

# Time-Delay Neural Networks and Independent Component Analysis for EEG-Based Prediction of Epileptic Seizures Propagation

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## Abstract

This research focuses on the development of a machine learning technique based on Time-Delay Neural Networks (TDNN) and Independent Component Analysis (ICA), to analyze EEG signal dynamics related to the initiation and propagation of epileptic seizures. We aim at designing a generative model to simulate EEG time-series after alteration of specific localized channels (electrodes) in order to explore the effects of brain surgery ex-vivo.

## Introduction

Epilepsy is a chronic illness that affects approximately 1-2% of the world's population. Up to 40% of epileptic patients are refractory to medical therapy and may be candidates for brain surgery.

Intracranial electroencephalography (EEG) is a critical tool in the pre-surgical analysis of patients with medication-refractory epilepsy. Epileptic seizures correspond to an abnormal oscillatory electric activity visible on EEG. Since EEG is recorded with several localized electrodes across the brain, it can be used to identify the seizure onset zone, which is defined as a small region of cortex whose removal could abolish seizures.

So far, Convolutional Neural Networks (CNN, LeCun et al., 1998b) and TDNN have not been applied to EEG data and no epilepsy study has tried to directly predict EEG time-series using machine learning.

Independent Component Analysis (ICA) is a well established technique for signal processing that isolates statistically independent signal components that have been mixed. It has successfully been applied to EEG data (Urrestarazu et al., 2004) to isolate event-related potentials.

## Methodology

### Intracranial Electro-Encephalogram Data

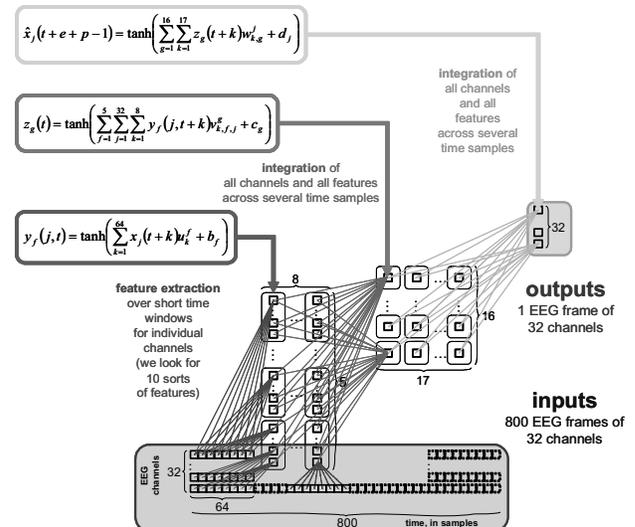
32-channel EEG data was obtained from intracranial grid recordings on 2 patients with epilepsy (Patients NE and TE). EEG electrodes were spatially contiguous and data was sampled at 400 Hz. In order to increase neural network training efficiency (LeCun et al., 1998a), EEG data was normalized to zero mean and variance.

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## Training of Time-Delay Neural Networks

In order to perform time-series prediction of EEG data, we chose the Time-Delay Neural Network (TDNN) architecture of CNN, more specifically with weights sharing across the time dimension, to emphasize the temporal component of the EEG 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 figure below, the specific TDNN architecture we used would take 800 time samples  $x(t-799)$  through  $x(t)$  of 32-channel EEG and would predict 1 time sample  $x(t+1)$  of 32-channel EEG.

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. A learning rate of  $\eta=0.0001$  was utilized for the gradient descent with a regularization parameter of  $\lambda=0.0001$ . A "serial" prediction training method was implemented for the time-series prediction problem.



## Prediction of EEG Waveforms with TDNN

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 800 time step EEG window as an input and predicts the next EEG time sample.

## Modeling Channel Deactivation

After adequate training of the TDNN predictor, specific channels were in turn altered in both patients in an attempt to simulate a potential surgery of areas underlying each group of channels. This was performed by setting the input channel data to zero prior to running through the predictor. EEG channels were “deactivated” by groups of 4 or 8.

Each time, we iterated the TDNN to predict EEG time-series immediately following a pre-seizure state, to check whether predicted time-series correspond to epileptic activity.

## Filtering with Independent Component Analysis

In order to enhance the neural network training, we propose to isolate Independent Components (IC) in EEG data prior to feeding it to the TDNN, using the FastICA algorithm (Hyvarinen and Oja, 2000).

Once the TDNN is trained on ICA-transformed EEG, and instead of deactivating groups of EEG channels to see the outcome of EEG predictions, we propose to deactivate groups of independent component in order to identify ICs that trigger the seizure. The original EEG channels contributing to each IC are then recovered from the ICA un-mixing matrix.

## Results

Results of initial experiments conducted on two patients' data have shown that a combination of ICA and TDNN managed to correctly learn patterns in EEG time-series and that the EEG predicted after simulated surgery of various zones of the brain was conform to medical diagnostic.

**Results with TDNN only.** Although the TDNN predictor was able to memorize the time-series patterns of one seizure of a patient (we evaluated a prediction horizon of 3 seconds), it failed to accurately reproduce the time-series of a similar seizure in the same patient.

**Results with ICA+TDNN.** These results show the enhancements of TDNN predictions with ICA filtering of EEG data. When the TDNN was trained on Patient NE's seizure 2 and tested on seizure 1, the cross-validation MSE was very low and the frequency behavior of EEG during various 3-second predictions matched that of original data.

The TDNN was trained on 26 Independent Components resulting from ICA of EEG from patient NE, seizure 2. From the original 32 Independent Components, 6 ICs qualified as artifacts had been discarded. Using the ICA

mixing matrix and clinical knowledge of the seizure localization, independent components contributing to EEG channels responsible for the seizures were identified (“ictal ICs”).

Various groups of ICs were deactivated from the data (replaced by zero values) prior to TDNN predictions on seizures 1 and 2, and a significant decrease in epileptic activity was observed for combinations of ictal ICs. By contrast, removing several non-ictal ICs did not decrease epileptic activity, and generated ictal signals on other ICs.

## Discussion

Due to the limitations of the predictor because of accumulated error, only short epochs of EEG could be used as inputs, with 2-3 second output windows.

The main limitation of the simulation of surgical effects by deactivating groups of EEG channels or ICs was that the TDNN predictions for those deactivated channels continued to be influenced by the oscillatory pre-seizure activity of surrounding channels. Moreover, the TDNN continues to generate time-series for those deactivated channels. However, deactivation of channels responsible for the seizures did result in an attenuation of the EEG signal, suggesting the efficacy of the TDNN in predicting post-surgical changes. Current research focuses on generative models such as Kalman filters to replace the approach of deactivating EEG channels.

## Acknowledgements

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