Detecting Epileptic Seizures in Advance Using Optical and Electrical Recordings

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***Abstract* — This paper presents preliminary results on epileptic seizure detection. Combination of functional Near Infrared Spectroscopy (fNIRS) and Electroencephalogram (EEG) recordings shows enhanced performance compare to EEG recordings alone. Moreover, some results concerning the anticipation at which a seizure can be detected are also presented.**

Keywords—epilepsy, seizure, detection, prediction, fNIRS, EEG, multimodal

I. INTRODUCTION

Epilepsy is one of the top three most common neurological disorders; it is just below strokes and Alzheimer disease [1]. It is estimated that 65 million people around the world suffer from epilepsy, which represents approximately 1% of the global population [2]. On average, 60 new cases of epilepsy 100,000 people emerge every year [2]–[4].

Epileptic seizures are the hallmark of epilepsy. They are brief episodes of perceptive or behavioral disturbances due to an abnormal excessive synchronization of a large group of neurons within the cerebral cortex. These episodes may last from few seconds to few minutes [1], [2].

Unpredictability of epileptic seizures represents one of the main problems for patients with this disorder [5]. Therefore, reliable and early detection of epileptic seizures is a problem of interest [6]. For years, several methods have been proposed to solve this problem; however, most of them have focused on the solely analysis of EEG recordings [6]. Nonetheless, recent publications suggest that information contained within fNIRS recordings (i.e., relative concentration of oxyhemoglobin, HbO, and deoxyhemoglobin, HbR) can be used to solve this problem [7]-[9].

Being able to detect epileptic seizures in advance would unfailingly derive in improvements to the quality of life of patients with this condition. Detecting seizures could allow patients with epilepsy and/or their caretakers to take precautions before the occurrence of an epileptic event. This would drastically minimize potential risks.

This work is organized as follows: in the second section a brief description of EEG and fNIRS recordings is presented. Third section describes the methodology followed in this work: 1. The investigation of including multi-modal data and 2. Variations on the definition of pre-ictal window. Results from the applied methodology are presented and discussed in section number four. Finally, our conclusions as well as some guidelines on our future work are given in fifth section.

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II. EEG AND FNIRS RECORDINGS

EEG is a technique, which consists on placing electrodes either in the surface of the brain (intracranial) or in the scalp (extracranial) to measure the electrical activity of the brain and therefore acquiring information of its functionality. When performing an extracranial electroencephalogram, electrodes are placed all over the scalp in specific locations, usually determined by the International Federation 10-20 system [10] (Fig. 1).

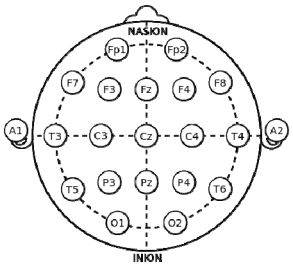

Fig. 1. International Federation 10-20 system. (taken from [10])

Functional Near Infrared Spectroscopy (fNIRS) is a relatively new technique to obtain information regarding the functionality of the brain [12]. This technique consists on injecting at least two wavelengths of near infrared light (690 and 830nm, in our case) into the scalp through an emitter and then measuring the backscattered light with some detector (as shown in Fig. 2). By taking advantage of the fact that hemoglobin in blood has different absorption spectrum depending on its level of oxygenation, fNIRS technique can semiquantitatively / quantitatively monitor important physiological parameters like the relative level of oxygenated hemoglobin (HbO) and deoxygenated hemoglobin (HbR), which at the same time, are tightly related to the brain activity [12].

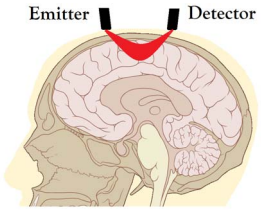

Fig. 2. functional Near Infrared Spectroscopy (fNIRS) (modified from [13]

III. METHOD

Two classifiers were implemented in MATLAB employing its specialized toolboxes. The first one was an artificial neural network (ANN). For the ANN, the default parameters values of MATLAB were used (1 hidden layer with 10 neurons, 1000 Epochs, trained using scaled conjugate gradient backpropagation and mean squared normalized error performance function). The second classifier was a support vector machine (SVM) with a fine Gaussian kernel. Both classifiers were fed with data from a 49-year-old male patient with refractory epilepsy. This data was obtained in a previous EEG-fNIRS study [14]-[16].

Data consisted of approximately 82 minutes of recordings from the patient. Three sets of data were simultaneously recorded: 19 channels of EEG, 133 channels of HbO and 133 channels of HbR signals. During these 82 minutes, four epileptic events were recorded but we concentrated in just one of them, due to the applied methodology, i.e. the need of a sufficiently long pre-ictal window.

For the first part of this work seven sets of classifiers were implemented. Each one of the seven sets of classifiers was fed with a different set of data. Table 1 summarizes the input used in each set of classifiers. Each row in Table 1 corresponds to one of all possible combinations of available data (EEG, HbO and HbR).

TABLE I. INPUT DATA OF THE SEVEN SETS OF CLASSIFIERS

Set of classifiers	Input data
1	EEG
2	HbO
3	HbR
4	EEG+HbO
5	EEG+HbR
6	HbO+HbR (fNIRS)
7	EEG+fNIRS

Given their different nature, EEG and fNIRS signals were acquired at different sampling frequencies. EEG signals were recorded at 500Hz while fNIRS signals were sampled at 19.5312Hz. In order to use a single classifier as well as to avoid losing electrical information, fNIRS signals were interpolated to match EEG sampling frequency. However, given the number of fNIRS channels, this process resulted in a huge amount of data, whose processing would have required a high amount of computation time. For this reason both set of signals were afterwards decimated by a factor of 2. It is worth mentioning that even with these considerations, it took more than 36 hours to obtain a single result.

EEG and fNIRS signals had different ranges of values. To prevent this discrepancy from causing poor classification performance, all data were standardized to have zero mean and unit standard deviation.

Original recordings were analyzed and manually classified by an epileptologist, using two labels: ictal (seizure) and interictal (no seizure). Our approach to detect epileptic seizures in advance consists in detecting the state before a seizure (preictal). For this reason, a third label, corresponding to preictal state, was added to data. Since there is no convention on how long preictal state lasts [17], we arbitrarily defined a preictal window of 5 min before the start of the seizure (as shown in Fig. 3).

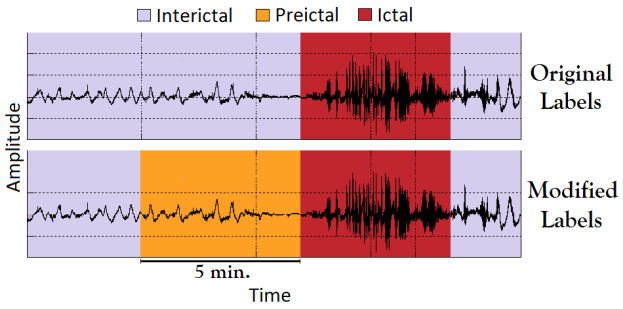

Fig. 3. Labels modifications.

For the second part of this work, following the methodology in [18], we investigated the feasibility of redefining the preictal window to improve early detection. In this case, the 5-minute-long preictal window was moved away from the start of the ictal state, four times, at steps of 2.5 minutes, as illustrated in Fig. 4. Data between preictal and ictal state were discarded (as shown in Fig. 4). For this part, we considered both, the ANN-based as well as the SVM-based classifiers but in this case only two different inputs were examined: EEG and EEG + fNIRS.

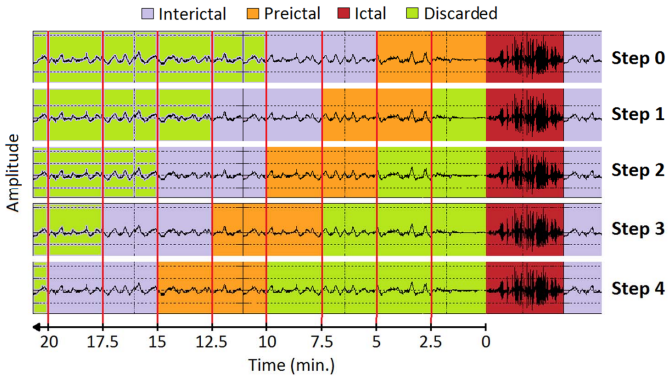

Fig. 4. Process to study the feasibility of sliding the preictal window away from the ictal start. Only one EEG channel is shown

All results were validated using a 10-fold cross-validation model, a technique to assess how well the classifier will work with data it has not already seen. k-fold cross-validation consists on randomly dividing all available data into k equal-sized subsets to run k cross-validation processes. In each of the k cross-validation process, k-1 different subsets are used to train the classifier while the left one is used to test the performance of the trained model.

IV. Results

For the first part of this work, Table 2 summarizes the positive predictive value (PPV) of each classifier for the state of interest (preictal) considering different input data. PPV was computed using equation 1:

$$PPV = \frac{TP}{TP + FP} \text{ x } 100 \quad (1)$$

where TP stands for True Positives and represents the number of times that the classifier classified correctly a sample of the state of interest; while FP stands for False Positives and indicates the number of times that the classifier identified incorrectly a sample of a different state as one of the state of interest. In this case, the PPV represents the probability of identifying a sample of the preictal state, therefore 100% represents the ideal case.

TABLE II. PPV FOR TWO CLASSIFIERS CONSIDERING SEVEN DIFFERENT INPUTS

	EEG	HbO	HbR	EEG + HbO	EEG + HbR	fNIRS (HbO + HbR)	EEG+fNIRS
ANN	59.7	100	100	100	100	100	100
SVM	96.6	100	100	100	100	100	100

a.

From Table 2 we can appreciate that, as expected, the SVM-based classifier showed better performance than the ANN-based classifier. However, it is more interesting to see that using or including fNIRS signals to identify preictal-state samples leads to better results than using EEG signals only (independently of the classifier).

Results of the second part are presented in Table 3, where the column titles indicate the time discarded between the end of the 5-minute-long preictal window and the start of the ictal state. In this table, we are also reporting the PPV for the preictal state of both, the ANN and the SVM classifiers, for the two different inputs (EEG and EEG+fNIRS).

TABLE III. PPV FOR ANN-BASED AND SVM-BASED CLASSIFIERS, FOR TWO DIFFERENT INPUTS, MOVING PREICTAL WINDOW.

		0min	2.5min	5min	7.5min	10min
ANN	EEG	59.7	63.9	54.8	46.5	43.1
	EEG/fNIRS	100	100	100	100	100
SVM	EEG	96.6	98.4	97.1	95.6	93.8
	EEG/fNIRS	100	100	100	100	100

For a better visualization, data from Table 3 were plotted and it is displayed in Fig. 5. From this figure, it is easier to observe that, regarding early detection of epileptic seizures using EEG signals only, performance tends to decrease as the preictal window is moved away from the start of the ictal state, except for the slightly increased performance at 2.5 minutes. Furthermore, we can appreciate that adding fNIRS signals as features for classification not only improves the performance of the classifier but also stabilizes its performance as the preictal window is moved away from the start of the seizure.

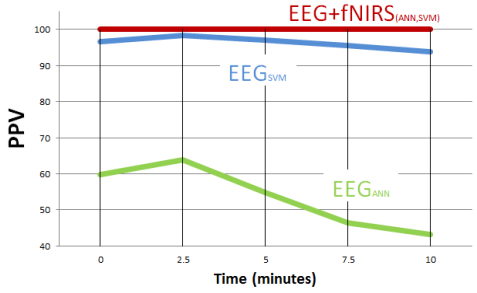

Fig. 5. Results from the study of sliding the preictal window away from the ictal start

V. Conclusions and Future Work

Even though results from a case-study are not conclusive, Table 2 suggests that adding fNIRS features to an EEG-based detector will considerably improve its performance. Furthermore, from Table 3 and Fig. 5 we confirmed that information contained within fNIRS can help to detect seizures much earlier. Given these promising results, our future work will be to try the same approach with others classifiers on a larger sample. We will also focus on extracting new and better classification features out of the fNIRS signals and combine them with features extracted from EEG recordings. One limitation of our work is the lack of implementation of a feature selection algorithm, although it may not be needed, given the promising results using only the amplitude of signals as features. The choice of optimal parameters in our machine learning approaches, such as SVM kernel type and its associated parameters, number of neurons in the ANN hidden layer as well as a feature selection process will be tackled in future work.

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