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Active participation during walking reduces single trial connectivity in sensorimotor areas

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Abstract

Active contribution to a movement is crucial for motor learning. Previously, we showed that active participation is related to a suppression of mu and beta band activities over sensorimotor areas. In the current analysis, we aim at differentiating active and passive movements during robotic assisted gait training based on measures that quantify interactions between brain areas. Due to high artifact contamination of the EEG during walking, the data was pruned using independent component analysis (ICA). Single trial connectivity between brain sources was estimated using the ffDTF (full frequency directed transfer function). Three frequency bands were used for classification: μ (7-12Hz), β (15-21Hz), and a subject specific frequency band ranging from 24-40 Hz. Based on the connectivity measures, we were able to separate active and passive movements with classification accuracies of 81.0% $\pm$ 6.7 on average. However a major challenge for the online application of these methods during gait rehabilitation remains automatic artifact correction.

1 Introduction

Extensive training in gait rehabilitation after stroke may be provided by using a robotic gait orthosis. Robotic rehabilitation requires little effort from the individual and can lead patients to move passively. However active contribution to a movement, has been shown to be crucial for motor learning [3].

Neural correlates of active participation during gait training have previously been shown by our group. We showed significant differences between active and passive walking in EEG μ and β sensorimotor rhythms over the foot area of the sensory cortex [6]. The Authors showed that it is possible to distinguish between active and passive walking in single trials (mean accuracy: 68%) in 6 subjects using EEG band power features [5].

In the current manuscript, we show single trial connectivity analysis from the EEG recorded during active and passive walking in a gait robot. The goal of this analysis is twofold: First, we want to evaluate whether single trial connectivity measures allow to distinguish between active and passive walking. Second, we want to investigate the cortical networks related to active participation in gait training. This may help to better understand the underlying mechanisms and the optimal activation patterns for gait recovery.

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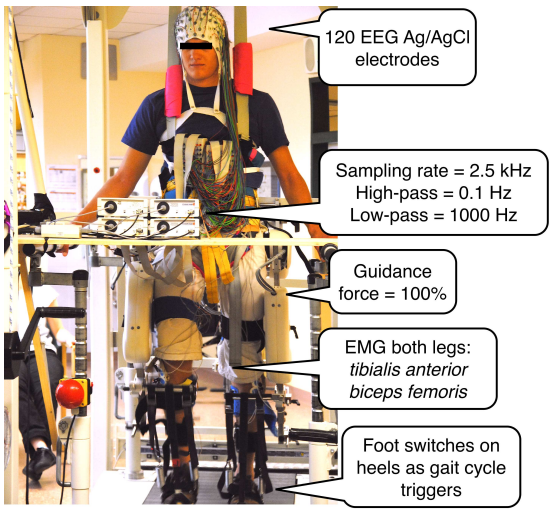

Figure 1: Experimental setup. Walking in the robotic gait orthosis. Speed (1.8-2.2 km/h) and body weight support ($\sim$ 30 %) were adjusted for each participant.

Participant	mean accuracy	std
1	76.4	6.0
2	83.7	7.9
3	75.7	4.7
4	82.3	4.5
5	75.6	5.9
6	92.8	3.8
mean	81.0	6.7

Table 1: Mean classification accuracy and standard deviation (std) for each participant in %.

2 Methods

We recorded the electroencephalogram (EEG) from 120 sites from 6 healthy volunteers (24 ± 2 years, 5 male) during active and passive walking (4 runs of 6 min each) with a robotic gait orthosis (Lokomat, Hocoma). In the active walking condition, participants were instructed to walk independently in the gait robot at the speed of the treadmill supporting their own weight. Passive walking demanded participants to let their legs be moved by the robot. Foot contact was measured by electrical foot switches placed on the heels of both feet. Figure 1 summarizes the experiments. For a more detailed description of the experiment see [6]

2.1 EEG Analysis

Preprocessing

Due to the high artifact contamination of the EEG during walking the data was pruned using Independent Component Analysis (ICA) prior to single trial analysis. Preprocessing for ICA included filtering from 1 to 200 Hz, resampling at 500 Hz, and manual rejection of non-stereotyped artifacts. Typical stereotyped artifacts (eye movements, muscle tension) were kept in the analysis as they are separated by ICA into only a few independent components (ICs). Infomax ICA [4] decomposed the EEG into ICs, representing brain, muscle, and artifact sources. The ICs were then categorized into cortical sources and artefact components considering scalp map, power spectrum, and event-locked time course. This procedure left on average 14 cortical sources per participant (range: 6-18 ICs). These cortical sources were then backprojected to the EEG data. To minimize computational effort, only 62 channels equally distributed over the scalp were selected for further analysis. PCA (Principal Component Analysis) was applied to the remaining 62 channels to reduce the dimensions of the remaining EEG channels to the number of backprojected ICs. The data was segmented from -0.5 to 2.5 seconds around the right heelstrike (time between contralateral steps 1 s). Around 250 trials were used for each class.

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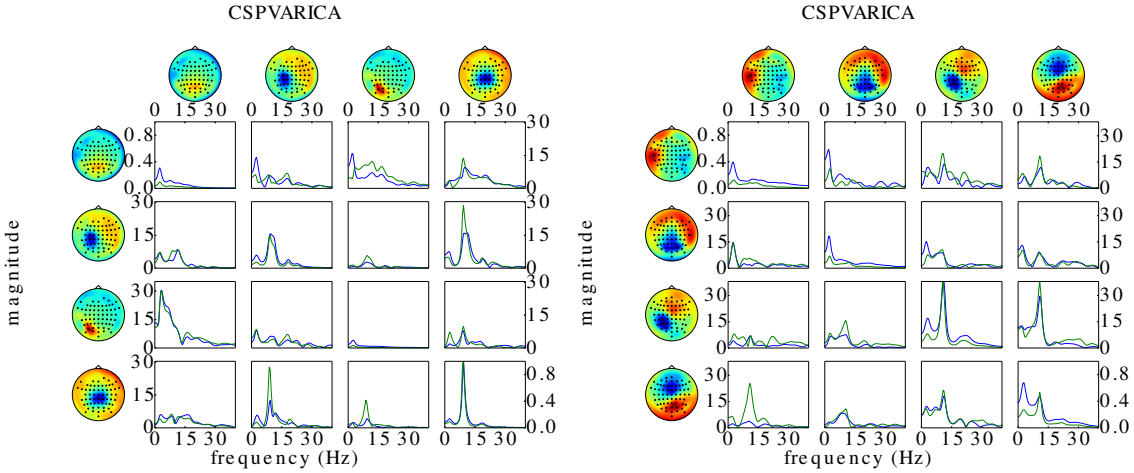

Figure 2: Directed connectivity with CSPVARICA for participant 1 (left) and 6 (right). The ffDTF between four components is plotted for active (blue) and passive (green) walking. The x-axis corresponds to the frequencies from 0 to 40 Hz, the y-axes to the magnitude of the ffDTF (in arbitrary units). Columns represent sources and rows sinks. The power spectral density of each source is plotted along the diagonal.

Single trial connectivity analysis

For single trial connectivity analysis, the Python-based source connectivity toolbox SCoT [1] was used. Single trial analysis is performed in two steps. In the first step independent components are estimated with CSPVARICA [1]. The method transforms the EEG with Common Spatial Patterns (CSP) to find components that maximize the variance between conditions. Then a VAR model is fitted to the CSP components, and the residuals of the VAR model are decomposed by ICA to estimate the final unmixing matrix U. In the second step single trial component activations are obtained by multiplying the EEG with U. Then an autoregressive model is fitted for these component activations. The ffDTF (full frequency directed transfer function) [2] was calculated from the model to measure connectivity. This method estimates the direction of causal influences between sources. The ffDTF was averaged in the frequency bands μ (7-12Hz), β (15-21Hz) and a subject specific frequency band ranging from 24 to 40 Hz. We have previously shown in [6] that these frequency bands account for differences between active and passive walking. The number of components was four and model order was set to 100. This resulted in 48 features for classification. Classification was performed with linear discriminant analysis. The whole procedure was applied in a 10 fold cross-validation to estimate the performance. For a more detailed description of the method see [1].

3 Results

Connectivity measures allowed differentiation between active and passive movements with an average classification accuracy over subjects of 81.0% $\pm$ 6.7. Classification accuracies for single subjects are displayed in Table 1. Visual inspection revealed that connectivity magnitude in classification relevant frequency bands μ and β was higher during passive compared to active walking. Most participants had at least one contributing source in the central midline area and in posterior areas. For the results of two exemplary subjects see Figure 2.

4 Discussion

Our results show that it is possible to separate active and passive walking in single trial EEG data based on connectivity measures. Classification accuracies were above chance in all subjects, and were on average 10% higher compared to our previous results using band power features [5]. However, it still has to be evaluated whether this improvement is due to the method used, the features or to the pruning of the EEG with ICA prior to feature selection. Furthermore, a major challenge for the online application of these methods during gait rehabilitation remains automatic artifact correction.

From a neurophysiological perspective, the analysis revealed that connectivity magnitude in μ and β bands between sensorimotor sources is higher during passive compared to active walking. The magnitude of the ffDTF depends on spectral power, thus the results fit with our previous findings showing a suppression of μ and β bands related to active participation. Suppression of μ and β rhythms has previously been related to the activation of sensorimotor areas. Thus, our results suggest that active walking increases the activation of sensorimotor regions and reduces information flow between these areas. Further analysis should evaluate in more detail the sources contributing to differences in connectivity over subjects. This may reveal neural networks underlying active participation in gait training.

5 Acknowledgements

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