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Space-Time Adaptive Processing for Improved Estimation of Preictal Seizure Activity

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Abstract— **Detection of precursory, seizure-related activity in electroencephalograms (EEG) is a clinically important and difficult problem in the field of epilepsy. Seizure detection methods often aim to identify specific features and correlations between preictal EEG signals that differentiate them from interictal/nonictal signals. Typically, these methods use information from nonictal EEGs to establish detection thresholds, and do not otherwise incorporate their characteristics into the detection. A space-time adaptive approach is proposed to improve detection of seizure-related preictal activity in scalp EEG, using multiple patient-specific baseline signals to optimize the estimate of the baseline covariance matrix. A simplified model of the preictal EEG is assumed, which describes this signal as a linear superposition of seizure-related activity and baseline activity (treated as an interference signal). It is shown that when an improved estimate of the baseline covariance is included in the preictal detector, the true positive rate increases significantly and also the false positive rate decreases significantly.**

I. INTRODUCTION

Seizure prediction and early detection prior to clinical onset are of significant clinical interest. For patients with medically intractable epilepsy, accurate detection of seizure-related activity in the preictal interval may significantly increase their therapeutic options and accelerate the development of novel, patient-specific approaches for seizure prevention. Despite a large number of promising studies, early seizure detection and/or prediction from electroencephalographic (EEG) data, remain challenging problems in the field [6]. Epileptic seizures are transient and dynamically evolving events, with precursory seizure activity often staring at least several minutes prior to clinical and/or electrographic ictal onset, if not earlier [5]. However, seizure precursors may be difficult to detect, particularly in scalp EEG recordings, which are highly complex and noisy signals that measure aggregate neural activity from multiple sources. Preictal and ictal EEGs may, therefore, be superpositions of seizure-related activity from the epileptogenic region, baseline neural activations, contributions from unrelated sources and noise. These contributions make it difficult for precursory seizure activity to be identified in preictal EEGs.

Several seizure detection studies have used nonictal/interictal EEGs for comparison purposes, i.e., to assess the sensitivity and specificity of proposed algorithms and measures of precursory activity to impending seizures, e.g., [14], [7], [2], [1], [9]. These studies do not otherwise incorporate nonictal signals into the detection of preictal seizure-related activity. Yet, baseline neural activity may have a significant contribution to preictal, and possibly ictal EEG signals. Therefore, methodologies that incorporate knowledge from baseline signals to improve estimates of precursory seizure activity are desirable. Space-time adaptive processing (STAP) is a set of signal processing methods that simultaneously combine signals from an entire array of sensors and from multiple time-intervals. STAP is widely used in radar, to improve target detection in the presence of unrelated and interfering signals [13], [4]. Although its main application to radar systems is evidently very different from detection of seizure precursors, the basic principles of STAP are relevant to a broad range of signal detection and array processing problems. Therefore, detection of seizure activity in preictal EEGs signals may be thought of as an adaptive processing problem, with spatially distributed and dynamic baseline activity as the interfering signal, which is correlated in space and time. For improved detection, information from multiple nonictal signals may be incorporated as a priori information into processing. This preliminary study investigated i) optimization of baseline covariance using an adaptive approach to combine prior and current sample estimates, and ii) the effects of this optimization on improving the detection of precursory seizure signals.

II. METHODS

A. Electrophysiological Data

All data were recorded in the Clinical Neurophysiology Laboratory of the Comprehensive Epilepsy Center at Beth Israel Deaconess Medical Center. A standard international 10-20 clinical EEG system was used, with a referential montage (channel Cz was selected as the reference channel). All EEGs were sampled at 500 Hz. Five subjects with diagnosed temporal lobe epilepsy, in the age range 33-47 years (μ=40.8, σ=5.2), were chosen from adult patients admitted to the epilepsy monitoring unit for non-invasive neurophysiological studies. All patients had least two complete seizures and corresponding preictal intervals 30s or longer (typically $\sim$2-3 min. All seizures occurred during wakefulness. For each patient, at least five periods of nonictal EEG during wakefulness were selected, 30s -5 min in duration and partially covering a long period of time (several hours). All nonictal intervals were recorded more than 12-24 hours remote from a clearly defined seizure. Ictal onset and offset times were estimated using standard clinical

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methods of EEG interpretation. Table I summarizes patient demographics and respective number of nonictal and preictal segments analyzed in the study.

TABLE I
CLINICAL/DATA INFORMATION

Pat.#	Age	Etiology	Preictal	Nonictal
			Segments	Epochs
1	33	R-Mesial Sclerosis	7	9
2	43	Cryptogenic	5	6
3	42	Cryptogenic	11	5
4	47	L-Mesial Scleroris	9	6
5	39	Cryoptogenic	2	5

B. EEG preprocessing

Power-line noise was attenuated with a stopband filterbank of 3rd order elliptical filters centered at the 60 Hz harmonics of the noise, in the range 60-250 Hz, with a 1 Hz bandwidth, 20 dB attenuation in the stopband, and 0.5 dB ripple in the passband. Signals were filtered in both forward and reverse directions to eliminate potential phase distortions due to the non-linear phase of the filter. Eye blinking-related artifacts were suppressed using a matched-filtering approach [8]. Interictal spikes in EEG signals that were localizable to the region of seizure onset, were preserved, as they were considered to be part of a patient's non-ictal baseline.

C. Space-time adaptive processing

STAP is used to process dynamic data simultaneously from an array of receivers (here the EEG electrodes). At time t we obtain a snapshot of the entire EEG array:

$$\vec{x}(\vec{r},t) = [x_1(\vec{r}_1,t),...x_N(\vec{r}_N,t)]^T \tag{1}$$

where N is the number of array elements (here $N = 20$), and $\vec{r}_i$ their corresponding position vectors. In its simplest form, detection of precursory seizure activity at snapshot t may be expressed as a decision rule:

$$\begin{aligned} &\vec{x}(\vec{r},t) = \vec{x}_b(\vec{r},t) && H_0\text{: no seizure activity} \\ &\vec{x}(\vec{r},t) = \alpha(t)\vec{x}_s(\vec{r},t) + \vec{x}_b(\vec{r},t) && H_1\text{: seizure activity} \end{aligned} \tag{2}$$

where $\vec{x}_b$ is baseline activity, and includes inherent non-neural noise, $\vec{x}_s$ is seizure-related activity, and $\alpha(t)$ a time-varying weight, since seizure activity is not constantly present in EEG signals. Thus, in the presence of seizure precursors, EEG signals may be expressed as a weighted linear superposition of baseline and seizure-induced activity. This is a simplistic model, as baseline activity may be modulated by seizure precursors, and thus the two may be coupled in ways that are not clearly understood to be adequately modeled. However, in this preliminary study we assumed a linear model that describes the preictal EEG signal as a linear superposition of contributions from seizure-related and baseline sources. Note that prior to ictal onset and propagation of seizure activity to large areas of the brain, the component $\vec{x}_s$ may be restricted to a subset of electrodes $N_s \leq N$, e.g., those covering the epileptogenic region, i.e., the decision rule is spatio-temporally specific.

The first step in the detection of seizure precursors is to obtain a robust estimate of the statistics of baseline activity that may be used in adaptive processing of preictal signals. As previously stated, $\vec{x}_b(\vec{r},t)$ is a superposition of uncorrelated baseline neural $s(t)$ and noise ν (assumed to be normally distributed), i.e., $\vec{x}_b = \vec{s}_b(\vec{r},t) + \nu(\vec{r},t)$, $\nu(\vec{r},t) \sim \mathcal{N}(0,\Sigma)$. The corresponding covariance matrix R_b is, therefore, given by:

$$R_b = E\{\vec{x}_b\vec{x}_b^T\} = R_s + R_\nu \tag{3}$$

At each time point and/or coherent processing interval, an estimate of R_b may be obtained from the data. In an unrelated study, [12] proposed a method for combining covariance matrix estimates to obtain a optimum estimate of R_b in a mean-squared error (MSE) sense. Therefore, assuming that we have initial and subsequent estimates $\hat{R}_{b,0}$ and $\hat{R}_{b,1}$ of the baseline covariance, we can obtain a new estimate as:

$$\tilde{R}_b = a_0\hat{R}_{b,0} + a_1\hat{R}_{b,1} \tag{4}$$

with a_0, $a_1 > 0$. For every new sample covariance matrix $\hat{R}_{b,k}$, a new $\tilde{R}_b$ can then be obtained by linearly combining weighted previous estimates with $\hat{R}_{b,k}$ according to Equation 4. Our goal is then to find a_0 and a_1, such that the MSE of $\tilde{R}_b$ is minimized, where $MSE = E\{\|\tilde{R}_b - R_b\|^2\}$, $\|\cdot\|$ denotes the Euclidean norm, and the true baseline covariance matrix R_b is unknown. We assume that the sample covariance matrix is an unbiased estimate, i.e., $E\{\hat{R}_b\} = R$.

The following formulas for estimating coefficients a_0 and a_1 have been derived in [12]. Details on these expressions may be found there. In this study they were used to obtain a robust estimate of the baseline covariance matrix of $\vec{x}_b(\vec{r},t)$ from multiple nonictal EEG segments.

$$\hat{a}_1 = \frac{\hat{\gamma}}{\hat{\gamma} + \hat{\rho}} \tag{5}$$

$$\hat{c} = \frac{tr(R_{b,0}\hat{R}_{b,1})}{\|R_{b,0}\|^2} \tag{6}$$

$$\hat{\rho} = \frac{1}{T^2}\sum_{t=1}^{T}\|x_b(t)\|^4 - \frac{1}{T}\|\hat{R}_{b,1}\|^2 \tag{7}$$

$$\hat{\gamma} = \|\hat{c}R_{b,0} - \hat{R}_b\|^2 \tag{8}$$

$$\hat{a}_0 = \hat{c}(1 - \hat{a}_1) \tag{9}$$

where $tr(\cdot)$ denotes the matrix trace, and T is the length of the processing interval.

Once a robust estimate $\tilde{R}_b$ has been obtained, the next step is to define the space-time processor that combines the spatial samples from the EEG array with the temporal samples in the processing interval $[t, t+T]$. The signature of the seizure precursory signal x_s is entirely unknown. The space-time processor increases the gain in the range and direction of x_s and suppresses unrelated signals in other directions. We assume that x_s is a seizure-precursor steering vector, i.e.,

$$\vec{x}_s(\vec{r},\omega_s,t) = [1e^{j\omega_s t}...e^{j(Ns-1)\omega_s t}]^T \tag{10}$$

where N_s, the number of electrodes that measure the precursory signal. For simplicity it is assumed that $N_s = N$, i.e.,

all electrodes (N=20). The characteristic precursor frequency ω_s is also unknown. In a previous study, we estimated transient precursory signals with characteristic frequencies in the range 100-180 Hz, but this frequency varied between individual precursors [9]. Therefore, each preictal EEG signal was segmented into processing intervals, and decomposed into its dominant components using a modified mode decomposition approach [3], [10], [11]. A separate steering vector was estimated at each dominant frequency and used in the detection. Seizure activity was not decoupled from baseline activity in these decompositions, and thus the estimated ω_s may not represent a true precursor (target) frequency. However, in the absence of a priori knowledge this was the only available data-derived estimate. The baseline covariance matrix $\tilde{R}$, data snapshot $\vec{x}(\vec{r},[t,t+T])$ and steering vector in Equation 10 were then used in an adaptive matched-filter detector with decision rule:

$$\frac{\vec{x}_s(\omega_s)\tilde{R}^{-1}\vec{x}}{\vec{x}_s(\omega_s)\tilde{R}^{-1}\vec{x}_s} \underset{H_1}{\overset{H_0}{\lessgtr}} \eta \qquad (11)$$

where η is a detection threshold, which varied between patients.

III. RESULTS

In previous studies [9], we have estimated that baseline neural dynamics in the epileptic brain vary with a period of ~4-5 s, in which signal stationarity may also be assumed. We, therefore, assumed a 5 s sliding window for coherent processing , and estimated all covariance matrices in each interval. New coefficients a_0 and a_1 were estimated sequentially. The proposed optimization was performed on the data of each patient individually.

A. Estimation of baseline covariance from multiple segments

For each patient, we obtained robust estimates of the baseline covariance matrix, by updating this matrix using previous estimates as prior knowledge and estimating new coefficients a_0 and a_1 for every new snapshot, according to Equation 4. Figure 1 shows examples of sample covariance matrices and Figure 2 shows the variation of the coefficients with increasing number of samples. As expected, when a_0 increases, a_1 decreases and vice versa. As the estimate of the baseline covariance matrix improved, higher spatial correlations between some EEG signals were estimated.

B. Detection of preictal seizure precursors

To assess the performance of the detector, a set of preictal intervals and nonictal intervals were shuffled together. We assumed that true positives corresponded to detections within any of the preictal intervals, and false positives to detections outside these intervals. 1 s bins were processed through the detector. Figures 3 and 4 show the performance of the detector with and without an optimized estimate of the baseline covariance.

Overall, optimization of the baseline covariance matrix increased the true positive rate (TPR) by at least 7% and decreased the false positive rate (FRP) by at least 13%. In some patients, this optimization resulted in a significantly

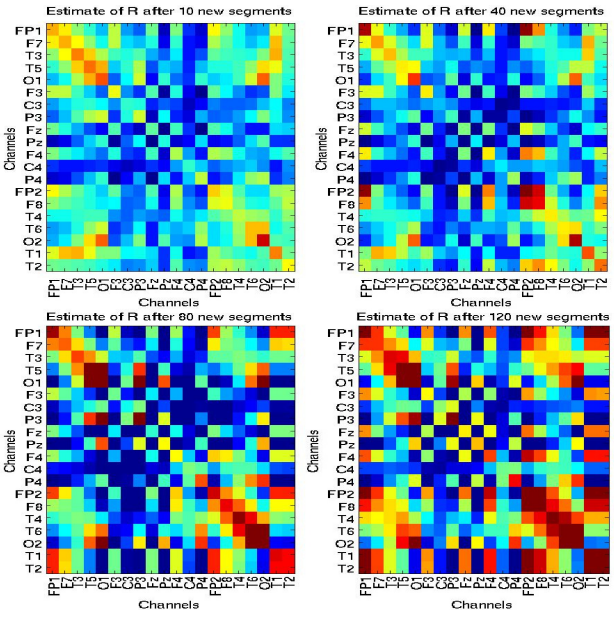

Fig. 1. Sequential estimates of the baseline covariance matrix by combining previous estimates (prior knowledge) with new sample estimates, after 10, 40, 80, 120 new segments (from top left to bottom right). The latter panel shows the final covariance estimate.

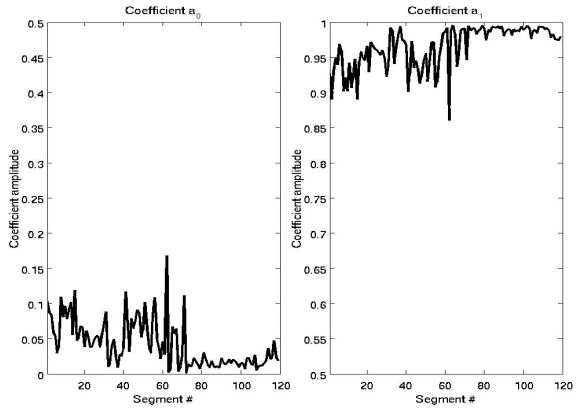

Fig. 2. Variation of coefficients a_0 and a_1 for linear combination of baseline covariance matrices with increasing number of samples.

increase in TRP of ~34%. Therefore, a large number of nonictal signals covering long periods of time (or continuously recorded baseline EEGs for several hours), may be used to significantly improve detection of preictal seizure precursors.

IV. DISCUSSION

We have proposed an adaptive space-time processing approach for detection of seizure-related activity in preictal EEGs, using prior information from nonictal signals to obtain robust estimates of the necessary baseline (interference) covariance matrix. We have shown that optimization of this matrix results in a significant improvement in detection, at least in the case of the adaptive matched-filter detector. Being preliminary, this study only assessed the relative performance of this detector. We have applied this approach to 5 patients with multiple nonictal and preictal signals, and have shown

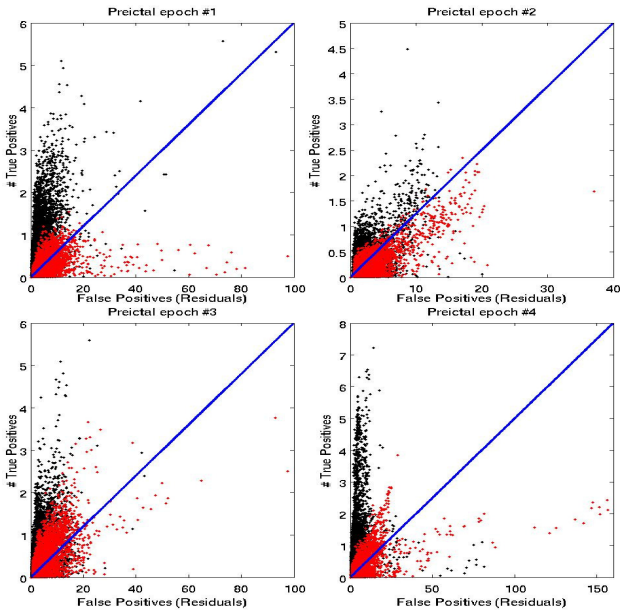

Fig. 3. Detector performance estimated from 4 preictal epochs (132, 156, 162 and 120 segments, respectively), without optimization (red) and following optimization (black), for patient #1 in Table 1. Each data point corresponds to a distinct segment and channel.

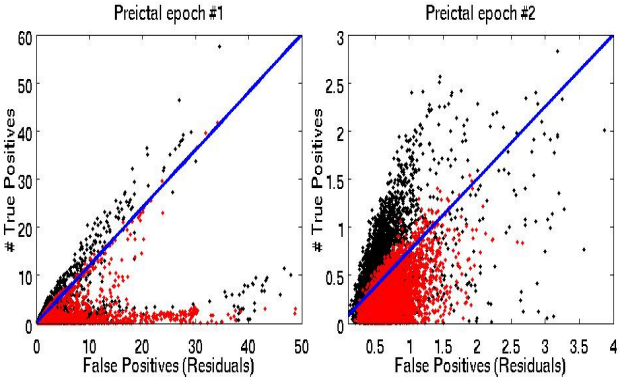

Fig. 4. Detector performance estimated from 2 preictal epochs (120 and 180 1s segments, respectively) without optimization of the baseline (red) and following optimization (black). for patient # 5 in Table 1. Each data point corresponds to a distinct segment.

at least a 7% increase in the true positive rate and at least 13% decrease in the false positive rate. There are several additional optimizations that may improve these detections further. For example, in the absence of a priori knowledge of the spectral characteristics of seizure-related signal contributions to preictal intervals, we decomposed these signals into dominant modes with distinct characteristic frequencies. However, some of these frequencies may be associated with components that are unrelated to seizure activity. Therefore, in a extended study, comparison of multiple baseline and preictal spectra may improve the estimation of spectral peaks associated primary with non-baseline, and thus potentially with seizure-related activity. Finally, since the signature(s) of seizure precursors are a priori unknown, the performance of several detectors may be compared to identify one with the highest sensitivity and specificity to seizure activity. Nevertheless, despite being preliminary this study presents a promising approach to improve detection of seizure precursors, which may ultimately facilitate therapeutic intervention for seizure prevention.

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