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Removing Artifacts and Background Activity in Multichannel Electroencephalograms by Enhancing Common Activity

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Abstract–**Removing artifacts and background EEG from multichannel interictal and ictal EEG has become a major research topic in EEG signal processing in recent years. We applied for this purpose a recently developed subspace-based method for modelling the common dynamics in multichannel signals. When the epileptiform activity is common in the majority of channels and the artifacts appear only in a few channels the proposed method can be used to remove the latter. The performance of the method was tested on simulated data for different noise levels. For high noise levels the method was still able to identify the common dynamics. In addition, the method was applied to a real life EEG recording. Also in this case the muscle artifacts were removed successfully. For both the synthetic data and the analyzed real life data the results were compared with the results obtained with principal component analysis (PCA). In both cases the proposed method performed better than PCA.**

Keywords– **Common dynamics, artifact removal, background EEG removal, interictal EEG, singular value decomposition, subspace based, exponentially damped sinusoids.**

I INTRODUCTION

Typical waveforms appear in the EEG of patients with epilepsy. Ictal EEG (activity during a seizure) and interictal events (epileptic activity between seizures) can be distinguished. This activity can be identified on the majority of the EEG electrodes if the underlying electrical sources (the epileptogenic region) are located in deeper cortical structures as in Mesial Temporal Lobe Epilepsy (MTLE). In reality noise is added to this EEG obscuring the brain function of interest and making the interpretation of the EEG less straightforward. Some typical contributors are the heart, muscle and eye-movement artifacts. In general, these artifacts appear on a limited number of channels in EEG recordings. Apart from these electrical active tissues, many brain areas other than the epileptogenic region are active too. For the purpose of the present study the non-epileptogenic EEG is considered as background.

Many methods exist in the literature which attempt to remove or attenuate artifacts and background EEG from the multichannel interictal and ictal EEG. Among them are broadband filtering methods, regression methods, and component based methods such as principal component analysis (PCA) and independent component analysis (ICA).

In this paper we introduce a new approach towards removing artifacts and background EEG. A new subspace based method is used to model the common dynamics in a multichannel recording [1, 2]. With common dynamics we mean the same waveform appearing over multiple channels. As the time course of the signals at the different scalp electrodes appears in or out of phase and with different amplitude, we allow the common waveform to have a different phase and amplitude for each channel. The proposed method can be exploited to remove artifacts when epileptiform activity appears in the majority of channels and the artifacts only in few. When the spatial correlation of the background EEG is low, the background EEG will also be removed by applying this method.

II METHODS

A. *Exponentially damped sinusoidal model*

A way to analyze EEG signals is to quantify them directly in the time domain by means of model-based (or parametric) methods. We used the parametric exponentially damped sinusoidal (EDS) model where the signal is modelled as a finite sum of K discrete-time exponentially damped complex sinusoids:

$$\begin{aligned} x(n) &= \sum_{k=1}^{K} c_k z_k^n + e(n), \qquad (1) \\ n &= 0, 1, \ldots, N-1. \end{aligned}$$

where $c_k = a_k \exp(j\phi_k)$ is the complex amplitude, $z_k = \exp\left((-d_k + j2\pi f_k)\Delta t\right)$ is the signal pole, $j = \sqrt{-1}$, $n\Delta t$ is the time lapse between the origin and the sample $x(n)$, Δt is the sampling interval, and $e(n)$ is white gaussian noise. The parameters of this model are the amplitudes a_k, the phases ϕ_k, the damping factors d_k and the frequencies f_k. Since exponentially damped sinusoids are a set of basis

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functions, they can be used to model any arbitrary signal sufficiently closely provided the model order is high enough. The EDS model can be extended to real-valued signals since any real-valued sinusoid can be expressed as a superposition of two complex sinusoids. Consequently, the model order K is equal to twice the number of sinusoids that comprise the real-valued signal. The EDS model is proven to be useful for modelling non-stationary signals containing transients such as speech [3], in-vivo near infrared spectra and blood pressure [4].
The algorithm consists out of two parts a single-channel preprocessing step and an common dynamics extraction step.

B. Single-channel preprocessing

- *Step 1*. For every channel $s, s = 1, \ldots, S$ arrange the data points $x_s(n), n = 0, \ldots, N-1$ in a Hankel matrix H_s of dimensions $L \times M$ as follows:

$$H_s = \begin{bmatrix} x_s(0) & \cdots & x_s(M-1) \\ x_s(1) & \cdots & \vdots \\ x_s(2) & \cdots & \vdots \\ \vdots & \vdots & x_s(N-2) \\ x_s(L-1) & \cdots & x_s(N-1) \end{bmatrix}, \quad (2)$$

  where N=L+M-1.
- *Step 2*. Compute the Singular Value Decomposition (SVD) of each Hankel matrix H_s:

$$H_s = U_s \Sigma_s V_s^H, \quad (3)$$

  where the superscript ^{H} denotes the hermitian conjugate. According to [5], in the absence of noise the SVD of H_s reduces to the product

$$H_{s_{K_s}} = U_{s_{K_s}} \Sigma_{s_{K_s}} V_{s_{K_s}}^H, \quad (4)$$

  where $U_{s_{K_s}}$, $V_{s_{K_s}}$ are respectively the first K_s columns of U_s, V_s and $\Sigma_{s_{K_s}}$ is the leading $(K_s \times K_s)$ submatrix of Σ_s. In the presence of noise H_s is full rank. In this case, the truncated SVD, $H_{s_{K_s}}$, of H_s is the best rank-K_s approximation of H_s and the column vectors of the truncated matrix $U_{s_{K_s}}$ span the signal subspace [5].

In practice the number of sinusoids present in a given signal and thus the corresponding model order K_s is not known a priori. Therefore, we introduce the following rule for truncating the U_s matrices in step 3. The U_s matrices are truncated when $\sigma_s^2(K_s) \geq d \cdot \sigma_s^2(1)$ and $\sigma_s^2(K_s+1) < d \cdot \sigma_s^2(1)$, with $\sigma_s(k)$ the k^{th} largest singular value corresponding to the k^{th} left singular vector in U_s. The parameter d, which can be defined by the user, determines which left singular vectors belong to the signal subspace.

C. Common dynamics extraction

- *Step 1*. Stack the truncated $U_{s_{K_s}}$, $s = 1, \ldots, S$ matrices into a $L \times \sum_{s=1}^{S} K_s$ matrix

$$U_{stacked} = [U_{1_{K_1}} | U_{2_{K_2}} | \ldots | U_{S_{K_S}}]. \quad (5)$$

  and compute the SVD of this resulting matrix

$$U_{stacked} = U_c \Sigma_c V_c^H. \quad (6)$$

  In [1] it is explained why the SVD of $U_{stacked}$ directly gives information about the number of common poles and the common subspace spanned. Assuming that there are K_c poles common to S signals, the diagonal core matrix Σ_c contains a first set of K_c values equal to $\sqrt{S}$. The K_c first vectors of the left singular vector matrix $U_{c_{K_c}}$ span the common subspace related to the common signal poles. We select these vectors by truncating U_c to a matrix of rank K_c, $U_{c_{K_c}}$.

- *Step 2*. The frequency and damping parameters of the EDS are estimated from $U_{c_{K_c}}$ as fully described in [1, 2].
- *Step 3*. The corresponding estimates for amplitudes $a_{s,k}$ and phases $\phi_{s,k}$, $s = 1, \ldots, S; k = 1, \ldots, K_c$ of the common signal poles are determined for each channel separately as described in [1, 2].

III SIMULATION STUDY

A. Synthetic seizure activity

The EEG of the ictal activity was generated using a fixed dipole in a three-shell spherical head model with a moment having a 4 Hz sinusoidal waveform (for example typical in patients with MTLE). The time course of the scalp potentials was stored in a 250-by-19 dimensional matrix A.

B. Noise

Let B denote a 250-by-19 noise matrix representing awake background EEG activity from a normal subject, 50 Hz line noise, and muscle artifact. Since the spatial correlation of the selected background EEG is low, no common waveform appears on all channels of B.

C. The simulated signal

In the simulation study the noise matrix B is superimposed on the signal matrix A containing the common dynamics:

$$X(\lambda) = A + \lambda \cdot B, \quad (7)$$

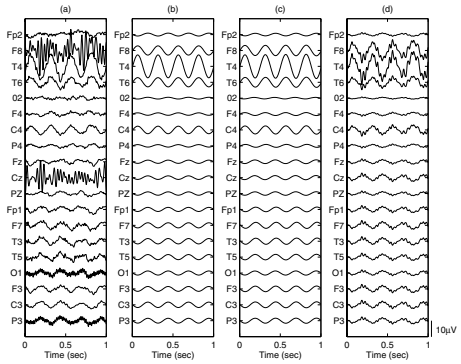


Figure 1. (a) The simulation data matrix $L(\lambda)$ for a noise level equal to $nl = 0.95$. (b) The signal matrix A containing the common dynamics. (c) The reconstructed EEG based on the common signal poles. (d) The reconstructed EEG based on the first principal component.

with $\lambda \in \mathbb{R}$. The Root Mean Squared (RMS) value of the signal is then equal to

$$RMS(A) = \sqrt{\frac{1}{S \cdot N} \sum_{s=1}^{S} \sum_{n=0}^{N-1} A_s^2(n)}. \qquad (8)$$

An important measure is the noise level (nl) which is defined as follows,

$$nl = \frac{RMS(\lambda \cdot B)}{RMS(A)}. \qquad (9)$$

Changing the λ parameter alters the noise level of the simulated signal.
The performance of the method to enhance common activity is expressed in terms of the Relative Root Mean Squared Error (RRMSE):

$$RRMSE = \frac{RMS(A - \hat{A})}{RMS(A)} \cdot 100[\%], \qquad (10)$$

where $\hat{A}$ is an estimate of the common activity.

D. Results of the simulation study

Fig. 1(a) shows a simulated data matrix X under study with a noise level equal to 0.95. The signal matrix A containing the common dynamics is shown in Fig. 1(b). The set of signals X was processed with the following parameters: $N = 250$, $L = 126$, $M = 125$. The U_s matrices are truncated with d equal to 0.1. Fig. 2 shows the resulting squared singular values σ_c^2 of the stacked matrix $U_{stacked}$ eqn. (6). There are two squared singular values close to 19, indicating that there are two common signal poles in all 19 channels. The reconstructed EEG based on these two signal poles according to step 2 and 3 in section 2.C had an

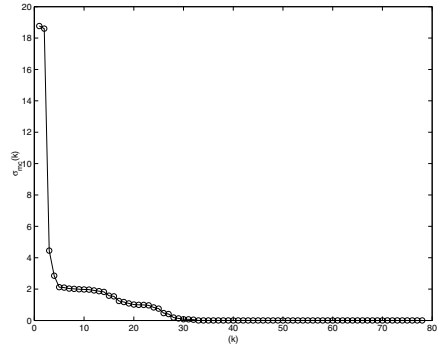


Figure 2. The singular values of the stacked matrix $U_{stacked}$ generated in the simulation study.

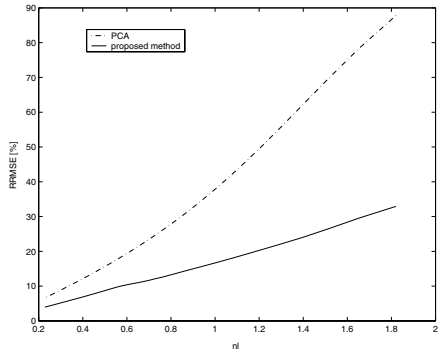


Figure 3. The RRMSE as a function of the noise level is shown for the proposed method and PCA.

RRMSE of 13% and is shown in Fig. 1(c). By modelling the common dynamics in the 19 channels the remaining noise after preprocessing was successfully removed.

For comparison, we applied SVD directly to the data matrix X to derive the principal components of the simulated EEG signal (= PCA). The $(N \times S)$ matrix X is then decomposed as a product of three matrices:

$$X = U\Sigma V^T, \qquad (11)$$

where U is an $(N \times S)$ matrix containing the S normalized component waveforms that are decorrelated linearly and can be remixed to reconstruct the original EEG. The first principal component contained the 4 Hz epileptiform waveform and was selected. The reconstructed EEG based on this truncation had an RRMSE of 34% and is shown in Fig. 1(d).
The RRMSE as a function of the noise level is shown in Fig. 3. In this figure a comparison is made between the proposed method and PCA. For all the given noise levels our method performed better than PCA.

IV METHOD APPLIED TO INTERICTAL ACTIVITY

The epileptic spike used for further analysis is shown in Fig. 4(a). By determining the common

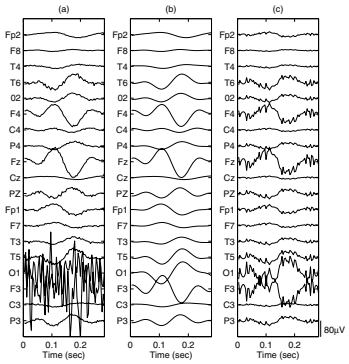


Figure 4. (a) Shows the original spike. The fit based on the common signal poles is shown in (b). The reconstructed EEG based on the first principal component is shown in (c).

dynamics present in all channels we wanted to enhance the spike activity and remove the artifact from channels O1 and F3. The following parameters were applied: $N = 70$, $L = 36$, $M = 35$. The U_s matrices are truncated with d equal to 0.01. The reconstructed EEG based on these common signal poles is shown in Fig. 4(b). The muscle artifact is removed successfully on channels O1 and F3.
For comparison, Fig. 4(c) shows the result of the noise removal based on the truncated SVD of the data matrix. Hereby, the first principal component is selected for reconstruction.

V DISCUSSION

In this paper, we introduced a new method for modelling the common dynamics in a multichannel recording. We showed that this method can be used to remove artifacts and background EEG from epileptiform EEG when they contain activity with a low spatial correlation.
It is important to notice that the proposed method can be used on any multichannel EEG recording starting from 2 to N channels. One is not obliged to use the method on all recorded EEG channels. The method can be used on a selection of EEG channels of interest to look for the common dynamics within the selected channels (for example, if a lateralization of the epileptic focus is a priori known).
When no prior knowledge is available of the location of the epileptic source then an average reference or a common reference (such as linked ears) should be used. The epileptic EEG will then appear in most of the channels and the proposed method will keep this activity and reduce the background activity. However, the method will not work so well when applying a bipolar montage, where two electrodes representing a channel, are located close to each other. Here the epileptic activity will only be present on a small number of channels and the interesting activity would rather be suppressed than amplified.
If one wants to automate the proposed method one must keep in mind that the EDS model becomes ineffective when the signals of interest are not yet started at the onset (n=0) of the selected time window. Consequently, the window length and onset must be chosen adaptively as suggested in [6].
Finally, the method can also be applied to other biomedical signals where there is a need to find the common information within a set of signals (e.g. [4, 7]).

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