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L1-norm Minimization based Sparse Approximation Method of EEG for Epileptic Seizure Detection

Younghak Shin* and Jin-Taek Seong**

Abstract Epilepsy is one of the most prevalent neurological diseases. Electroencephalogram (EEG) signals are widely used for monitoring and diagnosis tool for epileptic seizure. Typically, a huge amount of EEG signals is needed, where they are visually examined by experienced clinicians. In this study, we propose a simple automatic seizure detection framework using intracranial EEG signals. We suggest a sparse approximation based classification (SAC) scheme by solving overdetermined system. L1-norm minimization algorithms are utilized for efficient sparse signal recovery. For evaluation of the proposed scheme, the public EEG dataset obtained by five healthy subjects and five epileptic patients is utilized. The results show that the proposed fast L1-norm minimization based SAC methods achieve the 99.5% classification accuracy which is 1% improved result than the conventional L2 norm based method with negligibly increased execution time (42msec).

Key Words : epilepsy, overdetermined system, L1-norm minimization, seizure detection, sparse representation

1. Introduction

Epilepsy is a condition characterized by repeated seizures due to a disorder in the brain cells. It is one of the most common chronic neurological disorders and affects people of all ages. Approximately 50 million people worldwide have epilepsy [1]. Epileptic seizures reflect the signs of an excessive and hypersynchronous activity of neurons in the brain [2]. It can be observed by brain signals such as electroencephalogram (EEG). EEG signals are recorded on the scalp, which provides the electrical brain activity generated by billions of neurons and glia cells.

The surface-recorded EEG is a clinical standard for confirming epileptic activity [3] and localization of the epileptic focus [2]. Further, intracranial EEG (iEEG) which is observed by implanted electrodes can be used for pre-surgical evaluation of epilepsy patiens [4]. However, massive amount of EEG recordings is visually examined by highly trained professionals for diagnosis of epileptic seizure in general. This process is time-consuming, error-prone, and expensive. Therefore, computer-aided automatic detection of epileptic seizure can help clinicians reduce their miss detection rate.

EEG based epileptic seizure detection has been widely studied for many years. To address variations of signal amplitude and frequency, line length feature was adopted with low computational cost [5]. Nonlinear features such

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*AIBigdata Research Center, LGCNS
**Corresponding Author : Department of Convergence Software, Mokpo National University (jtseong@mokpo.ac.kr)
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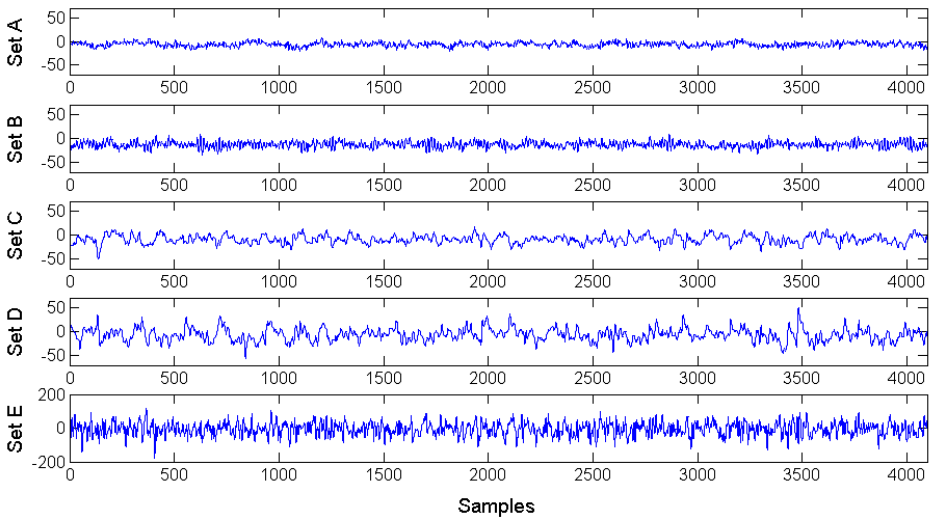

Fig. 1. One segment example of 23.6-sec EEG time samples (4097 samples) for five datasets (sets A-D). Sets A and B obtained from normal EEG segment during eyes open and closed respectively. Sets C, D and E obtained from iEEG segment during seizure activity within the epileptogenic zone (set E), and seizure-free intervals within the epileptogenic zone (set C) and opposite the epileptogenic zone (set D). The amplitude unit for all five datasets is microvolt.

as approximate entropy [6], largest Lyapunov exponent [7] and empirical mode decomposition (EMD) [8] were applied for automatic seizure detection problem.

In this study, we propose a sparse approximation based classification (SAC) scheme by solving a sparse representation of test samples using a collection of training samples. We adopt fast L1-norm minimization algorithms such as Homotopy [9] and FISTA [10] for sparse representation. In the proposed detection scheme, the conventional hand-craft feature extraction and/or dimensionality reduction methods are not needed. Therefore, we can save the time cost for those steps and parameter optimizations. In addition, thanks to the fast L1-norm minimization algorithms within the proposed scheme, the processing time for each testing is very fast and real-time detection can be applicable in practice.

To evaluate the proposed method we compare classification performance in terms of accuracy, sensitivity, specificity and computation time between the proposed SAC and conventional L2-norm based least square approximation methods.

2. Material and Methods

2.2 Clinical Data

The dataset used in this study was obtained from the Department of Epileptology, Bonn University, Germany. This dataset is publicly available, where detailed information is provided in [5]. The complete dataset consists of five sets (A-E), each containing 100 single-channel EEG segments of 23.6-sec duration. These segments were randomly selected and cut out from continuous multichannel EEG recordings from multi subjects.

Figure 1 visualizes the example segments of five datasets. The first two sets, A and B, consisted of surface EEG segments that are collected from five healthy subjects using a standardized electrode placement scheme. Sets A and B contain EEG segments when the subjects are relaxed and awake state with eyes open and eyes closed respectively. The data sets C, D and E consisted of intracranial EEG (iEEG) recordings of five epileptic patients undergoing pre-surgical diagnosis. For the sets C and D, iEEG recordings are performed during seizure-free intervals (interictal periods) using depth electrodes placed within the epileptogenic zone and opposite the epileptogenic zone at the symmetric hippocampal formations in brain respectively (see Figure 2 of [4]). On the other hand, data set E was recorded during the seizure activity (ictal periods) from within the epileptogenic zone.

All data sets were recorded with the same 128-channel amplifier system using an average common reference and digitized at 173.61 samples per sec using 12-bit resolution. Using a fourth order Butterworth filter we perform the band pass filtering with 0.1-49 Hz cutoff frequencies.

2.2 Sparse Representation based Classification

Here we briefly introduce general framework of the sparse representation based classification (SRC) scheme. The basic idea of SRC is aiming to find most compact representation of a testing sample $\mathbf{y} \in \mathbb{R}^m$ via the so-called sparsification (or sparse representation) $\mathbf{y} = \mathbf{Ax},$ step, i.e., where is a training dictionary. Each component $\mathbf{A} = [\mathbf{A}_1, \mathbf{A}_2, ..., \mathbf{A}_C] \in \mathbb{R}^{m \times Cn}$ $\mathbf{A}_i := [\mathbf{a}_{i,1}, \mathbf{a}_{i,2}, ..., \mathbf{a}_{i,n}] \in \mathbb{R}^{m \times n}$ matrix consists of n training samples $\mathbf{a} \in \mathbb{R}^{m \times 1}$ of class $i = 1, 2, ..., C$. Usually feature extraction and/or dimensionality reduction method is applied to original high-dimensional signal space to form low-dimensional feature space. Therefore, the number of column Cn in A is much larger than the feature dimension m, i.e., A is an overcomplete dictionary. To solve the sparsification step of a testing sample with a given dictionary, following formulation can be used [11]:

$$\min_{\mathbf{x}} \|\mathbf{x}\|_1 \text{ subject to } \mathbf{y} = \mathbf{Ax}. \tag{1}$$

After finding the sparse coefficient vector x by the sparsification step, the class label of the testing sample can be determined via a simple identification step:

$$\text{class }(\mathbf{y}) = \min_i r_i(\mathbf{y}), \tag{2}$$

where $r_i(\mathbf{y}) := \|\mathbf{y} - \mathbf{A}_i \mathbf{x}_i\|_2$, $\mathbf{x}_i$ is the scalar coefficient vector corresponding to the class I.

2.3. Sparse Approximation based Classification (SAC) for Overdetermined Systems

Since EEG signals are non-stationary and testing sample y is not measured data from the training samples in dictionary A, the testing sample y cannot be exactly represented with the training $\mathbf{y} \approx \mathbf{Ax}.$ samples, i.e., Therefore, (1) is not sufficient form for practical applications and we consider the following approximation problem

$$\mathbf{y} = \mathbf{Ax} + \mathbf{r}, \tag{3}$$

where r is the unknown vector that accounts for model errors or disturbances. For the underdetermined system of (3), following

Table 1. Classification performance of conventional basis pursuit based SAC method, fast L1 (FISTA and Homotopy) based SAC methods and conventional L2 norm method (Pseudo inverse) for two class classification problem using dataset D and E.

Set D vs E 23.59sec	SAC (Basis Pursuit)	SAC (FISTA)	SAC (Homotopy)	L2 (Pseudo inv.)
Sensitivity (%)	97	99	99	97
Specificity (%)	100	100	100	100
Accuracy (%)	98.5	99.5	99.5	98.5
Time (sec)	6.6932	0.0523	0.1211	0.0105
Residual	0.0264	0.0353	0.0286	0.0264

L1-norm optimization can still recover the sparse solution

$$\min_{\mathbf{x}} \|\mathbf{x}\|_1 \text{ subject to } \|\mathbf{y}-\mathbf{A}\mathbf{x}\|_2 \le \varepsilon, \quad (4)$$

where ε is a predefined tolerance of approximation error.

As shown in Figure 1, the iEEG segments show noticeable difference in time domain between the interictal and ictal (sets D and E). Therefore, in this study, we use the iEEG time samples without any further feature extraction steps to form the dictionary A in (4). In this case, we should consider the overdetermined system in (4). It is because the number of rows in A, i.e., the number of time samples m = 4097, is larger than the number of columns in A, i.e., the number of training segments Cn = 180 (for the case of C = 2 and 10-fold cross validation). This means that the dictionary is a tall matrix unlike the sparsification step in a conventional SRC.

For this overdetermined case, conventional L2-norm minimization, i.e., least square method, can be normally used to provide closed form solution by using the so called pseudo inverse method:

$$\hat{\mathbf{x}} = \left(\mathbf{A}^T\mathbf{A}\right)^{-1}\mathbf{A}^T\mathbf{y}. \quad (5)$$

However, L1-norm criterion is preferred method for noise contaminated approximation problem in overdetermined system. Therefore, in this study, we aim to apply the L1-norm minimization based sparse approximation based classification (SAC) scheme for overdetermined system. This means after obtaining the recovered coefficient x by (4), we perform identification step (2) for classification purpose.

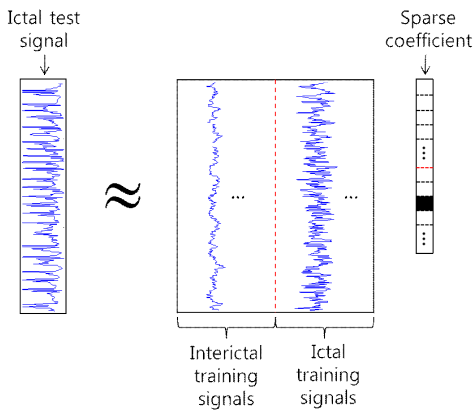

Fig. 2. Sparse approximation model for overdetermined seizure detection problem. Dictionary is consists of EEG training samples for different classes. The sparse coefficient for a test sample is obtained by the L1-norm minimization.

Figure 2 shows the concept of the proposed SAC for overdetermined system. The dictionary is simply formed by listing each class of EEG training signals, where the sparse coefficient vector can be recovered by the L1-norm minimization algorithm.

3. Results and Discussion

3.1. Experimental evaluation

For evaluation of the proposed methods in this paper, we compare classification performance of L1-norm based SAC methods and L2-norm based pseudo-inverse method. For reliable evaluation using the limited size of dataset, we use the 10-fold cross-validation.

We use statistical parameters such as sensitivity, specificity and classification accuracy for evaluation of classification performance. The definition of each parameter is as follows:

Sensitivity: number of correctly classified seizure segments/ total number of actual seizure segments.

Specificity: number of correctly classified normal (or non-seizure) segments/ total number of actual normal (or non-seizure) segments.

Classification accuracy: number of correctly classified segments/ total number of segments.

Furthermore, we compare running time of the L1-norm based SAC methods and the conventional L2-norm based method. Our evaluation for running time focuses on the L1 and L2 optimization steps.

3.2. Experimental results

For evaluation of the proposed methods, we compare classification performance of L1-norm based SAC methods and L2-norm based pseudo-inverse method using iEEG dataset. Furthermore, we examine classification performance for the different number of time samples (time duration) per one segment.

Table 1 lists of the classification results for Set D (interictal, opposite to epileptogenic zone) and Set E (ictal, within epileptogenic zone) that can be useful for pre-surgical evaluation of epilepsy and therefore.

We compare classification performance of the fast L1 (FISTA and Homotopy) based SAC methods with the conventional basis pursuit (BP) based SAC and L2-norm based pseudo inverse method. From the results of Table 1, FISTA and Homotopy based SAC methods show better sensitivity and accuracy than the L2-norm based method. Between FISTA and Homotopy based SAC methods, there is small running time difference with same classification accuracy. The BP based SAC method shows same classification results to the L2-norm based pseudo inverse method. However, running time of the initial BP based SRC is too slow. It takes 6.69 sec per segment which is averaged by all segments and it is not practically available. On the other hand, fast L1 based SAC methods show improved running time, i.e., 0.05 sec for FISTA and 0.1211 sec for Homotopy, with better accuracy and these are practically available for real time seizure detection application.

For the residual values which are represented in last low of Table 1, we compute the residual a s $r(\mathbf{y}) := \|\mathbf{y} - \mathbf{A}\hat{\mathbf{x}}\|_2$ similarly in (2), where $\hat{\mathbf{x}}$ is recovered coefficient by each L1- or L2-norm based method. Even though the classification accuracy of the fast L1-norm based SAC methods are better, L2-norm based method show smaller minimal residual.

In Table 2, we compare classification results for other classification problems using the proposed Homotopy based SAC method. For all datasets, the same 4096 samples per segment are used. First, in order to evaluate the performance of the proposed method in normal EEG datasets from healthy patients, we consider the classification problem with seizure activity (set E) and normal EEG (set A and B), i.e., set A and B obtained from normal EEG segment during eyes opened and closed.

As we can see in Table 2, for the case of set A vs E, the proposed Homotopy based SAC method can achieve 100% classification accuracy. On the other hand, we obtain 97.5% accuracy in the case of set B vs E. Second, we aim to classify interictal (set C) and ictal (set E) dataset within the same epileptogenic zone. This evaluation might be useful for providing an alarm of seizure activity of epileptic patients. In this case, similar to the results of Table 1 (set D vs E), the proposed method can achieve 99% classification accuracy.

Furthermore, in Table 3, we evaluate the multi-class classification performance using the proposed Homotopy based SAC method. In this classification, we use the dataset A, D and E, i.e., normal, interictal and ictal. Table 3 shows a confusion matrix which lists the detailed classification results. In this three-class classification, the proposed method shows 97.7% classification accuracy. The most difficult classification task is to make distinction between the normal (set A) and the interictal (set D) signal. The 5 normal segments are classified as interictal in Table 3. It might be because the EEG pattern in seizure free intervals (set D) is more similar to the normal EEG pattern (set A) in terms of signal amplitude and shape compared with seizure intervals (set E) as shown in Figure 1.

Table 2. Classification performance of a Homotopy based SAC method for different classification problems.

Dataset	Sensitivity (%)	Specificity (%)	Accuracy (%)
A vs E	100	100	100
B vs E	100	95	97.5
C vs E	98	100	99

Table 3. Confusion matrix of a Homotopy based SRC method using data set A, D and E.

Homotopy	Set A (predicted)	Set D (predicted)	Set E (predicted)
Set A (actual)	95	5	0
Set D (actual)	1	99	0
Set E (actual)	0	1	99

Furthermore, in Table 3, we evaluate the multi-class classification performance using the proposed Homotopy based SAC method. In this classification, we use the dataset A, D and E, i.e., normal, interictal and ictal. Table 3 shows a confusion matrix which lists the detailed classification results. In this three-class classification, the proposed method shows 97.7% classification accuracy. The most difficult classification task is to make distinction between the normal (set A) and the interictal (set D) signal. The 5 normal segments are classified as interictal in Table 3. It might be because the EEG pattern in seizure free intervals (set D) is more similar to the normal EEG pattern (set A) in terms of signal amplitude and shape compared with seizure intervals (set E) as shown in Figure 1.

4. Conclusion

In this study, we propose a simple sparse approximation based classification (SAC) scheme for automatic seizure detection tasks.

The proposed scheme utilizes EEG time samples obtained from different states, i.e., normal, seizure and seizure free. A dictionary is formed using the training EEG samples and a sparse approximation of the test EEG sample is obtained by solving the efficient L1-norm minimization algorithms, i.e., Homotopy and FISTA. Finally, the recovered sparse coefficients are used for classification task using the minimal residual rule. Public dataset obtained from normal healthy subjects and epileptic patients are used for evaluation of the proposed method. The proposed fast L1-norm based SAC methods show improved classification accuracy than conventional L1- and L2-norm based methods.

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Author Biography

Younghak Shin [Member]

- Feb. 2016: Dep. Information & Communication Eng., GIST (Ph.D.)
- Mar. 2016 ~ Oct. 2018: Dep. Elect. Systems, Norwegian University of Science and Technology, Postdoctoral Researcher
- Dec. 2018 ~ Current: AIBigdata Research Center, LGCNS, Senior Research Scientist

〈Research Interests〉 Signal Processing, Artificial Intelligence, Machine Learning

Jin-Taek Seong [Member]

- Aug. 2014: Dep. Information & Communication Eng., GIST (Ph.D.)
- Mar. 2008 ~ Dec. 2010: LG Elec., Junior Researcher
- Sep. 2014 ~ Sep. 2016: DGMIF, Researcher
- Sep. 2016 ~ Mar. 2017: DAPA, Program Manager
- Mar. 2018 ~ Current: Dep. Convergence Software, Mokpo National University, Assistant Professor

〈Research Interests〉
Information Theory, Machine Learning, Communication Theory