Neural Decoding of Continuous Gait Imagery from Brain Signals

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Abstract

We present our ongoing work on neural decoding of gait imagery using non-invasive electroencephalography (EEG). We assess the feasibility of decoding EEG signals to trigger the movement of individual leg prosthesis while a motor-impaired user imagines the movement of legs. We apply our method with a paraplegic subject (T12 spinal cord injury) while attempting to walk in a slow pace of 3 to 4 seconds for each step. The results suggest that it is feasible to perform a continuous decoding of gait imagery with reasonably high reliability.

1 Introduction

We present a method for solving a problem of classifying left vs. right individual stepping imagery from EEG signals. Although there have been some works on gait intention decoding [1], [2], gait cycle phase analysis during treadmill walking [3], [4], neural decoding on treadmill walking [5], and walking vs idle state classification [6], our work differs from the above as the following: a) classification between individual stepping imagery, and b) no periodicity assumption in the model as we do not employ a treadmill and each stepping length is randomized. In this work, with an ultimate goal of using brain signals to trigger individual leg prosthesis, we present a gait decoding method and experiment with a paraplegic subject who suffers T12 spinal cord injury (SCI). The subject performs motor attempt (actively trying to move his disabled legs) instead of motor imagery (a healthy subject imagining moving his leg while inhibiting overt movement).

2 Method

The protocol is defined as in Figure 1. A trial starts with a resting period (5s), a readiness cue (2s), the first step cue (either left or right) (2s), followed by alternating left or right bars (3-4s, randomized), corresponding to each leg. It continues for 6 to 8 steps and the trial ends. The subject rests 3-5 minutes after every 10 trials. The subject is told explicitly not to move hands or head and minimize eye blinking during trials. The bar grows either left and right side during the stepping period, corresponding to left or right step, respectively. The growing speed of the bar changes according to the duration.

Signals are common average filtered and features are extracted by computing power spectral densities (PSD) of an overlapping sliding window in time using multitaper method [7]. Feature samples are extracted from a window of 500ms with a stride of 16 time points and they are computed for each channel independently. We compute PSD from 2 to 40 Hz with 2 Hz interval, resulting in 1220 (61 channels x 20 frequency bins) feature dimension. The classes are defined as Left (L), Right

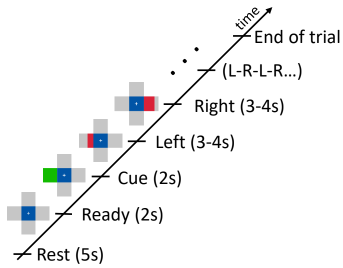

Figure 1: Training protocol. Cue shows which direction to start with, followed by 6 to 8 subsequent steps.

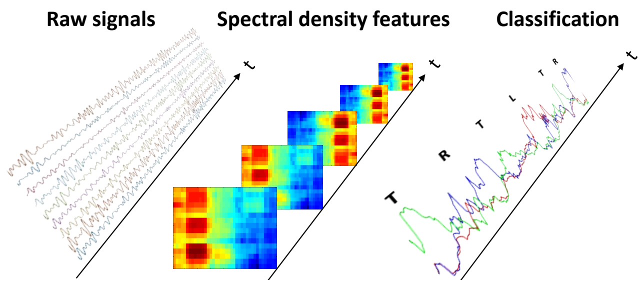

Figure 2: From raw EEG signals to classification.

(R) and Transition (T). L and R denote the period when the subject performs left and right stepping imagery, respectively. T is defined as a one-second period starting immediately after the time when the stepping direction changes. We choose Random Forest for classification, which is particularly powerful for training from data that has low trials-to-features ratio [8], a common case in human physiological data. We use 1000 trees with a maximum depth of 5 using the implemention of [9]. The overall process is shown in Figure 2.

We record EEG signals using AntNeuro eego mylab amplifier with a 64-channel Waveguard cap equipped with shielded cables and active electrodes effective at minimizing external signal interference. The electrodes are placed according to the standard 10-10 system while all impedances are kept below 20 kOhm. Sampling frequency is 512 Hz and all available EEG channels excluding 3 reference channels are used as input, resulting in 61 channels.

3 Experiment and Results

Each trial consists of 6-8 continuous steps and a total of 70 trials are performed with sufficient resting period in between. We perform an offline analysis on our data in two scenarios: with 2 classes (L vs. R) and with 3 classes (L, R and T). We perform leave-one-trial-out cross-validation among 70 trials, where each trial contains multiple feature samples from different windows. The sampled-based mean accuracy was 0.75 for 2 classes and 0.59 for 3 classes. Tables 1 and 2 show the confusion matrix for both scenarios, respectively. Figure 3 shows some simulated online results of trials showing likelihoods of each class.

Table 1: Confusion matrix for 2 classes

L	R
0.74	0.26
0.24	0.76

Table 2: Confusion matrix for 3 classes

L	R	T
0.62	0.22	0.16
0.21	0.65	0.14
0.29	0.24	0.47

4 Conclusion

The results show that it is feasible to decode the gait imagery by individual step without periodicity assumption. The results in Figure 3 show a new possibility of approaching the brain signal decoding problem as a sequence modeling problem, which could capture the dynamics of different states occurring in a human brain. The fact that a subject performs motor attempt instead of motor imagery is particularly beneficial as motor attempt is known to generate stronger signals than motor imagery [10] while avoiding major artifact problems caused by actual walking movements.

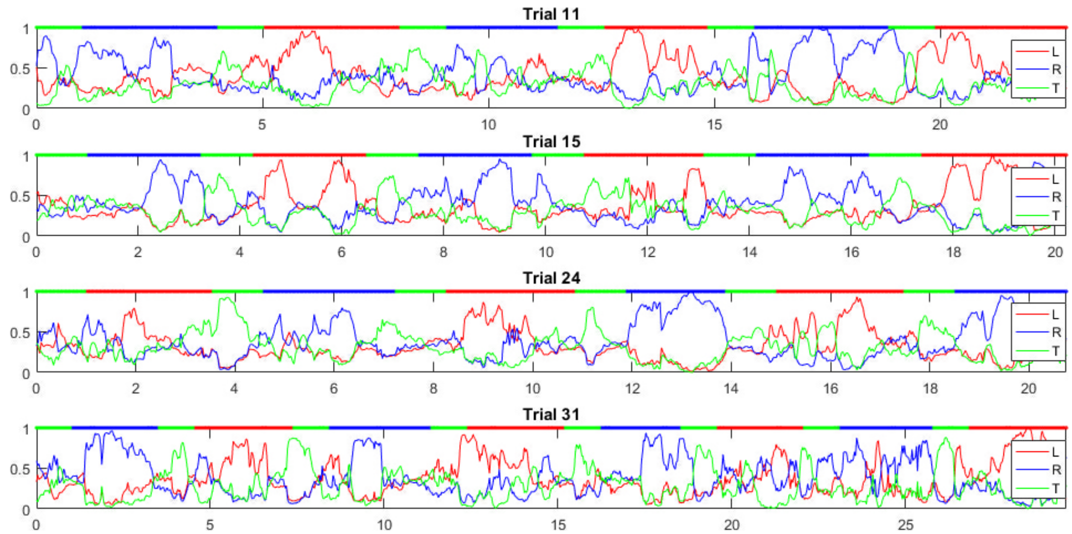

Figure 3: Simulated online results with 3 classes. Y-axis is the likelihood of each class and X-axis is time in seconds. **L** and **R** denote left and right step likelihoods, respectively, while **T** denotes the transition likelihood. The upper bar colors denote ground truth labels.

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