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ONLINE DETECTION OF EPILEPTIC SPIKES FOR USE IN EPILEPSY MONITORING

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ABSTRACT: Epileptic spikes, indicative of the seizure onset zone (SOZ), provide meaningful insight for neurosurgeons looking to find seizure locations, particularly during intraoperative procedures. Many algorithms have been proposed to detect epileptic spikes, primarily based on offline data analysis. However, none of these algorithms have been successfully adapted for online applications. In this study, we introduce a novel method for online detecting epileptic spike patterns in electrocorticography (ECoG) data. This algorithm dynamically models statistical distributions of signal envelopes, which could discriminate between signals containing epileptic spikes and those showing background activity. The effectiveness of the proposed algorithm is evaluated using resting-state data from two patients. The results reveal a sensitivity of 73% and a specificity of 95% for detecting epileptic spikes online, with an overall accuracy of 93% and an f1 score of 52%. Overall, these results validate the potential of online detection as a valuable method for epilepsy monitoring and diagnosis.

INTRODUCTION

Epileptic seizures result from the excessive and synchronized activity of large neuronal groups, making epilepsy one of the most common neurological disorders globally, impacting around 50 million individuals [1]. While many epilepsy patients effectively manage seizures with medication, approximately one-third continue to experience seizures despite treatment [2]. For these cases, surgical resection of the brain tissue responsible for seizures becomes a feasible treatment, which needs to identify SOZ accurately.

Clinical localization of the seizure onset zone (SOZ) requires implanting intracranial EEG (iEEG) electrodes, recorded over several days, to capture spontaneous seizures [3]. Electrodes within the SOZ are identified through visual inspection of iEEG recordings taken during seizures, guiding the removal of surrounding tissue during surgery. Despite serving as the current gold standard for mapping the epileptic brain clinically, this manual process is time-consuming, costly, and carries potential risks of morbidity [4]. Consequently, there is growing interest in automating SOZ localization to simplify epilepsy monitoring and facilitate the identification of the SOZ [5].

Interictal epileptiform discharges (IEDs) are transient electrographic events observed in patients with epilepsy. They serve various diagnostic and monitoring purposes, aiding in the identification of epileptic activity and the localization of epileptogenic tissue and SOZ. During presurgical evaluations [6], neurosurgeons often use information from interictal discharges to understand where the seizures start in the brain and to plan where and how much tissue to remove [7, 8]. Studies have indicated that resecting regions exhibiting frequent spikes correlates with improved surgical outcomes [9, 10]. Research has demonstrated that IEDs can effectively localize the seizure onset [11], with the most common types of IEDs identified through visual and semi-automated detection in long-term monitoring (LTM) and visual detection in high-density EEG (hdEEG) significantly aligning with the SOZ [12].

This study aims to address the growing need and to create an automated online epileptic spike detection method for SOZ localization. It leverages signal envelopes to model the statistical distributions of ECoG signals. This approach aims to enable real-time epilepsy, including intraoperative application. To achieve this goal, electrocorticography (ECoG) data from patients with epilepsy were used, in which half-second segments of data were analyzed to detect epileptic spikes. Later, a sequence detection algorithm was applied to the identified spikes to capture spatial information. This algorithm identifies spikes occurring across multiple electrodes in close temporal proximity, improving the understanding of epileptic activity distribution.

MATERIALS AND METHODS

The study utilized ECoG data from two patients

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undergoing diagnostic subdural grid implantation at Megumino Hospital in Japan. This data collection occurred within the Epilepsy Monitoring Unit (EMU) during the patients' resting-state sleep at night. The recordings were conducted under the influence of antiepileptic drugs (AEDs). As a result, it was expected that the recorded data would show a decrease in interictal epileptiform activity due to the administration of AEDs.

The patients underwent implantation of subdural grid electrodes to localize the SOZ and perform real-time functional mapping to identify critical brain function areas, aiming to minimize resection before surgery. The implanted grids, sourced from Ad-Tech in Racine, WI, USA, comprised platinum discs with a diameter of 4.0 mm, spaced apart at 5-10 mm intervals.

The ECoG signals were acquired in the EMU using a 256-channel g.HIamp biosignal amplifier (g.tec medical engineering GmbH, Austria). The signals were digitized with a high resolution of 24 bits at a sampling rate of 4800 Hz. Ground and reference electrodes were in the dorsal parietal cortex to ensure signal stability and consistency. 144 channels were recorded for patient 1 and 136 for patient 2 (280 channels total).

The online detection system for epileptic spikes was developed using MATLAB Simulink (MathWorks, Inc.) and comprises several key components. Initially, the signal was down-sampled to 200 Hz and subjected to a high-pass filter with a cutoff frequency of 2 Hz to eliminate DC offset. Later, each channel underwent an 8th-order Butterworth filtering within the 10-60 Hz band. Following this preprocessing step, the signals were processed using a common average reference (CAR) technique to mitigate noise and non-cerebral artifacts, a critical step for ensuring the accuracy of spike detection algorithms by reducing false positive events. The input signal was then segmented into half-second intervals to facilitate spike detection. The output of the spike detection block, depicted in scope with markers denoting detected events (Figure 1), relies on a real-time adaptation of the method outlined in [13].

To achieve real-time spike detection, the instantaneous envelope of each filtered channel was computed using the absolute value of the Hilbert transform. Spikes typically produce an energy increase, resulting in peaks in the envelope within the 10-60 Hz frequency band. Statistical distribution of the envelope was computed for each segment, and a model was fitted using a maximum likelihood algorithm (MLE). Later, the mode and median of the normalized (log-normal distribution) data were used to establish a threshold for detecting segments containing spikes from those displaying background activity. Statistical parameters such as mean and standard deviation were calculated for each window and accumulated for ongoing threshold adjustment to ensure adaptability. This adaptive thresholding mechanism optimizes spike detection performance across varying signal conditions.

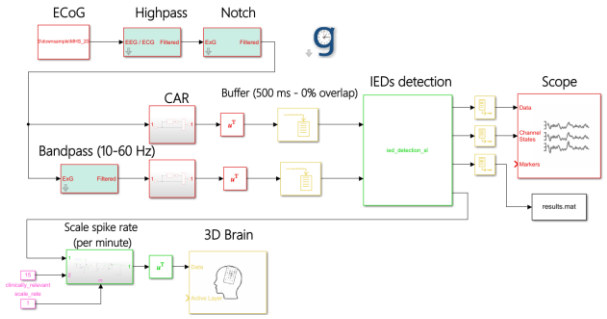

Figure 1: The Simulink model of real-time epileptic spike detection.

ECoG data were examined for interictal discharges to assess the model's performance. For this purpose, a 10-minute segment of ECoG data was selected. The signals were analyzed using g.BSanalyze software (g.tec medical engineering GmbH) to identify spikes. IEDs typically start with a sharp wave or spike, indicating a brief, high-amplitude deviation from baseline. Subsequently, a slow wave component may follow, characterized by a slower and more prolonged deflection than the sharp wave [14]. Figure 2 illustrates the labeling of epileptiform discharges.

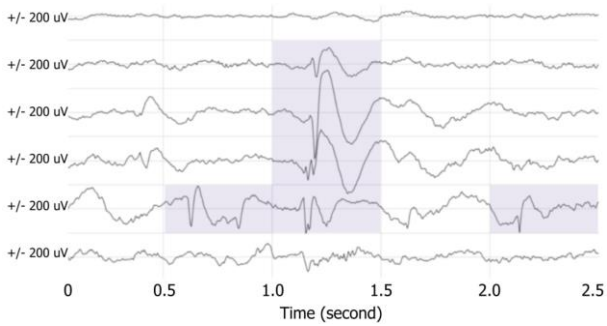

Figure 2: Annotation of epileptiform discharges for use compared to the detected event.

After the completion of the simulation, the detected events are saved in a file, which are indicators of spike occurrence in the signal. Later, these events are organized into vectors for each channel. Each vector represents the spike times detected for the corresponding channel. For the evaluation, true positive (TP) is defined as an event where the predicted event is located on the marked event in ground truth, i.e., at least some samples overlap. A false positive (FP) is defined as an event where the predicted event does not overlap with the marked event. A false negative (FN) is defined as an event where the predicted event does not overlap with the event in ground truth. A true negative (TN) is defined as an event where no event is predicted, and no event is in the ground truth. Several performance metrics based on these definitions are calculated. Accuracy measures the proportion of correctly identified events, computed as accuracy = (TP + TN) / N. Sensitivity reflects the model's ability to correctly identify true events, calculated as sensitivity = TP / (TP + FN). Specificity gauges the model's proficiency in identifying true negative events, determined by

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specificity = TN / (TN + FP). The F-score, the harmonic mean of precision and recall, is computed as F-score = (2×FP) / (2×TP + FP + FN).

RESULTS

The proposed system was applied to two patients, including data collected under the influence of AEDs. Figure 3 displays an example output from the scope, illustrating the detected epileptic spikes for patient 1. This visual representation clearly depicts the identified epileptic activity within the recorded ECoG data, aiding in assessing and analyzing epileptic spike detection performance.

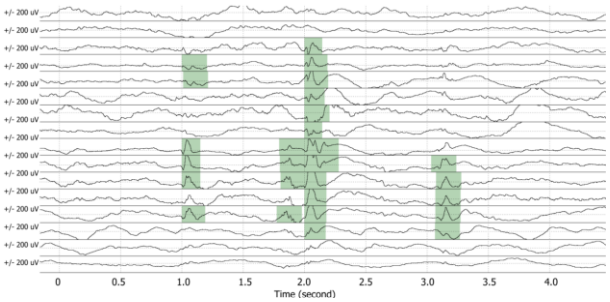


Figure 3: Visualization of online detection of epileptic spike.

Upon running the model, sensitivity, specificity, accuracy, and F-score are calculated for model evaluation, as depicted in Table 1. This table presents the average performance metrics for patients, where the predicted values of the proposed system are compared with the ground truth labels of epileptic spikes. The data used for analysis were extracted from minutes 3 to 10 of the recording. This duration includes 7 minutes of data, during which the model's performance was considered stable. This specific timeframe was focused on ensuring that the analysis is conducted on data where the spike detection algorithm has reached a consistent and reliable performance level. First, thresholds were established to detect epileptic spikes with 95% specificity for the entire patient. Then, sensitivities for detecting epileptic spike events were calculated on the patients with those thresholds. A comparison from Table 1 shows that the performance of the online system closely resembles that of offline reference methods. This observation highlights the effectiveness of the online system in accurately detecting epileptic spikes, demonstrating its potential as a feasible alternative to traditional offline methods. The low F1 score in the comparison is primarily due to the high number of false positive (FP) events, which arise from the complexity of the comparison. In this scenario, the time samples of detected spikes with those of marked spikes (ground truth) across all channels were compared. This presents a significant challenge because the detected spike should be aligned with the time sample of a spike in the ground truth. In contrast, some other research groups solely compare the spike detection algorithm's spike rate with the SOZ or spike rate in the ground truth across all channels, resulting in higher scores. However, this approach overlooks the temporal validation aspect.

Table 1: Performance results of the proposed system for datasets

Methods	TP	TN	FP	FN	Sens.	Spec.	Acc.	F1
ONLINE	44	737	43	17	0.73	0.95	0.93	0.52
REF [13]	47	743	39	11	0.70	0.95	0.94	0.45
REF [15]	18	768	34	20	0.39	0.95	0.94	0.23
REF [16]	46	742	39	13	0.69	0.95	0.94	0.48

Figure 4 demonstrates the calibration time of the proposed method for detecting spike events in the ECoG signals. Here, it can be seen that after minute 3, the method could reach a stable detection period.

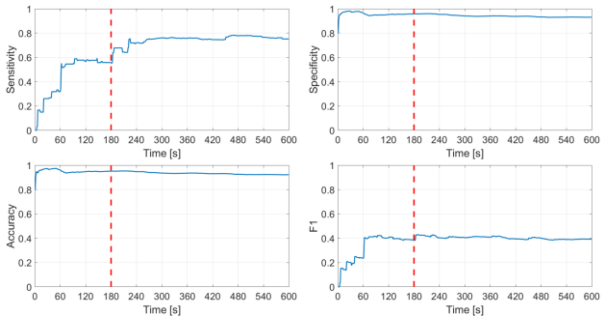
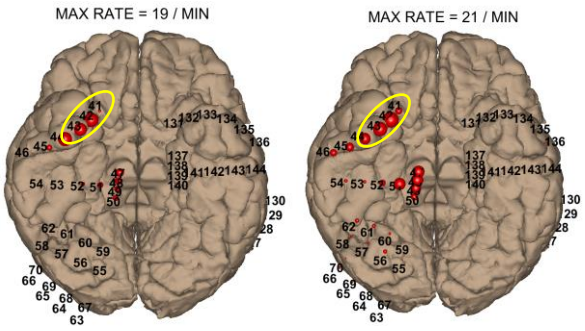


Figure 4: Calibration time of epileptic spike detection for use in real-time BCI application.

Figure 5 illustrates the spatial distributions of epileptic spikes for different methods in a 3D brain schema for patient 1. To represent the spatial distribution, the spike rate for each channel is calculated in terms of spikes per minute. Notably, the seizure onset location for patient 1 is in channels 41-43, shown in yellow electrodes. By reviewing Figure 5, it becomes evident that channels in the models exhibiting high spike rates are either located within the SOZ or close to it, which is why the proposed method aligns with the offline method for pointing the SOZ location. This observation strengthens the correlation between epileptic activity and the SOZ, emphasizing the importance of accurately localizing the SOZ for effective diagnosis and treatment of epilepsy.



(a) Ground truth (b) ONLINE

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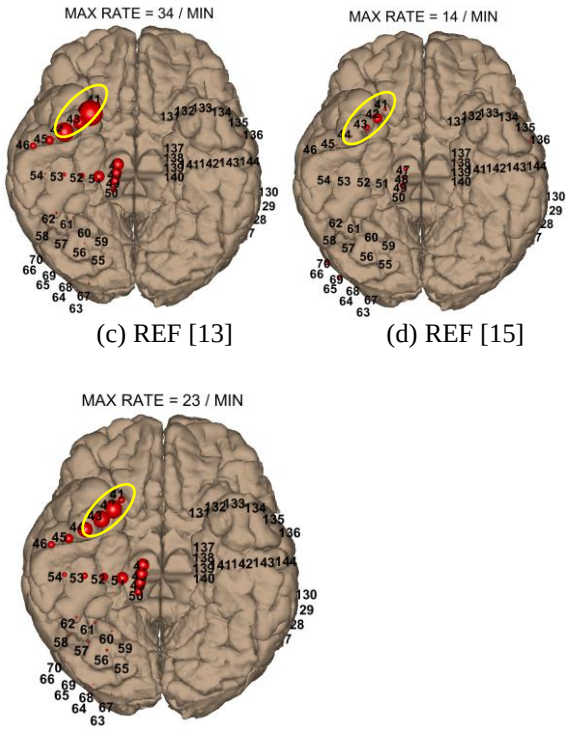

(c) REF [13] (d) REF [15]

(e) REF [16]

Figure 5: Epileptic spike rate in 3D brain schema for the models. Electrodes 41-43 indicate SOZ. Subfigures a-e indicate the epileptic spike rate for ground truth, online method, method ref [13], and method ref [15].

DISCUSSION

In contrast to the approach described in [16], the current study presents a novel online epileptic spike detection method. Unlike the existing offline methods [13, 15, 16], which necessitate the use of the full length of the signal for detection, the approach in this work utilizes only a half-second segment to model the statistical distribution of ECoG signals for detecting epileptic spikes. Changes to the method described in reference [13] have enhanced its online performance. This distinction highlights the efficiency and effectiveness of the online method, offering potential advantages in terms of computational resources and speed of analysis compared to traditional offline methods.

In this research, the proposed approach involves relying solely on a reviewer for signal labeling, which introduces potential limitations. This could be a reason why comparing spike occurrences solely in the time domain can be challenging due to the inherent variability in EEG signals and the potential for small temporal deviations between ground truth and detected spikes. Furthermore, inherent limitations, such as mislabeling or biases towards specific markers, may exist. These factors could contribute to the observed low sensitivity, specificity, and accuracy values when comparing spikes in the time domain to ground truth.

However, analyzing spike activity in the spatial domain, such as plotting the rate of spikes across different channels, offers a more comprehensive understanding of the underlying neural activity. Spatial information provides insights into the specific regions or electrodes where spikes frequently occur, allowing for a more robust comparison between ground truth and predicted data. Therefore, integrating spatial analysis can reduce some of these limitations and provide a more reliable assessment of spike detection performance.

One of the primary challenges hindering the practical implementation of a brain-computer interface (BCI) is the long calibration period required. However, this paper proposes a novel approach utilizing adaptive thresholding, which accumulates statistical characteristics of the ECoG signal. This method demonstrates stable epileptic spike detection in terms of specificity after approximately 3 minutes, thereby significantly reducing the calibration time required for spike detection in epilepsy monitoring applications. The experimental results depicted in Figure 4 illustrate that the proposed algorithm rapidly achieves a predefined performance level. This capability suggests that the algorithm can facilitate real-world applications of spike detection without the need for extensive data to train a model. Instead, it leverages only a small amount of initially available data, making it highly practical for deployment in clinical settings.

One of the limitations of this study lies in the limited data population of epileptic patients and the reliance on a single signal reviewer for marking epileptic spikes. It would be beneficial to involve multiple signal raters to enhance the robustness and reliability of the statistical distribution used to establish thresholds for spike detection. By incorporating input from multiple reviewers and considering the intersection of their marked events across time samples, biases toward specific spike patterns can be reduced. This approach can improve sensitivity and specificity in spike detection, as it captures a more comprehensive range of epileptic activity patterns. Therefore, future studies should consider involving a larger pool of signal reviewers, a longer length of ECoG data, and more patient data to address this limitation and enhance the accuracy of spike detection algorithms.

CONCLUSION

The study introduces a novel automated method for real-time detection of epileptic discharges to support evaluation for epilepsy surgery. The method employs adaptive thresholding based on the statistical characteristics of signal envelopes. This approach also incorporates spikes' spatial information to capture spike propagation patterns. The automated real-time epileptic discharge detection system can potentially reduce the duration of long-term ECoG monitoring in the EMU.

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Furthermore, it could be utilized in intraoperative monitoring to assist neurosurgeons in localizing the SOZ, thus enhancing surgical precision and patient outcomes.

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