Online SSVEP-based BCI using Riemannian Geometry

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Abstract

Challenges for the next generation of Brain Computer Interfaces (BCI) are to mitigate the common sources of variability (electronic, electrical, biological) and to develop online and adaptive systems following the evolution of the subject's brain waves. Studying electroencephalographic (EEG) signals from their associated covariance matrices allows the construction of a representation which is invariant to extrinsic perturbations. As covariance matrices should be estimated, this paper first presents a thorough study of all estimators conducted on real EEG recording. Working in Euclidean space with covariance matrices is known to be error-prone, one might take advantage of algorithmic advances in Riemannian geometry and matrix manifold to implement methods for Symmetric Positive-Definite (SPD) matrices. Nonetheless, existing classification algorithms in Riemannian spaces are designed for offline analysis. We propose a novel algorithm for online and asynchronous processing of brain signals, borrowing principles from semi-unsupervised approaches and following a dynamic stopping scheme to provide a prediction as soon as possible. The assessment is conducted on real EEG recording: this is the first study on Steady-State Visually Evoked Potential (SSVEP) experimentations to exploit online classification based on Riemannian geometry. The proposed online algorithm is evaluated and compared with state-of-the-art SSVEP methods, which are based on Canonical Correlation Analysis (CCA). It is shown to improve both the classification accuracy and the information transfer rate in the online and asynchronous setup.

Keywords: Riemannian geometry, Online, Asynchronous, Brain-Computer Interfaces, Steady State Visually Evoked Potentials.

1. Introduction

Human-machine interactions without relying on muscular capabilities is possible with Brain-Computer Interfaces (BCI) [1] They are the focus of a large scientific interest [2, 3, 4], especially those based on electro-encephalography (EEG) [5]. From the large literature based on the BCI competition datasets [6, 7, 8], one can identify the two most challenging BCI problems: on one hand, the inter-individual variability plagues the models and lead to BCI-inefficiency effect [9, 10, 11], on the other hand the intra-individual changes calls for the development of online algorithms and adaptive systems following the evolution of the subject's brain waves [12, 13, 14]. To alleviate these variations, several signal processing and machine learning techniques have been proposed, such as filtering, regularization or clustering [15, 16] without the emergence of an obvious "best candidate" methodology.

A common vision is shared by all the most successful approaches to reduce signal variabilities: they are applied on covariance matrices instead of working in the input signal space. Common Spatial Pattern (CSP) [17, 18, 19], which is the most known preprocessing technique in 2-class BCI, try to maximize the covariance of one class while minimizing the covariance of the other. Similarly, Principal Components Analysis (PCA) [6, 7], also applied for spatial filtering in BCI, is based on the estimation of covariance matrices. Canonical Correlation Analysis (CCA) is another example of a technique relying on covariance estimates successfully applied on EEG for spatial filtering [15, 20]. Covariance matrices are also found in classifiers such as the Linear Discriminant Analysis (LDA), which is largely used in BCI. In all cases, they are handled as elements of an Euclidean space. However, being Symmetric and Positive-Definite (SPD), covariance matrices lie on a subset of the Euclidean space, with reduced dimensionality and specific properties, the *Riemannian manifold*. Considering covariance matrices in their original space would reduce the search area for an optimization problem [21, 22]. As Riemannian manifolds inherently define a metric, the distance between SPD matrices takes into account the space where they lie on; approximating it to an Euclidean space introduce inaccuracies and results in ill-conditioned matrices.

Recently, studies have been done to consider covariance matrices obtained from multichannel brain signals in their

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