Real-time Navigational Intent Detection from Hippocampal EEG: A Proof of Concept

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1 Introduction

Human navigational intent decoding from brain activity through brain-computer interfaces (BCIs) has clear clinical applications such as wheelchair control [2]. However, previous navigational intent decoders face limitations, notably delays in the feature extraction phase and reliance on prior knowledge of when turns were possible, making them unsuitable for real-time use [5]. This study proposes a pipeline for real-time navigational intent decoding using only raw hippocampal electroencephalography (EEG) activity data. During navigation, hippocampal activity is characterised by theta-band (2–8 Hz) oscillations visible in EEG [1]. Notably, Seeber et al. identified that theta amplitude increases before a turn [6], suggesting a promising predictive value of theta. To enable rapid feature extraction of theta band amplitude, we use a state space modelling approach to tracking oscillations (SSO) [8], which combines a state space architecture with sample-by-sample Kalman Filtering to extract oscillatory amplitude in real-time and avoids delays that exist in traditional buffer-based approaches such as bandpass filtering. The present study employs features derived from SSO to predict turns in a virtual environment through a Poisson Generalised Linear Model (GLM).

2 Methods

Data were collected from 3 epileptic patients taking part in an experiment consisting of a car-driving virtual game [5]. During the experiment, hippocampal activity was recorded through stereo-EEG (sEEG) across channels, with turn events marked by rapid changes in driving orientation. During recording, 9, 3, and 7 channels of hippocampal activity were measured for patients 1, 2, and 3, respectively. Each channel was bipolar-referenced and decomposed into multiple oscillators, out of which only theta-band frequency (<8 Hz) oscillators are used. With SSO, instantaneous oscillatory amplitude is tracked in real-time through state equations and averaged across 250 ms bins, across the 3 seconds prior to every turn prediction. Poisson GLM (Equation 1) with elastic net regularisation, suitable for sparse events [7], is trained independently for each patient. Within each patient, the models were fit on the above-mentioned amplitude features concatenated across theta oscillators to predict turns.

$$E[\text{turn}] = \exp\left(\beta_0 + \sum_{n=1}^{13} \beta_n \, x_n^{\theta}\right) \tag{1}$$

, where x_n^{θ} are the past 13 amplitude bins for each theta oscillator, and β_n^{θ} are the corresponding trained coefficients. The data were split into train-validation-test to avoid leakage. Additionally, cluster-based permutation testing [3] as implemented in FieldTrip [4] is applied across oscillators to observe if theta amplitude differs in the 3 s before turn from the baseline theta amplitude.

3 Results

The pipeline is evaluated on the test set area-under-the-ROC. Single channel model only uses theta oscillators from one channel, while the multi-channel model concatenates all channels. Only for

patient 1, significantly above-chance models are noted, specifically, an AUC of 0.68 for channel 8 and 0.64 for multi-channel. However, cluster-based permutation testing showed that 7 out of 19 channels (5, 0 and 2 for patients 1,2 and 3, respectively) were decomposed into oscillator(s) with significant cluster(s) indicating periods of time when the theta amplitude deviated from baseline. Fig. 1 shows 2 oscillators from different channels, one with a significant cluster around 3.0 to 2.4 s before turn, and the other at 2.9 to 2.6 s, alongside their amplitude ERP before turns, suggesting consistent deviation.

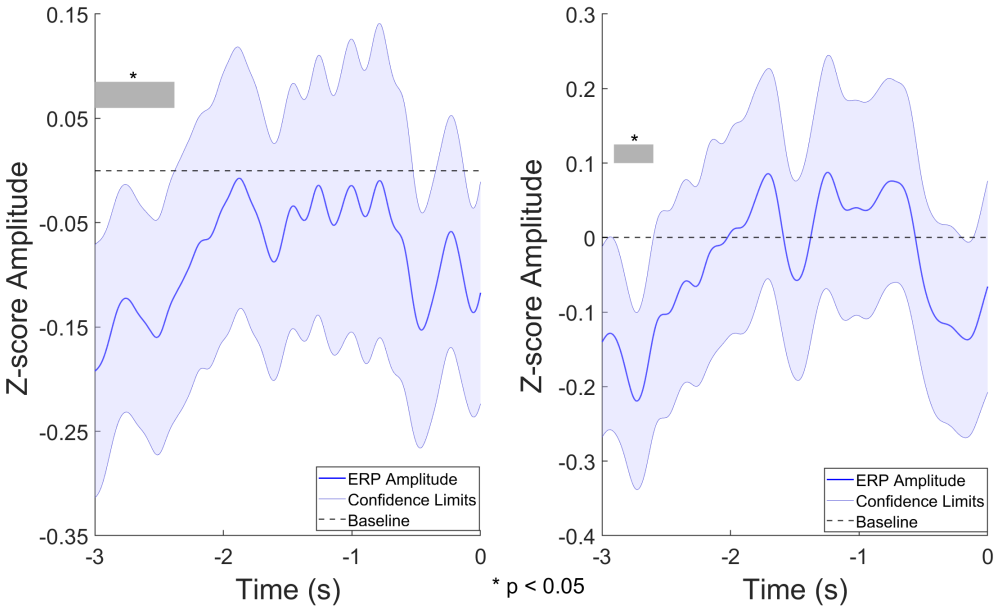

Fig. 1. Standardised theta amplitude (0.8 Hz oscillator) before a turn (averaged across turns) is shown as a dark blue line with confidence intervals (shaded blue regions) for two channels of Patient 1. The significant clusters (p value < 0.05) are illustrated in rectangles. Furthermore, there is a trend to the overall amplitude profile.

4 Conclusion

This work demonstrates a proof-of-concept for decoding navigational intent from hippocampal data in real-time using SSO-derived amplitude features fitted with Poisson GLMs. Based on statistical testing, certain oscillators' theta amplitudes differed significantly before turns compared to baseline, confirming their importance as predictive features. Patient 1's above-chance accuracy models demonstrate the potential of high performance of the pipeline if larger datasets are available. Latency of the algorithm can be split into two parts: first is the latency of signal decomposition into different oscillators and the second is the latency due to the bin-size used for the Poisson-GLM. The latter latency is significantly greater and in future studies should be assessed in greater detail. Here, the bin size for the Poisson GLM was 250 ms, which is sufficiently fast as to suggest the pipeline is real-time capable. Other performance-limiting factors include turn labels that aren't perfectly timed and channel location placement, which are likely to have a big impact on decoding results. To increase accuracy and generalisability, these limitations need to be addressed, paving the way towards reliable real-time navigational intent decoders for BCI applications such as wheelchair control.

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