 10% threshold with respect to local maximum ensures to be above the baseline noise level (due to the physiological postural adjustments of the quite stance). The lower level of intrinsic noise from the force plate is visible comparing the left and the right parts of the figure (before and after the subject left the force plate).

2.5. MRCP template extraction

The 'cleaned' EEG of the training run was used for MRCP template extraction. A Laplacian spatial filter (LSF) was applied to channel Cz and the 8 channels around it (Fz, FC1, FC2, C3, Cz, C4, CP1, CP2, and Pz). The surrogate 'Cz' channel after LSF was used to extract the MRCP template.

The antero-posterior and medio-lateral components of the signal of the standing force plate were rectified and used to detect the postural sway prior to the actual gait initiation. A threshold of 10% on the local maximum (i.e. for each trial) was set to detect the sway and used to establish the time from which MRCP templates would be extracted. In order to prevent false detections of the sway, it was detected within a window of 2 s whose last sample was aligned with the weight acceptance sample on the receiving force plate. For each trial (i.e. before the subject stepped on the receiving plate) the local maximum of the medio-lateral sway of the standing plate was determined and its 10% was used to determine the latest time instant during which the subject was not moving. It is clear that since the threshold was >0%, the subject was actually moving when the crossing of the threshold occurs, but we considered this value as the minimum we could confidently distinguish from the baseline noise. This procedure is illustrated in Fig. 1.

Three seconds before and three seconds after these reference points was chosen as the time range for the full MRCPs and the ensemble average of all MRCP segments from the surrogate 'Cz' channel of the training run were used as the full MRCP template. Because it is not practical to use to 4-s long full MRCP for detection, only part of the first negative phase of the full MRCP template was used for subsequent detection. This part was [−1.5 s, −0.5 s] from the peak negativity of the full MRCP template, and was called the detection MRCP template. This portion of the MRCP included the readiness potential (RP) (Gilden et al., 1966) and the first portion of the motor potential (MP) (Deecke et al., 1976). This choice had the purpose of obtaining a balance between the detection accuracy and the detection latency.

2.6. MRCP detection

Once the detection MRCP template was extracted from the training run, the classic matched filter detection was performed on the surrogate 'Cz' channel of the testing runs, which was obtained by exactly the same preprocessing as the training run, *i.e.* ICA followed by LSF. To evaluate the performance of the detection, three performance measures were calculated: true positive rate (TPR), false positive rate (FPR), and detection latency (DL). TPR was defined as the number of true detections divided by the

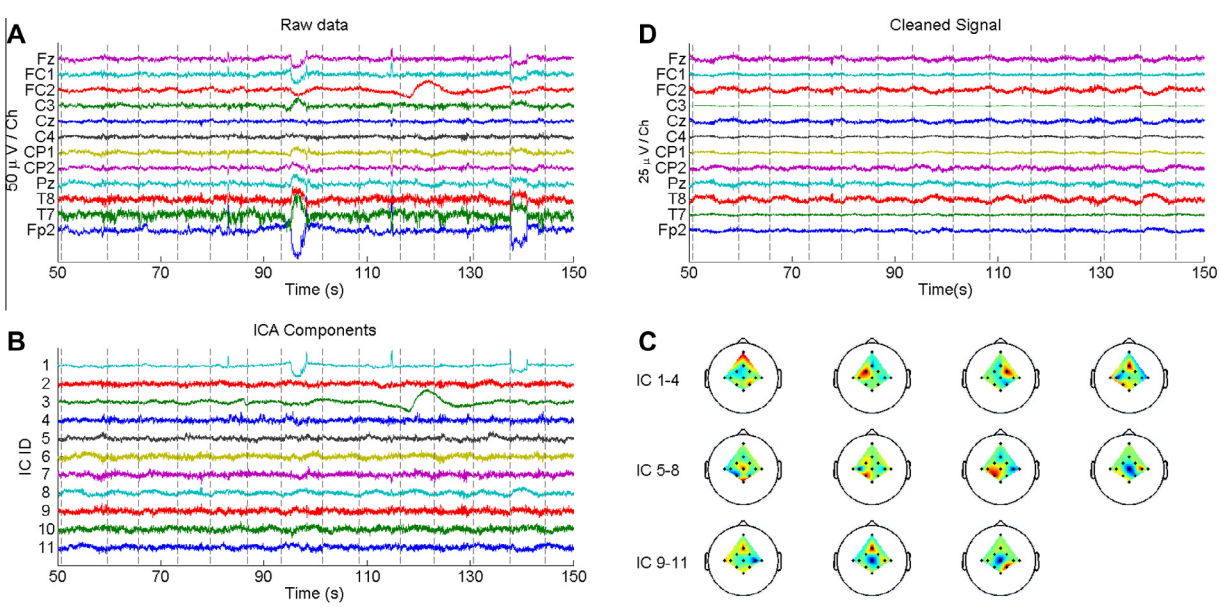

Fig. 2. A representative sample of the artifact rejection procedure using ICA. (A) The 12-channel raw EEG, where very strong artifacts exists. Two types of artifacts unwanted components are clearly presented. At 95 s and 140 s, the artifacts were present across all channels with different magnitude. At 120–125 s, an unwanted component was only present in FC2; (B) ICA components of the signals in A. The two artifacts in A were isolated as distinct ICA components (IC1 and IC3); (C) the scalp map of the independent components (ICs). The spatial pattern of the artifact ICs also confirmed the observation in the raw signals: IC1 is likely due to eye movements and IC3 is a localized unwanted component in FC2. Both B and C were used to identify components to be used for further processing. In this example, IC8, IC10, and IC11 were kept, while all other components were rejected. The resulting signals are presented in D. The grey vertical dashed lines in A, B, and D indicate the detected step initializations.

total number of true events. FPR was defined as the number of false detection divided by the total number of events. DL is time difference between the peak negativity of the MRPC template and the detection time obtained by the detection algorithm, as defined in Niazi et al. (2011, 2012). The receiver operating characteristics (ROC) curves of the detection were obtained from the training run. The working point was selected on the midpoint of the turning phase of the ROC curve, which allowed a balance between TPR and FPR. The detection performance indices, TPR, FPR and DL, were calculated based on the detection threshold of the working point. The initiations of both forward steps and backward steps generate MRCP (Do Nascimento et al., 2005). As such, the detections made within $[-1, 1]$ s around both forward and backward step initiation time were considered as positive detections in the subsequent analysis.

3. Results

All subjects successfully completed the experimental session. A representative example of the ICA artifact rejection procedure is presented for one of the subjects in Fig. 2. By properly selecting independent components both from the time course and the scalp map, the artifacts within the EEG were effectively removed. The ICA algorithm (FastICA) converged for all but one subject (SUB6), in which case the original raw EEG was used for subsequent processing.

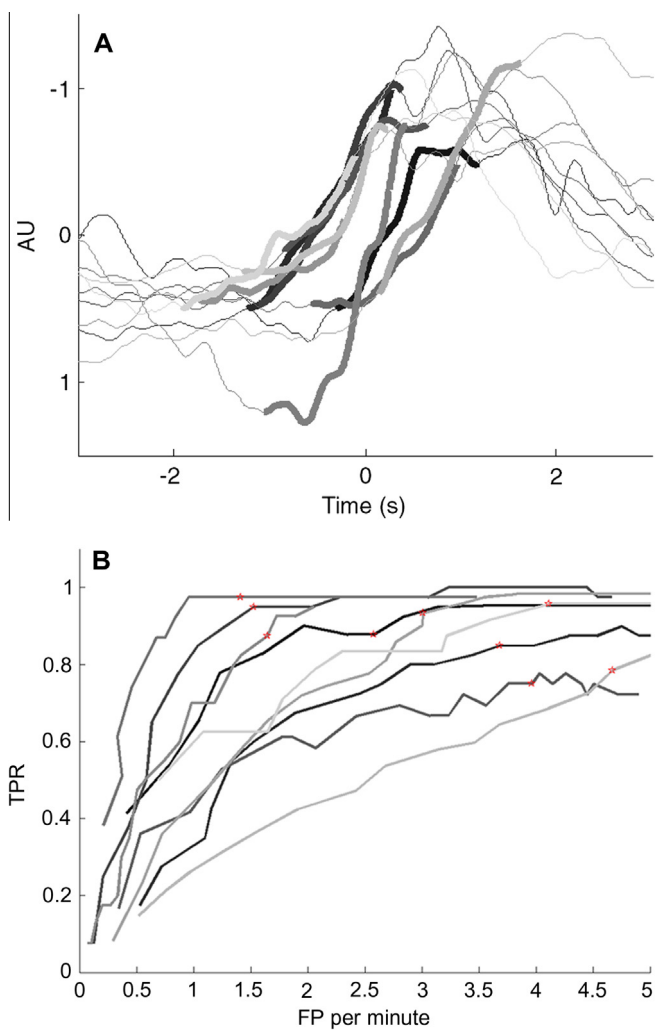

Fig. 3. (A) The full MRCP templates and the detection templates for all subjects. Time zero is the time of initial sway detected at the standing force plate. The thick part is the detection template ($[-1.5, -0.5]$) s prior to the peak negativity of the full MRCP template. In the figure, the magnitudes of all MRCPs are normalized with respect to their magnitude ranges. The original range of amplitudes of the MRCPs is between ~5 μV and ~25 μV. (B) The ROC curves for all subjects, averaged over all folds. The operational points selected for each subject are indicated by the stars.

The MRCP templates of all subjects, obtained through ICA preprocessing, are presented in Fig. 3A. The full MRCP templates are presented, and the detection template used for subsequent matched filtering was taken from $[-1.5, -0.5]$ s of the full MRCP template. Note that the MRCPs presented in the figure were the average of all runs. Fig. 4 shows a representative example of the matched filter procedure, including the detection template, the surrogate channel at Cz after ICA and LSF operation, and the output of the matched filter, using the data segments shown in Fig. 2. The segments of the matched filter output corresponding to the detections are highlighted along with the events marked by force plate signals.

The ROC curves for all subjects are reported in Fig. 3B. The detection results of all subjects are presented in Table 1. Across all subjects (including SUB6 for which ICA did not converge), the TPR was 76.9 ± 8.97%. The FP was 2.93 ± 1.09 per min. The average detection latency with respect to peak negativity of the MRCP template was −180 ± 354 ms. The within-subject variability of these indices, characterized by the coefficient of variation, was 13%, 34% and 170% for TPR, FP and latency, respectively (average value for all subjects). In order to quantify the effect of the ICA preprocessing on the detection performance, we also calculated the detection performance without the ICA preprocessing step (Table 1). The TPR and FP in this case was 63.3 ± 14.3% and 3.37 ± 1.16%, respectively. Repeated measure *t*-test showed that ICA preprocessing significantly improved the TPR ($N = 8$, $p = 0.005$). However, no statistical significance was found for FP ($N = 8$, $p = 0.09$).

4. Discussion

We demonstrated the possibility of single trial detection of the intention of gait initiation from scalp EEG of healthy individuals during normal gait. Across subjects, the best performance corresponded to TPR 83% and FPR 1.64 per min. The average detection performance was similar to prior studies on isometric dorsiflexion detection when subjects were in seated position (Niazi et al., 2011). The experimental condition (standing and gait) in the current study was more challenging than the seating condition of the previous studies, since standing corresponds to tonic muscular activations at the lower extremities for posture balance that manifest at the cortical level with similar EEG activities as MRCPs (Slobounov et al., 2005). The relatively high FPR presented was likely due to these postural related activities.

We also demonstrated the capability of using ICA as a preprocessing step to remove various artifacts for the ultimate online BCI applications. Artifacts in EEG, such as those caused by eye movements or facial muscle contractions, are usually several orders of magnitude larger than EEG. In many cases, they overlap with targeted components of EEG, both in the time and frequency domain. For example, the eye movement artifact is similar in shape to an MRCP and has greater amplitude. The ICA preprocessing step proposed in the current study effectively removed these artifacts, either present as common mode or spatially located in certain channels (Fig. 2). Further, we showed that the ICA preprocessing step significantly improved the performance of the subsequent MRCP detection, particularly in relation to TPR. This effect is especially significant on any data set with very poor performance without the ICA preprocessing (low baseline performance), such as the data sets from SUB1, SUB3 and SUB8. For data sets with higher

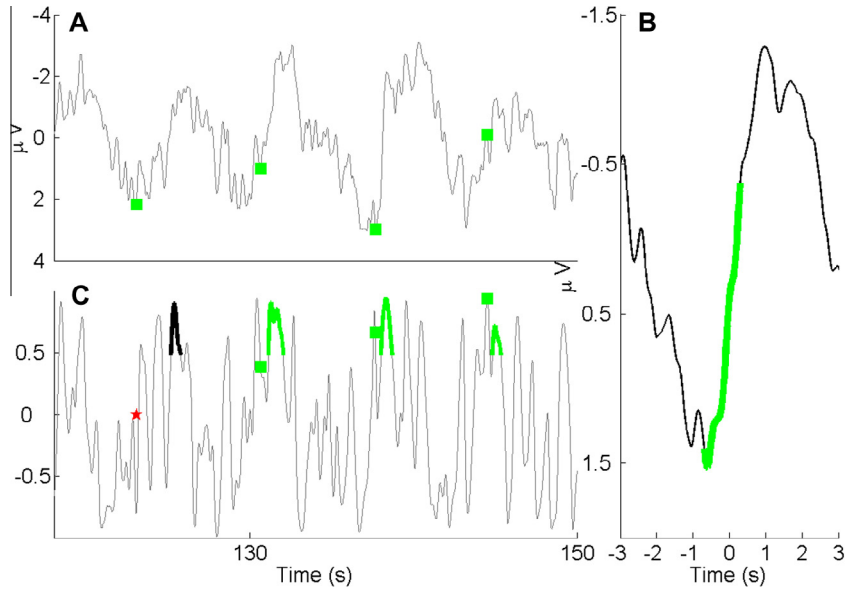

Fig. 4. A representative example of the matched filtering procedure. (A) The surrogate Cz channel after ICA denoising and LLSP spatial filtering. The step initiation events are marked by the square markers. (B) The MRCP template used. The thin solid line is the full MRCP template, and the thick segment was the template used for match filtering. (C) The output of the match filter. The highlighted segments with thick (green) lines are the true positive detections, with square marker (green) indicating the corresponding actual events. The highlighted segments with thick lines (black) are the false detections, and star (red) markers indicated the false negatives (events not detected). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 1
Summary of the detection results from all subjects.

Sub. ID	With ICA			Without ICA		
	TPR (%)	FP (per min)	Mean latency (ms)	TPR (%)	FP (per min)	Mean latency (ms)
Sub1	81	1.55	−924	62	2.80	−998
Sub2	74	4.45	78	65	4.91	−48
Sub3	87	3.84	−176	53	3.23	−93
Sub4	68	2.97	421	64	3.40	443
Sub5	83	1.64	−374	83	1.12	−280
Sub6	N/A	N/A	N/A	82	2.71	−256
Sub7	88	1.74	−336	75	3.28	−350
Sub8	61	3.8	−166	40	4.46	−462
Sub9	68	3.67	106	46	4.49	−82
Mean ± STD	76.9 ± 8.97	2.93 ± 1.09	−156 ± 369	63.3 ± 14.3	3.37 ± 1.16	−236 ± 363

baseline performance (for example from SUB5), the effect of ICA preprocessing is limited. This is likely due to the better signal quality for these data sets. Visual inspection confirmed that there were less artifacts in the data set from SUB5 than those from SUB1, SUB3 and SUB8. In future online applications, the IC components can be obtained from a short calibration recording, during which the subjects are instructed to actively produce possible artifacts by blinking their eyes or clinching the jaws or turning their heads. In subsequent recordings, the IC components corresponding to the artifacts can be conveniently rejected online with minimal computational cost since only linear operations would be necessary (matrix multiplication).

The amount of user training is one of the main limiting factors in BCI applications. Even after extensive training, a non-negligible portion of individuals (20–25%) cannot use classic BCI systems based on motor related EEG potentials, such as sensory-motor rhythms (SMR) (Vidaurre et al., 2011). Conversely, the MRCP can be easily produced even by naïve BCI users. Indeed, in the current experiment, all but one subject (SUB6) were naïve BCI subjects, who never experienced any EEG recording prior to the experiment. Yet the detection performance (after ICA preprocessing) of 4 naïve subjects was better than that of the experienced subject (higher TPR and lower FPR). Further, it has been shown that the MRCPs from different subjects have high similarity (Niazi et al., 2013). These characteristic makes it possible to develop a BCI system with minimal subject training. In addition, MRCP is known to have session-to-session and day-to-day repeatability and stability (Kropp et al., 2000). Therefore, BCI systems based on MRCP should require less frequent recalibration and retraining.

An even more important characteristic of the MRCP-based motor intention detector is its limited detection latency. For SMR-based studies, the latency of detection was not a topic of interest (Pfurtscheller and Solis-Escalante, 2009), and usually not reported. In studies that did report it, the detection latency was least 1 s (Blankertz et al., 2010; Hashimoto and Ushiba, 2013). To our best knowledge, there is no BCI technique based on SMR with a detection latency smaller than 1 s. This is in sharp contrast with the detection studies using MRCP, in which the detection latency is usually in the order of hundreds milliseconds (Niazi et al., 2011; Xu et al., 2014). Since detection latency is a critical factor in effective induction of cortical plasticity (Mrachacz-Kersting et al., 2012), we believe that MRCP-based BCI holds great potential as a neuromodulation tool for neurorehabilitation. However, it has to be noted that in this study we show detection and not prediction of gait

initiation. The delay reported in this study refers to the first reliably detectable physical measurement of gait initiation, *i.e.* the initial sway, which takes place after complex physiological processes.

In long-term perspective, the aim is to develop a BCI-based assistive system for patients with difficulty in voluntarily initialize gait, such as many Parkinson patients. The system should have the capability of detecting the intention of gait initiation directly from the EEG activity for these patients. It has been shown that deep brain structures, such as basal ganglia, cerebellum, and thalamus play important roles in gait initiation (Rektor et al., 2001a,b,c). Recently, the pathological changes of these deep brain structures have been shown to have manifestation in the scalp EEG (Heida et al., 2014; Toledo et al., 2014). Therefore, it is likely that these pathological changes will also change the MRCP morphology in Parkinson patients. However, it is reasonable to anticipate that the morphology of the MRCP would remain relatively stable at the individual patient basis. As such, the proposed method should still be applicable for these patients. Subsequent studies on patients are required to investigate this possibility.

In conclusion, we showed that it is possible to detect the intention of step initiation from scalp EEG on a single trial basis of healthy subjects. The ICA preprocessing step can significantly improve the online detection performance by removing various artifacts during online experiments. The presented detection performance is suitable for online application of triggering a gait rehabilitation exoskeleton device for stroke patients both for the purposes of function restoration/replacement and for neuromodulation.

Acknowledgment

This work was supported and by the EU project BETTER (contract # 247935) (to D.F.).

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