A Statistical Method for EEG Channel Selection

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Abstract: - A new statistical analysis of medical signals is proposed based on information extracted for diagnosis. Several specialized tests can be run on electroencephalography (EEG) signal due to its nonlinear behavior. Epileptic EEG signals are the main topic of this research. A statistics-based approach is proposed for the automatic selection of the relevant channels that will not only provide more accurate characterization but also require fewer computing resources. Moreover, the outcomes given by specific electrode pairs might indicate epileptic focus. By selecting the most efficient electrode placement, alarms for detecting inappropriate medical behavior could then be triggered.

Key-Words: - EEG, epilepsy, channel selection, probability density function, cumulative distribution function, statistical methods.

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1 Introduction

This paper proposes a new method for medical signal interpretation by considering the EEG (electroencephalography) signal as a vector that is computed to extract statistical features, [1]. Such interpretation is oriented toward characterization in a specific case study: epileptic activity.

Epilepsy is one of the most common neurological diseases and affects people of all ages, ethnic groups, socioeconomic levels, and geographical regions, [2]. Despite not being a mental disease, epilepsy affects the brain and frequently causes seizures, [3]. Seizures are temporary spikes in brain activity that can cause a wide range of symptoms, such as trembling uncontrollably, unconsciousness, stiffness, tingling, fainting, etc. [4]. EEG is a low-cost, accurate time-resolution method of non-invasively measuring the electrical fields of the brain with the aid of electrodes placed on the scalp, [5], [6]. Depending on how the electrodes are placed and distributed across the surface of the scalp, potential differences between certain pairs of electrodes or the difference between a single electrode and the reference electrode may be measured. The resulting signals are amplified and displayed in quasi-real time as particular sequences of waves.

A strategy for choosing the best acquisition channels is suggested using statistical analysis in order to improve the effectiveness of the signal processing on those channels, shorten acquisition times, and optimize the entire process, [7]. This approach can also be used to distinguish between signals with epileptic seizures and normal ones or to determine the epileptic focus of the seizures based on the channel locations, [8].

In Section 2, some medical information is recalled to support the diagnosis claimed in this paper. The results of the statistical analysis are presented in Section 3. The conclusion is given in the final section of the paper.

2 Problem Formulation

2.1 Various Methods for Channel Selection

In order to obtain the best possible results from a potential seizure classification, choosing the optimal recording channel is a very important step, focusing on the channels that contain the most useful information. This process is essential for reducing computational complexity and time, enabling the use of portable headsets at a low cost, or activating only certain electrodes in that region.

Using the CHB-MIT database, the paper [9] proposes a multi-objective optimization approach for EEG channel selection that is based on the non-dominated sorting genetic algorithm. With only one EEG channel, the results showed an accuracy of up to 100%, indicating that portable EEG seizure detection systems and the classification of epileptic seizures with a few electrodes are feasible. Papers

[10] and [11] present a method for EEG channel selection and seizure prediction based on statistical probability distributions of the EEG signals. To reduce the use of memory and computational complexity while making the system suitable for real-time applications, the paper [12] proposes a channel selection algorithm, which includes testing every feature for every channel and selecting the best outcomes. This algorithm is also tested on the CHB-MIT EEG database. Using Model Agnostic Meta-Learning (MAML) applied to a Deep Neural Network (DNN), the paper [13] provides an improved channel reduction for seizure prediction, selecting and optimizing the number of channels from all the subjects of the CHB-MIT Dataset.

The channels can be selected based on the results obtained from feature extraction, as mentioned before [9], [12]. The disadvantage of this method is that it is time-consuming to test all features on all channels. The channels can also be chosen according to the location of the epileptic seizure and its nature, but the disadvantage of this method is that the type of seizure must be known, and, in the case of a general seizure, all the channels seem to be relevant.

Therefore, the proposed method involves a statistical method that uses the probability density function (PDF). A probability density function shows the values that, for a certain draw or time, are most likely to occur in a data process. This method can also represent a solution to determine the type of epileptic seizure because finding the optimal channel means determining the best pair of electrodes. Depending on the location of this pair, the exact type of seizure can be identified [14], such as a partial or generalized seizure, as presented in Figure 1.

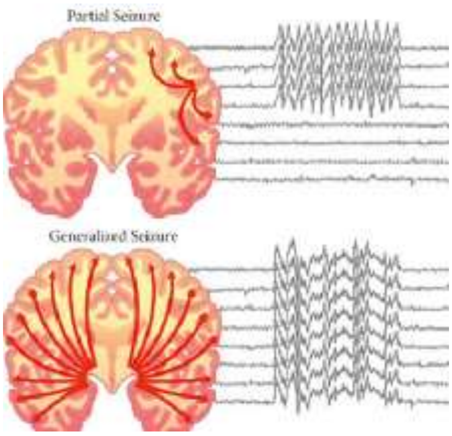

Fig. 1: EEG signals with partial and generalized seizures, [15]

2.1.1 Database

For testing the proposed algorithm, a database from PhysioNet, named CHB-MIT Database, was used [16]. This database, obtained at Boston Children's Hospital, contains EEG recordings from 23 children with intractable seizures. The subjects were monitored for several days after stopping the antiepileptic medication to characterize their seizures and evaluate their suitability for surgical interventions. As the purpose of this paper is to determine the best channels for epilepsy detection, only seizure signals were selected from 24 subjects (subject 1 was recorded twice), resulting in 140 signals on 23 channels (other additional channels were removed). The signals were sampled at a 256 Hz rate.

3 Problem Solution

The EEG signals from the database recalled in the previous section were computed in separate channels, resulting in a total of 3220 signals. The probability density function was applied to compute the mean (μ) and standard deviation (σ), values that are then used to select the best channels for each subject (Figure 2).

Fig. 2: The block diagram of the proposed method

As mentioned in [17], the same EEG signals with the best binary classification results were the filtered ones. Therefore, a bandpass filter was used in order to keep the frequencies in the [0.5, 12] range, where most of the seizures occur, [18].

All 23 channels that are first used are shown in Figure 3, displayed in the same range ([-2000, 2000]) μV in order to highlight variations in amplitude.

Fig. 3: Patient 1, signal 18 – the 23 corresponding channels

Signals with seizures have larger amplitudes and repetitive wave sequences than those without; therefore, both μ and σ are larger. Due to these factors, this method can also be used to discriminate between signals with and without seizure or ictal (seizure) and inter-ictal (seizure-free) epochs, [19]. Inter-ictal epochs have smaller, constant amplitudes, while ictal epochs are identified by a sudden increase in the amplitude, [20]. Good channels contain a lot of information, and the weaker channels contain less information. However, channels that contain too much information might be affected by noise or artifacts, which is why the filtering stage is necessary. Due to these factors, the data was normalized in the [0, 1] range, and some thresholds were set compared to the mean values of μ and σ. Figure 4 presents three PDF representations from three channels of one signal from subject 1, with different means and probabilities of the outcomes.

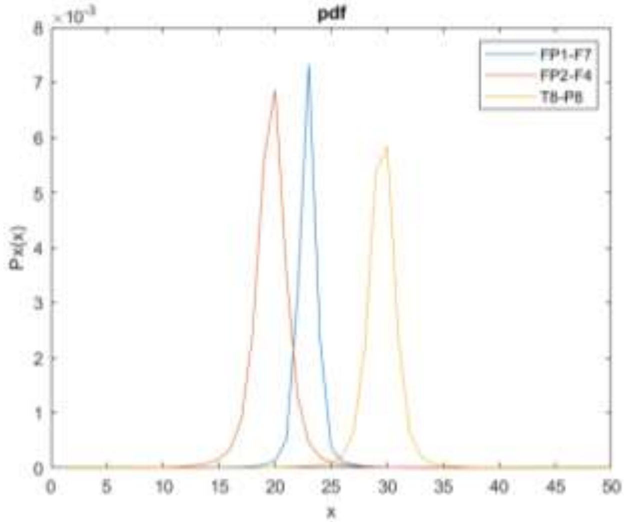

Fig. 4: Three PDF representations - same signal, different channels

For a better visual representation, the cumulative distribution function (CDF), another method used to describe the distribution of random variables, was computed for the same three signals (Figure 5).

The mean and standard deviation were computed for each signal and for each subject. If both values were in the proper range (between 20% and 70% higher than the mean value), that channel was stored in a vector, and the rest were removed. For each subject, it resulted in a vector with all the stored channels, and the number of times a channel appeared was computed. The channels that appeared the most were finally kept. The channel selection algorithm is presented in Figure 6.

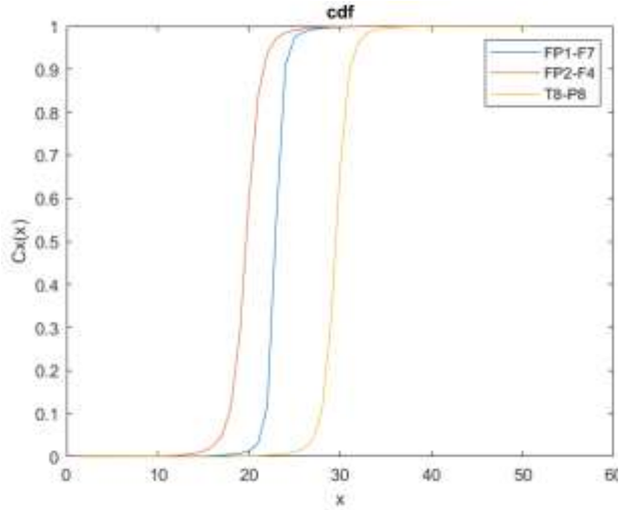

Fig. 5: CDF representations corresponding to the previous channels

Two different results for each channel are presented in Figure 9: the number of appearances and the number of times each channel appeared the most. In the first case, channels FP1-F7, F7-T7, FP1-F3, FP2-F4, F8-T8, P8-O2, and P7-T7 have the highest number of appearances. If the subjects with less than 5 seizure signals are removed, these channels still have the highest number of appearances, except for the P7-T7 channel. As for the number of times each channel appeared the most, the F7-T7 channel is the first one, followed by the P7-T7 channel.

Some channels never appeared or had never been the most efficient ones, such as T8-P8, F4-C4, or C4-P4. Therefore, these channels can be removed from the computations or simply deactivated during the recording sessions.

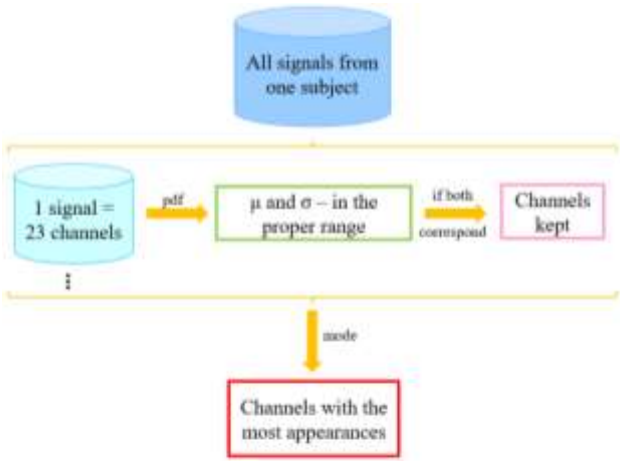

Fig. 6: Block diagram of the channel selection algorithm

To illustrate the facts mentioned above, Figure 7 and Figure 8 present two PDF and CDF representations of one of the best channels (F7-T7) and one of the weakest (T8-P8).

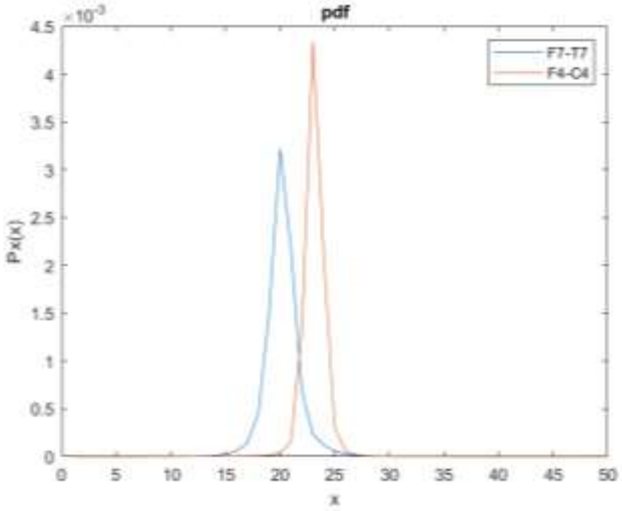

Fig. 7: PDF representations – 2 different channels

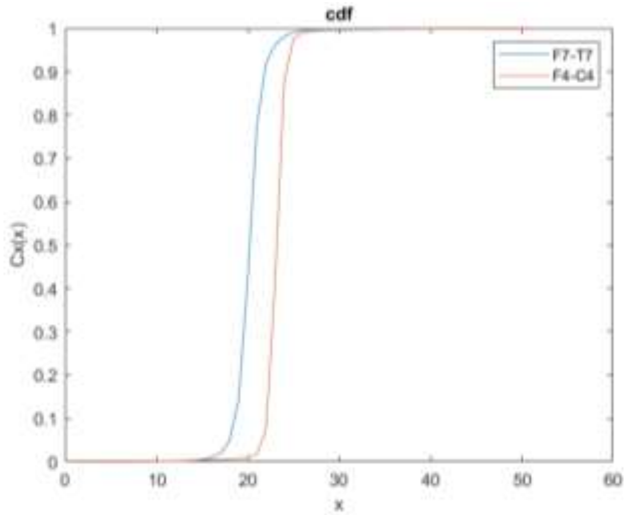

Fig. 8: CDF representations – 2 different channels

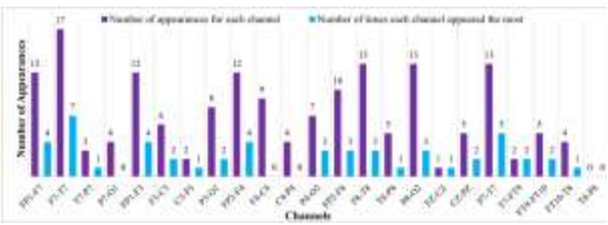

Fig. 9: Channels statistics

The fact that for most of the subjects, there were a few efficient channels means that they experienced partial seizures since a generalized seizure is visible on every channel. Besides the removal or deactivation of the inefficient pairs of electrodes, the type of seizure can be identified depending on the location of the electrodes. It is known that the International 10-20 system of EEG electrode positions and nomenclature was used for these recordings. In Figure 10, these electrode placements are presented alongside the highlighted electrodes and the marked pairs.

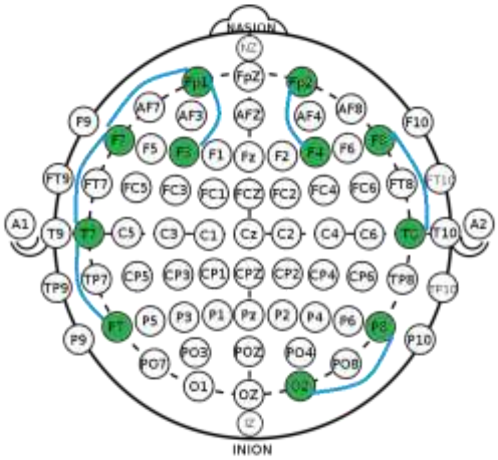

Fig. 10: The International 10-20 system of EEG electrode positions and nomenclature and the best pairs of electrodes.

From Figure 10, it can be seen that the pairs are located on the exterior of the hemispheres and not in the center. Also, the positions are almost symmetrical on the left and right sides. These locations suggest that even though the type of epilepsy might be different (although all subjects seem to experience partial seizures), the same channels offer the best information. This means that there is no need to use all the channels; therefore, the weaker channels can be removed from the computations or deactivated during the recording sessions. There are improvements in time, computing complexity, and the risk of inaccurate data in both scenarios.

4 Conclusion

This study attempted to determine the optimal acquisition channel of an EEG signal using statistical methods, more specifically PDF, which is also crucial for obtaining accurate and effective characteristics. If the best channel is not selected, then the corresponding signals will contain too little useful information or too much information affected by noise and artifacts, and will also complicate the computations due to the higher number of signals (channels), some of which do not even contain relevant information.

On one hand, this method can be used to identify the type of epileptic seizure. If the seizure appears on all channels, it means that the subject experiences generalized epilepsy. If the seizure occurs on specific channels, it means it is partial epilepsy (e.g., frontal lobe epilepsy). As was previously presented, the best channels were mostly located in the frontal and temporal lobes, indicating two common types of epilepsy.

On the other hand, by discovering a method to detect the optimal channel according to the location or type of seizure, an algorithm that "filters" the channels can be obtained, i.e., automatically activates only certain electrodes and sends the best-acquired signals without the need to manually choose the best channel. However, finding the best channel means finding the best pair of electrodes, and based on their placement, the specific type of seizure can be recognized.

The proposed approach is very simple but effective, with relatively few computations. Thus, the algorithm can be used in a portable device for real-time EEG signal acquisition since the channel selection is precise as well as fast.

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Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

The authors equally contributed in the present research, at all stages from the formulation of the problem to the final findings and solution.

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Conflict of Interest

The authors have no conflicts of interest to declare.