

MASTER

A brain-computer interface for walking using EEG

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A Brain-Computer Interface for walking using EEG

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in partial fulfilment of the requirements for the degree of

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in Human-Technology Interaction

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Preface

This thesis is the last step to complete the Master program in Human-Technology Interaction at the University of Technology Eindhoven. It is the result of several months of hard work, not only mine but also from a group of people who helped me to make this possible. First of all, I would like to thank my wonderful supervisors Marianne Severens, Raymond Cuijpers and Jason Farquhar for their inspiring ideas, support, patience and enthusiasm. Also, I would like to thank Bart Nienhuis from the Sint Maartenskliniek for his help during the setup of the experiments, for his advices regarding signal processing, and for his feedback. I thank Antal Haans for his advice regarding the statistical analysis and the design of the questionnaires. My sincere gratitude to all the people from the Research and Education Department of the Sint Maartenskliniek for making pleasant my internship, for their advice during the presentations and for conducting the meetings in English just for me. Also, to Victor Camelo and Monserrat Corona who kindly proofread this thesis. Thanks to all participants of the experiment and, finally, thanks to my family, whose support has been invaluable.

Summary

Brain-Computer Interfaces, or BCIs, allow the use of neurophysiological signals of the brain to control external devices without using any other part of the body (Birbaumer & Cohen, 2007). Recently, it has been suggested that BCIs can be used in rehabilitation. In the case of stroke patients, there is some evidence that imaginary movements might be helpful by providing a means for practice when no actual movement can be performed (Mulder, 2007), and BCIs can provide feedback for this imaginary-movement practice.

A common problem after a stroke is the loss of the ability to walk. Therefore, a BCI using imaginary walking or attempted walking could help patients to relearn how to recover this ability. The present study proved the feasibility of decoding walking using EEG. Two different types of Event-Related Spectral Perturbations were used to distinguish walking from no-walking in both actual walking and imaginary walking. Furthermore, an online BCI for walking was implemented successfully with classification rates analogous to the offline classification. Importantly, the results were robust for different levels of automaticity in the walking task (simple walking, complex walking, and backwards walking).

In order to maximize the system performance, several tasks and features were chosen and compared, namely, task (simple and complex walking), spectral modulations (inter-stride modulations and intra-stride modulations) and frequency band (mu, beta and mubeta). The mubeta band improved performance when compared with the mu and beta bands separately. However, neither differences in the automaticity of walking nor in the spectral modulations were found. Only the effect of walking modality and spectral modulations was significant, showing that inter-stride modulations are better features during imaginary walking, whereas the the intra-stride modulations yield better results during actual walking.

The interactions among task, performance and three subjective measures (sense of agency, satisfaction and learnability) were also assessed. However, no significant effects of task and performance on the sense of agency, satisfaction and learnability were found.

Herein, recommendations are provided for the design of a BCI for rehabilitation. Inter-stride modulations could help during early stages in the rehabilitation process, whereas intra-stride could be more useful to tune practice according to the gait cycle phases. Furthermore, the mubeta band proved to be more suitable to achieve high performance. However, due to the high variability between subjects, it is recommended to choose the best frequency band per user.

Contents

Preface	3
Summary	4
1. Introduction	6
2. The Brain-Computer Interface cycle	8
3. The role of BCI in rehabilitation	11
4. EEG during Human Gait	13
5. The current study	16
6. Feasibility analysis: forward versus backward walking	19
Methods	19
Analysis	22
Results	24
Conclusions	29
7. Online BCI: simple versus complex walking	30
Methods	30
Analysis	34
Results	35
Conclusions	39
8. General discussion	41
9. Conclusions	44
Appendixes	48
A. Forward versus Backward Walking	48
B. Simple versus Complex Walking	52

1. Introduction

Most children have dreamed about being a superhero granted with special abilities and powers: the power to fly, super-strength, telekinesis, perhaps even the ability to read minds. Such extra-sensorial and extra-motor powers seem to be confined to our imagination. However, they are not impossible anymore: advances in technology now make it possible for these dreams to come true. Technological extensions of the body can grant us abilities that previously would have been impossible. In fact, evidence of these extended capabilities already exists: airplanes have granted us the ability to fly, and vehicles have let us lift enormous weights. However, the control of such abilities still depends on physical interaction, using these technological extensions as elements external to our bodies.

Furthermore, the usage of such external tools is usually complicated. Interaction is so complex, that it requires investing a huge amount of time on intensive training before being able to optimally use such tools. Due to the inherent complexity of such technologies, the feeling that humans are directly controlling the actions of the machine (i.e., sense of agency) and that the technology itself is part of their own body (i.e., sense of ownership) is almost imperceptible. To solve this problem, there are some trends in Human Computer Interaction which suggest several alternatives to diminish the complexity of the interfaces. Most of them coincide in their emphasis on simple, one-purpose, location specific, interconnected devices (Buxton, 2001; Clark, 2003). Andrew Clark (2003) suggested that as tools become easier to use and more transparent, they become natural extensions of our body and of our mind and therefore, humans can be considered Natural-Born Cyborgs.

On the other hand, the possibility remains of fusing such interfaces and functionalities as extensions of our minds, *literally*. What would you feel if you could lift objects from a certain distance, with the sole will of your mind? What about controlling new stronger arms and legs as if they were your natural limbs? What would happen if you could see and hear more frequencies of sound and light, besides the ones that our natural senses allow? What about warping all your senses and your will to a faraway place? ... Perhaps a virtual one?

The first step towards the implementation of a direct extension of our mind and bodies has already been taken through the introduction of so-called Brain-computer Interfaces (BCIs). BCIs are a direct link between devices outside the body and mental activity (van Gerven, Farquhar, Schaefer, Vlek, Geuze, Nijholt, Ramsey et al., 2009). They allow the use of neurophysiological signals of the brain to control external devices (Birbaumer & Cohen, 2007). BCIs have the potential of providing a good alternative for improving the sense of agency and ownership provided by technology. However, their development is still rudimentary, and there is still much work left in order to reach a perfect coupling between human minds and machines.

Nowadays, BCIs are typically used for communication and control (Wolpaw, Birbaumer, McFarland, Pfurtscheller and Vaughan, 2002). One example of BCI for communication is the so-called ‘visual speller’. This is a device that allows people to spell a word by selecting letters from a grid. The interface consists of a matrix of letters which flash in rows and columns. When the desired letter flashes, a P300 evoked potential is generated 300 ms after the presentation of the stimuli, making it possible to estimate which letter the user is attending to (Wolpaw et al., 2002). On the other hand, BCIs for control have been used with the explicit purpose of compensating for loss of motor ability in disabled patients.

A BCI could, for example, allow patients to drive external devices such as a wheelchair or prosthesis (Millán, Renkens, Mouriño and Gerstner, 2004; Enzinger, Ropele, Fazekas, Loitfelder, Gorani, Seifert, et al. 2008).

Since a BCI can provide feedback of imaginary and attempted movements when no actual movement can be executed, it has been suggested that it can be used in rehabilitation of stroke patients as well (Daly & Wolpaw, 2008; Vries & Mulder, 2007; Enzinger et al., 2008; Mulder, 2007; Prasad, Herman, Coyle, McDonough, & Crosbie, 2010; Cramer, Orr, Cohen, & Lacourse, 2007). By providing feedback of an attempted movement, BCIs can facilitate practice of a lost brain functionality. There is some evidence that the use or disuse of a brain representation can influence cortical representations (Mulder, 2007). Therefore, as a result of constant training and facilitation of this training, reorganization of neural structures could be enhanced and lost motor abilities could be relearned.

A common problem after a stroke is the loss of the ability to walk. A BCI using imaginary walking or attempted walking could help patients to recover this ability through relearning. The aims of this study are twofold. First, use EEG signals in order to determine whether a (healthy) person is walking or not, for actual walking. Second, to build a BCI for imaginary walking, with similar brain signals. Different features and tasks will be compared in order to choose the combination that provides the best system performance. Furthermore, interactions between tasks, performance and the subjective assessment of the user about the usability and the sense of agency of the interface will be explored. Recommendations for further improvements of such BCI will be generated, focusing on necessary adaptations of the BCI for improved performance, while providing a good sense of agency and usability.

The structure of this report is as follows: in Section 2, a detailed description of the methodologies used to implement a BCI are provided. Section 3 describes current evidence of the impact of BCIs in rehabilitation and Section 4 introduces relevant features of EEG signals during human gait. Section 5 describes the research questions and hypothesis of the current study. Section 6 describes a feasibility study of the classification of the EEG during walking, and the technical details for such classification. Section 7 describes the main experiment of this study, where the BCI was tested in an online setup and its subjective qualities were assessed. Finally, Section 8 and 9 provide a general discussion of the results and conclusions, respectively.

2. The Brain-Computer Interface cycle

Despite the broad range of applications and paradigms that are used for implementing BCIs, most implementations follow a common set of steps. Gerven et al. (2009) proposed a cycle for a BCI interface (Figure 1), from the measurement of the signal, to its transduction into observable phenomena. In this cycle, the first stage corresponds to the sensing of mental activity while the user engages in a cognitive task. Then, the signal is preprocessed in order to filter noise and extract the characteristic features of the signal that will be used for classification. Next, machine learning algorithms are used to make a prediction about the intention of the user. Finally, this prediction is used to give feedback to the user, or to regulate the task at hand. The outcome signal can also be used to control a specific device. Since the user becomes aware of the device behavior, he is enabled to adjust his mental activity, towards the desired end.

In the following sections, each step of the BCI-cycle is described in detail.

Measurement. The required neurophysiological measurements of the brain are recorded using two different types of methods. Invasive methods require the implantation of electrodes on or in the brain. An example of an invasive method is the electro-cardiogram (ECoG), which provides a good signal-to-noise ratio and good detection of high frequencies. Other examples are the “Single microelectrode” (ME) and the “Micro-electrode array” (MEA), which consist of a single or multiple electrodes implanted in the brain, respectively. These methods are capable of detecting many forms of electrical potentials, single or multi-neuron spiking, as well as local field potentials. Both methods have fairly good temporal and spatial resolutions; however, they also have disadvantages such as the maintenance of the electrodes and difficulties with the communication of the internal device with external processing units (Gerven et al., 2009).

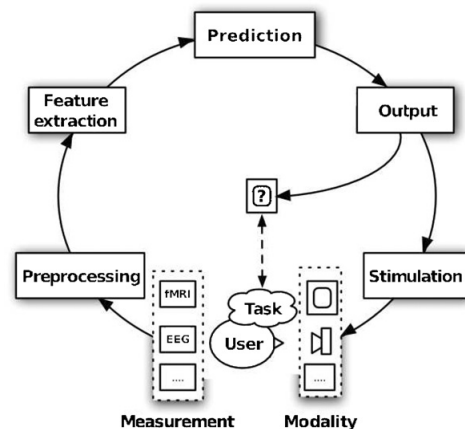


Figure 1. : The BCI cycle as proposed by Gerven et al. (2009). While the user performs a cognitive task his brain activity is measured. The signals acquired are then preprocessed to remove confounds. Then, the interesting characteristics for classification (features) are extracted. Next, a prediction is made about the nature of the features. Finally, this prediction is given as feedback or it is used to modify the user’s task.

Non-invasive methods record the signals from outside the brain. Examples of non-invasive techniques are the Electroencephalogram (EEG) and the Magnetoencephalogram (MEG) technologies. The temporal resolution of both systems is very good when measuring mental activity in the brain. However, they do not provide a good spatial resolution and they are susceptible to eye and muscle movements. Another example is the functional Magnetic Resonance (fMRI), which measures brain activity comparing the blood-oxygen level among tasks. The fMRI achieves better spatial resolution than the EEG or MEG, at the cost of losing temporal resolution (Juola, 2009).

Due to its temporal resolution and relative portability, EEG is particularly suitable for BCI. Its working mechanism is based on using electrodes to measure electrical activity generated in the brain and transmitted on the scalp. These potentials are neurophysiological signals that can be used to identify patterns useful to build a BCI.

Preprocessing. Before the signal measured by the EEG can be used, it has to be 'cleaned.' In other words, the signal of interest has to be identified and confounds have to be removed. This is called *preprocessing* and implies the removal of faulty channels and outliers. Also, the signal is usually 'detrended' to remove trends in the measurements caused by changes in the conductance between the electrode and the skin. Further preprocessing includes the rejection of artifacts such as eye blinks, saccades and other EMG components detected by the EEG electrodes.

Feature extraction. The next step is to identify the characteristics of the EEG signal that are interesting for the problem at hand. Signatures are the association of a brain signal with a mental state that uniquely caused it (Gerven et al., 2009). These signatures have been classified into evoked and induced potentials. Both of them are responses locked to a stimulus; the difference between them is that the evoked potentials are responses phase-locked in the time domain and the induced potentials are locked in spectral power (i.e., in the frequency domain) to the event (Gerven et al., 2009).

An example of induced response potentials are Event-Related Spectral Perturbations (ERSP). Within this category, Event-Related Spectral Desynchronizations (ERSD) and Event-Related Spectral Synchronizations (ERSS) are of special interest because they are related to motor activity and movement preparation (Pfurtscheller, Stancák and Neuper, 1996; Pfurtscheller, Brunner, Schlögl and Lopes da Silva, 2006). ERSDs are induced potentials that correspond to a decrease in spectral power during planning and execution of a movement. ERSDs are followed by an ERSS, which is the increase in spectral power after the movement (Pfurtscheller, Brunner, et al., 2006).

ERSD in the mu-rhythm frequencies (described in preceding paragraphs) in humans has been linked to somatosensory stimulation or movement. Evidence for this has been found especially for hand movements (Pfurtscheller et al., 1996). Interestingly, ERSDs and ERSSs are present not only during actual movement, but also during imagery tasks (Pfurtscheller, Brunner, et al., 2006; Neuper et al., 2005). Motor imagery refers to the cognitive image of performing a movement, without executing the actual movement. If the imagery is performed in a first person perspective, it is called Kinesthetic Motor Imagery (KMI) and there is some evidence that it elicits stronger desynchronizations than Visual Motor Imagery (VMI), which is the imagery of seeing oneself walking (i.e., from an outside perspective) (Neuper, Scherer, Reiner and Pfurtscheller, 2005).

Since motor imagery can elicit specific changes of potentials in the brain, it is a prime candidate for implementation of BCIs. Furthermore, it can be used at will, giving the user of the BCI the power of steering the interaction. The mu-rhythm and beta-band rhythms are of special interest for identifying motor imagery. Mu-rhythm refers to an oscillation of about 8-14 Hz in the EEG signal, whereas beta-rhythm refers to an oscillation from 12-25 Hz. Modulations in both frequency bands can be seen not only with actual movement, but also if one imagines a movement (Pfurtscheller et al., 1996; Prasad et al., 2010). However, mu-band ERSDs for foot movements are more difficult to detect because the foot area is located within the mesial wall in the interhemispheric fissure. Beta-band oscillations are also generated in the somatosensory cortex, but in contrast to mu-rhythms, they are easier to detect, and time courses of recovery after desynchronization are faster in beta than in mu-rhythms (Pfurtscheller et al., 1996).

Prediction. Once the features are selected, they are fed into a classifier. A classifier is an algorithm that assigns an external observation to one of several classes (Müller, Krauledat, Dornhege, Curio, and Blankertz, 2004). The rule to do this classification is found by analyzing the data and fitting a model that indicates a boundary between classes. A simple approach, is to use a linear regression to fit the data and use a threshold function to differentiate between different classes. If there are only two classes, logistic regression can be used (Russell & Norving, 2010).

Such models are usually built by reducing the error between values predicted by the model and the actual data. However, this might not always be beneficial. Especially in small samples, deviations might be large, and by reducing the error to explain the variances in the sample (Müller et al., 2004), the classifier might *overfit* the data. As a result, it will not generalize to other samples of data. To solve the overfitting problem, a regularization parameter can be added to the regression problem (Müller, Krauledat, Dornhege, Curio, & Blankertz, 2004), which introduces restrictions (through penalizations) on how much data is required to switch the classification threshold. The more data is available within a boundary, the more confident the classifier is that it belongs to a certain class and the lower the penalization due to few data points.

Feedback. Finally, the result of the prediction can be used to control an external device or can be shown to the user as feedback, so that he can adapt to the outcome of the classification. The range of modalities in which the feedback can be provided is wide and should be designed according to the specific application of the BCI.

When such feedback is provided, the BCI is considered as “online.” In contrast to an offline setup where all data is gathered first and classification is done afterward, an online BCI should do the classification in real-time and should be robust to changes in the mental activity of the user and his adaptation to the feedback itself.

In summary, BCIs work in a closed loop which starts with measuring the brain activity of a person while he engages in a cognitive task. Then the signal is preprocessed and the relevant features extracted. Based on those features, a classifier can learn about the user’s brain signals and make a prediction about the intentions of the user and provide feedback according to the results. Since the user is part of this loop, both machine learning and human learning are complementary; the proceeding section will explain how this interdependence can be useful for rehabilitation of stroke patients.

3. The role of BCI in rehabilitation

A BCI using imaginary movements could help in rehabilitation, not only by providing the means of bypassing spinal cord injuries, but also helping both Spinal Cord Injury (SCI) and stroke patients maintain and recover their brain functionalities by giving direct feedback of imagined movements.

Motor impairment and functional disability are the major consequences of Spinal Cord Injury (SCI) and stroke. The damaged spinal cord of SCI patients obstructs the communication between the brain and several parts of the body, depending on the level of the injury. On the other hand, a stroke is related to a distortion of the capacity of the brain to process neural information after a disturbance in the blood supply to the brain.

Even though both problems may result in motor impairments, the brain functionality in patients with SCI is assumed to be intact and capable of driving limb movements (Cramer et al., 2007; Enzinger et al., 2008), while in a stroke, the motor impairment is caused by brain damage (Vries & Mulder, 2007). Consequently, rehabilitation strategies for these impairments follow different paths. Rehabilitation after a stroke is mainly based on therapy and practice. In this case, functional recovery is attributed to the processes of reorganization and substitution in the damaged brain. For SCI, rehabilitation could use BCIs, which allow the use of neurophysiological signals of the brain to control external devices (Birbaumer & Cohen, 2007), and could therefore be used to bypass damaged areas in the spinal cord and drive prosthesis or even the patients' muscles.

Even if the damage that caused the impairment is not localized in the brain, some abnormalities have been described in the brain motor functions of SCI patients, including reduced activation, abnormal activation patterns and higher thresholds and latency for motor evoked potentials (Enzinger et al., 2008; Cramer et al., 2007). These abnormalities suggest that indeed the disuse of a brain functionality can influence cortical representations. In other words, reorganization of neural structures takes place as the result of deprivation of sensory input due to movements (Sadato et al., 1998; Halligan et al., 1993), and constant training is required in order to maintain the brain's motor system functionalities in good shape.

Unfortunately, for an injured patient it is not always possible to practice the required movements, either because he cannot move or because movements are painful. There is some evidence that imaginary movements might be helpful by providing a means of practice when no actual movement can be performed Mulder (2007). The use of motor imagery would be beneficial for rehabilitation because it is a direct representation of the movement that the patient would like to recover.

Motor imagery training could be enhanced by providing the patient with feedback of the movement. There are several types of feedback, including proprioceptive and visual feedback. In stroke physiotherapy, a therapist helps the patient move the paralyzed limbs, enhancing proprioceptive feedback. Another example from therapy is the Lokomat System (Hocoma Inc.), which is a device designed to help injured patients simulate the movement of walking with slightly better results than traditional therapy (Mayr, Kofler, Quirbach, Matzak, Fröhlich & Saltuari, 2007). The simulation of movement is achieved by using a treadmill with weight support and motorized boots. Visual feedback can also be provided by the Lokomat Pro, which shows visual cues of walking on a screen with a virtual environment,

in which the patient walks and completes some tasks. This augmented feedback enhances the patient's active participation in the task.

Despite the potential of BCI and its possible benefits in rehabilitation, few studies have explored its feasibility. One example is the study by Prasad, Herman, Coyle, McDonough, & Crosbie (2010), where a game-based neurofeedback BCI was used to enhance movement recovery in stroke patients. The lack of feasibility research is mainly due to the difficulty in identifying signatures in the brain signal.

Some attempts to create a BCI for virtual walking using mental imagery of the hands and feet have been successful (Pfurtscheller, Leeb, et al., 2006); however, they required extensive training of three subjects, from which only one showed a steady increase in his control of the interface. Furthermore, they do not use imaginary walking to produce the walking movement in the virtual environment.

Since imaginary movements can activate sensory-motor areas in the brain (Mulder, 2007), they are considered embodied. A task that is more natural to the body -such as the simple act of walking- could improve the sense of agency of the patient as well as the quality of the feedback he can gain from using a BCI. Accordingly, cortical representations of walking during human gait have to be considered. To this aim, the next section will provide a brief introduction to human gait and its cortical representation.

4. EEG during Human Gait

The Gait Cycle. Whittle (1996) defined walking as 'a method of locomotion involving the use of the two legs, alternately, to provide both support and propulsion,' and, when talking about normal gait, the difference with running is that at least one foot is in contact with the ground at all times. However, describing normal gait is difficult because there are large differences in walk patterns depending on sex and age.

Furthermore, he defined the gait cycle as 'the time interval between two successive occurrences of one of the repetitive events of walking.' Thus, in order to define a gait cycle, a start reference should be taken into account. Usually, an initial contact of a foot with the ground is considered the starting point of the gait cycle, and it continues until the same foot touches the ground again. Between these two contacts, several phases have been identified. Namely, initial contact, opposite toe off, heel rise, opposite initial contact, toe off, feet adjacent and tibia vertical. For the purposes of this study, only toe offs and heel strikes will be considered for each foot: only left toe off (LTO), left heel strike (LHS), right toe off (RTO) and right heel strike (RHS) are considered.

Figure 2 shows the different phases of a gait cycle for forward and backward walking. The start of the gait cycle was set to left toe off (LTO) in forward walking and left toe strike (LTS) in backward walking. As can be observed from this figure, backward walking has analogous gait-cycle phases to forward walking. In fact, Grasso, Bianchi and Lacquaniti (1998) compared the kinematics and kinetics of both directions of locomotion. According to their results, the kinematics (i.e., the spatial trajectory followed by the limbs during walking) of forward walking are very similar to those of backward walking when mirrored in time. However, the kinetics (i.e., the muscle activation during walk) of such movements are different.

Several measures have been used to characterize the timing of the walking process. Three of them are stride length, cadence, and walking speed (Whittle, 1996).

- The stride length corresponds to two consecutive steps (i.e., one gait cycle). On the other hand, the step length corresponds to the distance from one foot strike to the next, regardless of which foot touched the ground.

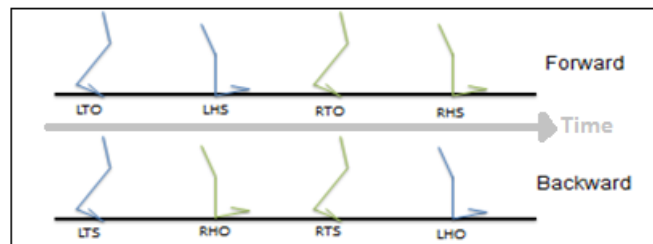


Figure 2. : Gait cycle phases. Four phases are considered within a step. In forward walking: left toe off (LTO), left heel strike (LHS), right toe off (RTO) and right heel strike (RHS). In backward walking: left toe strike (LTS), right heel off (RHO), right toe strike (RTS) and left heel off (LHO). The figure above shows the correspondence of phase between forward and backward walking. Forward walking is quite similar to backward walking when mirrored in time. When a LTO occurs in forward walking, a LTS occurs in backward walking.

- Cadence is the number of steps taken in a given time (usually minutes), thus, it is a measure of time for half-gait cycles. An alternative is to measure cadence in steps per minute (heretofore referred to as stepping frequency).

- The speed of walking is the distance covered by the whole body in a given time and is usually measured in meters per second.

Given these definitions, the relationship among step length, stepping frequency and speed of walk can be simplified to the definition of velocity: the speed of walking is given by the product of stepping frequency and step length (Whittle, 1996).

Measuring EEG during walking . The ultimate goal of this study is to use a BCI to provide feedback about imaginary walking movements, which could be applied in rehabilitation to improve the process of learning to walk again. To develop such a brain-computer interface, it is crucial to identify the correlations between patterns of movements during the human gait cycle and EEG potentials.

The main challenge of using EEG during actual walking is to remove movement artifacts inherent in the walking process and EMG artifacts generated from face and neck muscles. Several attempts to remove these kinds of artifacts have been made for spoken language production (De Vos, Riès, Vanderperren, Vanrumste, Alario, Van Huffel, & Burle, 2010) and walking (Gwin, Gramann, Makeig and Ferris, 2010; Gwin, Gramann, Makeig and Ferris, 2011; Severens, Nienhuis, Desain and Duysens, 2012). In these studies, the aim was to uncorrelate artifactual components from the EEG signal of interest.

Gwin et al. (2010) used Independent Component Analysis (ICA) to separate the measured signal into maximally independent components and subsequently applied a component-based template regression to identify and spatially filter gait-related movement artifacts. In a second study, Gwin et al. (2011) confirmed the potential of ICA to identify artifactual components. Here, they used current dipole estimation for every component using an inverse modeling approach. Components that exhibited significant coupling with intra-stride changes of spectral power were located in the anterior cingulate, posterior parietal, and sensorimotor cortex, suggesting that EEG recordings could identify cortical involvement during human gait. In particular, peaks in the beta and alpha bands' spectral power were found in the heel-strike and (approximately) in the middle of the double support phases, respectively.

Both studies demonstrated the potential of using ICA to remove gait-related artifacts. However, this requires a considerable amount of data, and the processing required to calculate all components is time-consuming. Furthermore, it has to be combined with other algorithms or visual selection to detect which components are useful. Unfortunately, in an online BCI context, time is not an abundant resource, and therefore, other alternatives should be considered.

Aiming to remove muscle artifacts from EEG recordings of spoke language production, De Vos et al. (2010) proposed the use of a Blind Source Separation (BSS) technique called Canonical Correlation Analysis (CCA) and compared it to other techniques such as ICA. CCA is a statistical method used to estimate the correlation between two variables. EEG and EMG components can be separated by combining CCA with the assumptions that (1) EEG and EMG sources are uncorrelated and that (2) EEG sources, contrary to EMG, are individually uncorrelated. In their particular application, De Vos et al. (2010) showed that indeed BSS-CCA outperformed ICA in preserving the shapes of the ERP after removing

artifactual EMG components.

In another study, Severens et al. (2012) showed that CCA can also be successfully applied to disentangle EEG from EMG during walking. After removing EMG artifacts, the synchronizations between the gait cycle and the spectral power of the beta band, as showed by Gwin et al. (2011), were confirmed. During the study of Severens et al. (2012), participants had to walk at different speeds, and the tasks also included stepping in place. It was shown that the intensity of activity is greater in heel-strike and toe-off phases of the gait cycle, and also that uncommon walking activity such as stepping in place and walking fast involves stronger modulations of cortical activity. This might suggest that cortical activity depends on experience and familiarity with the movements (Peters, 2011; Severens et al., 2012).

In summary, the results of Gwin et al. (2011) and Severens et al. (2012) suggest that it is feasible to use EEG as tool to measure cortical activity during walking, and that there is cortical involvement during gait.

Severens et al. (2012) found two types of modulations in spectral power. The first is an overall power decrease in the mu and beta bands along the whole time span during which steps were performed (i.e., inter-stride modulations); the second refers to spectral modulations (SM) in the same frequency bands coupled to the gait-cycle (i.e., intra-stride modulations). Figure 3 shows a schematic representation of such modulations, where the orange line shows the inter-stride spectral modulation and the red one the intra-stride spectral modulation. These two modulations show that there is cortical involvement during gait, which could be used as a feature to implement a BCI for walking.

5. The current study

As previously described, the main idea behind BCIs is to use machine learning techniques in order to identify signatures in the measured brain activity. Ideally, the BCI would be able to automatically learn and adapt to the user, so that the training required from the user is reduced to a minimum and the achieved classification performance is maximized (Müller et al., 2004).

Nevertheless, state-of-the-art BCIs are still slow, require extensive training from the user, and have to be calibrated for every subject. One of the main causes of these limitations is the variability in the signals used for BCI, which vary widely between and within subjects due to several factors such as trends in the measurements, degree of practice, fatigue and motivation (Birbaumer, Ghanayim, Hinterberger, Iversen, Kotchoubey and Kübler, 1999).

In fact, for each new iteration in the BCI cycle, the brain signatures that are used for classification change due to the feedback given in the previous iteration. An alternative approach used in BCI implementations, called neurofeedback training, directly relies on the ability of people to produce changes in their brain activity. Ideally, cognitive tasks used in neurofeedback training should let the subject voluntarily control brain activity. With enough training, these control tasks may become automatic, and could be performed without

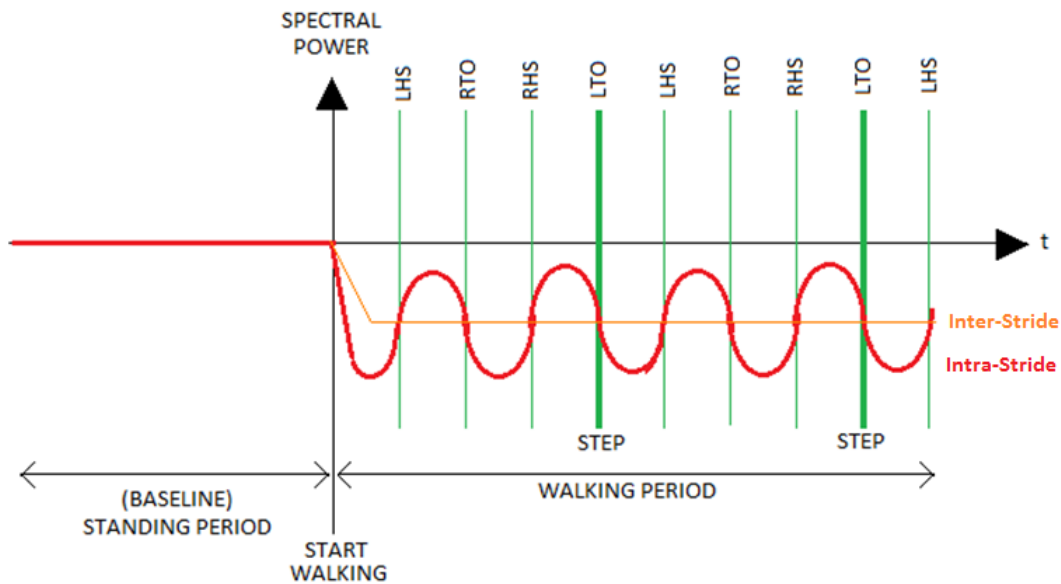


Figure 3. : Modulations in spectral power during gait. Two types of modulations in spectral power have been identified. The first is the Inter-stride modulation, depicted in orange. The second is the Intra-stride modulation, depicted in red. The Inter-stride modulation is a negative offset from a baseline spectral power that corresponds to a standing period (i.e., no walking). The Intra-stride modulation is mounted on the inter-stride modulation, and it has increases and decreases of spectral power coupled with the gait cycle phases. The phases of the gait cycle are represented by the green lines in the plot: starting with left toe off (LTO), heel strike (LHS), right toe off (RTO), and right heel strike (RHS).

conscious effort or attention (Curran, 2003; Elbert, Rockstroh, Lutzenberger and Birbaumer, 1980). User learning and user adaptation to the interface are key factors in the performance of the BCI. It is the human's capability to adapt that allows for another application of BCIs: they can be used as a tool for practice by providing feedback of the user's mental state (Nauper et al., 1999).

Other factors can also alter the performance of the BCI. There is some evidence that the automaticity or the mental effort required to do a task also modifies the quality of the signature measured from the brain. For instance, Müller-Putz et al. (2007) found some evidence that SCI patients showed better imagery vividness than able-bodied subjects, maybe because they required more mental effort. Also, Severens et al. (2012) found some evidence that spectral power modulations during gait were stronger when the movement was less automatic. Consequently, less automatic movements could improve the performance of the machine learning algorithm by making the boundary between classes more prominent.

For the purpose of rehabilitation, it is desired that the patient relearns how to control his brain activity in order to recover a lost ability. However, even when the goal is to learn how to control one's brain activity, given the difficulty of making accurate predictions of a mental state or instruction through a BCI, there is usually a chance that the prediction will be wrong and that the instructions given by the user will be misinterpreted by the prediction algorithm. This implicit error might alter the experience of the user by giving him the feeling that he is not the one controlling the interface. According to cognitive neuroscience, this experience of controlling one's actions and -through this control- affecting the external world is called 'sense of agency' (Coyle, Moore, Ola, Kristensson and Fletcher, 2012;Gallagher, 2000). As a result of a decreased sense of agency, the patient's motivation to practice using the interface might decrease. Consequently, a balance between machine learning, neurofeedback training and task design should be considered when designing a BCI for rehabilitation.

Based on these considerations, the aim of the present study is to build a BCI to determine if a person is actually walking or not, and to assess the tradeoff between the achieved system performance, and the sense of agency, learnability and satisfaction of the user. Different features and tasks will be explored in order to improve performance.

With this aim, two experiments were conducted. The first experiment used a comparison of forward and backward walking to prove the feasibility of using EEG to differentiate walking and no-walking conditions using cortical activity (either in actual or imaginary walking). Furthermore, different features and tasks were tested to determine which method provides best system performance.

It was expected that the less automatic the movement, the more modulation in mu and beta bands of activity over the motor cortex, resulting in increased classification performance. Backwards walking and complex walking, being less automatic, could increase the performance of the BCI when compared with forward walking and simple walking. However, it might improve performance at the expense of usability and the sense of agency.

A second experiment was designed to test the BCI in an online setup. During this experiment, simple walking and complex walking (i.e., walking at varying speeds) were compared while assessing sense of agency, learnability and satisfaction. Again, simple walking was less automatic than complex walking, and therefore better classification rates were expected. Furthermore, the sense of agency, satisfaction and learnability were assessed using

a questionnaire about the feedback provided. It was expected that:

- The higher the system performance, the better the sense of agency.
- The satisfaction and learnability will decrease with the complexity of the tasks.

However, there might be a mediating effect of system performance: the better the performance, the better the satisfaction.

Recommendations for further improvements of the BCI will be presented with the aim of adapting the BCI to maximize performance, while providing a good sense of agency, learnability and satisfaction at the same time.

6. Feasibility analysis: forward versus backward walking

The goal of this experiment is to prove that walking (either actual or imaginary) can be distinguished from no-walking in an offline BCI setup. Different tasks (forward and backward walking) will be compared in order to determine the relationship between the classification performance and the automaticity of the movement. Different frequency bands will also be tested in order to determine which one provides best system performance.

Methods

Experiment Design. The experiment used a 2x2 within-subjects design. The two factors were the type of task (forward vs. backward walking) and the walking modality (actual walking vs. imaginary walking). These four conditions were presented in eight blocks. In every block, each condition occurred once, in random order. In other words, all participants went through a total of eight repetitions of every condition (32 trials in total).

Four walking tasks were executed by the participants: forward walking, imaginary forward walking, backward walking and imaginary backward walking. A trial overview is shown in Figure 4. Every trial consisted of five seconds of standing (i.e., baseline period), followed by the presentation of the instructions on screen (one second). In the forward and backward walking conditions the treadmill was then turned on at a constant velocity of 3 km/h. The walking task lasted 45 seconds plus nine seconds at the beginning, which is the time the treadmill takes to reach the desired speed. After the walking period, 10 seconds were given to let the treadmill stop completely.

Participants. Twelve healthy volunteers with no history of major lower limb injury and no known neurological or locomotor deficits participated in this study. The mean age of the participants was 29 ($SD=5.94$) years. Before the start of the experiment, the participants were asked to read and sign a standard informed consent form, approved by the Ethical Committee for Behavioral Scientific Research of the Faculty of Social Sciences, Radboud University Nijmegen.

Experimental Setup. EEG was recorded using a TMSI-REFA 72-channel amplifier (Twente Medical Systems International, the Netherlands) and a 64-channel electrode array in a 10-20 electrode placement system. The ground electrode was placed on the AFz-electrode

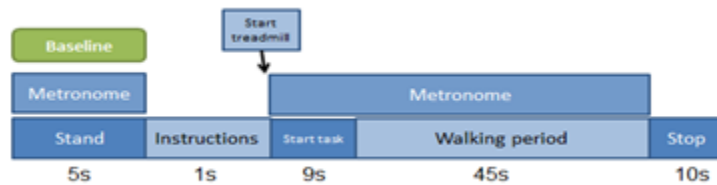


Figure 4. : Trial overview. A trial started with a baseline (standing) period that lasted five seconds, followed by on-screen instructions about the next condition. Then, nine seconds were required to start the treadmill. The subject walked or imagined himself walking for 45 seconds and, finally, 10 seconds were required to stop the treadmill during actual walking conditions.

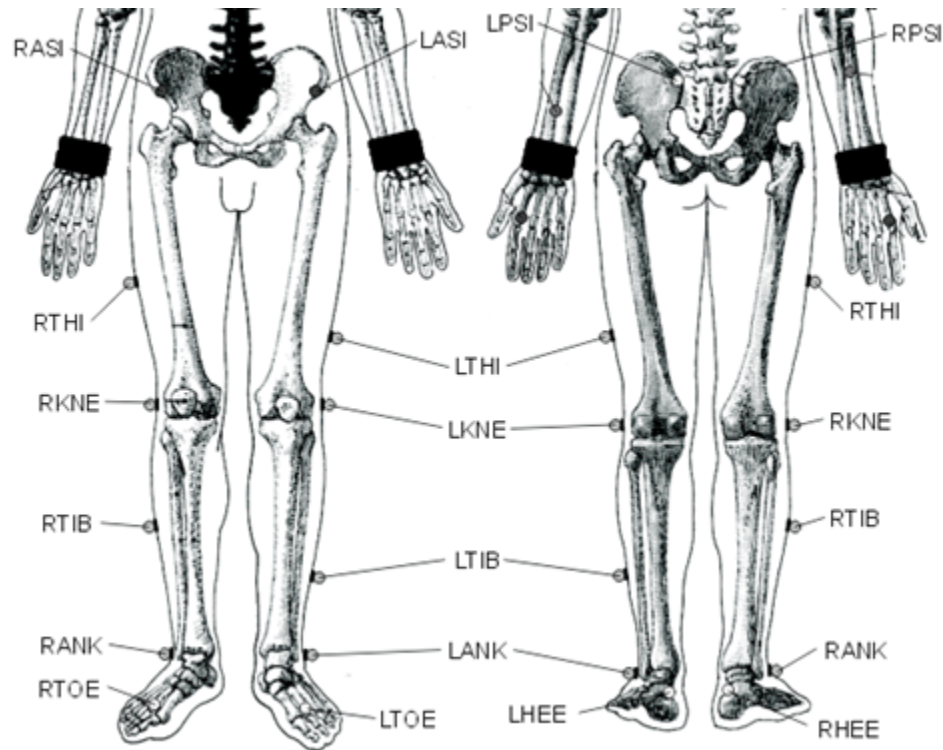


Figure 5. : Plugin-Gait Model. Sixteen reflective markers were placed on the lower limbs; their locations were determined relative to the position of a bone as indicated in the picture. The markers were stuck directly on the skin with a double-sided tape.

location. The TMSI REFA amplifier sampled the EEG signals at 500 Hz. Prior to the measurement, electrode gel was used to ensure that the impedance was less than 50 kilo ohms for each channel. The positions of 22 reflective markers were recorded using a ten-camera motion capture system (Vicon, Vicon Motion Systems Inc.). Marker positions were sampled at 100 Hz. The markers were placed according to the Plugin-Gait Model. Sixteen markers were placed on the lower limbs as indicated in Figure 5, and six markers were placed on the cap to track the movements of the head during walking.

Subjects walked on a programmable treadmill at a velocity of 3 km/s, facing a monitor screen placed 40 cm above the floor and 150 cm away from the treadmill. In order to walk backwards, participants had to turn around (for both actual and imaginary walking). Identical screens were placed at both ends of the treadmill, to facilitate change of direction, as shown in Figure 6. In order to reduce movement artifacts, the EEG cap cable was clipped to a cable that hung on the ceiling with a device that could move along with the subject, and then connected to the amplifier (see Figure 6).

The control of the flow of the experiment was programmed using Brainstream (DCC, Radboud University Nijmegen, <http://www.brainstream.nu>), a Matlab application (The Mathworks, Natick, MA).

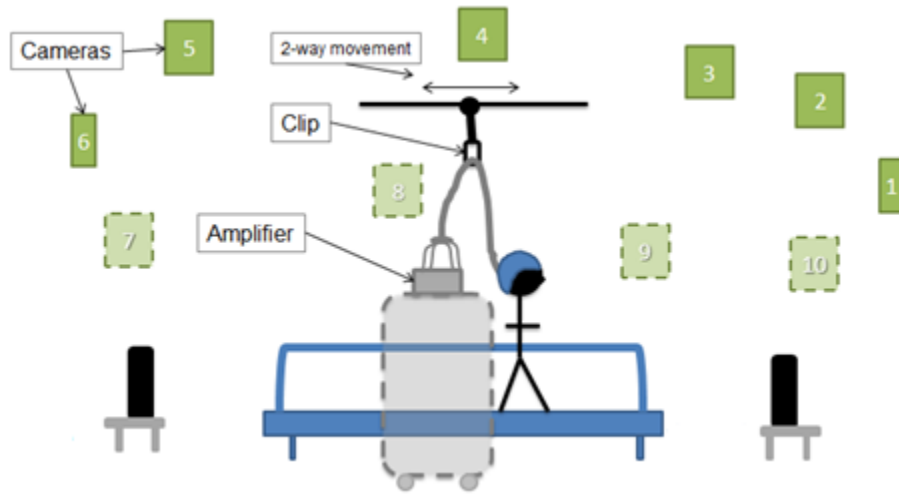


Figure 6. : Experiment setup. Green blocks represent Vicon cameras to track the reflective markers attached to the subject. Dim blocks are nearer to the observer perspective. Two screens showing the same stimuli were placed at both sides of the treadmill. The EEG cable connecting the cap and the amplifier was hung to the ceiling with a special device, as a means of reducing movement artifacts.

Stimuli. Visual stimuli consisted of a green fixation cross during the baseline period, an instruction about the condition, and a black fixation cross during the task. Between trials, the researcher asked the participants to turn around when the next condition was in a different direction than the previous one. Every condition was practiced once before the start of the experiment.

Procedure. After a brief introduction about the experiment was given, participants were asked to sign the informed consent form. Subsequently, the participant's height and weight were measured. Then, the EMG electrodes, EEG cap and the reflective markers were put in place. Measures of the leg length, knee width and ankle width were taken, in order to model the position of the limbs with the Vicon System. The Vicon system was calibrated by taking static video samples of the subject. Position of the markers was then checked by the experimenter, and corrected if necessary.

Next, participants were asked to walk on the treadmill for a few minutes to reach a comfortable step length while the experimenter adjusted the metronome speed to the stepping rate. The metronome was adjusted for forward walking and it was kept the same for backward walking. A metronome was adjusted to the stride frequency of the participant, and it was played both during the baseline period and the task period.

Participants were instructed not to chew and to blink as little as possible during the trials. A set of written instructions for each condition was given to the participants. They were explicitly encouraged to imagine themselves (kinesthetic imagery) walking during the imaginary conditions. They were also instructed to synchronize their walking to the metronome (which was already adjusted to their comfortable cadence), both during imaginary and actual walking.

Analysis

The position of the markers was recorded, modeled and labeled using the Vicon Nexus 1.7.1 Software. Each marker was labeled automatically by the software, according to a pre-defined model: the model for the legs was the plugin-gait model, and a custom-made model was used for the head consisting of one different label for each marker. All trials were inspected visually and any labeling errors were fixed manually. If a marker was missing during one or more capture frames, the gaps had to be filled by choosing one of the trajectories suggested by the Vicon Nexus Software. Two types of interpolation were suggested by Vicon Nexus: either spline interpolation, or a Nexus-generated trajectory based on a selected marker located in the same bone as the missing marker. The second interpolation method was preferred because the spline fill algorithm is susceptible to erratic motion in the last frames before and after the marker gap. The spline method was used only when no markers were available in the same segment. Missing markers in the limbs were caused by occlusion of the camera view with the treadmill's side handrails, with the amplifier, and with its support (Figure 6). After labeling and reconstructing the model, the information was exported to a c3d file with the Vicon Nexus software.

The EEG data was first imported to Matlab using the BioSig toolbox (Graz Technical University) and was further processed using Matlab (Matworks Inc.). Additional preprocessing and classification toolboxes were developed in-house at the Donders Institute, and can be provided upon request.

A program to classify walking and no-walking was implemented for Intra-stride spectral modulations and another was created for Inter-stride spectral modulations, as described in the proceeding subsection. Representative data for no-walking was taken from the baseline period; for walking, representative data was used from the trial period after the instruction. The data was analyzed using a classifier with different frequency bands as features. These frequency bands were the mu rhythm (8-12Hz), beta rhythm (12-25Hz) and both rhythms together (8-25Hz).

All classifiers were applied separately to the data of each condition of the experiment design (i.e., walking vs. no-walking was assessed for forward walking, backward walking, imaginary forward walking and imaginary backward walking data independently). As a result, the analysis yielded to 24 classification rates per participant (i.e., 2 tasks x 2 walking modalities x 2 spectral modulation categories x 3 frequency bands).

Classification. The data was analyzed offline according to the flow diagram shown in Figure 7. The first step was to import the EEG data into Matlab. In order to reduce processing times, the data was downsampled from 500 Hz to 250Hz. Afterwards, the data was sliced according to the 32 trials of the experiment, and was analyzed separately for different conditions. From this point, the preprocessing steps for the Inter-stride modulations was different from the Intra-stride modulations.

Inter-stride classification. Each trial was sliced into epochs of 2.5 s, and each epoch as then labeled as walking (1) for the period after the instruction, or no-walking (-1) for the data taken from the baseline period. Next, a Common-Average Reference (CAR) was calculated, the data was detrended and bad channels and outliers were excluded. Then, the data was re-referenced using CAR and then EMG artifacts were removed using Canonical Correlation Analysis (CCA) with 0.7 as the minimum correlation threshold and 1.5 as the

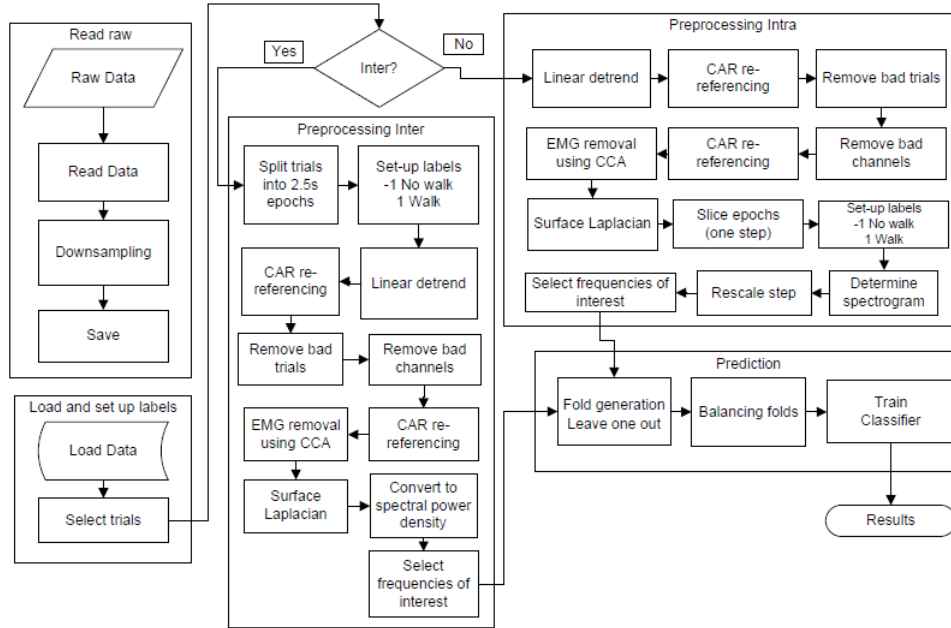


Figure 7. : Classification flow diagram. Trials of different conditions were analyzed separately using two different classifiers. The first was designed for Inter-stride spectral modulations, and the second for Intra-stride modulations. The main difference between both implementations was the preprocessing, as epochs were sliced differently.

standard deviation threshold. Next, Surface Laplacian was used to improve the EEG spatial resolution and to recalculate the values of the electrodes that were previously removed and the Spectral Power Density per frequency bins of 2 Hz was calculated using overlapping Hanning windows and the Welch method. Afterward, the frequency band of interest was selected. Finally, a linear logistic regression classifier was trained and tested using leave-one-out cross-validation.

Since the duration of the baseline was only five seconds and the trial itself lasted 45 seconds, the amount of data for the no-walking condition was less than the data for the walking condition. As a consequence, the classifier weights were adjusted to account for the smaller amount of information available for the no-walking class.

Intra-stride classification. The intra-stride classification is similar to the inter-stride classification, except that the epochs were sliced differently. Here, the trials were sliced into epochs of the same duration of a gait cycle, as detected from the markers for motion tracking. A function was designed to detect online heel-strike and toe-off occurrences based on the kinematics of the feet and position of the markers. For actual walking conditions, the detected heel-strike and toe-offs were used to determine the phases of the gait cycle. However, in imaginary conditions, movement is not performed and these labels are not available. Therefore, the metronome was used to generate time points of the step rhythm of the participant in the imaginary conditions.

Since stride length varies from one gait cycle to another, every epoch was rescaled using spline interpolation so that every gait cycle could be comparable with the next. However,

a disadvantage of rescaling is that the frequency content of the signal is altered. Because of this, the order of the preprocessing steps changed. First the signal was detrended, CAR was applied, bad channels and outliers were removed, the signal was re-referenced again, cleaned from EMG artifacts using CCA, the surface Laplacian was calculated and only then was the signal sliced into epochs and a label of no-walking (-1) was assigned to the data corresponding to the baseline period, and walking (1) to the data measured after the condition's instruction. Following this process, the data was detrended once more and transformed into the frequency domain using a Short-Time Fourier Transform algorithm with overlapping Hanning windows. Afterwards, the steps were rescaled and normalized so that time in every epoch represented the percentage of completion of the gait cycle. Then, the frequency band of interest was selected and finally, a linear logistic regression classifier was trained and tested using leave-one-out cross-validation. Analogous to the inter-classification, the classifier weights were modified to account for the disbalanced amount of data available for the two classes.

Additionally, the grand average of the data after the preprocessing stage was calculated and plotted. Plots of the EEG spectrum over all participants were analyzed for every electrode. Furthermore, the Areas Under the Curve of the Receiver-Operating Characteristic curve were also calculated after the preprocessing stage and plotted per subject. By looking at these plots it is possible to assess if the classifier was trained on motor activity and if it was influenced by motion artifacts and residual EMG artifacts.

Dependent variables. First, performance was defined as a balanced Classification Rate (CR), in which the mean classification rate of one class is averaged with the mean classification rate of the second. CR rates were calculated per participant, across all blocks. Confidence intervals for the classification rates were calculated using a binomial proportion confidence interval as described by Müller-putz, Scherer, Brunner, Leeb and Pfurtscheller (2008).

SPSS 19 was used as a statistical package for data analysis. The effects of the task, walking modality and the features used on the classification performance of the two types of classification was assessed using a repeated measures ANOVA. Performance was the dependent variable and four within subjects factors were added to the model: task (forward vs. backward), walking modality (actual vs. imaginary walking), frequency band (mu vs. beta vs. mubeta) and the type of spectral modulation used for classification (intra vs. inter).

Contrasts within the repeated measures ANOVA factors were used to assess the hypotheses proposed. It was expected that Actual walking would yield better system performance, because ERSDs are stronger than in Imaginary walking. Backward walking was expected to afford better performance because the less automatic the movement, the more modulations can be observed in the spectral power of the EEG.

Contrasts were also used to do pair-wise comparisons of the performance among different frequency bands. Finally, differences in performance between the two classifiers was also assessed.

Results

This section is divided in two parts. First, plots of the EEG spectrum and AUCs after the preprocessing stage will be described, to check that the signals used for classification are EEG, and not EMG artifacts. Second, the CRs of the tested combinations of tasks and

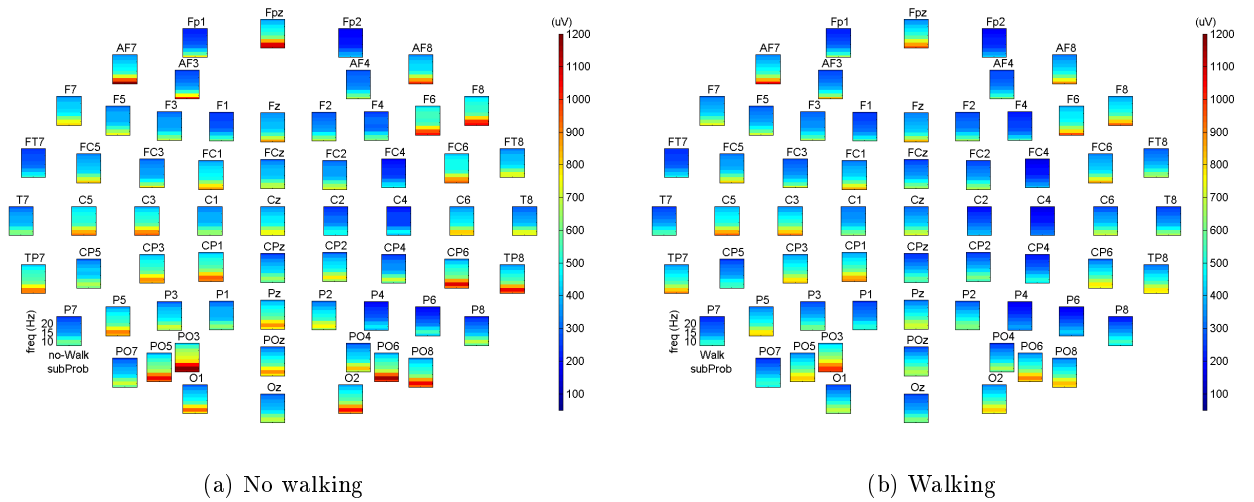


Figure 8. : Grand average spectral power in the mu-beta band for the inter-stride modulation in Backwards Walking. A relative change of spectral power can be observed when comparing both plots. Over all electrodes, the power during walking periods was less than in no-walking periods.

features will be presented, and significant differences in performance will be highlighted to answer the question of what combination of tasks and features provides the best performance.

After the preprocessing stage of the classification algorithm, the frequency content of the signals that were used for classification were inspected. The grand average over all participants showed both the inter-stride (figure 8) and the intra-stride spectral modulations (figures 9 and 10). These figures show both the spectrograms per electrode, of the no-walk class in the right and of the walk class in the left. The inter-stride change of spectral power is shown for backward walking and it is visible when comparing figure 8 (a) and (b). This ERSD is visible as a widespread decrease in power in the walking class with respect to the non-walking class. It is most visible near the motor cortex, lateralized around electrode C4 (and in CP5 to a lesser extent) .

Intra-stride modulations are also visible when comparing walking and no-walking. Figure 9 shows the spectrum for forward walking plotted with a relative baseline. As can be seen, during the walking class, there are regular modulations of power across the whole scalp, and they are specially visible at the C2 and CP5 electrodes. In contrast, these modulations are not present in the no-walking class. Interestingly, by eye inspection, intra-stride modulations are more noticeable during forward walking than during backward walking.

On the other hand, the intra-stride modulations are not as clear for Imaginary Walking. Figure 10 shows the case of Imaginary Forward Walking. Small modulations can be seen near the C4 and CP2 electrodes, approximately in phase with the modulations observed in actual walking conditions, but the magnitude of the power modulations across the scalp is almost zero.

The AUCs of the spectral densities were also explored to assess in more detail the differences in spectral power between the positive and the negative classes. These differences

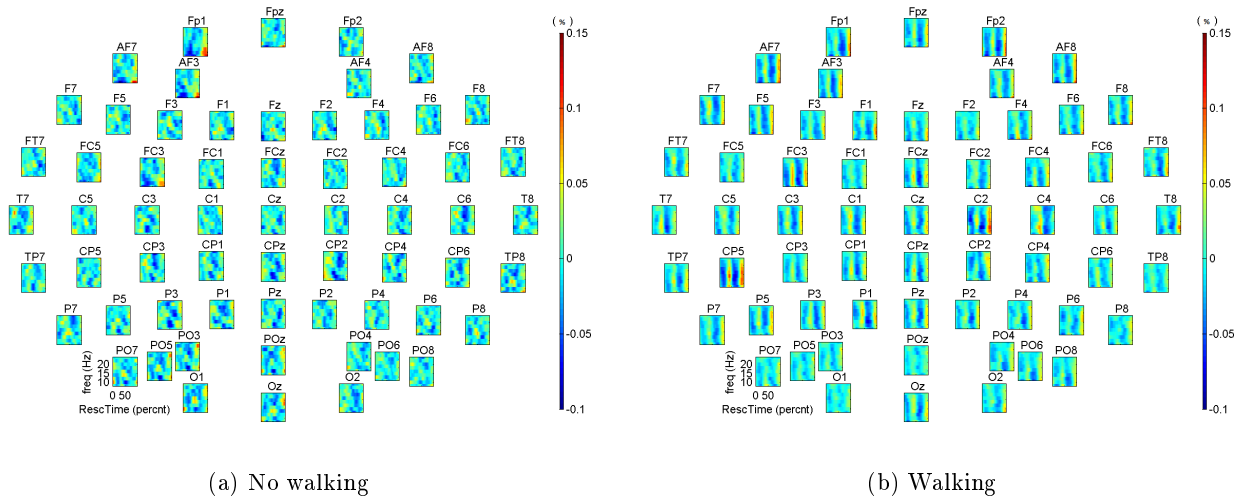


Figure 9. : Grand average spectral power in the mu-beta band for the intra-stride modulation in Forward Walking. Intra-stride modulations can be observed during walking, especially in the C2 and CP5 electrodes. Note that this is a plot relative to the baseline, and the color scale represents relative changes.

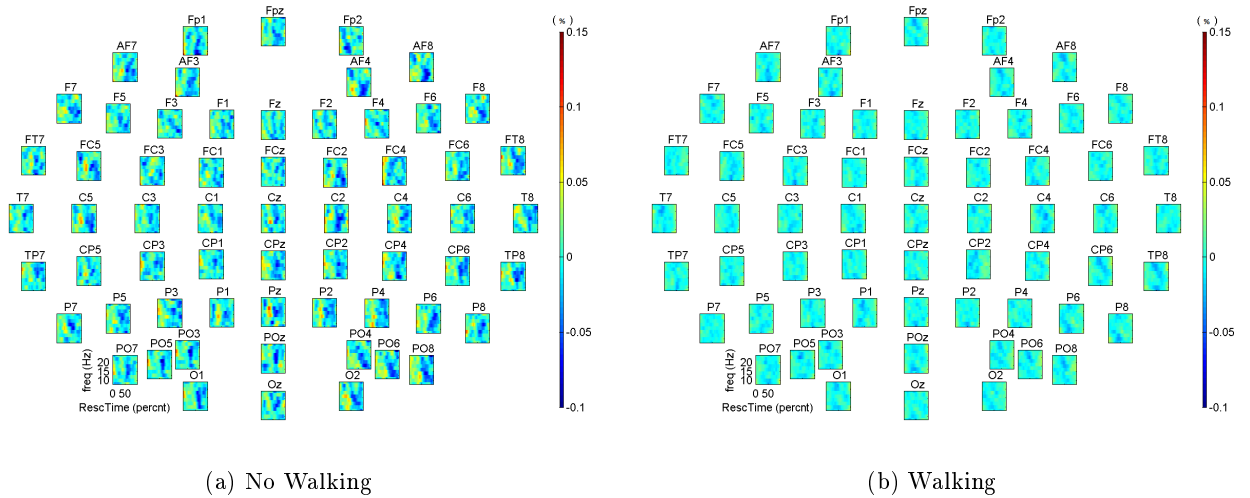


Figure 10. : Grand average spectral power in the mu-beta band for the intra-stride modulation, Imaginary Forward Walking. Slight intra stride modulations can be observed specially in CP2 and CP4 in the walking period. Note that this is a plot relative to the baseline, and the color scale represents relative change.

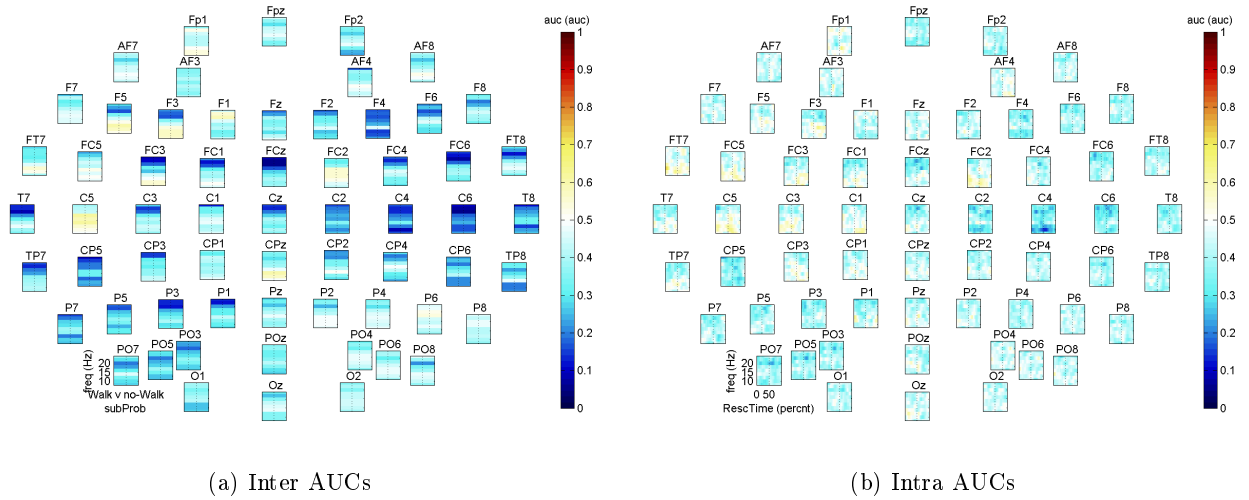


Figure 11. : AUCs for backwards walking subject 5. Both Intra and inter analysis show that the relative change of power is more prominent around the C4, FCz and CP5 electrodes.

are the ones that the classifier will probably consider, so they hint whether or not classification could use the ERSDs of interest. An AUC value of one is related to more power in the walking class than in the no-walking one, and an AUC value of zero to more power in the no-walking class than in the walking class.

Figure 11 shows the AUCs for Backward Walking. As can be observed from the picture, the ERSD change was stronger around FCz in the beta band and C4 and CP5 in both mu and beta bands.

Consistently with the inter-stride AUCs, the intra-stride version also showed that the relative change of power between walking and no-walking periods was bigger in the area of the CP4 electrode and its surroundings. Also, around CP5 the relative change was slightly of higher magnitude than in other areas of the head.

Average classification performance per subject per condition per spectral modulation and frequency band varied considerably between and within subjects (figure 12). For the inter-stride version, averaged CRs ranged from 53% to 86%. Error bars in figure 12 (left) also show that for two subjects classification rates reached 90%. In these two conditions, for the intra-stride classifier, CRs also varied considerably, ranging from 52% to 82%, and the maximum CR trial-wise was around 89%, whereas the smallest CR was almost at chance level. In the inter-stride classification, eight out of 12 participant had CRs significantly above chance level for all frequency bands, whereas for the intra-stride seven out of 12 performed above chance level (95% confidence intervals).

From these plots, it seems that CRs for intra-stride modulations are worse than those for the inter-stride. Figure 13 shows the average CRs per type of classifier, grouped per condition. From here it can be observed that indeed the inter classification seems to perform better than the intra, but only in Imaginary conditions. For Actual conditions, intra-stride modulations seem to give better performance. Furthermore, this pattern was consistent for all frequency bands. A repeated measures ANOVA revealed that this interaction of walking

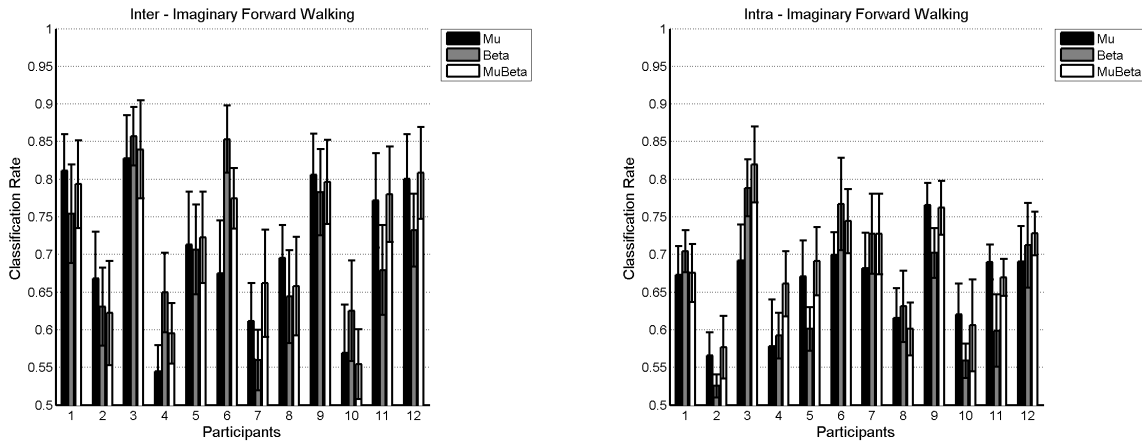


Figure 12. : Offline classification rates per subject for Imaginary Forward walking

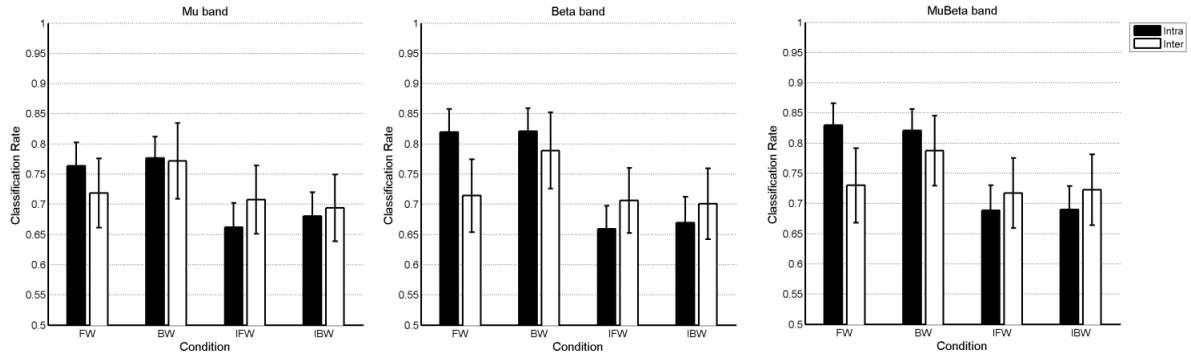


Figure 13. : Offline classification rates for Intra vs. Inter classifications in the three frequency bands

modality and spectral modulation had a significant effect on classification performance, $F(1,11)=13.001$, $p<0.01$, $\eta^2=0.0697$.

As seen in figure 13, regardless of the condition and type of classification, classification performance for the three frequency bands is quite similar, although the mubeta band seems to perform consistently better than the other two. Indeed, the main effect of the frequency band used as a feature on performance was significant, $F(2,22)=6.039$, $p<0.5$, $\eta^2=0.017$. Pairwise comparisons revealed that the mu and the beta bands significantly differed from the mubeta band, but not between each other.

In the inter-stride classification, CR for Backward Walking is slightly higher compared to Forward Walking, but not in the imaginary walking modality. For the intra-stride classification, this performance did not change much between task modalities. Differences between the different levels of task and spectral modality were not significant (all $p>0.05$).

Results show that the main effect of the walking modality significantly affected the performance, $F(1,11)=15.377$, $p<0.01$, $\eta^2=0.288$. This can also be confirmed from the plots in figure 13, as actual walking was more easily detected in both classifier types.

Conclusions

Classification of walking versus no-walking was successfully implemented based on the two types of spectral modulations proposed. Furthermore, classification rates were significantly above chance for most subjects.

Because actual walking can elicit stronger modulations than imaginary walking, walking modality was a factor that influenced performance significantly, as expected. Differences between different frequency bands were also found. In most of the cases, the combined mu and beta bands gave better results than did taking them separately. Contrary to the initial expectations, no significant differences between tasks were found, this is, backward walking did not differ in classification rate from forward walking.

As can be seen from the error bars in figure 12, there was high variability within-subjects, and from figure 13, variability was also large between-subjects. This is a well known problem in BCI, and might imply that even if a feature outperformed another, not all subjects can benefit from this choice.

Despite these differences, a grand average of the EEG power spectra showed that both types of modulations are located approximately on top of the motor cortex area and the posterior parietal area. Although both types of modulations are stronger on top of the motor cortex, the most prominent modulations were observed in areas related to hand movement.

7. Online BCI: simple versus complex walking

The previous experiment proved the feasibility of classifying EEG measurements into walking or no walking for both actual and imaginary walking. The aim of this experiment was to extend the findings of the previously implemented BCI to an online setup, and to assess the relationship between the performance of the BCI, the automaticity of the task (i.e., simple and complex walking), and three subjective qualities, namely, sense of agency, learnability and satisfaction. Furthermore, an offline analysis of the data was performed, in order to compare the classification results with the previous experiment.

Methods

Experiment design. Two interdependent variables were considered for the online setup in a 2x2 within-subjects design: walking modality (i.e., actual vs. imaginary walking) and task (i.e., simple walking vs. walking at varying speeds). These four conditions were presented in 16 blocks. In every block, each condition occurred once, in a counterbalanced order. All participants went through a total of 16 repetitions of every condition (64 trials in total). The first half of the blocks were used as input data to train the classification for every subject, and the second half were used to test the classification performance of the BCI. During the second half, participants received feedback about the outcome of the classification.

Two blocks out of the eight blocks available for feedback were used as “challenge” blocks: during the imaginary conditions of that block, the participant was instructed to alternate between walking and no-walking at will. The purpose of this was twofold. First, it let the participant have a better feeling of the interface in a less controlled scenario. Second, it was used to prevent the participant from changing between walking and no-walking without explicit instruction due to skepticism that the interface is working. The order of the challenge blocks was counterbalanced within the feedback blocks. Challenge trials were not included in the data analysis.

For offline performance analyses, an extra variable was included: frequency band of the selected features (i.e., mu and beta band). Dependent variables were classification rate, as a technical measure of performance, and the sense of agency, satisfaction and learnability as part of the subjective assessment of the BCI.

Four walking tasks were executed by the participants: simple walking, imaginary simple walking, complex walking and imaginary complex walking. A trial overview is shown in figure 14. Every trial consisted of 10 seconds of standing (i.e., baseline period), followed by the presentation of the instruction on screen (1 second). In the simple walking conditions the treadmill was then turned on at a constant velocity of 3 km/h. During complex walking the velocity of the treadmill changed four times. Both velocity and time intervals for each velocity were randomized. Velocities varied from 2.5 km/h to 4.5 km/h in steps of 0.5 km/h, time intervals varied from 6 s to 12 s. Together, the four velocity intervals lasted 35 s. The walking task lasted 30 seconds plus five seconds at the beginning, which is the time the treadmill takes to reach the desired speed. After the walking period, 10 seconds were given to let the treadmill stop completely.

Participants. Eleven healthy volunteers with no history of major lower limb injury and no known neurological or locomotor deficits participated and completed the first half of

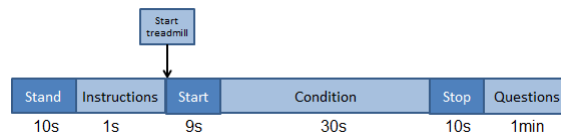


Figure 14. : Trial overview. A trial started with a baseline (stand) period that lasted 10 seconds, followed by instructions on screen about the next condition. Then, 9 seconds were required to start the treadmill. The subject walked or imagined himself walking for 30 seconds and finally 10 s were required to stop the treadmill during actual walking conditions.

this study, and nine out of the 11 also completed the feedback blocks. The mean age of the participants was 25 ($SD=2.19$) years. Before the start of the experiment, the participants were asked to read and sign a standard informed consent form, approved by the Ethical Committee for Behavioral Scientific Research of the Faculty of Social Sciences, Radboud University Nijmegen.

Experimental Setup. The experiment setup was similar to the setup of the previous experiment (as described in section 6), with some minor changes. The first difference was that instead of the whole Plugin-Gait Model, only seven markers were placed on the shoes of the participants: the RANK, RTOE, RHEE, LANK, LTOE and LHEE of the Plugin-Gait Model were used. An additional marker was added in the left shoe, as asymmetry between both feet improved the online labeling of the Vicon Nexus software during the online setup.

Subjects walked on a programmable treadmill at a velocity programmed according to the speed of the walking condition, facing a monitor screen placed 80 cm above the floor and 150 cm away from the treadmill. In order to reduce movement artifacts, the same clip setup was used as in the previous experiment (see figure 6).

The control of the flow of the experiment was programmed using Brainstream (DCC, Radboud University Nijmegen, <http://www.brainstream.nu>), and an application in Matlab (The Mathworks, Natick, MA).

Stimuli.

- **Offline training**

The visual stimuli consisted of a virtual treadmill, as depicted in figure 15. In the baseline period (no-walking) it was shown as a static picture without colors (figure 15-a). During the walking period, the light stripes moved towards the participant in an animation loop. Stepping instructions were given as color cues. The central stripe of the treadmill flashed in orange to indicate that a heel strike with the right foot should be made, and it flashed in blue to indicate a left heel strike.

The distance between bars was adjusted to the step length of the participant and the frequency of the orange-blue cues was set to the stepping frequency of the participant, as determined before the experiment (See previous section).

- **Feedback**

During the feedback part of the experiment, classification rates were color coded on top of the visual stimuli for stepping (figure 16). The class predicted by the classifier was determined by the color of all stripes (orange was no-walking, blue was walking). The transparency of

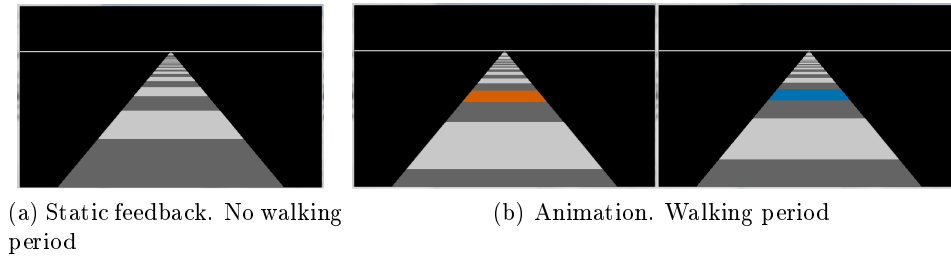


Figure 15. : Stimuli during the offline training part of the experiment. The leftmost figure shows the virtual treadmill during the standing phase, without cues for stepping. The two rightmost figures show two frames of the animation for walking. The stripes moved towards the user in an animation loop and the middle bars flashed in orange when the participant had to do a heel strike with his right foot, and blue when he had to do it with his left foot.

the bars was also modulated by the predicted probability that the class was indeed walking or not walking. The more transparent the color, the more close was the prediction to chance level. The more opaque the stripes became, the higher the probability the predicted class was correct.

In the baseline period (no-walking) it was shown as a static picture with colors indicating the outcome of the classification. During the walking period, the colored stripes were animated, and the same stepping cues were provided to the participant, in addition to the classification feedback (figure 16).

Procedure. The experiment consisted of three parts. During the first part, the participant went through eight blocks of four conditions each. This part will be referred as the 'offline training' of the experiment. The information obtained was used in the second part to build a classification model to distinguish between walking and no-walking. This period (heretofore referred to as 'train classifier'), lasted around 20 minutes in which the participant could take a rest. In the last part (called 'feedback'), the participant tried out the interface. Basically, the participant did the same task as in the offline training, but now on top of the visual stimuli, feedback was given about the classification rate of the classifier. After each condition, participants completed a questionnaire of nine questions about sense of agency, satisfaction and learnability had to be completed. The feedback part of the experiment also consisted of eight blocks of four conditions each, and the participant had an extra questionnaire after the 4th and 8th blocks. If requested by the participant, a short break after the 4th feedback block was taken.

Analogous to the first experiment, participants received a description of the experiment, and signed an informed consent form. Then, the participant's height was measured and the EMG electrodes, the EEG cap, and the reflective markers were put in place. The Vicon system was calibrated by taking static video samples of the subject.

Next, participants were asked to walk on the treadmill for a few minutes to reach a comfortable step length while the experimenter adjusted a metronome speed to determine their cadence. Stride length was calculated using the speed of the treadmill (3 km/h) and their stepping frequency.

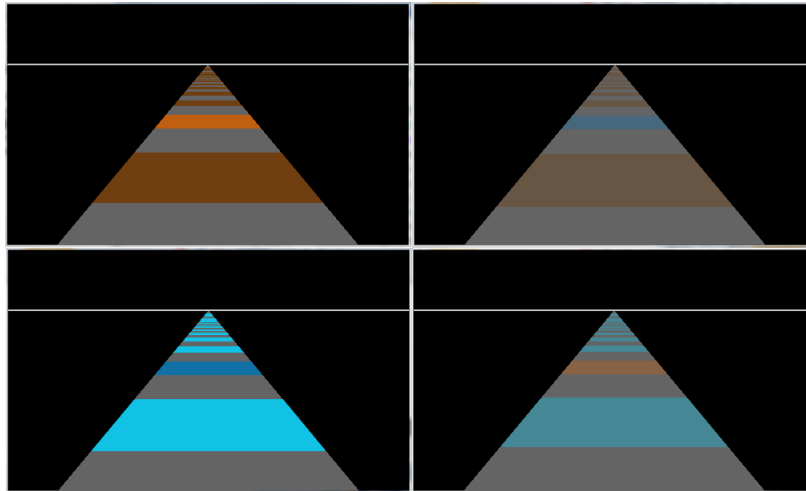


Figure 16. : Feedback Stimuli. During the feedback part of the experiment, the participants saw the classification rate color coded on top of the animation used to indicate the stepping rate. When all the stripes were orange, the classifier guessed no-walking, and when blue, it guessed walking. Furthermore, the more transparent the stripes became, the less certain was the classifier of its classification. In the top two figures, no-walking was guessed, and in the top left, the predicted probability of no-walking was higher than in the top right. Analogously, in the bottom figures, walking was guessed, and in the bottom left one the probability of the person walking was higher than in the bottom right one.

Finally, participants were instructed not to chew and to blink as little as possible during the trials. A set of written instructions for each condition was given to the participants. They were explicitly encouraged to imagine themselves (kinesthetic imagery) walking during the imaginary conditions. They were also instructed to synchronize their walking to the visual stimuli, both in imaginary and actual walking. Before beginning the actual experiment, participants practiced the four conditions at least once, and as many times as they requested.

Measurements. A questionnaire of nine items was designed to measure sense of agency, satisfaction and learnability. Each dimension was represented by three questions: a prototypical item and two synonyms. The prototypical question for sense of agency was based on the questionnaire designed by Wegner, Sparrow and Winerman (2004). The satisfaction question was based on a usability questionnaire and was of the type “How satisfying was your experience with the interface?”. The prototypical question for perceived learnability was also based on usability questionnaires and was of the type “To what extent do you think you would need further practice in order to master the interface or not?”

Participants answered the questionnaire in a continuous scale of 10 cm, once after each trial, and were explicitly asked to answer the questions thinking only about the trial they just experienced.

Analysis

Since intra classification was less effective for imaginary walking in the previous experiment, it was decided that for the online setup, only inter-stride classification would be used. Also, after four pilots runs it became evident that intra-classification was difficult to implement online using the Vicon Nexus 1.7.1 Software. Motion tracking of the feet using the Vicon system was not suitable for detecting heel strikes in real time. The labeling of the markers was not done consistently and it had to be checked after the experiment. Furthermore, the time required to train an intra-stride classifier is approximately four times that required for its inter-stride counterpart, which is lengthy for an online setup.

Online BCI implementation. The data analysis began in the second part of the experiment. The data gathered during the first eight blocks was used to train three classifiers, one for each of the three proposed frequency bands: mu, beta and mubeta.

Afterwards, the three classifiers were compared and the frequency band that gave the best performance for that specific user was chosen and used during the online classification showed to the participant during the last eight blocks. In other words, the online classifier used the classifier recommended for that specific participant from his own data during the offline training part. This method was chosen because of the large differences in classification rates between subjects during the previous experiment.

As in the previous experiment, the EEG data was first imported to Matlab using the BioSig toolbox (Graz Technical University) and was further processed using Matlab (Matworks Inc.). Additional pre-processing and classification toolboxes were developed in house at the Donders Institute and can be provided upon request.

The offline inter-stride classifier developed during the previous analysis was used during the train classifier part of the experiment. The data used for offline classification was gathered during the first eight blocks. Next, the classifier weights were extracted as a regression equation that could generate decision values for online classification.

During the online experiment, data was recorded in 2.5 second segments. Each segment was then analyzed following all preprocessing steps as described in figure 7 for the inter-stride classification. Finally, the decision value was calculated using the preprocessed data and the classifier weights extracted during the train classifier analysis.

Each decision value was mapped to a p value ranging from 0 to 1 with the logistic function, where 0 represented the walking class, 1 the no-walking class and 0.5 chance level. In other words, p represents the probability that a piece of data belongs to one class or another.

The p value was used to calculate the level of opacity of the stripes in the feedback animation, hence, the BCI cycle was complete and feedback was given to the user approximately every 2.5 seconds.

Classification rates were calculated by considering first the CR of the no-walking part of the trial (baseline), and then averaging it with the CR of the walking part (after the instructions), which allowed for a balanced loss classification rate to be obtained.

Subjective Assessment. The scores of each dimension of the questionnaire were aggregated into one measure. By averaging the three equivalent questions per questionnaire. Afterwards, both the scores of the questionnaires and the classification rates per trial were

grouped into conditions and averaged over blocks. Next, the effects of task and walking modality on the classification performance, sense of agency, satisfaction and learnability were assessed using a repeated measures ANOVA. Finally, the effects of performance on each one of the dimensions of the questionnaire were assessed using pairs of correlations.

Classification rates were also grouped per condition, averaged over participants, and plotted to inspect possible trends in the performance over blocks.

Offline performance analysis. After the experiment, the training data was used to check the effects of task, walking modality and frequency band on the classification rates. Also, the spectrograms and AUC's were inspected to check for correct artifact removal and the localization of the ERDs used for classification.

Results

First, results of the online performance analysis are given, as well as the results of the analysis of the relationship between performance and the subjective measures. Next, results of the offline analysis of performance are given.

Online performance analysis and subjective assessment. Figure 17 shows the average online classification rates per participant. Large error bars illustrate high within-subjects variations. Mean classification rates per participant range from 52% to 96%. In average, classification seems to be best for Simple walking, followed by Complex walking. The imaginary conditions seem to have similar classification rates among them, although for Imaginary complex walking between-subjects variability is larger than for imaginary simple walking. Indeed, a trend was found in the effect of walking modality on performance: contrasts revealed that Actual walking has significantly better performance than Imaginary walking, $F(1,8)=3.766$, $p<0.05$, $\eta^2=0.1128$. However, the effects of the task on performance were not significant ($p>0.05$). From the three frequency bands available, the mu band was chosen as the best feature option for 3 subjects (33%), the beta band for one (11%), and the mubeta band for five subjects (55%).

Sense of agency was rated, in average, as 75% for Actual walking conditions and 69% for imaginary conditions. Satisfaction was rated as 74% for actual walking conditions and 69% for imaginary walking. Sense of agency was positively correlated with satisfaction in the four conditions ($p<0.01$). Finally, learnability was rated as 52% for Actual walking conditions and 50% for Imaginary conditions. A trend of the influence of tasks on the sense of agency was observed $F(1,8)=4.163$, $p=0.076$, $\eta^2=0.018$. However, effects of the task and walking modality on the sense of agency were not significant. For satisfaction, no effects of task and walking modality were found. Finally, the effect of performance on the sense of agency, satisfaction and learnability was assessed using correlation pairs - none of them was significant.

In order to explore possible learning trends reflected in the classification rates obtained by the participants along blocks, CRs were grouped by condition and averaged over participants. Figure 18 shows the resulting plot. Over the eight consecutive blocks a slight increase in performance for simple walking can be observed, whereas for complex walking classification rate seems to decrease. For the Imaginary simple walking condition, performance seems to increase, but for complex walking the opposite effect can be seen.

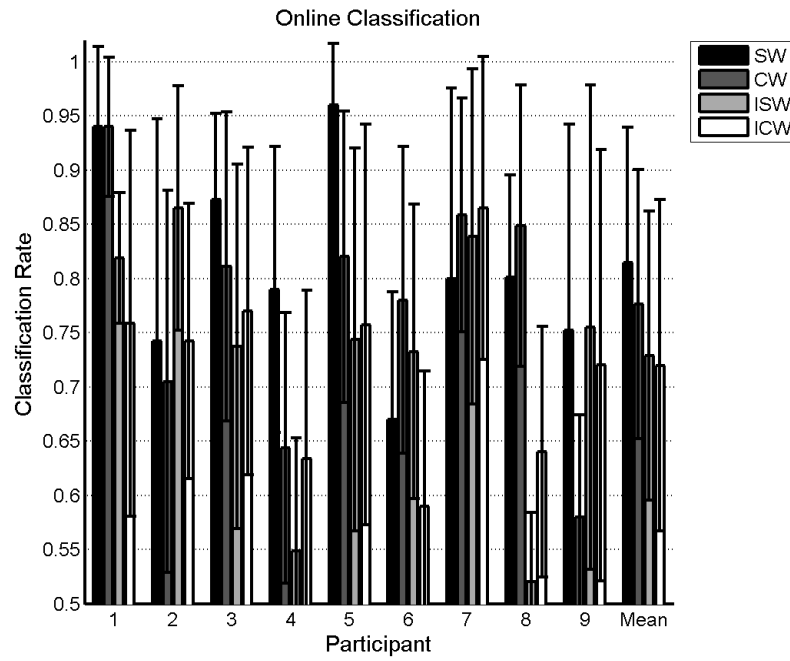


Figure 17. : Online average classification rates per participant and condition. The last group represents the mean classification rates overall participants.

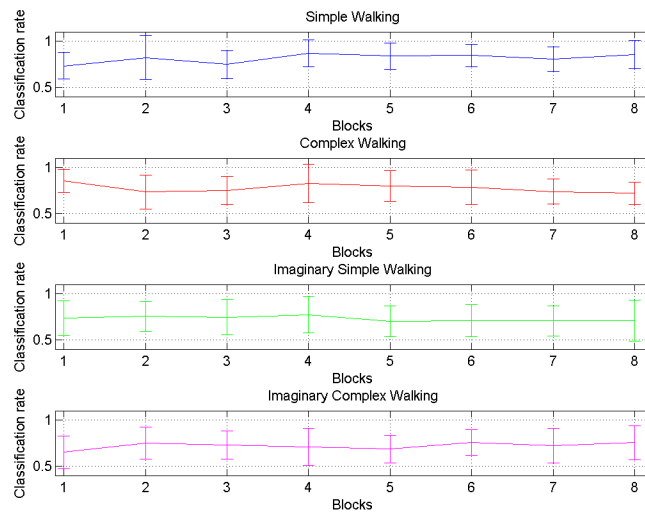


Figure 18. : Learning trends. Online average classification rates per block per condition. Error bars represent the standard deviation.

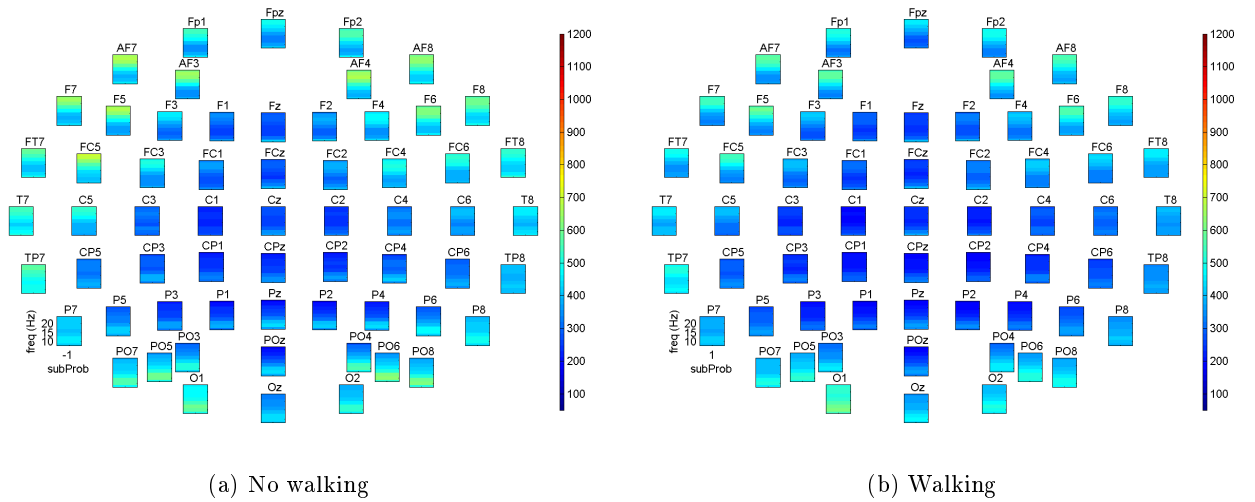


Figure 19. : Grand average spectral power in the mu-beta band for the inter-stride modulation in Imaginary Simple Walking. The relative drop of power of the walking period with respect to the no-walking period is centered in the Cz electrode, where the feet representation in the motor cortex is located.

Offline performance analysis. After the online experiment, the grand average of all participants' spectral power plots was calculated on the train data. Figure 19 shows multiplots for the no-walking class (left) and the walking class (right) in the simple walking condition. ERSDs can be seen around the feet area on the motor cortex (Cz electrode), this is, the spectral power is less in the walking period (and it is widespreaded over more electrodes) than in the no-walking period. A similar pattern is observed in the spectrograms of the other three conditions.

By examining the AUCs, it is easier to see the relative change of spectral power from no walking to walking. Figure 20 shows the AUCs for subject 9, Complex walking is depicted in the left and Imaginary complex walking in the right. For both conditions, the percentage of change of spectral power during the ERSD was more prominent around the CPz electrode, as well as around some electrodes in the parietal area. Interestingly, in some electrodes in the occipital and frontal areas, an ERSS can be observed. For subject 9, it can be observed that the change in power is more prominent in complex walking than in Imaginary complex walking.

As in the previous experiment, average classification performance per subject per condition and frequency band varied considerably between and within subjects (figure 21). Classification rates ranged from 58% to 97% in imaginary simple walking, and from 65% to 99% in Imaginary complex walking. The large error bars also show that there were large within-subjects changes in performance. In both conditions, classification rates for nine out of 11 participants (81%) were above chance level (95% confidence intervals).

Figure 22 shows the CRs averaged over participants. In line with previous results, the mu-beta frequency band performs better than the other two, except during simple walking, where the mu band is slightly better. Indeed, the effect of the frequency band used as a feature

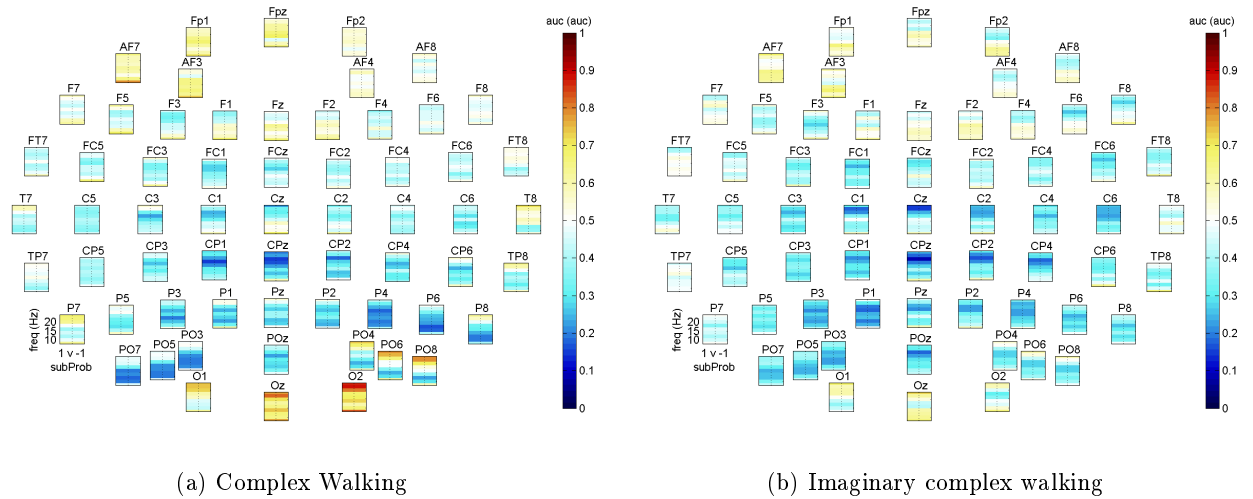


Figure 20. : Inter AUC for Subject 9. Relative changes of spectral power are more prominent around the CPz electrodes.

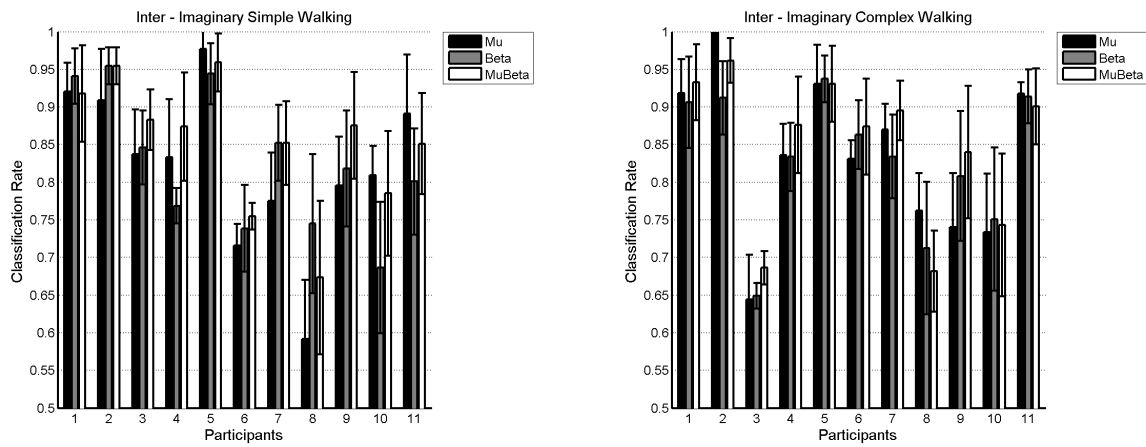


Figure 21. : Simple Imaginary Walking and Complex Imaginary Walking classification rates per participant.

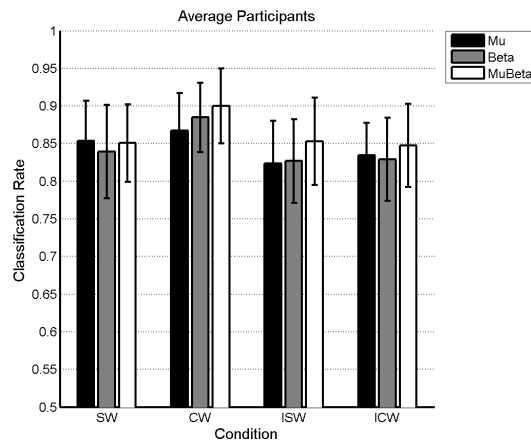


Figure 22. : Average classification rates per condition and different frequency bands. Classification rates for complex walking are slightly higher to their simple walking counterpart, for both walking modalities. Furthermore, the mubeta band achieves higher classification rates than the other two frequency bands.

for classification was significant, $F(2,20)=4.29$, $p<0.05$, $\eta^2=0.009$. Pairwise comparisons showed that the mu band performed significantly different from the mubeta band and that the beta band differed significantly from the mubeta band.

A trend was found in the effect of walking modality on performance. Contrasts were used to test the hypothesis that Actual walking has better performance than Imaginary walking, which resulted as significant $F(1,10)=4.869$, $p<0.05$, $\eta^2=0.031$.

Although, the influence of the task on performance was not significant, CRs for the complex walking condition are slightly higher than those for simple walking.

Conclusions

Whereas the BCI for walking was successfully adapted to an online setup for the inter-stride classification, the intra-stride version had real-time requirements for labeling and processing that could not be met with the software and hardware available. Furthermore, classification rates for the inter-stride classification were similar to those obtained offline.

Classification rates per subject did not change significantly from one block to another, suggesting that no significant improvement due to human learning can be gained within one session. However, some interesting trends can be observed from figure 18. In actual walking conditions, simple walking seems to increase performance in the long term, whereas complex walking decreases it. The inverse happens for imaginary walking conditions: simple walking performance decreases slightly over time, whereas the classification rates of complex walking improve. Despite these trends, average classification rates did not differ from one task to another.

Furthermore, perceived learnability was not significantly different from one condition to another. Neither were satisfaction and sense of agency (besides a small trend on the type of task). This suggests that the task does not influence the subjective assessment of the BCI.

Even though mean scores for sense of agency, satisfaction and learnability were, by eye, similar to mean classification rates, they were not correlated to performance¹. In other words, changes in the sense of agency, satisfaction and learnability are not related to changes in performance.

Even though the sense of agency was not related to changes in performance, it is interesting that the sense of agency did not change from actual walking to imaginary walking: this suggest that a link between one's intentions and the interface was created. Despite the interesting results, it must be noted that the sample size was small, especially for the subjective assessment.

Overall, the mubeta band achieved better performance than the mu and beta bands separately, confirming results from the previous experiment. This result indicates that the differences among both bands are complementary and that the more information the classifier has, the better the achieved classification rates.

As expected, Actual walking yielded better classification results than imaginary walking because modulations are stronger. However, this effect is small (about 3%). It is possible that the sample size (11 participants, offline analysis) was not large enough to find the effect. However, it is promising that the achieved performance in imaginary walking is similar to that in actual walking.

The grand average of the spectrograms for this experiment showed an ERSD surrounding the Cz electrode where the feet area is located. This effect was confirmed by the AUC plots, which showed that differences in spectral power between walking and no walking periods are larger around the CZ electrode. However, the AUC plots also showed increases in spectral power in the walking periods with respect to the no-walking around frontal and occipital electrodes and bigger in magnitude during actual walking conditons. This might be related to residual movement artifacts causing differences between walking and no walking especially in the neck area. Since complex walking implies an actual movement, the difference between spectral power in walking and no-walking picked up in the back electrodes is more prominent.

¹The correlation could be overestimated because of the within-subjects design.

8. General discussion

The main goals of this study were to prove the feasibility of using walking imagery and EEG to implement a BCI for walking, and to determine which combination of tasks and features could maximize the performance of the BCI while providing a good sense of agency, satisfaction and learnability. In order to achieve this, a BCI was successfully implemented using different combinations of features (spectral modulations and frequency bands), tasks (forward and backward walking) and walking modalities (actual and imaginary walking). The BCI was tested offline using the data from the first experiment. Afterwards, the same processing pipeline was used to implement an online BCI for complex walking and simple walking. During the online experiment, sense of agency, satisfaction and learnability were assessed.

Despite the large variability among and within subjects, average classification rates were above chance level for most participants, demonstrating that we were successful in our goal of making a BCI for walking. Such variability should be considered when designing new BCIs, in order to choose the best combination of relevant features for every subject. For instance, the online version of the BCI was based on the best frequency band per subject. Among the aforementioned frequency bands, the mu and beta bands together gave better results than when tested separately. A possible explanation is that the more information available, the better the classifier can discriminate between the two classes.

An initial concern was the measurement of EEG during walking and the removal of artifacts such as EMG and artifacts induced by movement. In order to partially solve this issue, CCA was applied to the data at a preprocessing stage, with satisfactory results as can be seen in figure 9, this process was fast and worked well enough.² Usually, EMG artifacts are high frequency components coupled to the gait cycle, similar to the EEG. However, in this plot it can be seen that the signals detected by most occipital electrodes are filtered and that the modulations picked up by the EEG are clearly represented above the motor and the parietal cortex.

Even though CCA was useful in removing EMG artifacts, some artifacts might remain due to movement, as shown by the differences between the spectrograms and AUCs of walking and no-walking in the occipital electrodes in both experiments. As Severens et al. (2012) already suggested, an alternative would be to track head movements and uncorrelate them from the EEG signal. This could be considered for further analysis of the current data. A second alternative would be to train the classifier using less and more central electrodes to ensure that only signals of interest are being considered for classification. Previous studies have already showed that, with enough training, a person is capable of adjusting his mental activity to control a BCI even with only one electrode (Wolpaw & McFarland, 2004).

In order to select the important electrodes for classification, the localization of the ERSDs of interest is also important. Our results suggest that cortical activity varies along

²Note: care must be taken in interpreting the off-line results as they may be over-estimated as the EMG removal filter was estimated on all the data before the classifiers cross-validation loop was used to estimate performance. This may lead to a double-dipping problem. According to Kriegeskorte et al. (2009), double dipping is the use of the same data set for selection and selective analysis which often yields overestimated classification rates. However, whilst a concern, as the on-line results (where this is not a problem) were similar to the off-line results we do not believe this is a significant issue. Follow-up studies should take this into account and include the CCA inside a nested cross-validation for offline analysis.

the gait cycle (as previously described by Gwin and colleagues (2011) and Severens et al. (2012)), and that these variations are located approximately in the vicinity of the primary motor cortex and the posterior parietal areas. Posterior parietal cortex has been linked to selective and rhythmic attention, combination of sensorimotor and visuomotor information, and bimanual coordination (Gwin et al., 2011; Lange et al., 2005).

Another promising result is that the achieved performance in imaginary walking is similar to that of actual walking, which confirms theories that motor imagery is represented as an actual movement, to some extent (Lange et al., 2005). This is, participants were able to achieve classification rates of 70% in average for imaginary conditions within one session. Therefore, using motor imagery of walking, being a more intuitive movement, results in better classification performance when compared to the use of other imaginary movements such as simple hand and feet movement as the movements used by Pfurtscheller, Leeb, et al. (2006).

Despite both types of spectral modulations were stronger in electrodes located on top of the motor cortex, the most prominent changes in the forward versus backward experiment were usually located in areas related to hand movement. This might be because the representation of one foot in the brain is opposite to the other, and the projection of the current dipoles generated by them is attenuating each other and thus, the differences of potential detected by the EEG are those that are projected with different angles (Pfurtscheller, Brunner, et al., 2006). Another possibility is that walking is a whole-body movement that is not limited to the feet and, therefore, hand movement might be playing a role in the classification. Indeed, a potential disadvantage of the inter-stride spectral modulations is that it is based on a motor ERSD, which any kind of movement can generate. Therefore, by using inter-stride modulations there is no guarantee that the BCI is really working for foot imagery. In contrast, intra-stride modulations are coupled to the gait cycle, but are much weaker in magnitude than the inter-stride modulation, and resultingly are more difficult to measure.

Although no significant differences between the two types of classification were found, the interaction of spectral modulation type and walking modality was significant: intra-stride classification seems to work better for Actual walking, and inter-stride classification for Imaginary walking. This might be because the subject did not perform the task correctly. Probably people are unable to imagine every phase of the gait cycle while keeping the step frequency of the metronome (or the visual stimuli, in the second experiment). Thus, intra-stride modulations are not clear during imaginary conditions. Furthermore, during actual walking conditions the phases of the gait cycle were reliably identified using the Vicon reflective markers and, in contrast, during imaginary walking conditions it was up to the ability of the participant to synchronize every step with the metronome. If the stepping rate was not locked to the stimuli, then the intra stride modulations would be dephased from each other as well, and would be cancelled out during the averaging. This may indicate that performance could be better with better trained subjects who can imagine detailed feet movements according to a predefined rhythm.

Advantages and disadvantages of both types of spectral modulations during walking can be considered when designing a BCI for rehabilitation. Intra-stride modulations were better for classifying actual walking, whereas inter-stride modulations were better for imaginary walking. This finding suggests that an inter-stride modulated BCI could be used at the

beginning of the rehabilitation process to detect any kind of imagery or attempted movement that the patient can elicit. In this way, the timeless inter-stride modulations will help the patient in the early stages of rehabilitation, and as his motor control improves, the practice could be tuned with intra-stride modulations that could give time-sensitive feedback and consider individual phases of the gait cycle. Further research should be conducted in order to improve both types of classification and to match their special qualities to develop a BCI that could help patients relearn to walk. For example, a patient suffering from a stroke would have limited -if any- motor abilities in his legs. In order to recover this functionality, the rehabilitation process suggests constant practice. Right after the stroke, motor activity in the brain would be limited, therefore, inter-stride modulations would be suitable to detect ERSDs related to attempted movements, even if the attempt was not accurate. As the training process goes on, the patient will gain mastery in imagining movements and he will regain movement as well, little by little. Once at this stage, the patient could use the intra-stride version of the BCI to practice every step according to the gait cycle. At the latest stages of the rehabilitation, if the patient can already produce some movements, the proposed BCI could also be used to give feedback during actual walking.

For the rehabilitation process, it is important that a BCI provide senses of agency, enabling the patient to attribute the BCI feedback to his own efforts. The results of this experiment also showed that the sense of agency did not differ much between different walking modalities: although a change in feedback is caused just by imagining a movement, to some extent, participants attributed the change to themselves. This phenomenon is evidence in support of using motor imagery for rehabilitation. Imaginary and actual walking could be considered as interchangeable, and their consequences in the world are both attributed to the self will power (Wegner et al., 2004; Gallagher, 2000).

Other effects of task and performance on the sense of agency, satisfaction and learnability were not significant. Even within the few significant results described above, the effect sizes were relatively small. The first possible explanation is the small sample size used during this experiment. Another limitation of this study was that the questionnaire used was not validated beforehand. It would have been beneficial to test more subjects or to do more pilot runs to test the questionnaires. However, given the length of the experiments and the time available for this project, a whole validation of the questionnaire and methodology would not have been possible.

Given that setting up a BCI and testing it is time-consuming, and tiring for end-users, an alternative could be to simulate the BCI application, so that it can be tested quickly and improved according to the user's needs during the design process. For instance, Boland, Quek, Tangermann and Williamson (2011) suggested performing fast prototyping of BCIs using simulations of the expected BCI accuracy. By using these simulations, experiment set up times could be reduced and therefore, times between each iteration of the design cycle could be optimized.

Future work could also include decoding of the direction of the movement or the walking speed. Direction could be decoded by looking at the lateralization of the inter-stride modulations, whereas the speed could be inferred from the intra-stride modulations.

The high offline classification rates achieved for forward and backward walking were consistent with the ones obtained in the offline and online analysis of the simple and complex walking. This suggest that the BCI is robust for different walking tasks and modalities.

9. Conclusions

The present study proved the feasibility of decoding walking and walking imagery using EEG. Two different types of ERSPs were used to distinguish walking from no-walking in both actual walking and imaginary walking. Furthermore, an online BCI for walking was implemented successfully with classification rates analogous to the offline classification. Importantly, the results were robust for different levels of automaticity in the walking task (simple walking, complex walking, backwards walking).

In order to maximize the system performance, several tasks and features were chosen and compared: task (simple and complex walking), spectral modulations (inter-stride modulations and intra-stride modulations) and frequency band (mu, beta and mubeta). The mubeta band improved performance when compared with the mu and beta bands separately. However, no significant differences were found between either the automaticity of walking or the spectral modulations. Only the interaction between walking modality and spectral modulations was significant for the first experiment, showing that the inter-stride modulations are better at classifying during imaginary walking while the intra-stride modulations are better at classifying during actual walking.

The interactions between task, performance and three subjective measures were also assessed. However, no significant effects of task and performance on the sense of agency, satisfaction and learnability were found, probably due to the small sample size.

Recommendations for the design of a BCI for rehabilitation were also given. Findings of the current research suggest that the intra-stride and inter-stride classification methods could constitute two phases of patient rehabilitation. Inter-stride modulations could help during early stages in the rehabilitation process, whereas intra-stride could be more useful to fine tune practice according to the gait cycle phases. Furthermore, the mubeta band proved to be more suitable to achieve high classification performance. However, due to the high variability between subjects, it is recommended to choose the best frequency band per user.

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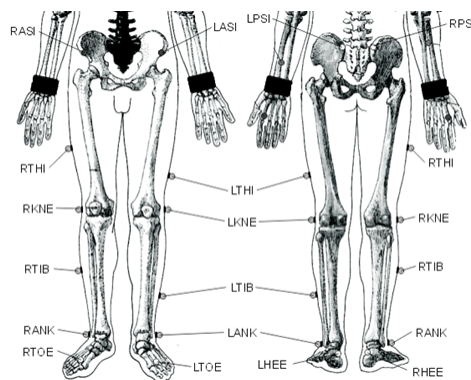
Appendixes

A. Forward versus Backward Walking

Instruction forms . Welcome and thank you for participating. In this experiment we are looking at EEG brain signal differences between forward and backward walking. Therefore, I will ask you to walk into this treadmill in both directions. This research will be helpful for rehabilitation as well as for Brain-Computer Interfaces, this is, people could move virtual avatars, prosthesis, etc. with their minds. This is another reason why you will also be asked to imagine yourself walking backwards and forward while we take the appropriate measurements.

You will use an electrode cap, which has some electrodes on it. After you put it on, each electrode will be filled with gel, in order to improve conductivity. You will also be required to wear shorts, in order to place reflective markers on several places from the hips to your feet. In the schema below you can see the location of your body where the markers will be placed. As you can see, the references are your bones, so the researchers will locate the appropriate bones first, they will make some crosses where I'll put them later. Four electrodes will also be placed in your neck to measure electrical signals from your muscles, this will help us to reduce noise in the EEG signal.

In light of this explanation, please sign the informed consent form in next page. With this form you acknowledge that you know your basic rights as a participant: the data from this experiment, including the video recording, will be treated with confidentiality and respect and it will only be used for research purposes. If at any point during the experiment you do not want to continue, you can quit without consequences. If you don't have any more questions I would like to ask you to read the form and sign it.



MODEL 1

INFORMED CONSENT*

for participation in the scientific study:

Sensorimotor cortical activity during human gait: forward versus backward walking

- I am satisfied with the information about this experiment. I have read the written information (*version code: 1*) carefully. I was given the opportunity to ask questions about the experiment, and my questions were answered to my satisfaction. I have carefully considered my participation in the experiment. I understand that I have the right to withdraw my participation in the experiment at any moment without having to give a justification.

- **I consent with participation in this experiment.**

- **I consent that the data collected during this experiment and made anonymous can be used for publication.**

Name :

Date of birth :

Signature :

Date:

- Signatory declares that the person named above has been informed both in writing and in person about the experiment. Also, he/she declares that the participant may terminate participation in the experiment at any time without consequence.

Name :

Function :

Signature :

Date:

** This form is intended for research on people of 18 years and older able to give informed consent. In this type of research, it is mandatory for the person concerned to give his or her consent personally.*

General instructions

Please stand on the treadmill and look to the fixation point on the screen. During the trial, please blink as less as possible, and please don't chew. Also, please try to keep your head as still as possible, this is, try NOT to move much. This is important because the described movements (blinking, chewing and moving the head) would create noise in the recordings.

At the beginning you will see a green cross, please stand still and wait for the instruction on screen. Four conditions are possible, and for each one of them you will have to do as described below.

Forward Walking

You will see an instruction on the screen. When the black fixation cross appears the treadmill will start moving. Please start walking and look at the fixation cross also on the screen. Try to keep your head still and your stride length constant. This is, the size of your steps should remain more-less the same. You will hear a metronome during the whole trial, which has been adapted to your walking speed. Try to synchronize your toe off with the tick of the metronome, this is, every time you hear a tick, try to lift your foot from the ground.

Backward Walking

Please turn around. You will see an instruction on the screen. When the black fixation cross appears the treadmill will start moving. Please start walking and focus on the fixation-cross presented on screen. Try to keep your head still and your stride length constant. This is, the size of your steps should remain more-less the same. You will hear a metronome during the whole trial, which has been adapted to your walking speed. Try to synchronize your toe touching the ground with the tick of the metronome.

Imaginary Forward Walking

A black fixation cross will appear right after the instruction on screen. Then, start imagining that you are walking while looking at the fixation point on the screen. You will hear a metronome with two different ticks. The loud tick will correspond to the left foot, and the soft one to the right foot. You can use the metronome as a guide to imagine that your feet are touching the ground, one after the other. Imagine that you are moving your feet and legs as in the forward walking trial. One step after the other, imagine the rhythm you used, the constant stride length. Please imagine that you are walking in first person, this is, imagine the movement as if you were walking on the treadmill as in a real movement (not just imagining looking at yourself walking). Please remember that this is just imaginary walking, so don't contract or move any muscles at all.

Imaginary Backward Walking

Please turn around and stand on the treadmill. A black fixation cross will appear right after the instruction on screen. Then, start imagining that you are walking while looking at the fixation point on the screen. You will hear a metronome with two different ticks. The loud tick will correspond to the left foot, and the soft one to the right foot. You can use the metronome as a guide to imagine that your feet are touching the ground, one after the other. Imagine that you are moving your feet and legs as in the backward walking trial. One step

after the other, imagine the rhythm you used, the constant stride length. Please imagine that you are walking in first person, this is, imagine the movement as if you were walking on the treadmill as in a real movement (not just imagining looking at yourself walking). Please remember that this is just imaginary walking, so don't contract or move any muscles at all.

B. Simple versus Complex Walking

Instruction forms . Welcome and thank you for participating. In this experiment we are looking at EEG brain signal differences between walking and no walking in four different conditions. Therefore, I will ask you to walk into this treadmill. This research will be helpful for rehabilitation as well as for Brain-Computer Interfaces, this is, people could move virtual avatars, prosthesis, etc. with their minds. This is another reason why you will also be asked to imagine yourself walking while we take the appropriate measurements. The experiment will have three parts. During the first, we will gather some information of how your EEG looks like during walking, so that in the second part, the computer can build a model to distinguish between walking and no walking. In the second part, you do not have to do anything, so it is break time. During the last part, you will have the opportunity to try out the interface. By doing the same task as in the first part, the computer will try to guess if you are walking or not, or if you are imagining yourself walking or not. After each condition, we will ask some questions about what do you think and how do you like the interface. You will use an electrode cap, which has some electrodes on it. After you put it on, each electrode will be filled with gel, in order to improve conductivity. You will also be required to wear reflective markers on your shoes or bare feet (this is your choice). Four electrodes will also be placed in your neck to measure electrical signals from your muscles, this will help us to reduce noise in the EEG signal. In light of this explanation, please sign the informed consent form in next page. With this form you acknowledge that you know your basic rights as a participant: the data from this experiment, including the video recording, will be treated with confidentiality and respect and it will only be used for research purposes. If at any point during the experiment you do not want to continue, you can quit without consequences. If you don't have any more questions I would like to ask you to read the form and sign it.

MODEL 1

INFORMED CONSENT*

for participation in the scientific study:
Brain-Computer Interface for Walking

- I am satisfied with the information about this experiment. I have read the written information (*version code: 1*) carefully. I was given the opportunity to ask questions about the experiment, and my questions were answered to my satisfaction. I have carefully considered my participation in the experiment. I understand that I have the right to withdraw my participation in the experiment at any moment without having to give a justification.

- **I consent with participation in this experiment.**

- **I consent that the data collected during this experiment and made anonymous can be used for publication.**

Name :

Date of birth :

Signature :

Date:

- Signatory declares that the person named above has been informed both in writing and in person about the experiment. Also, he/she declares that the participant may terminate participation in the experiment at any time without consequence.

Name :

Function :

Signature :

Date:

** This form is intended for research on people of 18 years and older able to give informed consent. In this type of research, it is mandatory for the person concerned to give his or her consent personally.*

General instructions

Please stand on the treadmill and look to the middle of the virtual treadmill on the screen. During the trial, please blink as less as possible, and please don't chew. Also, please try to keep your head as still as possible, this is, try NOT to move much. This is important because the described movements (blinking, chewing and moving the head) would create noise in the recordings.

At the beginning you will see a static version of the treadmill, please stand still and wait for the instruction on screen. This instruction will describe which of the four possible conditions is next. For each one of them, you will have to do as described below.

Simple Walking

You will see an instruction on the screen. When the virtual treadmill appears, the treadmill will start moving as well. In the treadmill you will see that two of the stripes are changing colors. Please start walking and try to synchronize your steps with the colors on the screen. When the orange stripe appears, please try to do a heel strike with your right foot, this is, every time you see the orange stripe appear, try to touch the ground with your right heel. Similarly, when the blue stripe appears, please try to do a heel strike with your left foot. Try to keep your head still, and look to the same point during the whole trial.

Complex Walking

You will see an instruction on the screen. The mechanism will be the same as in simple walking, with the sole difference that the velocity of the treadmill will be changing. After the name of the condition, the virtual treadmill appears, the treadmill will start moving as well. Try to synchronize your heel strikes of the right foot with the orange color, and the heel strikes of the left foot with the blue color. Again, try to keep your head still, and look to the same point during the whole trial.

Imaginary Simple Walking

A virtual treadmill will appear right after the instruction on screen, however, the treadmill will not move. Then, start imagining that you are walking while looking at the colors of the stripes on the screen. You can use the colors as a guide to imagine that your feet are touching the ground, one after the other. Imagine that you are moving your feet and legs as in the simple walking trial. One step after the other, imagine doing a heel strike with the right foot when seeing the orange color, and a heel strike with the left foot when looking at the blue stripe. Please imagine that you are walking in first person, this is, imagine the movement as if you were walking on the treadmill as in a real movement (not just imagining looking at yourself walking). Please remember that this is just imaginary walking, so don't contract or move any muscles at all.

Imaginary Complex Walking

Analogously to the imaginary simple walking condition, a virtual treadmill will appear right after the instruction on screen and the treadmill will not move. Then, start imagining that you are walking while looking at the colors of the stripes on the screen. You can use the colors as a guide to imagine that your feet are touching the ground, one after the other. Imagine that you are moving your feet and legs as in the complex walking trial. One step

after the other, imagine doing a heel strike with the right foot when seeing the orange color, and a heel strike with the left foot when looking at the blue stripe. The frequency of the changes in the color of the stripes will vary, so that you have to imagine yourself walking faster or slower, according to what you see. Please imagine that you are walking in first person, this is, imagine the movement as if you were walking on the treadmill as in a real movement (not just imagining looking at yourself walking). Please remember that this is just imaginary walking, so don't contract or move any muscles at all.

Feedback instructions

Now we are going to test the interface. The instructions are the same as for the train block, but now the guess of the classifier will be color coded on the screen. Walking is represented with light blue and no walking with orange. You will see that all the stripes of the treadmill are changing between these two colors according to the guess of the classifier on what you are doing. In other words, you should see the stripes in orange before the instruction, because you won't be walking, and blue after the instruction, because you will be walking. If the classifier is pretty sure about its guess, then you will see solid colors, and you will see the colors become transparent as the classifier becomes unsure about the condition.

Even though the colors of all the stripes are changing, you will still see that two stripes are changing between orange and blue, as before. Please use them to guide your steps while walking or imagining yourself walking, just as you did in the training part.

Please remember to look to the middle of the virtual treadmill on the screen. During the trial, please blink as less as possible, and please don't chew. Also, please try to keep your head as still as possible, this is, try NOT to move much. This is important because the described movements (blinking, chewing and moving the head) would create noise in the recordings.

Questionnaire . (Next page)

Block: _____
Condition: _____
Trial: _____

How much control did you feel that you had over the movement?

Not at all |-----| Very much

To what extent you think you would need further practice in order to master the interface or not?

Not at all |-----| Very much

How satisfying was your experience with the interface?

Not at all satisfying |-----| Very satisfying

To what degree did you feel you were causing the movement?

not at all |-----| Very much

Was the level of control you perceived over the trial constant or not?

Not constant at all |-----| Very constant

How content are you with the interaction?

Not at all content |-----| Very content

Did you feel an increase or a decrease of the control you had over this condition?

decrease |-----| Increase

To what extend you enjoyed or not the interaction?

Not enjoyed it at all |-----| Enjoyed it very much

Did you feel as if your skill in generating signals decreased or increased over the trial?

not at all |-----| Very much