Deep Learning-based Neurofeedback Targeting Semantic Memory in Alzheimer's Disease

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Introduction

During childhood, humans acquire many concepts organized into semantic knowledge. This semantic network becomes denser and denser as the child grows to store concepts and their meanings. In the opposite, as Alzheimer's Disease (AD) spreads semantic memory will decline.

Based on the retrogenesis hypothesis, the memory deterioration process should follow the inverse mechanism than memory development during childhood [1]. Therefore, understanding the development of semantic memory in children would help investigate the deterioration mechanisms.

Nowadays, there is good evidence that semantic memory is part of an integrated memory system grounded in the sensorimotor system (fig. 1) [2]. In this view, children sensorimotor cortex supports low-level concepts encoding. This knowledge is then stored in semantic memory.

Training AD patients to activate the neuronal circuits responsible for the interaction between sensorimotor and semantic systems could therefore slow down the memory loss. In that way, a neurofeedback treatment is an interesting lead that has already shown encouraging preliminary results [3]. This project aims to develop a neurofeedback prototype for AD patients targeting the sensorimotor-semantic circuits from electroencephalogram (EEG) signals.

Methods

The first step is to transform EEG data into the corresponding brain activation through inverse modeling. Then, the connectivity analysis will allow us to identify the interaction between the targeted brain regions, while microstates analysis and Hidden Markov Models (HMM) [4] will be used to extract the sequence of states leading to the targeted activation (i.e. the dynamics of the system) [5].

From this new knowledge, a convolutional neural network (CNN) will be trained from EEG recordings of 210 patients (including children, adults and elderly people with or without AD → ~300 minutes recordings) to recognize the targeted activation in a robust way that is generalizable across patients [6]. Analyzing the latent space will help us to interpret the classification [7].

Finally, a neurofeedback prototype will be designed in a custom way through a transfer learning approach to fit EEG signals of each patient (fig. 2). The psychologists with whom we collaborate will perform an additional study at the end of this thesis to validate the efficiency of our neurofeedback treatment.

Conclusion:

This thesis aims to: 1) identify the interaction between sensorimotor cortex and semantic memory over the lifespan, 2) create a CNN-based model to classify this interaction in the EEG domain. Given the medical context, an additional study will be led to interpret the result of this classification, 3) develop an EEG-based neurofeedback prototype that targets the identified co-activation between sensorimotor and semantic systems.

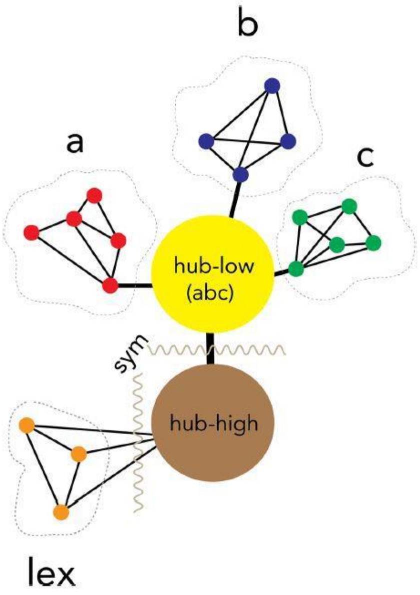

Figure 1: Semantic memory model. Multi-level, multi-hub model where a,b and c represent sensorimotor systems (e.g. vision, audition, motor), the low-hub is the center of low-level concepts where sensorimotor features converge, "lex" is the lexical knowledge center bringing the symbolic features to stream information from low to high-order concepts in a "high-hub" region [2].

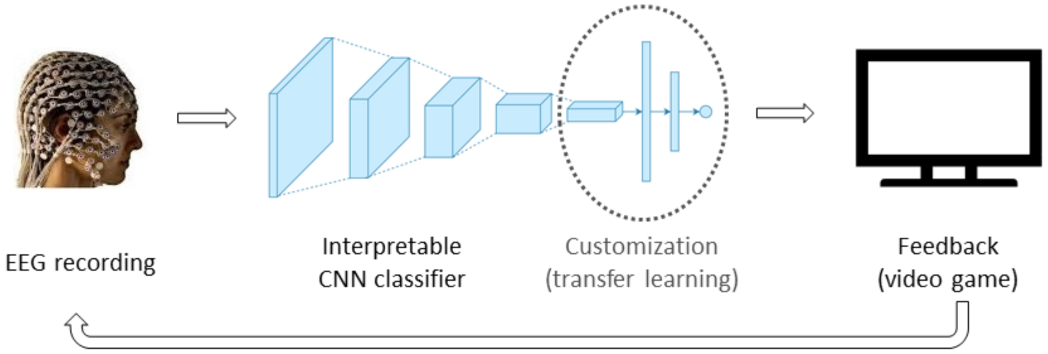

Figure 2: Neurofeedback schematic. The neurofeedback is a biofeedback system training patient to self-regulate specific brain circuits, and thus stimulate neural plasticity in a targeted way. The prototype we will develop aims to customize the treatment to every patient using his/her own EEG data to retrain the last layers of the model. The name "prototype" expresses the fact that the clinical validation is out of the scope of this thesis. This step will be ensured by psychologists at the end of the project.

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Acknowledgments:

Luca La Fisca is funded through a PhD grant from the "Fonds pour la Formation à la Recherche dans l'Industrie et l'Agriculture" (FRIA), Belgium.