Sensorimotor cortical activity during human gait: forward versus backward walking
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Abstract
In previous studies, cortical activity was found as related to the gait cycle, and these modulations seem to vary according to the level of automaticity of the movement. In this study, we aimed to distinguish whether these modulations were due to sensor or to motor processing using EEG, and whether or not they can be used to distinguish forward versus backward walking. Four conditions were compared in a within subjects experiment: forward walking, backward walking, imaginary forward walking and imaginary backward walking. Results shown that EEG measurements are coupled with the gait cycle, however, differences between sensor and motor processing could not be distinguished. Further analysis should be done in order to remove movement artifacts and to answer the question of interest. Therefore, two ICA approaches were proposed. Finally, observed modulations are promising features for a BCI for walking, especially in combination with tasks which maintain the user engaged. Such BCIs could help in the rehabilitation of stroke and spinal cord injury patients.

Introduction
Motor impairment and functional disability are the major consequences of Spinal Cord Injury (SCI) and stroke. SCI patients suffer from damage in the spinal cord, which 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, which is also known as CVA (Cerebrovascular Accident), is related to a distortion of the capacity of the brain to process neural information after a failure of blood supply.

Even though both problems present consequences related to motor impairments, the brain functionality in patients with SCI is assumed to be intact and capable of driving limb movements (Cramer, Orr, Cohen, & Lacourse, 2007; Enzinger et al., 2008), while in a stroke, the motor impairment is caused by brain damage (de Vries & Mulder, 2007). Therefore, rehabilitation strategies for both impairments follow different paths. Rehabilitation after a stroke is mainly based on therapy and practice. In this case, functional recovery is attributed to processes of reorganization and substitution in the damaged brain. For SCI, rehabilitation could follow two approaches. Firstly, repair of the damaged spinal cord and the use of cortical information to drive muscles, bypassing the area of damage. Secondly, Brain-Computer Interfaces, or BCI, allow the use of neurophysiological signals of the brain to control external devices (Birbaumer & Cohen, 2007), and could therefore be used to achieve the goal of bypassing damaged areas in the spinal cord and drive prosthesis or even the patients’ muscles.

Even if the damage which caused the impairment is not in the brain itself, 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 (Cramer et al., 2007; Enzinger et al., 2008). These abnormalities suggest that indeed the use or disuse of a brain functionality can influence cortical representations. In other words, reorganization of neural structures takes place as...
result of either depravation or increase of sensory input due to movements. Hence, 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 they cannot move or pain is involved with the movement. There is some evidence that imaginary movements might be helpful by providing means of practice when no actual movement can be performed (Mulder, 2007). Motor imagery refers to the cognitive image of performing a movement, without executing the actual movement. In fact, motor imagery can be thought as a tool which allows subjects to manipulate their movement representations, as internal models of actions (de Lange, Hagoort, & Toni, 2005). Imaginary movements are embodied and they can activate sensory-motor areas in the brain (Mulder, 2007). Indeed, research over the neural topography of movement representations has used imaginary movements to investigate how the brain deals with immediate action independently of movement execution: first, it combines somatosensory and visuomotor information (i.e. feedback) in the posterior parietal cortex; second, it generates an actual motor plan in the dorsal premotor cortex, and finally, it deals with movement execution in the motor cortex (de Lange et al., 2005).

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. In stroke physiotherapy, the patient is helped by a therapist to move the paralyzed limbs; therefore enhancing proprioceptive feedback. Another example from therapy are devices such as the Lokomat System (Hocoma Inc.), which have been designed to help injured patients to simulate the movement of walking with slightly better results than traditional therapy (Mayr et al., 2007). The simulation is achieved by using a treadmill with weight support and motorized boots. Visual feedback can also be provided by the Lokomat Pro. This system shows visual cues of walking on a screen with a virtual environment, where the patient is supposed to walk and complete some tasks. This augmented feedback enhances the patient active participation in the task. Therefore, a BCI using imaginary movements could help in rehabilitation, not only by providing the means of bypassing spinal cord injuries, but also to help both, SCI and stroke, patients to maintain and recover their brain functionalities by giving direct feedback of the imagined movements.

Despite the potential of BCI and its possible benefits in rehabilitation, there are few studies that 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 help movement recovery in stroke patients. The lack of proof is mainly due to the difficulty to identify “signatures” in the brain signal. Signatures are the association of a brain signal with a mental state that uniquely caused it (van Gerven et al., 2009).

EEG potentials are one example of neurophysiological signals that can be used to identify patterns useful to build a BCI. For motor imagery purposes, the mu-rhythm and beta-band are of special interest. Mu-rhythm refers to an oscillation of about 8-14 Hz in the EEG signal which cannot only be seen with movement, but also if one imagines a movement (Pfurtscheller, Stancák, & Neuper, 1996; Prasad et al., 2010). Central mu rhythms coincide with the alpha band (10Hz). An event-related desynchronization (ERD) in the mu-rhythm frequencies in humans has been linked to somatosensory stimulation or movement. Evidence for this has been found especially for hand movements. However, mu-band ERDs
for foot movements is more difficult to detect because the foot area is located within the mesial wall in the interhemispheric fissure. Beta band is also generated in the somatosensory cortex, but differently to mu rhythms, it is easier to detect, and time courses of recovery after desynchronization is faster in beta than in mu rhythms (Pfurtscheller et al., 1996).

The present research focuses on walking. The ultimate goal would be to provide feedback about imaginary walking movements, using a BCI. This could be applied in rehabilitation to improve the process of learning to walk again. Therefore, the identification of the correlation between patterns of movements during the human gait cycle and EEG potentials is crucial to develop such brain-computer interfaces.

A recent study by Gwin, Gramann, Makeig, & Ferris (2011), showed cortical involvement in EEG signals during human gait; they found intra-stride changes of activity in different brain areas, including the anterior cingulate, prefrontal cortex, posterior parietal cortex, and sensorimotor cortex. 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. The synchronizations between the gait cycle and the spectral power of the beta band were confirmed by a previous study (Peters, 2011). In this study, participants had to walk at different speeds, and 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 the cortical activity depends on experience and familiarity with the movements (Peters, 2011). From these results, the question arises on whether the found differences in cortical activity are caused by differences in the motor activity or changes in the sensory perceptions due to different movements.

Indeed, motor and sensor processing in the brain are highly interrelated, and sensory input can affect motor representations. Some research has suggested that action observation (sensory input) automatically triggers action stimulation and by this, action observation facilitates action execution (Mulder, 2007). It may also happen that the feedback connections between both sensory and motor components are so strong that they are indistinguishable and re-defined upon each other in a complementation loop (Duch, Bekkering, & Neggers, n.d.). A typical example is the discovery of mirror neurons, which fire not only while performing a movement, but also when someone else is seen executing a movement (Mulder, 2007; Rizzolatti & Craighero, 2004).

Therefore, it is important to consider the looping interaction between sensory feedback and motor control, in order to distinguish one from another. Specifically for human gait, it has also been stated that the control of movement includes both open-loop and feedback control strategies, and that the CNS plans and controls goal-oriented locomotion at a high cognitive level, independent of the motor implementation. However, the control of movement not only depends on the goal of the movement, but also on mental representations created by previous experiences of the person and sensory feedback. Several models have been proposed to describe the sensorimotor integration loop. Wolpert, Ghahramani, & Jordan (1995) proposed an internal model of sensorimotor integration, based on two models: a forward model that predicts the next state depending on the current state and the motor
command; and an inverse model that estimates the motor command according to sensory feedback and a particular state of transition. Furthermore, the type of model that is used depends on the user's experiences and how accurately the current state can be estimated. When the current state cannot be accurately estimated, then the control switches from a learned forward model, to sensory feedback. This model further evolved to include multiple paired models. Pham & Hicheur (2009) also modeled two interdependent control processes for trajectories during human locomotion, including an open loop component dependent only on the goal, and a feedback control schema, where sensory input helps to reach the goal by optimal feedback control. In addition, de Lange, Hagoort & Toni (2005) found that the occipito-temporal cortex deals with the subjects’ perceptual experience and modulates neural activity in order to create a motor plan in the frontal cortex and execute the movement through the primary motor cortex, following a loop similar to the one described by the aforementioned models.

From these models, three main elements can be extracted: sensory feedback, motor commands, and processing required to adjust the motor command given the actual sensory feedback and previous experience. In order to investigate the differences between these components, a task which implies a variation of the sensory feedback related to the type of motor command would be useful.

Regarding sensory input, five sources of response-related input in motor learning have been identified: proprioceptive, tactile, vestibular, visual and auditory (Mulder, 2007). Forward and backward walking seem to have similarities in most of them. Grasso, Bianchi and Lacquaniti (1998) compared the kinematics and kinetics of both directions of locomotion. The kinematics of forward walking are very similar to those of backward walking when mirrored in time, however, the kinetics of such movements are different, possibly implying different types of control (Figure 1). Therefore, sensory proprioceptive feedback is fairly similar in both conditions, and by choosing forward and backward walking as tasks, the other four sources of sensory feedback can be controlled during the experiment.

<table>
<thead>
<tr>
<th>Sensory Feedback</th>
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<th>Backward Walking</th>
<th>Imaginary Forward Walking</th>
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<td>Motor Command</td>
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<td>Control Processing</td>
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Figure 1. Experiment design. The sensorimotor integration loop consists of two basic blocks: Sensory feedback and motor processing. Within motor processing, motor command representation and control processing can be distinguished. Four conditions will be considered, forward (FW) and backward walking (BW), imaginary forward (IFW) and imaginary backward walking (IBW). By comparing FW vs. BW, differences in motor processing are expected, both in the motor command and control processing. By comparing imaginary walking vs. actual walking, sensory feedback is hypothesized to be different because of the lack of movement in imaginary walking.
Different motor commands will be evoked by letting the participants walk forwards and backwards. Different intensity of feedback will be achieved by comparing imaginary walking with actual walking. As shown in figure 1, we expect that the sensory component will be more intense during actual walking, and less intense during imaginary walking. We also expect to have different motor representations for forward and backward walking. Finally, there will be a control process component, which is expected to be more intense in less common movements, such as backwards walking. However, given the experimental design, it will be difficult to distinguish this control process from the motor command. Similitudes between forward walking (FW) and Backward Walking (BW) will give a clue of the sensory component and similarities between actual-imaginary walking pairs (i.e. FW vs. IFW, and BW vs. IBW) will help to identify the motor component within the measurements.

By differentiating changes of motor activity from the sensory representations, it could also be possible to use the motor part to determine whether the user wants to go in one direction or another. Hence, the aim of this study is to determine whether the differences in the observed perturbations in the EEG mu and beta bands, observed while walking, are caused by motor or sensory processing. Answering this question will shed light into whether these perturbations can be used to identify intended walking direction.

**Methods**

**Design**
The experiment design was a 2x2 within-subjects design. The two factors were the type of sensory feedback (actual walking, imaginary walking) and the type of walking behaviour (forwards and backward walking). These four conditions were presented in 8 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).

**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 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 kΩ 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. 16 markers were placed in lower limbs and 6 were attached to the EEG cap as indicated in figures 2 and 3.

Figure 2. 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 into the skin with a double-sided tape.

Neck muscle activity during walking was recorded on the m. trapezius with wireless EMG electrodes (Zerowire, Noraxon U.S.A. Inc.). Two pairs of electrodes (both active) were placed in the neck segment of this muscle, one pair in each side (left and right) of the muscle.

Subject walked on a programmable treadmill at a velocity of 3km/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 (both actual and imaginary walking). Identical screens were placed at both ends of the treadmill, to facilitate change of direction, as shown in figure 4.
In order to reduce movement artifacts, the EEG cap cable was clipped to a cable that hung to the ceiling with a device that could move along with the subject, and then connected to the amplifier (see figure 4).

![Figure 4. 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 were placed at both sides of the treadmill, showing the same stimuli. The EEG cable connecting the cap and the amplifier was hung to the ceiling with a special device, as mean of reducing moving artifacts.](image)

The control of the flow of the experiment was programmed using Brainstream (DCC, Radboud University Nijmegen, [http://www.brainstream.nu](http://www.brainstream.nu)), an application in Matlab (The Mathworks, Natick, MA). Three computers were used: the first for Vicon configuration, control and recording; the second for streaming of visual and auditory stimuli and online control/monitoring of stride length, heel strike and toe-off detection; and the third one as control computer for Brainstream and EEG recording.

**Procedure**

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 5. Every trial consisted of 5 seconds of standing (i.e. baseline period), followed by the presentation of the instruction on screen (1 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 9 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.
Figure 5. Trial overview. A trial started with a baseline (stand) period that lasted 5 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 45 seconds and finally 10 s were required to stop the treadmill during actual walking conditions.

**Experimental time course**

First, participants were welcomed, a brief introduction about the experiment was given, and then they were asked to sign the informed consent form. Subsequently, 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 as well, in order to model the position of their 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, meanwhile the experimenter adjusted the metronome speed to their stepping rate. This was done for both forward and 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.

Afterwards, participants were instructed not to chew and blink as less 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 also were instructed to synchronize their walking to the metronome (which was already adjusted to their comfortable cadence), both in imaginary and actual walking.

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. In between trials, the researcher asked the participants to turn around when the next condition was in a different direction compared to the previous one. Every condition was practiced once before the start of the experiment.

**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 predefined model. The model for the legs was the plugin-gait model, and the one for the head was custom made and consisted of one different label for each marker. All trials were inspected visually and any errors with the labeling of the markers were fixed by labeling them manually. In cases when a marker was missing during one or more capture frames, the gaps had to be filled by choosing one of the suggested trajectories by the Vicon Nexus Software. Two types of interpolation were suggested by Vicon Nexus, the first one used spline...
interpolation, and in the second, Nexus generate a trajectory based on a selected marker located in the same bone as the missing marker. The second method was preferred because the spline fill algorithm is susceptible to erratic motion in the last frames before and after the marker gap. Only when no markers were available in the same segment, spline was used. Missing markers in the limbs were caused by occlusion of the camera view with the treadmill’s side handrails, the amplifier and its support (Figure 4). Especially for head markers, the amount of flicker was considerably high because the cameras were pointing mainly to the feet, and for tall subjects the head markers were often out of range. Therefore, it was preferred to keep the data as it was, and interpolate the missing marker positions later on using Matlab. After labeling and reconstructing the model, the information was exported to a c3d file with the Vicon Nexus software.

Further analysis of the data was done using Matlab (Matworks Inc.). 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 then these labels are not available. Therefore, the metronome was used as time point of the step rhythm of the participant in the imaginary conditions. Figure 6 shows the different phases of a gait cycle, for both forward and backward walking. Start of the gait cycle was set to left toe off (LTO) in forward walking and left toe strike (LTS) in backward walking.

![Gait cycle phases](image)

Figure 6. Gait cycle phases. Four phases were 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. In other words, as forward walking is quite similar to backward walking when mirrored in time, when in forward walking a left toe off occurs, a left toe strike occurs in backward walking.

Head markers were averaged to give a single measure of translation of the head with three degrees of freedom. Previous to averaging, head markers which were visible 90% of the time or more were selected, and further gaps in the data due to missing markers were then filled using cubic spline interpolation. After averaging, the resulting marker data was sliced according to the detected steps. Since the steps have variable stride-length, they were rescaled to have a 0-100% scale. Afterwards, the head movement was averaged over conditions step-wise per subject.

For each subject, the movement of the head markers was compared to the EEG time-lock analysis of four electrode clusters: frontal (Fp1, Fpz, Fp2, AF7, AF3, AF4, AF8), central (C3, C1, Cz, C2, C4, CP3, CP1, CPz, CP2, CP4), temporal (F7, FT7, T7, TP7, P7, F8, FT8, T8, TP8, P8), and occipital (PO7, PO5, PO3, POz, PO4, PO6, PO8, O1, Oz, O2). The correlation between the movements and each channel was calculated.
Comparison analyses were performed per condition for FW and BW only, because in imaginary conditions movement tends to zero.

The EEG data was imported to Matlab using the BioSig toolbox (Graz Technical University) and was further processed using the ‘Fieldtrip’ toolbox (Oostenveld, Fries, Maris, & Schoffelen, 2011).

EEG data was sliced into epochs, which were equivalent to one step. Epoch length was calculated according to the detected steps for actual walking and to the metronome for imaginary walking. A pre-step and a post-step (both of 0.25 seconds) were kept in every epoch with the purpose of avoiding filter artifacts in the data of interest of each slice.

The data was visually inspected to reject outliers. Variance, minimum, maximum, range, kurtosis and z-value were used as measures. Extreme trials and channels were rejected. As result, several trials and only channel AF8 for subject 1 was rejected. For grand averages, AF8 was not considered for any of the subjects. Also, a notch filter was used to remove noise from the line (50Hz).

Time-lock analysis was performed per condition per subject. Before the time-lock analysis, detrend and demean preprocessing was done. All step-wise data was rescaled to have the same length.

Time-frequency analysis was run per subject and per condition. It was calculated for frequencies ranging from 5 to 100 Hz in steps of 5Hz. A multitaper time-frequency convolution (mtmconvol) with a hanning window was used. The time windows were centered on time points from 0 to 2 sec in steps of 0.1 sec (100 ms). The time-frequency grand average for all subjects was calculated using the individual outcomes of the time-frequency analysis.

A cluster randomization test was performed using Fieldtrip for the 20Hz-band. FW was compared to BW to look for differences in the motor component. Comparison between IFW and IBW also attempted to look for differences in the motor component and similarities in the FW vs. IFW and BW vs. IBW were compared to look for differences in the sensory component.

Independent Component Analysis (ICA) was performed for every subject on the detrended and demeaned data. Separate analyses were performed on every component per condition (50Hz filter, Time-Frequency Analysis, Time-lock Analysis), as described before. Most interesting components were selected visually, based on topography, Time-lock and Time-frequency analyses. A grand average of the similar components was calculated over all subjects’ Time-frequency analysis and topography data. For topography data, a correction was made in order to avoid mutual cancelation of components showing dipoles in different directions. This is, the most common direction between subjects was chosen and subjects’ components whose direction was the opposite, were multiplied by -1. Further statistical analysis was performed in the Time-frequency grand average of each of the selected components. The same conditions as described before were compared using a cluster randomization method, for 10, 15 and 20 Hz bands (Maris & Oostenveld, 2007).
Results

Head marker movement
Head marker movement was interpreted according to the axis direction. Given the coordinate system used to calibrate the VICON System, movement along the X axis represents lateral left-right movements during walking (called LLR-movement from now on); movement along the Y axis corresponds to the movement of participants when they stepped to the front, and then the treadmill pulled them back, it will be called anterior-posterior (AP) movement from now on; and finally, movement along the Z axis is the constant up and down of the head during walking, it will be called vertical up and down (VUP) movement from now on.

No consistent pattern of correlations between head movements and EEG was found among subjects, however, correlation between both signals was found at the individual level. A threshold of 0.3 was set in order to consider the correlation as significant. Figures 7, 8 and 9 show an example of the results for subject 3 only. The graphical comparison of the averaged and rescaled head marker movement per condition and the rescaled time-lock analysis for the different clusters shows that only the frontal cluster seem to vary weakly along with the LLR-movement in forward walking (figure 7). For backward walking, it also seems that the AP-movement varies with the frontal clusters; however such variation is not in phase with each other. On the other hand, the correlation analysis showed that, for forward walking, LLR-movement is correlated with frontal, temporal and occipital EEG channels, AP-movement mainly with frontal and central EEG, and VUP-movement especially with temporal EEG. For backward walking, LLR-movement was correlated with central and temporal clusters, AP-movement mainly with frontal, central and temporal channels, and the VUP-movement was correlated with all clusters (figure 9).

Figure 7. Example of head movement for subject 3, forward walking. The movement of the six head markers was averaged in a single measure of head movement and rescaled into a single step size ranging from 0 to 1000 samples, which corresponded to 1 to 100 samples of EEG data in four different clusters. First two plots represent head movement for forward and backward walking in the three directions Lateral Left-Right (LLR) in blue, Anterior-Posterior (AP) in red, and Vertical Up-Down (VUP) in green. The next 4 plots correspond to step-wise EEG measurements (mV) in four clusters of electrodes: frontal, central, temporal and occipital.
Figure 8. Example of head movement for subject 3, backward walking. The movement of the six head markers was averaged in a single measure of head movement and rescaled into a single step size ranging from 0 to 1000 samples, which corresponded to 1 to 100 samples of EEG data in four different clusters. First two plots represent head movement for forward and backward walking in the three directions Lateral Left-Right (LLR) in blue, Anterior-Posterior (AP) in red, and Vertical Up-Down (VUP) in green. The next 4 plots correspond to step-wise EEG measurements (mV) in four clusters of electrodes: frontal, central, temporal and occipital.

Figure 9. Example of correlation plots for subject 1. Left plot represent the correlation values for each direction of movement (LLR in blue, AP in red and VUP in green) with the different electrodes in forward walking and the right one is for backward walking. Dots in the upper part of the graphs represent whether or not the correlation was greater than 0.3, which was considered as a threshold to consider significant correlations.

Gait phases
The gait phases were identified in 32.87, 49.96, and 82.72% of the gait cycle (mean values) for forward walking LHS, RTO and RHS respectively. Since different steps have different lengths, phase localization varied in time. Standard deviations were 0.90, 1.30 and 1.33, respectively. Backward walking mean phase localization was at 14.12 (SD=1.46), 50.2 (SD=1.32) and 63.8 (SD=1.61)% for LHO, RTS and RHO respectively.
Time-lock analysis

Time-lock analysis showed greater amplitude variations in the frontal and occipital channels, however the channels over the motor cortex were considered as more interesting. Figure 10 shows an example of the time lock activity over electrode CP1 in the four conditions. Black lines represent the gait phases as detected from the feet markers. Thin purple lines around them represent the standard deviation of the phase localization.

Changes in amplitude seem to be related to the gait cycle phases. In FW, double support phases (between LHS and RTO, RHS and LTO) lead to an increase of amplitude whereas in BW they are related to a decrease of amplitude. For imaginary conditions similar peaks are present as well, but no information about the step phases is available.

Figure 10. Example of time-lock analysis for subject 11. First row figures represents actual walking, second row imaginary walking, first column of figures forward walking and second column backward walking. Percentage of completion of the step cycle is plotted in the x-axis and average potential difference in the y-axis. Note that scales in the y-axis are different for each condition and that in backward conditions plots are reversed in time (i.e. end of the step cycle first, and beginning at last), for an easier comparison. Gait-cycle phases are depicted with black lines and its standard deviation is represented with a purple line.
**Time-frequency analysis and its Grand average**

Time-frequency analysis was averaged over subjects. Modulations over all frequency bands are stronger in the occipital channels for actual walking conditions, which could be related to movement artifacts. In the frontal electrodes, modulations are less strong, but high intensity peaks can be seen in the 5Hz band, probably due to low-frequency eye-blink artifacts. Over the motor cortex, modulations are also evident. For further results, CP2 channel was chosen, as example of activity over the motor cortex because it was a representative example of the electrodes in that neighborhood for the Time-frequency Representations (TFR).

The grand average for the four conditions is shown in figure 11. Gait phase localization is shown with a black line, with their standard deviations. Modulations of activity can be easily seen in actual walking conditions in all frequencies, whereas for imaginary conditions such differences are not as clear.

Desynchronization occur during feet movement periods (i.e. between LTO and LHS, RTO-RHS in forward walking and LTS-LHO, RTS-RHO in backward walking), while synchronizations occur during feet support phases (i.e. LHS-RTO and RHS-LTC in FW; and LHO-RTS and RHO-LTS in BW). Observed desynchronization is stronger in backward walking than in forward walking. In contrast, synchronization is stronger in forward walking compared to backward walking. In imaginary conditions, weak modulations of alternating synchronization and desynchronization can be observed in low frequencies (10-25Hz) and around 80 Hz.
Figure 11. Grand average over of the time frequency representations (TFR) per condition. FW, BW, IFW and IBW are shown in this order from left to right and from top to bottom. BW and IBW are reversed in time, and actual walking gait phases are delimited by black lines and its standard deviation with purple ones.

Figures 12-13 show topo plots of activity for actual walking during feet support phases in the frequencies of interest (mu and beta bands).

In the forward walking condition (figure 12), increased synchronizations are localized approximately on top of the motor cortex, tending to the back. Also, a slight lateralization can be observed: synchronization is centered more to the left between LHS and RTO with respect to the RHS-LTO synchronization, which is centered more to the right.

Figure 12. Forward walking topo plots for selected frequency and time bands (dashed rectangle). Left figure includes times from 30 to 50% of completion of the step cycle and a frequency range from 10~35Hz. Right plot includes 85~99% and frequencies ranging from 10~35 Hz.

In the backward walking condition, topo plots for the same frequencies and equivalent phases of the gait cycle times did not show synchronization activity as strong as in forward walking. Instead, they showed desynchronization. Especially between LHO and RTS, the pattern is similar to FW
synchronization between RHS and RTO as shown in figure 13. For the RHO-LTS period, desynchronization is mainly in the occipital-parietal region, and there is also a weak trace over the motor cortex.

In the imaginary forward, the same frequencies and equivalent percentages of completion of the gait cycle did not coincide with event related synchronizations. When analyzing time-frequency ranges that showed slight synchronization in the mu and beta bands, its localization was mainly around the parietal area, and some traces of desynchronization can be observed over the motor cortex.

In imaginary backward walking, chosen time-frequency ranges coincided with a dipolar pattern. Synchronization was localized around central-parietal electrodes for 50~73% (10~25Hz), lateralized to the right, and more centrally located for the 1~20% period (10~25Hz). Desynchronization was also over the central-parietal region, lateralized to the left, and along the temporal and frontal parietal electrodes, respectively.

For high frequency bands (60~85 Hz) in imaginary conditions, strongly lateralized synchronization of activity was found near the central electrodes, as shown in figure 14. The same phenomenon was observed in TFR for the baseline period, as shown in figure 15. On the other hand, such activity was not found in the actual walking conditions.
Figure 14. Imaginary conditions high frequencies contained activation patterns which are more lateralized than activity found for low frequencies. Selected time-frequencies are marked in the TFR with a dashed rectangle.

Figure 15. Baseline. High frequency patterns of activation were found in the baseline, similar to those found in imaginary conditions. Selected time-frequencies are marked in the TFR with a dashed rectangle.

When looking at the trial TFR (figure 16), results show a pattern of desynchronization in the mu and beta bands. Such modulations are stronger especially at the beginning of the trial and become less visible as time passes. This pattern can be observed around 10 Hz and 20Hz, being less pronounced in the latter band. Initial desynchronization is stronger for FW than in BW, however, along the trial, desynchronization seems to be more constant in BW, especially for the 20Hz band. In Imaginary conditions such modulations are also present, but are weaker than in actual conditions.
Figure 16. Intra-stride spectral perturbations along one trial of each condition. Upper left graph represent FW, upper right BW, bottom left IFW and bottom right IBW. Desynchronization activity is stronger in actual walking and also at the beginning of the trial. As the trial goes on, desynchronization is less strong.

Cluster randomization test
In the forward versus imaginary forward walking comparison, significantly different clusters of activity (p<0.05) were found either around the frontal electrodes, or around the occipital and parietal-occipital channels. Posterior activity was significantly different during 14~86% of the gait cycle while anterior activity was significantly different only during the 38~48% period.

Similar results were found in the backward versus imaginary backward walking comparison, however, periods of significance varied slightly. Significantly different clusters were found in the frontal electrodes in the periods 0~26% and 42~98% of the gait cycle and occipital electrodes were also significantly different for the two aforementioned periods plus the 28~48% period.

Finally, no significant differences were found between Forward walking - Backward walking, and Imaginary Forward walking - Imaginary Backward walking.

As shown in figure 17, differences between actual walking and imaginary walking are red in the occipital area, meaning that the magnitude of the EEG recordings was bigger in actual walking conditions than in imaginary conditions. Even though it is not significant, a constant difference between actual walking and
imaginary walking can be observed approximately over the motor cortex. As it refers to desynchronization, it probably means that there is more desynchronization in actual walking conditions when comparing to imaginary walking conditions.

Figure 17. Representative topo plots for significantly different clusters for each comparison are depicted. Most significantly different clusters were found in the occipital and frontal areas, however, the magnitude of the differences varies depending on which conditions are compared. Less desynchronization is found in imaginary conditions than in actual walking conditions.

Independent Component Analysis (ICA)

After ICA, 62 maximally independent components of the EEG signal were obtained per subject. Explained variances of each component were below 1%. Components which explained the most variance usually corresponded to artifacts. Therefore, components were classified and interesting components were selected based on the topography of the component, its time-lock and frequency analyses per condition.

Artifact components were identified in most of the subjects by high intensity peaks in the time-frequency analysis, time-lock changes of amplitude in-phase with the gait cycle phases and specific localization of the peaks of activity. Figure 18 shows examples of the four types of artifacts detected with the ICA for one subject. Movement artifact can be identified by its localization in the back and low frequency peaks synchronized with the gait cycle. Muscle components are also localized mainly in the back and modulations of intensity are also coupled with the gait phases, but the intensity their high frequency band is similar to those occurring in their low frequency bands. Eye blinks are characterized by frontal topography and low-frequency peaks. Finally, eye saccades are detected as a dipole of frontal activity, also of low frequency.

<table>
<thead>
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<th>Type of component</th>
<th>Plot</th>
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<td>Movement Artifact</td>
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Two interesting components were selected according to the following criteria: firstly, topography should be similar for all subjects; secondly, activity should be widespread along several electrodes topography, so that the component does not reflect only the movement in one electrode; thirdly, Time-lock and Time-frequency analysis per component should be similar; and finally, similar components should be available for all subjects in their individual components. The selected components for each subject can be found in Appendix A.

Grand averages of the topography of the first component show synchronization activity in the neighborhood of the central-frontal electrodes, and slight desynchronization activity in the temporal and occipital regions. On the other hand, the second chosen component presents synchronized activity in the vicinity of the posterior parietal cortex, and intensity decreases as it tends to the frontal cortex. Both components are shown in figure 19.
Time-frequency analysis of the first component shows modulations of activity especially in the bands of 10, 15 and 20 Hz. Similar to previous analyses, modulations are stronger and wider spread over different frequency bands in actual walking than in imaginary walking. For imaginary forward walking, modulations are better seen in the 10Hz band and for imaginary backward walking, stronger desynchronization activity is more evident in the 15-20Hz band (figure 20).
Figure 20. Upper left TFR corresponds to FW, upper right to backward walking, bottom left IFW, and bottom right to BW for component 1. Gait-cycle phases are represented with a black line for actual walking. Backward conditions are reversed in time.

Grand average of the TFR for the second component showed similar results (figure 21). Modulations of activity are also present in low frequency bands in the four conditions. Modulations are the strongest in backward walking, followed by forward walking, and weak modulations are visible in imaginary conditions.
Cluster randomization test per component
No significant differences were found for the statistical analysis in the 10, 15, 20Hz bands, neither in component 1 or component 2.

Discussion
The questions of interest of this study were to determine whether modulations in cortical activity during walking were caused by sensor or motor processing, and whether these modulations could be used as feature for building a BCI for walking. TFRs show modulations of activity according to the gait-cycle phases. Such modulations are strong in backward walking, moderate in forward walking and weak in imaginary conditions. Comparisons among conditions found significant differences between FW and IFW; and between BW and IBW mainly in frontal and occipital clusters. When comparing actual versus imaginary walking, differences were constant over time. However, results shown that movement is correlated with EEG signals: head movement and the changes of amplitude in the time-lock analysis vary according to the gait-cycle phases, especially in frontal and occipital electrodes. Therefore, removal of artifacts is crucial to determine if the TFRs really represent cortical activity. Independent component analysis showed to be useful to identify artifacts and to select interesting components. For the two selected components as interesting, modulations of activity were consistent with previous analysis, especially in low frequencies. Even in imaginary conditions, slight modulations in low frequencies were found, and these are clearer than in previous analysis. Finally, for selected ICA components, no significant differences were found.

Indeed, our results suggest that cortical activity varies along the gait cycle, as previously described by Gwin and colleagues (2011). Beta and mu bands show stronger modulations in BW compared to FW. This might be related to increased effort to walk backwards when compared to the more-automatic forward walking. Peters (2011) already suggested that less automatic movements lead to more desynchronization and therefore stronger modulations in activity. These modulations were also present in high frequencies during actual walking conditions and still BW exhibited stronger modulations. This
could be related to a greater need to integrate visuomotor information into the sensorimotor loop and great need to detect and correct for errors, as suggested before by Gwin et al. (2011). Furthermore, both synchronization and desynchronization were located near the posterior parietal and sensorimotor cortex. Posterior parietal cortex has been linked to selective and rhythmic attention, combination of sensorimotor and visuomotor information, and bimanual coordination (Gwin et al., 2011; de Lange et al., 2005).

Also, a strong synchronization activity is present in high frequencies in imaginary walking near the auditory cortices. Because these are present in the baseline period as well, they could be due to the metronome. However, this is not present in actual walking. A possible explanation is that participants were encouraged to use the metronome as a cue to imagine the steps they were taking during their imaginary walks, and therefore they paid more attention to it than in actual walking conditions. Another explanation could be that this synchronization is averaged out during the analyses for actual walking.

In fact, significant differences among conditions seem to be related to movement artifacts and muscle activity differences. When comparing actual walking versus imaginary walking (i.e. FW vs. IFW and BW vs. IBW), differences are found in the occipital-parietal region of the brain and plots also show that variation is greater in actual walking than in imaginary walking, which is true for motion: movement is present in actual walking whereas in imagined walking there is no movement at all. Frontal significant differences might be caused by high intensity peaks due to eye-blinks and saccades. For the comparison FW vs. BW, non-significant differences suggest that movement activity is similar in both conditions. This could be confirmed by further analysis using the EMG recordings. Similarly, no significant differences in IFW vs. IBW could be due to the lack of movement in both conditions. These results seem to contradict our initial expectative of finding differences between forward and backward conditions, and no differences between actual and imaginary pairs. It could be that the test had not enough power to find differences other than the high-intensity movement artifacts.

On the other hand, differences between actual and imaginary walking conditions were constant over time. Especially, a strong difference in desynchronization was located approximately over the motor cortex. These differences seem to suggest that desynchronization is stronger in actual walking conditions than imaginary walking, in a constant manner. This phenomenon could be due to a difference of magnitude of the desynchronization, and not a difference in modulations of activity according to the gait cycle. In that line of thought, it might be that indeed motor activity is similar in FW and IFW and also in BW and IBW, but the magnitude of the observations is different, as previously expected. Removal of movement artifacts previous to the analysis or inclusion of more participants in the study might give enough statistical power to further explore this possibility.

From the statistical analysis, it is obvious that the described results should be considered carefully due to movement and muscle artifacts. First, head movement seems to be correlated with EEG signals; however such correlation does not seem consistent over all subjects. Different subjects exhibit significant correlations of different directions of movement with different clusters. Therefore, decorrelation of the EEG signal with the head marker is useful to reject possible movement artifacts. Second, time-lock analysis showed greater amplitude variations in the frontal and occipital channels,
which is most likely due to eye blinks in the front and muscle activity in the back. Similarly, modulations of activity showed by the TFR were also greater in frontal and occipital electrodes, which also suggested muscle and movement artifacts mixed with the EEG signal. Further evidence about the shape of the aforementioned artifacts was provided by the ICA decomposition, where muscle and movement components showed that synchronization quickly changes into desynchronization, similar to the modulations found in the first time-frequency analysis of the EEG signal and to the EMG patterns described by Gwin et al. (2011).

For the ICA analysis, the followed approach implied selection of interesting components from the output of the ICA and to perform similar analysis to the ones described before (i.e. time-lock and frequency analyses) in every component. Another approach could be to remove components considered as artifacts, reverse the ICA to obtain the EEG signal without artifacts, and then perform further analyses in the cleaned EEG. Due to time constrains, we decided to follow only the first approach; however, the second approach is strongly recommended for further analyses.

ICA showed to be helpful to identify eye blinks, saccades, muscle movement and movement artifacts quite nicely; however, identification of interesting components is more difficult. Identification of interesting components followed four intuitive “rules”: similarity of topography, widespread activity in the topography, similarities in the time-lock, time-frequency analysis per component, and availability of a similar component on all subjects. These criteria is still subjective and sometimes is difficult to discriminate one component from another, or to determine if the component is present for a certain subject, thus, results should be interpreted carefully.

Grand averages per component per condition show modulations in low frequency bands in all conditions. Less strong modulations occur in imaginary conditions, and the strongest modulations occur in BW. These results are in line with the analysis over the complete EEG signal, and as expected, by focusing only on interesting component, modulations can be observed more clearly than in previous analyses.

However, increased strength in the modulations for BW might still be caused by residual muscle activity or movement artifacts, because the head movement seems to be greater in this condition. Greater movement is possibly caused because people are less used to walk backwards than forwards, further EMG analysis should confirm this. Even though residual artifact activity might be present in the selected components, their topography shows that activity is localized mostly in non-occipital channels.

Statistical analyses on the selected components were not significant; nevertheless, non-significant results could be because main differences between conditions could be caused by a combination of different components and not only the activity in the chosen components. Furthermore, ICA separates maximally independent spatial components from their temporal occurrence. The differences we are interested in are mainly over time, and thus, looking only to their spatial representation will not give information about the differences among conditions. The aforementioned second approach to process ICA components could be therefore more profitable because it includes all interesting components and then they are reversed to reconstruct the EEG signal again, which also includes temporal information
and the possible combinations of interesting components. Results of this approach should be considered for further work.

The current experimental set-up and analyses could therefore not distinguish if the observed modulations where caused by sensor or motor activity. Points to consider are the theoretical assumptions of the experimental design. First, kinematics between forward and backward walking was assumed to be quite similar, which still has to be confirmed in further analysis of the joint movement. Secondly, imaginary walking was assumed to use lesser sensory feedback than actual walking. This also would imply that perceptual feedback is not imagined, and there has been some discussion about the so-called “central stimulation”, arguing that motor imagery also includes elements of kinesthetic sensations analogous to the sensory feedback received during actual movements (Mulder, 2007). Thirdly, even though an effort was made to exclude artifact components, residual artifacts or confoundings such as the metronome perception might still be mixed into the results. Fourthly, stride-variability might cause synchronization and desynchronization to be cancelling each other out in the average because the step-phases are not time-locked; in imaginary walking, we also do not have any clue about the stepping frequency and the location of the step phases, except by the metronome. Finally, limitations of EEG measurements might also play a role. Since the anatomical localization of the foot area in the motor cortex is located within the mesial wall in the interhemispheric fissure, its evoked potentials are difficult to measure with EEG, and even they might be interfering with each other because of the symmetric localization of both feet areas.

Despite all the limitations of EEG when dealing with foot movement and imagery, the modulations of cortical activity during walking could be used as feature to implement a BCI. Trial-wise TFRs showed that modulations of activity are clear in the four conditions, especially at the beginning of the trial in the 10 and 20Hz bands. A possible explanation could be that when people are not used to the movement, they require more effort to walk, and as the trial goes on their movement gets more and more automatic. Other explanation could be that at the beginning of the trial the speed up of the treadmill makes it difficult for the participant to keep track of the walking velocity, and therefore more desynchronization is evoked. BCI tasks could profit from this as well: by keeping the task as a challenge, users can remain engaged with it, and the classification performance could be then increased. Further work should explore this possibility.

Conclusions
This study aimed to distinguish if the perturbations in EEG mu and beta band during walking caused by motor or sensory processing and to answer the question of whether or not forward walking can be distinguished from backward walking by means of cortical activity measurements. With the current study, the first question could not be answered completely. However, findings suggest that indeed cortical activity is coupled with the step phases of the gait cycle. Modulations in activity are stronger as the movement is less automatic, even when people are imaging it. Therefore, since backward walking is less automatic than forward walking, strength of the modulations of activity in the mu and beta bands could be used as feature to distinguish forward and backward walking, and might even be used as feature to build a BCI.
References


## Appendix A

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### Plot

- **LHS**: Left Hemisphere Sides
- **RTO**: Right Temporal Orientations
- **RHS**: Right Hemisphere Sides
- **LTO**: Left Temporal Orientations

![Graphs and Heatmaps](image_url)