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Seizure pattern-specific epileptic epoch detection in patients with intellectual disability

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ABSTRACT

Electroencephalogram (EEG) features are crucial for the seizure detection performance. Traditional algorithms are designed for a population with normal brain development. However, for patients with an intellectual disability the seizure detection performance is still largely unknown. In addition, distinct EEG activities/patterns occur during the evolution of seizure events. However, few studies distinguished what EEG activities contribute to accurate seizure detections. To evaluate the effect of different seizure patterns on the seizure detection, we start from the four predefined seizure patterns: wave, fast spike, spike-wave complex, and seizure-related EMG artifacts. A wide range of promising EEG features in the time, frequency, time–frequency, and spatio-temporal domains, as well as synchronization-based features were extracted to characterize these patterns. The performance of seizure detection was evaluated in an epoch-based way. EEG recordings of 615 h from 29 epilepsy patients with intellectual disability were used in this study for validation. Results show that the seizure patterns of wave, and seizure-related EMG were easier to detect than the fast spike, spike-wave patterns, with sensitivities of 0.76, 0.74, 0.42, and 0.51, respectively (when specificity approximately equal to 1). We achieved the overall epoch-based detection performance with sensitivity of 68%, positive predictive value (PPV) 81%, and average duration of false detection 0.76 s per hour. Feature importance analysis indicated that the classification performance of traditional EEG features can be improved when combined with our newly-proposed features from the spatio-temporal domain and the synchronization-based methods.

1. Introduction

The electroencephalogram (EEG) is paramount for the diagnosis of epilepsy and the real-time monitoring of seizure detection. EEG feature-based automated epileptic seizure detection has been performed for populations with normal brain development [1–3]. Such seizure detection methods aim at differentiating between ictal (seizure) and interictal (non-seizure) stages in the EEG recordings of epileptic patients [1]. However, for patients with an intellectual disability, seizure detection performance is still largely unknown.

The abnormal brain development results in an intellectual disability which includes an abnormally low intelligence quotient (IQ) [4] and is often associated with epilepsy and other comorbidities [5]. Goulden et al. [6] documented a prevalence of intellectual disability in 28–38% of children with epilepsy. On the other hand, the prevalence of epilepsy is 25.5% for intellectual disabled adults and 40% for adults with both cerebral palsy and intellectual disability [7]. In addition, about 50% of those with profound learning disability and 10–20% of those with mild disability have suffered from seizures at some time in their life [5]. Despite the strong clinical relation between intellectual disability and epilepsy, automatic seizure detection in this population is scarce. The reasons are twofold. The required long-term ictal video/EEG of these patients is rarely recorded in hospitals due to behavioral and other problems. Furthermore, the annotation of EEG recordings is difficult and time-consuming, e.g., previous results showed that only one of six seizure events on average was clinically observed by specialized epilepsy nurses [8], because they did not witness them, especially during the night.

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Nomenclature

DWT	discrete wavelet transform
PSD	power spectral density
ApEn	approximate entropy
Hurst	Hurst exponent
PLI	phase lock index
SCS	synchronized channel size
DW	dynamic warping
ED	Euclidean distance
C_{max}	maximum linear cross-correlation
L/QDA	linear/quadratic discriminant analysis
SVM	support vector machines
RUSBoost	random undersampling AdaBoosting
RF	random forests
CV	cross validation
SFS	sequential forward selection
P–R	precision and recall
ROC	receiver operating characteristic
PPV	positive predictive value
Acc	classification accuracy
FD	false detection
FD_t/h	time of FD per hour of recording
AUC_{PR}	area under curve (AUC) of *P–R* curve
AUC_{ROC}	area under curve (AUC) of ROC curve

Generally both the ictal and interictal EEG of individuals with intellectual disability differ from that of intellectually normal epilepsy patients. This is often due to cortical damage that is the main cause for characteristic EEG patterns such as 'slow' EEG in patients with intellectual disability [9,10]. In clinical practice, we encounter differences on the following aspects: (1) abnormal background EEG (slow activity, no alpha), (2) abnormal sleep/wake cycles (difficult to interpret sleep/drowsiness EEG), (3) frequent occurrence of focal anomalies, (4) high levels of inter-ictal epileptic transients that resemble seizure activity, and (5) different seizure discharge patterns (for example predominant fast spikes in tonic seizures). Indeed, previous studies [8,11] showed that EEG-based seizure detection was difficult for this population. It is therefore necessary to evaluate the state-of-the-art EEG features for this specific population.

Aarabi et al. [12] used morphological based features such as amplitude, shape and duration of waveforms in neonatal seizures detection. The frequency domain information in EEG signals has been commonly used in the area of EEG analysis [13,14]. For example, the spike-waves (2–3 Hz) while awake and bursts of 10 Hz spikes can be used for characterizing the EEG abnormalities on patients with intellectual disability [5]. Generally the time–frequency analysis to characterize morphological features of the EEG signals achieved promising results [2]. Adeli et al. [15] showed that the epileptiform discharges of the patients with absence seizure can be characterized by using the discrete wavelet transform (DWT). Khan et al. [16] showed that the relative energy ratio based on the DWT coefficients can provide a good seizure detection performance on the intracerebral EEG recordings.

The frequency domain features can capture rhythmic oscillations in a signal, but are limited by the inability to detect the nonlinear properties of EEG signals [17]. The nonlinear technique is an important supplement for the seizure detection. The EEG signals of a seizure event often show a change from the complicated patterns in the normal background signals to some rhythmical and repetitive patterns. This process may represent the 'information loss' in the EEG signals, thus the algorithms, including Approximate Entropy (ApEn) [18], Lempel–Ziv complexity [19] and Hurst exponent [20] were used to evaluate the entropy and complexity of EEG signals.

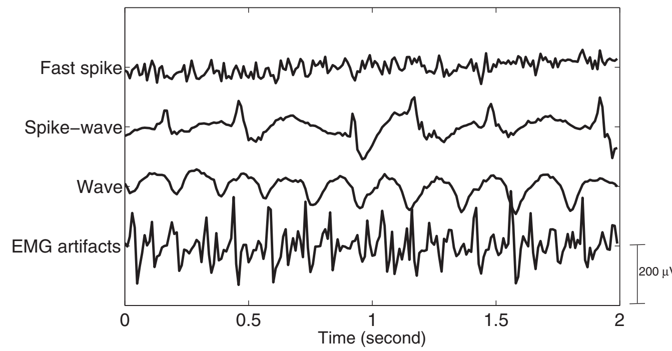

Fig. 1. The four predefined EEG seizure patterns. Each pattern of EEG epoch is from one channel of raw EEG signals in different patients. The amplitude range is 200 µV as the vertical bar in bottom.

Synchronization is now commonly accepted to play an important role in brain function and dysfunction as well as epileptic disorders [21], and therefore is promising feature for early seizure detection [22,23]. It has been suggested that synchronization analysis in the spatio-temporal domain [24] can detect an altered state of brain dynamics prior to seizure activity [25]. Thus the algorithms based on the phase-locking synchrony (PLS) [26,27] have been proposed for the seizure detection. Additionally, other algorithms including cross-correlation [23] and dynamic warping (DW) [28] are also used to quantify the synchronization across EEG signals that allows the time and the frequency shift.

According to the definition of the international league against epilepsy (ILAE) [29], there are different clinical seizure types, e.g., tonic–clonic, tonic, absence, myoclonic, etc. These are related to the morphologies of EEG patterns [2,30]. Taking the seizure morphology into account plays a crucial role in increasing the detection performance [31]. In this study four predefined EEG seizure patterns are shown in Fig. 1. These patterns are (1) fast spike, (2) spike-wave complex, (3) wave, and (4) seizure-related electromyography (EMG) artifacts. The seizure-related EMG artifacts are also considered here as a typical seizure pattern because we assume that it contains seizure information (e.g., high-frequency synchronization) so that it can be distinguished from the non-seizure EMG artifacts such as chewing. All the four patterns are ictal, (i.e., during seizures). Specifically, fast spikes exist in most tonic seizures; spike-wave patterns occur during absence-like seizures, or at the end of tonic–clonic seizures; slow waves may present during focal seizures, and rhythmic delta/theta seizures; seizure-related EMG can exist in most tonic, tonic–clonic and myoclonic seizures. The spike-waves and rhythmic waves can also occur in interictal EEG (i.e., non-seizure activities) with a shorter duration. The four seizure patterns may occur exclusively or in all possible combinations during a seizure. For example, an EEG recording of a tonic seizure [32] in ILAE's website show that, fast spikes lead a seizure onset, followed by wave patterns, and it eventually evolves into EMG artifacts. More details of the four seizure patterns are described in Table 2.

In this work, to characterize the predefined seizure patterns, we extracted a wide range of promising EEG features in the time, frequency, time–frequency, and spatio-temporal domains, as well as synchronization-based features. Several classifiers were compared to select the optimal one for classification between the non-seizure and seizure epochs. The performance of seizure detection was evaluated in an epoch-based way, i.e., evaluating on the basis of each 2-s EEG epoch instead of a whole seizure event. Additionally, as a comparison, we also used a traditional EEG feature set [33] that achieved a good seizure detection performance on the long-term EEG recordings of the intellectually normal. Overall, to study the