Neurocomputing 171 (2016) 497–502

Contents lists available at ScienceDirect

Neurocomputing

journal homepage: www.elsevier.com/locate/neucom

Automatic detection of absence seizures with compressive sensing EEG

Ke Zeng [a,b], Jiaqing Yan [c], Yinghua Wang [a,b], Attila Sik [d], Gaoxiang Ouyang [a,b,*], Xiaoli Li [a,b]

[a] State Key Laboratory of Cognitive Neuroscience and Learning & IDG/McGovern Institute for Brain Research, Beijing Normal University, Beijing 100875, China
[b] Center for Collaboration and Innovation in Brain and Learning Sciences, Beijing Normal University, Beijing 100875, China
[c] Institute of Electrical Engineering, Yanshan University, Qinhuangdao 066004, China
[d] College of Medical and Dental Sciences, University of Birmingham, Vincent Drive, Birmingham B15 2TT, UK

ARTICLE INFO

Article history:
Received 21 October 2014
Received in revised form
27 April 2015
Accepted 27 June 2015
Communicated by Dr. S. Hu
Available online 18 July 2015

Keywords:
EEG
Absence seizure
Compressive sensing
Permutation entropy
Classification

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.

1. 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

* Corresponding author at: State Key Laboratory of Cognitive Neuroscience and Learning & IDG/McGovern Institute for Brain Research, Beijing Normal University, Beijing 100875, China. Tel.: +86 10 58802032.
E-mail address: ouyang@bnu.edu.cn (G. Ouyang).

http://dx.doi.org/10.1016/j.neucom.2015.06.076
0925-2312/

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 2 briefly introduces the CS methodology. Section 3 presents the experiments and results. Section 4 discusses the results and concludes the paper.

2. 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.

2.1. Signal sparsity

Using $N \times N$ basis matrix (also known as dictionary matrix) $\boldsymbol{\Psi} = [\boldsymbol{\psi}_1 | \boldsymbol{\psi}_2 \dots | \boldsymbol{\psi}_N]$ 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

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

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.

2.2. 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:

$$\boldsymbol{y} = \Phi \mathbf{x} \tag{2}$$

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

$$\boldsymbol{y} = \Phi \Psi \boldsymbol{s} = \Theta \mathbf{s} \tag{3}$$

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]:

$$\min_{\boldsymbol{s}} \boldsymbol{s}_0 \ \text{subject to} \ \boldsymbol{y} = \Theta \mathbf{s} \tag{4}$$

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

2.3. 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:

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

and if

$$M \ge C \le \cdot \mu^2(\Phi, \Psi) \cdot K \cdot \log N \tag{6}$$

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].

3. Experiments and results

3.1. 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