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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.

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 [2–4], especially those based on electroencephalography (EEG) [5]. From a large literature based on the BCI competition datasets [6–8], one can identify the two most challenging BCI problems: on the one hand, the inter-individual variability plagues the models and leads to BCI-inefficiency effect [9–11], 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 [12–14]. 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) [17–19], which is the most known pre-processing 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 introduces inaccuracies and results in ill-conditioned matrices.

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Recently, studies have been done to consider covariance matrices obtained from multichannel brain signals in their original space [23–25]. Covariance matrices are the input features of the BCI system and the classifier algorithms rely on Riemannian metric for partitioning the feature space. The authors propose building specific covariance matrices in order to emphasize the spatial and frequential information of the multichannel brain signals [25]. The outcome of this approach is a simple processing tool chain, which achieves state-of-the-art classification performances.

This paper introduces an online version of the *minimum distance to Riemannian mean* (MDRM) algorithm [23], with an application to Steady-State Visually Evoked Potential (SSVEP) signals. In SSVEP, the subjects concentrate on stimuli blinking at fixed frequencies. Depending on the focus of their attention, brain waves will arise with the same phase and frequency as the stimulus chosen by the subject. The signals are recorded in an application of assistive robotics,[1] with a shared control scheme relying on an SSVEP-based BCI and a 3D touchless interface based on IR-sensors to operate an arm exoskeleton [26]. The long term objective is to equip a home environment with assistive technologies, including BCI, as proposed in [27,28]. In this context, it is important to design an online system, i.e. that adapt continuously to the user's brain signals, and asynchronous, i.e. that could be activated “on demand”.

Our online implementation[2] is similar to the unsupervised or semi-unsupervised learning scheme proposed in [29,30]; that has the potential of shortening (or even removing) the calibration phase. We apply a similar approach to the dynamic stopping criterion used in [31] to increase the speed of the BCI system. This approach allows to dynamically determine the trial length and ensure robustness in classification results. Our MDRM approach outperforms state-of-the-art algorithms in the offline setup. Moreover, these state-of-the-art algorithms, that are based on CCA, are inherently limited as they could not handle resting state. They must rely on an external command to be turn on or off, and are thus only suitable to lab environment.

When working with covariance matrices, a crucial point is to correctly estimate the covariance when the number of samples is small or heavily corrupted by noise. Several approaches have been proposed to build the covariance matrices, relying on normalization or regularization of the sample covariances. To assess the quality of the covariance matrices obtained from EEG samples, a comparative study of these estimators is conducted.

Hence, the contributions of this works are:

- a comprehensive review of the literature on Riemannian geometry applied to EEG and time-series,
- a thorough analysis of the covariance estimators and their impact on tools derived from information geometry,
- first online application of a Riemannian classification algorithm on SSVEP-based BCI,
- introduction of a novel algorithm for online and asynchronous BCI, including a resting state class, yielding better performance than state-of-the-art SSVEP algorithms. No phase synchronization is required for the SSVEP.

The paper is divided as follows: Section 2 reviews the state of the art in SSVEP-based BCI and the applications of Riemannian geometry in machine learning for BCI. Section 3 presents concepts of Riemannian geometry relevant to this work and estimators of covariance. In Section 4, the proposed classification algorithm for online SSVEP is introduced and the experimental results are presented in Section 5 for offline and online setups as well as without and with a resting state class.

2. State of the art

2.1. Steady-state visually evoked potential

Sensory evoked potentials often oppose Event Related Potential (ERP) and Steady-State Response (SSR) [32]. This distinction originates from the idea that the SSR may be generated by neural oscillations elicited by the repeated stimulations [33] whereas the ERP is the transient response to an event occurring at sufficiently long time interval to allow the system to return to its initial state [34]. We will focus on the visual SSR, called SSVEP and its application to BCI.

The SSVEP-based BCI is often employed as a dependent BCI [35], that is, some residual muscular capabilities are required to move the eye toward the blinking stimulus as opposed to independent BCI, such as Motor Imagery (MI), where the communication does not rely on any motor capability. It has been shown that SSVEP could be used as an independent BCI [36,37] as the brain oscillations are strongly related to the focus of attention. Using covert attention, i.e. shifting the focus of attention without moving the eyes, subjects can generate different SSVEP responses.

BCI have highly variable subject-specific performances. 20–30% of the subjects cannot operate correctly brain interfaces. This phenomenon is referred to as BCI illiteracy [9–11]. It affects SSVEP-based BCI and it is correlated with age and gender, male subjects being more afflicted than female ones [38]. Offline BCI, that is approaches where the learning algorithms are trained on a large dataset of subject's EEG recording, are also afflicted which indicate that a source of variability at the subject level is not handled correctly by the existing approaches. BCI illiteracy is also afflicting online approaches, where the algorithms are adapted to the subject's EEG as the experiment goes by.

Visual stimulus plays a crucial role, affecting the BCI performance, and should be designed carefully. An in-depth review of the literature [39] shows that LED stimuli provide better results than those obtained on computer screen. A cognitive study [40] indicates that any stimulation between 2 and 50 Hz induces visible oscillations in the visual cortex. Another study shows that a peak in signal to noise ratio is visible at around 15 Hz [41]. Common values employed in SSVEP studies are between 12 and 25 Hz, as they induce oscillations with higher amplitudes [39]. One should note that safety of the subject should be taken into account as some frequency ranges of the stimulation train could trigger epileptic seizure [42].

The phase of the stimulation signal can also be modulated, enhancing the BCI performance by boosting the Information Transfer Rate (ITR) [43,44]. An important constraint in that case is that the experimental setup requires a synchronization between the display and the recording system, to ensure the correct estimation of the stimulus' phase. Better alternatives are available when considering systems with such constraints: code-modulated VEP (c-VEP) has yield the highest ITR in BCI [45,46]. In c-VEP, the sole difference is that the stimulus flickering is based on pseudorandom sequences instead of the fixed frequencies of SSVEP. All these successful approaches in SSVEP and c-VEP rely on CCA. Given two sets of signals, CCA aims at finding the projection space that maximizes their cross-covariance while jointly minimizing their covariance [20,15,44]. The common methodology is to find the canonical space between the multichannel EEG trial on the one hand and reference signals, usually sine and cosine of target frequencies and harmonics, on the other hand.

[1] This dataset is freely available from https://github.com/sylvchev/dataset-ssvep-exoskeleton.

[2] The open source code is available on https://github.com/emmanuelkalunga/Online-SSVEP.