An Experimental Sensitivity Analysis of Gaussian and Non-Gaussian Based Methods for Dynamic Modeling in EEG Signal Processing

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INTRODUCTION

This article presents an experimental sensitivity analysis of several dynamic modeling methods applied to electroencephalographic signals (EEG). EEG are recordings of surface brain electrical activity taken at the scalp, each sensor capturing the combined signal from multiple neurons of the brain (Niedermeyer & da Silva, 2004). The sensitivity analysis aims to determine the dynamic adaptation capabilities of several Gaussian and non-Gaussian methods with respect to changes in EEG data distributions in simulated and real scenarios. The potential of the methods for clinical diagnosis from their parameters is discussed.

Electroencephalography is a useful clinical tool because some illnesses, typically seizures and sleep disorders, produce abnormal electric patterns in the electrical activity of the brain that can be identified by an expert. EEG are also the subject of much research on brain activity, given the lower hardware cost and higher temporal resolution of EEG when compared to other available techniques. Human sleep can be split in four different stages: wake, light sleep, deep sleep, and rapid-eye movement sleep (REM). The sequence of these stages can be used to diagnose different sleep disorders, illnesses (e.g. depression), and some drug addictions. Of particular importance is the detection of very short periods of wakefulness, also called micro-arousals, since their rate of appearance can help with the diagnosis of apnea and epilepsy (Guilleminault, 2005).

The sensitivity analysis was performed with the following methods: Bayesian Networks (BNT), Dynamic Bayesian Networks (DBN), Independent Component Analysis Mixture Models (ICAMM), and Sequential ICAMM (SICAMM). The BNT and DBN implemented Gaussian mixtures to model the probability densities of the data, while ICAMM and SICAMM work with non-Gaussian mixtures. Simulation data were formed with different source density mixtures that change in time, implemented to imitate nonlinearity and non-stationarity conditions intrinsic to the EEG. The real data application consisted of microarousal detection in EEG from sleeping apnea patients in the framework of computer-assisted sleep staging (Agarwal & Gotman, 2001). The performance of the methods was measured using the classification accuracy; the log-likelihood to fit the data; an EEG sample time-dependence parameter; and indices for measuring the distance between two ICAMM parameter sets. The results show relevant advantages of SICAMM, such as non-Gaussian source identification discernible for clinical interpretation and meaningful sub-space identification for analysis of neural regions of interest.

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The following sections describe the background and context of this work, a summary of the methods, and the results of the sensitivity analysis for simulated and real EEG data. Final sections include the conclusions and future work.

BACKGROUND

Sensitivity analysis is generally defined as the study of how the outputs of a method change under a given change of its inputs. It has many applications, such as testing the stability of a method or testing its robustness when the main assumptions no longer hold true. Sensitivity analysis has been used in many different fields, such as risk assessment, algorithm characterization, and medical studies (Saltelli, et al., 2008). Within medical research, there are many applications of sensitivity analysis on EEG signals, methods and equipment, such as: testing the influence of different factors (the scalp, electrodes…) on the EEG (Rice, Rorden, Little, & Parra, 2013); exploring the behavior of head conductivity and EEG models (Vallaghe, 2009; Dannhauer, Lanfer, Wolters, & Knösche, 2011); or performing meta-analysis studies (Gao & Raine, 2009).

As for the use of non-Gaussian mixtures in EEG processing, Independent Component Analysis (ICA) has been used in EEG applications since the 1990s (Makeig, Bell, Jung, & Sejnowski, 1996), particularly in EEG source location (Onton, Westerfield, Townsend, & Makeig, 2006) and source extraction (Makeig, et al., 2002). Source separation by ICA is statistical in nature and can correctly separate signals that overlap across time and/or frequency. This separation can be used for artifact removal (Nolan, Whelan, & Reilly, 2010) and to remove unimportant signals, thus reducing the workload of the expert and helping with tasks such as diagnosing ADHD (Attention Deficit Hyperactivity Disorder) (Mueller, Candrian, Grane, Kropotov, Ponomarev, & Baschera, 2011). A good review of the applications of ICA to EEG processing can be found in (Jung & Lee, 2012). A recent topic is the dynamic modeling of brain oscillations (Onton, Delorme, & S.Makeig, 2005). This research attempts to combine the advantages of ICA with the capabilities of certain dynamic models to deal with the temporal variability of EEG.

Related to the topic of this article, there have been some attempts to perform automatic classification of EEG from sleep stages (Agarwal & Gotman, 2001), including the use of ICAMM (Salazar, Vergara, & Miralles, 2010). However, a totally automatic system for sleep staging remains a challenge. Due to the recent use of ICAMM in dynamic modeling of EEG, a comparative study with state-of-the-art methods as the proposed in this article is not currently available.

APPLICATION OF NON-GAUSSIAN MIXTURES TO EEG CLASSIFICATION

Independent Component Analysis Mixture Models

The basic (noiseless) ICA model assumes that the observation at time sample n,

$$\mathbf{x}(n) = \left[x_1(n),\ x_2(n), \ldots,\ x_M(n)\right]^T,$$

is the result of a mixture of several independent random variables or 'sources',

$$\mathbf{s}(n) = \left[s_1(n),\ s_2(n), \ldots,\ s_L(n)\right]^T.$$

Therefore,

$$\mathbf{x}(n) = \mathbf{A} \cdot \mathbf{s}(n) \qquad (1)$$

where $\mathbf{A}$ is known as the mixing matrix. ICA methods estimate $\mathbf{A}$ and the sources $\mathbf{s}(n)$ simultaneously. For simplicity, we will assume that there are as many sources as observations ($L=M$) and that the mixing matrix can be inverted to find the de-mixing matrix, $\mathbf{W}=\mathbf{A}^{-1}$. Each individual source can be extracted separately, since the m-th source is

$$s_m(n) = \mathbf{w}_m^T \cdot \mathbf{x}(n),\ m = 1, \ldots, M,$$