The Riemannian Potato: an automatic and adaptive artifact detection method for online experiments using Riemannian geometry

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Abstract. Artifacts management is a critical problem in any applications involving on-line processing of EEG signals. This paper presents a multivariate automatic and adaptive method for identifying artifacts in continuous EEG data.

Keywords: EEG, Artifact detection, Riemannian geometry, BCI.

1. Introduction

In this work we consider as artifacts any kind of EEG signal different enough as compared to the normal baseline signal. Based on this new definition, covariance matrices are used as descriptors of EEG signals and a Riemannian metric is employed to compare these covariance matrices with an average covariance matrix estimated on the signal baseline. This framework is not specific to a particular kind of artifacts and allows us to take into account the spatial properties of the artifacts. A practical implementation of this method will be described, and results of the online detection will be shown.

2. Methods

The goal of the detection algorithm is to determine if a portion of EEG signal $X \in \Re^{N \times T}$ recorded during a time window of T samples over N electrodes contains artifacts. In order to achieve this, a trial X will be represented by its spatial covariance matrix $C = \frac{1}{T-1} XX^T$ and the criterion for the detection will be based on a Riemannian distance computation. The main idea is to estimate a reference covariance matrix $\overline{C}$ and reject every trial which is too far, in term of Riemannian distance, from this reference matrix. The Riemannian distance between C and $\overline{C}$ is defined by [Förstner and Moonen, 1999]:

$$d_R\left(C, \overline{C}\right) = \sqrt{\sum_{n=1}^{N} \log^2\left(\lambda_n\right)} \tag{1}$$

with λ_n the eigenvalues of $C^{-1/2}\overline{C}C^{-1/2}$. The trial corresponding to C will be considered as an artifacts if d_R is greater than a threshold *th*. Thus, the detection algorithm requires two parameters: $\overline{C}$, the reference point in the Riemannian manifold and the threshold *th* for the detection. The estimation of those two parameters is the important part of the algorithm. The reference point could be estimated in an adaptive manner during the whole recording session according to the following equation:

$$\overline{C}_{t+1} = (\overline{C}_t)^{1/2}\left[(\overline{C}_t)^{-1/2} C (\overline{C}_t)^{-1/2}\right]^{1/\alpha} (\overline{C}_t)^{1/2} \tag{2}$$

with $\overline{C}_t$ the reference matrix from the previous iteration, C the current covariance matrix and α a coefficient which defines the speed of the adaptation. This adaptation is done only when clean signal is detected, i.e., the distance is lower than the threshold. The threshold *th* is estimated based on the mean μ and standard deviation σ of the distance to the reference matrix defined in Eq. 1 :

$$th = \mu + 2.5\sigma \tag{3}$$

These two parameters define a region of interest in the Riemannian manifold. Since the Riemannian metric is non-linear, this region of interest corresponds to a “potato” in the Riemannian manifold. Fig. 1 shows the potato for a dataset of 100 2x2 covariance matrices on simulated data.
Each point represents a covariance matrix in the manifold. The big black point corresponds to the reference matrix and the grid represents the edge of the potato where the Riemannian distance to the reference point is equal to *th*.

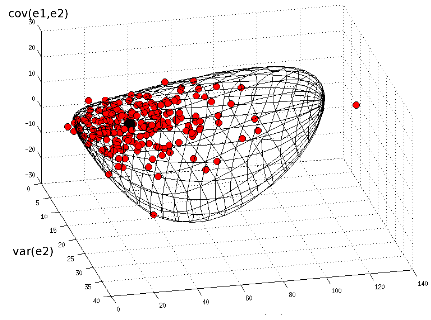

Figure 1: Riemannian potato for a set of 100 2x2 covariance matrices on simulated data.

3. Results

This algorithm was implemented in the OpenViBE software [Renard et al., 2010], and applied during a P300 experiment. EEG signals were recorded using a g.tec amplifier and 16 dry active electrodes. After a bandpass filtering (1-20Hz), signals are epoched using a sliding window of 1s (with a step of 100ms). The parameter α of the adaptation is set to 100, and the initialization of the reference point is done at the beginning of the session, where the user is instructed to stay still for 10 seconds.

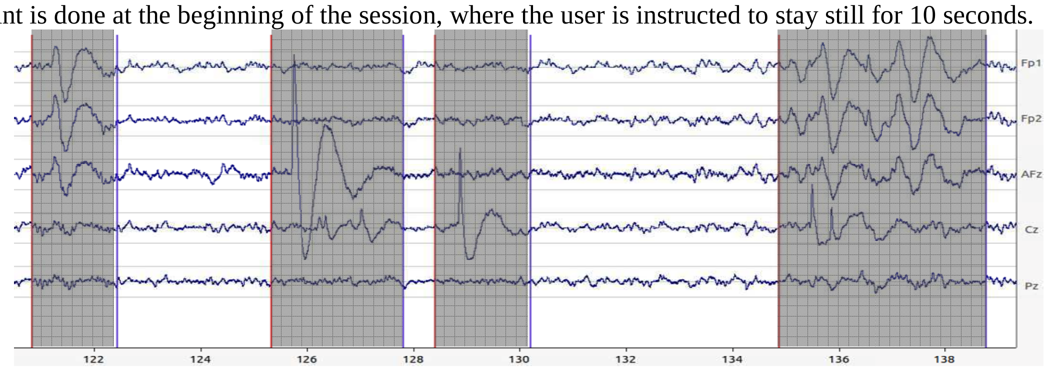

Figure 2: Results of the online detection for 20 seconds of signals recorded in OpenViBE. Only 5 electrodes are shown (Fp1,Fp2, AFz,Cz, Pz) .Grey areas correspond to time intervals where artifacts were detected.

In the example Fig. 2, the potato rejects blinks (1^{st} artifact), electrodes movements (2^{nd} and 3^{rd} artifacts) and eye movements (4^{th} artifact).

4. Discussion

The efficiency of this method is based on two facts: first, we use multivariate statistics by considering the covariance matrices as EEG signal descriptors. This allows us to take into account the spatial structure of the artifacts. For this reason the artifact detection is sensitive to the correlation structure of the EEG channels. Second, by using a strategy where an artifact is everything different enough from the reference activity, the algorithm is sensitive to many kinds of artifacts. Nonetheless, the initialization of the reference point is critical for the good functioning of this algorithm and its sensitivity and specificity strictly depend upon its correct initialization and correct adaptation. On the other hand, because of the good sensitivity of the Riemannian metric, the artifacts usually lie several standard deviations away from the reference point, so the threshold estimation is not critical.

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