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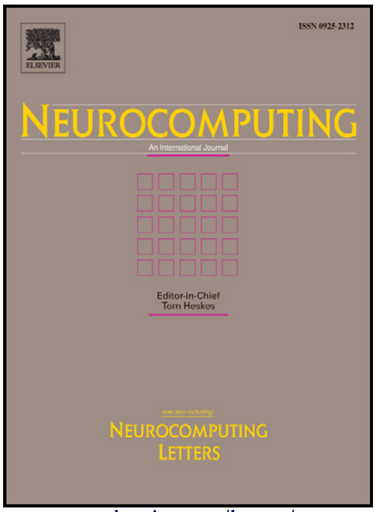

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Automatic detection of absence seizures with compressive sensing EEG

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Abstract

Absence epilepsy, a neurological disorder, is characterized by the recurrence of seizures, which have serious impact on the sufferers' daily life. The seizure detection has a great importance in the diagnosis and therapy of epileptic patients. Visual inspection of the electroencephalogram (EEG) signals for detection of interictal, pre-ictal and ictal activities is a strenuous and time-consuming task due to the huge volumes of EEG segments that have to be studied. In this study, we proposed a novel automatic detection method based on the altered compressibility of EEG during the three states with compressive sensing. To evaluate the proposed method, segments of interictal, pre-ictal and ictal EEG segments (100 segments in each state) were used. Two entropies, namely the Sample Entropy (SE) and the permutation Entropy (PE), and Hurst Index (HI) were extracted respectively from the segments to compare with the proposed method. Significant features were selected using the ANOVA test. After evaluating the performance of the selected features by four classifiers (Decision Tree, K-Nearest Neighbor, Discriminant Analysis, Support Vector Machine) respectively, the results show that the proposed method can achieve the highest accuracy of 76.7%, which is higher than HI (55.3%), sample entropy (71%), and permutation entropy (73%). Hence, the altered compressibility of EEG with CS can act as a good biomarker for distinguish seizure-free, per-seizure and seizure state. In addition, compressive sensing requires less energy but has competitive compression ratio compared to traditional compression techniques, which enables our method to tele-monitoring of epilepsy patients using wireless body-area networks in personalized medicine.

Keywords:

EEG; Absence Seizure; Compressive Sensing; Permutation Entropy; Classification

Introduction

Absence epilepsy is a common form of epilepsy, accounting for 10-17% of all cases of epilepsy diagnosed in school-aged children [1, 2]. Absence seizures are short in duration from few seconds to around a minute of impaired consciousness without major motor symptoms and may recur over 100 times a day, which would have significant impact on the educational development of sufferers [3]. Therefore, novel therapeutic approaches are urgently being sought to prevent seizure occurrence. Nowadays, surgery and stimulation methods have recently gained greater prominence and detection of absence seizures is the basis for these methods. Thus it is critical to find biomarkers which can be used to discriminate seizure-free, pre-seizure and seizure state for the patients with epilepsy.

EEG as a non-invasive recording of electrical activity from the scalp has become one of the most useful tools for studying the cognitive processes and the physiology/pathology of the brain, especially the processes involved in absence seizures [4-7]. Epileptic seizure detection techniques for finding the modification of EEG-based indexes can be divided into four categories: time domain, frequency domain, time-frequency domain, and nonlinear methods [8-11]. The time domain method searches for periodic, rhythmic patterns in EEG for the seizure state and provides a measure for rhythmicity [12]. In the frequency domain, seizure detection relies on the differences in the frequency domain characteristics of EEG [13], such as the 3–4 Hz spike-and-wave discharges (SWD) in EEG during the seizure state. Wavelet transform as a typical time-frequency method has also been used to capture and localize transient features like the epileptic spikes [14]. Nonlinear measures, such as sample entropy (SE) [15] and permutation entropy (PE) [16], can quantify the complexity of a time series and be used to track transient dynamics of EEG recordings.

In clinical application, portable EEG systems based on wireless sensors can be used for long term remote monitoring the patients provided they can solve technological problems (miniaturization and energy efficiency) [17]. In order to reduce airtime energy-hungry wireless links, data compression methods are used to compress EEG signal and then transmit. In this paper, the compression problem is viewed from a different perspective: the compressive systems not only reduce the throughput data but also discriminate seizure-free, pre-seizure and seizure state for the patients with epilepsy. A similar study has been applied to distinguish among patients with Alzheimer disease (AD), mild cognitive impaired (MCI) subjects and normal healthy elderly [18, 19]. And their result first showed that the compressibility can be a good marker to differentiate AD EEG from both MCI and healthy controls.

In this paper, we take full advantage of the altered compressibility of EEG in the transition of brain activities towards an absence seizure with compressive sensing (CS) [20] to discriminate seizure-free, pre-seizure and seizure state. The EEG in the seizure state exhibits three characteristics that make them reliable to be compressed: lower frequency (increase of relative power of delta and theta) [21], decreased complexity (increase of regularity/predictability) [22, 23], and stronger synchronization among multi-channel EEG recordings [24]. The CS adopted here, as an emerging data compression methodology, has superior performance to other conventional data compression methods such as wavelet compression in compressing non-sparse EEG signals [25]. Besides, compared to wavelet compression, CS can reduce energy consumption while achieving competitive data compression ratio [26], which enables our method for tele-monitoring patients with epilepsy through wireless body-area networks in personalized medicines.

The rest of the paper is organized as follows. Section II briefly introduces the CS methodology. Section III presents the experiments and results. The last section discusses the results and concludes the paper.

Methods

Compressive sensing (also known as compressed sensing) [20] is a signal processing technique for efficiently acquiring and reconstructing a signal. This method takes advantage of the signal's sparseness or compressibility in some domain, allowing the signal to be represented by relatively few measurements in that domain. This section mainly discusses the key theoretical concepts of CS method.

Signal sparsity

Using $N \times N$ basis matrix (also known as dictionary matrix) $\Psi = [\boldsymbol{\psi}_1 \mid \boldsymbol{\psi}_2 \ldots \mid \boldsymbol{\psi}_N]$ with the vectors $\{\boldsymbol{\psi}_i\}$ as columns, a one-dimensional discrete-time signal $\boldsymbol{x}$ of length N (viewed as an $N \times 1$ column vector) can be expressed as

$$\boldsymbol{x} = \Psi \boldsymbol{s} = \sum_{i=1}^{N} s_i \boldsymbol{\psi}_i$$

where $\boldsymbol{s}$ is the $N \times 1$ column vector of weighting coefficients. Clearly, $\boldsymbol{x}$ and $\boldsymbol{s}$ are equivalent representations of the signal, with $\boldsymbol{x}$ in the time and $\boldsymbol{s}$ in the Ψ domain.

The signal $\boldsymbol{x}$ is *K-sparse* if it is a linear combination of only *K* basis vectors, which means that only *K* of the s_i coefficients in (1) are nonzero and (*N*−*K*) are zero. In the practical application, signal $\boldsymbol{x}$ is compressible if $\boldsymbol{s}$ in the formula (1) has just a few large coefficients and many small coefficients.

Signal compression and reconstruction

The compressive sensing employs non-adaptive linear projections that preserve the structure of the signal, and the signal is then reconstructed from these projections using an optimization process [20].

In the compression system, a signal of length N, denoted by $\boldsymbol{x} \in \mathbb{R}^{N\times 1}$, is compressed by CS with a full row-rank matrix, denoted by $\Phi \in \mathbb{R}^{M\times N} (M \ll N, \mathrm{Rank}(\Phi) = M)$ as follows:

$$\boldsymbol{y} = \Phi \mathbf{x}$$

where $\boldsymbol{y}$ is the compressed data, and Φ is called the measurement matrix, which is set in advance. CS algorithms use the compressed signal $\boldsymbol{y}$ and the sensing matrix Φ to reconstruct the original signal. The accuracy of the reconstructed signal directly relies on the key assumption that the original signal is *K-sparse* ($K \ll N$). When this assumption does not hold, such as EEG, we can seek a dictionary matrix, denoted by $\Psi \in \mathbb{R}^{N\times N}$, so that $\boldsymbol{x}$ is *K-sparse* ($K \ll N$) in this Ψ domain. Then the CS model can be re-written as

$$\boldsymbol{y} = \Phi\Psi\boldsymbol{s} = \Theta\mathbf{s}$$

where $\Theta = \Phi\Psi \in \mathbb{R}^{M\times N}$.

In the reconstruction system, CS algorithms can firstly recover $\boldsymbol{s}$ using $\boldsymbol{y}$ and Θ, and then recover the original signal $\boldsymbol{x}$ by $\boldsymbol{x} = \Psi\boldsymbol{s}$. While the compression system is largely underdetermined ($M \ll N$ in (2) and (3)), there is an infinite number of $\boldsymbol{x}$ for a given $\boldsymbol{y}$. However, since the signal $\boldsymbol{x}$ we wish to reconstruct is *K-sparse*, CS algorithms thus aim to find the sparest solution. This corresponds to solve the following ℓ_0 optimization problem [27]:

$$\min_{\boldsymbol{s}} \|\boldsymbol{s}\|_0 \; \textit{subject to} \; \boldsymbol{y} = \Theta \mathbf{s} \qquad (4$$

where the ℓ_0 norm $\|\cdot\|_0$ counts the number of non-zero entries in $\boldsymbol{s}$.

Incoherent Measurement matrix

The minimum acceptable M that allows perfect reconstruction of signal $\boldsymbol{x}$ is not only related to the sparsity K of $\boldsymbol{x}$ in the dictionary matrix Ψ, but also to the coherence μ between Φ and Ψ. The coherence measures the largest correlation between any two elements of Φ and Ψ, which is defined as follows:

$$\mu(\Phi, \Psi) = \sqrt{N} \cdot \max_{1 \le i, j \le N} \left| \phi_i, \boldsymbol{\varphi}_j \right| \qquad (5)$$

And if

$$M \ge C \cdot \mu^2 (\Phi, \Psi) \cdot K \cdot \log N$$

for some positive constant C, the solution to (6) is exact with overwhelming probability. Therefore, the smaller the coherence, the smaller the value of M can be.

In order to construct an ideal measurement matrix Φ, one should have a hard search based on the dictionary matrix Ψ. Fortunately, incoherence can be guaranteed with high probability by selecting Φ as a random matrix [20]. In practical application, the random matrix Φ is often generated by independent and identically distributed Gaussian random variables or by Bernoulli random variables [28].

Experiments and Results

EEG recordings

EEG recordings were obtained from nine patients (five males and four females) aged from 8 to 21 years old with absence epilepsy. The study protocol had taken consent from the ethics committee of Peking University People's Hospital and the patients had signed informed consent that their clinical data might be used and published for research purposes. The EEG data were recorded according to the sites defined by the standard 10-20 international system at a sampling rate of 256 Hz by the Neurofile NT digital video EEG system. Nineteen electrodes were used and the impedance levels were set at less than 5 kΩ and they were filtered with a frequency band of 0.5 and 35 Hz which include the relevant bands of absence EEG recordings.

For the investigation in present work, interictal, pre-ictal, and ictal EEG epochs were selected and dissected from seizure-free, pre-seizure and seizure states respectively. The timing of onset and offset in spike-wave discharges (SWDs) was identified by an epilepsy neurologist, and these SWDs were defined as large-amplitude rhythmic 3-4 Hz discharges with typical spike-wave morphology lasting >1.0 s [29]. Just 2 seconds of EEG recordings were dissected for our study because 1) it is clinically difficult to obtain long EEG recordings during absence seizures; and 2) the duration of the pre-seizure state is only about a few seconds as determined from the rat model [30]. The artifact EEG epochs were rejected by the epilepsy neurologist and only the artifact-free epochs were used to analyze. At last, each state contains 100 EEG epochs of 2s duration.

Characteristics of Absence EEG

This section mainly investigates the characteristics of inter-ictal, pre-ictal and ictal EEG and pays the way for distinguishing three states by our proposed method.

(1) Slow effect of absence EEG

To investigate the spectral power distribution of EEG in these three seizure states, relative spectral power is computed by for four frequency bands: delta (1-4 Hz), theta (4-8 Hz), alpha (8-12 Hz), and beta (12-30 Hz). For a time course $x(t)$, power spectral density is obtain by the Fast Fourier Transform and the spectral power (P_{band}) in each frequency band can be calculated by integrating the power in the corresponding band from the power spectral density. The relative band spectral power can be calculated as P_{band} /P_{all}, where P_{all} is the spectral power in the band of 1-30 Hz.

The relative spectral power in four frequency bands for inter-ictal, pre-ictal and ictal EEG were the average result of all channels across all subjects and showed in Fig.1 (A). As illustration in the Fig.1 (A), the delta relative power in the ictal EEG occupying about 78% of the total power is the overwhelmingly dominant in the frequency band of 1-30 Hz, which is obviously higher than the delta relative power in both interictal (38%) and pre-ictal (43%) EEG. On the contrary, relative powers of ictal EEG in other band are obvious lower than both pre-ictal and interictal EEG. The one-way ANOVA tests also show that the pre-ictal EEG has significant higher delta (F (1,198) = 22.6, p < 0.05) and theta (F (1,198) = 18.9, p < 0.05) relative power than interictal EEG. And the beta relative power in the pre-ictal EEG is significant lower than interictal EEG (F (1,198) = 163, p < 0.05). In other words, a 'global' spectral power shifts to lower frequencies from interictal to pre-ictal and to the ictal state in turn.

(2) Enhanced sparsity of absence EEG

Continuous wavelet transform is adopted to analyze the time-frequency feature of the inter-ictal, pre-ictal and ictal EEG. The db4 is used here and the time-frequency distributions of the wavelet coefficients for representative channel EEG in three states are illustrated in the central plot of Fig. 1 (B), (C) (D) respectively. All the representative EEG segments are selected from channel C3 for illustration as this channel has shown significant different among the three states in our pervious study [23]. Time evolution of the original EEG is showed below the time-frequency plot. The box-plots on the left of time-frequency plots are the power spectral density (PSD) of the original signal.

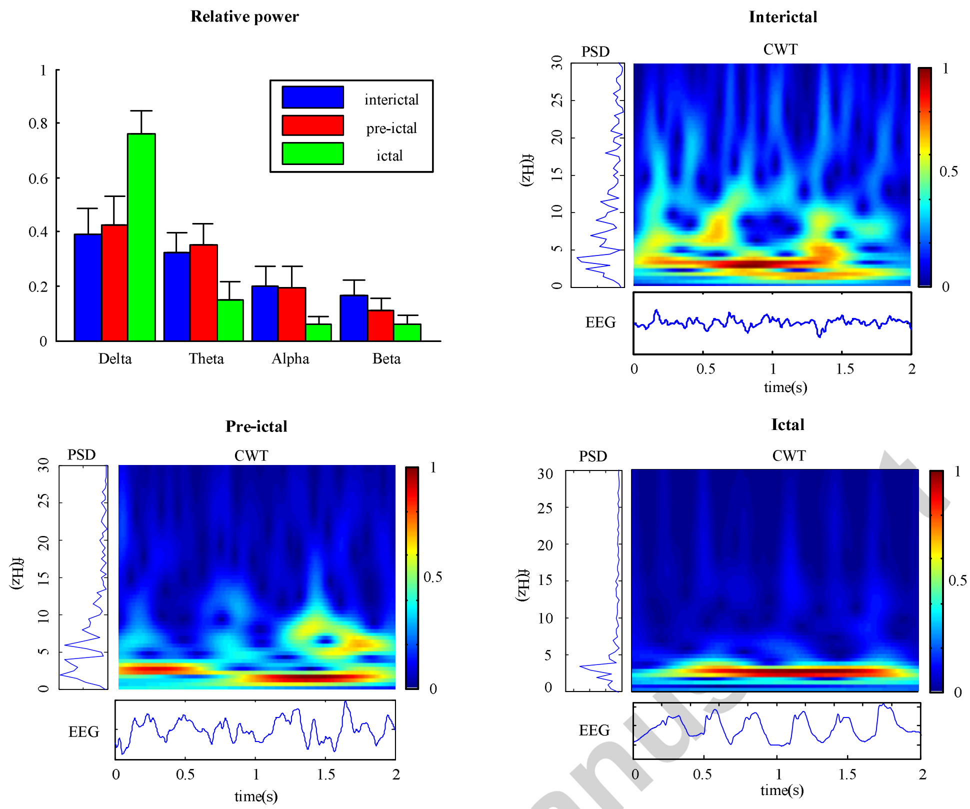

Fig.1. Characteristics of interictal, pre-ictal and ictal EEG. (A) The relative power of four frequency bands for the three states. (B), (C) and (D) are the time-frequency plots for three EEGs in the three seizure states respectively.

From the time-frequency plots in Fig. 1, it is easily seen that most of the power in pre-ictal and ictal EEG is concentrated in low-frequency bands and time-frequency plots of these two states are highlighted in the presence of characteristic “bumps” [31]. Therefore, the number of significant wavelet coefficients reduces in both pre-ictal and ictal EEG, which also means that the sparsity of these two states based on wavelet enhances relative to the interictal EEG. To quantify the sparsity of three states of EEG, a thresholding-based DWT compression algorithm is adopted [32], which just retains the significant wavelet coefficients above some presetting threshold to reconstruct the original signal. When the normal mean square error between the original signal and the reconstructed signal is 0.1, the number of wavelet coefficients of intericatal, pre-ictal and ictal EEG to be retained are $(45.72 \pm 3.42)\%$, $(38.9 \pm 5.55)\%$ and $(29.0 \pm 4.40)\%$ respectively. Thus, the sparsity of EEG largely varies among those three states as hypothesized (ANOVA test, $p < 0.05$).

Compressibility of Absence EEG with CS

Compressive sensing is applied to analyzing the compressibility of interictal, pre-ictal and ictal EEG. We choose the Gabor wavelet dictionary (Gaussian envelope sinusoids) as the dictionary matrix [33] and the sparse binary matrix generated by Bernoulli random variables as the measurement matrix [34]. Block Sparse Bayesian Learning (BSBL) algorithm [17] is adopted to reconstruct the original signal, which has been shown good performance for the non-sparse EEG. We adopt two performance metrics to quantify the compressibility (recovery quality) of the EEG during different states. The first one is the Normalized Mean Square Error (NMSE), defined as $\|x-\hat{x}\|_2^2/\|x\|_2^2$, where $\hat{x}$ is the reconstruction of original signal x. And the second one is the Structure SIMilarity (SSIM) [35], which may be a better performance metric than the NMSE to measures the similarity between structured signals (such as EEG). The range of SSIM metric is between -1 and 1, and higher SSIM means better reconstruction quality.

To effectively investigate the compressibility of EEG in three states, the compression ratio (*cr*) is set in the range from 2 to 10, and the recovery quality of interictal, pre-ictal and ictal EEG measured by NMSE and SSIM with the increase of compression ratio is illustrated in the Fig.2. As we can see, the compression loss of interictal EEG increases at the fastest rate with the increase of compression ratio, and the slowest is the ictal EEG, and the pre-ictal EEG is always in the middle. In other words, both the NMSE and SSIM metrics show that the ictal EEG is the most compressable, followed by the pre-ictal EEG and then the inter-ictal EEG. Hence, there exists altered compressibility of EEG in the transition of brain activities towards an absence seizure with compressive sensing.

Then, in order to investigate whether these observed differences are significant, the one-way ANOVA test is performed for EEG compressibility distributions over the three states in the compression ratio range from 2 to 10. The statistical test shows that all the compressibility distributions over the three states are significantly different at the level of $p < 0.01$ and the most significant is at the compression ratio 7 for both NMSE (F (2, 297) =298, p<0.001) and SSIM (F (2, 297) =332, p<0.001). In addition, the ANOVA test to all pairwise comparisons between the compressibility of the three states for each compression ratio suggests that the average compressibility for the pre-ictal EEG is significantly lower than ictal EEG, but significantly higher than interictal EEG.

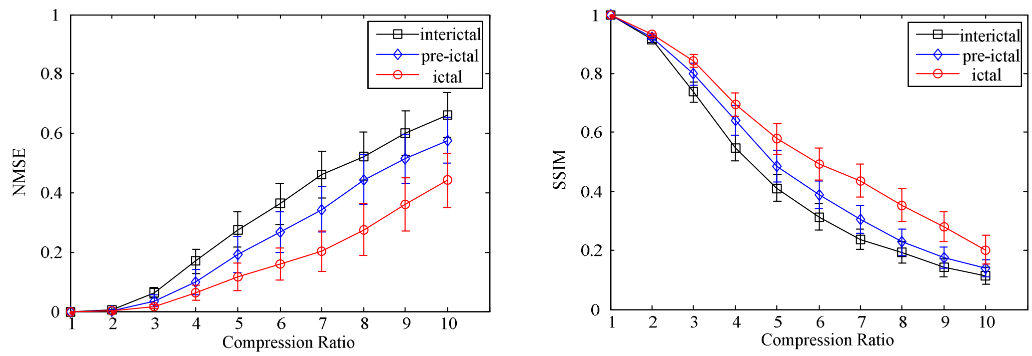

Fig. 2. Compressibility of interictal, pre-ictal and ictal EEG measured by NMSE and SSIM with the increase of compression ratio.

Classification of Absence EEG

As the compressibility is significant different among the interictal, pre-ictal and ictal EEG, we can choose a proper compression ratio to compress the EEG data and distinguish the corresponding state based on their different compressibility. From the section of the above, we can find that the difference among the compressibility of the three kinds of EEG reaches the most significantly state at compression rate 7 for both NMSE and SSIM measures. So the compression ratio 7 is chosen as the best candidate for compressive sensing to distinguish the three kinds of EEG. We defined here the compressibility of EEG measured by NMSE and SSIM with compressive sensing as CS-NMSE and CS-SSIM respectively.

To evaluate the distinguish ability of the altered EEG compressibility for the three states, we test our proposed features against other dominant features, including hurst index (HI) [36], sample entropy (SE) [15] and permutation entropy (PE) [16], in terms of seizures detection. To classify the EEG of three states with these features, we use four classifiers namely decision tree (DT) [37], K-nearest neighbor (KNN) [38], discriminant analysis (DA) [39], and support vector machine (SVM) [40]. The value of K in KNN is 5. The type of DA is quadratic. And the SVM type is nu-support vector classification (nu-SVC). In order to develop robust classifiers, we choose the ten-fold cross validation data resampling technique for training and testing the classifiers. The classification accuracy is used as a metric for evaluating the performance of these approaches.

Table 1 shows the results of accuracy recorded by the four classifiers using all the 5 features. Our results show that both CS-NMSE and CS-SSIM have competitive distinguish ability, which are remarkable superior to hurst index and outperform the sample entropy and the permutation entropy. In addition, we also can find that the discriminant analysis classifier performs better than the other classifiers by registering accuracy 74.3% for CS-NMSE and 76.7% for CS-SSIM, both of which are higher than HI (55.3%), sample entropy (71%), and permutation entropy (73%).

Table 1. The accuracy value recorded by four classifiers using all five features for training and testing.

	HI	**SE**	**PE**	**CS-NMSE**	**CS-SSIM**
DT	(51±5.0)%	(67±3.7)%	(69.3±3.1)%	(70.5±3.0)%	(71.8±2.8)%
KNN	(50.7±4.1)%	(68.7±3.6)%	(70.3±2.5)%	(71.7±2.7)%	(72.1±2.3)%
DA	(55.3±3.3)%	(71±2.8)%	(73±2.1)%	(74.3±2.6)%	(76.7±2.3)%
SVM	(51.6±4.7)%	(65.5±3.4)%	(71.3±2.2)%	(72.2±2.9)%	(74.3±2.5)%

Discussion and conclusion

The EEG signal is a measure of the summed activities of approximately 1—100 million neurons lying in the vicinity of the recording electrode. Since it may provide insight into the dynamics of the brain [41], various methods have been proposed to understand the mechanisms of absence seizure with EEG recordings. In this work, the spectral power distributions of EEG show that a ‘global’ spectral power shifts to lower frequencies from interictal to pre-ictal and to the ictal state in turn, which is in agreement with earlier studies that slow effect occurs in both before and during the ictal states [42]. And the investigation of compressibility of EEG exhibits enhanced compressibility characteristics from interictal to pre-ictal and to ictal EEG. Combined with sparsity analysis EEG with wavelet, we can find that the compressibility of EEG are significantly correlated with low frequency relative power (delta and theta) and inversely correlated with high-frequency relative power (beta). Our previous analysis about dynamic changes of absence EEG by PE has demonstrated that pre-ictal EEG exhibit lower complexity than interictal EEG, but higher than that in ictal EEG [22, 23]. The reduction of complexity from the seizure-free state to seizure state is also the result of the well-known slowing effect of EEG [43]. Therefore, there is also a significant correlation between the complexity modification and altered compressibility in the EEG signal when the brain switches from normal to absence seizure state.

The altered EEG compressibility was then used as feature to classify EEG in the three states. To evaluate the distinguish ability of EEG compressibility, we compared it with other dominant features, including hurst index, sample entropy and permutation entropy, in terms of seizures detection. Four classifiers namely decision tree, K-nearest neighbor, discriminant analysis, and support vector machine were used to classify the three states with these features. All the results of four classifiers consistently show that both CS-NMSE and CS-SSIM have competitive distinguish ability, which are remarkable superior to hurst index and outperform sample entropy and permutation entropy. Hence, we can conclude that the altered compressibility of EEG with CS would act as a good biomarker for distinguish seizure-free, per-seizure and seizure state.

In addition, compressive sensing requires less energy but has competitive compression ratio compared to traditional compression techniques [17], which enables our method to tele-monitoring of epilepsy patients using wireless body-area networks in personalized medicine. Of course, the results here described are limited to the available database and it is the intent of future studies to test our method with a larger database and cross-validate its performance with multiple independent databases. In future works, in order to assess the robust of the proposed method, we will investigate the effect of artifact on our method for detecting the absence seizures. And compressive sensing based on multivariate technique [44] will also be used to optimize our method, which can recover multichannel signals with both the temporal correlation within each channel signal and inter-channel correlation among different channel signals.

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Conflict of Interest Statement

None Declared.

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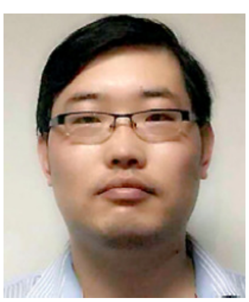

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