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.

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