Steady State Visual Evoked Potential Detection Using Subclass Marginal Fisher Analysis

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Abstract— Recently, SSVEP detection from EEG signals has attracted the interest of the research community, leading to a number of well-tailored methods, such as Canonical Correlation Analysis (CCA) and a number of variants. Despite their effectiveness, due to their strong dependence on the correct calculation of correlations, these methods may prove to be inadequate in front of potential deficiency in the number of channels used, the number of available trials or the duration of the acquired signals. In this paper, we propose the use of Subclass Marginal Fisher Analysis (SMFA) in order to overcome such problems. SMFA has the power to effectively learn discriminative features of poor signals, and this advantage is expected to offer the appropriate robustness needed in order to handle such deficiencies. In this context, we pinpoint the qualitative advantages of SMFA, and through a series of experiments we prove its superiority over the state-of-the-art in detecting SSVEPs from EEG signals acquired with limited resources.

I. INTRODUCTION

Steady State Visual Evoked Potentials (SSVEPs) have become an integral part of contemporary Brain Computer Interfaces (BCIs), offering new ways of communication to special groups of users with certain physical disabilities [1]. For example, they may allow people with mobility impairments to interact with computers using merely their eyes. SSVEPs are based on the concept that the human brain is perfectly tuned to an oscillating visual stimulus and thus the EEG activity of the brain parts, responsible for vision, exhibit similar frequency properties to the stimulus. Based on this assumption, there is a strong potential to detect the frequency generating the stimulus by looking for SSVEPs in EEG signals acquired from subjects during their exposition to the stimulus. However, in practice, noise artefacts and interference (e.g., severe contamination of EEG by eye movement, current noise, etc) hinder the correct SSVEP detection and in order to circumvent this barrier, reliable methods have to be invented.

Usually, a whole pipeline consisting of preprocessing (e.g., band-pass filtering), artefact removal/correction, feature extraction and feature classification is used for SSVEP detection [2]. In this paper, we mainly focus on the feature extraction step, although we also use some preprocessing and of course a classification step in our methodology. Along these lines, the recent intense activity of the research community around SSVEPs has led to the development of various feature extraction methods, which coupled with state-of-the-art classifiers, have allowed for the effective SSVEP detection

from EEG signals. For instance, a number of typical methods operating in the frequency domain, like Power Spectral Density Analysis (PSDA) [3], have been proposed. However such methods prove to be highly sensitive to background noise and require long time windows to estimate the signal spectrum with sufficient frequency resolution [4]. For overcoming this drawback, recently, a variety of time-domain methods has been proposed. Among these methods, Canonical Correlation Analysis (CCA) has become the baseline, because of its proven effectiveness and its ease of implementation. Based on its capability of revealing correlations between two sets of multi-dimensional variables, CCA identifies the target frequency based on the canonical correlation values between multi-channel EEG time-domain signals and predefined sinusoidal reference signals at stimulation frequencies [5].

A clear strong point of CCA is that it does not require calibration. However its functionality is affected by the interference of spontaneous EEG activities. For alleviating this shortcoming, some extensions of the standard CCA have been investigated in the literature. In [6], a number of CCA variants have been collectively presented and compared in SSVEP detection. Among these extensions, an Individual Template based CCA method (IT-CCA), which averages across multiple EEG trials from each subject has been proposed for optimising the reference signals per frequency stimulus [7]. In addition, a spatial filtering method, also known as Combined CCA (Comb-CCA), which combines correlation coefficients between a) projections of a test set, b) individual templates and c) sine-cosine reference signals, has been proposed in [8].

The above methods have been successfully used in laboratory settings (e.g., for biomedical purposes), where up to 256 channels are often used to acquire as many EEG trials as needed for the analysis. Moreover, these trials may have sufficient time-length ensuring the correct functioning of the detection methods. Nowadays though, there is an emerging demand to achieve top classification performance in real-time scenarios where all the above acquisition resources are limited. Indeed, an increasing number of EEG wearable devices (e.g., EMOTIV Epoc) is being used for everyday purposes in out-of-lab environments by arbitrary end-users with high expectations and little patience. Consequently, finding those methods that optimally combine computational efficiency, robustness to limited resource availability and SSVEP detection effectiveness may have a strong impact from both a technological and a commercial perspective.

In this paper, motivated by the above demand, we propose the use of Subclass Marginal Fisher Analysis (SMFA) [9]

in SSVEP detection from EEG signals. SMFA belongs to a general category of techniques, known as Subspace Learning (SL) [10], which in the process of feature extraction reduce the dimensionality of the raw data, while retaining as much discriminant information as possible. In general, SL methods have been applied to many different classification domains with noticeable success [11]. Amongst them, Linear Discriminant Analysis (LDA) [12] and Multi-Linear Regression (MLR) [4] have become baseline approaches, and a multitude of other methods build on them.

In contrast to typical SL methods, SMFA qualifies as the most appropriate method for SSVEP detection, as it collects a number of important advantages, which are explained in detail in the following sections. The most prominent characteristic of SMFA is that it exploits potential subclass structure within the classes of the data, which offers a clear advantage in the context of SSVEP detection. Indeed, according to some recent studies, EEG signals tend to form clusters based on their phase content [13] and this clustering information could be exploited by SMFA in achieving better classification accuracy. Along these lines, in this paper, through a series of experiments on a benchmark database, we show that SMFA outperforms the state-of-the-art in SSVEP detection using only very few (even 5 trials per frequency), short (down to 0.5sec) EEG signals, which have been acquired using only 3 channels. Therefore, it is highly recommended as an off-the-shelf solution to the SSVEP detection problem, outside the laboratory environment.

II. METHODOLOGY

In this section, we present the SMFA methodology proposed for SSVEP detection from EEG signals. The main concept of this methodology is to i) project the initial signals onto a lower dimensional space, while maintaining the class-discriminant information and ii) employ a baseline classifier on the obtained low-dimensional signals. As SMFA and generally SL methods stem from Linear Algebra, from now on, data trials will be referred to as vectors.

A. Subclass Marginal Fisher Analysis

Subclass Marginal Fisher Analysis has its inception in Subclass Graph Embedding (SGE), which is a general framework for developing algorithms that reduce the dimensionality of high-dimensional data samples [11]. In SGE, we seek for a projection matrix $\mathbf{V} \in \mathbb{R}^{n \times m}$ so that every vector $\mathbf{x} \in \mathbb{R}^n$ lying in the initial space can be projected to a low-dimensional vector $\mathbf{y} \in \mathbb{R}^m$, with $m < n$ via: $\mathbf{y} = \mathbf{V}^T \mathbf{x}$. The projection matrix $\mathbf{V}$ is learned by the use of a set of training vectors $\mathcal{X} = \{\mathbf{x}_1, \mathbf{x}_2, \cdots, \mathbf{x}_N\}$, which are represented by two graphs, namely, the *intrinsic graph* $G_{int} = \{\mathcal{X}, \mathbf{W}_{int}\}$ and the *penalty graph* $G_{pen} = \{\mathcal{X}, \mathbf{W}_{pen}\}$, where $\mathbf{W}_{int}$ and $\mathbf{W}_{pen}$ are the corresponding graph matrices. The intrinsic and penalty graph matrices model the similarity and dissimilarity connections, respectively, between every pair of training vectors that have to be reinforced after the projection. For both graph matrices, the larger their values

are, the stronger their effect on the respective pairs of training vectors will be.

SMFA, in contrast to typical unimodal methods like LDA, is aimed at exploiting potential subclass information within the classes. In reaching its goal, SMFA builds the intrinsic and penalty graph matrix in such a way that characterises the **within subclass compactness** and the **between class separability**, respectively [14]. Moreover, apart from supervised labelling, SMFA also uses the topology of the classes and subclasses, which is encoded as neighbouring information among the vectors. More specifically, the intrinsic graph matrix of SMFA is defined as:

$$\mathbf{W}_{int}(q,p) = \begin{cases} 1 & , \text{if } p \in \mathcal{N}_{k_{int}}(q) \text{ or } q \in \mathcal{N}_{k_{int}}(p) \\ 0 & , \text{otherwise} \end{cases}, \tag{1}$$

where $\mathcal{N}_{k_{int}}(q)$ denotes the index set of the k_{int} nearest neighbors of the q-th vector in the same subclass. On the other hand, the penalty graph matrix of SMFA is defined as:

$$\mathbf{W}_{pen}(p,q) = \begin{cases} 1 & , \text{if } p \in \mathcal{M}_{k_{pen}}(q) \text{ or } q \in \mathcal{M}_{k_{pen}}(p) \\ 0 & , \text{otherwise} \end{cases}, \tag{2}$$

where $\mathcal{M}_{k_{pen}}(q)$ denotes the set of vectors that belong to the k_{pen} nearest neighbours of q outside the class of q. It is worth noting that in contrast to the intrinsic graph matrix, the values of the penalty graph matrix depend merely on the class information regardless of the subclass labels. In this way, constraints between subclasses belonging to the same class are avoided, offering better generalisation chances [9].

Having constructed the two above intrinsic and penalty matrices, SMFA sets and solves the following optimisation problem:

$$\mathbf{X}\mathbf{L}_{int}\mathbf{X}^T\mathbf{v} = \lambda \mathbf{X}\mathbf{L}_{pen}\mathbf{X}^T\mathbf{v}, \tag{3}$$

where $\mathbf{L}_{int} = \mathbf{D}_{int} - \mathbf{W}_{int}$ is the intrinsic *Laplacian* matrix and $\mathbf{D}_{int}$ is the intrinsic *Degree* matrix defined as the diagonal matrix, which has at position (q,q) the value $\mathbf{D}_{int}(q,q) = \sum_p \mathbf{W}_{int}(q,p)$. Similarly are defined $\mathbf{L}_{pen}$ and $\mathbf{D}_{pen}$. Eq. (3) reduces to solving the following generalised eigenvalue problem

$$\mathbf{L}_{int}\mathbf{v} = \lambda \mathbf{L}_{pen}\mathbf{v}, \tag{4}$$

keeping the eigenvectors $\mathbf{v}_i \in \mathbb{R}^n$, $i \in \{1, 2, \ldots, m\}$ that correspond to the m smallest eigenvalues. The projection matrix $\mathbf{V}$ then contains the above eigenvectors as columns and the subspace learning process is completed.

1) A qualitative comparison of SMFA with CCA-based methods: In contrast to the majority of CCA-based methods, which calculating canonical correlations learn improved reference signals, SMFA digs deep into the data per se, looking for discriminant information. This is very important, as CCA-based methods strongly depend on the implicit assumption that test signals have common characteristics with the reference signals and there is no strong evidence that this assumption always holds. Moreover, lacking the ability to use the inherent discriminant information lying within the data may not permit the subtraction of potential noise and variation that accompany EEG signals.

2) A qualitative comparison of SMFA with typical SL methods: SMFA collects a number of advantages that render it a perfect candidate for SSVEP detection, against other SL methods. First of all, when using SMFA, there is no assumption on the data distribution, since the intra-subclass compactness is encoded by the nearest neighbours of the data belonging to the same subclass and the inter-class separability is modelled using the margins among the classes. Furthermore, the functionality of SMFA is based on two parameters, i.e., k_{int} and k_{pen}, which appropriately adjusted may lead to avoiding potential overfitting, therefore offering generalisation power to the method. Last but not least, the available projection dimensionality using SMFA is determined by k_{pen}, which almost always is much larger than that of methods like LDA.

B. Subclass extraction

From the presentation of SMFA, it is clear that an integral part of its operation is the use of subclasses. Therefore a question that naturally emerges is how many subclasses are there in each different class and what is the best way to extract these subclasses. Although these are general questions, in the context of SSVEP an answer could be provided by the use of signal phase information. Indeed, based on some previous studies [13], it has been shown that in front of a visual stimulus, signals tend to take two fundamental forms according to the brain hemisphere that is mainly working. By specifying the number of subclasses per class, a baseline clustering approach (e.g., K-means) usually suffices to effectively extract the clusters within each class that form the corresponding subclasses.

C. Classification

Having completed the dimensionality reduction process using SMFA, the resulting low dimensional vectors are used for training a classifier. Theoretically, under ideal conditions, SMFA achieves optimal discrimination of the several classes in Bayesian terms. For this reason, in general, a Nearest Cluster Centroid (NCC) approach can be used to classify correctly any test vector into the appropriate frequency stimulus [15].

III. EXPERIMENTS

A. Dataset description

For the experiments we used the publicly available SCCN dataset [6]. SCCN is a 12 class SSVEP dataset acquired from 10 subjects in a simulated BCI experiment. Each class represents a stimulus frequency in the range from 9.25Hz to 14.75Hz with increment 0.5Hz. More specifically, during the acquisition, each subject was sitting in a 60cm distance from a computer monitor with 60Hz refreshing rate and was asked to gaze for 4sec at one of multiple squares flickering at a specific frequency. 8-channel EEG signals were then recorded with 2048Hz sampling rate and downsampled to 256Hz. With the previous process, for each subject, 180 trials (15 trials per stimulus frequency), each of 1024 samples, were acquired.

B. Performance Evaluation

All the experiments in this paper were conducted using the eeg-processing-toolbox [16]. For evaluating the performance of the several methods we followed the same approach as in [6]. The classification accuracy was calculated in a "per subject" basis, using leave-one-block out cross validation, where each block consists of 12 trials, i.e., one trial per frequency. More specifically, in each of 15 cross validation rounds, 168 trials (i.e., 14 trials per each frequency) were used for training and the remaining 12 trials (i.e., 1 trial per frequency) were used for testing. In addition to classification accuracy, method performance was also evaluated by calculating the Information Transfer Rate (ITR) [6], which is perfectly suited for evaluating real-time performance, as it indicates the capability of a method to transfer SSVEP detection information from the user trials to the system. ITR is defined as:

$$ITR = \frac{60}{T} \cdot \left(\log_2 N_f + A \log_2 A + (1 - A) \log_2 \left(\frac{1 - A}{N_f - 1} \right) \right),$$ (5)

where T is the EEG trial length (in seconds), N_f is the number of different stimulus frequencies, and A is the classification accuracy. Following the instructions of [6], as regards the time-length T, in each experiment, we considered an extra 1sec duration which is due to gaze shifting.

C. Data preprocessing and parameter selection

In all experiments, following the pipeline approach presented in Section I, the data were first preprocessed using Infinite Impulse Response (IIR) digital band-pass Butterworth filtering of the 3rd degree, in 6-80Hz band. Finally, trial normalisation was ensured by mean signal referencing.

The parameters involved in SMFA (i.e., k_{int} and k_{pen}) were selected among a number of indicative values, as those that returned the best results in a set of preliminary experiments. For extracting the subclasses needed by SMFA, we employed K-means and for the sake of completeness we experimented with diverse numbers of subclasses. Interestingly, in accordance with the findings mentioned in Section II-B, two subclasses per class returned the best classification results in almost all cases.

Based on Section II-C, in our study we used NCC classifier. We also tried Support Vector Machines (SVMs) in both linear and RBF mode with diverse values of the several parameters. However, SVM performed consistently worse than NCC and for this reason the corresponding accuracy results have been omitted.

D. Standard experiment

In this experiment we evaluated the performance of the methods using all available resources. The average accuracy and ITR across all subjects, with different EEG time-lengths from 0.5sec to 4sec, are illustrated in Fig. 1 (a) and (b), respectively. From Fig. 1 (a), it is straightforwardly implied that Comb-CCA outperforms the rest methods in almost all cases, in terms of classification accuracy. However, interestingly, in 0.5sec SMFA shows the top performance, which is a strong indication of its robustness when using short EEG signals. Along the same lines, the most interesting remark from Fig. 1 (b) is that the best ITR, which is around
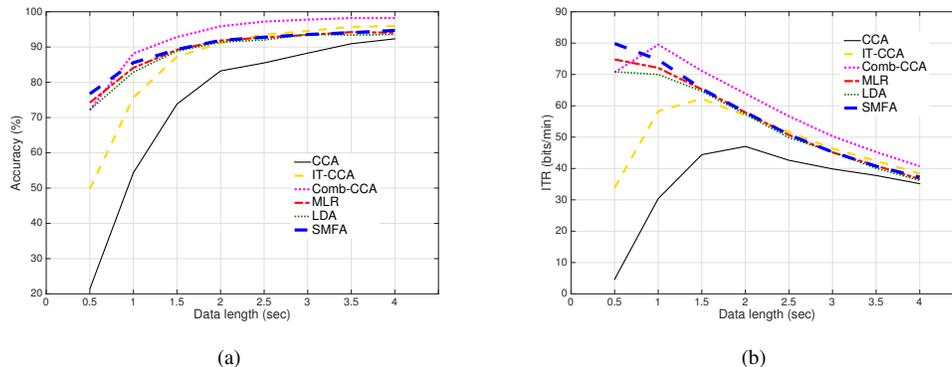
Fig. 1. Performance comparison of SSVEP detection methods using all 8 channels. (a) Averaged classification accuracy, (b) ITR.

80 bits per minute, is shared by SMFA and Comb-CCA. This finding proves the strong potential of SMFA in real-time SSVEP detection systems. Regarding the other methods, it is worth observing the superiority of SL methods over CCA-based, when using less than 2sec signals, in terms of both accuracy and ITR. Finally, standard CCA completely fails to compete with the other methods, with around 20% accuracy at 0.5sec, which can be attributed to the inadequacy of 0.5sec trials to correlate with the reference sinusoidal signals, accentuating at the same time the disadvantage of CCA to lack a calibration phase.

E. Comparing classification performance using three channels

In verifying the superiority of SMFA when using a small number of channels, we carried out an experiment using channels 6, 7 and 8. The selection of these channels is justified as follows. According to the 10/20 international reference system, channel 7 corresponds to O_z, whereas channels 6 and 8 are approximately equivalent to O_1 and O_2, which are connected to those areas of the occipital lobe that are most sensitive to visual stimuli. In addition, these channels are often used by common devices and thus conclusions about them can be extended to data acquired using such devices. The average accuracy results along with the corresponding ITRs are illustrated in Fig. 2.

From Fig. 2 (a), it is interesting to observe that SMFA in almost all cases outperforms the other methods. In particular, at 0.5sec, SMFA shows the top performance with accuracy 64.00%, which is around 4% over the 60.06% of the second in rank MLR. Interestingly, in general, Comb-CCA seems to fall short compared to SL methods and furthermore it shows worse performance than IT-CCA for longer than 1.5sec signals. Standard CCA shows again extremely low performance, which can be explained using the same arguments as in the standard experiment. Finally, from Fig. 2 (b), in terms of ITR, SMFA clearly returns the best result with 63.33 bits per minute using 1sec time-length signals, while Comb-CCA along with MLR and LDA hold the second rank with around 59 bits per minute.

Comparing Fig. 1 (a) with Fig. 2 (a), it is interesting to observe the robustness of SMFA and in general of SL methods when reducing the number of channels, in contrast to CCA-based methods, whose functionality seems to be strongly dependent on the number of available channels. For instance, Comb-CCA's best accuracy drops from 98% to 94% (at 4sec), while SMFA accuracy remains stable around 95% (at 4sec), between the two experiments. This finding, highlights the added value of using SL methods and in particular SMFA in settings where only a limited number of channels are available.

F. Comparing classification performance using different number of training trials

In this experiment, for each subject, we used all 8 channels in 0.5sec, varying the number of the training trials per frequency from 14 to 4. The mean accuracy results across all subjects are illustrated in Fig. 3. The first remark from Fig. 3 is that SMFA is consistently superior over the rest methods with mean accuracy 76.2% and 63.3%, for 14 and 4 training trials, respectively. On the other hand, the second position is held by Comb-CCA and MLR, for 4-10 and 11-14 training trials, respectively. More specifically, Comb-CCA has accuracy performance 60.8% for 4 training trials, whereas MLR has accuracy 72.1% for 14 training trials. In general, it is worth stressing that SL methods consistently outperform CCA-based ones – except for Combined CCA – proving the ability of SL methods to detect SSVEPs in settings where only a few EEG trials are available. Finally, it is interesting to notice the stable performance of standard CCA across different numbers of training trials, which is expected given that CCA is devoid of training and thus its performance is independent of the number of used training trials.

IV. CONCLUSIONS

In this paper, we proposed the use of Subspace Learning methods and in particular SMFA for SSVEP detection from EEG signals, in cases where there is deficiency in acquisition resources, such as small number of channels, limited EEG trials and short time-length signals. Through an experimental study, we demonstrated that in such cases, SMFA outperforms a number of state-of-the-art CCA-based methods well-tailored to the SSVEP detection problem. The superiority
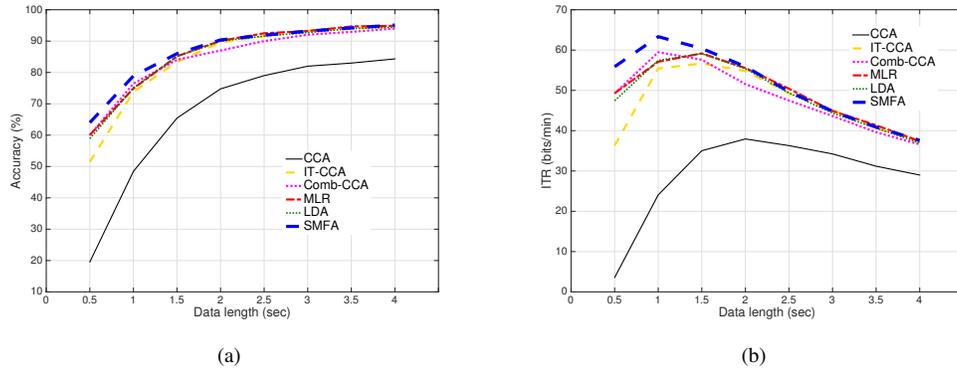
Fig. 2. Performance comparison of SSVEP detection methods using channels 6, 7 and 8. (a) Averaged classification accuracy, (b) ITR.
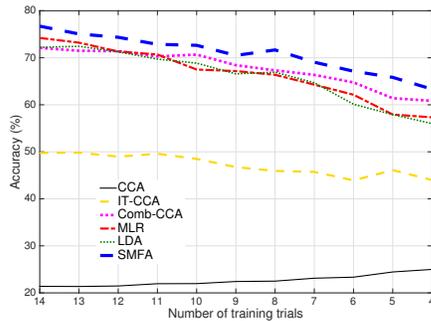

Fig. 3. Classification accuracy using different numbers of 0.5 sec length training trials.

of SMFA is attributed to several qualitative advantages, which were discussed in this paper. In addition, from the experiments it was shown that SL methods, in general, outperform CCA-based ones. Another important remark is that all methods requiring training are impressively robust when using short trials, and along the same lines, it was explicitly proven that the time-length of the trials is very crucial for the correct functioning of the standard CCA.

In summary, the general conclusion of this paper is that SMFA constitutes an off-the-shelf solution to the SSVEP detection problem, that can be adopted in real-time BCI environments with limited resources for capturing EEG signals. Moreover, although in this paper the great potential of SMFA has been explicitly proven, these are only early results and there might be much more space for further improving its performance. More specifically, a great advantage of SMFA is that it contains a number of parameters, which appropriately adjusted can optimize its effectiveness. In the near future we intend to further experiment with these parameters as well as employ more sophisticated methods for extracting the subclasses.

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