Epileptic Seizure Classification based on Supervised Learning Models

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***Abstract*—This paper presents several aspects concerning epileptic seizures detection by EEG signal classification based on supervised learning models with associated learning algorithms that analyze data. In order to detect epileptic seizures has been used to support vector machine model. Support Vector Machine (SVM) is a classifier formally defined by a separating hyperplane being based on training data (supervised learning) and the algorithm outputs representing the optimal hyperplane. The adopted approach was to extract features from the data in order to be used to train and test data by using machine learning models in MATLAB. Seizures signals were obtained from EEG recordings from pediatric subjects with intractable seizures and ages 3-22 years.**

***Keywords*: signal processing, support vector machine, learning machine, epilepsy, seizures**

I. Introduction

The monitoring of epilepsy in real time is complicated and is a challenge because the epilepsy is a neurological disorder that determines the deterioration of the conscious and convulsions for the whole body of the patient [1].

Mostly used classification algorithms are Generalized Relevance Learning Vector Quantization (GRLVQ), ANN - Backpropagation, SVM (Support Vector Machine), and Random Forest, combined with Wavelet and PCA feature extraction [2, 3, 4].

The abnormalities of cerebral structure, which may be a consequence of seizure activity, are studied by magnetic resonance imaging (MRI), magnetic resonance spectrometry (MRS), electroencephalogram (EEG), functional MRI (fMRI) [5].

MRI test shows structural distortions in patients with primary generalized seizures [5, 6, 7]. MRS could detect neuronal damage specific to epilepsy, and that is not visible with structural magnetic resonance [8, 9, 10]. fMRI [11, 12, 13, 14, 15] is used in order to study the neural correlates of spontaneous generalized spike and waves discharge [5].

Analyzing the advanced Learning Machine techniques by comparison the ELM (Extreme Learning Machine) in terms of training time and classification with a Backpropagation Neural Network (BPNN) classifier and Support Vector Machines (SVMs), researchers concluded that ELM needs an order of magnitude less training time compared with SVMs and two orders of magnitude less compared with BPNN. The classification accuracy of ELM is similar to that of SVMs and BPNN [16].

Other researches show the EEG classification based on the extreme learning machine (ELM) algorithm has a good performance, in terms of time and classification accuracy (96.5% for interictal and ictal EEG signals), in comparison with the backpropagation algorithm (BP) and support vector machine (SVM). The ELM algorithm is used to train a single hidden layer feedforward neural network (SLFN) and nonlinear dynamical features in order to understand brain electrical activities. Nonlinear features extracted from EEG signals such as approximate entropy (ApEn), Hurst exponent and scaling exponent are used to characterize interictally (fig. 1) and ictal EEGs [17, 18, 19, 20, 21].

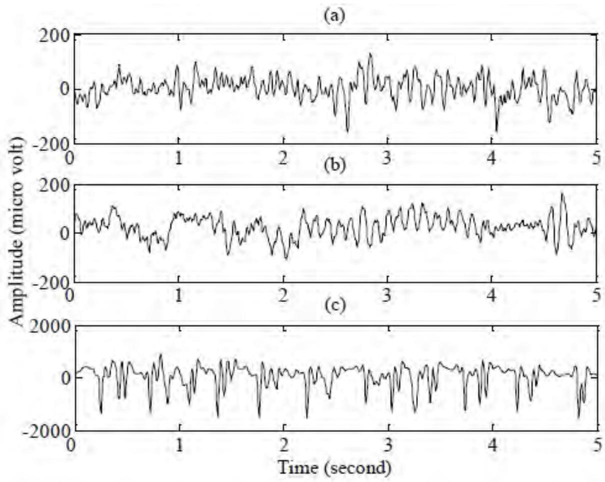

Fig. 1. Segments of EEG data: (a) Normal, (b) Interictal, (c) Ictal [21]

Another approach in the detection of epileptic seizures is to use the wavelets and statistical pattern recognition [22, 23, 24, 25, 26, 27]. For acquisition, the EEG signals use implanted intracranial electrodes (fig. 2) [21].

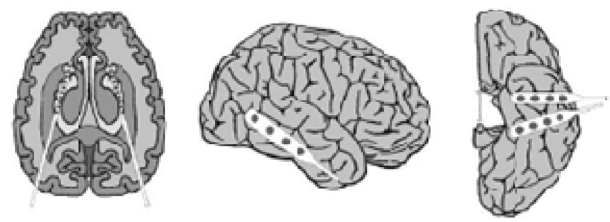

Fig. 2. Implanted intracranial electrodes [21]

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II. Signal Processing and Classification

A. *Signal Processing*

The analysis of the EEG signals can be used for the diagnosis and seizure detection in real time. In figures 3, and 4 are presented the EEG 2D-3D of an epileptic patient (child).

In order to filter the signal was used EEGlab.

Fig. 3. EEG raw signal from 23 signals

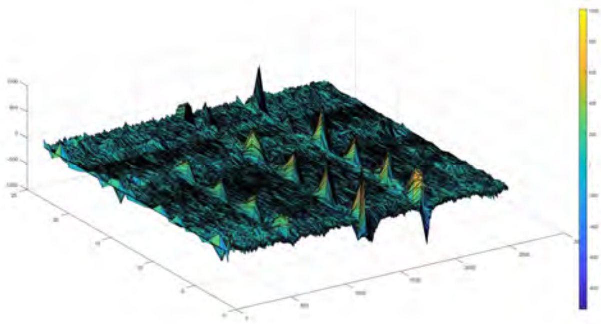

Fig. 4. 3D representation of epileptic seizure from EEG with 23 signals

In order to achieve processing, the signal was used wavelet method.

B. *Epileptic seizure classification*

Epileptic seizure classification of 23-channels scalp EEG data, obtained from CHB-MIT Scalp EEG Database, was done in MATLAB using a supervised classifier learner-support vector machine (SVM) that uses a linear kernel. Data were collected at the Children's Hospital Boston and contain EEG recordings from pediatric subjects with intractable seizures. The goal is to obtain the classifications that could be implemented in support decision systems in order to obtain easily a decision to continue the medication or to plan a surgical intervention. The sampling of the signals is 256 samples per second with 16-bit resolution. Subjects were monitored several days to analyze their seizures and to see if it is necessary surgical intervention. In figure 5 is presented the initial distribution of data, respective in figure 6 is presented the final data distribution for the predicted model. In figure 7 is presented the final data distribution after classification.

In figure 7 are represented parallel channels based on holdout validation (50% training and 50% testing).

In addition, using the multiclass method on-vs-all in linear SVM used in the classification of the epileptic seizure was obtained the predicted model (fig. 8).

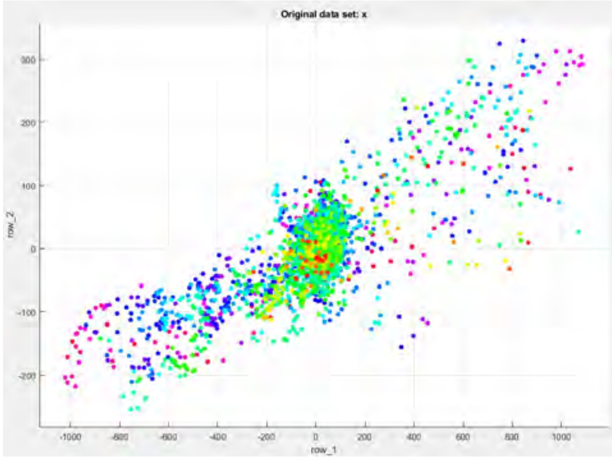

Fig. 5. Initial data distribution

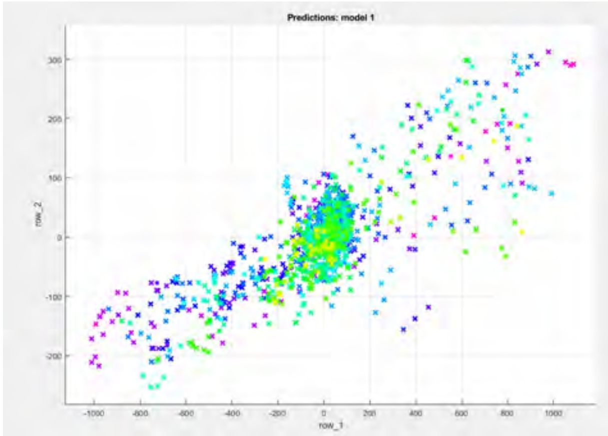

Fig. 6. Final data- predicted model

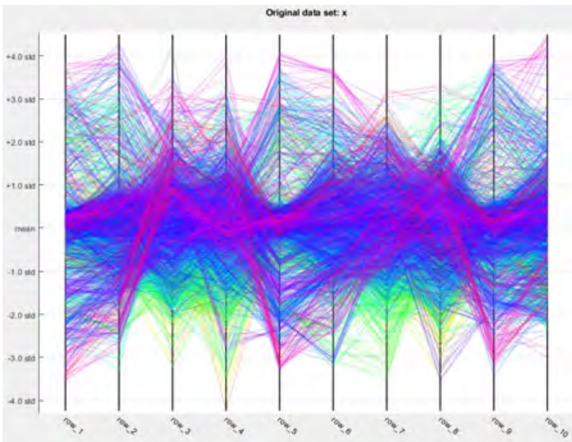

Fig. 7. Parallel coordinate plot – EEG

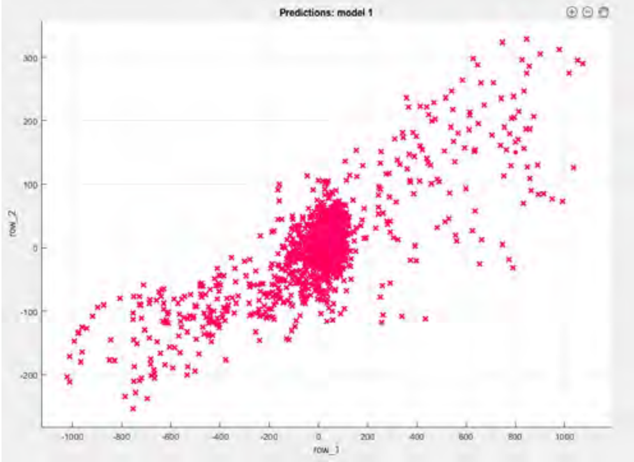

Fig. 8. EEG prediction based on SVM multiclass method

In order to obtain the predicted model a function was defined, using the following code:

```
function [trainedClassifier, validationAccuracy] =
trainClassifier(trainingData)
inputTable = array2table(trainingData', 'VariableNames',
{'row_1', 'row_2', 'row_3', 'row_4', 'row_5', 'row_6', 'row_7',
'row_8', 'row_9', 'row_10', 'row_11', 'row_12', 'row_13',
'row_14', 'row_15', 'row_16', 'row_17', 'row_18', 'row_19',
'row_20', 'row_21', 'row_22', 'row_23'});
predictorNames = {'row_1', 'row_2', 'row_3', 'row_4', 'row_5',
'row_6', 'row_7', 'row_8', 'row_9', 'row_10', 'row_11',
'row_12', 'row_13', 'row_14', 'row_15', 'row_16', 'row_17',
'row_18', 'row_19', 'row_20', 'row_21', 'row_22'};
predictors = inputTable(:, predictorNames);
response = inputTable.row_23;
template = templateSVM(...
   'KernelFunction', 'linear', ...
   'PolynomialOrder', [], ...
   'KernelScale', 'auto', ...
   'BoxConstraint', 1, ...
   'Standardize', true);
classificationSVM = fitcecoc(predictors, response,
   'Learners', template
     'Coding', 'onevsall')
```

In order to compute the validation predictors and validation accuracy we used:

```
✓    validationPredictors = predictors(x.test, :);
validationResponse = response(x.test, :);
[validationPredictions, validationScores] =
validationPredictFcn(validationPredictors);
✓    correctPredictions = (validationPredictions == validationResponse);
```

III. Conclusions

EEG seizures prediction in real time is a challenge for medical staff and researchers in order to see if pacient's symptoms have decreased or if it is necessary the surgery intervention. SVM classifies the EEG signal into seizure free and seizure [31, 32] in order to be used by medical staff in support decision systems for obtain easily the correct recommendation –drugs treatments or surgical intervention. The predicting accuracy of EEG signals can reach 99.9%. The prediction of EEG seizure based on SVM classifier can be useful for medical applications [33, 34, 35, 36].

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