Automated Analysis of Epileptic EEG Using a Toolbox

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***Abstract*—It is estimated that there are 50 million people affected by epilepsy worldwide. However, the study of this disease is still reserved for a reduced number of neurologists. Automatic detection of epileptic seizures can considerably improve the patients' quality of life. Current Electroencephalogram (EEG)-based seizure detection systems encounter defiances in real-life situations. Machine learning approach, support vector machines (SVM) and neural networks (ANN) may offered high performance in two-class EEG Classification. However, implementing this classifiers and improving their accuracy it's a real challenge. To address these challenge, we introduce the use of a toolbox that automatically extracts EEG features of epileptic and non epileptic seizures and also classifies the data using SVM and ANN algorithms. Specifically, to reveal ....**

***Index Terms*—Electroencephalogram (EEG), Epilepsy, Seizure detection, Toolbox, Machine Learning Classifiers.**

I. Introduction

Epilepsy is a chronic neurological disorder of the brain that affects people of all ages. It causes disorders of brain activity leading to clinical events called epileptic seizures. It is currently estimated that more than 50 million people worldwide suffer from this pathology [1], making it the second most common neurological diseases after migraine [2]. The diagnosis and treatment of epilepsy is an area of current research that has been expanded and improved by technological advances and the implementation of new algorithms for disease pattern recognition and seizure prediction.

A vast number of methods have been developed for automatic seizure detection using EEG signals. Extracting features that best describe the behaviour of EEGs is of great importance for automatic seizure detection systems' performance. Several feature extraction and selection techniques have been reported in the literature. Most of them use features in the time-domain, frequency-domain, time-frequency domain or sometimes in a combination of two domains.

This work introduces an automated toolbox to analyse epileptic EEG and to detect relevant patterns in the EEG signals of patients with epilepsy, using algorithms based on pattern recognition with machine learning approach, support vector machines (SVM) and artificial neural networks (ANN). The toolbox for MATLAB provides direct access to HUMANA database, which contains biomedical signals of epileptic patients from Epilepsy and Functional Neurosurgery Center (HUMANA) in Guatemala. It also allows users to load public domain EDF files with EEG data.

The Automated Analysis of Epileptic EEG Toolbox also provides functions useful for feature extraction and machine learning algorithms implementation. The Toolbox also contains a graphic interface that allows users to obtain classifications results quicker and easier. Thus this toolbox and also the HUMANA database provide a vital resource for MATLAB users who want to validate, and compare different automatic seizure detection systems. It is also intended for medics who wish to investigate and facilitate the diagnostic process of epilepsy.

II. Related Work

The problem of EEG epileptic seizure detection as two-class classification is to differentiate between two distinct classes; Normal and Ictal EEG patterns [3].

A. Two-class EEG Classification

Most of the two-class seizure detection problems focus on the classification between normal EEG segments taken from healthy persons and seizure EEG patterns taken from epileptic patients while experiencing active seizures [3],[4] y [5]. Polat et al. achieved a higher classification accuracy of 98.68% using a decision tree (DT) classifier [4]. Wavelet transform was also used in [6] to analyze the EEG signals into five approximation and detail sub-bands. Then, the wavelet coefficients located in the low frequency range of $0-32$ Hz were used to compute the EEG features of energy and normalized coefficients. The linear discriminant analysis (LDA) classifier was used to prove the potential of the extracted features in detecting seizure onsets with a classification accuracy of 91.80%.

In this study SVM and MLP classifiers were used, extracting time-domain features from EEG signals. Wavelet transform was also used to analyze EEG signals into five sub-bands which cover the frequency bands of the five brain waves; beta, alpha, theta, delta and gamma. Then, all wavelet coefficients were used to compute the feature vector to implement the SVM and MLP classifiers.

B. Epileptic EEG Feature Extraction

III. Methods

A. Architecture

IV. Results

V. Conclusions

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