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A common strategy and database to compare the performance of seizure prediction algorithms

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ABSTRACT

A reliable algorithm for the timely prediction of epileptic seizures would be a milestone in epilepsy research. Prediction performances have so far been determined using retrospective data assessment, leaving open the question as to whether they prove statistically significant and clinically useful under prospective conditions. To this aim, a Seizure Prediction Competition has been set up. Here, the background and the details of this competition are described.

1. Introduction

A holy grail of epilepsy research is reliable prediction of apparently unforeseeable seizures [1]. If successful timely seizure prediction was possible, novel therapeutic interventions could be envisaged that might improve the treatment of several million epilepsy patients worldwide [2]. It would be of particular interest to include those patients who cannot be treated with common strategies like antiepileptic drugs and surgery.

In contrast to several optimistic claims about the ability to reliably predict epileptic seizures in the past decade, recent studies have demonstrated that seizure prediction algorithms show statistically significant prediction performance, but need to be improved to achieve high clinical relevance [3–10]. However, this statistical significance has so far been achieved only for retrospective analysis, leaving open the question of whether seizure prediction algorithms can perform above chance level when analyzed prospectively.

The "long and winding road" [11] toward seizure prediction is additionally made more tortuous by the fact that results from different groups usually cannot be compared as each group develops and evaluates the performance of their algorithms on their own data sets. This is why a prospective analysis of seizure prediction performance on a common data set is mandatory if seizure prediction performance above chance level should be claimed. To this aim, the Seizure Prediction Competition was initiated in 2007 as part of the 3rd International Workshop on Epileptic Seizure Prediction, which took place in Freiburg, Germany.

The first part, a common data pool of three patients with epilepsy undergoing continuous long-term EEG recordings, is provided to registered researchers to train individual seizure prediction algorithms. The second part of the data is used to evaluate seizure prediction performance prospectively. This, for the first time, enables a rigorous comparison and evaluation of seizure prediction performance.

Some details of the seizure prediction competition are discussed below. More details on the contest itself and the opportunity to participate can be found on the seizure prediction competition webpage: http://epilepsy.uni-freiburg.de/prediction-contest.

2. Data and methods

In this section clinical information on the training data and details of the methodology of prediction assessment are provided.

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2.1. Training and optimization

To train, optimize, and evaluate seizure prediction algorithms, continuous long-term intracranial EEG signals recorded from three patients are used. The data are provided by the Epilepsy Center of the University Medical Center, Freiburg, Germany. For training purposes only the first part of the data can be used; the characteristics are outlined in Table 1.

This first section of EEG data contains at least 36 hours of raw EEG signals for each patient and at least five seizures (Fig. 1). For all patients, all recorded channels are provided, which results in up to 60 intracranial channels. The data are recorded with a sampling rate of 512 Hz using strip, depth, and grid electrodes. All patients underwent surgery with an Engel Ia outcome.

Details of the testing data are not provided as it should be impossible to use such information to tailor seizure prediction algorithms to this information. To make sure that the contest is honest, a program named Datareader has to be used by the seizure prediction algorithms. This program provides the data in ASCII format epochwise. This program can be used by contest participants in training their algorithms and is used for the analysis of testing data.

2.2. The Datareader

To ensure application of the submitted prediction algorithms in a prospective manner of operation, the program Datareader is used as an interface for the prediction algorithms to access epochs of the EEG data consecutively. It is supplied to contest participants together with the training data such that the optimization can be performed using the same infrastructure.

2.2.1. Compilation and configuration

Datareader is written in C++, which is platform independent and can be compiled and used on various platforms.

The data sets of each patient have to be stored in separate folders accompanied by a file called patient.txt, which contains basic information about each patient (sampling rate, number and names of EEG channels, time at start of the first recording). The raw data are supplied in a binary format split in blocks of 1-hour duration. Information about each data block is given in text files with the file extension ".info," containing the start and end times of the data block and a list of events that occurred during the block interval. The time is specified as the sample number since start of recording.

2.2.2. Using Datareader

When started, Datareader stores the requested section of EEG data in a text file including information about particular events that occurred during the recording. The number of samples that are provided as one epoch of data can be set according to the seizure prediction algorithm. When requesting the next epoch of data, the algorithms have to specify whether they issue an alarm. The alarm, when issued, is raised immediately after the current epoch of data.

Together with the information on whether or not an alarm is raised, the prediction horizon has to be provided. The prediction horizon is the time interval in which the onset of the seizure is predicted to occur. There must be a minimum time interval of 10 seconds between the alarm, that is, the first sample of the next data block, and the onset of the prediction horizon specified by the algorithm if the alarm should be considered to be a prediction. If this interval is less than 10 seconds the alarm is considered an early detection, as the uncertainty in the determination of the seizure onset is on the order of a few seconds. Moreover, the prediction horizon is not allowed to start within the current sample interval.

The electroencephalographic and clinical events that occurred during data recording are written as an event flag to the second column of the output file of Datareader. Table 2 specifies the events that can occur and the event type numbers assigned to the events.

Please note that for the testing data, only the information when the seizure terminated is provided and not the information when seizures started. This information may or may not be used.

Table 1
Details of the three patients.

	Patient 1	Patient 2	Patient 3
Age at monitoring	30	17	10
Sex	Female	Male	Male
Surgical outcome	Engel Ia	Engel Ia	Engel Ia
Seizures recorded	SP/CP/SG	SP/CP/SG	SP/CP/SG
Electrodes	Strip, depth	Strip, grid	Strip, depth
Number of channels	60	44	22
Sampling rate	512 Hz	512 Hz	512 Hz
Filter	97 Hz	97 Hz	97 Hz

Note. SP, simple partial; CP, complex partial; SG, secondarily generalized tonic–clonic seizures. Filter: low-pass filter. EEG Amps: 97 Hz ± 15% (−3 dB). The filter is first order (−6 dB/octave).

2.3. Evaluation

The optimized algorithms will be evaluated by the Freiburg group on the second part of the EEG data, the testing set, to investigate the predictive power of the algorithms. A ready-to-apply algorithm has to be provided. This algorithm has to use Datareader.

The issued alarms will be categorized into true and false predictions. A true prediction is an alarm where the seizure starts in the corresponding prediction horizon. A false prediction is an alarm where no seizure begins within the corresponding prediction horizon.

All prediction performance results will be presented in detail on the webpage. We will show the fraction of correctly predicted seizures, that is, the sensitivity of the algorithm. The specificity is presented as the number of false predictions with respect to time, that is, the false prediction rate, with respect to the total number of predictions as well as the time under false warning. The time under false warning is thereby defined as the total time over which seizures are predicted that never occur. Both sensitivity and specificity will thereby be discussed relative to the prediction time and duration of the prediction horizon. Moreover, computational needs will be presented.

Performance of the submitted algorithms to a random predictor [6,9] will be compared. The results will be ranked using the sum of the squared specificity and sensitivity. As it might be of particular importance to have algorithms with high sensitivity or specificity, the "best" algorithm with respect to this will also be presented.

More details can be found on the corresponding webpage.

3. Participation

Researchers interested in contributing to the seizure prediction contest are invited to register at: http://epilepsy.uni-freiburg.de/prediction-contest. A fee of 1000 Euro is required to register for the contest to ensure participation in the contest afterward; 500 Euro will be returned once an algorithm is submitted; 250 Euro will go into the prize offered for the best prediction. The remaining 250 Euro will be used to maintain this competition.

All groups active in the field of seizure prediction are encouraged to participate in this competition.

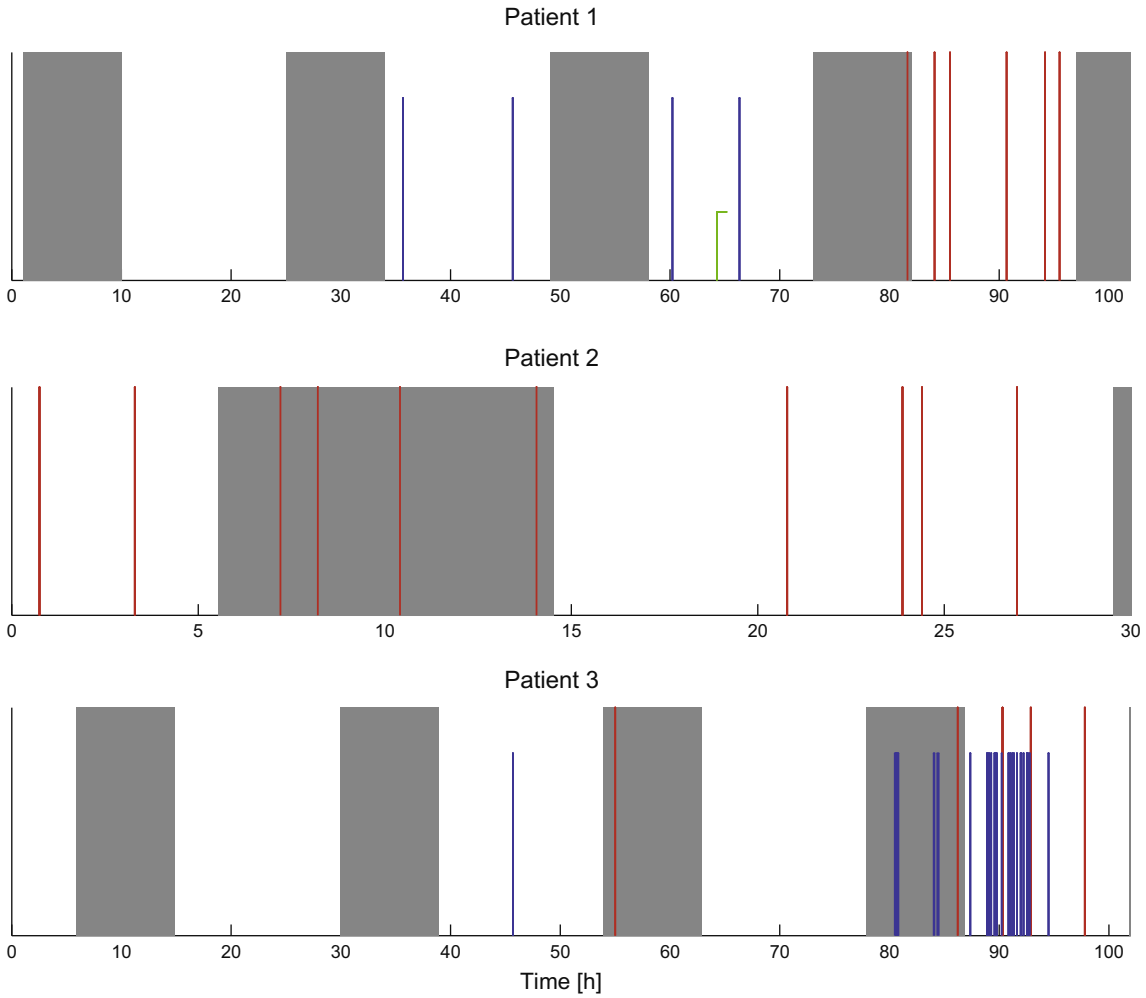

Fig. 1. Details on the training data for patients 1 (upper row) to 3 (lower row). Gray areas mark the nighttime, defined as the time between 10 PM and 7 AM. Red bars mark clinical seizures, blue bars subclinical seizures, and green bars periods of electrical stimulation.

Table 2
Events that can occur during data recording.

ESO	Electrographic seizure onset	Type 1
EST	Electrographic seizure termination	Type 3
CSO	Clinical seizure onset	Type 5
CSO NA	Clinical seizure onset not available	Type 7
CST	Clinical seizure termination	Type 8
CST NA	Clinical seizure termination not available	Type 10
SSO	Subclinical seizure onset	Type 11
SST	Subclinical seizure termination	Type 14
STS	Start of stimulation interval	Type 17
STE	End of stimulation interval	Type 18
ART	Artifact	Type 19
MRX	Measurement range exceeded	Type 21
EBD	Electrode box disconnected	Type 24
EBR	Electrode box reconnected	Type 25
No Data	Gap in the recording	Type 26

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