

# EEG AND HUMAN LOCOMOTION

## *Descending Commands and Sensory Feedback should be Disentangled from Artifacts Thanks to New Experimental Protocols*

### *Position Paper*

Thierry Castermans<sup>1</sup>, Matthieu Duvinage<sup>1</sup>, Guy Cheron<sup>2</sup> and Thierry Dutoit<sup>1</sup>

<sup>1</sup>TCTS lab, Faculty of Engineering, Université de Mons, 31 Boulevard Dolez, 7000, Mons, Belgium

<sup>2</sup>LNMB lab, Université Libre de Bruxelles, CP 168, 50 Av F. Roosevelt, Brussels, Belgium

**Keywords:** EEG Analysis, Human Locomotion, Artifacts, Brain-computer Interfaces.

**Abstract:** The main challenge when studying EEG signals related to human walk control comes from the fact that signals of many different origins are mixed up. Indeed, descending commands from the brain are generated, while ascending sensorimotor information coming from the feet is sent to the brain. In addition to the inherent complexity of the human control mechanism, experimental investigation of the cerebral activity elicited during walk is highly challenging: electrode movements are produced by movements of the head, but also by the shocks undergone by the whole body at each step, which – albeit significantly attenuated – are transmitted to the head and degrade the quality of EEG signals. Recently, different EEG studies of human locomotion have been published. These are based on different hypotheses and/or produce results that are contradictory. After reviewing and describing the discrepancies between the different approaches, we propose new experimental protocols which should help to solve important issues.

## 1 INTRODUCTION

Human locomotion is known to be based on a very complex hierarchical system which includes several control networks located at spinal and supraspinal levels (Hanakawa, 2006). Basically, high-level motor commands are sent by the brain to a spinal network composed of central pattern generators (CPG) and, at the same time, each level of motor control receives peripheral sensory information (sensory feedback) which is used to modify the motor output at that level.

The central pattern generators network consists in coupled antagonist oscillators specifically dedicated to extensor or flexor muscles acting at the different joints. Their mechanism allows to generate simple and coordinated rhythmic movements such as those involved in steady walk (Kiehn, 2006). Ahead of the CPG, supra-spinal networks (i.e. the brainstem, cerebellum and cortex) are of crucial importance in the control of walking. Indeed, as summarized in (Presacco et al., 2011) and references therein, significant changes in motor and cognitive demands (i.e. spatial attention) have been observed in the con-

text of bipedal walking in unknown or cluttered dynamic environments. Functional neuroimaging studies have shown that the primary motor cortex is recruited during rhythmic foot or leg movements. Additionally, the technique of functional near-infrared spectroscopy (fNIRS) has allowed to detect involvement of frontal, premotor and supplementary motor areas during walking (Harada et al., 2009), (Suzuki et al., 2008).

Electroencephalography (EEG) represents an interesting complementary technique for investigating neural processes governing walk. Indeed, while standard functional imaging is characterized by a good spatial resolution, EEG is the only wearable and non-invasive measurement technique which offers a temporal resolution good enough in order to study the dynamics of brain. However, electrophysiological investigation of the cerebral activity elicited during walk is highly challenging. Indeed, head and body movements constitute an important source of mechanical artifacts strongly affecting the EEG signals quality. This explains why very few papers have been written on the subject.

Recently, EEG studies of human locomotion have

been undertaken but give incompatible results. In this context, the objective of this paper is twofold: (1) review and discuss the new available results, emphasizing contradictory aspects as well as discrepancies with independent experimental results; (2) propose new experimental protocols to resolve the ambiguities.

## 2 EEG STUDIES OF HUMAN LOCOMOTION

### 2.1 Static vs Dynamic Approaches

EEG signals are by essence noisy and difficult to measure (a few microvolts only). This is due to the fact that each EEG scalp electrode is only able to measure the combination (superposition) of the electrical potentials generated by thousands of neurons, which are weakened and smeared by the volume conduction effect of the skull (Nunez et al., 1997). Moreover, EEG signals may be affected by different kinds of artifacts generated either by extracerebral physiological activity (blinks, eye movements, muscle or cardiac activity), by interference with power line, or by recording electrodes and equipment. On top of this, typical artifacts related to gait further degrade EEG signals quality when the measurements are made in ambulatory conditions (see for instance (Castermans et al., 2011) for a review). The combination of these multiple effects renders EEG study of human locomotion extremely complex.

Consequently, the main strategy generally used to overcome these experimental difficulties consists in focusing on simplified foot or leg movements which imply common cerebral processes with gait. In these experimental protocols, subjects are mainly static and produce only limited lower limb movements. A strong advantage of this approach is of course that motion artifacts are drastically limited. In this case, however, the full neural activity related to walk is not available and, for instance, cerebral processes involved in posture and balance control are missing. Recording EEG signals of subjects walking on a treadmill include of course all these aspects but then requires a powerful analysis technique to discriminate the different artifact contributions from the real cortical signal. Analysis results of these two approaches, *static* on the one hand and *dynamic* on the other hand, are reviewed hereinafter.

### 2.2 Electrocortical Potentials related to Lower Limb Activation in Static Condition

The cortical activity associated to bilateral anti-phase and in-phase rhythmic foot movements produced by subjects sitting on a chair was investigated in (Raethjen et al., 2008). In this study, the authors found significant corticomuscular coherence between EEG signals and the anterior tibial muscles, at the stepping frequencies in the central midline region, extending further to the frontal mesial area. During isometric cocontraction of the calf muscles, coherence appeared between 15 and 30 Hz, concentrated on the central midline area. This is the first study demonstrating that there exists a representation of rhythmic foot motor patterns in the cortex, transmitted to the muscles and fed back to the cortex with delays compatible with fast corticospinal transmission, which may be important for gait control.

Assisted lower limb movements have also been investigated using electroencephalography (Wieser et al., 2010). In this study, subjects performed standardized, assisted stepping movements (i.e. mimicking walk) in an upright position, while being secured to a tilt table. Electrocortical sources associated to the movement-related potential were localized in the primary motor cortex, the premotor cortex, the supplementary motor cortex, the cingulate cortex, the primary somatosensory cortex and the somatosensory association cortex (i.e. in accordance with the findings of functional brain imagery). The authors demonstrated that a clear succession of activations and deactivations was present in the movement-related potential, in direct relationship with specific phases of the gait-like leg movements. In particular, it was shown that cortical activity was the greatest during transition between flexion and extension of the legs and vice versa.

Given the obvious possibility to detect electrocortical potentials related to lower limb activation, two studies were undertaken in order to develop brain-computer interfaces (BCI) for motor augmentation.

In (Gwin and Ferris, 2011), it was shown that knee contractions could be distinguished from ankle contractions (subjects performed these exercises sitting on a bench) using an independent analysis mixture model applied on high-density EEG, without prior knowledge of the exercise. An inverse modeling approach indicated the presence of electrocortical current dipoles significantly different for the knee and ankle exercises. This finding is of course very promising for new applications in neurorehabilitation of gait and control of robotic lower-limb exoskeletons.

In (Do et al., 2011), a non-invasive EEG-based BCI governing a functional electrical stimulation (FES) system for ankle movement is presented. In this application, healthy subjects perform repetitive foot dorsiflexions. EEG patterns underlying this action are detected in real time, and this information is subsequently used to trigger the FES of the tibialis anterior of the contralateral foot so as to achieve its dorsiflexion. In fact, the trigger (or non-trigger) information is given by a linear Bayesian classifier trained using a vector of spatio-spectral features which optimally discriminate the idling and dorsiflexion states. The authors state that analysis of subject-specific prediction models demonstrated that the EEG power changes in the  $\mu$ ,  $\beta$  and low  $\gamma$  bands observed over mid-central areas (i.e. electrode Cz) were the most informative features for classification. This likely corresponds to activity within the primary motor cortex's foot representation area and/or supplementary motor area (which is not surprising from a brain anatomy standpoint) and is in perfect agreement with prior studies (Neuper and Pfurtscheller, 1996), (Solis-Escalante et al., 2008).

### 2.3 Electrocortical Potentials related to Walk

To our knowledge, two very recent studies addressed the dynamic approach of the problem (i.e. where subjects are really walking). The first analysis of EEG during walk on treadmill was published by (Gwin et al., 2011). By using a method based on independent component analysis (ICA) combined with an inverse modeling approach, the authors claimed they could discriminate electrocortical sources, muscle sources and other artifacts from the raw EEG signals. They found that cortical activity in the anterior cingulate, posterior parietal and sensorimotor cortex exhibited significant and smooth intra-stride changes in spectral power. More precisely, alpha and beta band spectral powers increased in or near the left/right sensorimotor and dorsal anterior cingulate cortex at the end of each stance phase (i.e. as the leading foot was contacting the ground and the trailing foot was pushing off). According to this study, power increases in the left/right sensorimotor cortex were more important for contralateral limb push-off (ipsilateral heel-strike) than for ipsilateral limb push-off (contralateral heel-strike). Finally, the authors reported evidence of intra-stride high-gamma spectral power changes in anterior cingulate, posterior parietal and sensorimotor cortex.

In parallel, (Presacco et al., 2011) showed for the first time that the kinematics of the ankle, knee and hip joints during human treadmill walking can be inferred from EEG signals. Successful decod-

ing of these signals was done basically by filtering them (0.1 – 2 Hz) and passing them through a linear autoregressive model. According to this study, gait trajectories were inferred with accuracies comparable to those from neural decoders based on multiple single-unit activity recorded in non-human primates (Fitzsimmons et al., 2009). The results of this study indicate a high involvement of a fronto-posterior cortical network in the control of walking and suggest that EEG signals can be used to study in real time the cortical dynamics of walking and to develop brain-machine interfaces aimed at restoring human gait function.

## 3 DISCUSSION

### 3.1 About the Spatio-frequential Characteristics of the Detected Potentials

The results produced by the different analyses presented in previous section are in some way contradictory. Table 1 summarizes the brain areas activated during walk (or gait-like exercises) as well as the frequency bands of interest, as reported by the different authors.

From the spatial point of view, all the studies found activations of the brain globally compatible with the primary motor cortex's foot representation area and/or supplementary motor area, except one. Surprisingly, (Presacco et al., 2011) report the activation of a complex, distributed and sparse cortical network, in which scalp areas over anterior, right lateral and right anterior-occipital scalp areas seem to equally contribute (at least to their decoding of the kinematics of the right leg, for subjects walking on a treadmill).

From the frequential point of view, spectral power variations were generally found from alpha to gamma bands but, astonishingly, a successful neural decoding of treadmill walk was realized by (Presacco et al., 2011) using EEG signals band-pass filtered between 0.1 and 2 Hz. This is particularly surprising, because it was shown in another study, conducted to assess EEG signal quality in motion environments (Kerick et al., 2009), that EEG spectra in the walking (or jogging) condition exhibit frequency peaks consistent with the fundamental stride frequency as well as its harmonics. The authors also state that motion artifacts affect signal integrity most prominently at low frequencies (i.e. the delta band) during steady walk. In their analysis protocol, (Presacco et al., 2011) do

Table 1: EEG studies of human locomotion: a schematic view of recent results obtained with static and dynamic experimental protocols. M1 is the primary motor cortex, PMC is the premotor cortex, SMA is the supplementary motor cortex, CC is the cingulate cortex, S1 is the primary somatosensory cortex and SA is the somatosensory association cortex.

Publication	Aim of the study	Approach	Activated brain areas	Frequency bands of interest
Raethjen et al., 2008	Rhythmic foot movements	Static	Central midline region + frontal mesial area	Stepping frequency + $\beta$ band (15 – 30 Hz)
Wieser et al., 2010	Assisted lower-limb movements	Static	M1, PMC, SMA, CC, S1, SA	No frequency analysis. Activations are directly related to specific phases of the gait-like movements
Do et al., 2011	BCI dedicated to a FES system for ankle movement	Static	Mid-central areas (electrode Cz)	$\mu$ , $\beta$ and low- $\gamma$ bands
Gwin et al., 2011	EEG activity during treadmill walking	Dynamic	Anterior cingulate, posterior parietal and sensorimotor cortex	$\alpha$ and $\beta$ bands + clear evidence of high- $\gamma$ intra-stride spectral power changes
Presacco et al., 2011	Neural decoding of treadmill walking from EEG signals	Dynamic	Involvement of a broad fronto-posterior cortical network	Delta band (0.1 – 2 Hz)

not mention any pre-processing method aiming at either correcting or discriminating these motion artifacts from the real cortical signals. The only way for them to make the choice of this frequency band legitimate is the fact that good results are obtained and, moreover, other studies exploited the same portion of the EEG spectrum to decode upper limb movements. We strongly emphasize the fact that, in the latter studies, no motion artifacts due to gait are produced. Consequently, this might suggest that the decoding of kinematics of walk – *periodical* movement – on the basis of the EEG signals is done by (Presacco et al., 2011) with a linear autoregressive model exploiting the *periodical* motion artifacts present in the EEG recordings. This option is furthermore supported by the fact that no spectral information is given under 3 Hz in the study of (Gwin et al., 2010).

### 3.2 About the Origin of the Detected Signals

Among all the works described in section 2, only (Raethjen et al., 2008) try to determine the origin of the information flux contained in the studied signals (descending commands from the brain or sensory feedback sent to the brain). This is done by computing time delays between EEG time series and electromyographic activity of the involved lower limb muscles by means of the “maximising coherence method” (Govindan et al., 2005). Actually, other studies presented in section 2 do not consider this aspect and give no indication on the direction of the brain-muscle interaction (i.e. if it is up-going or down-going). It is therefore unknown, for instance, if the intra-strides spectral power variations found by

(Gwin et al., 2010) are due to voluntary movements or sensory feedback (or a combination of both). The same question arises concerning the EEG decoding presented by (Presacco et al., 2011). Resolving this ambiguity is particularly crucial, though, for the development of gait rehabilitation systems. Indeed, if the information detected in the EEG signals is purely due to a sensory feedback of the gait-related movements, it would be unusable to drive any device, given that no valid *prediction* of a movement can be done exploiting sensory information *resulting* from it.

Most importantly, studying EEG signals in treadmill walking also requires the need to exclude gait-related artifacts. Only one study tackles this issue (Gwin et al., 2011). Using an ICA analysis coupled with an inverse solution approach, these authors claim that they could disentangle muscular contributions and other artifacts from real cortical signals. However, in a previous study, the very same authors (Gwin et al., 2010) clearly stated that:

“Unlike more spatially stationary artifacts in EEG signals arising from eye movements, scalp muscles, fMRI gradients, etc., which may be resolved by ICA decomposition into a subspace of one or more independent components, we found that gait-related movement artifact remained in many if not most of the independent components. This prevented us from removing only a small subset of components capturing the movement artifacts.”

For this reason, they considered the removal of motion artifacts from EEG during walking and running on treadmill using an artifact template subtraction method. Such method allowed to enhance the detection of P300 potentials in ambulatory conditions. Nevertheless, the study of cerebral processes involved in human locomotion is not possible using a subtrac-

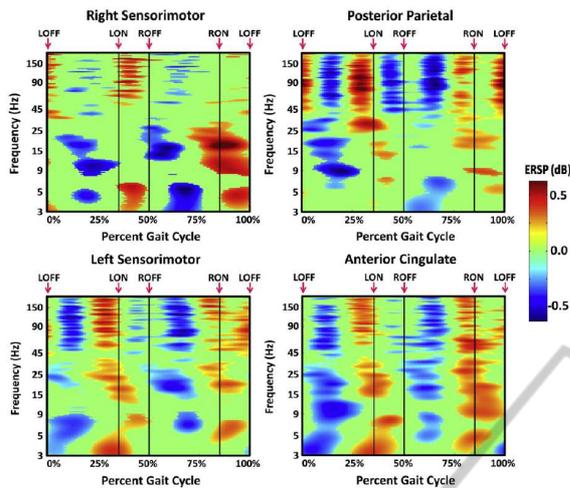


Figure 1: Gait event-related spectral perturbation (ERSP) plots showing average changes in spectral power during the stride cycle relative to the full gait cycle baseline for different brain areas (Figure from (Gwin et al., 2011)).

tion method, as it would undoubtedly remove interesting signal from the EEG recordings. For this reason, the authors used only the ICA approach to clean the EEG signals (Gwin et al., 2011). In this study, the issue of motion artifacts was completely eluded and no mention was made of any appropriate treatment to reject them. Thus, it can be doubted that the time-frequency analysis plots shown in that paper do not contain any motion artifact contribution (see Figure 1). Figure 2 shows, for instance, a time-frequency analysis of the signal of an accelerometer placed on the head of a subject walking at 1.67 m/s on a treadmill. Periodic power spectral changes over large frequency bands can be observed, in a similar way to the results obtained after ICA (see Figure 1) by (Gwin et al., 2011).

## 4 FUTURE WORK

Several contradictory results coming from different recent EEG studies of human locomotion have been discussed. We have shown that the discrepancies concern the spatio-frequential characteristics of the detected potentials and that the presence of motion artifacts is not to be excluded in certain studies.

In this context, it seems necessary to define several experimental protocols in order to disentangle the different signals (are they associated to descending or ascending pathways, are they artifacts, ...).

First, we propose to characterize the descending brain commands which are involved in human walk control in a *static* approach (inspired by (Raethjen

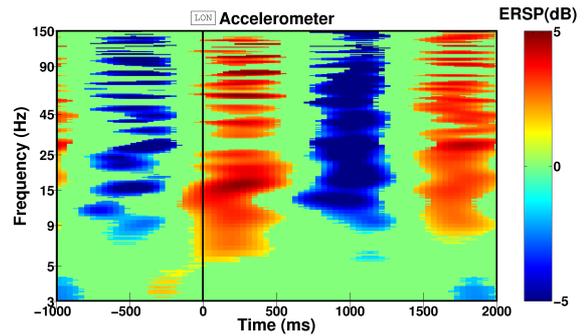


Figure 2: Representative ERSP plot obtained with the output signal of an accelerometer placed on the head (thus undergoing the same shocks as the EEG electrodes) of a subject walking at 1.67 m/s on a treadmill. The horizontal axis is time (and not a percentage of gait cycle like in Figure 1) as no time-warping analysis was done. Reference time ( $t=0$ ) corresponds to the left heel strike (LON) instant. The same alternating spectral power changes are also observed at other speeds.

et al., 2008)), in order to ensure absence of EEG mechanical artifacts. To this aim, the EEG signals of subjects sitting on a chair will be recorded. The subjects will then be asked to produce voluntary rhythmic foot movements, staying at the same tempo. The feet will not be in contact with the ground, to ensure a minimal sensorimotor feedback. Several tempos will be produced. We will also record EEG when the subject is sitting and not moving the feet, to define a baseline, necessary when using brain imagery tools like LORETA (Pascual-Marqui, 2002). To assess the presence (or absence) of mechanical artifacts, an accelerometer will be placed on his neck. A complete characterization of these data will then be realized, by analysing the event-related spectral perturbations (ERSP) combined with a time-warping transformation (Gwin et al., 2011), and by computing cortico-muscular coherence and in particular delays between EEG and EMG time series (to assess the information flow direction).

Then, we will characterize EEG signals caused by somatosensory information coming from the feet of the subject when sitting (again, to prevent any mechanical artifacts). More precisely, the same experiment as above will be realized, with the feet in contact with ground, this time. By comparing the two states (contact/no contact), it will be possible to emphasize the contribution of sensory feedback. Alternatively, we intend to use special factors to stimulate the feet, mimicking the sensation of walk and will study the properties of the EEG signals that are phase-locked with this stimulation.

Additionally, in order to characterize the motion artifacts contribution in an independent way, we pro-

pose to use an EEG test setup analog to the one described in (Nonclercq and Mathys, 2010), comprising a generator that produces cerebral-like waves, a dummy head, an electrode/gel/skin interface model, electrodes, and leads. Placing this setup in the reference frame of a subject walking on a treadmill would produce realistic gait-related motion artifacts (it would indeed undergo the same shocks as the EEG electrodes) and should give valuable information to subsequently reject them.

Finally, if we correctly reject motion artifacts, provided we know the signals due to descending commands (voluntary rhythmic movements) and those due to tactile stimulation (tactors, mimicking the sensation of walk), we should be able to disentangle the contribution of posture and balance control when the subject is standing and walking.

## ACKNOWLEDGEMENTS

This work was funded by the FEDER support (BIO-FACT). M. Duvinage is a FNRS (Fonds National de la Recherche Scientifique) Research Fellow. This paper presents research results of the Belgian Network DYSCO (Dynamical Systems, Control, and Optimization), funded by the Interuniversity Attraction Poles Programme, initiated by the Belgian State, Science Policy Office. The scientific responsibility rests with its author(s).

## REFERENCES

Castermans, T., Duvinage, M., and Dutoit, T. (2011). Optimizing the performances of a P300-based Brain-Computer Interface in ambulatory conditions. *IEEE Journal on Emerging and Selected Topics in Circuits and Systems (JETCAS), Special Issue on "Brain Machine Interfaces" (in Press)*.

Do, A.-H., Wang, P.-T., King, C.-E., Abiri, A., and Nenadic, Z. (2011). Brain computer interface controlled functional electrical stimulation system for ankle movement. *Journal of NeuroEngineering and Rehabilitation*, 8(49).

Fitzsimmons, N. A., Lebedev, M. A., Peikon, I. D., and Nicolelis, M. A. L. (2009). Extracting kinematic parameters for monkey bipedal walking from cortical neuronal ensemble activity. *Frontiers in integrative neuroscience*, 3(March):19.

Govindan, R., Raethjen, J., Kopper, F., Claussen, J., and Deuschl, G. (2005). Estimation of time delay by coherence analysis. *Physica A: Statistical Mechanics and its Applications*, 350(2-4):277 – 295.

Gwin, J. and Ferris, D. (2011). High-density EEG and independent component analysis mixture models distinguish knee contractions from ankle contractions. In

*Proc. of the 33rd Annual International Conference of the IEEE EMBS, Boston, Massachusetts, USA*, pages 4195 – 4198.

Gwin, J., Gramann, K., Makeig, S., and Ferris, D. (2010). Removal of movement artifact from high-density EEG recorded during walking and running. *Journal of Neurophysiology*, 103(6):3526–3534.

Gwin, J., Gramann, K., Makeig, S., and Ferris, D. (2011). Electro-cortical activity is coupled to gait cycle phase during treadmill walking. *NeuroImage*, 54(2):1289 – 1296.

Hanakawa, T. (2006). Neuroimaging of standing and walking: Special emphasis on parkinsonian gait. *Parkinsonism and Related Disorders*, 12(Supplement 2):S70 – S75. Proceedings of the 1st International Symposium on Dopaminergic and Nondopaminergic Mechanisms in Parkinson's Disease (ISDNMPD).

Harada, T., Miyai, I., Suzuki, M., and Kubota, K. (2009). Gait capacity affects cortical activation patterns related to speed control in the elderly. *Experimental Brain Research*, 193(3):445–454.

Kerick, S. E., Oie, K. S., and McDowell, K. (2009). Assessment of EEG signal quality in motion environments. *Army Research Laboratory Report*.

Kiehn, O. (2006). Locomotor circuits in the mammalian spinal cord. *Ann. Rev. of Neuroscience*, 29:279 – 306.

Neuper, C. and Pfurtscheller, G. (1996). Post-movement synchronization of beta rhythms in the EEG over the cortical foot area in man. *Neuroscience Letters*, 216(1):17 – 20.

Nonclercq, A. and Mathys, P. (2010). Quantification of the movement artifact reduction in EEG recording. *IEEE trans. on Biom. Eng.*, 57(11):2746 – 2752.

Nunez, P., Srinivasan, R., Westdorp, A., Wijesinghe, R., Tucker, D., Silberstein, R., and Cadusch, P. (1997). EEG coherence. *Electroencephalography and Clinical Neurophysiology*, 103(5):499–515.

Pascual-Marqui, R. (2002). Standardized low-resolution brain electromagnetic tomography (sloreta): technical details. *Methods Find. Exp. Clin. Pharmacol.*, 24(D):5–12.

Presacco, A., Goodman, R., Forrester, L., and Contreras-Vidal, J. (2011). Neural decoding of treadmill walking from non-invasive, electroencephalographic (EEG) signals. *Journal of Neurophysiology*. in press.

Raethjen, J., Govindan, R., Binder, S., Zeuner, K. E., Deuschl, G., and Stolze, H. (2008). Cortical representation of rhythmic foot movements. *Brain Research*, 1236:79 – 84.

Solis-Escalante, T., Müller-Putz, G., and Pfurtscheller, G. (2008). Overt foot movement detection in one single laplacian EEG derivation. *Journal of Neuroscience Methods*, 175(1):148 – 153.

Suzuki, M., Miyai, I., Ono, T., and Kubota, K. (2008). Activities in the frontal cortex and gait performance are modulated by preparation. An fNIRS study. *NeuroImage*, 39(2):600 – 607.

Wieser, M., Haefeli, J., Büttler, L., Jäncke, L., Riener, R., and Koeneke, S. (2010). Temporal and spatial patterns of cortical activation during assisted lower limb movement. *Exp. Brain Res.*, 203:181–191.