Prediction and Analysis of Ictal Dynamics Using Computational Neural Networks

Introduction

Epilepsy is a chronic illness that affects approximately 1-2% of the world's population [REFERENCE]. Up to 40% of these patients are refractory to medical therapy and may be candidates for resective surgery. Intracranial electroencephalography (iEEG) is a critical tool in the presurgical analysis of patients with refractory epilepsy. It is the primary method used to identify the seizure onset zone, which is defined as the region of cerebral cortex whose removal is both necessary and sufficient to abolish seizures. This research focuses on the development of machine learning techniques, specifically **Artificial Neural Networks** (ANNs), to **analyze and predict iEEG signal dynamics related to the initiation and propagation of seizures**. We present and discuss the results we obtained, as well as the limitations of that method. We also propose an enhancement of our EEG prediction scheme, based on **Independent Component Analysis** (ICA).

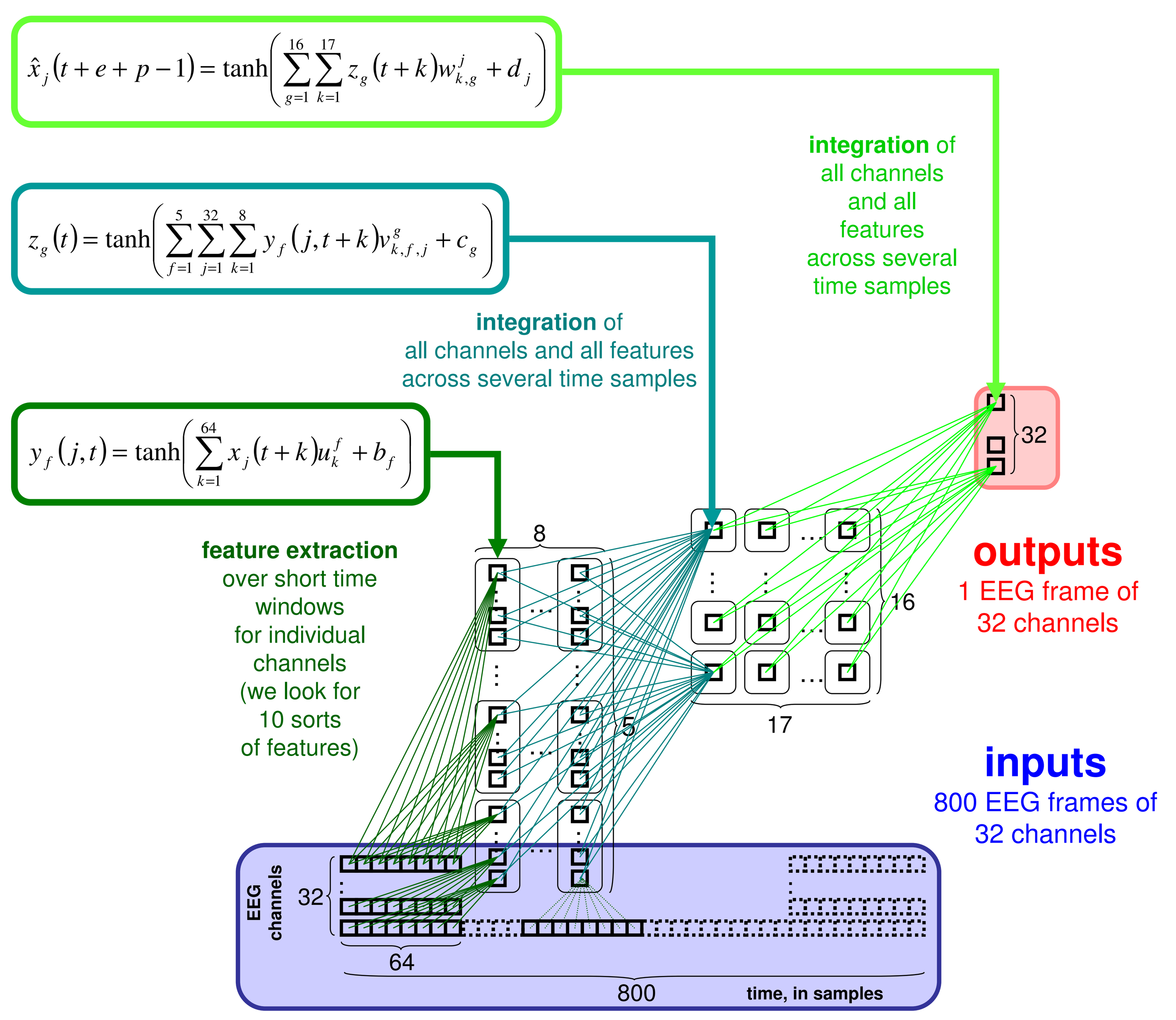
Methods

[1] Data Preparation

iEEG data was obtained from 64 contact grid data from a patient with nonlesional neocortical epilepsy (Patient NE), and with mesial temporal epilepsy with neocortical spread (Patient TE). Grid data was exclusively used in order to ensure that the data used in training and testing the CNN was spatially contiguous. Data was obtained at a sampling rate at 400 Hz, with 32 EEG channels (64 contacts in a bipolar montage), and converted to a numerical comma-separated ASCII format.

Prior to training of the CNN, the iEEG data was normalized to zero mean and variance in order to increase neural network training efficiency [LeCun et al., 1998a]. Once normalized output was obtained, this was scaled back to its original mean and variance.

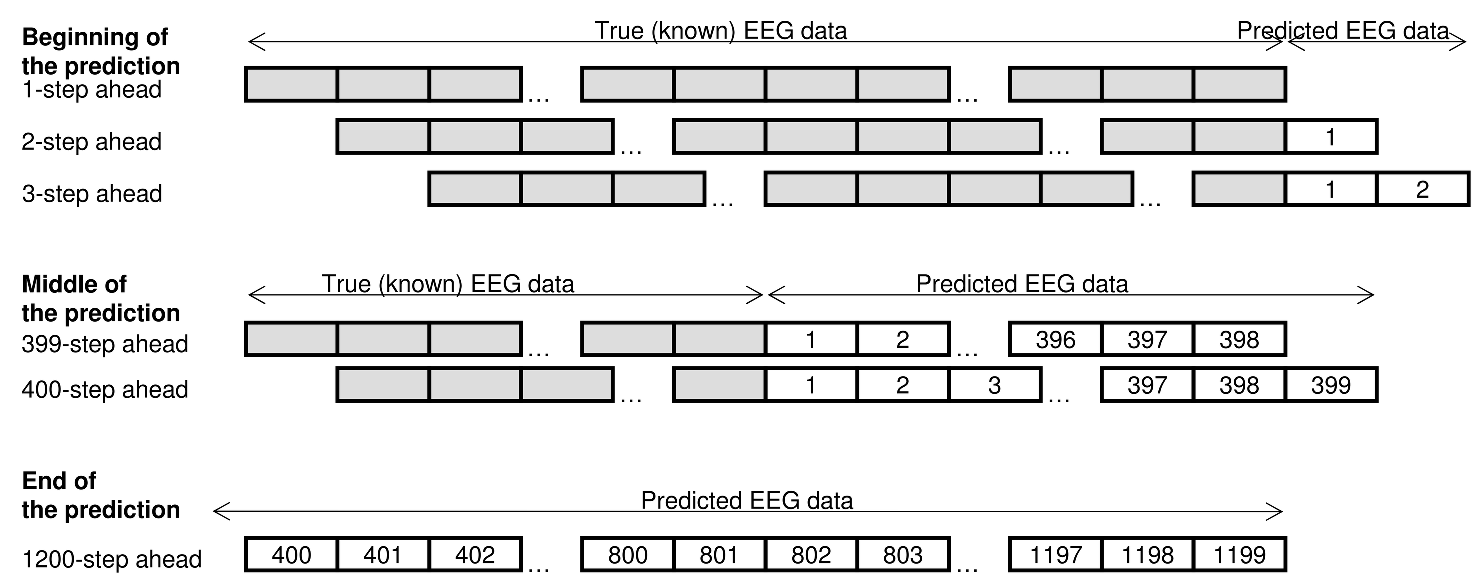
[2] Training of **Convolutional Neural Networks**



In this study, we specifically utilized a Convolutional Neural Network (CNN), [LeCun et al., 1998b] architecture to perform time-series prediction of iEEG data. The specific type of CNN utilized for this study was a Time-Delay Neural Network (TDNN), with weights sharing across the time dimension, to emphasize the temporal component of the iEEG as an individual feature of the overall signal. The TDNN was constructed using Lush®, an object-oriented programming language optimized for Machine Learning. As illustrated on the left figure, the specific TDNN architecture we used would take 800 time samples **x**(t-799) through **x**(t) of 32-channel iEEG and would predict 1 time sample **x**(t+1)of 32-channel iEEG.

Training of the Time-Delay Neural Network (TDNN) was performed using stochastic online gradient descent [Rumelhart et al., 1986], where input/output data pairs are iteratively presented before each learning step(18, 19). A learning rate of η=0.0001 was utilized for the gradient descent with a regularization parameter of λ=0.0001. A "serial" prediction training method was implemented for the time-series prediction problem.

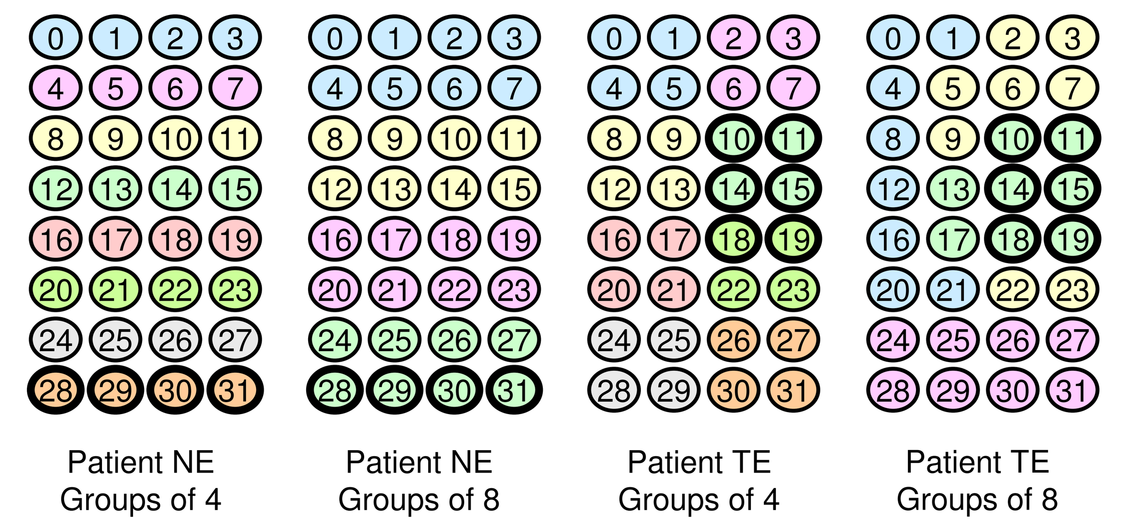
[3] Prediction of EEG Waveforms With Neural Networks



We trained one Neural Network per prediction step, up to 1200 prediction steps ahead (i.e. 3 seconds for data sampled at 400Hz). Each Neural Network takes a 800 time step iEEG window as an input and predicts the next iEEG time sample.

[4] Modeling Channel Deactivation

After adequate training of the TDNN predictor, specific channels were altered in both examples in an attempt to simulate a potential resection of areas underlying each group of channels. This was performed by setting the input channel data to zero prior to running through the predictor. Channels were removed according to the schematic illustrated on the right figure.



[5] Filtering with Independent Component Analysis

Independent Component Analysis (ICA) [Bell and Sejnowski, 1995] is a well established technique for signal processing that isolate statistically independent signal components that have been mixed. It has successfully been applied to EEG data [Urrestarazu et al., 2004] and we propose to apply it in the case of iEEG, to isolate Independent Components (IC) prior to the neural network learning. We used the FastICA algorithm [Hyvarinen and Oig, 2000] and the EEGlab software [Delorme and Makeig, 2004] to perform ICA on iEEG data from patient TE and NE.

Several modalities are possible in the utilization of ICA combined with Neural Network predictions.
[1] A visual inspection of Independent Component results enables to identify one or several ictal components that trigger the seizure. By inspecting the ICA mixing matrix, we compared the weights (contributions) of those ictal Independent Components to each of the iEEG channels, with the CNN predictions, in order to compare the predictions of the localization of the onset zone.
[2] ICA enables to isolate, in specific Independent Components, iEEG artifacts. We propose to use it as a data preprocessing filter before applying those data to the Neural Network.
[3] ICA can work as a dimensionality reduction and data normalization technique. By removing Independent Components with only artifact information, and by separating the iEEG into statistically distinct Independent Components, we propose to thus enhance Neural Network learning of iEEG data.