



Inter-channel Granger Causality for Estimating EEG Phase Connectivity Patterns in Dyslexia

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Presentation Outline

- 1. Introduction
- 2. Hypothesis
- 3. Methodology
- 4. Results
- 5. Conclusions





Introduction

 Developmental dyslexia (DD) refers to a learning difficulty that hampers learners' reading skills acquisition irrespective of their mental age or level of schooling. It results in reading and learning difficulties.

• A precise diagnosis plays a decisive role to start the treatment in the early stages of the disease.





- Newly models are pointing to atypical dominant neural entrainment for three main rhythm stimuli categories:
 - Slow rhythmic **prosodic** (0.5–1 Hz)
 - Syllabic (4–8 Hz)
 - Phoneme (12–40 Hz)
- Learners with DD perform atypical oscillatory sampling using at least one temporal rate, introducing phonological difficulties in the comprehension of certain linguistic units, e.g. phrases, phonemes or syllables.
- Not all EEG frequency bands (i.e. Delta, Theta, Alpha, Beta, and Gamma) equally experience this phenomenon of atypical neural connectivity.





- We focus in connectivity analysis, referring to the analysis of measures linking two signals that have been acquired through separate channels, e.g. correlation, covariance and causality.
- Using these parameters in the context of brain signals emanating from different regions provides an inkling of the underlying neural network, thereby upholding the hyperconnected model of the brain.





Our hypothesis

Impaired neural oscillatory tracking of **slow amplitude modulation patterns** is one plausible **source of impaired rhythm** tracking in dyslexia.

The AM-based measure **revealed atypical rhythmic entrainment** by dyslexic participants to prosodic/syllable patterns in speech.

Previous research support the view that rhythmic entrainment at **slow (<5 Hz) rates** is atypical in dyslexia. (<u>https://doi.org/10.1016/j.heares.2013.07.015</u>)





Our hypothesis

Estimating **channels' connectivity** involves the analysis of these **channels' phases**.

The statistical hypothesis test known as the **Granger causality** test reveals whether **a time series is a factor**, thereby helping to predict the characteristics of further time series.

Granger causality **matrices** establish **sufficient patterns to classify** the subjects.





Methodology Data

We utilized EEG data from the University of Málaga's Leeduca Study Group.
97 participants.



Introduction



Hz



Methodology Preprocessing

- Independent component analysis.
- Removing artefacts.
- Filtering in the five EEG frequency bands.



Figure from https://doi.org/10.3390/s21217061





Methodology

Hilbert Transform

$$\mathcal{H}[x(t)] = \frac{1}{\pi} \int_{-\infty}^{+\infty} \frac{x(t)}{t - \tau} d\tau$$

Analytic signal z_i(t)

$$z_i(t) = x_i(t) + j\mathcal{H}x_i(t) = a(t)e^{(j\phi(t))}$$

Instantaneous, unwrapped phase

$$\phi\left(t\right) = tan^{-1}\frac{im\left(z_{i}\left(t\right)\right)}{re\left(z_{i}\left(t\right)\right)}$$

Introduction





Methodology

Granger Causality Test

It fundamentally asserts that "the past and present may cause the future, but the future cannot cause the past".

$$\widehat{y_{t}}_{1} = \sum_{k=1}^{l} a_{k} y_{t-k} + \varepsilon_{t}$$

$$\widehat{y}_{t2} = \sum_{k=1}^{l} a_k y_{t-k} + \sum_{k=1}^{w} b_k x_{t-k} + \eta_t$$





Methodology

Machine Learning Classification

We used **cross-validation** method with 20 folds and a parameters grid (GridSearchCV library).

Algorithm	Parameter	Range
Ada Boost	n_estimators	1 to 25
	Learning rate	1 to 3.5
	Boosting algorithm	SAMME, SAMME.R
Gradient Boosting	N_estimators	1 to 10
	Loss	deviance, exponential
	Learning rate	0.05 to 0.5
	Criterion	friedman_mse, squared_error, mse, mae
	Min_samples_split	0.1 to 3
	Min_samples_leaf	0.1 to 3
	Max_depth	1 to 4





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GradientBoostingClassifier

Results



AdaBoostClassifier

Introduction





Results

Algorithm	Band	Accuracy	Precision	Recall	AUC
Ada Boost	Delta	$\textbf{0.75} \pm \textbf{0.16}$	0.86 ± 0.15	0.85 ± 0.16	0.76
	Theta	0.61 ± 0.26	0.83 ± 0.12	0.62 ± 0.29	0.73
	Alpha	0.61 ± 0.17	0.83 ± 0.14	0.68 ± 0.21	0.65
	Beta	0.77 ± 0.15	0.84 ± 0.14	$\textbf{0.89} \pm \textbf{0.18}$	0.75
	Gamma	$\textbf{0.78} \pm \textbf{0.18}$	0.91 ± 0.09	0.90 ± 0.17	0.79
Gradient Boost	Delta	$\textbf{0.77} \pm \textbf{0.19}$	0.80 ± 0.17	0.91 ± 0.14	0.97
	Theta	0.70 ± 0.22	0.80 ± 0.15	0.87 ± 0.22	0.87
	Alpha	$\textbf{0.73} \pm \textbf{0.16}$	0.85 ± 0.13	$\textbf{0.89} \pm \textbf{0.14}$	0.77
	Beta	$\textbf{0.79} \pm \textbf{0.17}$	0.84 ± 0.14	$\textbf{0.89} \pm \textbf{0.19}$	0.97
	Gamma	0.74 ± 0.17	0.90 ± 0.11	0.89 ± 0.17	0.84





Conclusions and future work

- The causality matrices between channels allow the classification of subjects with and without DD.
- This implies that the interconnection of the different zones is not the same in subjects with DD.
- The delta band seems to be where these differences are most accentuated, and allows a clearer classification. Thus, a precision of 0.77 and AUC of 0.97 are achieved using the Gradient Boosting classifier.
- However, the performance ratios are also acceptable in the beta and gamma bands, which indicates that at these frequencies a different interconnection of the brain areas is also taking place.
- It is noteworthy that the results are consistent with the two classifiers used.





Conclusions and future work

 As future work, we intend to test the validity of the proposed method with two other stimuli, corresponding to syllabic and phoneme levels.





Thanks

Introduction