31st Annual International Conference of the IEEE EMBS
Minneapolis, Minnesota, USA, September 2-6, 2009

Feature Extraction of Linear Predictors at Spectral Bands of Interest

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Abstract—**Intra-cranial electroencephalograms (EEG) from two patients diagnosed with epilepsy are sampled at 1kHz, enabling analysis and feature extraction at frequency bands above the gamma range. This study focuses on the extraction of linear features (including autoregressive, autoregressive-moving average and Fourier coefficients) obtained at both low (below 100Hz) and high (100-500Hz) bands of the signal spectrum. Comparisons of the performance of each feature are made based on a binary hypothesis test of statistical distributions from inter-ictal and pre-ictal epochs. Results are obtained from pre-ictal time periods as assessed by an expert epileptologist.**

I. Introduction

SEIZURE prediction based on intracranial EEG recordings of patients diagnosed with epilepsy has been studied in the context of linear features [1] as well as non-linear time-series analysis [2,3]. Subsequently, feature extraction techniques emphasized comparisons of seizure precursors to non-ictal or *baseline* EEG time segments in the context of *sensitivity* and *specificity*, or probability of false positive and false negative detection [4]. Some of these techniques employed probabilistic neural networks [5], k-nearest neighbors [6], and hypothesis testing [7].

Epilepsy is characterized by a tendency for recurrent seizures. It is the second most common brain disorder after stroke. Currently about 3 million Americans and 40 million people worldwide (about 1% of population) suffer from epilepsy [8-10]. A great challenge of epilepsy treatment is the unpredictability of recurrent seizures. The purpose of this study is to pave our way in seizure prediction research. The framework proposed herein is designed to search for signal processing techniques that may be applied to EEG waveforms to optimally predict the occurrence of an epileptic seizure through online classification/monitoring algorithms. This research may subsequently lead to clinical investigations of the effects of timely therapeutic interventions to control/abort seizure occurrences. In particular, this study compares linear features obtained from both high (100-500Hz) and low (below 100Hz) frequency bands of intracranial EEG recordings sampled at 1000Hz. The feature set includes autoregressive (AR), autoregressive-moving average (ARMA) and Fourier coefficients (FFT), while the selection criterion is based on a binary hypothesis test.

Manuscript received April 23, 2009.
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II. Methods

A. Regions of Interest

The intracranial EEG dataset from RWJ-UMDNJ contains continuous long-term (2 to 7 days) recordings from bilaterally implanted depth electrodes in the hippocampus and grid macroelectrodes on the temporal surface of 8 patients. EEG recordings were acquired using a Stellate recording system with 1,000 Hz sampling rate. All EEG recordings were viewed by two independent neurophysiologists to determine the number and the type of recorded seizures, seizure onset and end times, and seizure onset zones.

Two data sets were used, each from a different human subject. In addition, each data set contained two visually identifiable ictal events occurring after a long (greater than 3 hour) inter-ictal period. Within these data sets, epochs of 50s duration were chosen with start times at roughly 2 and 10 minutes pre-ictally. These *pre-ictal* epochs were chosen as the clearest 50s portion of the EEG at the times of interest. Also, *inter-ictal* epochs were chosen as the clearest 50s portion of the EEG furthest away from an ictal event (typically 1½ to 2 hours away). Furthermore, the "clarity" of the epochs was determined by excluding portions exhibiting artifacts and brief epileptiform activity (buzzes) as observed visually. This was done in order to minimize distortions in the analysis while also constraining the study to those features that are not readily visible to the eye.

B. Preliminary Signal Processing

Each segment or epoch (inter- and pre-ictal) is fifty seconds long. Before dividing the epochs into contiguous 500ms windows, they are subjected to two separate treatments, each intended to prepare the segment for processing at the particular band of interest (2-100Hz or 100-500Hz). Moreover, all filtering is accomplished using FIR Hamming windowing techniques [13]. In particular, for the low frequency band, the epoch is first low-pass filtered by a 200-width FIR with a -6dB cutoff frequency of 95Hz, then down-sampled to 200Hz. Next, 60Hz artifacts are attenuated by applying a 200-width band-stop filter with -6dB cutoff at 58Hz and 62Hz. To avoid non-stationary drifts

or "trends" in the 500ms processing window, the EEG is further high-pass filtered using a 500-width FIR filter with -6dB cutoff at 2.5Hz.

For the high-frequency band, 60Hz artifacts in the EEGs are first filtered with a series of 240-width band-stop filters centered at 60Hz and harmonics thereof with -6dB cutoff at a 7Hz distance from the centers. Next, to avoid redundancy with respect to the low-frequency band analysis, the EEGs are high-pass filtered with a 200-width FIR filter and -6dB cutoff at 95Hz.

Each time series is normalized to lie within {-1,+1} in order to avoid distortions in the results due to changes in signal amplitude related to electrical disturbances and offsets.

C. Feature Extraction

AR and ARMA coefficients of order 10 as well as Fourier coefficients spaced at 2Hz are derived from each data window of each track using the Levinson-Durbin, Prony and Fast Fourier Transform algorithms respectively. Distributions of each feature for each track within a particular epoch are derived using 20-bin histograms. Next, considering the distribution of a particular feature in the inter-ictal epoch F_i and pre-ictal epoch F_p, the probability of misclassification of a particular feature is then estimated from the epochs under consideration as

$$P_e = \frac{F_i \bigcap F_p}{F_i \bigcup F_p} . \qquad (1)$$

Subsequently, those features with the smallest misclassification probability are chosen as candidates of interest.

D. Practical Computing Considerations

Due to the potentially large number of feature/track permutations where this analysis is applicable, the algorithm minimizes the amount of required memory by processing 484 permutations at a time and saving the distributions of only the best 22 (with smallest P_e). Then on a second run, the top 10 of those are chosen as candidates of interest.

E. Cross-Validation

To cross-validate the results, the two inter-ictal and pre-ictal epochs were interchanged within each set of data. This produced four sets of data per subject, each from a particular contrived scenario. However, no contrived scenario across the two human subjects was considered due to the possible distortions introduced by changes in the wiring and electrical setup to accommodate each particular medical case.

III. Results

Those features that show saliency on the same electrode channel over multiple contrived scenarios are ordered by the number of times they appear in the results (in parentheses).

TABLE I
LOW FREQUENCY FEATURES

Patient	2 minutes pre-ictal	10 minutes pre-ictal
A	1st pole coef. (28) 2nd pole coef. (15) 2nd AR coef. (10) 1st AR coef. (8)	1st pole coef. (26) 2nd pole coef. (12) 2nd AR coef. (8) 1st AR coef. (3)
B	1st pole coef. (30) 2nd pole coef. (26) 1st AR coef. (5) 3rd pole coef. (4)	1st pole coef. (36) 2nd pole coef. (22) 1st AR coef. (6) 78.4Hz component (1)

The resulting measures are organized in tables dividing features according to the subject (patient A and B) and according to pre-ictal epoch (2 minutes and 10 minutes).

TABLE II
HIGH FREQUENCY FEATURES

Patient	2 minutes pre-ictal	10 minutes pre-ictal
A	2nd pole coef (11) 2nd AR coef (9) 1st AR coef (9) 1st pole coef (8)	9th AR coef (9) 1st AR coef (7) 2nd pole coef (6) 9th pole coef (5)
B	2nd pole coef (35) 3rd pole coef (30) 1st pole coef (28) 2nd AR coef (13)	2nd pole coef (49) 3rd pole coef (36) 1st pole coef (35) 2nd AR coef (14)

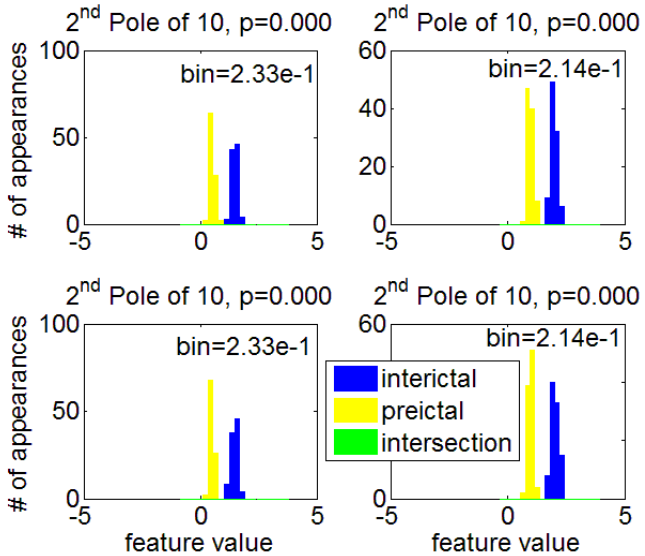

Fig. 1 Distributions of the 2nd pole coefficient as extracted from the high frequency band at 10 minutes pre-ictally for patient B. Probability of error (p) shown.

The most prominent features from the low frequency band are the first and second pole coefficients of the ARMA model, appearing in both epochs (starting 2 and 10 min pre-ictally). Also, there is a higher prominence of these features in the data from patient B.

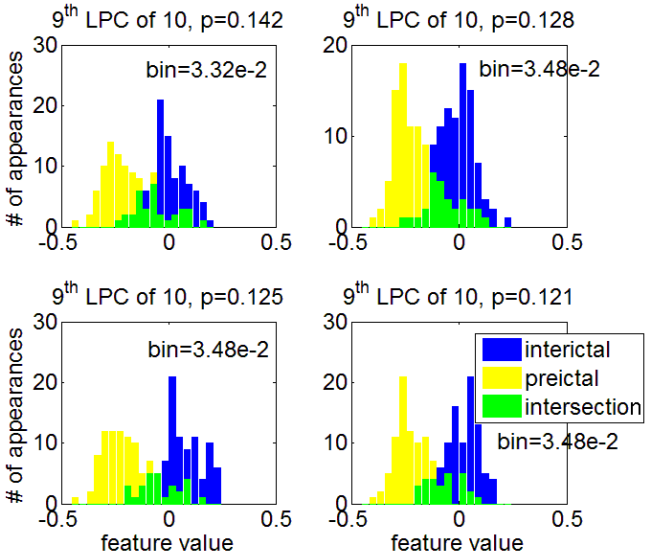

Fig. 2 Distributions of the 9th AR (LPC) coefficient as extracted from the high frequency band at 10 minutes pre-ictally for patient A. Probability of error (p) shown.

For high frequency analysis, the 2nd and 3rd pole coefficients are ubiquitous over all scenarios and in both patient data sets. Moreover, as can be seen in Fig.1, the feature distributions of pre-ictal and inter-ictal do not overlap for patient B.

IV. Discussion

Linear features including AR and ARMA model coefficients of order 10 as well as Fourier coefficients, have been shown to display some saliency when used to compare pre-ictal EEG recordings to inter-ictal EEG recordings for both low frequency (less than 100Hz) and high frequency (100-500Hz) bands. This indicates a possibility that these features may provide some robust discerning characteristics. However, using only two ictal events and two patients, there is not enough evidence statistically to suggest that these features are consistent across particular electrode channels for long periods of time. To investigate this possibility, the ARMA model coefficients should be extracted from larger volumes of EEG data including more patients and ictal events.

From the high frequency band analysis, the 2nd and 3rd pole coefficients seem compelling as a candidates for seizure prediction. Moreover, the consistency of these features across the two patient data sets encourages further study including pre-ictal epochs at earlier times before a seizure as well as a larger data set. Overall, the ARMA model coefficients seem to have the most successful discerning capabilities for both the low and high frequency bands, while the low error probabilities in the high frequency band (see Fig.1) present some intriguing results that require further investigation.

Appendix A

Histograms of error probabilities are shown for the top 10 features of epochs starting at 2 and 10 minutes pre-ictally for patients A and B. For the low frequency band, results from both patients are shown. However, for the high frequency band, histograms for patient B are omitted because they are all zero at the resolutions used (see Fig.1).

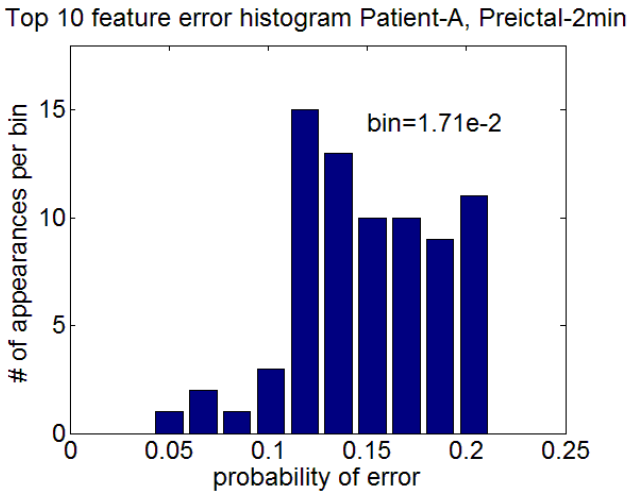

Fig. 3 Histogram of the probabilities of error of the top 10 features as extracted from the low frequency band of the epoch starting at 2 minutes pre-ictally for patient A.

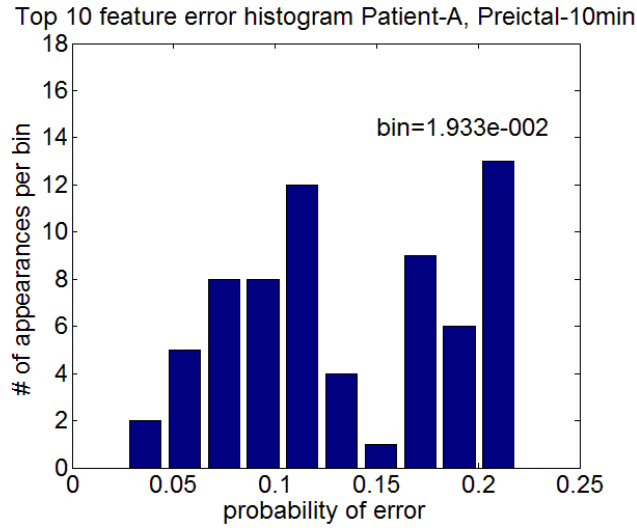

Fig. 4 Histogram of the probabilities of error of the top 10 features as extracted from the low frequency band of the epoch starting at 10 minutes pre-ictally for patient A.

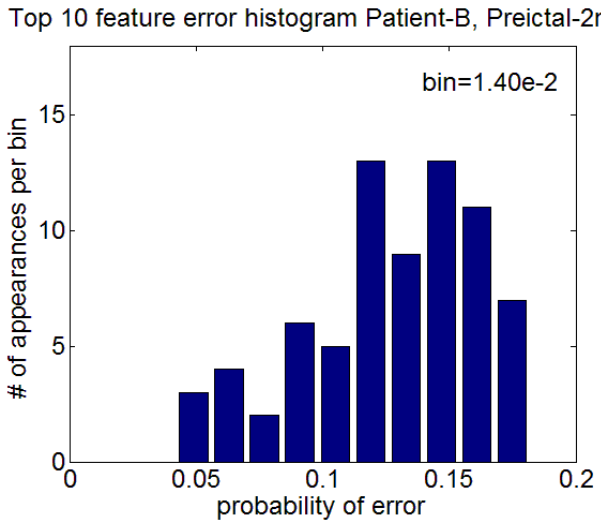

Fig. 5 Histogram of the probabilities of error of the top 10 features as extracted from the low frequency band of the epoch starting at 2 minutes pre-ictally for patient B.

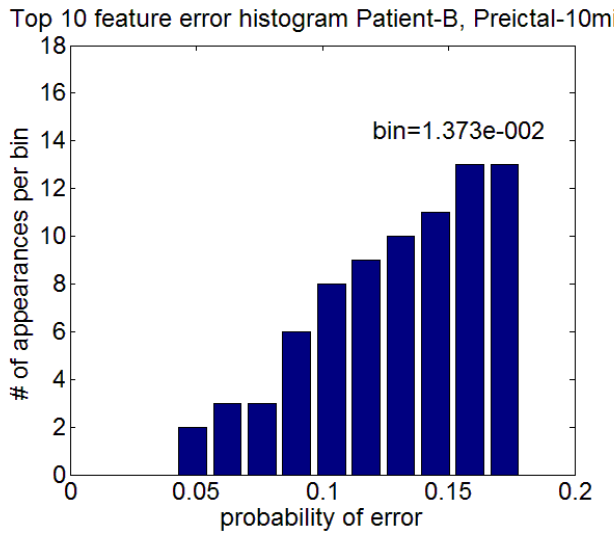

Fig. 6 Histogram of the probabilities of error of the top 10 features as extracted from the low frequency band of the epoch starting at 10 minutes pre-ictally for patient B.

The zero error probabilities of high frequency feature distributions for patient B suggest a high seperability for this particular case. This might be expected as the ICTAL events of this particular patient were associated with a more severe seizure as compared with patient A. Furthermore, this encourages further analysis at frequency bands above 100Hz with a larger, statistically significant number of patient studies. Also, this encourages analysis of earlier pre-ictal periods (earlier than 10 minutes) to determine how far back error probabilities remain low.

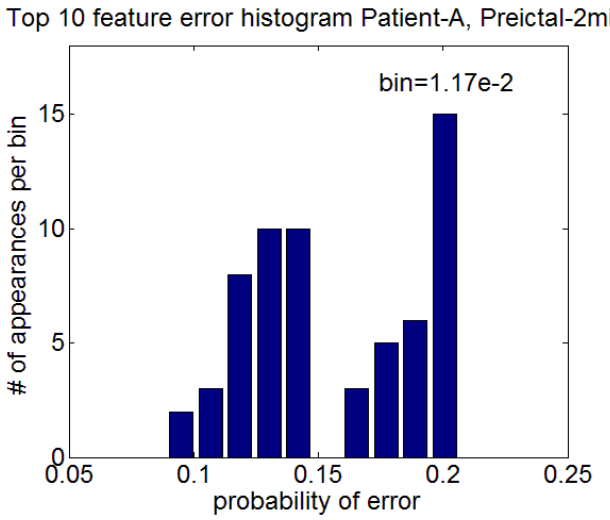

Fig. 7 Histogram of the probabilities of error of the top 10 features as extracted from the high frequency band of the epoch starting at 2 minutes pre-ictally for patient A.

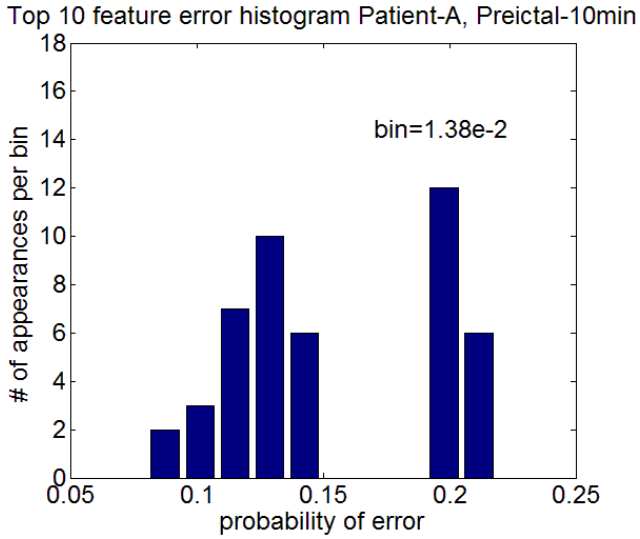

Fig. 8 Histogram of the probabilities of error of the top 10 features as extracted from the high frequency band of the epoch starting at 10 minutes pre-ictally for patient A.

APPENDIX B

Autoregressive coefficients, also known as LPC coefficients can be derived from a particular time series

$$\vec{x}, \tag{2}$$

a set of *m* data points. The LPC procedure determines a set of *p*+1 values defined by vector

$$\vec{a} \tag{3}$$

that solve the equation

$$X\vec{a} = \vec{b} \tag{4}$$

in a least squares sense, where

$$X = \begin{bmatrix} x(1) & 0 & \cdots & 0 \\ x(2) & x(1) & \ddots & \vdots \\ \vdots & x(2) & \ddots & 0 \\ x(m) & \vdots & \ddots & x(1) \\ 0 & x(m) & \ddots & x(2) \\ \vdots & \ddots & \ddots & \vdots \\ 0 & \cdots & 0 & x(m) \end{bmatrix}, \quad (5)$$

$$\vec{a} = \begin{bmatrix} 1 \\ a(1) \\ a(2) \\ \vdots \\ a(p+1) \end{bmatrix} \text{ and } \quad (6)$$

$$\vec{b} = \begin{bmatrix} 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix}. \quad (7)$$

Moreover, an efficient algorithm for completing this task is known as the Levinson or Levinson-Durbin algorithm [11].

Given some impulse response h(n), the autoregressive moving average (ARMA) model defines an infinite impulse response (IIR) filter that has an impulse response that fits h(n) as closely as possible. Moreover, there are a number of methods available for building an ARMA model. One of these is the Prony method [12] that utilizes the Levinson-Durbin algorithm to find the poles of the filter, then solves for the zeros using the method of least squares.

ACKNOWLEDGMENTS

The authors wish to thank the members of the reviewing committee for their constructive input to this study.

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