Epileptic EEG marking with machine learning approach

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***Abstract*—In the present study we implemented machine learning approach to detect seizures on epileptic EEG data. We aimed to propose a method for preliminary EEG marking, that can possibly find application in clinical decision support system.**

***Index Terms*—epilepsy, electroencephalogram, machine learning**

I. Introduction

Epilepsy is a group of neurological disorders characterized by recurrent seizures, that vary from brief undetectable episodes to long periods of vigorous shaking [1], [2]. According to global statistics, epilepsy is one of the most common neurological diseases [3]. Seizures are accompanied by involuntary movement and state of incapacity, that can be dangerous for patients and surrounding people. Additionally, patients with epilepsy are more prone to cognitive and behavioral deficits [4]. Thus, epilepsy affects the professional, social and everyday life of a patient, and antiepileptic treatment is critical. Seizures can be controlled — up to 70% of patients could become seizure-free with the appropriate use of antiseizure medicines [5]. However, 80% of people face problems in receiving proper antiepileptic treatment [6]–[8], which leads to necessity of practical and accessible methods for epilepsy diagnostics. Epileptic discharges are poorly predictable and require advanced mathematical techniques for analysis [9]–[11]. This makes it difficult to develop non-drug cures for epilepsy, such as those based on the brain-computer interfaces [12]–[14].

The epilepsy diagnostics faces many problems: epilepsy can occur due to various reasons (brain injury, stroke, tumor, congenital disabilities, etc) and exact underlying cause is usually unknown [15]–[17], which results in high variability of epileptic activity — for example, focal and generalized seizures [18]. One of the most common approaches to epilepsy diagnostics is electroencephalogram (EEG) study: the patients are monitored for a prolonged period with occasional functional trials to stimulate the arousal of epileptiform activity [19]. The method is fairly reliable, but its main issue is the necessity of manual EEG data deciphering. The common way of doing this is visual EEG analysis, however, it requires much effort and involves human factor. Therefore, this direction of epilepsy diagnostics is in dire need of automation. While fully automated detection of epileptic seizures seems very attractive, even the modern methods in this field still possess a high chance of misdiagnosis. Such a mistake can have a heavy impact on the patient's physical and mental health and require its own treatment and rehabilitation. The probable solution here is partial automation in epilepsy diagnostics — some algorithm performs data analysis and provides preliminary results, but the expert makes the final decision. This principle lies in the foundation for Clinical decision support system (CDSS) development [20].

One of the most promising approaches to automated epileptic seizure detection is machine learning (ML) [21]. A wide variety of ML techniques have been applied to this task, including support vector machine (SVM) [22], [23], k-nearest neighbor (KNN) [24], deep learning [25]. However, epileptic data can be variable and heavily under-represented leading to a non-robust EEG footprint of an epileptic pattern. Epileptic pattern can differ greatly between patients and even between seizures of the same patient since there are many types of epilepsy and disease can progress with time [16].

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This issue leads to situation where direct application of ML classifier to raw EEG dataset may not produce enough sensible patterns. ML approach requires use of informative input features, that are commonly derived from time and frequency domains of EEG data [26]. For example, repeatability, regularity (periodicity), synchronicity and amplitude variation of EEG can be considered as major time-domain features able to differentiate epileptic seizure from normal activity [27]. Different types of transformation techniques are used for the extraction of significant statistical features including discrete wavelet transformation (DWT), continuous wavelet transformation (CWT), Fourier transformation (FT) [28], [29]. Many researchers proposed time-domain based features — for example, line length, frequency and energy in works of Logesparan et al. [30] and Guerrero-Mosquera [31]. However, it is crucial to analyze obtained feature space in order to find the most important features and perform feature reduction procedure. In this work, we aimed to propose ML-based approach to epileptic EEG marking that uses specific set of features instead of raw EEG signals.

II. Materials and Methods

A. Dataset

The experimental dataset was provided by National Medical and Surgical Center named after N. I. Pirogov of Russian Healthcare Ministry (Moscow, Russia). The dataset includes anonymized long-term EEG and video-monitoring data of 30 patients, who were treated in the Department of Neurology and Clinical Neurophysiology between 2017 and 2019. The data were collected during routine medical procedures and include continuous EEG and video monitoring during everyday activity. During the monitoring, patients kept a regular daily routine with occasional standard physiological trials such as photic stimulation and hyperventilation. Length of the monitoring varied from 8 to 57 hours and depended on the patient's condition and diagnosis. Each patient had from one to five epileptic seizures during the time of the monitoring. While all the patients were subjected to physiological trials, none of the seizures was triggered by photic stimulation or hyperventilation; i.e., all epileptic seizures were spontaneous. The long-term EEG and video-monitoring data of the patients were analyzed by the experts from the Center. All 30 patients were diagnosed with focal epilepsy, and all epileptic seizures were marked on the data.

B. Data acquisition and preprocessing

A "Micromed" encephalograph (Micromed S.p.A., Italy) was used for EEG recording. EEG signals were recorded for 25 channels according to the international "10–20" system with a ground electrode placed on the forehead and reference electrodes placed at the ears. EEG signals were recorded with sampling rate of 128 Hz. A video-monitoring system was used to monitor patients' states for easier analysis and segmentation of experimental data.

Experimental EEG data can be contaminated by various external noises (for example, power grid or cellphone interference) as well as physiological artifacts (heartbeat, breathing, muscle activity), especially during prolonged recording [32], [33]. To restrain these noise components we applied bandpass filter with cutoff frequencies of 1 and 60 Hz and 50-Hz notch filter. Some artifacts like blinking can interfere with effective frequency range of EEG signals ($1 - 30$ Hz). To remove these artifacts, we used the standard procedure based on an Independent Component Analysis (ICA) [34].

To prepare the data for further feature analysis we performed a time-frequency analysis of EEG signals using continuous wavelet transform (CWT) with Morlet mother wavelet function [35], [36]. We considered wavelet power (WP) in range $2 - 30$ Hz [37]:

$$W_n(f,t) = |w_n(f,t)|, \tag{1}$$

where n = 1, 2...N is the number of EEG channel ($N = 25$ for the considered dataset), f and t are the frequency and time point, $w_n(f,t)$ are the coefficients of CWT.

Then we "downsampled" the data. At first, we averaged WP over the 25 EEG channels. This step can be explained by the features of the analyzed data. During focal seizures, few EEG channels near the focus demonstrate distinct activity, so even after averaging over the channels WPs for normal and pathological activity differ drastically. Thus, we calculated WP averaged over EEG channels (AWP) as:

$$E(t) = \frac{1}{N}\sum_{n=1}^{N} W_n(f,t)df, \tag{2}$$

Then we divided each EEG recording into 60-second intervals T_m, where $m = 1, 2...M$, $M = L//60$, L — the length of EEG recording in seconds, "//" stands for integer division. The choice of such interval length is justified by the average duration of an epileptic seizure — from 30 to 120 s [38]. AWP values were calculated for each time interval m and averaged over the whole length of the interval to obtain downsampled AWP (DAWP):

$$e_m = \frac{1}{\Delta T}\int_{t\in T_m} E(t)dt, \tag{3}$$

where ΔT is the length of each interval T_m ($\Delta T = 60$ s).

C. Feature extraction and machine learning

We have chosen downsampled averaged wavelet power in range $2 - 30$ Hz as a basic feature. Then we introduced additional features based on seizure behavior in EEG data. It is well-known that epileptic seizures demonstrate distinct activity on EEG signals [2], so we considered some standard measures that can help to detect this activity — $Mean$ and $Variance$. Additionally, in our recent works [23], [39] we showed that during the seizure WP differs between low frequency ($2 - 5$ Hz) and high frequency ($5 - 30$ Hz) ranges. According to this observation we considered difference between DWPs averaged over low and high frequencies as another feature ($FreqDiff$). If we consider DWP spectrum in each time interval T_m as a

vector, then we can introduce cosine similarity between two spectra. Cosine similarity is often used to assess similarity in data, and it is especially popular in ML methods [40], [41]. For our research we used two cosine similarity-based features. The first feature ($SimToMean$) was introduced as cosine similarity between DWP spectrum at given time interval T_m and mean DWP spectrum for the patient. We suppose that this feature can additionally emphasize the peculiar behavior of seizure in contrast to normal EEG. The second feature ($SimToNeighbours$) was introduced as mean cosine similarity between DWP spectrum at given time interval T_m and each DWP spectrum from neighboring intervals (T_{m-3}, T_{m-2}, T_{m-1}, T_{m+1}, T_{m+2}, T_{m+3}). This feature is aimed to help in detection of "sudden" epileptic behavior.

Thus, we derived five new features from the data: $Mean$, $Variance$, $SimToNeighbours$, $SimToMean$, $FreqDiff$. We aimed to use them along with original DWP spectra to construct ML model. However, each DWP spectrum contains many features — spectrum was calculated in $2-30$ Hz range with 0.1 Hz step. Large number of features negatively affects time for ML model training. Moreover, DWP on neighboring frequencies, such as 2.1 and 2.2 Hz, are highly correlated, which leads to data redundancy. To lower the dimensionality of feature set we used Principal Component Analysis (PCA) [42]. The analysis showed that first two components ($PCA0$ and $PCA1$) contain 97.18% of all information from the initial data. Additionally, correlation analysis showed high correlation between $Mean$ and $PCA0$, so we decided to remove $Mean$ from the feature set. In the end, for constructing ML model we used six features: $PCA0$, $PCA1$, $Variance$, $SimToNeighbours$, $SimToMean$, $FreqDiff$.

We considered several candidates for ML model, including RandomForest [43], ExtraTrees [44] and GradientBoosting [45] Classifiers. We chose XGBoost Classifier [46] since it commonly provides exceptional classification.

In training ML model we used custom cross-validation function. In our case the model is trained on 29 patients and tested on the one remained patient. This approach imitates situation in medical practice when we have ML algorithm trained on K patients and we need to diagnose a new, $K+1$-th, patient, after that we can retrain the algorithm on $K+1$ patients and prepare it for $K+2$-th patient etc.

III. Results

To assess the efficiency of classifier we considered several characteristics derived from a confusion matrix [47]. Any binary confusion matrix uses the four kinds of results (true positives, false negatives, false positives, and true negatives) along with the positive and negative classifications. In our research epileptic episodes are referred as "positive" cases and normal activity episodes are referred as "negative" cases. According to this labeling:

- True Positive (TP) — number of correctly identified epileptic seizures.
- True Negative (TN) — number of correctly identified episodes of normal EEG.

Table1. Results of data analysis with ML classifier

Patient #	TP	TN	FP	FN	recall	precision	F1 score
1	3	1708	0	0	1	1	1
2	1	371	0	0	1	1	1
3	2	3427	0	0	1	1	1
4	1	325	0	0	1	1	1
5	1	321	0	0	1	1	1
6	2	236	0	0	1	1	1
7	1	409	0	0	1	1	1
8	1	428	0	0	1	1	1
9	2	395	0	0	1	1	1
10	1	1	0	0	1	1	1
11	1	426	0	0	1	1	1
12	5	2981	0	0	1	1	1
13	0	412	0	1	0	0	0
14	1	1154	0	0	1	1	1
15	4	3205	0	1	0,8	1	0,89
16	1	311	0	0	1	1	1
17	1	341	0	0	1	1	1
18	2	431	0	3	0,4	1	0,57
19	1	438	0	0	1	1	1
20	1	157	0	0	1	1	1
21	1	419	0	0	1	1	1
22	2	318	0	1	0,67	1	0,8
23	2	1633	0	0	1	1	1
24	3	2005	0	0	1	1	1
25	1	396	0	0	1	1	1
26	4	349	0	0	1	1	1
27	1	191	0	0	1	1	1
28	1	420	0	0	1	1	1
29	1	424	0	0	1	1	1
30	4	367	0	0	1	1	1
mean					0,929	0,966667	0,942
SE					0,039504	0,033333	0,036136

- False Positive (FP) — number of wrongly identified epileptic seizures, i.e. episodes of normal EEG identified as seizures.
- False Negative (FN) — number of missed epileptic seizures, i.e. seizures identified as episodes of normal EEG.

Using these characteristics, we evaluated the efficiency of our algorithm in terms of $recall$, $precision$ and F_1score, where

$$recall = \frac{TP}{TP+FN}, \tag{4}$$

$$precision = \frac{TP}{TP+FP}, \tag{5}$$

and F_1score is the harmonic mean of the $precision$ and $recall$.

For the analyzed dataset the ML algorithm provided the following results (see Table 1).

As one can see from Table 1, the classifier provides: $recall = 0.93 \pm 0.04$ (mean $\pm$ standard error), $precision = 0.97 \pm 0.03$, $F_1score = 0.94 \pm 0.04$.

IV. Conclusion

In this work, we proposed ML-based approach to epileptic EEG marking. We analyzed raw EEG data and derived a set of

features from it. We trained ML model with custom approach that imitates application of such classifier in medical practice.

The algorithm demonstrated high efficiency in classifying epileptic EEG data, especially taking into account high variability of patients' diagnoses. We suppose that developed approach could be used in CDSS, where the classifier is used for preliminary EEG marking.

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