MINISTRY OF EDUCATION AND RESEARCH

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FACULTY OF AUTOMATION AND COMPUTER SCIENCE
COMPUTER SCIENCE DEPARTMENT

SUMMARY
of the License Thesis entitled:

LEARNING DYNAMIC BRAIN CONNECTIVITY FROM EEG SIGNALS WITH A SPATIAL-TEMPORAL GRAPH CONVOLUTION APPROACH

Author: **Cristian-Ioan BLAGA**
Advisor: **Prof. Dr. Eng. Mihaela DINSOREANU**
Consultants: **Dr. Eng. Raul MUREȘAN, Dr. Eng. Vasile V. MOCA (TINS)**

1. **Requirements**:

The goal of this solution is to analyze and extract multiple sets of **Dynamic Networks** from **EEG signals**. The signals were recorded on subjects having the task of **visually recognizing** a deformed object, with each visual stimulus representing a trial. The **windowing parameters** for the trials also need to be identified in order for the network extraction to capture discriminatory information about the cognitive processes based on the type of response given by the subject.

2. **Proposed solutions**:

The solution has been designed as a joint, sequential effort by my teammate, Vlad-Cristian Buda, and I, comprising the following conceptual components: **Dataset Statistics –** analysis of the EEG signals with respect to the underlying data distribution; **Dual Ensemble Classifier (DEC)** – multilabel classifier using a set of windowing parameters to classify the signals with respect to the stimuli and response classes; **DEC Hyperparameter Tuning –** identify the best windowing by analyzing the performance of the DEC model on multiple trainings with different hyperparameters; **DEC Analysis –** analysis of the best performing DEC model based on its classification performance in order to gain insight into the learning limitations imposed by the dataset; **Recurrent Graph WaveNet (RGW)** – a learning pipeline capable of extracting a set of Dynamic Networks from each trial. The *Graph WaveNet*[1] model is applied on each window, solving a problem of multivariate timeseries forecasting together with learning a *self-adaptive adjacency matrix of hidden dependencies*. The result from one window is fed onto the next window, together with the statistically generated Functional Network[2][3], creating a learning pipeline closely imitating the state evolution of the brain during a trial (Figure 2.1); **RGW Hyperparameter Tuning –** tuning of the RGW approach with respect to both pipeline and model parameters. **Graph Visualization** – aggregation and visualization of the networks by grouping signals together based on their relative sampling position inside the brain; **Graph Analysis –** similarity matching between different stimuli based on the evolution of graph metrics using *Dynamic Time Warping (DTW)* [4].

3. **Results obtained**:

The best windowing parameters identified using the Dual Ensemble Classifier are a window size of **275** with a window offset of **75**. The performance distribution on this set of parameters has an average f1-score of **0.29** on stimulus and **0.49** on response.

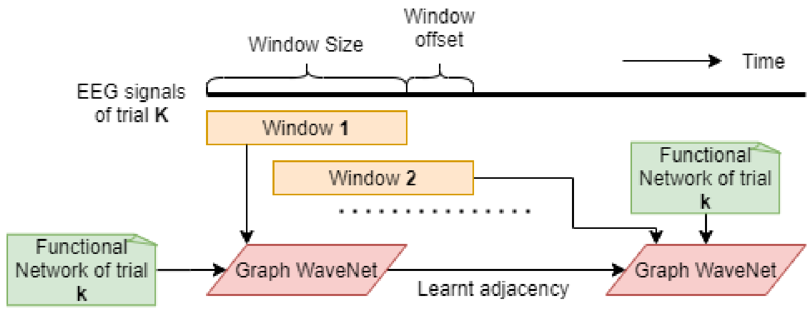

Figure 2.1. RGW conceptual architecture.

The analysis on the best performing DEC model showed that the performance was limited by the trial length, with the classification accuracy decreasing as a function of the length, suggesting a loss of information from long trials due to the windowing process.

The DTW analysis on pairs of stimuli indicates a similarity of over **90%,** with the warping path being constructed optimally in a locality constraint of ± 10 windows.

Finally, the Dynamic Networks have been validated using the current benchmark available, namely the binary DCGNN[5] classifier, obtaining an accuracy of **59.95%** on all subjects and as high as **72.82%** on an individual subject, with previous results obtaining an accuracy no better than random guessing (50%).

4. Tests and verifications:

The validation on the DEC model has been done with respect to the average f1-score on both classification problems in two steps. From a set of **27** sets of parameters studied, **3** were chosen that were further validated using the performance distribution over a total of **10** runs. The validation of the generated Dynamic Networks has been done using the classification accuracy of the DGCNN model.

5. Personal contributions:

From a **conceptual** point of view, to the field of Neuroscience, the <u>solution</u> designed and developed by my teammate and I stands as a powerful Deep-Learning pipeline, capable of extracting dynamic correlations from multivariate timeseries data, at a self-identifiable granularity level, with evaluation and validation tools provided at each step. In the context of **visual recognition**, it is able to capture meaningful cognitive processes occurring in the brain.

From an **implementation** perspective, my <u>personal contribution</u> can be observed in the functionality provided to modules that have been either solely developed by myself, such as the study of the DEC best model performance, DTW matching or RGW data preprocessing, or developed together with my colleague, such as DEC or RGW training.

The current solution will also be the subject of an article submitted to a **Neuroscience journal**.

6. Documentation sources:

[1] Z. Wu, S. Pan, G. Long, J. Jiang, and C. Zhang, "Graph wavenet for deep spatial-temporal graph modeling," 08 2019, pp. 1907–1913.

[2] D.-A. Dumitru, "Studiul modalitatilor de extragere a retelelor din creier in contextul perceptiei vizuale," Bachelor Thesis, Technical University of Cluj-Napoca, 2018.

[3] E.-B. Ceuta, "Analiza metodelor de obtinere a retelelor functionale din creier folosind semnale eeg," Bachelor Thesis, Technical University of Cluj-Napoca, 2018.

[4] H. Sakoe and S. Chiba, "Dynamic programming algorithm optimization for spoken word recognition," IEEE Transactions on Acoustics, Speech, and Signal Processing, vol. 26, no. 1, pp. 43–49, 1978.

[5] L.-D. Palcu, "Brain functional networks - an interpretable graph classification solution," Bachelor Thesis, Technical University of Cluj-Napoca, 2019.

Date: 11.07.2020 Author: Blaga

Coordonator: Prof. Dr. Eng. Mihaela DINSOREANU