Optimal preictal period in seizure prediction

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Abstract. A statistical method for finding the optimal preictal period to be used in epileptic seizure prediction algorithms is presented. As supervised machine learning methods need labeled training samples, the adequate selection of preictal period plays a key role in the training of an efficient classifier employed in seizure prediction. The proposed method uses amplitude distribution histograms of a candidate feature extracted from electroencephalogram (EEG) signals. The method is evaluated on 135 hours of intracranial EEG (iEEG) recordings related to 27 epileptic seizures.

Keywords: Seizure prediction, preictal period, classification.

1 Introduction

In nature every phenomenon has at least one cause, and epileptic seizure is not an exception. Although the exact reason of seizures has not been discovered yet, the studies approve the existence of transient changes in the state of brain prior to initiation of seizure onsets. Quantification of these changes can be derived from EEG signals, and provides the prediction capability for epileptic seizures. Prediction of epileptic seizures could promote the living conditions of patients with pharmaceutically resistant seizures, significantly [1].

For some patients and for some features, the epilogenic transient changes develop very late close to seizure onset, whereas for some others appear much earlier several tens of minutes prior to the onset. Therefore, the optimal preictal period for each patient (and feature) should be chosen separately. In fact, the improper choice of preictal lengths can affect prediction results drastically. The preictal periods larger than the optimal value will increase false predictions, while the smaller values can decrease the sensitivity of prediction [2].

As there is not yet a clinical agreement about the value of preictal interval, some previous machine-learning-based approaches examined different preictal periods to train/test the classifier in order to find a proper interval [3]. Morman et al. [2] used statistical analysis of several univariate and bivariate features to prove the existence of such preictal period, which should lead to the prediction of seizures. They have used the Amplitude Distributions Histograms (ADHs) of preictal and interictal samples achieved from four predefined preictal periods of 5min, 30min, 120min, and 240min, and then calculated the Receiver Operating Characteristic (ROC) curve of these two distributions to find out the predictability of epileptic seizures.

We recently developed a method for feature selection based on ADHs of preictal and non-preictal samples, but using four predefined preictal periods [4]. Here we propose a novel method to find the most discriminative preictal periods. The remaining of this paper is organized as follows: Section II presents methodology. Section III provides the simulation results. Finally some conclusions are made in section IV.

2 Methodology

2.1 Data

The intracranial EEG recordings of 5 patients with focal epilepsy from European Epilepsy Database EPILEPSIAE [5] are used. Recordings were obtained at the epilepsy unit of the University Hospital of Freiburg, Germany, at sampling rate of 1024 Hz. Patient characteristics are summarized in Table 1. For each patient, 1 channel located on the focal area is selected for the study. The EEG data is first segmented into 2 seconds windows with 50% overlap, and then are filtered using an infinite impulse response (IIR) forward-backward Butterworth 50 Hz notch filter to eliminate sinusoidal distortion of the ac power supply.

Table 1. Information of 5 studied patients

Patient	Sex	Age	Onset age	Rec. time (h)	#Seiz	Localize
A	f	29	10	183	9	Right T
B	f	32	1	162.6	9	Left T
C	f	11	3	155	14	Right T
D	f	32	8	151.6	9	Left T
E	f	18	6	127.8	13	Right T
A./T.		24.4	5.6	780	54	

❖ Localize: Localization of seizures; Right T: Right temporal lobe, Left T: Left temporal lobe.

2.2 Optimal preictal criterion

A novel criterion to find the optimal preictal period is introduced based on amplitude distribution histograms (ADHs) of preictal and non-preictal samples. An ADH is the representation of the samples of a given feature associated with one class, where the feature axis is discretized into a number of equal smaller bins, each representing the accumulated amount of amplitudes falling within that interval. For our two-class preictal/interictal problem, two different ADHs are considered. The basic idea of the method is the selection of the preictal period that provides the minimum common area of two normalized ADHs. The common area between two normalized ADHs of a two-class problem is calculated as (1),

$$C_{ADHs} = w * \sum_{i=1}^{n} min(ADH_{norm1}, ADH_{norm2}) \quad (1)$$

where C_{ADHs} is the common area of two normalized ADHs (Fig.1), w is the bin-width, ADH_{normj} is the normalized ADH of the class j, n is the number of bins, and i indexes the bins. The features are normalized to fall inside the interval [0 1], and the feature axis is discretized into 100 bins ($w = 0.01$), as required for calculating amplitude

distribution histograms. The normalized ADHs of interictal and preictal classes are achieved by (2),

$$ADH_{normj} = \frac{ADH_j}{ns*w} \quad (2)$$

where ADH_j is the original histogram of class j, ns is the number of feature samples of class j, and w is the bin-width. The net area under each normalized ADH is one. Also the common area (C_{ADHs}) has a value in the real interval [0 1]. Lower C_{ADHs} values represent higher separability between samples of the two classes for a given feature. As a result, the preictal period having the lowest C_{ADHs} is the ideal choice of preictal period and is more likely to improve the seizure prediction performance.

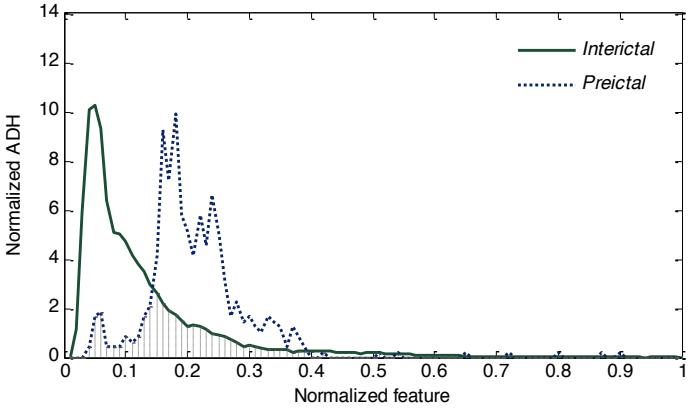
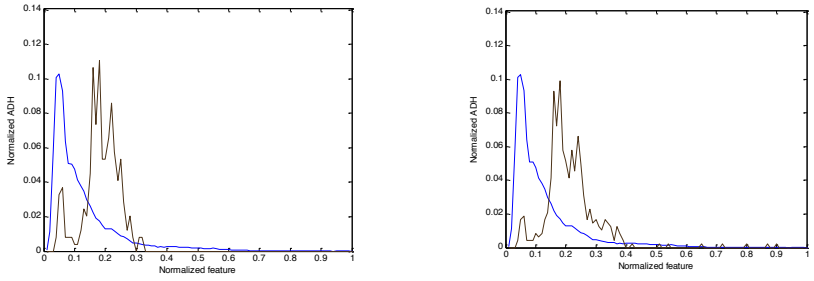
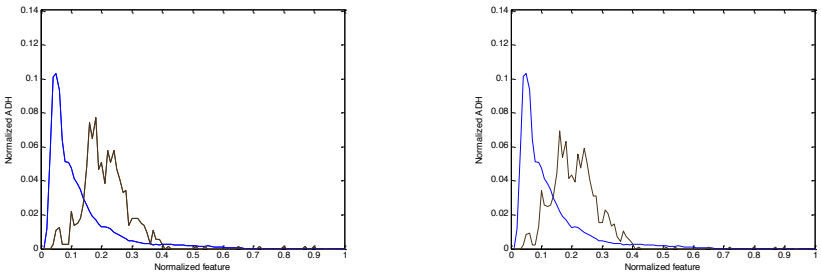


Fig. 1. Normalized ADHs of preictal and interictal samples for a studied feature; the green ADH is for interictal, and the dotted blue ADH is for preictal. C_{ADHs}=0.37.

Fig.2 presents the ADHs of a sample feature corresponding to one of the studied seizures, for preictal values of 5, 10, 15 and 20 minutes. As seen from this figure, the lowest common area of ADHs is obtained for the preictal period of 10 minutes, among the four preictal periods. It can be argued that the differences are so small that they may result from numerical approximations.



(a) (b)



(c) (d)

Fig. 2. Finding the proper preictal period among four preictal periods (a) 5min, C_{ADHs} = 0.37 (b) 10min, C_{ADHs} = 0.34 (c) 15min, C_{ADHs} = 0.36 (d) 20 min, C_{ADHs} = 0.41.

In order to better choose the optimal preictal period, it is helpful to draw common areas of ADHs for a range of preictal periods starting from 1 min and ending at 120 min, with 1 min increments. This diagram is depicted in Fig.3 for 16 features for one of the studied seizures. According to figure 3, it is found that the optimal preictal period for almost all features is located around 15 minutes.

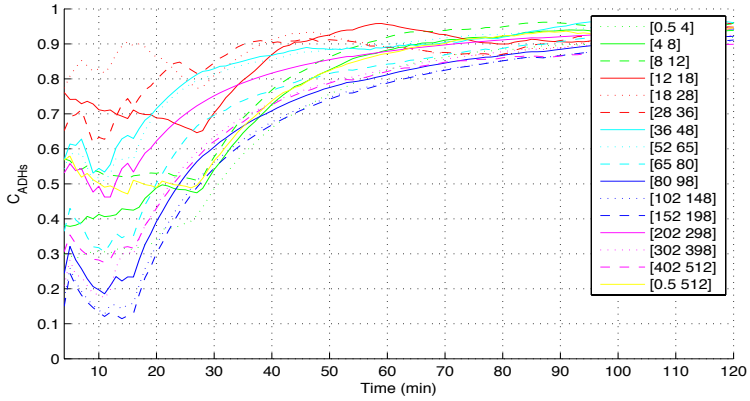


Fig. 3. Finding the optimized preictal period for labeling the samples using the proposed method. The graph presents the common area under ADHs (C_{ADHs}) of two classes with respect to different preictal periods, and for the 16 features of one of the studied seizures.

It should be noted that preictal period is seizure-specific, and this should be taken into account during the training of related classifier. Throughout training, the exact information regarding the optimal preictal period for each seizure is available, and we can therefore label the samples properly. For the test step however, the average value of optimal preictal periods employed during the training of classifier can be used. The optimal preictal period is also feature specific, however for a set of features extracted from a common domain, e.g. spectral power features, the optimal preictal periods corresponding to different features should not differ too much.

2.3 Spectral Power Features

In order to evaluate the proposed method of finding the optimal preictal period, the spectral power features are extracted from the windowed EEG signals. A previous study by Rasekhi et al. [3] had shown that these features produce better results in competition with other univarite features.

Spectral power of sub-bands represents the power distribution of a signal or time series across predefined frequency sub-bands [6]. To achieve better frequency resolution, the iEEG signal is considered in narrow sub bands. Instead of using the well-known frequency sub-bands alpha, beta, …, in this work fifteen new spectral sub bands are selected: 0.5-4 Hz, 4-8 Hz, 8-12 Hz, 12-18 Hz, 18-28 Hz, 28-36 Hz, 36-48 Hz; 52-65 Hz, 65-80 Hz, 80-98 Hz, 102-148 Hz, 152-198 Hz, 202-298 Hz, 302-398 Hz, 402-512 Hz, as well as the total power. Spectral power of raw iEEG is obtained using Power Spectral Density (PSD) function evaluated by Welch method. To calculate the power within desired sub-bands, only an integration/summation over PSD values falling in that subband is required. The absolute values of spectral power feature are calculated by (3),

$$p_i = \sum_i PSD(x) \tag{3}$$

where p_i is spectral power of i-th band, x is the windowed raw iEEG signal, i indexes i-th frequency sub-band, and $PSD(x)$ is the PSD of signal. The spectral power features were extracted from each channel using a rectangular moving window. The length of window was 2 seconds with 50% overlap, providing a feature sample each second.

3 Results

Continuous iEEG recordings of 5 patients were used to evaluate the proposed method. The total length of recordings of all patients was 780 hours, including 54 seizures. In this study, instead of the whole recordings, we have used only 5 hours of the recording before each seizure, to evaluate the proposed method. For a proper evaluation of the method, we have considered only those seizures that occur after at least 6 hours of seizure-free data. Doing so makes sure that every seizure activity has faded out during the 5 hours before the candidate seizures.

The extracted features from the 5 hours preceding each studied seizure were initially labeled as preictal and interictal classes. By choosing different preictal periods, and comparing the resulting discrepancies between two normalized ADHs, the optimal preictal period was achieved.

As the optimal preictal period may differ from seizure to seizure, the results are presented for individual seizures, as well as for individual features. The results of optimal preictal time for the studied seizures are tabulated in Table II, for three highest ranked features. The high ranked features are those features having the lowest C_{ADHs} among all features.

Table 2. Optimal preictal periods of 27 studied seizures for three high ranked features.

Pat. ID	Sz. ID	Feature 1			Feature 2			Feature 3		
		O.P.	C_{ADHs}	Freq. Hz	O.P.	C_{ADHs}	Freq. Hz	O.P.	C_{ADHs}	Freq. Hz
A	1	68	0.17	402-512	68	0.31	302-398	32	0.67	202-298
	2	48	0.26	402-512	65	0.56	152-198	64	0.62	102-148
	3	27	0.15	302-398	51	0.23	202-298	51	0.25	402-512
	4	16	0.52	402-512	22	0.67	202-298	16	0.68	52-65
	5	16	0.30	302-398	18	0.47	402-512	20	0.63	65-80
	6	57	0.04	302-398	57	0.21	402-512	57	0.25	202-298
	7	42	0.12	302-398	64	0.14	402-512	41	0.37	202-298
B	8	142	0.57	65-80	142	0.58	80-98	142	0.66	202-298
	9	18	0.39	302-398	18	0.43	402-512	18	0.44	102-148
	10	150	0.33	8-12	150	0.35	0.5-512	150	0.37	12-18
	11	8	0.71	18-28	8	0.74	12-18	8	0.75	4-8
C	12	6	0.64	36-48	6	0.66	18-28	6	0.67	28-36
	13	37	0.56	202-298	35	0.57	302-398	35	0.63	102-148
D	14	54	0.46	302-398	47	0.55	80-98	47	0.56	65-80
	15	91	0.57	102-148	92	0.59	202-298	92	0.60	152-198
	16	32	0.50	80-98	45	0.51	302-398	30	0.57	65-80
	17	73	0.08	202-298	73	0.11	152-198	74	0.14	302-398
E	18	30.5	0.02	402-512	30.5	0.05	202-298	30.5	0.07	302-398
	19	60.5	0.63	0.5-512	62	0.64	0.5-4	60	0.68	8-12
	20	53	0.65	0.5-4	53	0.67	0.5-512	56	0.81	4-8
	21	4	0.48	28-36	4	0.63	36-48	3.5	0.72	18-28
	22	21.5	0.22	302-398	17	0.13	402-512	17	0.45	152-198
	23	42	0.23	152-198	42.5	0.24	102-148	42.5	0.26	80-98
	24	7	0.61	102-148	7.5	0.64	152-198	7.5	0.68	302-398
	25	32.5	0.13	152-198	24.5	0.14	102-148	24.5	0.16	302-398
	26	22.5	0.63	36-48	22.5	0.64	28-36	22.5	0.64	80-98
	27	11	0.12	152-198	10.5	0.13	102-148	10.5	0.17	302-398

- O.P.: Optimal preictal period in minute
- C_{ADHs}: Common area under two ADHs

The results also exhibited that the optimal preictal times corresponding to different features and extracted for a same particular seizure are very close. However they vary from one seizure to another, demonstrating that the optimal preictal time is more of seizure-specific than feature-specific. The high frequency oscillations (HFOs) provided less C_{ADHs} in most seizures of the Table 2, and repeated as: 202-298Hz (10 times), 302-398Hz (15 times), and 402-512Hz (10 times).

4 Conclusion

Examining different preictal periods, and through the investigation of the proposed measure, we could find the best discriminative preictal periods for each seizure/feature. We have also found that the optimal preictal periods vary significantly from seizure to seizure, even for the seizures of a same patient. This reminds that all detection methods should be designed to be both feature and seizure specific. Furthermore, the high frequency features were found to be more discriminative among the features.

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