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Predicting low gamma- from lower frequency band activity in electrocorticography

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Abstract. Electrocorticography (ECoG) has witnessed increasing interest from brain modelers for spanning a broader spectral band than EEG. As human brain activity exhibits broadband modulations, we hypothesize that this should also be reflected by ECoG signal predictability across frequency bands. As a concrete case, we consider the prediction of low gamma- (40-70 Hz) from lower frequency band non-task related activity using the recently developed Block Term Tensor Regression (BTTR) algorithm. As a result, we achieved prediction accuracies up to 89% (Pearson correlation coefficient), providing evidence for a substantial degree of low gamma predictability.

1 Introduction

Using depth electrodes implanted in patients scheduled for brain surgery, task-related modulations in local field potential (LFP) activity have been observed throughout a broad frequency range extending to 150-200 Hz, showing that the human brain exhibits broadband phenomena [1, 2, 3]. Broadband power shifts were also shown to be more reliable predictors of neuronal spiking than narrowband ones [4]. Likewise, using electrodes placed on the cortical convexity, electrocorticography (ECoG) signals recorded in response to a motor task were observed to be modulated simultaneously at all frequencies [5], rather than being limited to a particular frequency band. In fact, low gamma oscillations (40-70 Hz) can be difficult to distinguish from broadband fluctuations because both phenomena appear at overlapping frequency bands. The question we wanted to address is whether broadband activity also allows for an accurate prediction of low gamma signal amplitude. To this end, we considered a regression model,

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mapping low frequency activity (< 40 Hz) to low gamma activity (40-70 Hz) using a sliding time window.
We opt for a multiway or tensor-based regression approach [6] as it accounts better than conventional vector- or matrix-based techniques for ECoG signals being structured at least in frequency, space (electrodes) and time. Recently, Camarrone [7] developed a multiway algorithm called Block Term Tensor Regression (BTTR) that predicts finger trajectories from ECoG signals recorded in humans and outperforms HOPLS and the conventional linear regression model in training speed in decoding accuracy [7]. Given these promising performances, we adopt BTTR to predict low gamma signal amplitudes from lower frequency band amplitudes. In what follows we introduce our methodology that also considered electrode selection, report our results and discuss their relevance.

2 Materials and Methods

2.1 Experimental paradigm

At UZ Gent a male patient was recruited that suffered from drug-resistant epilepsy. To locate the epileptogenic region, the patient was implanted with a subdural ECoG grid of 6x8 platinum electrodes embedded in silastic (AdTech, USA) covering the precentral gyrus and the superior and middle frontal gyri of the right hemisphere (see electrode grid placement in Figure 2). The electrode positions were extracted from the pre-implant MRI and post-implant CT scans, using a procedure described elsewhere [8, 9]. ECoG signals were continuously recorded at 256 Hz using an SD LTM 64 Express from Micromed (Treviso, Italy). During the clinical workup phase the patient volunteered to participate in several experiments after signing the informed consent form. The study was prior approved by the ethical committee of UZGent.
The experiment consisted of an instruction, a pause, and task performance. Here we consider only activity between tasks, further called baseline activity, but the results also pertain to task performance, which will be shown elsewhere as our focus is to show the potential of tensor-based techniques to regress ECoG signals across frequency bands.
The raw signals were re-referenced to the common average reference (CAR) of all subdural channels, and the powerline interference removed using a 4th order Butterworth notch filter between 49 and 51 Hz. Next, 3-second epochs were cut from the continuous signals, locked to the offset of the instruction but before the task, further referred to as 'baseline epochs', 60 in total. Finally, for each baseline epoch, the activity in 6 frequency bands was extracted using 4th order Butterworth bandpass filters: δ (0.5-4 Hz), θ (4-8 Hz), α (8-12 Hz), β_1 (12-24 Hz), β_2 (24-40 Hz) and the low gamma band (40-70 Hz). Figure 3c shows the power spectral density (PSD) for one baseline epoch, for the original- (including 50Hz notch-filtering), the low gamma bandpass filtered- and the predicted signal. Note that bandpass filtering tapers the PSD of the original signal.

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2.2 Notation

We denote tensor, matrix, vector and scalar with $\underline{\mathbf{T}}, \mathbf{M}, \mathbf{v}, S$ respectively. The mode-n product between $\underline{\mathbf{T}}$ and $\mathbf{M}$ and the Kronecker product are denoted as $\times_n$ and $\otimes$ respectively. The mode-n unfolding of $\underline{\mathbf{T}}$ is denoted with $\mathbf{T}_{(n)}$, the vectorization of $\underline{\mathbf{T}}$ with vec($\underline{\mathbf{T}}$) and a mode-n factor matrix with $\mathbf{M}^{(n)}$.

2.3 Feature representation and electrode selection

The input to our multiway regression model consists of a 3-dimensional tensor per time sample, computed by sampling the band-pass filtered signals (δ, θ, α, β_1, β_2) in a 58.6 ms sliding window looking back in time for each electrode. The input tensor $\underline{\mathbf{X}}$, thus, has the following four dimensions: *Samples, Frequency* bands, *Electrodes* and *Time*. The corresponding output $\mathbf{y}$ is one-dimensional, constructed by sampling the low gamma signal.
To promote accuracy we considered a greedy electrode selection procedure: at each iteration, the procedure selects the electrode that maximally increases regression performance (forward selection) of the current subset until 5 electrodes are selected, an empirically chosen stopping criterion.

2.4 Modeling

In order to predict low gamma activity from the five other frequency bands, we adopted Block-Term Tensor Regression (BTTR) [7], which utilizes a deflation-based approach to iteratively model the relationship between predictor and response as a series of maximally correlated blocks (see Figure 1). Given a set of multiway data $\underline{\mathbf{X}}_{train} \in \mathbb{R}^{Samples \times Frequency \times Electrodes \times Time}$ (see section 2.3) and a vectorial response $\mathbf{y}_{train} \in \mathbb{R}^{Samples}$, BTTR training consists of automatically identifying K blocks s.t.:

$$\underline{\mathbf{X}}_{train} = \sum_{k=1}^{K} \underline{\mathbf{G}}_k \times_1 \mathbf{t}_k \times_2 \mathbf{P}_k^{(2)} \times_3 \mathbf{P}_k^{(3)} \times_4 \mathbf{P}_k^{(4)} + \underline{\mathbf{E}}_k \qquad \text{and}$$

$$\mathbf{y}_{train} = \sum_{k=1}^{K} \mathbf{u}_k + \mathbf{f}_k \qquad \text{with } \mathbf{u}_k = \mathbf{t}_k \mathbf{b}_k,$$

with $\underline{\mathbf{G}}_k \in \mathbb{R}^{1 \times R_2^k \times R_3^k \times R_4^k}$ the core tensor for the k-th block, $\mathbf{P}_k^{(n)}$ the k-th loading matrix for the n-th dimension, $\mathbf{u}_k$ and $\mathbf{t}_k$ the score vectors, $\mathbf{b}_k$ the regression coefficient, and $\underline{\mathbf{E}}_k$ and $\mathbf{f}_k$ the residuals. When trained thus $\underline{\mathbf{G}}_k$, $\mathbf{P}_k^{(n)}$ and $\mathbf{b}_k$ are computed, the model's final prediction for new set of samples $\underline{\mathbf{X}}_{new}$ is as follows:

$$\mathbf{y}_{new} = \mathbf{T}_{new}\mathbf{b} = \underline{\mathbf{X}}_{new(1)}\mathbf{W}\mathbf{b}$$

where each column $\mathbf{w}_k = \left(\mathbf{P}_k^{(4)} \otimes \mathbf{P}_k^{(3)} \otimes \mathbf{P}_k^{(2)}\right)\text{vec}(\underline{\mathbf{G}}_k)$.
The dimensions of $\underline{\mathbf{G}}_k$ and $\mathbf{P}_k^{(n)}$ are automatically determined using Automatic Component Extraction (ACE). Because of space restrictions, an exposition of

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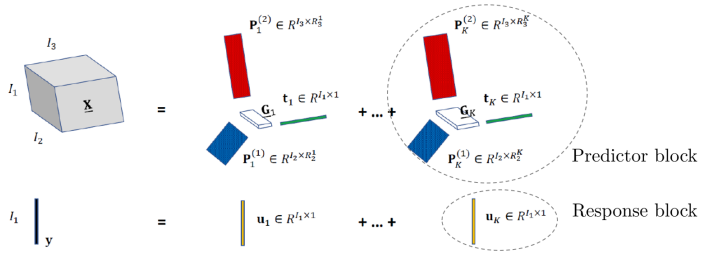

Fig. 1: Scheme of BTTR algorithm with a predictor 3-dimensional $\underline{\mathbf{X}}$ and one-dimensional response $\mathbf{y}$. Note that in our case the predictor is 4-dimensional.

ACE is omitted (for details, see [7]). The only model parameter left undetermined is K, the number of blocks used in the deflation scheme.

2.5 Cross-validation strategy

The performance of the regression model per electrode is assessed by using 5-fold cross-validation. The folds are constructed by shuffling the baseline epochs over folds, such that each fold consists of 12 randomly chosen, but complete epochs. In total, 20 models are developed per electrode using 3 training-, 1 validation- and 1 test fold, which are shuffled among models. Training and validation folds are downsampled by a factor 3 to reduce computational costs. After training each model on 3 folds, the optimal number of blocks (K_{opt}) is chosen based on model performance on the validation fold. Model performance is assessed in terms of the Pearson correlation between the predicted and the desired low gamma band signal amplitude. For K, we considered a range between 1 and 400. Performance on the validation fold was also used by the greedy electrode selection procedure. In this way, models remain independent of each other and reflect the performance distribution over different data partitions. Finally, the performance of the validated model is computed on the test fold. The mean performance per electrode is obtained by averaging over the 20 models. This is repeated for each electrode in the grid.

3 Results

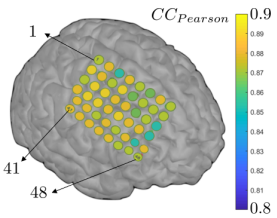

Fig. 2: Electrode grid placement and mean performance per electrode.

We applied the BTTR algorithm to predict the low gamma band signal from the corresponding lower frequency signal in the case of baseline ECoG recordings. Figure 2 shows the mean prediction performance per electrode for low gamma (40-70 Hz) on the electrode grid. The performance averaged over electrodes is 87.61% (min 84.95%, max 89.44%). To illustrate the behavior of the method, we focus on a randomly picked model. Figure 3a shows the electrodes selected at each iteration for this

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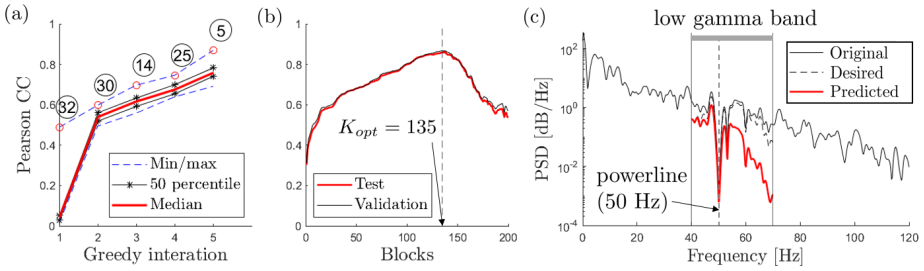

Fig. 3: Results for a model predicting electrode 32. (a) Greedy selection: at each iteration the performance distribution over sub-iterations and the chosen electrode (circled) are shown. The retained model uses electrodes $32, 30, 14, 25$ and 5. (b) Performance on the test- and validation fold with number of blocks. (c) Power spectral densities of the original (50Hz notch-filtered) signal, the desired signal (bandpass-filtered) and its prediction.

model. The predicted and desired amplitude for a baseline epoch from the test fold is shown in Figure 4, together with the instantaneous phase-locking value (PLV), a value between 0 and 1, with 1 indicating perfect phase synchronization. The instantaneous PLV is computed over a centered sliding window (97.7 ms) applied to the phase extracted with the Hilbert transform.

4 Discussion

The performance is consistent across electrodes, as shown in Figure 2. Figure 3a shows that greedy selection yields a narrow performance distribution over sub-iterations, indicating that the selection is not that important, except for the first iteration, where for all models select the to be modeled electrode. This finding motivates the use of a less rigorous and faster selection technique, *e.g.*, by randomly taking subsets (including the modeled electrode) and picking the best one. Figure 3b shows a similar performance for the validation and test set, as both are unseen data to the model. Therefore, the optimal number of blocks is close to optimal for the test set. The high number of blocks indicates

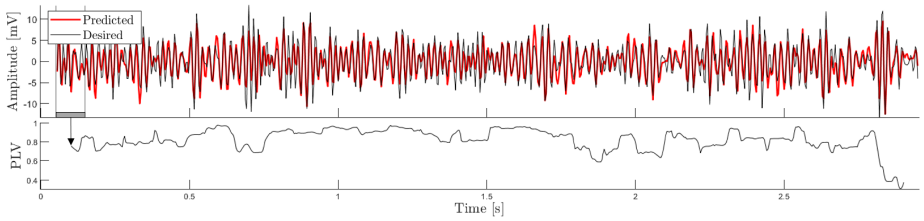

Fig. 4: Comparison of predicted and desired low gamma amplitude on a test trial and the instantaneous PLV.

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a high model complexity, which might be demoted when resorting to wavelet features [7] or adopting a multi-scale approach [10]. Figure 3c shows that the difference between the desired and predicted PSD widens when approaching the high gamma band, indicating the predictability is highest for frequencies adjoining the β_2 band as expected.
Figure 4 shows that the low gamma signal is predicted rather well except perhaps for extremal and small amplitudes. Importantly, the phase is preserved which is important as gamma oscillations are thought to be our best candidate to unravel the role of aggregate electrical activity in predicting synchronized spiking of individual neurons [11]. We consider the predictability of low gamma signals, in amplitude and phase, from low frequency activity, to be due to ECoG signals being broadband modulated. If true, we suggest modelers to also consider the broadband approach, in particular when recordings are scarce, even though model complexity could increase. We showed that the tensor-based approach could be a good starting point.

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