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The detection of epileptic seizure signals based on fuzzy entropy

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HIGHLIGHTS

- A novel FuzzyEn based method of state inspection of epileptic seizures.
- Comparison of the seizure classification performance between FuzzyEn and SampEn.
- Higher performance of our method compared with the existing methods.

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ABSTRACT

Background: Entropy is a nonlinear index that can reflect the degree of chaos within a system. It is often used to analyze epileptic electroencephalograms (EEG) to detect whether there is an epileptic attack. Much research into the state inspection of epileptic seizures has been conducted based on sample entropy (SampEn). However, the study of epileptic seizures based on fuzzy entropy (FuzzyEn) has lagged behind.
New methods: We propose a method of state inspection of epileptic seizures based on FuzzyEn. The method first calculates the FuzzyEn of EEG signals from different epileptic states, and then feature selection is conducted to obtain classification features. Finally, we use the acquired classification features and a grid optimization method to train support vector machines (SVM).
Results: The results of two open-EEG datasets in epileptics show that there are major differences between seizure attacks and non-seizure attacks, such that FuzzyEn can be used to detect epilepsy, and our method obtains better classification performance (accuracy, sensitivity and specificity of classification of the CHB-MIT are 98.31%, 98.27% and 98.36%, and of the Bonn are 100%, 100%, 100%, respectively).
Comparisons with existing method(s): To verify the performance of the proposed method, a comparison of the classification performance for epileptic seizures using FuzzyEn and SampEn is conducted. Our method obtains better classification performance, which is superior to the SampEn-based methods currently in use.
Conclusions: The results indicate that FuzzyEn is a better index for detecting epileptic seizures effectively. The FuzzyEn-based method is preferable, exhibiting potential desirable applications for medical treatment.

1. Introduction

Entropy is a nonlinear index that reflects the degree of disorder of a given system, enabling it to be employed for studies of the chaotic behavior of the brain (Azarnoosh, 2011). Recently, entropy has been broadly applied in the analysis of electroencephalogram (EEG) signals. Furthermore, the concept of entropy has been expanded in several different fields, and some new concepts have emerged, such as sample entropy (SampEn), approximate entropy (ApEn), wavelet entropy (WE), multiscale entropy (MSE), and permutation entropy (PE). All of these indexes have been applied in varying degrees in the analyses of cognitive mental states and sleep states employing EEG signals (Koenig et al., 2009; Korotchikova et al., 2009; Takahashi et al., 2010; Yun et al., 2012). These studies demonstrate that an entropy analysis of the

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brain may be a promising prospect in the field of EEG-based evaluation.

Epilepsy, a chronic disease of the nervous system, is a quite common malady that afflicts people of all classes and backgrounds. The incidence of epilepsy is high, and approximately 1% of the world's population suffers from this condition (Duncan et al., 2006). Epileptic seizures are characterized by paroxysmal, sudden and transient brain disorders induced by the repeated and hyper-synchronous discharges of cerebral nerve cells, which can cause major disruptions to patients' work and lives. Acute seizures can inflict serious injury or death upon the patient. Currently, EEG analysis is the primary method used in the study of epilepsy. Various types of entropy have been calculated from the EEG data, and they are now widely used for identifying the various epileptic states (non-seizure or seizure).

These entropy-based methods for identifying whether an epileptic seizure has occurred are quite similar because the entropy of the EEG signals for different patients at different periods can be calculated and classifications can be performed using a machine-learning algorithm. Kumar et al. (2010) studied the classification of epilepsy signals based on the calculated WE, with a classification accuracy up to 94.5% (Kumar et al., 2010). Using multiple wavelet transformation (WV) and an artificial neural network (ANN), Guo et al. (2010) conducted a classification of epilepsy based on the calculated ApEn, obtaining an accuracy as high as 99%. Using the extreme learning machine (ELM), Song et al. (2012) optimized SampEn for epilepsy classification, and their accuracy was quite high, up to 99%. Ocak et al. (2008) performed epilepsy classifications based upon ApEn using WV, with an accuracy of 94.3%. Using the index of ApEn, Kannathal et al. (2005) performed epilepsy classifications and obtained an accuracy of up to 90%. Wang et al. analyzed the EEG signals of epileptics based on WE, and their prediction accuracy was reported to be 100%. On the basis of PE, Nicolaou and Georgiou (2012) were the first to perform an epilepsy classification using support vector machines (SVM), and their obtained classification accuracy was 94.38%. Using ANN, Akareddy et al. (2013) studied the EEG signals of epileptics based on ApEn, with a classification accuracy of 90%. With the calculated SampEn adopted as the index, Shen et al. (2013) also conducted classifications of epilepsy, and their calculated accuracy was as high as 91.18%. As stated above, favorable classification results have been achieved with the adoption of multiple types of entropy, suggesting that in general, entropy-based methods are promising for the EEG analysis of epilepsy.

However, few studies have been conducted that compare these classification results directly using calculated entropy with different definitions. Fuzzy entropy (FuzzyEn), which has been proposed based upon the theory of fuzzy mathematics, is a nonlinear index used to evaluate the probability of newly generated modes. In 2007, Chen et al. (2007) performed modifications of the SampEn-based algorithm and, from this, proposed a definition for FuzzyEn. Since then, the index of FuzzyEn has been successfully applied in feature extraction and in the classification of surface electromyography (EMG) signals. The FuzzyEn-based algorithm retains several characteristics of the SampEn-based algorithm, such as the relative uniformity and the suitability for the processing of short datasets. Additionally, by making the similarity measurement formula fuzzy, the FuzzyEn-based algorithm precludes the limitations of the SampEn definition, as FuzzyEn can transit smoothly through varying parameters. Recently, limited studies have been reported on the detection of epilepsy using the index of FuzzyEn, but almost no related comparative studies have been performed for EEG analysis using the two indexes, SampEn and FuzzyEn. In the present study, we used two open-source databases, provided by CHB-MIT and BONN, and we studied the detection of epileptic seizures using both the FuzzyEn and SampEn calculations. The performance of these two methods in epilepsy detection using EEG signals was compared with several other classification indexes, to determine the accuracy, specificity and sensitivity of our methods.

2. Data and methods

2.1. The open-source EEG data from epileptics

Two open-source EEG datasets from epileptics were used in our study. One is the CHB-MIT database (http://physionet.org/cgi-bin/atm/ATM), and the other is the Bonn database (http://www.meb.uni-bonn.de/epileptologie/science/physik/eegdataold.html). The CHB-MIT database is from a group of epileptic children, with EEG data provided by the Massachusetts Institute of Technology (MIT), USA. These data were collected from 23 subjects at Boston's Children's Hospital. With data integrity taken into account, the data from 18 subjects (4 males and 14 females) were used, whose ages ranged from 1.5 to 22 years. Each subject was required to stop medicinal treatment one week before data collection, and the data were collected successively for 916 h, with a sampling frequency of 256 Hz. During the recording process, any position changes that may have occurred in the EEG electrodes did not affect the results. According to expert judgments, the duration, start time and end time of each seizure have been labeled explicitly in the data. For each subject, the numbers and durations of seizure events varied. The EEG signals in the database reflect the occurrence of 198 individual epileptic seizure episodes.

The above data were recorded from scalp electrodes; in this study, we also used a data set of intracranial electrodes provided by the department of epileptology of Bonn University for our comparison. The whole dataset consisted of five sets (denoted as *Z*, *O*, *N*, *F* and *S*), each containing 100 single-channel EEG segments of 23.6 s duration, with a sampling rate of 173.6 Hz. Sets *Z* and *O* were carried out in five healthy volunteers. Sets *N*, *F* and *S* originated from an EEG archive of pre-surgical diagnosis. Segments in set *F* were recorded from the epileptogenic zone, and those in set *N* were recorded from the hippocampal formation of the opposite hemisphere of the brain. While sets *N* and *F* contained only activity measured during seizure-free intervals, set *S* only contained seizure activity. All EEG signals were recorded with the same 128-channel amplifier system, using an average common reference. The data were digitized at 173.61 samples per second using 12-bit resolution, and they were recorded at the spectral bandwidth of the acquisition system, which varied from 0.5 Hz to 85 Hz. In this study, we used this dataset to carry out two classification experiments, one based on the *N* and *S* datasets (denoted as *N*/*S*), and another based on the *F* and *S* datasets (denoted as *F*/*S*).

2.2. Principles of analysis method

Fig. 1 shows the procedure for the detection of epileptic seizures based on entropy. First, the entropy (SampEn or FuzzyEn) of all of the EEG electrodes was extracted, and second, features were selected to form classification eigenvectors. Usually, in this step, we selected those electrodes whose entropy exhibited significant variation during the seizure and non-seizure periods as features (labeled as s_1, $s_{2,\ldots}$, s_m, respectively); the entropy values of these selected electrodes then constituted the eigenvectors. Finally, the classifier was trained using support vector machines (SVM), an algorithm for classification training. In this step, all training samples composed of eigenvectors together with their labels (seizure free or seizure) were input into the SVM to train a classifier. Once a classifier was obtained, those sample eigenvectors with no labels could be labeled by this classifier; therefore, we could use this classifier

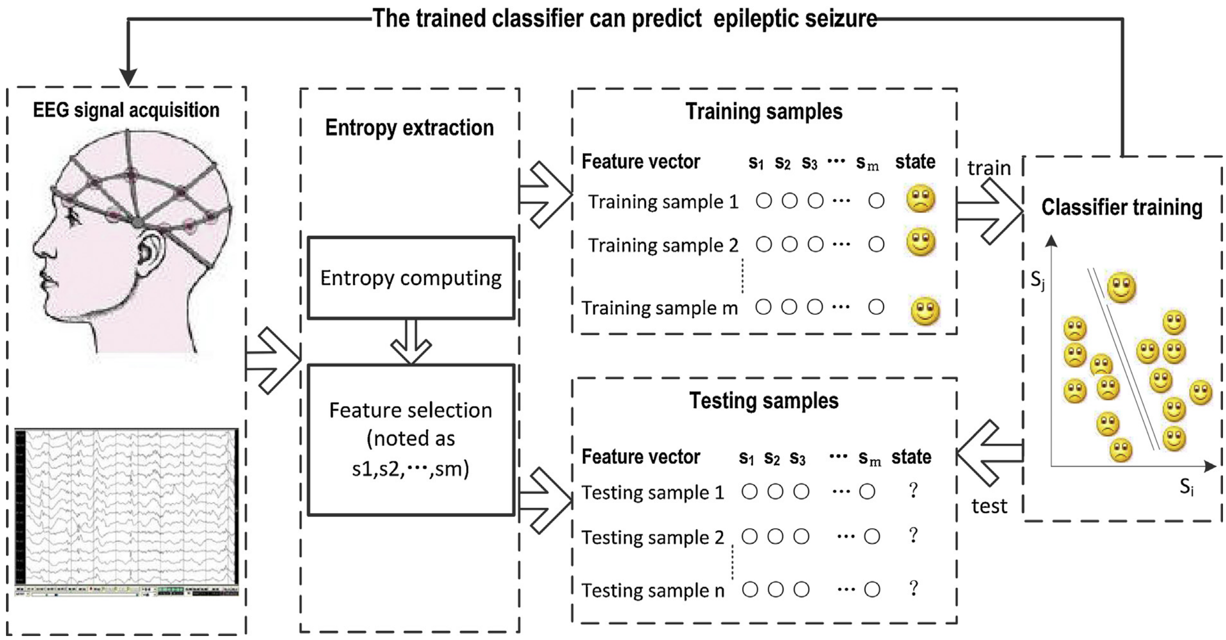

Fig. 1. Principles of epilepsy detection based on entropy.

to analyze an unknown EEG dataset, with the goal of identifying when and whether an epileptic seizure occurred.

2.2.1. Fuzzy entropy and sample entropy

SampEn has been broadly applied in the field of epilepsy detection. In the definition of sample entropy (Richman and Moorman, 2000), the degree vector similarity is described by the Heaviside function:

$$\theta(z) = \begin{cases} 1, & z \geq 0 \\ 0, & z < 0 \end{cases} \tag{1}$$

The Heaviside function is a two-valued function. The input samples used to satisfy prescribed conditions are grouped into one class, while the samples that did not meet these requirements are grouped into another class. However, in the natural world, the borders of these different classes are often ambiguous; therefore, the input sample cannot always be confidently placed into a single class. To solve this problem, Chen et al. (2007) used a fuzzy membership function to measure the degree of similarity of vectors, rather than the two-valued function in the SampEn-based algorithm, such that the calculated entropy values are continuous and smooth. The procedure for the FuzzyEn-based algorithm is described in detail as follows.

(i) Set a N-point sample sequence: $\{u(i) : 1 \leq i \leq N\}$;

(ii) The phase-space reconstruction is performed on $u(i)$ according to the sequence order, and a set of m-dimensional vectors are obtained ($m \leq N-2$). The reconstructed vector can be written as

$$X_i^m = \{u(i),\ u(i+1), \ldots, u(i+m-1)\} - u_0(i) \tag{2}$$

in which $i=1, 2,\ldots, N-m+1$, and $u_0(i)$ is the average value, with the definition listed in the following equation:

$$u_0(i) = \frac{1}{m}\sum_{j=0}^{m-1} u(i+j) \tag{3}$$

(iii) d_{ij}^m, the distance between two vectors, X_i^m and X_j^m, is defined as the maximum difference values between the corresponding elements of two vectors, i.e.,

$$d_{ij}^m = d\left[X_i^m, X_j^m\right] = \max_{k\in(0,m-1)} \left\{ \left| u(i+k) - u_0(i) - (u(j+k) - u_0(j)) \right| \right\} \quad (i,j = 1 \sim N-m, \quad j \neq i) \tag{4}$$

(iv) According to the fuzzy membership function $\mu\left(d_{ij}^m, n, r\right)$, the similarity degree D_{ij}^m between two vectors, X_i^m and X_j^m, is defined as

$$D_{ij}^m = \mu\left(d_{ij}^m, n, r\right) = \exp\left(\frac{-\left(d_{ij}^m\right)^n}{r} \right) \tag{5}$$

in which the fuzzy membership function $\mu\left(d_{ij}^m, n, r\right)$ is an exponential function, while n and r are the gradient and width of the exponential function, respectively.

(v) Define the function $\phi(n, r)$

$$\phi(n, r) = \frac{1}{N-m}\sum_{i=1}^{N-m}\left[\frac{1}{N-m-1}\sum_{j=1, j\neq i}^{N-m} D_{ij}^m\right] \tag{6}$$

(vi) Repeat the steps from (2) to (5) in the same manner, a set of $(m+1)$-dimensional vectors can be reconstructed according to the order of sequence. Define the function:

$$\phi^{+1}(n, r) = \frac{1}{N-m}\sum_{i=1}^{N-m}\left[\frac{1}{N-m-1}\sum_{j=1, j\neq i}^{N-m} D_{ij}^{m+1}\right] \tag{7}$$

(vii) Define the fuzzy entropy for a given time series:

$$\mathrm{FuzzyEn}(m, n, r) = \lim_{N\to\infty}\left[\ln\phi^m(n, r) - \ln\phi^{m+1}(n, r)\right] \tag{8}$$

When N is limited, the fuzzy entropy for the time series with a sequence length of N can be expressed as

$$\mathrm{FuzzyEn}(m, n, r, N) = \ln\phi^m(n, r) - \ln\phi^{m+1}(n, r) \tag{9}$$

in which m and r are the dimensions of phase space and similarity tolerance, respectively. Generally, too large of a similarity tolerance will lead to a loss of useful information. The larger the similarity tolerance, the more information may be missed. However, if the similarity tolerance is underestimated, the sensitivity to noise will be increased significantly. In the present study, $m = 2$ while $r = 0.25 \times \mathrm{SD}$, where SD denotes the standard deviation of the time series.

2.2.2. Feature selection

Feature selection plays a crucial role in classification, and suitable features can improve the classification accuracy effectively. For the Bonn database, which contains a series of EEG data obtained from intracranial electrodes planted in the epileptogenic zone and in the hippocampus of the opposite hemisphere, these areas likely reflect the EEG variations between seizure and non-seizure periods very well; therefore, we used these nodes as features directly. However, for the CHB-MIT database, the EEG electrodes were placed at different positions on the patient's head surface, reflecting the electro-physiological activities of different cerebral nerve cells. Consequently, we could not guarantee that all of the electrodes were properly situated and accurately reflected EEG variations between seizure and seizure-free periods. After selection, only those electrodes whose signals exhibited significant variations between seizure and seizure-free periods were adopted as features. In previous studies (Wang et al., 2012, 2013), a paired *T*-test was used for screening electrodes with significant differences. However, this method is limited because it must be conducted within the assumption that all samples are normally distributed. Because the fuzzy entropy of the EEG signals cannot meet the criteria for a Gaussian distribution, a paired *T*-test cannot be used. As well known, the Kolmogorov–Smirnov (*K*–*S*) test can be performed on both normal and non-normal distributions. Using the *K*–*S* test (Ivanov and Riccardi, 2012), a single group can be tested for whether the samples are distributed in accordance with a certain theory and, moreover, the two groups can be tested for whether significant differences exist between them. It has been demonstrated that the *K*–*S* test is an effective and stable non-linear statistical test, primarily because of its strong anti-noise performance and high sensitivity to nonlinear signals (Hou et al., 2007). In the present study, using 1 s as the sliding time window, the entropy values of all the test channels were calculated during seizure and non-seizure periods, respectively. Subsequently, the electrodes with significant signal differences were filtered using a *K*–*S* two-sample test.

2.2.3. Support vector machine (SVM)

The classifier algorithm also plays a crucial role in the detection of epileptic seizures based upon the EEG signals. In many machine learning algorithms, SVM belongs to the family of kernel-based classifiers, and they are very powerful classifiers, as they can perform both linear and non-linear classification simply by changing the "kernel" function utilized (Li et al., 2014). The main concept of an SVM is to implicitly map the data into the feature space wherein a hyperplane (decision boundary) separating the classes may exist. This implicit mapping is achieved via the use of Kernels, which are functions that return the scalar product in the feature space by performing calculations in the data space. The simplest case is a linear SVM trained to classify linearly separable data. In the case of non-linear classification, kernels, such as radial basis functions (RBF), are used to map the data into a higher dimensional feature space in which a linear separating hyperplane could be found. Now, most studies use RBF as the kernel. In this paper, we also used RBF as the "kernel" of the SVM. The RBF is defined as follows:

$$K\left(X_i, X_j\right) = \exp\left(-\gamma \|X_i - X_j\|\right)^2 \tag{10}$$

where X_i and X_j are the vector that we want to classify, γ is the kernel parameter.

As a prevalent method in the field of machine learning, the SVM exhibits a favorable generalization capability, which is especially suitable for solving small sample, non-linear and high-dimensional learning problems. By comparing the classification performance of different classifiers in epilepsy detection, many researchers have used SVM in their study, e.g., Acharya et al. (2012) concluded that the SVM algorithm is preferable in terms of accuracy, sensitivity and specificity. In the present study, the SVM classifier was trained using the libSVM toolbox (Chang and Lin, 2011), and the RBF kernel function was adopted as the kernel function.

2.2.4. Grid search

To improve the accuracy of the SVM, a pair of the parameters, C (penalty factor) and γ, should be set to adjust the hyperplane. In this study, a grid search approach was used to find a proper parameter setting to improve the SVM classification accuracy. The grid search approach (Kaya and Kaya, 2014; Liu et al., 2010) is an alternative to finding the best C and γ when using the RBF kernel function. The first step of the grid search method is to identify the range of each parameter. In our paper, the ranges of C and γ are $[2^{-8}, 2^{8}]$, and the step is 1. The second step is to obtain a few group parameter combinations according to certain rules in the range of each parameter. The third step is to calculate each combination of parameters and to calculate the root mean square error of prediction using the method of leave one out; the best parameter value is the smallest root mean squared prediction errors of parameter combinations.

To guarantee that the present results are valid and can be generalized for making predictions regarding new data, the data set is further randomly partitioned into training and independent testing sets via a k-fold cross validation. Each of the k subsets acts as an independent holdout test set for the model trained with the rest of $k-1$ subsets. The advantages of cross validation are that the impact of data dependency is minimized and the reliability of the results can be improved (Liu et al., 2014). In this study, a 10-fold cross validation (Chalimourda et al., 2004) was selected to examine the classification performance, i.e., the sample set was divided into a set of ten disjointed subsets with the number of samples in each subset roughly equivalent. The nine training subsets were selected for training the classification model, in which the optimal parameters of the kernel function in the SVM model were identified using a grid searching optimization method. Subsequently the left subset was used for verifying the performance of the developed classification model. The above process was repeated ten times, and thus, each subset was involved in the detection. Finally, the expected generalization errors were estimated according to the mean values of the obtained mean square errors after ten iterations and a set of optimal parameters was then determined.

2.2.5. Classification performance

The indexes for assessing the classification performance included accuracy, sensitivity, and specificity. P denotes the number of samples during a seizure period; N denotes the number of samples during a non-seizure period; FP denotes the number of samples for a non-seizure period but are mistaken for a seizure; FN denotes the number of samples at a seizure period that are mistaken for a non-seizure; and TP and TN denote the numbers of samples which are accurately classified. These three indexes, accuracy, sensitivity and specificity, can be calculated as follows:

$$\text{Accuracy} = \frac{TP + TN}{P + N} \tag{11}$$

$$\text{Sensitivity} = \frac{TP}{TP + FN} \tag{12}$$

Table 1
FuzzyEn and SampEn of each subject at seizure and non-seizure periods (CHB-MIT).

	FuzzyEn				SampEn			
	Non-seizure period	Seizure period	*p*	Variation	Non-seizure period	Seizure period	*p*	Variation
1	1.453	1.858	0.00001	0.405 ↑	0.612	0.535	0.04561	0.077 ↓
2	2.243	1.88	0.00003	0.363 ↓	0.926	0.538	0.00000	0.388 ↓
3	1.633	2.461	0.00000	0.828 ↑	0.785	0.908	0.00044	0.123 ↑
4	1.763	2.189	0.00000	0.426 ↑	0.594	0.594	0.49341	0.000 ↑
5	2.075	1.789	0.00001	0.286 ↓	0.877	0.471	0.00000	0.406 ↓
6	1.772	1.621	0.01321	0.151 ↓	0.653	0.438	0.00000	0.215 ↓
7	1.673	1.46	0.00018	0.213 ↓	0.59	0.441	0.00000	0.149 ↓
8	1.741	1.562	0.00098	0.179 ↓	0.611	0.484	0.00000	0.127 ↓
9	1.602	1.491	0.02533	0.111 ↓	0.536	0.467	0.00000	0.069 ↓
10	0.845	1.075	0.00000	0.230 ↑	0.575	0.678	0.00000	0.103 ↑
11	1.008	1.266	0.00000	0.258 ↑	0.565	0.647	0.00004	0.082 ↑
12	1.071	1.313	0.00000	0.242 ↑	0.58	0.649	0.00021	0.069 ↑
13	0.924	1.277	0.00000	0.353 ↑	0.544	0.639	0.00001	0.095 ↑
14	0.973	1.372	0.00000	0.399 ↑	0.558	0.657	0.00000	0.099 ↑
15	0.983	1.32	0.00000	0.337 ↑	0.548	0.651	0.00000	0.103 ↑
16	1.062	1.281	0.00000	0.219 ↑	0.571	0.639	0.00034	0.068 ↑
17	1.079	1.339	0.00000	0.260 ↑	0.571	0.649	0.00007	0.078 ↑
18	1.359	1.479	0.04557	0.120 ↑	0.645	0.636	0.35103	0.009 ↓

$$\text{Specificity} = \frac{TN}{FP + TN} \quad (13)$$

Sensitivity and specificity are the important indexes in medical statistics. In disease diagnosis, sensitivity is referred to as the probability of false positive diagnosis, while specificity is the probability of false negative diagnosis. In our study, sensitivity is the ability of a false positive diagnosis of epileptic seizure, while specificity reflects the possibility of a false negative diagnosis.

3. Experimental results

3.1. The results of CHB-MIT database

3.1.1. Comparisons of entropy at different seizure States

For each subject, the data were marked with the seizure states according to the provided dataset, and the fuzzy entropy and sample entropy were calculated at an interval of 1 s, respectively. Table 1 displays the mean values of entropy for the subjects and the related test results during seizure and non-seizure periods, respectively. The row labeled by variation in Table 1 represents the variation of the seizure period compared with non-seizure period; specifically,↑denotes an entropy increase in seizure periods, while ↓ denotes an entropy reduction in the seizure period.

3.1.2. Classification results

In this study, the FuzzyEn and SampEn were calculated for each subject, and the electrodes displaying significant differences between seizure and non-seizure periods, which were selected by the *K–S* test, constitute the eigenvectors. With the use of libsvm toolbox, the SVM classifier for each subject was trained using grid searching optimization. Fig. 2 summarizes the comparison of the classification performance for each subject calculated by FuzzyEn and SampEn. Generally, the seizure state can be detected effectively based on either FuzzyEn or SampEn. It appears that the FuzzyEn-based classification exhibits a remarkably higher accuracy, sensitivity and specificity than the SampEn-based classification. The mean accuracy of classification calculated using FuzzyEn was 98.31%, which was significant higher than the accuracy calculated using sample entropy (97.16%, $p < 0.05$). Similarly, both the mean sensitivity and specificity calculated using fuzzy entropy (98.27% and 98.36%, respectively) were significant higher than those calculated using sample entropy (97.01% and 97.34%, respectively, both: $p < 0.05$). It can also be observed that the classification performance of all subjects calculated using FuzzyEn was

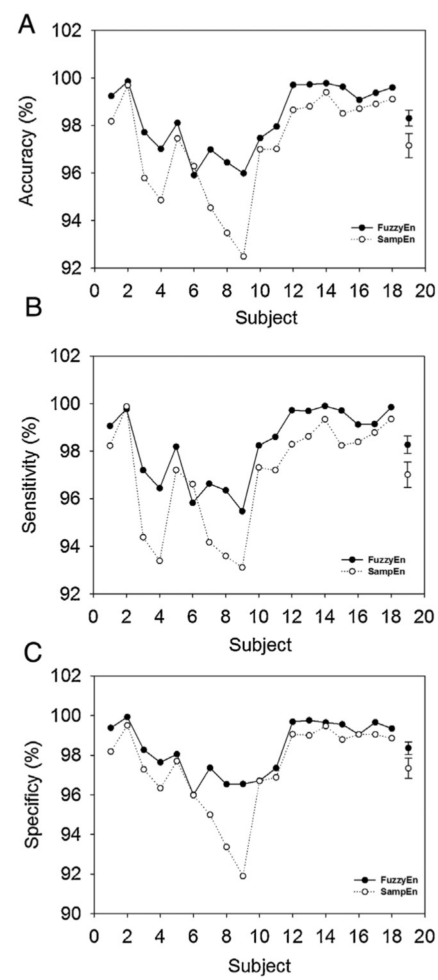

Fig. 2. The classification performance of sample entropy and fuzzy entropy (CHB-MIT). Part (A) shows the curves for accuracy, part (B) shows the curves for sensitivity, part (C) shows the curves for specificity. The solid-point curves represent the FuzzyEn performance, while the hollow-point curves are the results calculated using SampEn. The curves were plotted with the serial numbers of subjects and the average performance.

higher than the results from SampEn, except in the cases of subjects 2 and 6.

3.2. The results of the Bonn database

In this paper, we calculate the SampEn and FuzzyEn of the Bonn data sets of *F*, *N*, and *S* every second. Table 2 displays the mean values of entropy of *F*, *N*, and *S*, and the statistical test results between *F* and *S* as well as *N* and *S*, respectively. As shown in Table 2, whether the comparison was between *F* and *S* or between *N* and *S*, the FuzzyEn in the seizure period was higher than in the seizure-free period. However, in SampEn, this was not the case.

The results of the three data sets were used as the classification features to input into the trained classifier. The results of classification performances are shown in Table 3. In the *F*/*S* case, the accuracy, sensitivity and specificity of the classification are 100%, 100% and 100% and 87.6%, 90.79% and 85.70% for the FuzzyEn and the SampEn, respectively. It appears that the FuzzyEn-based classification exhibits a remarkably higher accuracy, sensitivity and specificity than the SampEn-based classification. It is consistent with the *N*/*S* case (the accuracy, sensitivity and specificity of classification are 100%, 100% and 100% and 88.5%, 90.36% and 87.63% for the FuzzyEn and the SampEn, respectively).

4. Discussion

It is generally accepted that entropy is an index used to measure the complexity of a system. As reported in Majumdar and Vardhan (2011), the complexity of epileptic brain activity signals exhibit significant differences between the seizure and non-seizure periods. Progress in understanding these states has been vigorous as a result of gains achieved by investigators employing the study of brain entropy. The indexes, datasets and the related classification performance adopted in previous studies are listed in Table 4.

Otherwise, FuzzyEn is a method for analyzing nonlinear time series using modified sample entropy; the validity it defines is not restricted by the parameter value. It can obtain robust estimates with short data, and it has good anti-noise and anti-jamming ability. Chen et al. (2009) also compared the SampEn-based and FuzzyEn-based methods theoretically. Owing to the introduction of fuzzy function, in addition to the advantages of the SampEn-based method, the FuzzyEn-based method can provide stable results for different parameters as well as strong anti-noise capacity. However, there has been little research using FuzzyEn to detect epilepsy. The classification performance depends on the selection of the index but is also closely related to the classification algorithm and the selected dataset. Using of the same CHB-MIT dataset, Zavar et al. performed epileptic seizure detection using the SVM classifier, choosing the Lyapunov exponent, fractional dimension and wavelet entropy as the features. In their study, the classification accuracy was approximately 96.29%. In the present study, only the index of fuzzy entropy was selected as the feature in the classification, yielding a detection accuracy of up to 98%. From the point of computational efficiency, the computational expense of our study is smaller than that of Zavar's work (2011). In our paper, we used the same classification method and used SampEn and FuzzyEn as the feature to detect epilepsy. The results are satisfactory: using the FuzzyEn and the SampEn as features, the average accuracies of the CHB-MIT are 98.31% and 97.16%, respectively. Akareddy et al. (2013) used the same data and used ApEn as a feature; his accuracy was only 90%, a result that is not better than ours. In this author's study, the specific indexes, such as accuracy, sensitivity and specificity, were not calculated. Additionally, using the same classification algorithm, the FuzzyEn-based classification is preferable to the SampEn-based results. This conclusion has also been verified by other studies using EEG signals. In their study regarding the classification of sleep EEG signals, Liu et al. (2010) compared results calculated by fuzzy entropy and sample entropy and found the accuracy of FuzzyEn-based classification to be higher.

In addition, we come to similar conclusions using the Bonn data. Although there has been previous research using SampEn and PE to study the Bonn data, the results were not as good as we achieved using FuzzyEn. Even when Kumar et al. (2014) used FuzzyEn to classify the Bonn data, the accuracy was only 95; however, in our research, the accuracy was 100%. This result further demonstrates that a study using a classification algorithm and FuzzyEn as the classification index is more reasonable.

Interestingly, using SampEn as the classification index, the accuracy of the *N*/*S* dataset was slightly higher than the *F*/*S* (88.5% vs. 87.6%). We speculated that this result might be caused due to the plant place of electrode. Set *F* was recorded from the epileptogenic zone, and Set *N* was recorded from the hippocampal formation of the opposite hemisphere of the brain. Even in the seizure-free period, the epileptogenic zone may display little disorder when compared with other non-epileptogenic zones. Therefore, the difference in chaos degree between seizure and non-seizure may be reduced. Using FuzzyEn as the classification index, the accuracy of *N*/*S* and *F*/*S* were very high (100%). The FuzzyEn was likely more suited for analyzing EEG data in epileptic seizures.

As we can see from Fig. 2 and Table 3, using a FuzzyEn-based classification, the accuracy of the different data sets was different. The accuracy of the Bonn dataset was 100%, and the average accuracy of the CHB-MIT dataset was as high as 98.31%. The accuracy was a little different, and the reason for this slight discrepancy might be that the Bonn dataset was collected from intracranial electrodes at the epileptogenic zone, while the CHB-MIT dataset was collected from scalp electrodes. For only the CHB-MIT dataset, FuzzyEn-based classification greatly enhanced the detection performance. Considering the ease of data sources and injury to the patient, the present results implied that scalp electrode data with analysis with FuzzyEn-based classification also had very high detection performance and are suitable for research into the detection of epileptic seizures.

There is another very important application. As there are more and more epilepsy patients, the sudden onset of epilepsy in more patients will bring many difficulties, which will affect these patients' daily life. Appropriate and timely preventive treatment should be given to patients to improve their quality of life. The ability to predict an impending seizure well ahead of its clinical or electroencephalographic onset provides an opportunity for new diagnostic and therapeutic applications that could revolutionize the medical and surgical management of epilepsy (Iasemidis et al., 2005). Some researchers have used ApEn (Zhang et al., 2014) and STLmax (Iasemidis et al., 2003) to predict seizures. They can predict seizures within 30 min, even 72 min. From this study, we found that the classification performance of FuzzyEn was better than SampEn; it is expected that FuzzyEn can also show better performance for seizure forecast. Although, the present study is based on the existing EEG data, the high performance of detection of epileptic seizures by using of FuzzyEn-based classification indicated well application on the real-time detection of epileptic seizures. To realize real-time detection of epileptic seizures, we only needed to record a period of EEG signals when epileptic seizure attacks and non-seizure attacks states, and then trained a FuzzyEn-based classification. Once saving the trained classification model, we could achieve real-time detection of epileptic seizures, and highly reduced doctor workload of the detection of EEG signal.

Table 2
The comparisons of FuzzyEn and SampEn between $F(N)$ and S (Bonn).

	F	S	p	Variation	N	S	P	Variation
FuzzyEn	1.182	1.733	0.00000	0.551 ↑	1.136	1.733	0.00002	0.597 ↑
SampEn	0.644	0.507	0.00000	0.137 ↓	0.483	0.507	0.00000	0.024 ↑

Table 3
The classification results of Bonn.

Classification	Accuracy (%)		Sensitivity (%)		Specificity (%)	
	SampEn	FuzzyEn	SampEn	FuzzyEn	SampEn	FuzzyEn
F/S	87.6	100	90.79	100	85.70	100
N/S	88.5	100	90.36	100	87.63	100

Table 4
Studies regarding epileptic seizure detection using different types of entropy.

Research group	Adopted index	EEG dataset	Accuracy of classification (%)
Kumar et al. (2010)	WE	The Bonn-Barcelona's	94.5
Guo et al. (2010)	ApEn	The Bonn-Barcelona's	99
Song et al. (2012)	SampEn	The Bonn-Barcelona's	99
Ocak (2008)	ApEn	Private clinical data	94.3
Kannathal et al. (2005)	ApEn	The Bonn-Barcelona's	90
Nicolaou and Georgiou (2012)	PE	The Bonn-Barcelona's	94.38
Akareddy et al. (2013)	ApEn	CHB-MIT	90
Shen et al. (2013)	SampEn	Private clinical data	91.18
Kumar et al. (2014)	FuzzyEn	The Bonn-Barcelona's	95
This study	FuzzyEn	CHB-MIT	98.31
	SampEn	CHB-MIT	97.16
	FuzzyEn	Bonn	100
	SampEn	Bonn	88.05

5. Conclusions

In the reported study, EEG electrodes with significant signal variations between different epileptic periods were screened to constitute the classification feature vector, and then a trained classifier based on SVM could identify the seizure.

According to all of our results, we can draw a conclusion that FuzzyEn is a better index of seizure detection than SampEn. The classification results indicate that epileptic seizures can be detected effectively using the reported method. Once a patient classification model is obtained, based on previous EEG data recorded in the seizure and non-seizure period, the classifier can be used in the future automatically to detect seizures, which can reduce the workload of doctors' inspecting EEGs. Despite these successes, the reported technique needs to be explored with further studies. We still believe that the FuzzyEn-based method is preferable, exhibiting potential desirable applications for medical treatment.

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