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Using actual and imagined walking related desynchronisation features in a BCI

Marianne Severens, Monica Perusquia-Hernandez, Bart Nienhuis, Jason Farquhar, Jacques Duysens

Abstract— **Recently, brain-computer interface (BCI) research has extended to investigate its possible use in motor rehabilitation. Most of these investigations have focused on the upper body. Only few studies consider gait because of the difficulty of recording EEG during gross movements. However, for stroke patients the rehabilitation of gait is of crucial importance. Therefore, this study investigates if a BCI can be based on walking related desynchronisation features. Furthermore, the influence of complexity of the walking movements on the classification performance is investigated. Two BCI experiments were conducted in which healthy subjects performed a cued walking task, a more complex walking task (backward or adaptive walking), and imagination of the same tasks. EEG data during these tasks was classified into walking and no-walking. The results from both experiments show that despite the automaticity of walking and recording difficulties, brain signals related to walking could be classified rapidly and reliably. Classification performance was higher for actual walking movements than for imagined walking movements. There was no significant increase in classification performance for both the backward and adaptive walking tasks compared with the cued walking tasks. These results are promising for developing a BCI for the rehabilitation of gait.**

Index Terms— **brain-computer interface (BCI), electroencephalography (EEG), event-related desynchronisation (ERD), gait, locomotion.**

I. Introduction

EACH YEAR, about 795 000 people in the US and about 1.1 million people in Europe experience a stroke event, often leading to motor impairments [1], [2]. Motor improvements can be reached with natural recovery and rehabilitation therapy, predominantly in the first year. Nevertheless, many of these patients suffer from some type of permanent paresis or paralysis, impacting their daily functioning. Recently the idea has risen that a brain-computer interface (BCI) could improve motor rehabilitation in stroke patients [3].

The hypothesis for using BCI in motor rehabilitation is that by training patients to produce brain signals that belong to movement execution and imagery with feedback on these signals, changes will be induced in the brain through use-dependent plasticity. This could in turn lead to a positive effect on motor capabilities. The idea of using BCI in motor rehabilitation comes from the motor imagery task that is often used in BCI research. Motor imagery induces event-related desynchronisations (ERD) during imagination [4]. Training participants in several sessions can increase the ERD and likewise can increase BCI performance. Such training of ERD signals could also be embedded in therapy for stroke patients [3]. Supporting evidence for BCI facilitated motor rehabilitation comes from recent findings that have shown that motor imagery training alone induces changes in brain networks [5] and has a beneficial effect on motor recovery [6], [7]. It can be expected that feedback on the brain signals accompanying motor imagery could increase this effect even more. Results of preliminary studies evaluating the effect of BCI sensorimotor rhythm training by imagining movement show contradictory results. Whereas some studies fail to show motor improvements [8], more and more short-term studies do report improvements in motor functioning [9]–[13]. Although there are no long term group studies that show a clinical relevance, there is enough evidence to support the assumption that BCIs could improve motor recovery [14].

Most of the investigations into the use of BCI in rehabilitation have focused on upper body rehabilitation [8]–[13]. However, for stroke patients the use of the lower extremities, and more specifically gait, is an important factor in becoming independent of the care of others. Therefore, it is interesting to know if a BCI can be based on brain activations associated with walking (for a review of the possibilities for using BCI in walking rehabilitation see [15]). However, the role of the cortex during walking has been under debate. It is thought that locomotion is coordinated by central pattern generators (CPGs) in the spinal cord [16] and that the basic motor pattern is then modified by sensory feedback and supraspinal control (for a review see [17], [18]). This control involves brain stem, cerebellum, basal ganglia and thalamus. In the last decades, it has been shown with neuroimaging methods that the supraspinal control also includes cortical areas, among which the dorsal premotor cortex (PMd) and supplementary motor area (SMA). These areas are active during walking [19], [20], and imagined walking [21]–[23].

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M. Severens, was with the Research department, Sint Maartenskliniek, Nijmegen, The Netherlands and the Donders Institute for Brain, Cognition and Behaviour, Radboud University Nijmegen, The Netherlands.

M. Perusquia-Hernandez was and B. Nienhuis is with the Research department, Sint Maartenskliniek, Nijmegen, The Netherlands.

J. Farquhar is with the Donders Centre for Cognition, Radboud University Nijmege, The Netherlands. (e-mail: j.farquhar@donders.ru.nl).

J. Duysens is with the Department of Kinesiology, KU Leuven, Belgium and with the Research department, Sint Maartenskliniek, Nijmegen, The Netherlands (email: jacques.duysens@faber.kuleuven.be)

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Although leg movements have often been investigated with electroencephalography (EEG), which is the method most often used in BCI, gait detection from EEG is not often done because of several reasons. First, due to the deeper location in the cortex and the orientation of the source of activity the detection is more difficult than upper body movements. Second, because of the gross movements during walking the data is susceptible to movement artifacts. Recently several methods have been used to remove these artifacts from the data [24], [25]. This has led to reports of cortical activity during walking measured with EEG. A relationship between spectral perturbations and the step cycle has been found [24], [26], [27]. Others have decoded the EEG during walking and found correlations with gait kinematics [28], [29]. Two of these studies investigate the ERD [24], [27], which probably is the most robust signal for use in a BCI for the rehabilitation of gait. Only few attempts have been made to classify EEG signals related to actual or imagined walking movements. For example, imagined gait could be used to control ambulation in a virtual reality environment [30]. Furthermore, in a single-subject study a robotic gait orthosis could be controlled with imagined walking movements [31]. Finally, active and passive walking movements were separated based on the brain signals [32].

Walking is a very automated process, and automated motor processes cause a general decrease of activity in distributed networks involving cortico-basal ganglia and cortico-cerebellar pathways [33], [34], for a review see [35]. Inversely, less automatic movements could increase the brain signals related to walking movements and in this way increase performance of a BCI using these signals. As there have been only a few studies that looked at different walking behaviors (for example walking with virtual reality, see [36]) there is a need to expand the variety of locomotor tasks. One unexplored task is walking backwards. In a recent review, it was pointed out that such task should rely on a combination of spinal and cortical activations [37]. Similarly, walking at continuously changing speed should also require substantial cortical activation.

In the present paper we will investigate the possibility of controlling a BCI using brain signals related to walking, more specifically the ERD, versus brain signals during rest in healthy subjects. Walking tasks that produce the strongest brain activations are probably most useful in the BCI and for rehabilitation. Therefore, we used simple and more complex walking tasks to investigate the effect of automaticity of the performed or imagined movement on the BCI performance. An increased performance with the BCI controlled by the more complex tasks is expected. Both tasks were executed under two conditions, namely when actually performed and imagined. The brain signals are expected to be less strong during imagined walking, hence resulting in lower performance of the BCI in this condition.

II. Methods

Two experiments were conducted, which both tested the effect of the complexity of the walking task on the performance of the BCI. In the first experiment classification performance was calculated off-line, whereas the second experiment was designed such that it also included an online evaluation session.

A. Experiment 1

In the first experiment, actual and imagined walking movements were performed in the forward and backward direction. Backward walking was chosen as the more complex task, because it is more demanding yet very similar to forward walking in movement trajectories of the legs and joint angles [38], [39]. Therefore, if differences in brain signals are found these cannot be attributed to differences in kinematics.

1) Participants

Twelve healthy volunteers (mean age 29 year, SD 5.6) participated in experiment 1. They all gave written informed consent before the start of the experiment. The experiment was approved by the ethical committee of the faculty of social sciences at the Radboud University Nijmegen.

2) Task

Subjects executed two actual and two imagined walking tasks on a treadmill (ENRAF Nonius, Type EN-tred Reha). They walked forward (FW) and backward (BW) at a slow speed (3 km/h). Furthermore, they had to imagine walking forward (IFW) and backward (IBW). For the backward trials, subjects had to turn around on the treadmill, hence facing the back of the treadmill. During all tasks, subjects could hold on to safety bars at the sides of the treadmill. The eyes were open in all conditions.

Before the start of the experiment subjects walked on the treadmill for about 2 minutes in forward and backward direction to become accustomed to walking at this speed on a treadmill. A metronome was adjusted to synchronize with the step frequency of the subject to make sure that subjects could walk at this pace in both forward and backward direction. Subsequently, subjects practiced a trial of each of the four tasks. They were instructed to synchronize the walking to the

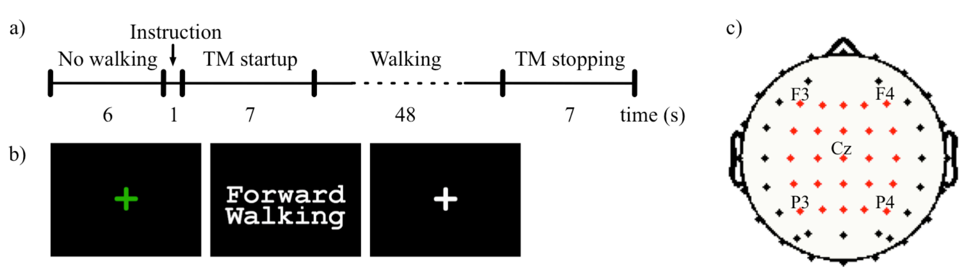

Fig. 1. (a) Schematical representation of a trial in experiment 1. TM = treadmill (b) The visual display during the trial: a green fixation cross during the no-walking period, an example instruction, and a white fixation cross during the walking period. (c) Positions of the electrodes with labels above the positions. The red dots indicate the subset of electrodes used for analysis and classification.

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metronome. Furthermore, they were asked to minimize head and eye movements. For the imaginary tasks, subjects were instructed to use kinesthetic motor imagery, i.e. imagining the feeling that actual performance produces. If subjects indicated they needed more practice for a particular task, another trial of that task was executed.

3) Design

In total, eight sequences were performed. Each sequence consisted of four trials: each of the four walking conditions was executed once in a random order. A trial started with a period of quiet standing while subjects looked at a fixation cross on a computer screen for six seconds, which was used as the no-walking task. Then an instruction was displayed telling the subject which task had to be executed next. In the actual walking tasks, the treadmill started, subjects walked for 48 s, after which the treadmill was stopped again. The treadmill took about 7 s to come up to speed and another 7 s to slow down and stop completely, hence adding up to a walking period of 62 s (see Fig. 1). During the no-walking and walking periods a fixation cross was displayed on a screen. In between trials there were a few seconds of rest. After each sequence, subjects could rest for a minute.

4) EEG Recordings

EEG was recorded with 62 electrodes with the ground placed on the AFz-electrode position. These signals were amplified using a TMSi Refa-72 amplifier (Twente Medical Systems International, The Netherlands) and digitized at a sampling rate of 500 Hz, referenced to an average of all channels. During fitting of the EEG cap, the impedance of each electrode was kept below 50 kΩ. Because the TMSi Refa amplifier has a very high input-impedance, this electrode impedance has a low influence on the measured signals.

5) Analysis

EEG data was first temporally downsampled to 250 Hz to reduce dimensionality, after which the data during no-walking (standing) and walking periods was cut into 1.2 epochs. In total the walking conditions contained 408 epochs (8 trials * 51 epochs) and the no-walking conditions contained 40 epochs (8 trials * 5 epochs). Linear trends were removed, and a common average reference was subtracted from the data. Subsequently, electrodes with bad signal quality were removed if the variance was more than 3.5 standard deviations greater than the median variance. On average one electrode was identified as outlier and removed. To remove the influence of these outlying electrodes on the remaining electrodes, a common average reference was subtracted from the data again.

To remove the influence of EMG activity on the EEG, a component analysis, namely canonical correlation analysis (CCA) [40], was performed to identify EMG components. This method has been used before in speech production [41] and walking [24]. In the actual walking tasks, the removal of EMG activity is particularly important, because inclusion of these class specific artifacts could overestimate the classification performance. One could argue that a selection of only a central channel set could also decrease influence of EMG. However, because of spreading of electrical activity, central channels could also be contaminated, although to a lesser extent, with EMG signals. With the component analysis method used in the current study, the EMG signals in peripheral electrodes are used for decomposition of EEG and EMG components. The EMG components are then removed from the whole data set, minimizing EMG influence even at central locations. To compute the EMG components, CCA was applied to the EEG data. EMG components were defined as components in which the power in the EMG frequency band (15 to 30 Hz) was more than 1.3 times stronger than in the EEG frequency band (1 to 15 Hz). These EMG components were removed from the EEG data. Subsequently, a central set of 25 electrodes (see Fig. 1) was selected to remove any remaining EMG activity in peripheral electrodes. On these remaining electrodes a surface laplacian based on spherical spline interpolation [42] was performed to improve spatial selectivity. To compute the power spectral density (PSD), Welch's method with a hanning window of 250 ms, and an overlap of 125 ms was used [43]. For feature selection, the frequency bins between 8 and 32 Hz with a resolution of 4 Hz were used.

To separate the classes (walking vs. no-walking) for each task a linear classifier was trained on the 1.2 second-epochs using a L_2 regularized logistic regression objective [44]. The logistic regression classifier finds the important features and hence no extra feature selection is necessary. The regularization strength was set with leave-one-trial-out cross-

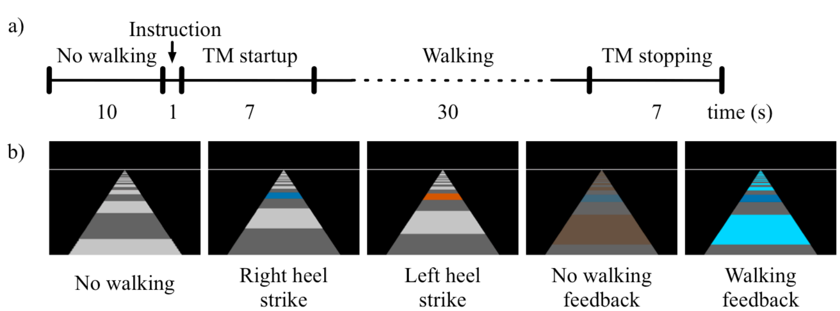

Fig. 2. (a) Schematical representation of a trial in experiment 2. TM = treadmill (b) Virtual path display. The first three images show the display during training: a static display during no-walking, an animated movement of the path, with the bars moving towards the subject during the walking period. Coloured bars indicate a right heel strike and a left heel strike. The two rightmost images show examples of the display during online feedback: transparent orange coloured bars indicate no-walking feedback with low predicted classification probability; opaque blue bars indicate walking feedback with high predicted probability.

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validation. To prevent over-fitting during this cross-validation process the EMG component removal was repeated for each fold using only the examples used to train the classifier. Because of the unequal number of examples in each class (5 no-walking vs. 51 walking epochs in each trial), the classes were weighted in the class training, such that each class had equal importance. In other words, a balanced loss was used such that the weighted summed error in the two classes was the same. Furthermore, a balanced classification performance was calculated by averaging the performance for the walking and no-walking epochs, such that 50% was the chance level for both classes.

6) Statistical Analysis

On the PSDs of Cz the ANOVAs were performed per walking task to test for significant differences in power over all frequencies between walking and no-walking epochs. On the difference (ERD) between walking and no-walking PSD an ANOVA was performed to test for differences between the four walking tasks and over the frequencies.

To test for a significant performance above chance level, the confidence bounds were calculated with a randomization test. For this, the labels were randomly permuted over the examples per subject and classification performance was calculated. This procedure was repeated 1000 times. This is comparable to the simulation method of [45], with the exception that it does not use simulated data, but real data from the experiment. The 95th percentile was chosen as the bound per subject and task. The largest confidence bound over all subjects and tasks was selected as threshold for significant classification performance, hence the chance level. To test for significant interactions and differences in classification rates between walking complexity (forward and backward) and modality (actual and imaginary), a 2x2 repeated measures ANOVA was used. The alpha level was set to .05 for all statistical tests.

B. Experiment 2

It is possible that subjects quickly learned to perform the backward walking task within the session in experiment 1, which could have possibly made the task less complex. To exclude the possibility that this fast learning of the backward walking task influenced the results in experiment 1, a second experiment was conducted. Here a more complex task was used that required constant adaptation of the motor program. The constant adaptation task may increase the signal measured from SMA and PMd because these areas are involved in sequencing and timing of limb movements and the control of gait under guidance of visual information respectively [23]. Furthermore, in this experiment online performance was evaluated. Unless mentioned otherwise, the methods used in experiment 1 were also applied in experiment 2.

1) Participants

Nine healthy volunteers (mean age 29 year, std 5.6) participated in experiment 2 (3 of these also participated in experiment 1).

2) Task

Four walking tasks were executed. Subjects walked forward on a treadmill with a constant speed (3 km/h) and imagined doing this, hereafter called constant walking (CW) and imaginary constant walking (ICW) respectively. These two tasks are similar to the forward walking conditions from experiment 1. Furthermore, they had to walk on the treadmill while the speed was changed during the course of the trial using a custom made matlab routine, to increase the complexity of the task. This required the need for constant adaptation of the walking commands. Therefore the speed of the treadmill varied between 2.5 and 4 km/h. The speed was changed three times during a trial, jittered (+/- 3 s) around 12, 20 and 30 seconds after starting the treadmill. The speed changes were randomized over trials. Subjects had to actually perform this adaptive walking task (AW) and they had to imagine walking with varying speeds (imaginary adaptive walking, IAW). Speed instructions were given via a computer screen (see below).

3) Design

The experiment was divided in two blocks: a training block for classifier training and an online feedback block. The training block consisted of eight sequences in which the tasks were each performed once. To be able to give instructions about the required walking speed, a virtual path was displayed during the tasks (see Fig. 2). The standing, or no-walking, period lasted 10 s, during which the display of the virtual display was static. Subsequently, an instruction was displayed telling the subject which task had to be executed next and the walking trial began. The walking period lasted 44 s including starting up and stopping of the treadmill in the actual walking tasks. During the walking period the virtual path moved simulating a view when subjects would actually walk on this path. Synchronized to the stepping speed, one bar changed color to indicate when subjects had to step down with their left and right foot (orange and green respectively). This was used to indicate the stepping speed during the actual walking trials and the speed of imagining walking. In a short practice session, the step length and step frequency were determined by walking on the treadmill at 3 km/h. This step frequency was used in the constant walking tasks. For the other speeds, the step frequency was calculated with the following formula:

$$f = v / 3.6 / l \tag{1}$$

in which f is the step frequency, v is the speed of the treadmill in km/h, and l is the step length in m. This ensured that subjects needed to adapt their step frequency, and not just the step length, thereby increasing the difficulty of the walking task. The step frequency was indicated to the subject by the frequency of appearance of the colored bars in the virtual path. Hence, the speed of the virtual path matched the speed of the treadmill during actual walking.

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In the online test block the subjects received feedback about the performance of the classification in 8 sequences. Due to technical problems, one subject only performed four sequences. The color of the bars in the virtual path indicated the estimated class, either walking or no-walking. The transparency of the path indicated the predicted probability of the classification, hence if the prediction was strong, i.e. low transparency, or weak, i.e. highly transparent (see Fig. 2).

In two of the eight imaginary tasks in the feedback block, subjects were instructed to freely test the performance, hence imagine walking or no-walking as they wished. These sequences were removed from further analysis.

4) Analysis

In experiment 2 the addition of feedback required online analysis. The pre-processing, as used online, differed from the analysis in experiment 1 in four ways. First, the data was sliced in 2.5 s epochs. Second, removal of EMG components did not use the relative power in the EMG and EEG frequency band, but was based on the auto-correlation of each component with a time-shifted version of that signal. A threshold for the auto-correlation and for the standard deviation of this auto-correlation was used to select EMG components. The selected components were removed from the EEG data. Third, the complete electrode set (62 electrodes) was used for classification. Finally, only the frequency bins between 8 and 24 Hz were included as features for classification. Other analyses were the same as in experiment 1. Because of the different designs, a different number of epochs was available. Each sequence consisted of 4 no-walking trials and 13 walking trials for each walking condition. The classifier trained during the training block was applied to the new unseen data from the test block, and these results were fed back to the subject via the changing colors of the virtual path.

To better compare results from experiment 1 and 2, the performance was recalculated offline with the same analysis methods as used for experiment 1, for the training as well as for the test block. For the latter to simulate online use, a classifier was trained on the data of the training block and applied to the new unseen data from the test block. On average one electrode was removed because of bad signal quality.

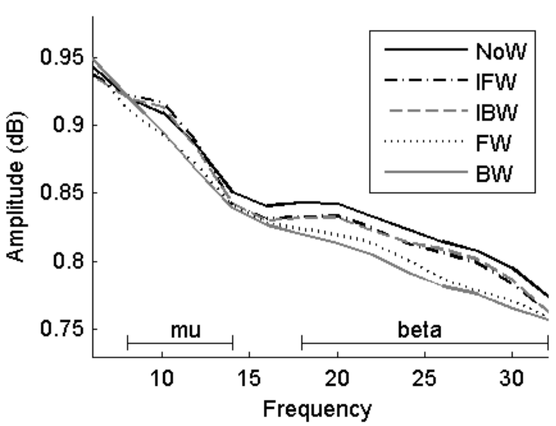

Fig. 3. Grand average spectral density at Cz over all subjects for the no-walking (NoW), imaginary forward (IFW), imaginary backward (IBW), forward (FW) and backward (BW) walking epochs in experiment 1.

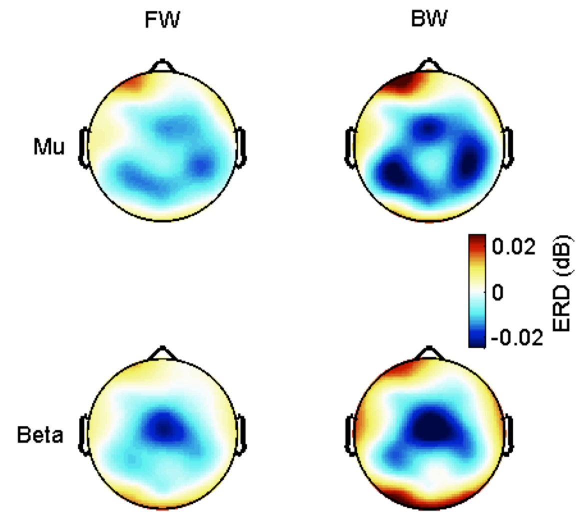

Fig. 4. Topography of ERD around the mu (8-14 Hz) and beta (18-32 Hz) band (walking minus no-walking) in the actual forward (FW) and backward (BW) walking epochs in experiment 1. Desynchronisation is indicated in blue, synchronisation is indicated in red.

Because starting and stopping of the treadmill in the CW task is similar to the AW task, these periods were removed from the analysis, leaving a walking period of 30 s. The different epoch slicing (1.2 s epochs) and the removal of these start-up and stopping periods resulted in sequences consisting of 8 no-walking trials and 25 walking trials for each walking condition.

5) Statistical Analysis

Statistical analyses were the same as for experiment 1. A randomization test was used to test performance above chance level. An 2x2 repeated measures ANOVA with the factors walking complexity (constant and adaptive) and modality (actual and imaginary) was used to test differences in performance between walking conditions.

III. Results

A. Experiment 1

A clear ERD was found above motor areas for the actual walking tasks around the mu and beta band. This can be seen in Fig. 3 as a decreased amplitude for each of the four walking tasks with respect to the no-walking task. These decreases in amplitude are significant, indicated by main effects for walking in both the FW, $F(1,154) = 9.35$, $p < 0.01$, and BW , $F(1,154) = 18.38$, $p < 0.001$, condition. No interactions with frequencies were found. For the imaginary tasks, the ERD was less clear around the beta band, and absent in the mu band in the Cz electrode. The ERD in both imaginary conditions was not significant. The ERD during both actual walking tasks was stronger than during both imagined walking tasks, $F(3,308) = 14.85$, $p < 0.001$.

During actual walking, the ERD around the mu band (8-14 Hz) was strongest in fronto-central and lateralized parietal areas (see Fig. 4). Around the beta band (18 to 32), the ERD was strongest above the central electrodes, with some spreading to lateralized parietal areas. The ERD around the mu and beta band were less clear during imagined walking.

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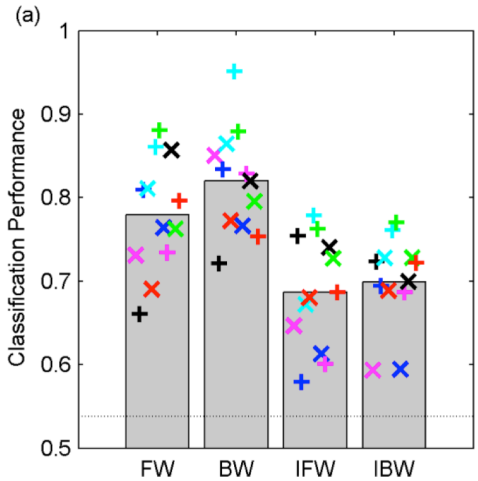

Fig. 5. Classification performance on the 1.2-second epochs for the forward (FW), backward (BW), imaginary forward (IFW), and imaginary backward (IBW) walking conditions in experiment 1. The bars indicate averages over all subjects; each individual subjects classification performance is indicated by the cross and plus markers, in which each subject has a unique combination of marker and colour. The dotted line indicates the chance level of the classification performance.

The ERD in the BW task was somewhat stronger and spread to a larger channel group than in the FW task.

Based on results of the randomization test the chance level was set to 54%. The average classification performance was 78% for the FW task, 82% for the BW task, 69% for the IFW task and 70% for the IBW task (see Fig. 5). For all walking tasks and all subjects this was significantly above chance. A main effect of modality was found, $F(1,44) = 33.53$, $p < 0.001$, indicating that the actual walking tasks had a higher classification performance than the imaginary walking tasks. No main effect of direction was found, $F(1,44) = 2.01$, and the interaction was also non-significant, $F(1,44) = 0.56$, $p > 0.05$.

B. Experiment 2

In the low beta band, a clear ERD was found for all walking tasks with respect to the no-walking period (see Fig. 6). The ERD was significant for the CW, $F(1,112) = 14.07$, $p<0.001$, AW, $F(1,112) = 12.54$, $p<0.001$, and IAW, $F(1,112) = 7.99$, $p<0.01$, condition. No interaction with frequencies was found. Around the higher beta band, the ERD was only visible for the actual walking tasks. This pattern of a strong ERD in low beta band and a weaker or no ERD around the higher beta band for the imaginary walking tasks was visible in four out of nine participants. Around the mu band a small ERD was seen in the central electrode, but a strong desynchronisation was present at parietal-occipital areas (see Fig. 7). The beta ERD during actual walking was strongest above central electrodes. No clear difference was seen between the constant and adaptive walking. The ERD during imaginary walking was less pronounced around both the mu and beta bands. A main effect of walking task on the ERD was found, $F(3,224) = 6.23$, $p<0.001$. Post-hoc analysis showed that the ERD during both actual walking tasks was stronger than during the ICW task.

The online performance of the feedback block was 79%, 78%, 70% and 69% for the CW AW, and ICW and IAW tasks

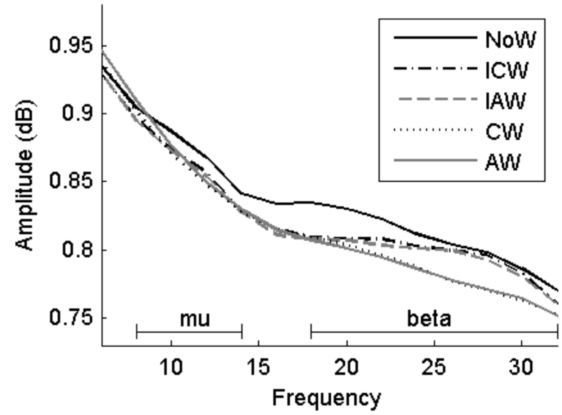

Fig. 6. Grand average spectral density at Cz over all subjects from the training block in experiment 2 for the no-walking (NoW), imaginary constant (ICW), imaginary adaptive (IAW), constant (CW) and adaptive (AW) walking epochs.

respectively. Since non-optimal parameters were used, EMG activity could have been included in the features used for classification, overestimating the true performance. Therefore, the data was re-analyzed offline.

For the training block the average recalculated classification performance was 87% for the CW task, 89% for the AW task, 71% for the ICW task, and 76% for the IAW task (see Fig. 7a). Classification performance of all tasks was significantly above chance (54%, as calculated by the randomization test). A main effect of modality was found, $F(1,32) = 50.37$, $p < 0.001$, indicating that performance was stronger in actual walking compared to imaginary walking. There was no effect of complexity of the walking task on the classification performance, $F(1,32) = 2.21$, and no interaction effect, $F(1,32)=0.46$, $p > 0.05$. Similar effects were seen when applying the recalculated classifier of the training block to the test block data (see Fig. 7b). The classification performance was 84% and 86% for the CW and AW tasks respectively. For both the ICW and IAW tasks, classification performance was 66%. Again these average performances were all above chance level (59%). Furthermore, classification performance

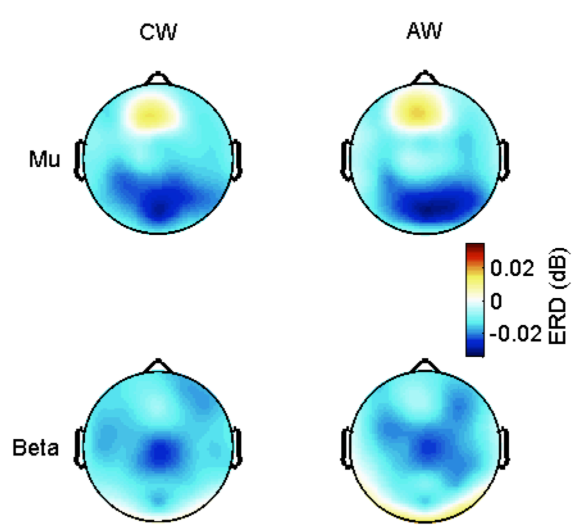

Fig. 7. Topography of the ERD around the mu (8-14 Hz) and beta (18-32 Hz) band (walking minus no-walking) in the actual constant (CW) and adaptive (AW) walking epochs in experiment 2. Desynchronisation is indicated in blue, synchronisation is indicated in red.

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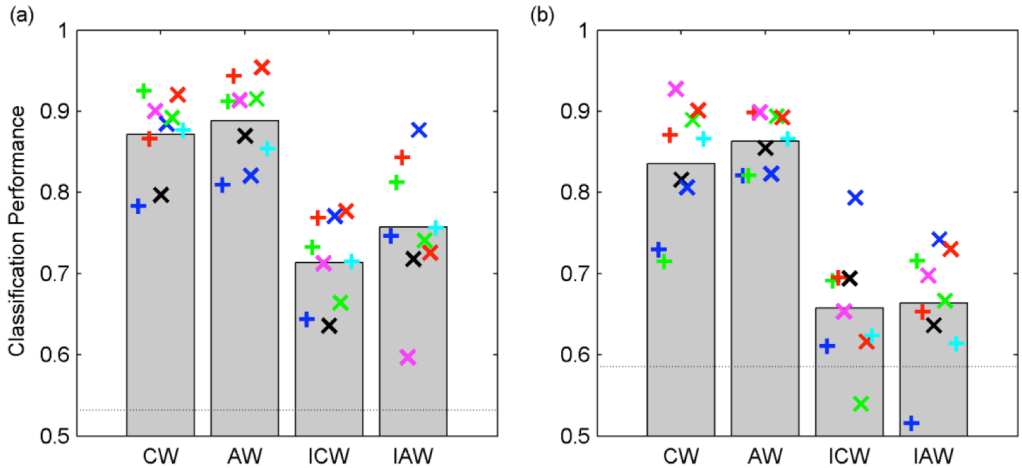

Fig. 8. Recalculated classification performance on the 1.2-second epochs for the constant (CW), adaptive (AW), imaginary constant (ICW) and imaginary adaptive (IAW) walking conditions in experiment 2. In (a) the offline performance of the training block is given. In (b) the performance of the test block, calculated with the classifier from the training block, is given. The bars indicate averages over all subjects; each individual subjects classification performance is indicated by the cross and plus markers, in which each subject has a unique combination of marker and colour. The dotted line indicates the chance level of the classification performance.

was higher during actual walking compared to imaginary walking, $F(1,32) = 76.03$, $p < 0.001$. The effect of complexity, $F(1,32) = 0.60$, and the interaction effect, $F(1,32) = 0.25$, $p > 0.05$, are non-significant.

IV. Discussion

In this paper we investigated the possibility of classifying EEG signals related to walking movements and the effect of increasing complexity of the movements on classification performance. Both actual and imagined walking movements could be classified above chance level, but as expected the actual movement tasks performed better than the imaginary movement tasks. In contrast to what we expected, complexity of movements did not significantly influence classification performance, although the mean classification performance of both complex tasks was higher than the simple tasks.

A. Cortical control of walking

All actual walking movements produced an ERD around mu and beta bands and could be classified. One could argue that this classification is mainly based on sensorimotor feedback from the muscles. However, even imagined walking movements, in which there is no sensorimotor feedback, could be classified above chance level. These results suggest that walking on a treadmill is under some form of cortical control. In the forward and constant walking tasks, subjects walked with a constant speed. Even under these conditions activity related to walking could be detected, indicating that this activity is not simply starting or stopping the walking movements, but is probably involved in the continuous control of the movement. The mu and beta ERD that we found is very similar in location and frequency to the ERD found during other leg movements [46]–[48]. Hence, at first sight, the aspect of cortical control of walking that can be measured with EEG does not appear very different from cortical control related to other movements. However, it should be mentioned that the present type of walking required some level of continuous guidance and corrections in the less complex tasks as well, since the subjects were required to follow a given cadence. In locomotor tasks that are even more automated it is possible that the role of the cortex is less prominent. However, an ERD has also been observed during walking on a robotic gait orthosis [27]. Although less prominent, the ERD was also visible during passive walking. In a later report, this difference could even be classified and used to assess the level of participation in the walking task [32].

B. Complexity

In agreement with a previous report [30], both actual and imagined walking movements could be classified versus rest above chance level. Although the difference in classification performance and ERD between normal and more complex walking tasks was not significant, the difference was in the expected direction for both experiments. The ERD around the beta band during actual forward walking was about 25% lower than during backward walking. Previously differences between forward and backward walking of up to 50% have been found in SMA, pre-central gyrus and superior parietal lobule with NIRS [49]. The discrepancy between these studies could have been due to differences in methodology, including the precision cadence that was required in the current study, and the difference in controlling hand position. Moreover, in the present study subjects walked at a speed closer to the average preferred walking speed, whereas walking speeds in the NIRS study were lower. Walking at very low speeds can produce different patterns of muscle activation [50], hence cortical control of slow walking could be different from the control of normal walking. A difference between normal and more complex walking tasks has also been shown with imagined locomotion. In fMRI [21] showed that, compared to motor imagery of normal gait, motor imagery of precision gait is accompanied by stronger activations in left and right

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superior parietal lobule, and the superior middle occipital gyrus. A similar trend was seen in PMd and cerebellum. La Fougère [51] proposed two different locomotion networks for steady-state and modulatory locomotion. In the direct pathway for steady-state locomotion execution signals from the primary motor cortex areas go directly to the CPG. Planning and modulation of movement is controlled by a separate pathway. Signals originating in prefrontal SMA are transmitted through the basal ganglia and brainstem locomotor regions to the spinal CPG. Taken together, these previous results suggest that more demanding locomotion tasks should produce stronger or at least different brain activity. However, with NIRS and fMRI a different aspect of brain activity is measured than with EEG, namely the hemodynamic response. Although correlations have been found between both responses [52], discrepancies between the two have also been described [53]. This could explain differences between the results in hemodynamic responses and the results from the present study. On the other hand, if the tasks are sufficiently different, it is sometimes possible to detect EEG changes. For example, Wagner *et al.* [36] compared 3 types of treadmill training with different complexities. A more difficult training with interactive virtual environment feedback was compared to two control conditions: walking with a visual attention paradigm, in which visual stimuli were unrelated to the motor task; and walking with mirror feedback (participants observed their own movement). The first task decreased mu, beta and low gamma rhythms compared to the other tasks [36]. This was taken to demonstrate that premotor and parietal areas show increased activity during walking under complex conditions.

Similar results for experiment 1 and 2 suggest that the absence of a significant difference between the classification of forward and backward walking was not caused by fast learning of the backward task. A factor that could have influenced the difference between the simple and more complex tasks is the cueing for the precision cadence. Attuning walking to both visual and acoustic cues is attentionally demanding [54], [55]. Hence, the simple tasks used in the present study were both already a somewhat complex task. Recently it has been shown that, visual cues, as used in experiment 2, require more attention than auditory cues [56]. Therefore, the CW task using visual cues from experiment 2 was probably more difficult than the FW task using auditory cues from experiment 1. Differences in complexity in both experiments, but specifically when visual cues were used, could have been too small to show up significantly different in the classification results.

In principle one could argue that when subjects walked in forward and backward direction in experiment 1, the different background could have caused changes in ERD patterns. However, the no-walking periods that preceded the walking periods were performed in the same direction as the walking periods. Therefore, if there is an effect of background, it will most likely influence the walking and no-walking periods in a similar way. Hence, the effect of background light can be neglected.

Although not significant, the more complex backward and adaptive walking tasks produced a stronger ERD and higher classification performance than the simple walking tasks. When using more data this effect may reach significance. However, because the effect did not show up with the amount of data used here, any complexity related effect is most likely relatively small, and thus of limited value for BCI applications.

C. *Actual and imagined walking*

Classification performance with actual walking tasks was higher than performance with imagined walking tasks. Although movement, muscle and EOG artifacts could boost performance especially in the actual walking tasks, we believe this was not the case, first because EMG activity was decomposed from the data. Second, EOG activity is likely not synchronized to the stepping, also because they were instructed to focus on the screen, and hence averaging will reduce influences from EOG artifacts. Third, movement artifacts were minimized by stabilizing both the cables and cap as much as possible. Furthermore the amplifier and shielded cables that were used during the measurements prevent contamination with movement artifacts from moving cables. Movement artifacts are particularly prominent at very low frequencies. Therefore frequencies below 8 Hz were not included in the feature selection. Finally, the ERD during actual walking was located above central and parietal areas. In prior work, both foot movement execution and foot movement imagination have been associated with a desynchronisation in mu and beta band above central electrodes [46]–[48]. Therefore, classification of actual walking tasks was likely solely based on brain signals.

Differences in the strength of brain signals during actual and imagined movements have been seen previously in EEG measurements, and were attributed to weaker afferent input [47]. Whether only this weaker afferent input causes this difference between actual and imagined movements, or whether there is also a difference in the motor component of the ERD remains an open question. The different ERD pattern around the high beta range between actual and imaginary tasks that was found in the current study could also partly reflect the difference in afferent input, or it could reflect a difference in motor components between the actual and imaginary tasks. However, this needs further investigation because this pattern was found in only a subset of the participants.

D. *Implications for rehabilitation*

The results from the current study are relevant for developing rehabilitation techniques that include BCI training. First, in stroke rehabilitation training, attempted movement will be more appropriate than imagined movement, although the latter being studied more frequently. In fMRI it has been shown that activity of attempted movement and imagined movement differs in strength in different areas [57]. For attempted walking movements, ERD levels and classification

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performance will probably be somewhere in between levels for actual and imagined movements. Therefore, the results for both actual and imagined walking movement give insight into what we could expect in rehabilitation settings. Secondly, the design of the current study will be more appropriate for rehabilitation training sessions than the standard BCI designs. In the latter, the (imagined) movement task is often performed for only a couple of seconds. But in rehabilitation, it will be more appropriate to have longer periods of (attempted) walking, while feedback is given at regular intervals, for example every second. Our results show that classification of short periods of time is also possible during continuous actual and imagined walking. Finally the results show that the influence of the complexity of the walking task on the classification performance, if present at all, is small. Hence, any precision walking task can be chosen in a rehabilitation program. An important question that remains for developing a BCI training therapy is how the ERD patterns during either actual, imagined or attempted walking in stroke patients compare to these results in healthy subjects.

V. Conclusion

In this paper we aimed to investigate the potential of EEG based detection of walking as a first step towards BCI based rehabilitation of gait. Our results show that despite the automaticity of walking ERD signals are present during all types of walking movements. By removing any movement-related interference with advanced signal analysis techniques, this ERD could be observed in the relevant cortical areas with EEG. This confirms an earlier report on walking with an exoskeleton [58] and walking combined with a variety of tasks [36]. Furthermore, this ERD could be classified during walking movements rapidly and with high reliability (average ~80% correct in 1.2s). A similar, though weaker (average ~70% correct), signal was found during imagined walking. We did not see a significant increase in signal strength when comparing cued walking and more complex walking (backward walking; walking with changing speeds). Despite the relatively deep location of the foot region and the automaticity of the walking movements, performance is similar to that when using superficial sources and less automatic movements, such as hand movements. Thus, walking movements are a viable alternative for BCI-based control applications. The work of [10] and [13] has shown improved rehabilitation of upper-limb movement after stroke at similar detection performance levels. Thus, this approach should be effective in lower-limb rehabilitation.

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