**DEEP LEARNING APPROACHES FOR AUTOMATIC ANALYSIS OF EEGS**

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Electroencephalograms (EEGs) are used in a wide range of clinical settings to record electrical activity along the scalp. Scalp EEGs are the primary means by which physicians diagnose brain-related illnesses such as epilepsy and seizures. Automated seizure detection using clinical EEGs is a challenging machine learning problem due to low signal to noise ratios, poor electrical conduction, movement artifacts, and nonlinearly distorted crosstalk between spatially adjacent sensors. Commercially available seizure detection systems suffer from unacceptably high false alarm rates. Deep learning algorithms that employ high dimensional models have not previously been effective due to the lack of big data resources necessary for building such models. However, a significant big data resource known as the TUH EEG Corpus has recently become available that can be used to leverage emerging deep learning algorithms.

In this chapter, we will introduce a variety of deep learning architectures for automatic interpretation of EEGs. Each of these architectures is a hybrid state-of-the-art system composed of one or more classes of neural networks including convolutional neural network (CNNs), long short-term memory networks (LSTM), gated recurrent units (GRUs), and residual neural network (ResNet). The TUH EEG Corpus along with supplemental data corpora from Duke University and Emory University were used to train and evaluate the performance of these hybrid deep structures. Beside presenting these EEG classifiers and comparing them, in this chapter we discuss the issues involved in EEG classification. We demonstrate that the performance of these deep learning-based systems is now approaching the threshold for clinical acceptance.

Exploiting spatial and temporal context in the signal is critical. Both contexts are required for accurate disambiguation of seizures from artifacts. Several architectures that implement Gaussian Mixture Models (GMMs), hidden Markov model (HMMs) and deep learning (DL) have been developed to model context. HMMs are among the most powerful statistical modeling tools available today for signals that have both a time and frequency domain component and have been used extensively in sequential decoding tasks like speech recognition to model the temporal evolution of the signal. Automated interpretation of EEGs is a problem very similar to speech recognition since both time domain (e.g., spikes) and frequency domain information (e.g., alpha waves) are used to identify critical events. Our baseline system used an HMM preprocessing step, and a Stacked denoising Autoencoder (SdA) postprocessor.

To improve our ability to model context, a hybrid system composed of an HMM and a Long Short‑Term Memory (LSTM) network was implemented. These networks are a special kind of recurrent neural network (RNN) architecture that is capable of learning long-term dependencies and can bridge time intervals in excess of 1,000 steps even for noisy incompressible input sequences. Convolutional Neural Networks (CNNs) have delivered state of the art performance on highly challenging tasks such speech and image recognition. CNNs are ideally suited to sequential processing and make strong assumptions about the locality of the data. We have integrated and evaluated a hybrid system using CNN and a multi-layer perceptron (MLP). Our best overall system is the combination of CNN and LSTM. This doubly deep recurrent convolutional structure models both spatial relationships (e.g., cross-channel dependencies) and temporal dynamics (e.g., spikes).

The primary error modalities observed were false alarms generated during brief delta range slowing patterns such as intermittent rhythmic delta activity. A variety of these types of artifacts have been observed mostly during inter-ictal and post-ictal stages. Training models on such events with diverse morphologies has the potential to significantly reduce the remaining false alarms. This is one reason we are continuing our efforts to annotate a larger portion of TUH EEG. Increasing the data set size significantly allows us to leverage advanced machine learning methodologies such as representation learning, transfer learning and one-shot learning. Since TUH EEG provides a large number of unlabeled EEG datasets, we will also discuss unsupervised pre-training methods used prior to training the recurrent convolutional network.