Two-Channel Epileptic Seizure Detection with Blended Multi-Time Segments Electroencephalography Spectrogram

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Abstract— Fully automated seizure detection with small number of electrodes based on clinical electroencephalogram (EEG) data have been a challenging problem for the last decades. Current solutions for tracking seizures include using epilepsy seizure diaries or mobile apps (to be maintained by patients or caregivers) as well as non-EEG wearable solutions (e.g. smartwatch). Commercially available seizure detection software suffer from unacceptably high false-alarm rates, and hardware solutions are often not based on EEG, which excludes a range of seizures. There is a trade-off in wearable EEG and how ambulatory it can be. The higher the number of electrodes, the lesser will be the length of the time it can be comfortably worn. However, are we able to achieve the same level of performance in seizure detection with just a handful of electrodes and through a few channels? This is a question we are trying to answer in this paper. EEG based devices, they often require to have more than 20 EEG electrodes recordings to be able to accurately detect and label seizures. In this paper, we demonstrate a technique capable of seizures detection with two channels that achieves a low false-alarm rate. Using a low number of electrodes is important because often EEG caps are uncomfortable to wear and sometimes they have to be worn for days. This work considers a blended time-segmented EEG signal processing for epileptic seizure detection using convolutional, long short-term Memory (Conv-LSTM). Extensive experiments have been conducted on Temple University Hospital (TUH) EEG corpus. We introduce a solution that involves electrode ranking, pre-processing as well as fusion of multi time-segmented EEG spectrograms in short-time Fourier transform (STFT) analysis. While the performance of our system is highly adjustable, in order to satisfy the scoring criteria for the Neureka 2020 Epilepsy Challenge, we report the result that reported the best outcome in the Challenge.

I. Introduction

Epilepsy is a common neurological disorder characterized by recurrent seizures. Statistically, 1 in 100 people globally have active epilepsy at any time but the lifetime-risk of being impacted by epilepsy is more than 3.5% which is about 800,000 people in Australia alone [1]. Even with the help of anti-epileptic drugs, the condition is intractable in about 30% of people living with epilepsy [2]. The symptoms include injuries, behavioural, developmental and cognitive disorders, and even death [3]. Sudden and unexpected death in people with epilepsy, SUDEP, is the leading cause of death if epilepsy is uncontrolled. Usually, at-risk individuals are otherwise healthy and autopsy provides no other explanation for the cause of death other than SUDEP. This means patients and their caregivers quality of life is significantly impacted [4, 5]. Long-term ambulatory physiology monitoring for brain signals using wearable electroencephalogram (EEG) signals could open the way for continuous monitoring but it is not turned into reality yet. One of the issues at the heart of the challenge in realizing long-term wearable monitoring is the lack of comfort and reliability of many EEG electrodes. If we can reduce the number of electrodes and yet maintain or even improve the accuracy of seizure detection we may be able to develop the technique for longer terms monitoring of EEG signals. Another challenge is to detect epileptic seizures accurately [6, 7]. Numerous researchers have attempted successful seizure detection using wearable EEG in a number of seizure detection devices. For the diagnosis of epilepsy, the occurrence of two unprovoked seizures are usually required, but one unprovoked seizure is sufficient for diagnosis if the risk of further unprovoked seizures is high. Therefore, the ability to correctly identify seizures and also assess the chance for further seizures play an important role in reducing epilepsy misdiagnosis and seizure management and therapy decisions. Further, manually interpreting EEG is a time-consuming task, given it requires input by highly trained experts with years of training and experience. However, due to the unacceptably high false-alarm rates, transforming automated EEG analysis technology into a commercial product for clinician usage has been largely limited [8]. Further compounding the issue is the complex, lengthy and sometimes painful process the patients must endure to reach a diagnosis. This includes the need to wear a full $10-20$ electrode headset for many days. Though the well-recognised $10-20$ electrodes configuration provides clinicians with enough information for seizure diagnosis, there are limitations in clinical practice due to the large data housing and computational power required to store and process this information.

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Recently, thanks to the big data collection [9] and rapid improvement in low-cost powerful computational infrastructure [10], the deep learning algorithm could apply into different areas to improve performance [7]. Using AI techniques to do seizure prediction and detection has also attracted growing attention [11, 12]. With the help of AI, patients' quality of life can dramatically increase.

In this paper, we describe an innovative method to optimize channel selection and minimize false alarm for seizure detection using convolutional long short-term memory network (Conv-LSTM) [13]. To this end, we proposed a detail solution for seizure detection named "Blended Multi-Time Segments for Seizure Detection" (BMTSSD) to minimize false alarm in seizure detection, including feature selection, channel selection, segmentation selection, model selection and post processing. Our proposed methods include (1) extract raw EEG spectrogram [14] features as deep learning input; (2) use F3-F7, P3-O1 two channels information instead of using the whole electrodes; (3) combine Conv-LSTM and dense layer for our detection; (4) using average methods for predicting seizure time in different time feature segmentation and overlap the detection results; (5) discard short seizure prediction and concatenate nearby long seizure prediction. (6) define a new score metric used to compare the performance with the consideration of sensitivity, specificity and number of channels used. The numerical experiments are compared using TUH EEG Seizure Corpus (TUSZ) dataset [9] to investigate the effectiveness of the proposed methods in minimizing false alarm for the seizure detection task. The algorithm used to get sensitivity and specificity and deal with the overlap between the hypothesis versus ground truth (i.e. reference) is Time-Aligned Event Scoring (TAES) [15]. Further points were awarded based on the Neureka 2020 Epilepsy Challenge. As far as we know, this is the first method using blended multi time-segments for seizure detection with only two channels.

The rest of the paper is organised as follows. The next section reviews the related literature (see Section II). Section III discusses the properties of the dataset that is used in this research. Section IV describes the method for optimizing channel selection. Section V introduces the proposed method of "Blended Multi-Time Segments for Seizure Detection" (BMTSSD). Section VI describes the numerical experiments and evaluation of the model. Finally, Section VII concludes the paper and discusses future directions for the work.

II. Related works and prior arts

A variety of seizure detection approaches have previously been applied to the TUH EEG dataset [9]. A hidden Markov model (HMM) [16] was used to achieve 30.32% sensitivity with 244 FA/24 hrs measured by Any-Overlap (OVLP) score [15]; CNN and LSTM combined methods are used to achieve 30.83% sensitivity with 6 FA/24 hrs [17]; Channel-based LSTM method reached 39.46% with 11 FA/24 hrs [8]. Researchers also tried to optimize channel selection, however, results decreased dramatically which reached 31.15% with 308 FA/24 hrs when using 2 channels [18].

The output of the related work mentioned above is measured by the Any-Overlap (OVLP) score, which assesses the overlap in time between a reference and hypothesis event. However, time-aligned event scoring (TAES) is more strict than the OVLP score metric which only considers the percentage of overlap between the two events. In other words, the results of the above work would become much worse when measured in TAES score. For example, the best performance from CNN and LSTM combined methods got 12.48% with 7.58 FA/24 hrs using all channels, the sensitivity is only one of third compared with measured by OVLP score with more false alarm.

Table 1. Summary of TUH EEG datasets characteristics.

Dataset attribute	Train set	Dev set	Eval set
File numbers	4597	1013	1023
Sessions	1185	238	152
Patients	592	50	50
Files with seizures	867	280	235
Sessions with seizures	343	104	78
Patients with seizures	202	40	42
Number of seizures	2370	673	511
Background duration (hours)	705.6	154.1	140.3
Seizure duration (hours)	46.7	16.2	10.5

III. Dataset

Table 1 summarizes the dataset being used in this work: the Temple University Hospital (TUH) seizure corpus dataset v1.5.1 [19]. The TUH dataset consists a total of 1185 sessions from 592 patients in the training set and 238 sessions from 50 patients in development dataset. There are 202 and 40 patients with seizures in the training and the development sets, respectively. Besides, the ratio of seizure duration and background duration in the training set and the development set are approximately 15.1:1 and 9.5:1, respectively. The majority of the EEG data was sampled at 250 Hz (87%) with the remaining data being sampled at 256 Hz (8.3%), 400 Hz (3.8%), and 512 Hz (1%). [20]. Two general unipolar montages are used in TUSZ, (1) Average Reference (AR) and (2) Linked Ears Reference (LE), which are used to help further classify three types of folders tcp_ar (AR Method only), tcp_le (LE Method only), and tcp_ar_a (both AR and LE Method). [20]. The first two folders contain 21 channels of EEG whereas the third one only includes 20 channels. In order to make a reliable prediction, we further split the training dataset into three sets, 60% for training, 20% for validation and 20% for testing (dev2), which means that we test our model twice (dev and dev2) before testing on final hidden evaluation dataset.

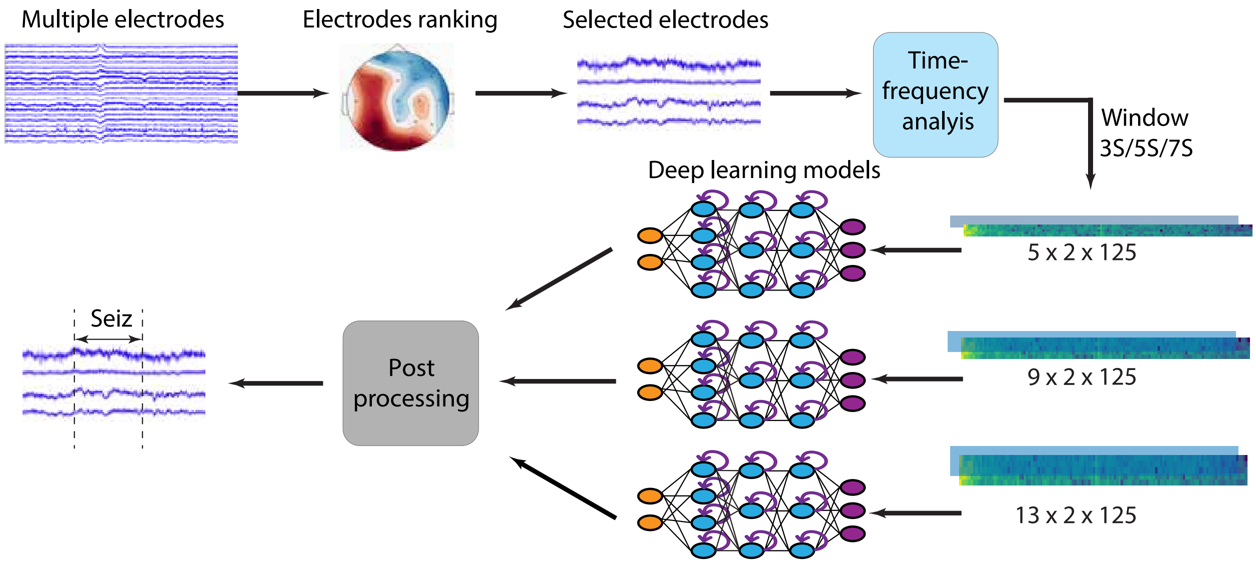

Figure 1. Electrodes selection and blended multi-time algorithm for seizure detection

IV. Channel Selection

We made the channel selection with two ranking techniques that is based on 1) our team's previous research output published in [21] and 2) feeding only one electrode information into a simple and fast CNN structure (EEGNet, as seen in [10]). We then selected channels by ranking valuation accuracy. We made our final channel selection decision based on two channel ranking results and did a further experiment on high ranking channels. The purpose of the two methods for channels selection is to make the selection more reliable. The procedure are shown in Fig. 2.

IV-A. Supervised Learning in Automatic Channel Selection

The automatic channel selection (ACS) approach was designed to be run offline, presenting a cost/time effective approach with regards to human resource time, and future online analysis. Firstly, the labelled data is transformed by applying fast Fourier transform (FFT) to the raw EEG data, to obtain frequency information from all channels. Next, the FFT values are sliced, transforming the data into 1 Hz bins in the range of 1–47 Hz. The $\log_{10}$ transform is then applied to the values. The resulting transformed data is a $N \times 47$ matrix, where 47 is the number of 1 Hz bins in the range of 1–47 Hz. Each individual channel is now a feature to be fed to the classifiers. At this stage, the between-channel correlation is disregarded. This is to avoid confusion arising from the importance of the correlation between channels, rather than the importance of the actual channels themselves. Consequently, the importance level of each feature or channel is determined by one or multiple classifiers. The various chosen classifiers included Gradient Boosting, AdaBoost and Random Forest. In cases where multiple classifiers were used the final importance level of each channel was the sum of importance values obtained from all classifiers.

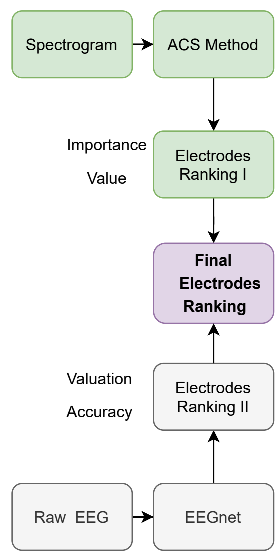

Figure 2. Channel ranking and selection procedure.

IV-B. Fast Single Electrode training for channel ranking

Another method we used for electrodes ranking is training the classifier to only feed one electrode one time and rank channels based on the valuation accuracy. In order to make this method less time-costly, we only trained one epoch for comparison as there are a total of 21 electrodes to test. In the meantime, the deep learning model structure we chose is "EEGNet" [10], a simple and fast CNN structure which has been widely used in the BCI domain. Unlike previously mentioned methods which use frequency information in training, this approach trains the raw EEG directly.

V. Blended Multi-Time Segments for Seizure Detection

This section presents our proposed method "Blended Multi Time-Segments" that can be used to largely decrease the false alarm for the seizure prediction and detection.

V-A. Pre-processing

Although raw EEG data information can be directly fed into the neural network, lack of frequency information will make the network harder to extract important features. Wavelet [22] and Fourier transforms [23] are two widely used methods that could translate time-series EEG into a three-dimension matrix that composed of both frequency and time information. In this work, we used the short-time Fourier transform (STFT) to translate raw EEG signals into a spectrogram with three different window lengths of $3, 5, 7$ seconds. Besides, due to differences in the recording sample rate, we re-sampled sample rate all into 250Hz. Therefore, a 3-s EEG signal with 2 channels will be transformed into a data shape of $(2, 750)$. We use window length of 250 (or 1 seconds) and 50% overlapping when doing the STFT, so the data shape will become $(5 \times 2 \times 126)$. Then the DC component (at 0 Hz) was removed in the spectrogram before feeding to the neural network, so the final data shape becomes $(5 \times 2 \times 125)$ as shown in Fig. 1. The Eq. 1 shows the Fourier transform that calculates the information for the frequency domain, where m represents the window length and n for the n^{th} sample. The magnitude is calculated by the square of the absolute value after the STFT [24].

$$X(m,\omega) = \sum_{n=0}^{end} x[n]\omega[n-m]e^{-j\omega n} \tag{1}$$

$$M(m,\omega) = |X(m,\omega)|^2 \tag{2}$$

One of the big challenges in many classification tasks is the data imbalance issue: that is the number of some classes is much more than the rest. [25] Seizure detection also encounters this issue; in the TUH dataset shown in the table 1, the ratio of background-to-seizure duration is $15.1 : 1$ in training dataset and $9.5 : 1$ in development dataset. If we train it without any further processing, it will be harder for the network to learn to predict the small number class (seizure in this case). To overcome this, first, we generate more seizure segments by using the overlapping techniques when doing the STFT. In particular, we slide a 1 s and 3 s window along the time axis when we select out the certain time segments for the seizure and background information respectively, which could decrease the imbalance ratio three times smaller. Furthermore, during the training, we put k times weight on getting predicting seizure loss based on the ratio of the background-to-seizure number k using Keras class weight function. For the valuation dataset, we up-sampled the seizure segments by randomly repeating to make it have the same number as the background segments.

V-B. Conv-LSTM

CNN and LSTM have been two widely used methods for computer vision and natural language processing [13, 26]. In this work, we use three Conv-LSTM blocks [13] combined with three fully connected layers. The code is implemented with Keras Conv-LSTM module, and the first Conv-LSTM layer has 16 $n \times 2 \times 3$ kernels using 1×2 stride where n represent the channel numbers. The next two Conv-LSTM blocks both use 1×2 stride and 1×3 kernel sizes, whereas the Conv-LSTM block 2 use 32 filters and Conv-LSTM block 3 use 64 filters. Following the three Conv-LSTM blocks are two fully connected layers with sigmoid activation and output sizes of 256 and 2, respectively.

V-C. Post Processing

In order to predict the seizure in every 1 s, the post processing is needed as we only have predictor that could predict seizure every M seconds ($M = 3, 5, 7$ seconds). Average methods are applied to help get every 1 s reliable prediction: 1) although predictor makes prediction every M seconds, it moves only 1 s after finishing once prediction; 2) The specific one-second possibility of having a seizure is equal to the average of the results that predictor predicts. After applying the average method for these three predictors, we classify the results based on the possibility threshold, which could help us select the high confidence prediction to decrease the false alarm. The system only selects the overlap area that 3S, 5S, 7S predictors predict. The reason for this is it allows the model to make predictions combining both short and long period information, which will be more reliable. We also discard the seizure prediction which is shorter than 5 s and concatenate the prediction if two seizure prediction periods are less than 10 s. As we found that the shortest seizure sustainable time in the training dataset is 5 s and the shortest space-time for two seizures is 10 s.

V-D. Evaluation Metrics

To evaluate the output of the model, the challenge organisers applied the TAES method. This metric was designed to consider the balance between correct detection of a number of events, as well as their duration. The critical parameters used in this challenge to calculate sensitivity and specificity measures such as true positives (TP), true negative (TN) and false positive (FP), are described in detail by Shah and colleagues [15]. The main objective of this work is to reduce the number of electrodes while achieving a low false alarm rate. We use the score formula proposed by the Neureka 2020 Epilepsy Challenge, which show in below:

$$\text{Points} = \text{SENS} - \alpha * \text{FA/24 hrs} - \beta * \frac{(\text{number of channels})}{19} \tag{3}$$

where the $\alpha = 2.5$, $\beta = 7.5$, and SENS, FA/24 hrs represent the sensitivity and the number false alarms per 24 hours, respectively. While our main research objective was to lower the number of electrodes before, during and beyond this Challenge as one of our ongoing research, this scoring formula created an incentive to lowering the false alarm, aggressively. The issue with sensitivity is known to us and the system improves its sensitivity dramatically when all 19 electrodes.

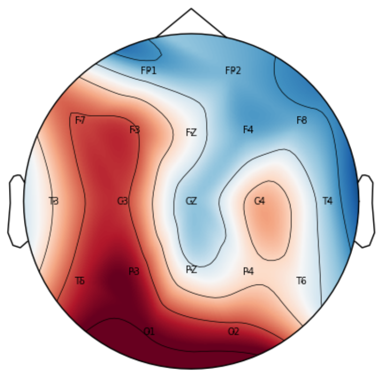

Figure 3. Channel ranking heatmap. Color changing from blue to red indicates increasing ranking of the electrodes.

VI. Results and Discussions

VI-A. Channel Selection

First, we applied the "Automatic channel selection" and "Fast single electrode training for channel ranking"methods to get the results of the electrodes ranking. We combined the two electrode ranking method results into Fig. 3, based on the importance value comes from method one which reflects how often it is used during training in the Random Forest classifier; the valuation accuracy comes from method two which reflects the first epoch results when we put a signal electrode into a fast structure training. As we can see from the Fig. 3, the five electrodes F3, F7, P3, O1 and O2 ranked the highest, and the electrodes we chose were paired in the format F3-F7 and P3-O1 as these are two pairs of nearby electrodes, to give the two channels format that was fed into the model. Interestingly, literature shows that left temporal lobe epilepsy is the common type of epilepsy, with focal seizures in the left temporal lobe seizures being the most common seizure type.

VI-B. Final Result

The threshold is an important factor that will influence the sensitivity, false alarm and score. The Fig. 4 shows the 3S, 5S, 7S segment alone and these three overlap curves which shows the variation for sensitivity and false alarm when threshold when choosing the threshold range from 0.1 to 1.0. From the figure we can see that, there is a trade off inside the sensitivity and false alarm, as the lower confidence threshold value, the higher sensitivity as well as a higher false alarm and vice versa. For the 3S, 5S, 7S segment, the performances

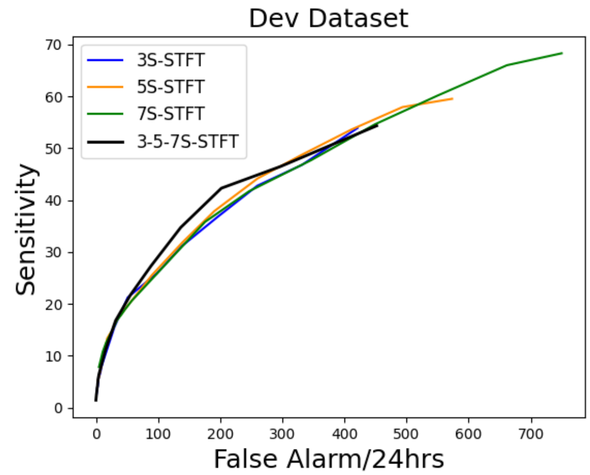

Figure 4. Overlapping time-segments (3-5-7 sec STFT) improves compare to individual STFT segments (3 sec, 5 sec or 7 sec STFT). The testing threshold for this result is ranging from 0.1 to 1.

Table 2. Neureka 2020 Epilepsy Challenge results: The top five teams performance score on the test dataset.

Rank	Teams	Sensitivity	FA/24 hrs	Channels	Score
1	Biomed Irregulars	12.37	1.44	16	2.46
2	**NeuroSyd**	**2.04**	**0.17**	**2**	**0.82**
3	USTC-EEG	8.93	0.71	17	0.45
4	RocketShoes	5.98	3.36	3	-3.6
5	Lan Wei	20.00	15.59	4	-20.56

are slightly different from one to another, however, it is clearly shown on the Fig. 4 that using blended multi-time segments has lower false alarms when sensitivity is the same. Moreover, in clinical settings, if the system will be used to help patients, then the false alarm should be as low as possible. For a reliable system, the false alarm should less than 1 FA/24 hrs. Thus the overlap 3, 5, and 7 seconds will be a better choice, as it performs best in minimizing the false alarm, and with the consideration that this task is trained and tested on totally different patients, and the TAES is the most strict metrics among the all seizure event detection tasks, the low sensitivity is understandable. For the competition, to get the highest score, we select a low sensitivity case, however, for general use, our model can generate higher sensitivity case based on the practical usage demand. Table 2 give the top five teams scores in the test dataset of the Neureka 2020 Epilepsy Challenge, our team ranked the second place which reaches 0.17 FA/24 hrs using only two channels. While it is appreciated that the sensitivity is always a FA as shown in Fig. 4, the algorithm is achieving a broad range of options for FA and sensitivity, and meet our primary goal of reducing the number of electrodes just to a few and channels just to two.

VII. Conclusion

Epileptic seizure prediction and detection capability have been studied and improved over the last four decades. A board-certified EEG specialist is required by law to diagnose the epilepsy, however, it takes several years of training and practice by the clinician, to obtain the capability in detecting seizures. If a machine is able to achieve accuracy at the level of or above an epileptologist or EEG technician, such a system could be used as an advisory system to the clinician in EEG analysis for epilepsy patients. It is also noted that if such a system includes a lesser number of electrodes it becomes more mobile and more comfortable for patients to wear. It is therefore important to demonstrate an accurate seizure detection system that relies on a small number of electrodes. Such a system could also pave the way for the future development of ambulatory seizure warning or logging systems and long-term EEG monitoring devices, which is particularly important for patients with refractory epilepsy management. our primary objective was to achieve seizure detection with small number of electrodes and improve on that in our future works. We were able to demonstrate such approach has the potential to be discussed and further improved despite having a low sensitivity, which is the topic of research improvement, we gained a low FA rate in 24 hrs.

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