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Reconstructing gait cycle patterns from non-invasive recorded low gamma modulations

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Abstract

This work presents a simple to set-up system for reconstructing gait cycle patterns from non-invasive recorded electroencephalographic (EEG) signals. It is based on the prior finding that low gamma amplitudes are modulated locked to the gait cycle in central sensorimotor areas. Therefore, we focused on a Laplacian Cz derivation and low gamma amplitude modulations to reconstruct the gait patterns. Our results show that this method was successful in reconstructing gait cycle patterns in 8/10 subjects during active walking and in every subject during passive walking. The median reconstruction error was 0.24±0.13 s for active and 0.26±0.10 s for passive walking. The presented methods and findings are a further step towards analysing and monitoring ongoing cortical activity during human upright walking.

1 Introduction

Reconstructing gait cycle patterns from brain activity could be a useful technique, e.g., first, to enable neuromonitoring for therapists, and second, to provide neurofeedback for patients during rehabilitation after brain injury. Using reconstructed gait related brain patterns for neurofeedback can potentially enhance training in individuals with impaired motor function. These signals could, e.g. be used for supportive control of functional electric stimulation or robotic gait orthosis. Recently, some efforts in gait kinematics reconstruction were made [4] using frequencies in the delta range (0.1-2Hz) for decoding. However, the usage of low frequency components for decoding movements was discussed controversially [1] and their cortical origin were doubted [2]. Previous work from our group [5], [6] showed that low gamma (24-40 Hz) amplitudes are modulated in relation to the gait cycle. These activities were localized in central sensorimotor regions. In this work, we suggest that these low gamma modulations can be recognized on single-trial level and thus enables the reconstruction of gait cycle patterns in real-time.

2 Methods

2.1 Experiment

Ten able-bodied subjects (S1-S10, 5 female, 5 male, 25.6±3.5 years) walked with a robotic gait orthosis (Lokomat, Hocoma, Switzerland). The experiment involved 4 runs (6 min each) of active and passive walking as well as 3 runs of upright standing (3 min each), which was used as a control condition. The walking speed was adjusted for every subject ranging from 1.8 until 2.2 km/h, and a body weight support of less than 30% was provided.

2.2 Recordings and Preprocessing

EEG was recorded form 120 sites with four 32-channel amplifiers (BrainAmp, Brainproducts, Munich, Germany). The sampling frequency was 2.5 kHz, filter settings were 0.1 Hz and 1 kHz for high and low pass respectively. The electrodes were arranged in accordance to the 5% international 10/20 EEG system (EasyCap, Germany). Left and right mastoids were chosen to place reference and ground electrodes. Electrode impedances were lower than 10 kΩ. The interval between two right leg heel ground contacts defined one gait cycle. Foot contact was measured by mechanical switches. Further details can be found elsewhere [6]. EEG data was filtered and down sampled to 500 Hz. Channels with a variance greater than 5 times the median variance were rejected from further analysis. If one channel exceeded a threshold of 200 μV, the according gait cycle epoch was removed from the EEG recordings. In total 94.1 % of the data were used for the analysis.

2.3 Reconstruction of the gait cycle

We built a model to reconstruct the gait cycle pattern from EEG recordings, based on physiological evidence; namely that the low gamma amplitudes are modulated with the step frequency in the sensorimotor feet area. To reconstruct the gait cycle pattern from EEG we consequently focused on the temporal modulations of low gamma (20-40Hz) amplitudes. To test a system that is in principle able to work in clinical practice we used five channels (FCz, C1, Cz, C2, CPz) to calculate Laplacian Cz derivation in this work, since we already know the spatial region of interest from previous work [5], [6].
The EEG data were split into two subsets. First, one third of randomly drawn EEG trials (max. 8 min) were used as training set to simulate clinically feasible system training durations. Second, the unseen two thirds of the data were concatenated and used for evaluating the gait cycle reconstruction. The training set was used to identify the parameters carrier frequency, mean step frequency and phase lag between low gamma modulations and actual foot contacts. Spectral analyses were performed using complex Morlet wavelets [3] (center frequency: 1 Hz, full width half maximum: 3). Low gamma amplitudes are a result of spectral analysis. To determine the frequency of an amplitude modulation (AM) these amplitudes were again wavelet transformed (center frequency: 1 Hz, full width half maximum: 6).
The frequencyin the low gamma range which amplitude were maximally modulated by the step frequency was used as optimal carrier frequency. The phase lag between low gamma AM and the actual foot contact was determined using the training data. Once we know the optimal carrier frequency for AM and the phase relation between the AM and the actual foot contacts; it is straightforward to reconstruct the foot contacts and thus the gait cycle patterns from EEG recordings.
Data of the evaluation set were analysed on single-trial level to simulate a real-time experiment. The EEG data were wavelet transformed at the optimal carrier frequency and the resulting amplitude were again analysed using a wavelet with the step (modulation) frequency to gain the phase of ongoing low gamma AM. The phase lag gained form the training set was then used to estimate the foot triggers. Reconstructed and mechanical measured foot contacts were then compared and errors were calculated as L1 norm. To test if these errors are significantly smaller than chance, we performed the same analysis using EEG data from the standing condition to evaluate the chance level errors. The reconstruction errors for active and passive walking were then statistically tested to be smaller than these chance level errors using the Wilcoxon rank sum test.

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3 Results

In 8/10 subjects the reconstruction of the gait cycle patterns during active walking were significantly better than chance ($p<0.05$). In the best subject, the mean error (L1 norm) was 120 ms. The reconstruction was also successful during passive walking in every subject. No significant difference ($p=0.77$, Wilcoxon signed rank test) was found between the errors of the active and passive condition. Detailed error reports are shown in Table 1 with the corresponding carrier frequency(f), p-values and the relative amount of trials in which the error was better than random (BTR). Note that in 6/10 the BTR percentage was greater than 90%. The error histograms are illustrated in Fig. 1.

	Active					Passive				
subject	f Hz	err_{recon} s	err_{chance} s	p	BTR %	f Hz	err_{recon} s	err_{chance} s	p	BTR %
S1	27	0.12	0.51	<0.001	100	26	0.09	0.51	<0.001	100
S2	34	0.14	0.50	<0.001	96.84	35	0.17	0.50	<0.001	92.91
S3	29	0.24	0.60	<0.001	92.56	29	0.30	0.62	<0.001	88.63
S4	31	0.22	0.59	<0.001	92.33	30	0.28	0.61	<0.001	88.73
S5	30	0.23	0.48	<0.001	91.80	27	0.24	0.53	<0.001	87.56
S6	29	0.21	0.52	<0.001	91.61	27	0.19	0.52	<0.001	93.91
S7	20	0.46	0.57	<0.001	63.79	20	0.39	0.56	<0.001	76.07
S8	27	0.47	0.47	0.54	53.75	34	0.34	0.48	<0.001	84.54
S9	20	0.29	0.54	<0.001	82.49	20	0.40	0.61	<0.001	68.62
S10	20	0.43	0.44	0.16	48.80	35	0.22	0.41	<0.001	88.44

Table 1: Low gamma carrier frequencies, reconstructed and chance level error means with according p-value and BTR percentage for active (left panel) and passive (right panel) walking.

4 Discussion

In this work we presented a system that is able to reconstruct gait cycle patterns from non-invasive EEG recordings. We were able to extract the low gamma modulation pattern, the carrier frequencies, and their phases (time lag relative to the heel strike) using only one third of the data for training. These values are consistent with previous analysis reported in [5], [6]. These findings suggest that the reconstruction method in this work indeed is based on the cortical activity not on artefacts.

The proposed method also works for passive walking in every subject while during active walking it was successful in 8/10. In the analysis we observed that the quality of the reconstruction is reduced when artefacts are present. Our data suggests that head/neck muscular activity is lower during passive walking than during active walking. This effect is notable at lateral and dorsal electrodes. Thus, it is plausible that the lower influence of muscular artefacts during passive walking is the reason why a good reconstruction is possible in all participants. However, EEG recordings are contaminated with muscular artefacts in a broad frequency range during walking [2]. Analysing EEG data on a single-trial level during walking is therefore very challenging. Further work is needed to evaluate to which extent muscular activities influences the reconstruction of gait related parameters in comparison to the overall performance. In this work, the reconstruction performance was found to be driven by physiological meaningful features. In conclusion, we consider this work as a further step towards analysing and monitoring cortical activity in real-time during human upright walking.

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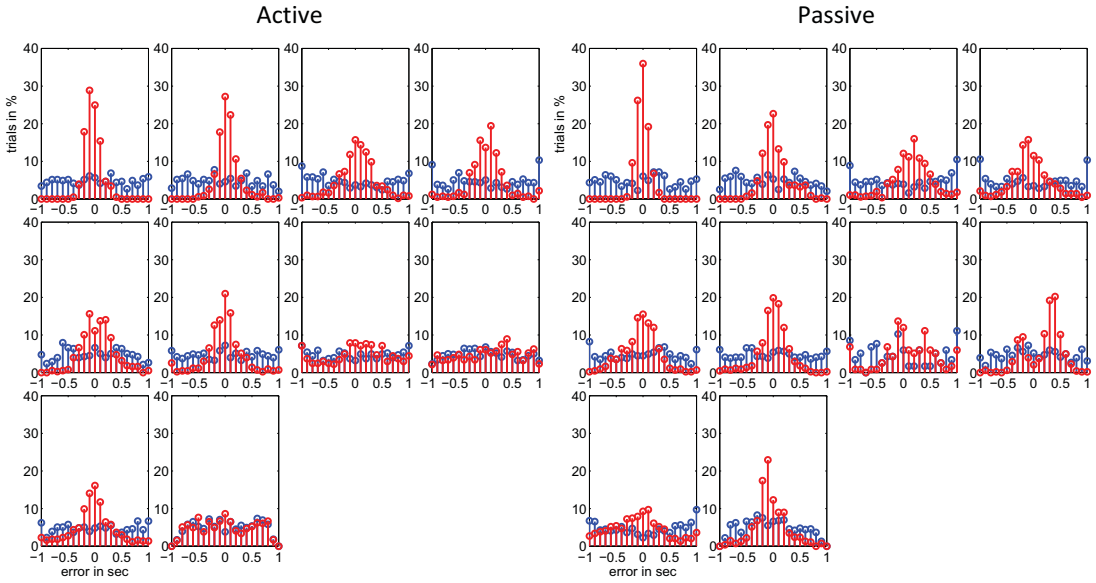

Figure 1: Error histograms for active (left) and passive (right) walking in red, for standing (chance level errors) in blue (S1-S10, top left to bottom right). Error distributions of the walking (red) conditions are centred around zero with an ideally small standard deviation for successful reconstructions. Standing condition errors (blue) seem to follow an uniform distribution.

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