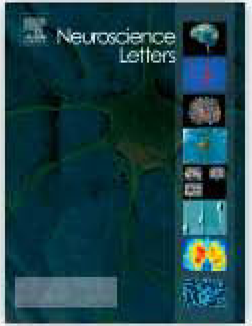

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Research article

Time-domain exponential energy for epileptic EEG signal classification

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ABSTRACT

Automatic classification and prediction of epileptic electroencephalogram (EEG) signal are of great concern to the research community due to its non-stationary and non-linear properties. Features with minimal computation cost are highly needed for the rapid real-time precise diagnosis and implementation in the EEG scanning devices. Even though energy is a well-known feature for the analysis of signals, it is very rarely used in EEG analysis. An exponential energy feature in the time domain is proposed in this study. The proposed exponential energy feature provides a classification accuracy of 89% in the Bern-Barcelona EEG dataset and 99.5% in the Ralph Andrzejak EEG dataset. The promising results open a wide applicability of exponential energy in biomedical signal analysis.

Epilepsy is a chronic disease which can affect any person at any age and have a variety of causes including brain malformations, intracranial hemorrhages, brain tumors, etc. [1,2]. Subjects may experience fears, strange smells, and unusual physical conditions depending on which neurons are affected [3]. During epilepsy, the subject suffers from recurrent and unprovoked seizures due to excessive and uncontrolled neuronal activity in the brain [4]. Noticeable symptoms/signs include jerking, uncontrollable movements and loss of consciousness [5]. Early and precise diagnosis is very important for the better treatment of epilepsy. The classical approach of epilepsy diagnosis is done by interpreting EEG signals with the help of an expert radiologist and/or a doctor.

Automatic classification of epileptic EEG signals with high accuracy is a primary requirement for the effectual understanding of the subject in medical diagnosis. The quality of features extracted from EEG signal will lead to a higher classification rate. Most of the literature work in EEG classification shows the relevance and importance of entropy features (flavors includes Shannon [6], Renyi [7], approximate [8], sample [9,10], phase [11], fuzzy [12], etc.) extracted directly from the signal and/or from the transformed domains (like frequency, time-frequency, empirical mode decomposition (EMD), etc.). Other features include features from regression, correlation, amplitude, mean, median, mode, variance, skewness, kurtosis, zero-crossing, Hjorth parameters, total variation, relative power and largest Lyapunov exponent, etc. [13,14].

Recent works in literature use a combination of various features extracted from either signal domain or transformed domains like EMD, fast Fourier transform (FFT), Wavelet, etc. For example, Sharma et al. used different types of entropies like Shannon, Renyi, Tsallis, permutation, fuzzy and phase entropies from wavelet domain for the classification of EEG signals [15]. Entropy features from the combination of EMD and wavelet domain is used by Das et al. for the discrimination of EEG signals [16]. Another such work which makes use of the combination of features is by Gajic et al., in which they make use of features from different domains like time, frequency, time-frequency, and non-linear features for EEG classification [13].

Certain literature works try to reduce the number of features by means of dimensionality reduction techniques (like PCA, LDA, PSO, etc.). One of the important work by Gajic et al. makes use of dimensionality reduction for reducing the features obtained from wavelet domain for effectual epileptic seizure detection [17].

The primary goal of any machine learning system is to have a less complex system (in terms of memory for hardware implementation and efficiency for life critical systems) learned with less number of features without any compromise on prediction accuracy, precision and recall. Real-time embedded applications will become less complex in term of memory, if there are less number of input features. Also the efficiency becomes one of the most prominent concern, when we try to design a life critical applications like epileptic prediction system in which seizure is predicted just 5 minutes before the occurrence of seizure. If a solitary feature, which is extracted from signal domain can discriminate the epilepsy EEG signals with high accuracy, precision and recall, then it will be one of the best features for the development of less complex system.

In this context, the study started for identifying a feature which can be best used for epileptic classification. We started the analysis using

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the energy feature, which is a well-known feature to characterize a signal and also is a measure of signal strength [18].

The capabilities of energy feature from sub-bands of EEG signal along with other features have been widely studied in the literature, most importantly in the works by Gandhi et al. [19], Panda et al. [20], Omerhodzic et al. [21], and Fergus et al. [22] in which energy features are extracted from the sub-bands of wavelet decomposition.

Even though there are works that use energy feature from sub-bands of EEG signals, the relevance and importance of energy directly from the EEG signal (i.e. in time-domain without any transformation) has not been utilized well for EEG classification. Comparing to energy feature from the transform domain, energy feature from signal domain will require less computational time, especially in embedded systems. Hence, this paper makes a study on the performance of EEG classification based on energy and other features directly from the time-domain.

Energy in the signal domain will be usually calculated by adding the squares of the signal values at every time instances. Hence it will not discriminate the signals having irregularities in amplitude of the signal (high changes in the amplitude can be seen in the case of epileptic signals than in the case of non-epileptic signals). Moreover, for longer signals or longer segments of the signal, due to the addition of the squares of the signal, the resultant energy will be a large numerical value and needs further normalization for effectual use with any machine learning algorithm.

Hence, this paper also proposes an exponential energy feature for EEG classification, which will be able to clearly differentiate the signals having irregularities in amplitude, as exponential energy considers (or give more importance to) low amplitude part of the signals. Moreover the resultant exponential energy so obtained is more suitable to machine learners when compared with energy of a signal. The results show that the exponential energy features (directly from the signal) provide comparatively good classification results with a minimum number of features.

This paper is organized as follows. A quick review of the variants of the most popular entropy features is given in Section 1. Section 2 describes the proposed exponential feature and its properties. The details of the dataset used for the study is given in Sections 3 and 4 deals with the experimental setup, results and discussion. Section 5 concludes the paper.

1. Review of the most popular entropy features

Various features are proposed by the research community for the analysis of EEG signals during the past few decades. Entropy is one of the most popular and widely used irregularities/disorders characterizing feature for the analysis of biomedical signals including EEG [6].

Let x be the time series of length N given by $x = \cup_{i=1}^{N}\{x(i)\}$. Some popular entropies measures are described below.

1.1. Indirect Shannon Entropy (IShE)

Shannon entropy (ShE) of signal (say x) is given by

$$\mathrm{ShE} = \sum_{i=1}^{N_1} p_i \log\left(\frac{1}{p_i}\right) \tag{1}$$

where p_i is the probability of a value $i \in x$ and N_1 is the number of unique values in x (if the values in x are continuous, then N_1 is the number of discrete bins) [6].

The most frequent usage of Shannon entropy in the literature is that obtained from the spectral transformation (most widely used one is “Fourier”) of the signal [23]. The distribution of the power as a function of frequency (namely, the “power spectral density”) will provide the power level (P_f) for each frequency f. Then the equation for spectral Shannon entropy is given by ShE_1

$$\mathrm{ShE}_1 = \sum_{f=1}^{N_2} p_f \log\left(\frac{1}{p_f}\right) \tag{2}$$

where N_2 is the number of unique frequency values (in case of continuous frequencies, N_2 is the number of discrete frequency bins). Many studies in the literature use ShE_1 as a feature for the analysis of EEG signals [24].

Instead of finding out the probability or power from the signal, we calculate indirect Shannon entropy (IShE), given by

$$\mathrm{IShE} = \sum_{i=1}^{N} x_i \log(\frac{1}{x_i}) \tag{3}$$

where N is the length of the signal, x.

1.2. Renyi Entropy

Similar to ShE_1, Renyi entropy (RE) also uses power level for each frequency [16] and is given by

$$\mathrm{RE}(\alpha) = \frac{1}{1-\alpha}\log\left(\sum_{f=1}^{N_1} p_f^{\alpha}\right) \tag{4}$$

where α ($\alpha > 0$, $\alpha \neq 1$) is the order of RE and N_1 is the number of discrete frequency components.

1.3. Log-energy entropy

Log-energy entropy (LEE) is another well-known variant of entropy which is widely used in the analysis of EEG signals [16]. If $x = \cup_{i=1}^{N}\{x(i)\}$ is the time series with length N and p_f is the power of *ith* frequency component, then the log-energy entropy can be computed as follows:

$$\mathrm{LEE} = \sum_{f=1}^{N_1} \log(p_f)^2 \tag{5}$$

where N_1 is the number of discrete frequency components.

In this paper, we have used x_i instead p_f for the calculation of indirect log-energy entropy as follows.

$$\mathrm{ILEE} = \sum_{i=1}^{N} \log(x_i)^2 \tag{6}$$

1.4. Approximate entropy

Approximate entropy (AE) is one of the most popular and widely used features to measure regularity in signals [25] and is given by

$$\mathrm{AE} = \frac{\sum_{i=1}^{N-m+1}\log(\phi^m(r,i))}{N-m+1} - \frac{\sum_{i=1}^{N-m}\log(\phi^{m+1}(r,i))}{N-m} \tag{7}$$

where $\phi^m(r, i)$ is given below with Θ as Heaviside function.

$$\phi^m(r,i) = \frac{1}{N-m+1}\sum_{j=1}^{N-m+1}\Theta(r - (\max_{k=1,\cdots,m}|x(i+k-1) - x(j+k-1)|)) \tag{8}$$

1.5. Sample entropy

Sample entropy (SE), proposed by Richman and Moorman [9] is an improved version of AE by avoiding self-match counting problem [26]. SE can be computed as

$$\mathrm{SE} = -\log\left(\frac{\frac{1}{N-m+1}\sum_{i=1}^{N-m+1}\phi^m(r,i)}{\frac{1}{N-m}\sum_{i=1}^{N-m}\phi^{m+1}(r,i)}\right) \tag{9}$$

1.6. Fuzzy entropy

The similarity of vectors in AE and SE are having a sharp decision based on Heaviside function [12]. The fuzzy entropy (FE) will eliminate this sharp decision using a fuzzy function instead of Heaviside function.

Fuzzy entropy (FE) for any given m, n, r, N can be calculated as follows.

$$\mathrm{FE} = \log\left(\frac{N-m}{N-m+1}\frac{\sum_{i=1}^{N-m+1}\left(\frac{\sum_{j=1}^{N-m+1}\phi^{m}(r,i,j)}{N-m+1}\right)}{\sum_{i=1}^{N-m}\left(\frac{\sum_{j=1}^{N-m}\phi^{m+1}(r,i,j)}{N-m}\right)}\right) \tag{10}$$

where $\phi^m(r, i, j)$ is given as

$$\phi^m(r, i, j) = e^{-\frac{1}{r}k(i,j)} \tag{11}$$

where $k(i, j)$ is defined as

$$k(i, j) = (\max_{k=1,\cdots,m}|x(i+k-1) - x(j+k-1) - \mu_i + \mu_j|)^n \tag{12}$$

$$\mu_i = \frac{1}{m}\sum_{q=0}^{m-1} x(i+q) \tag{13}$$

$$\mu_j = \frac{1}{m}\sum_{q=0}^{m-1} x(j+q) \tag{14}$$

2. Exponential energy – a novel feature

As described in the introduction, energy is a well-known feature in signal processing to measure the strength and to characterize the signal [18]. The energy of a continuous-time signal x(t) is the area under the square of the function and is defined as follows.

$$E = \int_{-\infty}^{\infty} |x(t)|^2 \mathrm{d}t \tag{15}$$

For a discrete signal of length N, the energy can be defined as follows.

$$E = \sum_{n=1}^{N} |x(n)|^2 \tag{16}$$

The abnormal signals such as signals affected with noise and sudden disturbances (namely irregularities) will have steeper peaks (with higher amplitudes) than normal signals (both in positive and negative direction). These irregularities will get added up in the energy of the signal (according to Eq. (15), & (16)). Usage of certain peak functions will enable us to detect such types of abnormalities. There are various modified exponential/Gaussian/normal (peak) type functions widely used in various disciplines including bio-medical domain [27]. To speed up the learning process in feed-forward artificial neural network, Ahamed et al. [28] finds the energy (as the sum of squared error) and substitutes it in an exponential function. But a summation of instantaneous exponential energy is rarely found in the literature, especially in the EEG applications.

Hence we have proposed an exponential energy feature which will give lesser importance/values to the signals having a higher amplitude and thereby leading to a good measure of signal strength. The exponential energy of a discrete signal (x) of length N can be defined as follows:

$$\mathrm{ExpEn}(x) = \sum_{n=1}^{N} e^{-\left(\frac{|x(n)^2|}{\sigma}\right)} \tag{17}$$

where σ is a free parameter which determines the width of the function/curve. Exponential energy for various σ is shown in Fig. 1.

The proposed exponential energy function can also be considered as a fuzzy function (centered at zero and having a spread specified by a free parameter, σ) which takes the amplitude of the signal (at any instance) as input and provides the membership grade in the interval [0 1]. The exponential energy will be higher for those signals where the amplitudes of the signals are comparatively less (near to zero). If the free parameter (σ) becomes 1, then the amplitudes in the range [-2.15 2.15] will get a considerable exponential energy greater than or equal to 0.01. Since these amplitudes in the range [-2.15 2.15] are of at-most importance in categorizing epileptic signals, the σ is fixed as 1 for our experiments. Table 1 shows the results of classification, when σ is fixed as 0.2, 0.5, 0.8, 1, 2, 3, 4, 5, SD(standard deviation) and $2 * SD^2$. The results reveal that the features using exponential energy function with $\sigma = 1$ provides better results for epileptic classification.

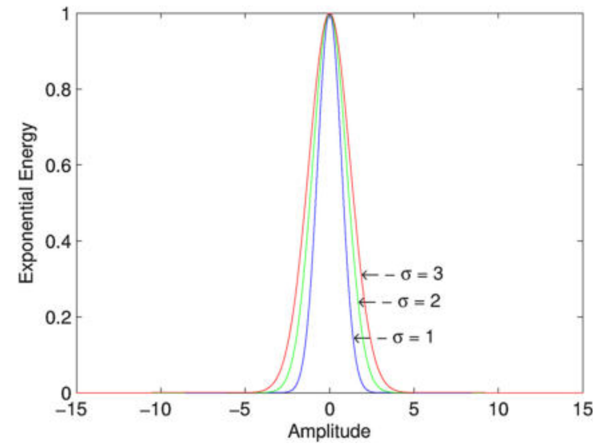

Fig. 1. Exponential energy function for different σ.

2.1. Relationship between exponential energy and energy

Let $E_t = x_t^2$ and $\mathrm{ExpEn}_t = e^{-x_t^2}$ are respectively the instantaneous signal energy and instantaneous exponential energy at time instance t. Then the exponential energy (*ExpEn*) can be defined in terms of instantaneous signal energy as

$$\mathrm{ExpEn} = \sum_{t=1}^{N} e^{-E_t}. \tag{18}$$

Similarly, the energy of the signal can be defined in terms of instantaneous exponential energy as

$$E = \sum_{t=1}^{N} -\log(\mathrm{ExpEn}_t). \tag{19}$$

It can be observed that the instantaneous energy of a signal at time instances t is equal to the negative logarithm of the instantaneous

Table 1
Classification accuracy (%) of various datasets (Bern-Barcelona EEG dataset and Ralph Andrzejak EEG dataset. Descriptions of the datasets are given in Sections 3.1 and 3.2 respectively) for different values of σ.

σ	Bern-Barcelona	Ralph	Ralph	Ralph
		Z vs. S	Z vs. N vs. S	Z vs. F vs. S
0.2	87	97.5	88	86
0.5	87	97.5	89	87
0.8	87	99	90	87.67
1	**89**	**99.5**	**91.67**	**89.33**
2	86	99	90	89
3	86	91.5	91.33	89
4	85	99.5	91.67	89
5	85	99	91.33	88.33
SD	88	97	90	87
$2 * SD^2$	78	97	71	78

Z:Healthy, N and F: Interictal, E: Ictal.

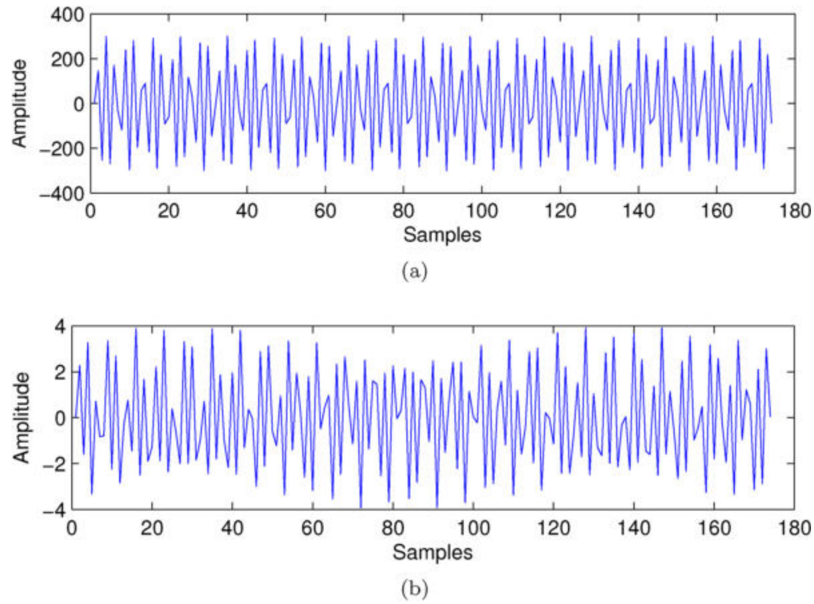

Fig. 2. (a) High amplitude signal (Exponential Energy = 4.1287, Approximate entropy = 0.2596, Signal Energy = 7.8123e+06) (b) Low amplitude signal (Exponential Energy = 36.1901, Approximate entropy = 1.0771, Signal energy = 868.5101).

exponential energy at time instances t.

2.2. Behaviour of exponential energy

In order to see the changes/ behaviour of *ExpEn* feature the following three types of cases are considered.

1 Two random signals, one with smaller amplitude and another signal with higher amplitude are taken as shown in Fig. 2 ((a) signal with smaller amplitude and (b) signal with higher amplitude).
2 3 signals of same amplitude but different frequencies as shown in Fig. 3 ((a) 30 Hz, (b) 15 Hz and (c) 3 Hz).
3 Two segments of EEG signals (one with an eye blink and other without eye blink) as shown in Fig. 4.

The approximate entropy, exponential energy and signal energy are calculated for all the three cases and are shown in Table 3. It can be clearly seen that the exponential energy's ability to discriminate low amplitude and high amplitude signals. The upper limit and lower limit of the values of exponential energy is much suitable for any classifier when compared to the signal energy.

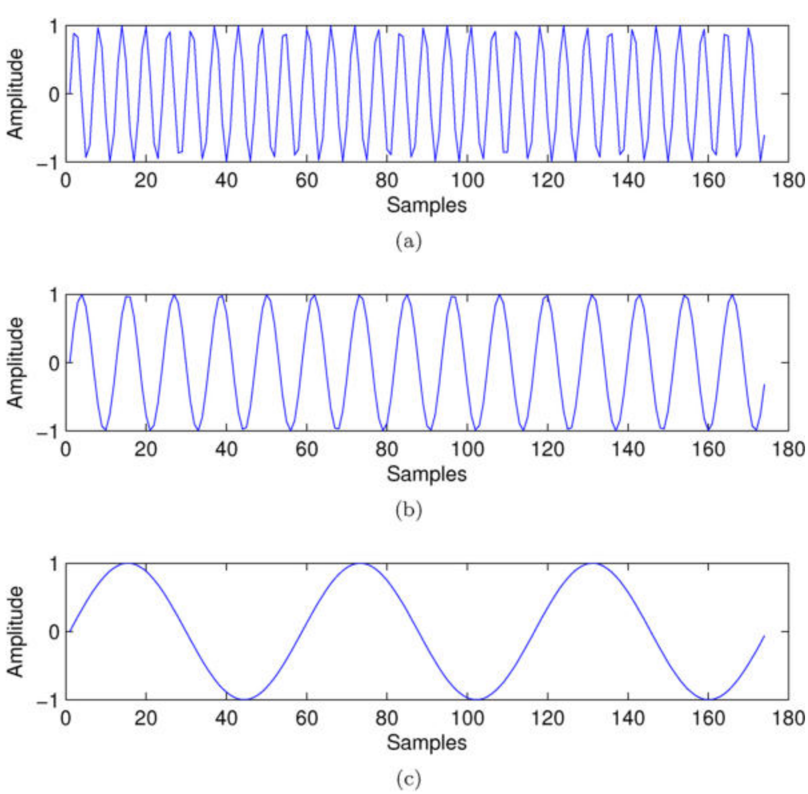

Fig. 3. Effect of exponential energy for different frequency signals (a) Signal with frequency 30Hz [Exponential Energy = 112.3742, Approximate Entropy = 0.0885, Signal Energy = 86.8109] (b) Signal with frequency 15Hz [Exponential Energy = 112.3755, Approximate Entropy = 0.1602, Signal Energy = 86.8024] (c) Signal with frequency 3 Hz [Exponential Energy = 112.3780, Approximate Entropy = 0.3124, Signal Energy = 86.8001].

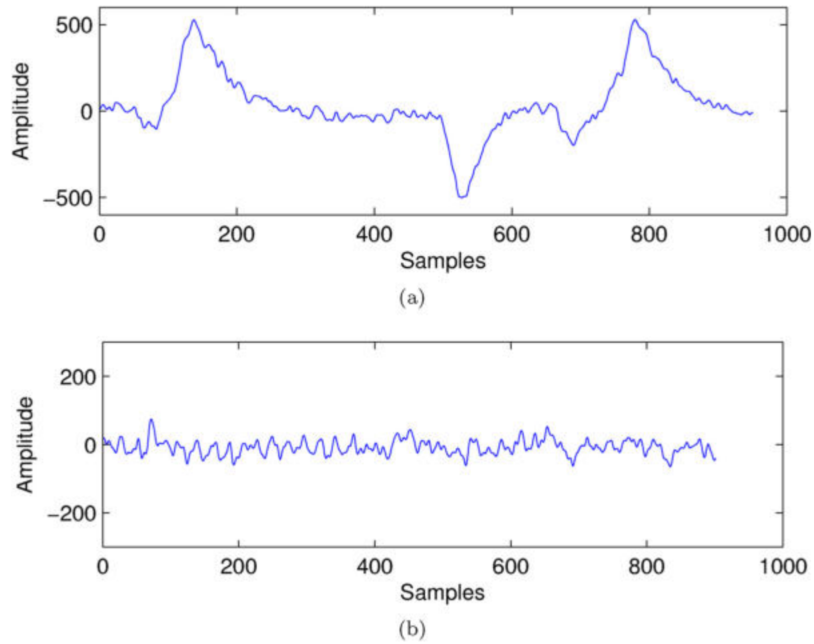

Fig. 4. EEG signal segment (a) with an eye blink, (b) without an eye blink.

2.3. *Comparison of exponential energy with approximate entropy and energy*

In order to validate the performance of the exponential energy, we have considered Upenn and Mayo clinic's seizure detection challenge dataset [29]. The details of the dataset can be had from the paper by Baldassano et al. [30]. Table 2 shows the comparative results of classification based on the features like exponential energy, approximate entropy and energy. It can be seen from the results that exponential energy feature discriminates the epileptic signals comparatively better than the other two features.

Table 2
Results of validation of exponential energy feature in Upenn and Mayo Seizure detection challenge dataset.

Data	Approximate entropy	Signal energy	Exponential energy
Dog 1	93.8%	97.32%	**99.16%**
Dog 2	92.8%	97.65%	**99.09%**
Dog 3	92.2%	96.25%	**98.12%**
Dog 4	91.43%	92.66%	**97.11%**

Table 3
Approximate entropy (AE), signal energy and exponential energy (ExpEn) of various signals.

Signals		AE	Energy	ExpEn
Random signals	High amplitude	0.2596	7.8123e + 06	4.1287
	Low amplitude	1.0771	868.5101	36.1901
Sine waves	3 Hz	0.3124	86.8001	112.3780
	15 Hz	0.1602	86.8024	112.3755
	30 Hz	0.0885	86.8109	112.3742
EEG signals	Normal	0.5619	2649100	77.7709
	Eye blink	0.1159	69598419	36.1155

3. Datasets

Two benchmarking datasets, namely, Bern-Barcelona EEG dataset [31] (dataset 1) and Ralph Andrzejak EEG dataset [32] (dataset 2) are used for the experiments and the description of the datasets are given in following subsections.

3.1. *Bern-Barcelona EEG dataset (Dataset 1)*

The dataset contains two classes of EEG signals namely, focal (obtained from the epileptic area of the brain) and non-focal (obtained from non-epileptic area of the brain) [31]. Each class contains 3750 pairs of signals (In case of focal class, one from the channel where epileptic signals are originated and another from the neighboring channel. In the case of non-focal class, signals are obtained from two neighboring channels which are not from the epileptic region). The signals are of 20 seconds duration with a sampling frequency of 512 Hz. In order to compare with the existing works, we have considered the same number of signals for the experimentation as specified by Zhu et al. [33], Sharma et al. [24,15,34], Das et al. [16].

3.2. *Ralph Andrzejak EEG dataset (Dataset 2)*

The dataset consists of five groups of signals, namely, group Z (healthy group - recorded from healthy subjects during eyes open), group O (healthy group - recorded from healthy subjects during eyes closed), group S (ictal group - collected from epileptic subjects during the seizure), group N (interictal activity - from hippocampal location) and group F (interictal activity - from epileptogenic zone). Each group contains 100 EEG signals of 23.6 seconds duration with a sampling rate of 173.61 Hz (thus contains 4097 samples per record) [32]. The following classifications are conducted using the dataset.

1 Classification between group Z (healthy group) and group S (ictal group) as specified by Kannathal et al. [35], Wang et al. [36] and Kumar et al. [37].
2 Classification of group Z, group N and group S as specified by Abualsaud et al. [38].
3 Classification of group Z, group F and group S as specified by Sadati et al [39].

4. Experiments, results and discussions

The performance of the proposed exponential energy feature is evaluated on two different epilepsy datasets (see Section 3). Before

Table 4
k-fold classification accuracy for different k values.

Dataset	Accuracy (%) for k-fold				
	K = 2	k = 5	k = 10	k = 15	k = 20
Bern-Barcelona	87	89	88	87.78	87
Ralph EEG (Z vs. S)	98.5	99.5	99	98.97	99
Ralph EEG (Z vs. N vs. S)	90.67	91.67	91	91.33	90.67
Ralph EEG (Z vs. F vs. S)	87	89	88	87.78	87

extracting features (from the signals or from its derivatives) of a channel, the frequencies beyond 60 Hz are removed using a 6th order Butter-worth filter and are segmented into 10 non-overlapping segments. For all the datasets, binary support vector machine (SVM) classifier with linear kernel is used (when the number of classes in the datasets is more than 2, we have trained separate SVMs for each pair of the classes and then majority voting scheme is adopted). k-fold cross-validation is adopted in all the experiments. In k-fold validation, we divide the entire dataset into k-equal parts. Then k-1 folds will be used for training and the left-out folder will be used for testing. This will be repeated for k times. Hence the minimum and maximum value of k are 2 and M (where M is the total number of records or samples). When k becomes equal to M, the k-fold validation becomes equivalent of leave-one-out classification. There is no universal rule to fix the value of k. Hence, we have done validation with various k such as 2, 5, 10, 15 and 20. The results in Table 4 show that the k-fold validation with k = 5 provides comparatively better classification result. Hence, in the rest of the comparisons we have only shown the results with k = 5.

The following subsection explains the experimental methods and results for each of the datasets in detail.

4.1. Results on Bern-Barcelona EEG dataset (Dataset 1)

Bern-Barcelona EEG dataset is used as a benchmark in some recent studies including but not limited to the following. Zhu et al. [33] used delay permutation entropy (DPE) from the time domain signal with feature vector length of 50 and they achieved an accuracy of 84% with SVM classifier. Sharma et al. [15] extracted Shannon, Tsallis, Permutation, Renyi, fuzzy and phase entropies from sub-bands of the discrete wavelet transform (DWT) coefficients and have achieved an accuracy of 84% using least square SVM (LS-SVM). In, another attempt Sharma et al. [34] decomposed signal into various intrinsic mode functions (IMFs) using empirical mode decomposition (EMD) and features extracted from each IMFs. Average sample entropy (ASE) for IMF3, IMF5, IMF6 and average variance of instantaneous frequencies (AVIF) for IMF1, IMF3 are used as features and achieved a classification accuracy of 85% using least square support vector machine (LS-SVM).

Fasil et al.'s [40] extracted features from both time domain (x, y, $x - y$, $x * y$, $|(x - y)|$) & differential domain (i.e. x', y', x'' and y'') and achieved an accuracy of 86% using SVM. An EMD based method is proposed by Sharma et al. [24] in which various entropy features such as Shannon entropy, Renyi entropy, approximate entropy, sample entropy and phase entropies (Phase 1 and Phase 2) are extracted from 10 IMFs and finally reduced the feature length to 13 using student's t-test and achieved an accuracy of 87% using LS-SVM classifier. Fasil et al. [41] achieved an accuracy of 88.14% with the features (log energy entropy and signal energy) from different variations (x, y, $x - y$, $x * y$, x', y', x'', y'') using SVM classifier.

For our experiments in this paper, in addition to the two channel signals (say x and y) in the dataset, we have considered the signal variants like channel's first derivative (namely x' and y'), second derivative (namely x'' and y''), channel difference (namely x-y), absolute channel difference ($|x - y|$) and product of channels (namely $x. * y$). The signals and its variants are divided into equal segments of 2 seconds duration. From each of these signals including the variants, we have extracted the features from all the segments. The features extracted from each of the segments includes approximate entropy, sample entropy, Shannon entropy, log energy entropy, fuzzy entropy and signal energy. The features are averaged across the segments.

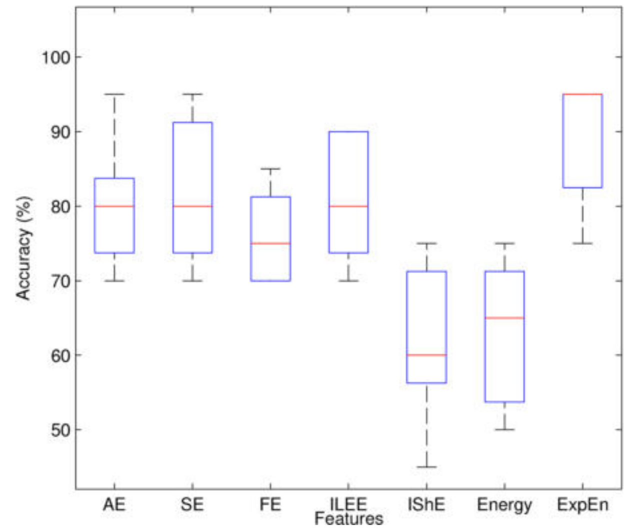

Fig. 5. Box plot of focal and non-focal signal classification accuracies (k-fold cross validation is performed with k = 5) for various entropy features, signal energy and exponential energy.

Fig. 5 shows the accuracy of focal and non-focal classification for each of the features. It is clear that exponential energy provides an average classification accuracy of 89% which is better when compared with other features. A comparison of the performance of the proposed feature for the classification of focal and non-focal signal with other methods in the literature (which uses the same dataset) is given in Table 5.

4.2. Results on Ralph Andrzejak EEG dataset (Dataset 2)

Ralph Andrzejak EEG database is used as a benchmark in some recent studies including but not limited to the following. Kannathal et al. [35] attempted to classify healthy and ictal EEG signals using entropy features (Shannon & Renyi from frequency domain and approximate entropy & Kolmogorov-Sinai entropy from time domain) using adaptive neuro fuzzy inference system (ANFIS) classifier and achieved an accuracy of 92.2%. Subasi [42] proposed a mixture of experts model using mean, average power, standard deviation, the ratio of absolute mean

Table 5
Comparison of classification performance for the Bern-Barcelona EEG dataset (Dataset 1).

Study	Domain	Features/Classifier	n.f[a]	Acc.[b]
Zhu et al.[33]	Time	Delay permutation entropy &SVM	50	84 %
Sharma et al.[15]	DWT	Shannon, Renyi, Tsallis, permutation, fuzzy and phase entropies &LS-SVM	7	84 %
Sharma et al.[34]	EMD	ASE, AVIF &LS-SVM	5	85 %
Fasil et al.[40]	Time	Log energy entropy, signal energy &SVM	18	86 %
Sharma et al.[24]	EMD	Shannon, Renyi, approximate, sample and phase entropies &LS-SVM	13	87 %
Fasil et al.[41]	Time	Log energy entropy, signal energy &SVM	16	88.14 %
Proposed method	Time	Exponential energy &SVM	9	**89 %**

[a] No.of features, [b] Accuracy.

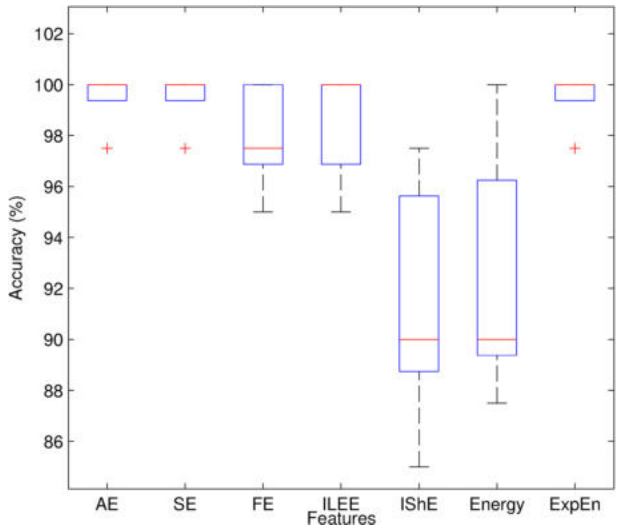

Fig. 6. Box plot of healthy and ictal group EEG signal classification accuracies (k-fold cross validation is performed with k = 5) for various entropy features, signal energy and exponential energy.

Table 6
Comparison of classification performance for the Ralph Andrzejak EEG dataset (Dataset 2).

Study	Domain	Features/Classifier	n.f[a]	Acc.[b]
Healthy(Z) vs. Ictal(S)				
Kannathal et al. [35]	Frequency and Time	Shannon, Renyi, Kolmogorov-Sinai entropies &ANFIS	4	92.2 %
Subasi [42]	DWT	Statistical features &ANN	16	94.5 %
Nigam et al.[43]	Time	Relative Spike amplitude, Spike occurence frequency &ANN	2	97.2
Patidar et al.[44]	TQWT	Kraskov entropy &LS-SVM	4	97.75 %
Kumar et al. [37]	Gabor	Histogram of 1D-LBP &NN classifier	17	98.33 %
Polat et al.[45]	FFT	Welch PSD estimate &Decision tree	129	98.72 %
Wang et al.[36]	Multi-domain	Statistical features from FFT &DWT, EMD-PSR, entropy &SVM	14	99.25 %
Proposed method	Time	Exponential energy &SVM	3	**99.5 %**
Healthy(Z) vs. Interictal(N) vs. Ictal(S)				
Abualsaud et al. [38]	DWT	Statistical features &Ensemble Classifier	32	90 %
Proposed method	Time	Exponential energy &H-SVM	3	**91.67 %**
Healthy(Z) vs. Interictal(F) vs. Ictal(S)				
Sadati et al. [39]	DWT	Energy	6	85.9 %
Proposed method	Time	Exponential energy &H-SVM	3	**89 %**

[a] No. of features, [b] Accuracy.

values of adjacent sub-bands from 4 DWT sub-bands (A5, D3-D5) and achieved an accuracy of 94.5%. A LAMSTAR artificial neural network (ANN) is utilized by Nigam et al. [43] for the automated detection of epilepsy using relative spike amplitude and spike occurrence frequencies as features and achieved an accuracy of 97.2%.

Patidar et al. [44] extracted Kraskov entropy from the sub-bands of tunable-Q wavelet transform (TQWT) and obtained an accuracy of 97.75 % using LS-SVM classifier. Kumar et al. [37] used histograms of the one-dimensional local binary pattern (1D-LBP) from segments of four Gabor filter responses and achieved an accuracy of 98.33%. In a method proposed by Polat et al. [45], the Fast Fourier Transform (FFT) based Welch spectral analysis and decision tree classifier is combined and developed a hybrid system and attained an accuracy of 98.27%. Wang et al.[36] extracted 83 features (from various domains such as time, frequency, time-frequency and EMD-PSR(Phase Space Reconstruction)) and reduced to 14 features using PCA to obtain an accuracy of 99.25% using SVM classifier.

For our experiments in this paper, in addition to the one channel signals (say x) in the dataset, we have considered the signal variants like channel's first derivative (namely x') and second derivative (namely x''). The signals and its variants are divided into equal segments of 2.36 seconds duration. From each of these signals including the variants, we have extracted the features from all the segments. The features extracted from each of the segments includes approximate, sample, fuzzy, Shannon, Log-energy entropies and signal energy. The features are averaged across the segments.

Fig. 6 shows the accuracy of healthy and ictal EEG signal classification for each of the features. It is clear that exponential energy provides an average classification accuracy of 99.5% which is promising when compared with other features.

Apart from healthy and ictal binary classification, we have also considered the classification of (i) group Z, group N and group S (as specified in [38])and (ii) group Z, group F and group S (as specified in [39]). A comparison of the performance of the proposed feature for the classification with other methods in the literature (which uses the same dataset) is given in Table 6.

5. Conclusion

In this article, we have proposed a time domain energy-based feature called exponential energy which can effectively classify the epileptic EEG signals from normal EEG signals. Since exponential energy feature alone is considered, the number of features is much less when compared to other similar works reported in the literature. Moreover for real-time implementation, especially in embedded system, it is almost better to have less number of features which can be calculated much efficiently.

The performance of the proposed feature has been evaluated in two benchmark epilepsy dataset and achieved a promising result which is much better than entropy-based features. Since the exponential energy is extracted in the time-domain, it can easily be adopted into real-time EEG scanning devices and mobile epileptic prediction systems. As part of our future calibration of the proposed work, we will consider more realistic datasets, namely, the Freiburg dataset and the CHB-MIT scalp EEG dataset, which will enable the proposed method for real-time clinical applications.

Conflict of interest

Authors have no conflict of interest to declare.

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