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Quantitative detection of seizures with minimal-density EEG montage using phase synchrony and cross-channel coherence amplitude in critical care

S. Abdullateef, B. Jordan, V. Rae, A. McLellan, J. Escudero, *Senior Member, IEEE*, V. Nenadovic, T. Lo

***Abstract*— Seizures frequently occur in paediatric emergency and critical care, with up to 74% being sub-clinical seizures making detection difficult. Delays in seizure detection and treatment worsen the neurological outcome of critically-ill patients. Gold-standard seizure detections using multi-channels electroencephalograms (EEG) require trained clinical physiologists to apply scalp electrodes and highly specialised neurologists to interpret and identify seizures. In this study, we extracted phase synchrony and cross-channel coherence amplitude across 4 and 8 pre-selected scalp EEG signals. Binary classification is used to determine whether the signal segment is seizure or non-seizure, and the predictions were compared against the gold-standard seizure onset markings. The application of the algorithm on a cohort of forty routinely collected EEGs from paediatric patients showed an average accuracy of 77.2 % and 76.5% using 4 and 8 channels, respectively.**

***Clinical Relevance*— This work demonstrates the feasibility of seizure detection with pre-defined 4 and 8 EEG electrodes with an average accuracy of 77%. This means, for the first time, seizure detection is possible using an EEG montage that can be applied readily at the bedside independent of expert input.**

I. Introduction

Seizures commonly occur in paediatric critical care, and up to 74% of these seizures do not have clear clinical markers, i.e. being sub-clinical, making their detection difficult [1], [2]. Seizures are a sudden surge of synchronized electrical activity in the brain and can cause involuntary changes in patients' sensations, behaviour, and even loss of consciousness. The duration of the seizure can extend from a few seconds to an hour or more. Prolonged seizures are also known as status epilepticus and defined as seizures lasting 15 minutes or more. Studies have shown that undetected and delayed treatment of the seizures in patients requiring Intensive Care Unit (ICU) leads to poor neurological outcome [3].

Electroencephalogram (EEG) signals capture the changes in brain electrical activity. Epileptiform EEG patterns, such as sharp spikes and waves, can classify the seizures and are currently used as the gold-standard seizure detection [1], [4]. However, EEG-based analysis is highly laborious and costly as it involves visual analysis of recorded EEG signals from multiple scalp electrodes. Highly trained physiologists and neurologists are required for placement of the electrodes and interpreting the signals, respectively [5].

Possible solutions for accelerating the above-mentioned process and reducing the cost of required staff can be 1) to select a limited number of EEG channels instead of using all (usually 20 channels or more), and 2) to use an automated seizure detection algorithm.

As clinical studies have shown [6], [7], trained bedside critical care staff were able to accurately mark seizures with reduced number of EEG channels. Seizure detection with reduced number of channels (from above 20 to less than 8) will require less time for applying them on patients' scalps [8], and increases the feasibility of accurate placement of EEG electrodes by intensive care clinical staff without specialist neurophysiological training [5], [9].

In the realm of engineering, limiting the number of channels can reduce the computational time and complexity of seizure detection algorithms. However, with fewer EEG channels there will be fewer data points and thereby a compromised accuracy. Therefore, developing an algorithm that could accurately detect seizures with limited channels is of great clinical interest as it can facilitate EEG acquisition and prompt seizure detection at the bedside with minimal delays [10], [11].

EEG signals capture the electrical activities of groups of neurons. These electrical activities can oscillate in multiple frequency bands, such as delta (0.5 - 4 Hz), theta (4 - 8 Hz), alpha (8-12 Hz), beta (12- 25), and gamma (above 25 Hz) [12]. During a seizure, the synchrony between these oscillations from neurons in different regions of the brain increases. Thus the synchrony of the signals can be used as an indicator of seizure [13]–[16]. In order to quantify the amount of synchrony between two sites, phase-locking value or phase synchrony can be used.

This study aims to develop an algorithm that can detect seizures accurately in paediatric EEG data with limited pre-selected EEG signals as few as 8 and 4 channels. As the scope of this study is to develop an algorithm to be used in critical care, we focus on certain pre-selected channels and consider

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S. Abdullateef and J. Escudero are with the School of Engineering, Institute for Digital Communications, University of Edinburgh, Edinburgh EH9 3FB, UK (e-mail: sabdull2@ed.ac.uk, javier.escudero@ed.ac.uk).

B. Jordan, V. Rae, and A. McLellan are with Royal Hospital for Children & Young Person, Edinburgh EH16 4TJ, UK. (email: brian.jordan@nhslothian.scot.nhs.uk, ailsa.mclellan@nhslothian.scot.nhs.uk, Valerie.Rae@nhslothian.scot.nhs.uk).

V. Nenadovic is founder of BrainsView, Khan Crescent, Ontario, L5V 2R4, Canada, previously working at University of Toronto (e-mail: vnenadovic@brainsview.com).

T.M. Lo is with the Centre of Medical Informatics, Usher Institute, University of Edinburgh EH16 4UX, UK and Royal Hospital for Children & Young Person, Edinburgh EH16 4TJ, UK. (e-mail: mils.lo@ed.ac.uk)

the changes because of seizures on EEG regardless of their underlying pathology. The reader is referred to [9], [17] for patient-specific channel reduction methods. The 8-channel montage is based on a commercially available circumferential headgear [18], and the 4-channel arrangement is already in use in paediatric critical care [19]. Our algorithm combines two features extracted from the pairs of signals and uses machine learning to classify of two groups: seizure and non-seizure. We have achieved an average of 77 per cent accuracy using 4 EEG signals.

II. Materials and Methods

A. Data

Forty (40) fully anonymised routinely collected EEG from the Royal Hospital for Children and Young People in Edinburgh were used in this study. The scalp EEG electrodes were applied using the 10-20 international electrode placement system. All of the recordings were annotated as part of routine clinical reporting, and the seizures were marked by a neurologist. Since the data had been collected in the clinical setting of an electrically noisy environment, it included real-life artefacts. Table 1 presents a summary of the recordings used in the study.

Table 1. Information of the recordings used in the study.

No. recordings	Age range	Total duration	No. seizures	Seizure duration
40	12 days - 12 years old	38.5 hrs	236	2.7 hrs

B. Pre-processing

All the recordings are pre-processed in MATLAB 2021b. For each recording, 8 EEG channels (T3, T4, T5, T6, O1, O2, F7, F8) and 4 channels (C3, C4, P3, P4) are extracted. The location of electrodes in 4 and 8 channels montage is shown in Figure 1.

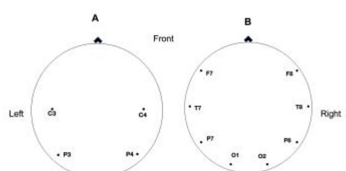

Figure 1. Electrode placement in A) 4-channel arrangement used in the Paediatric critical care, and B) 8-channels montage in sub-hairline commercial headgears.

We first apply the surface Laplacian filter to minimise the effect of volume conduction and avoid the possible influence of the common reference electrode on synchronisation [20], [21]. We then apply a 6th order high-pass Butterworth filter with cutoff frequency of 1 Hz to eliminate the slow frequencies. Finally, by using a least-square finite impulse response filter to select the delta range (1- 5 Hz in this study) of the signals for analysis.

C. Feature Extraction

We combine two separate features for seizure detection as below.

1) Phase synchrony (PS)

Phase synchrony is the phase-locking between the signals of two electrodes at a certain time [16]. For quantifying the phase synchrony, the *R* index or the mean phase coherence is calculated for all possible pairwise signal combinations [15]. We used the analytical method of Hilbert Transform to extract the instantaneous phases of two signals and estimated the phase difference for two signals across time. The index was calculated for a 1-second running window [22].

After calculating the phase synchrony between pairs of signals in the delta band, a connectivity matrix is obtained with the average value of each 1 s window of the synchrony index. We binarised the connectivity matrix using a predefined threshold, resulting in a 0 entry if the synchrony index is lower than the threshold or 1 otherwise. Two EEG channels are defined as connected if the corresponding binary entry is 1[22].

In the next step, we defined a complexity measure that considers the number of connected pairs of signals at each instance. Based on the binomial coefficient, there is a maximum of 28 pairwise combinations for 8 channels and 6 pairwise combinations for 4 channels of EEG signal. The complexity matrix has two arrays which are the number of synchronised pairs of signals and the connectivity**.** For a detailed description of the analytical procedure, the reader is referred to [15], [22].

2) Cross-channel coherence amplitude (CA)

Since the seizures cause a dramatic increase in the amplitude of the signals [23], we use a pairwise amplitude coherence as the second feature for seizure detection [4]. The cross-channel coherence amplitude estimates the degree of synchronisation between the activity measures of two signals [24]. The CA is calculated using the EEGLAB toolbox in MATLAB, using 3 wavelet cycles and a window size of ~4 seconds. Similar to PS, CA is calculated for a combination of pairs of signals which is 28 possible combinations for 8-channels montage and 6 combinations for 4-channels. The maximum value of the coherence amplitude is selected for each combination and saved in a matrix. In the next step, the mean value of the coherence is calculated, and a threshold is selected for the connectivity decision. Using an automated patient-specific threshold would take into account the possibility of abnormal alterations in signals in the non-seizure period. The maximum value of CA for each combination is compared with the threshold and if (CA> Threshold), the algorithm replaces the value with 1. In the final step, similar to PS, a complexity array is defined that considers the sum of the connectivity of all pairs at each time point. This array is used as a feature in the classification step.

D. Classifier and performance evaluation

In order to classify the signals into non-seizure and seizure classes, we use a boosted-tree classifier [25] for each patient. Boosted tree classifiers have high prediction performance and do not need feature scaling. The adaptive boosting for binary classification is used as we define two classes seizure (0) and non-seizure (1).

To avoid the potential over-fitting due to class imbalance, we under-sample the non-seizure data only for the training data. The classifier's predictions were compared against the gold-standard annotation provided by the neurologist using a 5-fold cross-validation method. Accuracy, sensitivity, specificity, and false negative rate (FNR) are computed by comparing the classifiers' predictions against the ground truth provided by the annotations in the dataset.

III. Results

In this study, we use two features for each time instance for seizure detection. Both features capture the number of connections between the pairs of channels. Figure 2 depicts a single EEG signal with a duration of 8 minutes and three seizures. Seizures are highlighted using black boxes. The middle graph shows the changes in the phase synchrony during the recording. The arrows highlight the occurrence of seizure where the synchrony increases with seizure onset. In the bottom graph of Figure 2, which is the cross-channel coherence amplitude, there are peaks in the maximum CA values. As shown, the delta band is used for the analysis.

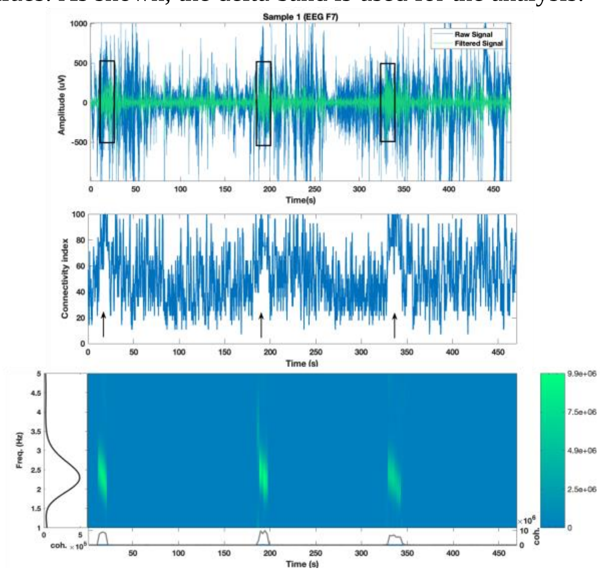

Figure 2. Features of the EEG signals shown in the top row, middle) pairwise synchrony, and bottom) Cross-channel coherence amplitude. Black boxes and arrows indicate the occurrence of a seizure.

First, we used only PS and then CA separately for classifying the events. The average accuracy for all 40 subjects, for both methods, were approximately 66.2±5 % using 4-channels and 67.2±3% using 8 EEG signals. By combining the two features, the average accuracy increased to 77.2 % and 76.5% for 4-channels and 8-channels, respectively. Figure 3 shows the average performance of the classifier when using PS(A) and CA (B).

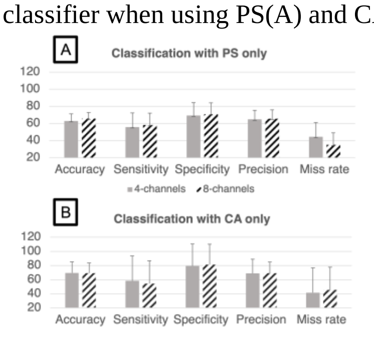

Figure 3. The average performance of the classifier for seizure detection using 4 and 8-channel montages. The bars show the standard deviation across 40 samples.

The performance of the classifier using both features is shown in Figure 4.

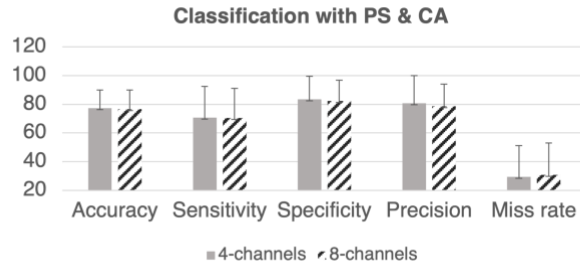

Figure 4. The average performance of the classifier for seizure detection using 4 and 8-channel montages two features. The bars show the standard deviation across 40 samples. The performance of the classifier improved by 15%, combining the two features PS and CA.

Using two features improved the accuracy for both 8 and 4-channels seizure detection. In addition, there was a reduction in the average false discovery rate in both EEG montages, as shown in Table 2.

TABLE II. The average False Discovery Rate (FDR) in all recordings using one (only PS or CA) and both (PS + CA)

Features	Number of EEG channels	
	Eight	**Four**
PS	0.35	0.35
CA	0.34	0.29
PS+CA	0.22	0.21

IV. Discussion

In this study, we introduce a novel approach for seizure detection which uses two separate low-density EEG montages in 40 clinical EEG recordings. Our aim is to demonstrate the feasibility of seizure detection using pre-selected montages that are fast to apply on patients in a critical care units rather patient-specific reduction of EEG channels as proposed in previous studies [9], [26]. Moreover, the seizure detection algorithm needs to provide the calculation with minimum delays and in order of few seconds, which makes the complex and computational-expensive techniques unattainable [4].

PS has shown to be a reliable marker for seizure detection [27], as the neural groups become more synchronized during a seizure. Our results, shown in Fig. 2, depict an increase in connectivity index as the seizure starts. Similar trend is reported in [21], [27]. However, using only the PS limited the accuracy and precision of seizure detection to below 65%. Considering the few numbers of EEG signals used for the analysis, this outcome is somewhat expected. While using CA, on its own, did not improve the accuracy, using CA in combination with PS improved the classification outcome. The average accuracy for seizure detection in the 40 recordings has enhanced by 12% and reached approximately 75%. CA captures the correlation between the spectral amplitude of pairs of signals which increase during a seizure.

Although 8 channels of EEG signal provide more data points for the analysis, we observed higher accuracy and lower FNR in seizure detection using only 4-channels (Fig. 3). The FDR did not differ between two montages. One possible explanation for the lower accuracy in 8-channels montage is the location of the channels that record more circumferential brainwaves compared to 4 channels (Fig. 1). In addition, EEG used in this study originated from infants and children and the results might indicate that in children, seizures mostly originate in central and temporal areas of the brain. Further research is required to confirm this observation and determine the optimal electrode positionings for patients of different ages.

A reliable computer-aided detection algorithms in clinical environment need to have high accuracy and low false alarm rate in analysis of noisy data. Although our algorithm was trained on heavily noisy data and achieved average 77% accuracy, the FDR needs to be improved. Therefore, future work will focus on reducing the FDR. Further improvements will include a better re-referencing method (instead of Laplacian) and optimisation of the thresholding methods.

V. Conclusion

To the authors' knowledge, this work is the first to demonstrate the feasibility of seizure detection with a limited pre-selected EEG electrodes. Using two feature extraction methods has improved the results for both 4 channels and 8 channels seizure detection.

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