International Journal of Bioelectromagnetism
Vol. 13, No. 2, pp. 106 –107, 2011
www.ijbem.org

Bayesian detection of asynchronous EEG patterns

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Abstract. We proposed a Bayesian model for the detection of asynchronous EEG patterns. Based on a skew normal model of the pattern of interest in the time-domain and on the assumption that background activity can be modeled as colored noise, we estimate both the pattern of interest and the time onset in each trial from the data using a Monte Carlo Markov Chain algorithm. Initial tests on synthetic data showed that the methods estimated correctly the pattern and the time onsets in all trials..

Keywords: Electroencephalography (EEG), detection of asynchronous patterns, Bayesian estimation, Monte Carlo Markov Chain (MCMC)

1. Introduction

Due to the variability of timing, asynchronous EEG patterns are difficult to detect on single trial. As a consequence many induced activities such as visual awareness or event related potentials triggered by non-controlled stimulus have been barely exploited in BCI. Initial attempts have been made to detect and classify such asynchronous patterns [Bourdaud et al., 2008]. In the current work, we propose a new theoretical framework based on Bayesian modeling to detect these asynchronous EEG patterns.

We consider the problem of detecting a common unknown short activity in several epochs of data (trials) while its time onset may be different in each trial. In this context, we have modeled in the time domain the relevant pattern as a sequence of independent points following each a skew normal distribution [Fruhwirth-Schnatter et al., 2010]. The samples in the trial that do not correspond to the relevant distribution (we will call them later the non-informative samples) are modeled as colored noise. We estimate the parameters of these models and the time onsets using a Bayesian approach through a Monte-Carlo Markov Chain (MCMC) algorithm [Robert, 2007]. The model and algorithm have been tested on synthetic data simulating event-related potentials with a random time onset.

2. Signal Model

We model the data in each trial in the time domain. We consider that each trial contains a subpart that corresponds to the relevant pattern we want to detect in each trial. This pattern may slightly vary from a trial to another but follows a common probability distribution in the time domain if all trial were realigned to that pattern. We model each time point in the pattern using a Gaussian distribution with a skewness parameter. This model favors patterns that have stable phase signature (i.e. relative timing between each peaks of the pattern) while allowing a certain variability in the value of the positive and negative peaks which is the case of several evoked potentials.

The data points that do not correspond to the relevant pattern are modeled as colored noise. This is achieved by modeling the evolution of the amplitude and the phase of their analytical signal $x_a(k)$ as a:

$$x_a(k) = A_k e^{i(f_k t + \phi_0)} \text{ with } \begin{array}{c} \text{amplitude } A_k = \lambda_A A_{k-1} + (1-\lambda_A)\mu_A + \epsilon_k \text{ and } \epsilon_k \sim \mathcal{N}(0, \sigma_A^2) \\ \text{frequency } f_k = \lambda_f f_{k-1} + (1-\lambda_f)\mu_f + \epsilon'_k \text{ and } \epsilon'_k \sim \mathcal{N}(0, \sigma_f^2) \end{array} \quad (1)$$

3. Bayesian Estimation

Assuming the models of the relevant pattern and the non-informative samples, we estimate their parameters from the data using a Bayesian approach. This approach has the advantage to easily incorporate any prior knowledge we could have about the problem (if any), thus allowing to adapt the method to a particular application.

The parameters comprise all the parameters of the models described in the previous section plus the time onsets of the detected patterns in each trial. They are estimated from the mean of their posterior distribution which is the estimator that minimizes the squared-error loss. Given the relative complexity of the models used, we achieve this by sampling their posterior distribution using a MCMC algorithm (an iterative algorithm) [Robert, 2007]. This algorithm is particularly efficient since all conditional posterior distributions (those of the parameters of the distribution of the pattern, the time onsets and the parameters of the model of the non-informative samples) can be easily sampled individually.

4. Test on Synthetic Data

We have tested the method on synthetic data simulating Error related potentials [Ferrez et al. 2005] with artificial jitter in each trial. We synthesized 500 trials of 1 second using a sampling frequency of 128 Hz. The initial values of the parameters of the non-informative samples were set to the correct values (in real applications those can be easily estimated from the raw data) but the parameters of the pattern and the time onset were initialized to wrong values (the pattern was initialized to a flat one and the time onsets to the middle of each trial).

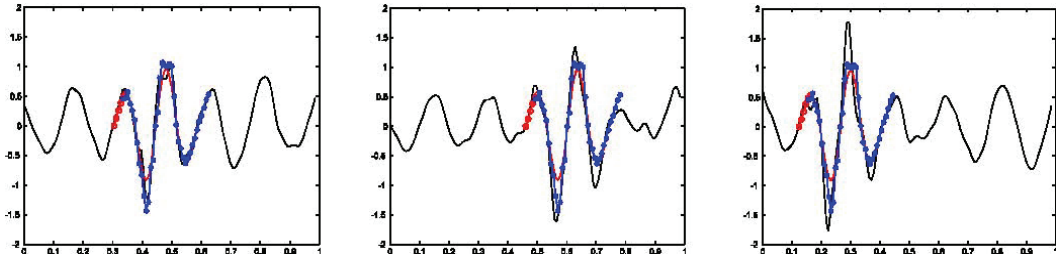

Figure 1. *3 examples of trial: In black the raw signal, in red dots the mode of the distribution of the pattern used to generate the data located the correct time onset, in blue stars the mode of the estimated distribution*

Although we did not used any prior, the estimation has converged accurately to the correct pattern (see Fig.1) with a small time shift and all the time onsets were correctly estimated with a small constant bias due the small time shift of estimated pattern (deviation from the correct time onset: mean=31ms, standard deviation=0.0416ms).

5. Conclusion

We have proposed a new Bayesian approach to detect asynchronous EEG patterns. This approach is based on the model of the pattern in the time-domain with the assumption that its phase signature is relatively stable across trials.

In its current state, the algorithm assumes that the trials contains the pattern and will converge to the closest pattern even if a trial contains only non informative samples. Without much work, it can be modified into a classification method. This will be the focus of future steps of the study.

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