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Learning brain connectivity features for improving BCI performance

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ABSTRACT: Brain computer interfaces (BCIs) rely on the decoding of information embedded in brain signals for applications ranging from neurofeedback to device control. While power spectral features are widely used in motor imagery-based BCIs, recent evidence suggests that considering network interactions between sensors could improve performance. In practice however, connectivity between different brain signals is impaired by the high variability of classical estimators for short noisy segments. To address this issue, we propose a deep learning framework trained to recover ground-truth imaginary coherence from complex simulated signals. Here, we show that our framework learns to reconstruct smooth coherence spectra, designed as Gaussian mixtures. Evaluation on an electroencephalography dataset across three motor execution and imagery tasks, shows that connectivity matrices derived from the proposed method consistently outperform those obtained with Welch's estimator. These results demonstrate the feasibility of using deep learning to obtain stable informative coherence estimations in sparse and noisy contexts, supporting the use of functional brain networks for BCI applications.

INTRODUCTION

Modeling the brain as a network can provide highly informative insights in brain-computer interfaces [1]. The resulting interactions reflect the functional or statistical relationships between brain regions during different tasks. This concept is intuitive, and brain connectivity has long been central in network neuroscience, as it captures distributed coordination that cannot be inferred from local activity alone. For instance, recent advances have shown potential in using connectivity for motor imagery based Brain Computer Interfaces (BCIs), as including those connectivity features in mental states classification led to an increase in accuracy [2–4].

However, estimating connectivity from brain signals presents significant challenges. Classical models typically assume stationary long signals, whereas in EEG-based BCIs, signals are noisy and trial windows are short. Such biases can render connectivity estimates noisy and highly unstable across time windows, trials, or subjects, limiting their practical utility. Due to their variability, connectivity estimators need careful attention and expertise to be used properly, which is why they have been less popular than power spectra counterparts [5].

In this study, we explore whether Deep Learning can optimize the estimation of connectivity features for short and noisy signals, by outperforming traditional approaches. Using a combination of temporal convolutions, an attention mechanism and synthetically driven supervision, where imaginary coherence was designed as a Gaussian mixture, we are able to better reproduce connectivity in simulated signals compared to Welch's method. We test our approach on motor imagery and execution tasks from the PhysioNet EEG Motor Movement/Imagery Dataset [6], and are able to obtain better classification performance with matrices derived from our method, compared to matrices derived from Welch's.

MATERIALS AND METHODS

Imaginary Coherence: Imaginary coherence measures phase-lagged coupling between two signals $x(t)$ and $y(t)$ while ignoring contributions close to zero-lag correlations caused by volume conduction [7]. It ranges from 0 to 1.

Method summary: The objective of this study is to estimate imaginary coherence in the 1–40 Hz range from short EEG segments. Because ground-truth coherence cannot be accessed in real recordings, we first train a deep learning model on simulated signal pairs for which imaginary coherence is analytically defined. The learned estimator is then evaluated on three motor execution or imaginary tasks using the PhysioNet EEG Motor Movement/Imagery Dataset [6].

Synthetic data generation: Precise control over coherence values is required to supervise training. Signal pairs are therefore simulated according to the Fourier decomposition principle, allowing direct parameterization of amplitude and phase at each frequency (Eq. 1). Amplitudes $A_{x,f}$ and $A_{y,f}$ are sampled uniformly in [0,1], and phases ϕ_f in [0, 2π]. Frequencies range from 1 to 40 Hz with a resolution of 0.05 Hz. Sampling rate is 100 Hz. A total of 10,000 pairs of signals are generated.

$$\begin{cases} x(t) = \sum_f A_{x,f} sin(2\pi f t + \phi_f) \\ y(t) = \sum_f A_{y,f} sin(2\pi f t + \phi_f + \Delta\phi(f)) \end{cases} \quad (1)$$

To ensure a smooth yet structured spectral maxima, the

10.3217/978-3-99161-093-9-026

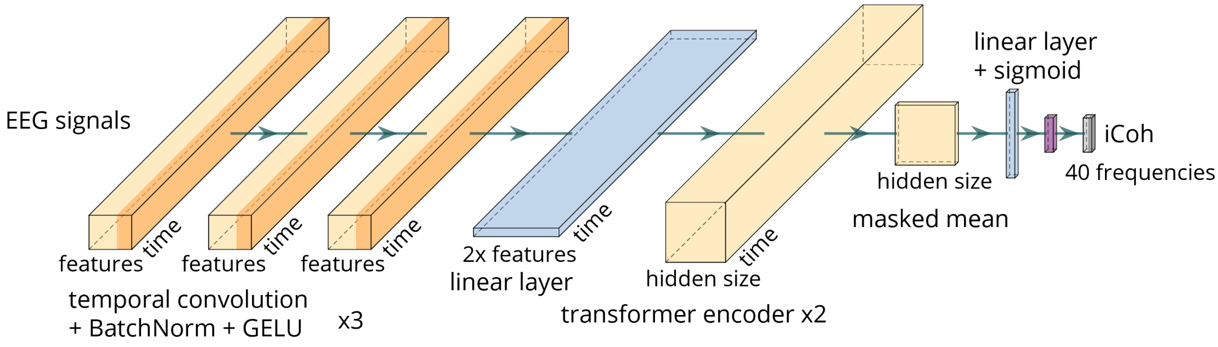

Figure 1: **Model architecture.** The architecture is composed of three temporal convolutional blocks, each followed by batch normalization and GELU activation. Features extracted from the two signals are then concatenated and projected into a higher dimensional space and processed by two Transformer encoder layers. The representations are averaged across the temporal dimension, and fed into a linear layer with 40 outputs. A sigmoid activation clips predictions between 0 and 1.

phase difference spectrum $\Delta\phi(f)$ is modeled as a Gaussian mixture in which Gaussians' widths σ_p range from 0.5 to 6 Hz, centers $f_{c,p}$ from 1 to 40 Hz, and amplitudes A_p from -π to π. This formulation ensures smooth spectral lobes while preserving variability and sharp transitions.

Twenty percent of the simulated data are held out for validation. Standardization is performed on the signals using statistics computed on the training set. Furthermore, noise will be added during training and windows will be randomly cropped (see section Model training).

EEG data processing: Evaluation is conducted on the PhysioNet EEG Motor Movement/Imagery Dataset. Signals are band-pass filtered between 1 and 43 Hz using a 10th-order Butterworth filter (f_s = 160), epoched from 0 to 3 seconds after cue onset, and linearly detrended.

Model architecture: Local temporal patterns are first extracted using three convolutional layers (kernel size 3, 32 filters, Batch Normalization, GELU activation [8]). This stage captures short-range dependencies and yields 64 feature maps for each signal pair.

The features are then projected into a 512-dimensional embedding space and processed by two Transformer encoder layers (4 attention heads, hidden dimension 512), enabling the modeling of longer-range temporal interactions. Before entering the encoder, features undergo layer normalization and sinusoidal positional encoding.

The temporal dimension is averaged prior to a final linear layer of size 40, corresponding to the frequency bins. A sigmoid activation constrains the predicted imaginary coherence to the [0,1] interval (Fig. 1).

Model training: The model is trained using L1 loss optimized with Adam (learning rate 10^{-5} , batch size 16). To promote robustness to noise and short segments, each simulated pair is augmented four times with additive Gaussian noise, with standard deviation linearly spaced between 0 and a randomly selected maximum between 1.8 and 2. In addition, signals are cropped four times using window lengths linearly spaced between a minimum randomly drawn between 100 and 120 samples, and 300 samples. These augmentations increase variability during training and increase the effective batch size from 16 to 256.

Welch's computation: We compare our model to Welch's method, which estimates power spectra by averaging periodograms of overlapping windows before computing imaginary coherence. Using the Python SciPy library implementation, 3-second segments sampled at 160 Hz are analyzed with 1-second windows (160 samples), 0.9-second overlap, and a Hann window to reduce spectral leakage.

Classification: To evaluate the quality of our prediction, we compute for each 3-second epoch the pairwise upper triangle coherence matrix (2016 pairs, 1–40 Hz, 40 frequency bins) using both Welch's method and the proposed model. Each epoch corresponds to either a first condition (left hand closing, left hand closing imagination, or hands imagination) or second condition (right hand closing, right hand closing imagination or feet imagination). A logistic regression classifier with standard data scaling is trained under a subject-wise 5-fold cross-validation scheme. Balanced accuracy is used to assess performance.

RESULTS

Performance on simulated data: The model is first trained on simulated data, as described in Materials and Methods. The L1 validation loss reached 0.114. Since the analytical imaginary coherence spectrum is known in this setting, it is possible to directly assess spectral fidelity across frequencies and compare it with Welch's method. Coherence is estimated on 3-second validation segments. The model closely follows the analytical target across the full frequency range, whereas Welch's estimates exhibit higher noisiness (Fig. 2). This behavior is consistent with the known sensitivity of Welch's method to short segment length and windowing effects.

Validation on EEG-based BCI data: After confirming spectral accuracy on simulated data, we assess whether the learned estimator transfers to real EEG recordings from the PhysioNet EEG Motor Movement/Imagery

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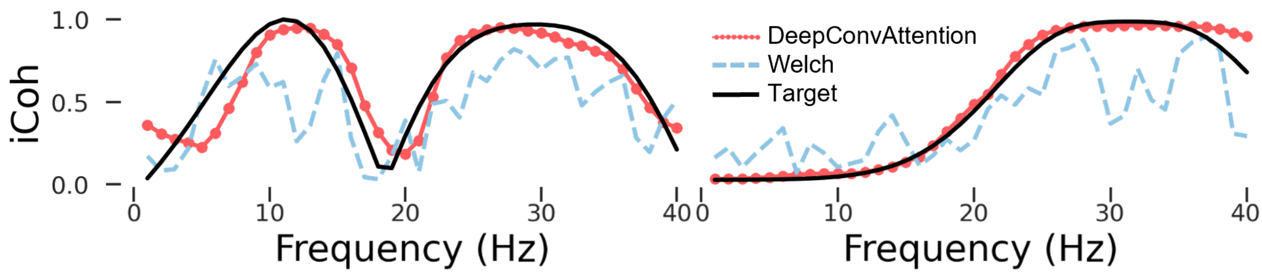

Figure 2: **iCoh spectrum in simulated data**. Predicted imaginary coherence is compared to Welch's method on validation data. The proposed model better matches the analytical target across frequencies, while Welch's estimates show increased noisiness.

Dataset, while real data was not seen during training. Connectivity matrices are computed across the two methods and averaged in the alpha band (8 to 13Hz) and the beta band (13 to 25 Hz). Fig. 3 displays those matrices for a representative subject (subject 1). Results show that the model recovers structured and spatially consistent connectivity patterns that align with established properties of phase-lagged interactions. Channel pairs located close to the diagonal exhibit weaker connectivity, reflecting reduced phase differences between neighboring electrodes. In contrast, more distant regions display stronger long-range interactions. Although absolute scales differ between methods, the spatial organization remains comparable (Fig. 3).

Classification performance on BCI tasks: The usability of our method is assessed using coherence matrices (2016 pairs, 1–40 Hz) as features for three BCI tasks from the PhysioNet's EEG Motor Movement/Imagery Dataset: (i) left vs. right hand execution, (ii) left vs. right hand imagery, and (iii) hands vs. feet imagery. Using only a simple logistic regression classifier (Materials and Methods), we demonstrate that matrices derived from our method yielded superior classification performance across the three tasks (Tab 1). Both the minimum and maximum subject-level performances were higher with the proposed method. The inter-subject variability is comparable between approaches, with mean standard deviations of 0.101 for the proposed method and 0.103 for Welch.

DISCUSSION

Connectivity estimation in BCI remains constrained by non-stationarity and limited data length. Classical approaches rely on windowing and averaging to stabilize spectral estimates. Although those methods have been widely used, they still yield variable connectivity patterns as EEG data remain particularly challenging. Using ground truth imaginary coherence in noisy and sparse data settings however, encourages the model to learn a stable spectral representation. Transfer from simulation to EEG is enabled by carefully designing the source domain to reflect properties of real signals. Namely, resting-state EEG typically exhibits smooth spectral organization over extended recordings, motivating the use of Gaussian mixtures to model phase differences. In addition, Gaussians' parameters were chosen to simulate more complex phase portraits. Lastly, a dense set of sinusoids is used to approach the infinite frequency resolution of EEG signals. To further improve estimation quality on EEG data, a systematic investigation of the simulation parameters and their underlying statistical distributions is warranted. It would also be of interest to explore other more complex simulation frameworks, based on multivariate autoregressive (MVAR) models for instance, that can fully capture time-varying phase couplings [5].

Although power spectral density remains the dominant feature in motor imagery BCIs, the present work highlights the discriminative value of functional connectivity. Using a deliberately simple classifier, connectivity matrices derived from the proposed estimator consistently outperformed those obtained with Welch's method. This suggests that improving the stability of connectivity estimation can directly enhance downstream decoding performance. However, further analysis needs to be conducted to assess how these connectivity features compare to power spectral density features, and how combining the two approaches could ultimately improve decoding performance.

Finally, the comparison is restricted to Welch's estimator. Alternative short-window spectral methods, such as autoregressive approaches, should be considered in future work. Moreover, the framework could potentially be extended to learn other spectral or connectivity estimators, opening perspectives for broader applications.

CONCLUSION

Despite its potential, the use of functional connectivity and network analysis in BCIs remains a difficult challenge because of the variability of current estimators. Here, we demonstrate that training a deep learning architecture for estimating imaginary coherence provides more precise and less variable estimates, especially in short-time noisy windows, compared to Welch's method. When applied to a 64-channel EEG-BCI dataset, the proposed framework consistently improves classification performance over standard Fourier-based estimation. These results support the feasibility of learning-based connectivity estimation and encourage further ex-

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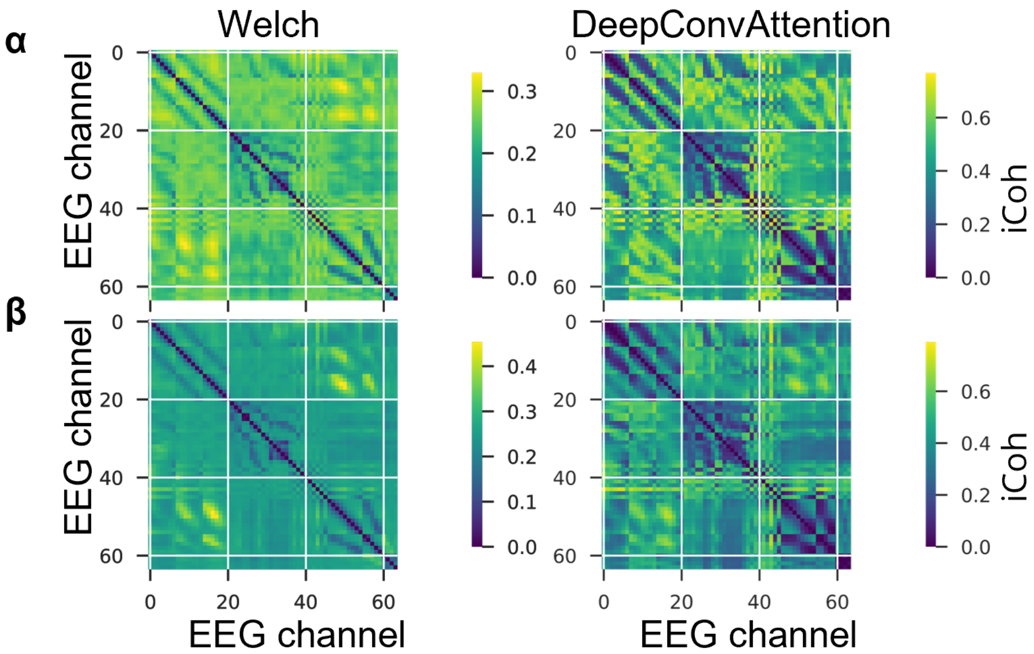

Figure 3: **iCoh connectivity matrices comparison in the alpha and beta bands for a representative subject**. Using PhysioNet's EEG Motor Movement/Imagery Dataset, connectivity matrices are computed in subject 1 for Welch's method and the proposed model. While the model was not trained on real EEG data, band-averaged coherence (alpha [8, 13] Hz, beta [13, 25] Hz) reveals consistent spatial patterns across methods, showing the transferability of our method to EEG data. Our method produces finer spatial resolution while preserving physiologically plausible organization.

Table 1: Balanced accuracy on three BCI tasks

Model/Task	Execution left vs right hand	Imagery left vs right hand	Imagery hands vs feet
Welch	0.564 ± 0.095	0.567 ± 0.082	0.556 ± 0.080
DeepConvAttention	0.678 ± 0.101	0.667 ± 0.106	0.603 ± 0.095

ploration of connectivity-driven representations in BCI decoding frameworks.

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