Epilepsy & Behavior 25 (2012) 230–238

Contents lists available at SciVerse ScienceDirect

Epilepsy & Behavior

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

Seizure prediction using EEG spatiotemporal correlation structure

James R. Williamson [a,*], Daniel W. Bliss [a], David W. Browne [a], Jaishree T. Narayanan [b]

[a] MIT Lincoln Laboratory, Lexington, MA, USA
[b] Department of Neurology, University of Massachusetts Medical School, Worcester, MA, USA

ARTICLE INFO

Article history:
Received 26 March 2012
Revised 2 June 2012
Accepted 14 July 2012
Available online 2 October 2012

Keywords:
Epilepsy
Seizure prediction
Multivariate features
Electroencephalogram
Correlation structure
Machine learning
Eigenvalues
Principal components
Support vector machines

ABSTRACT

A seizure prediction algorithm is proposed that combines novel multivariate EEG features with patient-specific machine learning. The algorithm computes the eigenspectra of space–delay correlation and covariance matrices from 15-s blocks of EEG data at multiple delay scales. The principal components of these features are used to classify the patient's preictal or interictal state. This is done using a support vector machine (SVM), whose outputs are averaged using a running 15-minute window to obtain a final prediction score. The algorithm was tested on 19 of 21 patients in the Freiburg EEG data set who had three or more seizures, predicting 71 of 83 seizures, with 15 false predictions and 13.8 h in seizure warning during 448.3 h of interictal data. The proposed algorithm scales with the number of available EEG signals by discovering the variations in correlation structure among any given set of signals that correlate with seizure risk.
© 2012 Elsevier Inc. All rights reserved.

1. Introduction

Epilepsy affects approximately 1% of the general population [1]. Epilepsy puts patients at higher risk for injuries. Seizures can cause many injuries including falls, submersion injuries, burns, and many others. These happen because seizures can be sudden and occur without warning, leaving the patient unable to protect him- or herself. A review of epilepsy-related injuries found that patients with epilepsy, especially children, are at higher risk for submersion injuries [2]. Epilepsy also results in a higher risk for fractures, burns and motor vehicle accidents. If seizures can be reliably predicted and a preictal state can be identified with high sensitivity and specificity, it could help significantly in reducing these injuries.

Research into seizure prediction has focused on several types of features that discriminate between interictal (period of time between seizures) and preictal (period of time immediately before a seizure) states. These include univariate features, such as the power spectral density or autoregressive modeling coefficients of single electroencephalogram (EEG) channels, as well as bivariate features that measure pairwise correlations between EEG channels, such as maximum cross correlation or phase synchrony [3,4]. Comparisons of feature extraction techniques have indicated greater discriminability for bivariate compared to univariate features, with similar discriminability for both linear and nonlinear bivariate features [3].

In addition to the question of feature discriminability is the question of how best to combine features to generate accurate and reliable seizure predictions. Recent machine learning approaches using high-dimensional feature vectors have demonstrated significant improvements over approaches of retrospectively selecting univariate or bivariate features [5–8].

As technology improves and the number and quality of available EEG channels increase, it will become increasingly important to develop a scalable approach for signal analysis that extracts all the available useful information. The high levels of phenomenological variation of brain dynamics, both within a single patient over time and between different patients, imply the need to discover patterns that potentially involve all the available EEG channels across a range of temporal scales.

These considerations motivate our algorithm, which generalizes and extends approaches for feature *selection* among multiple bivariate signal coherence features into an approach for feature *extraction* from a multivariate representation of correlations across channels and time. Feature extraction is based on the eigenspectra of *space–delay* correlation and covariance matrices, which are computed from multichannel EEG signals at multiple relative time delays. These eigenspectra comprise the spatiotemporal correlation structure of the EEG signals. We hypothesize that preictal periods of increased seizure risk are reflected in changed brain dynamics that can be detected by changes in the spatiotemporal correlation structure. We describe in detail the feature

* Corresponding author at: MIT Lincoln Laboratory, Group 48, Bioengineering Systems and Technologies, 244 Wood Street, Lexington, MA 02420-9108, USA. Fax: +1 781 981 7848.
E-mail address: jrw@ll.mit.edu (J.R. Williamson).

1525-5050/$ – see front matter © 2012 Elsevier Inc. All rights reserved.
http://dx.doi.org/10.1016/j.yebeh.2012.07.007

extraction, machine learning, and seizure prediction components of our algorithm and demonstrate its performance on the Freiburg EEG database, with comparisons to previously published results.

2. Methods

2.1. EEG database and patient characteristics

Our seizure prediction algorithm was evaluated on the Freiburg EEG database, which contains the intracranial EEG (iEEG) recordings from 21 patients suffering from medically intractable focal epilepsy. The data were recorded while the patients were undergoing invasive pre-surgical epilepsy monitoring at the Epilepsy Center of the University Hospital of Freiburg, Germany [9]. The data consist of six channels (i.e., recordings from six different electrodes) sampled at 256 Hz. Three of these are focal channels (located near the epileptic focus), and three are extrafocal. The electrodes were referenced to a contact located in a brain structure with lowest epileptic activity. The data records for each patient are divided into *ictal* and *interictal* records. The ictal records contain epileptic seizures notated by experienced epileptologists, with at least 50 min of preictal data preceding each seizure. The interictal records contain approximately 24 h of recordings without seizure activity, at least 1 h removed from the nearest seizure. The median time period between the last seizure and the interictal data set was 5 h and 18 min, and the median time period between the interictal data set and the first following seizure was 9 h and 36 min. The seizures occurred spontaneously and at different times of the day. Antiepileptic medication was reduced from usual levels in a majority of the patients; however, the types and levels of medications were not identical across patients as these treatments had to be adapted to their individual clinical needs.

Three or more seizures were recorded for 19 of the 21 patients. Our algorithm was evaluated only on these 19 patients to ensure that at least two other preictal periods from the same patient could be used by the algorithm's machine learning (i.e., model estimation) step for each preictal period that it was evaluated on. The epileptic focus was located in neocortical brain structures in 10 of these 19 patients, in the hippocampus in seven, and in both brain areas in two. Table 1 lists many of the patient and database characteristics. For more extensive information about the data set, see [9].

The data records were preprocessed via bandpass filtering between .5 and 120 Hz and a notch filter to remove line noise at 50 Hz. Finally, each channel was normalized over a patient's entire data set into standard units of zero mean and unit variance to control for different power levels between the channels.

2.2. Feature extraction

The feature extraction approach finds correlation patterns, both within and across EEG channels that exhibit the most significant changes over time. The correlation patterns are derived from the eigenspectra of the space–delay correlation and covariance matrices, which are obtained from multichannel EEG signals at multiple relative time delays, using several delay scales. These spatiotemporal correlation structure features are well suited to a problem in which it is unknown a priori which sets of correlations across space and time are predictive of seizures. The components of spatiotemporal correlation structure that explain most of the data variance provide the basis set from which a mapping to seizure predictions is obtained using machine learning. This feature extraction approach was initially described in an earlier version of the current work [10] and has since been applied to the analysis of cardiopulmonary correlation structure for apnea prediction in preterm infants [11]. Table 2 summarizes the parameters and variables used in the feature extraction process. High-dimensional feature vectors are extracted from space–delay covariance and correlation matrices, computed from 15-s blocks of data at multiple delay scales. The term *space* refers to the spatial array of EEG sensor channels, and the term *delay* refers to the set of time delays applied to each channel. At each delay scale, these matrices contain covariance and correlation coefficients computed from the product set of EEG channels and time delays defined for that scale.

Let $\mathbf{Z}_{\mathbf{t(j)}}$ be a set of signals for the jth block of data, where $t(j)$ is the time stamp for the jth block in units of seconds. The start of each successive 15-s block is contiguous with the end of the preceding block. $\mathbf{Z}_{\mathbf{t(j)}}$ has dimensionality $(n_s \times n_c)$ where n_s is the number of samples per 15-s block ($n_s = 3840$) and n_c is the number of channels ($n_c = 6$). $\mathbf{X}_{\mathbf{jk}}$ is a set of time-delayed multichannel signals,

$$\mathbf{X}_{\mathbf{jk}} = \left(\mathbf{Z}_{\mathbf{t(j)}-\tau_{1k}}, \ldots, \mathbf{Z}_{\mathbf{t(j)}-\tau_{n_d k}}\right), \tag{1}$$

where τ_{ik} is the ith time delay at the kth delay scale. $\mathbf{X}_{\mathbf{jk}}$ has dimensionality $(n_s \times n_c n_d)$. The spacing of time delays depends on the delay scale: $\tau_{ik} = (i-1)\delta_k$s, with $\delta_1 = \frac{1}{64}, \delta_2 = \frac{1}{16}, \delta_3 = \frac{1}{4}$, and $\delta_4 = 1$. Multiple delay scales are used so that the spatiotemporal correlation structure

Table 1
Patient and EEG database characteristics.

Patient	Sex	Age	Seizure type	H/NC	Electrode types	# of seizures	# of seizures per day	Interictal duration (h)	# of inter. intervals
1	F	15	SP, CP	NC	g, s	5	6.3	24	1
2	M	38	SP, CP, GTC	H	d	3	2.8	24	2
3	M	14	SP, CP	NC	g, s	5	0.6	24	1
4	F	26	SP, CP, GTC	H	d, g, s	5	0.4	24	1
5	F	16	SP, CP, GTC	NC	g, s	5	1.7	24	3
6	F	31	CP, GTC	H	d, g, s	3	0.9	24	1
7	F	42	SP, CP, GTC	H	d	3	0.2	25	1
9	M	44	CP, GTC	NC	g, s	5	1.6	24	2
10	M	47	SP, CP, GTC	H	d	5	1.1	24	1
11	F	10	SP, CP, GTC	NC	g, s	4	0.6	24	1
12	F	42	SP, CP, GTC	H	d, g, s	4	1.0	25	1
14	F	41	CP, GTC	H and NC	d, s	4	6.3	24	5
15	M	31	SP, CP, GTC	H and NC	d, s	4	0.4	24	1
16	F	50	SP, CP, GTC	H	d, s	5	4.5	24	2
17	M	28	SP, CP, GTC	NC	s	5	1.0	24	1
18	F	25	SP, CP	NC	s	5	6.6	25	1
19	F	28	SP, CP, GTC	NC	s	4	3.6	24	3
20	M	33	SP, CP, GTC	NC	d, s	5	5.1	24	1
21	M	13	SP, CP	NC	s	5	0.2	24	2

Seizure types: simple partial (SP), complex partial (CP), and generalized tonic–clonic (GTC). Seizure origin: hippocampal (H) and neocortical (NC). Electrodes: grid (g), strip (s), depth (d).

Download English Version:

https://daneshyari.com/en/article/6013697

Download Persian Version:

https://daneshyari.com/article/6013697

Daneshyari.com