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Comparative study of approximate entropy and sample entropy in EEG data analysis

Cao Rui, Li Li, Chen Junjie*

College of Computer Science and Technology, Taiyuan University of Technology, Taiyuan 030024, (CHINA)

ABSTRACT

ApEn and SampEn are widely adopted in the Biomedical Signal Processing in recent years. This paper makes a comparative study on the application of both in the analysis of EEG data. Theoretically, SampEn has higher accuracy and needs much less computation time than ApEn. Experiments based on two EEG data sets show that SampEn can better classify different emotions and can more accurately distinguish the alcoholism from controls than ApEn. This study indicates that SampEn is more suitable to be used to analyze EEG data than ApEn, which has relatively high significance for the quantitative analysis of EEG.

KEYWORDS

EEG;
Approximate entropy;
Sample entropy;
Alcoholism;
Emotion recognition.

INTRODUCTION

Electroencephalogram (EEG) is a complicated biomedical signal. Comparing to the traditional analysis methods, nonlinear methods in EEG data analysis have already attracted more attentions[2]. In recent years, some scholars promoted the concept of "Entropy" and defined them, including the Approximate Entropy (ApEn)[13], Sample Entropy (SampEn)[14], Wavelet Entropy (WE), etc. All these concepts are widely used in information theory and nonlinear dynamics. Among these "entropy", ApEn and SampEn are suitable to analyze the short data especially and have good robustness. Both are important indexes to measure the nonorder of system and the complexity of time series, which are used widely in biomedical signal (e.g. EEG) analysis.

Atefeh Goshvarpour et al.[1] detected in his study that the ApEn of EEG data had obvious corresponding variations in different sleep stages. Liu et al.[11] took the ApEn of EEG signal as feature, using KPCA–HMM (Kernel Principal Component Analysis and Hidden Markov Mode) to recognize mental fatigue. The accuracy can reach to 84%. Although the ApEn is widely used to measure the complexity of EEG signals, it still has following deficiencies: the approximate entropy related to the data length and lacks relative consistency. SampEn which was introduced by Richman is a new method to measure the complexity of time series. Scholars in variety of fields made many studies on the EEG data by means of SampEn. Song et al.[16] proposed an optimized sample entropy (O-SampEn) algorithm by which the SampEn of EEG signal was calculated and taken as classification feature which is used to identify the epilepsy combined with extreme learning machine (ELM). The highest classification accuracy can reach to 99.00%. Chouvarda et al.[4] studied sleep EEG by means of SampEn and found out that SampEn can well

FULL PAPER

display the complexity of EEG activities in the sleep stages. Yan Nan et al.[18] proposed that SampEn can be used as feature to analyze and classify attention-related EEG signals, meanwhile adopting the SVM classifier to conduct classification. The classification accuracy can reach to 85.5%.

Large amount of studies have showed that ApEn and SampEn have good application prospect in the EEG. But which one is more suitable for the EEG signals processing? Presently, comparative study on the approximate entropy and sample entropy in the EEG data is relatively less. This paper discusses that which entropy is more suitable as EEG features by means of algorithm analysis and empirical validation based on two groups of EEG data sets.

METHODS

ApEn

ApEn is an index to quantitatively describe the irregularity of complex system. It reflects the conditional probability of the similar vectors remaining the similarity when they increase from m to m+1 dimension. The physical significance is the probability of the generation of a new model in the time series when the dimension changes. The larger the probability of generating a new model is, the larger the relative ApEn will be which means the more complex the data series will be. ApEn indicates the complexity of the time series through statistics and represents the diversity and variety of the dynamic system. ApEn has the following features: needing shorter data in calculation; has relatively good ability in noise proof and jam proof; suit for both certain and random signals; suit to represent nonstationary biological signals.

SampEn

SampEn is a new measurement for the complexity of the time series. Its physical significance is similar to the ApEn. The lower the SampEn is, the higher the similarity of the series will be. The larger the SampEn is, the more complex the time series will be. However, the algorithms of ApEn and SampEn are different. The ApEn algorithm compares the data and itself, which may result in bias, while the SampEn doesn't make this kind of comparison. Because entropy is the measurement for the probability of the new information generation, it is meaningless to compare the data and itself.

Theoretical comparison of the ApEn and SampEn

In order to facilitate the analysis, B was defined as similarity probability of m dimension time series and A was defined as similarity probability of m+1 dimension time series, then CP=A/B[19]. Both algorithms are based on –ln (CP) model and calculate the average value of all models. The ApEn calculates the sum of logarithm, while the SampEn calculates the logarithm of sum. Therefore, in order to avoid the occurrence of ln (0) in the calculation, obvious comparison of the data segments should be made in the algorithm of ApEn. However, certain bias may occur. While the SampEn doesn't compare the data segments, it is the accurate value of –ln (CP). Besides, SampEn has better consistency, i.e. if the SampEn of one time series (S1) is higher than another (S2), the S1>S2 will remain for other value of m and r. However, ApEn cannot achieve this. In conclusion, SampEn has a higher precision than ApEn in theor

RESULTS

Theoretically, SampEn is an improved algorithm of ApEn. This paper tests that which algorithm is more suitable as EEG feature basing on two groups of EEG data sets.

Pincus[13] suggested that m be 1 or 2, and r be $0.1SD$ to $0.25SD$ (SD is the standard deviation of the data), for data lengths (N) ranging from 100 to 5,000 data points. In this paper, in the calculation of approximate or sample entropy, the parameters are typically chosen as m=2 and $r = 0.2 * SD$.

Experiment 1

Data 1

DEAP[10] is an open database, which contains EEG data gotten while 32 subjects watching 40 periods of music video, available for emotion recognition research basing on physiological signals. Before data acquisition, the videos have been marked with emotions through a number of behavioral experiments and VAD (Valence - Arousal - Dominance) model, a generally used emotion model, which consists of 3 dimensions of emotions. While watching the video, subjects were in-

structed to evaluate the videos using the 9-point scale of VAD according to their own emotional experience. In terms of the value of VA, the videos are divided into four types of emotion: high arousal high valence (HAHV), low arousal high valence (LAHV), low arousal low valence (LALV), high arousal low valence (HALV).

The sample frequency of the EEG signals is 512Hz, 40 channels are collected, 32 of which are EEG signal channels. The sample frequency of the EEG signal after preprocessing will be 128Hz. The sample length will be 63 seconds. These EEG data has been processed through artifacts rejection and filtering. The data of 4.0-45.0Hz will be kept after processing.

Result 1

We selected those videos whose behavior experiment is in line with subjects labeling. And taking the affective priming time and fatigue effect into consideration, we removed the first 23 seconds and last 20 seconds of the EEG data, only reserve the middle 20 seconds which contains 2560 time points. We made digital filtering using wavelet packet decomposition[6], keeping β band signal of 13-30Hz, and calculated the ApEn and SampEn of each data segment after filtering.

Kolmogorov-Smirnov (K-S) test which is an effective, stable nonlinear test measure unit can figure out whether there're significant differences in the overall distribution of two groups of samples[9]. So, we analyzed the electrode which has significant differences in the data of HAHV and HALV, using the K-S double sample test. There showed no electrodes with significant differences ($P<0.5$) when analyzing the ApEn, while showed electrodes with significant differences when analyzing the SampEn. The distribution of the electrodes was as the TABLE 1 shows.

The experiment results showed that no electrodes obviously related to emotion activities can be found when analyzing the significant difference of each electrode using ApEn. While the brain region where electrodes of F3, CP5, FP2, Fz and FC2 stay was found to be obviously related to the emotion activities. And these electrodes have significant differences under HAHV and HALV.

TABLE 1 : Electrodes with significant difference between SampEn of emotion labeled with HAHV and HALV

Electrode number	Channel name	P
3	F3	0.037068
9	CP5	0.037068
17	Fp2	0.042291
19	Fz	0.028289
23	FC2	0.037068

Experiment 2

Data 2

Both the alcoholics' and controls' EEG data sets used in this paper are the public data sets of the University of California[17]. 122 persons received the test and each was tested 120 times. In each of the test, the subjects were exposed to visual stimuli pictures chosen from 1980 Snodgrass and Vanderwart picture sets. In this experiment, 64 electrodes were placed in the subjects' heads in accordance with international standards, the sampling frequency of the facility was 256Hz and 1 sec data for each trial was recorded. Because the EEG signals of the data set are not complete, the complete data of 30 alcoholic subjects and 30 controls are chosen in random as the EEG data used in this study[5,20].

Result 2

First of all, calculate the ApEn and SampEn values respectively using the 64 electrodes EEG data of the fiftieth trail of the selected 60 subjects. Secondly, analyze the significance of difference of ApEn and SampEn of each electrode ($P<0.05$) using K-S test, and record the electrodes with significant difference. Then, according to the results of K-S test, choose ApEn and SampEn of electrodes with difference significant respectively to form feature vectors. Finally, use SVM-Weight algorithm to classify the alcoholics and controls, and adopt the 3-fold cross-validation and LOPO (Leave One Person OUT) as two authentication methods.

Figure 1 illustrates the experiment results of 20 times 3-fold cross-validation. The average accuracy was 74.25% taking the ApEn as features and was 80.25% taking SampEn as features in the 3-fold cross-validation.

60 LOPO verifications were done to 60 subjects in this experiment, the average classification accuracy as shown in TABLE 2. The average accuracy was 70% taking ApEn as features and was 73.33% taking

FULL PAPER

SampEn as features.

Comparison of time complexity

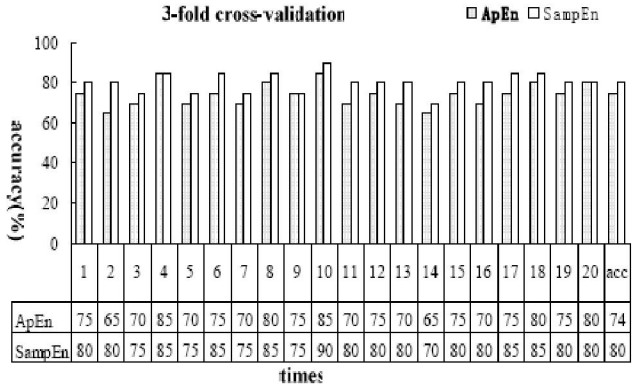

Figure 1 : Result of 3-fold cross-validation

TABLE 2 : Average accuracy of 60 times cross-validation based on leave one person out (LOPO)

Type of algorithm	ApEn	SampEn
Average accuracy (%)	70	73.33

The 64-electrodes EEG data of alcohol addict co2a0000364 in 001 trial was used as test data to analysis time complexity of the two algorithms. ApEn and SampEn values were respectively calculated basing on this test data. Figure 2 reflects the 10 computing times of ApEn and SampEn in this experiment.

As can be seen from Figure 2, for the same test data, the computation time of SampEn was almost a half of computation time of ApEn.

DISCUSSION

The result of experiment 1 shows that SampEn can detect the electrodes with differences, that is, the SampEn of F3, CP5, FP2, FZ, FC2 has significant differences, and these electrodes are mostly located in prefrontal. The conclusion consists with conclusions of previous studies. Petrantonakis and Hadjileontiadis[12] used the signals of FP1, FP2, F3, F4 electrodes to recognize emotions. Hosseini and Naghibi[8] used the EEG signals in five channels (FP1, FP2, T3, T4 and Pz) to recognize emotions and achieved better results. Hoseingholizade et al.[7] also confirmed another nonlinear index—correlation dimension has a significant difference in FP2, F3, FZ electrodes under different emotions.

The classification result of experiment 2 shows that

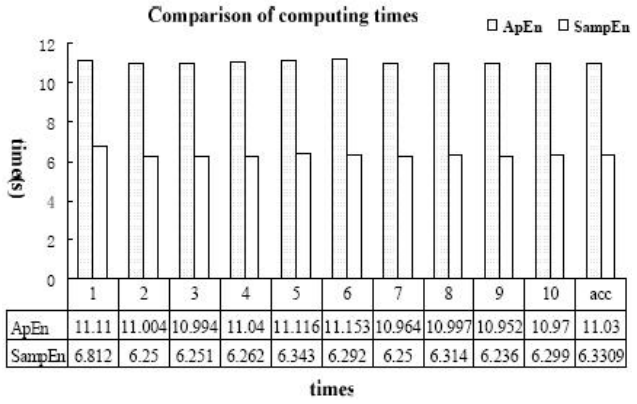

Figure 2 : Comparison of computing times of ApEn and SampEn

the average accuracy when using ApEn or SampEn as feature is higher than in random level. It indicates that the electrodes with significant differences using ApEn and SampEn can both distinguish alcoholics from controls. But taking 3-fold cross-validation and LOPO validation, the classification accuracy of using SampEn as feature is higher than that of using ApEn as feature, which indicates that SampEn as feature is more suitable to identify alcoholics and controls. In addition, the result of LOPO validation shows that the average accuracy of is 73.33% using sample entropy to identify alcoholics subjects and controls, which indicates that this method has certain generalization ability.

From the results of comparison of computing times, the computation efficiency of SampEn is higher than ApEn. The experiment result consists with the theoretical result.

The conclusion drawn in this paper consists with the previous studies. The study of Roldan et al.[15] pointed out that SampEn and ApEn both can explicitly distinguish the EEG signals of epileptics from normal people. But when the sample loses in large scale, the SampEn shows stronger ability than ApEn. Bai et al.[3] pointed out that the ApEn and SampEn would explicitly decrease during epileptic seizure, but the decrease scale of SampEn obviously larger than ApEn, and comparing to the ApEn, the decrease scale of SampEn evaluated 15%-20%.

CONCLUSION

This paper makes comparative study on the ApEn and SampEn algorithms, and further makes compara-

tive study on the ApEn and SampEn as EEG features basing on two groups of public EEG data sets. The experiment results show that using SampEn as feature can better reflect the active brain regions controlling the emotion activities than ApEn; using SampEn as classification feature vector can better identify alcoholics and normal persons than using ApEn. The result of the LOPO validation experiment also indicates that using SampEn as feature to distinguish alcoholics from controls has certain generalization ability. Meanwhile, for the same test data, the computational efficiency of SampEn is higher than ApEn. Therefore, we can give priority to SampEn in analyzing EEG data, especially a large amount of EEG data. Of course, further comparative studies on ApEn and SampEn of EEG signal in other fields should be continued, in order to support the paper's conclusion that the SampEn is more suitable as EEG feature than ApEn.

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