Spike detection in EEG by LPP and SVM*

E.I. Zacharaki, K. Garganis, I. Mporas, V. Megalooikonomou *Member, IEEE*

***Abstract*— This study presents a computer algorithm to detect epileptiform discharges (spikes) in electroencephalography (EEG) that are manifestations of an epileptogenetic abnormality of the brain. Visual analysis is rater-dependent and time consuming, especially for long-term recordings, such as in sleep studies or in ambulatory EEG. Computerized methods can improve efficiency in reviewing long EEG recordings. The proposed method applies coarse to detailed modeling of the spike waveform and classifies the transients based on Locality Preserving Projections (LPP) and Support Vector Machines (SVM). The method achieves high sensitivity with low false positive rate in a intra-patient cross-validated setting and thus constitutes a valuable tool for automatic spike assessment.**

I. INTRODUCTION

The detection of epileptiform discharges in interictal EEG is important for the diagnosis of epilepsy. Interictal spikes are brief (< 250 msec), morphologically defined events observed in the EEGs of patients predisposed to spontaneous seizures of focal onset [1]. The spikes are generated by the synchronous discharges of a group of neurons in a region referred to as the epileptic focus [1]. The detection of spikes is difficult to accomplish due to their similarity to waves that are part of normal EEG or artifacts and the wide variability in spike morphology and background between patients. Also the spike definitions are imprecise and vary among neurophysiologists who often do not mark the same events as spikes.

A comprehensive review on automated spike detection methods was presented in [2], and later updated in [3], according to which, the methods are classified into different categories based on the spike detection criterion. Specifically, some methods extract distinctive attributes of the spikes, such as height and duration, mimicking the criteria used by the neurophysiologists or utilize knowledge-based rules (spatial and temporal). Other methods characterize the spikes in time or frequency domain and through morphological analysis decompose the EEG signal and separate the background activity. There are methods in which a template is created by averaging expert-defined spikes and used for matching against the extracted EEG waveforms. Also a few methods assume local stationarity of the noise and detect spikes as deviation from that stationarity by applying parametric models. Finally many methods use independent component analysis, apply artificial neural networks, clustering techniques, or classification methods.

Most spike detection methods consist of two stages, feature extraction to adequately describe the spike morphology and classification to classify the extracted transients as spikes or non-spikes. Commonly the amount of data processed by the classifier is significantly reduced by first extracting candidate waveforms based on low level spike detection analysis or a spike enhancement stage prior to classification aiming to increase the sensitivity of the overall method, while maximizing selectivity [2]. Similarly, the proposed method consists of two major steps. The method first detects candidate spikes based on a mimetic approach, and afterwards it classifies the candidates based on machine learning techniques. Specifically, in the 1st step, the major peaks are detected and the EEG signal around the peaks is broken down into half-waves. Thresholding of morphological characteristics extracted from the half-waves, such as amplitude and duration, is applied to produce a number of candidate spike locations. The 'raw' EEG signal is then extracted from these candidate locations and classified in the 2nd step as spike or background by performing dimensionality reduction and supervised classification.

The rest of this paper is organized as follows. Section II provides details about the framework and the applied algorithms. The data and achieved results are presented in Section III followed by some discussion in Section IV. Finally in Section 4 we conclude this work.

II. METHOD

The current study involves whole night sleep EEG recordings with inter-ictal discharges. The method first applies coarse modeling of the shape of the spike and extracts spike-like transients by simple thresholding. Subsequently, it classifies the candidate transients by learning the patterns of spikes based on dimensionality reduction and non-linear supervised classification. With this method we prefer to achieve high sensitivity and minimize missed events, even at the expense of reduced specificity, because the detected events can later be checked by a neurophysiologist. We aim in a reduction of the time needed to analyze the long recordings.

A. Preprocessing

The raw EEG recordings is first downsampled at 100 Hz to reduce dimensionality and then a notch filter is applied with

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E.I.Z, I.B. and V.M. are with the Department of Computer Engineering and Informatics, University of Patras, 26500, Greece (corresponding author phone: +30-2610-997534; e-mail: ezachar@upatras.gr, imporas@upatras.gr, vasilis@ceid.upatras.gr.

K.G. is with the St. Luke's Hospital, 552 36, Greece (e-mail: gkkap@the.forthnet.gr).

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