EPILEPSY DETECTION FROM SCALP EEG: A MACHINE LEARNING APPROACH

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I. INTRODUCTION

Epilepsy refers to a group of chronic brain disorders which are characterized by unpredictable seizures. It is rated as the fourth most common neurological disorder by the Epilepsy Foundation. Approximately 65 million people are affected worldwide. An electroencephalogram (EEG) is a recording of the electrical activity of the brain collected by placing electrodes on the scalp of subjects. Interictal epileptiform discharges (IEDs) that appear in the EEG are distinctive biomarkers of epilepsy. IEDs are further categorized into sharp waves, spikes, spike-wave-complexes and polyspike-wave-complexes. We primarily focus on spikes in this research. The presence of spikes allows a physician to make a confident diagnosis of epilepsy, predict seizure recurrence, and prescribe an appropriate treatment. In current clinical practice, spikes have to be visually identified by neurologists. This process is tedious and time-consuming. Moreover, there is significant disagreement over EEG interpretation amongst experts. Spike detection is a difficult task as the spikes exhibit a large morphological variety across patients. In addition, a standard definition of spikes is not available. Consequently, the reliability of the diagnosis heavily depends on the experience and expertise of the experts. There exists a great need for epilepsy diagnosis system based on automated spike detection. Automated spike detection would be more objective, faster, and potentially more accurate. Several methods have been tested to develop reliable automated spike detection systems. Unfortunately, these methods have not been validated on a sizable dataset and consequently are not universally accepted. We developed an automated EEG classification system to detect epileptic EEGs based on IEDs. The system comprises of three major modules: preprocessing, waveform-level classification, and EEG-level classification. The pre-processing module performs the necessary filtering, normalization, and configures the EEG montage. The waveform-level classification module detects the various IED patterns in the EEG signal. The EEG-level classification module is developed based on the output of the waveform-level classification to identify epileptic EEGs. We employ a Convolutional Neural Network (CNN for waveform-level classification and a Support Vector Machine (SVM) with Gaussian kernel for EEG-level classification. We developed and validated the system by applying a dataset of 156 subjects (93 epileptic and 63 non-epileptic) with 18,164 annotated IEDs. The data was recorded according to the International 10-20 electrode system from Massachusetts General Hospital (MGH), Boston. We achieved a mean 4-fold classification accuracy of 83.86% for identifying EEGs with and without IEDs on the MGH dataset. We evaluated our system trained on the MGH dataset, on EEG data recorded at different centers. We compared our system with Persyst's, the current market leader. Our system significantly outperformed Persyst for IED identification.

II. PUBLICATIONS

1) Rajamanickam Yuvaraj, **John Thomas**, Tilmann Kluge, and Justin Dauwels, Sydney S. Cash, and M. Brandon Westover. ”A deep Learning Scheme for Automatic Seizure Detection from Long-Term Scalp EEG.” Accepted for presentation at Asilomar Conference on Signals, Systems, and Computers 2018 to be held on Oct. 28-31 at Pacific Grove, CA, USA.
2) **John Thomas**, Rahul Rathakrishnan, Jing Jin, Justin Dauwels, Sydney S. Cash, and M. Brandon Westover. ”Machine learning-based epileptic EEG identification system: a multi-center study.” Accepted for presentation at American Epilepsy Society Annual Meeting 2018 to be held on Nov. 30-Dec. 4 at New Orleans, LA, USA.
3) Yuvaraj R, **John Thomas**, and Justin D. Hybrid deep convolutional neural network and hidden markov model for automatic seizure detection from long-term scalp EEG. ICNF Neuroinformatics 2018, (doi: 10.7490/f1000research.1115871.1).
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