

PPARIS

GRAPH NEURAL NETWORKS FOR IMPROVED EEG ANALYSIS IN THE **CONTEXT OF ALZHEIMER'S DISEASE**





Auteur

Maxime Bedoin

Equipe encadrante

Nesma Houmani Jerôme Boudy

Bernadette Dorizzi



Context

- Alzheimer's disease (AD) : a chronic neurodegenerative disease that provokes a decline in memory and cognitive functions.
- Electroencephalography (EEG) : a non-invasive and inexpensive neuromaging technique. It allows to have access to fast brain dynamics due to its great temporal resolution.
- Many studies in the literature have already proven the effctivenness of using EEG to detect AD at the early stage.
- AD is considered as a disconnection syndrome. -







Preliminary study : first results

- To perform deep learning methods, we segment the EEG signals into different epochs.
 - \rightarrow Question arises: is there an optimal time configuration (time scale)?
- We generate epochs of different size (20s, 10s, 5s, 4s, 2,5s and 2s) and study the classification performance (SVM classifier) of each time scale, when discriminating Subjective Cognitive impairment (SCI) patients from AD patients.

Classification performance of epochs \rightarrow using shorter epochs give lower performance compared to when using EEG signal of 20s.

Classification performance of patients



AD diagnosis using **EEG**

- Various measures are used to quantify Functional Connectivity between all pairs of electrodes' signals : phase-lag index, coherence, mutual information, etc.
- Application of Graph theory to analyze the topological organization of brain functional connectivity in AD patients.
 - → Graph formalism shows a better characterization of different cognitive conditions.
- Using deep learning methods on Phase Spectral Density matrices or Functional Connectivity matrices allows good classification performance.
- Towards Graph Neural Networks to extract automatically relevant EEG markers.



Epoch time (s)	AUC	Accuracy (%)	Sensitivity (%)	Specificity (%)
20	0.804	82	89.3	72.7
10	0.789	80	92.9	63.6

- For each patient, we average the SVM probabilistic scores across epochs of such patient. Then, we classify all the patients based on the aggregated scores.
- The classification performance of all time configurations become comparable \rightarrow By gathering more data for each patient leads to an increase of classification performance.

Fusing different time scales

- Aggregating the probablistic scores of different time scales allows a better classification performance:
 - AUC=0,938, Acc= 90%, spec = 80,8%, sens=96,4%, when fusing 20s, 10s, 4s \rightarrow and 2s

5	0.724	74	89.3	54.5
4	0.825	82	78.6	86.4
2.5	0.791	76	75	77.3
2	0.774	76	71.4	81.8



maxime_bedoin@telecom-sudparis.eu Contact

www.telecom-sudparis.eu