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Seizure Onset Detection in EEG Signals Based on Entropy from Generalized Gaussian PDF Modeling and Ensemble Bagging Classifier

Antonio Quintero-Rincón, Carlos D’Giano, and Hadj Batatia

Abstract This paper proposes a new algorithm for epileptic seizure onset detection in EEG signals. The algorithm relies on the measure of the entropy of observed data sequences. Precisely, the data is decomposed into different brain rhythms using wavelet multi-scale transformation. The resulting coefficients are represented using their generalized Gaussian distribution. The proposed algorithm estimates the parameters of the distribution and the associated entropy. Next, an ensemble bagging classifier is used to perform the seizure onset detection using the entropy of each brain rhythm, by discriminating between seizure and non-seizure. Preliminary experiments with 105 epileptic events suggest that the proposed methodology is a powerful tool for detecting seizures in epileptic signals in terms of classification accuracy, sensitivity and specificity.

Keywords Entropy · Generalized Gaussian distribution · Ensemble bagging classifier · Wavelet filter banks · EEG · Epilepsy

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1 Introduction

Epilepsy is a chronic disorder resulting from disturbed brain activity of nerve cells, causing seizures. Electroencephalography (EEG) is the predominant modality to study and diagnose epilepsy. The amplitude of the EEG epileptic signal strongly depends on how synchronous or asynchronous is the activity of the underlying neurons, because small electric signals sum to generate one larger surface signal when a group of cells are excited simultaneously. This excitation is related to seizures and it may exhibit abrupt intermittent transitions between highly ordered and disordered states [12], allowing its features quantification to study the seizure onset detection (SOD). The literature abounds with EEG signal processing methods to detect brain seizures. Many existing methods rely on feature extraction and classification approaches using various techniques, such as time-frequency descriptors [8, 15, 16, 30, 35], component analysis or common spatial patterns [1, 11, 23], entropy [5, 7, 14, 17, 21, 22, 32, 42] or supervised machine learning, such as support vector machines (SVM) [15, 36], discriminant analysis [19] or k-Nearest Neighbors [1, 13, 39]. See [24, 28] for more details of the state of the art on EEG seizure onset detection.

Ensemble machine learning methods have been developed to enhance the performance of individual classifiers [43]. The underlying principle is to combine a collection of *weak* classifiers in a suitable manner. The most popular combination schemes are arithmetic or geometric averaging, stacking and majority voting rules [37]. Ensemble bagging (standing for **B**ootstrap **A**ggregating) relies on bootstrap replicates of the training set [4]. The classifier outputs are combined by the plurality vote. This technique allows increasing the size of the training set, decreasing the variance, and increasing the accuracy and narrowly tuning the prediction to expected outcome [43]. Such classifiers can be optimal in terms of stability and predictive accuracy for datasets with imbalanced class distributions, unstable models or for data mining [33, 34, 38]. Ensemble bagging is widely used in bioinformatics, particularly in protein prediction [2, 41] and recently was used in automatic detection of iEEG bad channels [38].

In this work, we study the Shannon entropy of brain rhythms, based on the generalized Gaussian distribution (GGD). The brain rhythms are obtained through wavelet decomposition. An ensemble bagging method is used to classify EEG signals as seizure or non-seizure. The classification parameters use the entropy and the scale and shape parameters from the GGD. The motivation relates to the fact that averaging measurements can lead to a more stable and reliable estimate, as the influence of random fluctuations in single measurements is reduced. By building an ensemble of slightly different models from the same training data, we can be able to similarly reduce the influence of random fluctuations in single models [9]. The random fluctuations in epilepsy, consisting mainly of spontaneous (or chaotic) neural activity, can be assessed using the entropy. The idea is to characterize the dynamic EEG signal by determining the sudden changes in the epileptic signals [31, 40]. Therefore, the random fluctuations that are typical of the variation of the

uncertainty can be determined when the entropy is used [20]. In this study, we train decision trees having low bias and high variances to discriminate between seizure and non-seizure [3, 9]. To accurately predict responses, we combine these tree by an ensemble technique in order to reduce the variance and maintain the bias interchangeably low.

The remainder of the paper is structured as follows. Section 2 presents the proposed method, with its three main steps detailed in Sect. 2.1 a statistical model is introduced, next in Sect. 2.2 an entropy estimation is presented and in Sect. 2.3 an ensemble bagging classifier is proposed. Section 3 presents a range of experimental results with EEG recordings from the Children’s Hospital Boston database and reports detection performance in terms of sensitivity, specificity, and accuracy. Advantages, limitations, conclusions and perspectives for future work are finally reported in Sect. 4.

2 Methodology

Let $\mathbf{X} \in \mathbb{R}^{N \times M}$ denote an EEG signal composed of M channels at N discrete time instants. The original signal \mathbf{X} is divided into a set of 2-s segments with an overlap of 50%. The proposed method proceeds through four successive steps. First, a multi-resolution wavelet decomposition using a Daubechies (Db4) wavelet filter bank is performed on the signals to extract spectral bands representing brain rhythms (δ (0–4 Hz), θ (4–8 Hz), α (8–16 Hz), β (16–32 Hz), and γ (32–64 Hz) frequency bands). Second, the resulting coefficients are represented using a parameterized GGD statistical model where a couple of parameters $[\sigma, \tau]$ are estimated for each rhythm. Third, the Shannon entropy $[\varepsilon]$ is then calculated using these two parameters. Finally, in stage four, an ensemble bagging classifier is used to discriminate between seizure and non-seizure signals, through the feature predictor vector $\mathbf{p} = [\sigma, \tau, \varepsilon] \in \mathbb{R}^3$ associated with each 2-s segments of the EEG signal. The following sections introduce the generalized Gaussian statistical model, the entropy estimation and the ensemble bagging classifier.

2.1 Statistical Modeling

The signals are transformed using a Daubechies wavelet (dB4) transform at 6 scales. The resulting wavelet coefficients have been grouped into separate spectral bands. A generalized Gaussian distribution is fitted to the histogram of wavelet coefficients of each segment in a given spectral band, where the probability density function (PDF) is

$$f(x; \sigma, \tau) = \frac{\tau}{2\sigma \Gamma(\tau^{-1})} \exp\left(-\left|\frac{x}{\sigma}\right|^\tau\right) \quad (1)$$

where $\sigma \in \mathbb{R}^+$ is a scale parameter, $\tau \in \mathbb{R}^+$ is a shape parameter that controls the density tail, and $\Gamma(\cdot)$ is the Gamma function. The maximum likelihood method has been used to estimate the parameters σ and τ associated with each spectral band (see [25–28] for more details). The entropy calculated using these parameters is used to discriminate between seizure and non-seizure signals.

2.2 Entropy Estimation

Rényi entropy for the PDF from Eq. (1) is defined by

$$\mathcal{J}_R(\zeta) = \frac{1}{1-\zeta} \log \left\{ \int f^\zeta(x; \sigma, \tau) dx \right\} \quad (2)$$

where $\zeta > 0$ and $\zeta \neq 1$, then solving the integral of equation (2) for the PDF from Eq. (1) one obtains

$$\begin{aligned} \int_{-\infty}^{\infty} f^\zeta(x; \sigma, \tau) dx &= \int_{-\infty}^{\infty} \frac{\tau^\zeta}{(2\sigma)^\zeta \Gamma^\zeta(\tau^{-1})} \exp\left(-\left|\frac{x}{\sigma}\right|^\tau\right) dx \\ &= \frac{\tau^\zeta}{(2\sigma)^\zeta \Gamma^\zeta(\tau^{-1})} \frac{2\sigma \zeta^{-(\tau^{-1})} \Gamma(\tau^{-1})}{\tau} \int_{-\infty}^{\infty} \frac{\tau}{2\sigma \zeta^{-(\tau^{-1})} \Gamma(\tau^{-1})} \exp\left(-\left|\frac{x}{\sigma \zeta^{-(\tau^{-1})}}\right|^\tau\right) dx \\ &= \frac{\tau^\zeta}{(2\sigma)^\zeta \Gamma^\zeta(\tau^{-1})} \frac{2\sigma \zeta^{-(\tau^{-1})} \Gamma(\tau^{-1})}{\tau} \end{aligned} \quad (3)$$

Thus, Eq. (2) takes the expression

$$\mathcal{J}_R(\zeta) = \frac{\log \zeta}{\tau(1-\zeta)} - \log \left\{ \frac{\tau}{2\sigma \Gamma(\tau^{-1})} \right\} \quad (4)$$

Shannon entropy defined by $E[-\log f(X)]$ is the particular case of Eq. (4) for $\zeta \rightarrow 1$. Then limiting in (4) and using L'Hopital's rule, one obtains the entropy for the generalized Gaussian Distribution PDF

$$\varepsilon = E[-\log f(X)] = \tau^{-1} - \log \left\{ \frac{\tau}{2\sigma \Gamma(\tau^{-1})} \right\} \quad (5)$$

We refer the reader to [6, 18] for a comprehensive treatment of the statistical theory.

2.3 Ensemble Bagging Classifier

Let $\mathcal{M}_t : \mathcal{C} \rightarrow \{0, 1\}$ be the binary class for the weak tree classifier t_{th} for $t = 1, \dots, \mathcal{T}$, with 0 being the non-seizure event and 1 the seizure event; and $\mathbf{p} = [\sigma, \tau, \varepsilon] \in \mathcal{C}$ the parameters to be classified. Then to combine the outputs $\mathcal{M}_1(\mathbf{p}), \dots, \mathcal{M}_{\mathcal{T}}(\mathbf{p})$ into a single class prediction, a weighted linear combination of the outputs of the weak classifiers, can be used through an ensemble prediction function $\mathcal{M} : \mathcal{C} \rightarrow \{0, 1\}$ such that

$$\mathcal{M}(\mathbf{p}) = \text{sign} \left(\sum_{t=1}^{\mathcal{T}} \omega_t \mathcal{M}_t(\mathbf{p}) \right) \quad (6)$$

where $\omega_1, \dots, \omega_{\mathcal{T}}$ is a set of weights, according the majority vote results.

Consider a dataset $\mathcal{D} = \{d_1, d_2, \dots, d_N\}$ with $d_i = (\mathbf{p}_i, c_i)$, where c_i is a class label. The bagging algorithm (see Algorithm 1) returns the ensemble as a set of models. The predictions \mathcal{T} from the different models are combined by voting, and the predicted class corresponds to the majority vote.

Algorithm 1: Bagging($\mathcal{D}, \mathcal{T}, \mathcal{A}$) train an ensemble of models from bootstrap samples, adapted from [9]

Data: data set \mathcal{D} ; ensemble size \mathcal{T} ; learning algorithm \mathcal{A}

Result: ensemble of models whose predictions are to be combined by voting or averaging.

for $t=1$ to \mathcal{T} **do**

build a bootstrap sample \mathcal{D}_t from \mathcal{D} by sampling $|\mathcal{D}|$ data points with replacement;

run \mathcal{A} on \mathcal{D}_t to produce a model \mathcal{M}_t ;

end

We refer the reader to [4, 43] for a comprehensive treatment of the properties of ensemble bagging classifier.

3 Results

In this section, we evaluate the proposed method using the Children Hospital Boston database. This dataset consists of 22 bipolar 256 Hz EEG recordings from paediatrics subjects suffering from intractable seizures [10, 35]. In this work, we have used 105 events from 11 different subjects that have the same 23 channels montage. Each recording contains a seizure event, whose onset time has been labeled by an expert neurologist. Here we used the expert annotations to extract a short epoch from each recording such that it is focused on the seizure and that it

contains both seizure and non-seizure signals. The neurologist annotated each signal to indicate the beginning and end of the seizure epochs and, in addition, two adjacent non-seizure signal segments. For each subject, three epochs of the same length were selected. They are used as ground truth. Figure 1 shows the discrimination properties of the proposed vector representation $\mathbf{p} = [\sigma, \tau, \epsilon] \in \mathbb{R}^3$, obtained from the wavelet coefficients. We can see the direct relation between σ and ϵ ; both increase as they grow in the scale of their values for the seizure events (yellow circles) with respect to non-seizure events (blue circles). Figure 2 shows the different ranges in the box plots for the entropy. For each brain rhythm, the maximum and minimum values of each box together with the quartiles can be used to set a threshold that differentiates between seizure or non-seizure events.

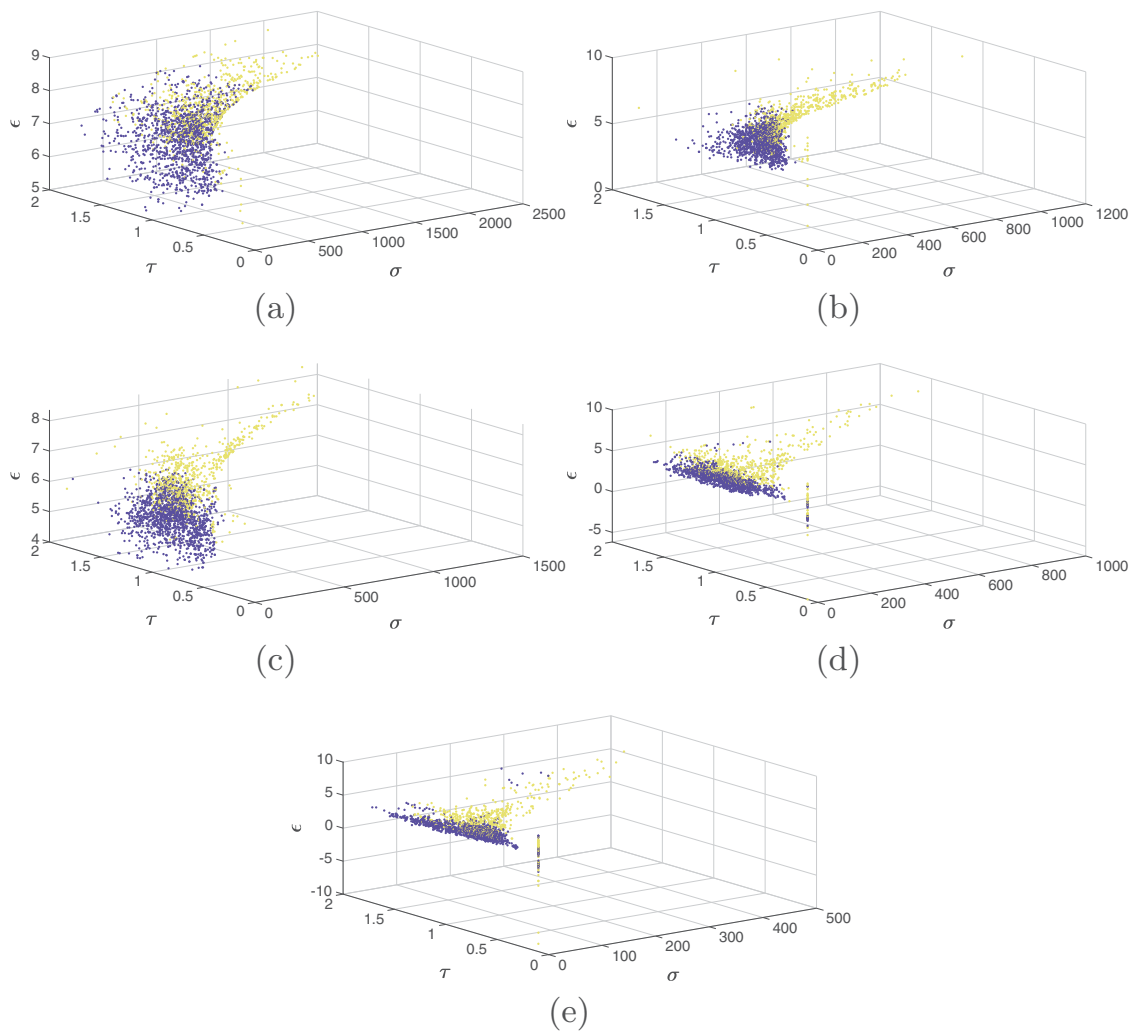


Fig. 1 Scatter plots from vector $\mathbf{p} = [\sigma, \tau, \epsilon]$ observed through all brain rhythms using 105 events: 35 *seizures* (yellow dots) and 70 *non-seizures* (blue dots). We can see how the *seizure* event concentrates on high values of σ and ϵ . (a) Delta band. (b) Theta band. (c) Alpha band. (d) Beta band. (e) Gamma band

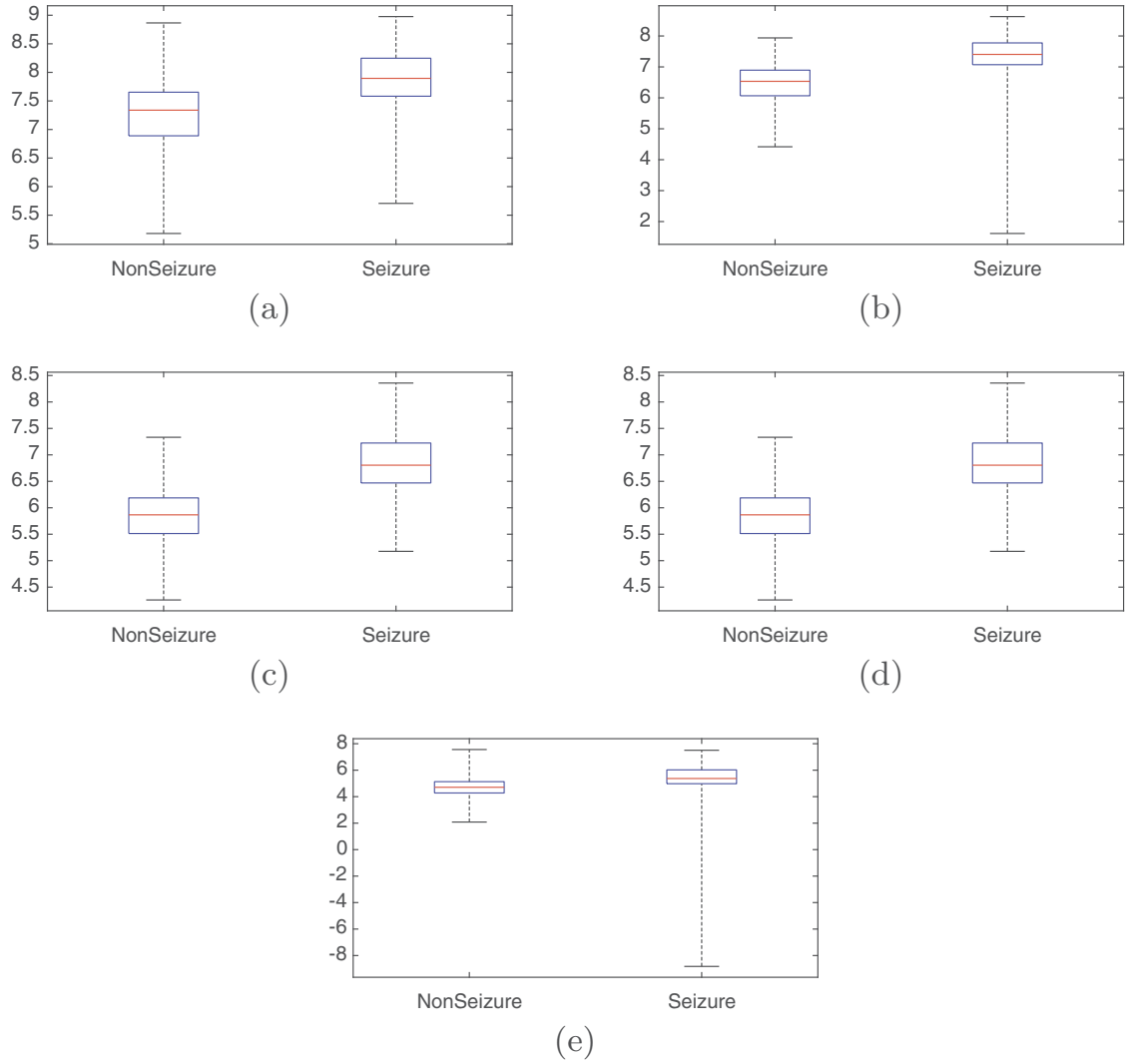


Fig. 2 Box plots of Shannon Entropy observed through all brain rhythms using 105 events (35 seizures and 70 non-seizures). The maximum and minimum values for each box together with the quartiles can help to classify based on a thresholding approach. **(a)** Delta band. **(b)** Theta band. **(c)** Alpha band. **(d)** Beta band. **(e)** Gamma band

Table 1 reports the mean and standard deviation of the entropy for all signals showing a clear difference between a seizure and non-seizure events. The 95% confidence interval (IC95%) permits to set a threshold for detecting the seizure. This can help to determine the duration, amplitude, and classification between seizure events and non-seizure events [29].

To assess the performance of the proposed method, we adopted a supervised testing approach and used the 105 events described above to train and test the method with a 10-fold cross-validation technique of the vector $\mathbf{p} = [\sigma, \tau, \varepsilon] \in \mathbb{R}^3$. Table 2 reports the percentage of good classification in terms of: TPR = True Positives Rate or *Sensitivity*; TNR = True Negative Rate or *specificity*; FPR = False Positive Rate; FNR = False Negative Rate; Error Rate; and ACC = Accuracy (ACC).

Table 1 Comparison between *means*, *standard deviations* of the entropy and 95% confidence interval (*IC95%*) of seizure and non-seizure, using 105 events (35 seizures and 70 non-seizures) for each brain rhythm. We can see how one can set a threshold for detecting the seizure

Bands	Non-seizure			Seizure		
	Mean	Std	IC95%	Mean	Std	IC95%
Delta	106.23	75.09	[102.28, 110.17]	202.78	122.53	[193.68, 211.89]
Theta	25.84	19.60	[24.81, 26.87]	85.55	67.49	[80.54, 90.56]
Alpha	22.08	14.15	[21.34,22.83]	75.11	67.32	[70.10, 80.11]
Beta	11.96	6.95	[11.59, 12.32]	37.44	44.05	[34.16, 40.71]
Gamma	6.83	6.21	[6.50, 7.15]	35.01	43.57	[31.78, 37.30]

Table 2 Ensemble bagged seizure detection performance for all brain rhythm in 105 events (35 *seizure* and 70 *non-seizure*) from the Children’s Hospital Boston database, in terms of: TPR = True Positives Rate or *Sensitivity*; TNR = True Negative Rate or *specificity*; FPR = False Positive Rate; FNR = False Negative Rate; Error Rate; and ACC = Accuracy, expressed as the percentage of good classification

Metric	TPR	TNR	FNR	FPR	Error rate	ACC
Brain rhythms	85.06	96.02	14.94	3.98	7.23	92.77

4 Conclusions

This paper presented a new algorithm for epileptic seizure onset detection and classification in EEG signals. The algorithm relies on the estimation of the entropy in the time-frequency domain of the data. Precisely, the data is projected into 5 different brain rhythms using wavelet decomposition. The distribution of the coefficients in each brain rhythm is approximated by a generalized Gaussian law. The algorithm estimates the parameters of the distribution and its Shannon entropy, at each brain rhythm. Next, an ensemble bagging classifier is used to discriminating between seizure and non-seizure. The proposed method was demonstrated on 105 epileptic events of the Children’s Hospital Boston database. The results achieve a classification with high accuracy (92.77%), sensitivity (85.06%) and specificity (96.02%). The advantage of the proposed algorithm requires only estimating and classifying two scalar parameters. This sets the way to implementing powerful soft-real-time tools for detecting seizures in epileptic signals.

However, the main limitation relates to defining the sliding time-window and the overlap of epochs due to the very high dynamics of epileptic signals.

Future work will focus on an extensive evaluation of the proposed approach in order to implement deep learning techniques to handle unstable dynamic epileptic EEG signals.

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