Reconstructing EOG From EEG Timeseries: A Spatial Filtering Approach

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***Abstract*— Unobtrusive mental state monitoring based on neurosphysiological signals has seen thriving developments over the past decade, with a wide area of applications, from rehabilitation to neuroergonomics and neuromarketing. Particularly, electroencephalography (EEG) and electrooculography (EOG) have been popular techniques to obtain cognitive-relevant biosignals. However, current wearable systems may still pose practical inconvenience, motivating further interest to integrate EOG+EEG recording into streamlined frontal-only sensor montages with sufficient signal fidelity. We propose, here, a spatial filtering approach to reliably extract EOG signals from a reduced set of frontal EEG electrodes, placed on non-hair-bearing (NHB) areas. Within a common signal analytic framework, two distinct schemes are examined. The one is based on standard linear least squares (LLS) and the other on Least Absolute Shrinkage and Selection Operator (LASSO). Both schemes are data-driven techniques, require a small amount of training data, and lead to reliable estimators of EOG activity from EEG signals. The LASSO-based technique, in addition, provides guidelines that generalize well across subjects. Using experimental data, we provide some empirical evidence that our estimators can replace the actual EOG signals in algorithmic pipelines that automatically detect oculographic events, like blinks and saccades.**

I. INTRODUCTION

Mental state monitoring has seen significant advances over the past decades, with a variety of promising neuroergonomic and rehabilitative applications. One relevant context is automated vehicle driving, where the ability to objectively track drivers' cognitive states in real-time is highly valuable for adaptive driver-vehicle interfacing [1]. Among the sensor modalities that can support mental state monitoring, electroencephalography (EEG) and electrooculography (EOG) stand as the most popular ones. EEG can capture brain-activity information regarding the wearer's safety-critical affective and cognitive states, including fatigue [2], workload [3], and trust-in-automation [4]. EOG can be used to track eye-related activity like blinks, fixations and horizontal/vertical displacements of gaze that are known to reflect cognitive states (like vigilance and drowsiness) and mental workload [3].

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However, one major barrier to the uptake of EEG and EOG is sensor obtrusiveness. Despite considerable advances in the development of wearable EEG+EOG devices, state-of-the-art headsets with full montages may still pose significant inconvenience in practical settings. This drives strong interest to design more streamlined sensor architectures. Prior work has demonstrated that signals related to key cognitive states (e.g. fatigue [5], trust-in-automation [4], workload [6]) have significant origins in frontal and prefrontal cortical sources, pointing towards the viability of frontal-only EEG measures on non-hair-bearing (NHB) areas. In contrast, EOG still relies on bilateral temple-based sensors to record horizontal EOG (hEOG) and above- and below-eye sensors to record vertical EOG (vEOG); such circumocular montages may be inconvenient to set up and wear for prolonged periods. Therefore, it is highly desirable to explore the feasibility of extracting EOG features from frontal EEG time-series, with the goal of developing integrated EEG+EOG frontal-based sensor designs.

A. Motivation

Blind Source Separation (BSS) is an umbrella term for a variety of methods with profound application in neuroscience. It is commonly employed to separate artefactual components from neural data by means of linear decomposition. The most commonly anticipated BSS algorithms are based on Independent Component Analysis (ICA) [7]. ICA defines a generative model for the observed multivariate data, which is typically given as a large database of samples. In this model, the data variables are assumed to be linear mixtures of some unknown latent variables, and the mixing system is also unknown. The latent variables are assumed nongaussian and mutually independent, and they are called the independent components, or sources, and can be uncovered by ICA.

Although the eye movements are reflected in the EEG recordings, they are produced by a different source, the eyes. Therefore, the eye-related source signals could be obtained by means of ICA. However, several limitations accompany such an approach, making its use impractical in many domains of application [8]. Firstly, the obtained source signals have a different scaling (even scaled by a negative scaling factor) and the signal energies may deviate significantly from the observed recordings. Therefore, algorithms trained on actual EOG signals may fail to operate equally well on the obtained, eye-related, source signals. The second limitation is connected to the source identification. Even under the assumption that the source signals are accurately computed, an automated way to identify the generator should be developed (e.g. a system that identified the source signals that stem from the eyes). Finally, the number of extracted components is inextricably connected to the number of recorded signals (i.e. electrodes) and therefore is not a suitable approach in few-electrode montages.

In the present work, we propose a computationally efficient framework that can reliably infer the EOG activity from frontal EEG recordings. In essence, our approach is based on calculating a spatial filter, through which the EEG activity is ”canceled out”, leading to the EOG signal as it would haven recorded by EOG-dedicated electrodes. The proposed methodology mitigates the aforementioned, BSS-related, limitations and is capable of reconstructing the EOG activity either in a personalized or in subject-independent manner. Despite the requirement for a short training process in the former case (i.e. personalized spatial filters), our study provides evidence that the subject-independent variant of our framework manages to trade-off this requirement without any significant loss in terms of EOG reconstruction fidelity.

II. Methodology

A. Participants Recruitment and Experiment Description

Fifteen participants completed the experiments part of a larger study involving driving simulation conducted at the Cognitive Engineering Laboratory in the National University of Singapore (NUS). The sample (11 males; 4 females) had an average age of 23.6 years (range 18 – 30 years). Before the experimental session, participants gave written informed consent to take part in the study procedures approved by the NUS Institutional Review Board (IRB).

Participants manually drove a simulated vehicle in a practice driving tour for familiarisation before the actual experiment. During the experiment, they kept hands on the wheel and passively observed the autonomous vehicle (Level 3 automation) as it drives through the a road loop of the simulated urban environment. The autonomous vehicle was travelling at a constant speed of 50km/hr. During the experiment, they did not experience any simulation-induced nausea, dizziness or sickness.

B. EEG Data Acquisition and Analysis

EEG data were recorded using Waveguard^{TM} caps (CA-142; ANT Neuro, Netherlands) which have 64 Ag/AgCl electrodes configured according to the International 10-10 system, sampled at 512 Hz. The data acquisition software was AsaLabTM, version 4.7.12 (ANT Neuro, Netherlands). Electrode impedances were kept below 15 kΩ. Additional electrodes were placed on both left and right temples, as well as below and above the right eye, to record horizontal and vertical electroculogram (hEOG and vEOG) respectively.

For this study, 120 seconds long epochs were selected for predicting EOG activity from the EEG signals, using the spatial filtering approaches described in the sections below. The entire driving tour contained no traffic events or junctions. The driver was not required to intervene or perform any other driving tasks (i.e., no braking, no steering, no switching to manual mode).

C. EOG reconstruction from EEG

Let $\mathbf{X} \in \mathbb{R}^{C \times T}$ be a multichannel EEG signal with C denoting the number of channels and T the number of samples. Then, let us denote by $\mathbf{Y}_v$ and $\mathbf{Y}_h \in \mathbb{R}^T$ two univariate signals, namely the vertical and horizontal EOG signals respectively. The key concept of our method is to uncover two spatial filters, $\mathbf{w}_v$ and $\mathbf{w}_h \in \mathbb{R}^C$, such that $\mathbf{X}^\top \mathbf{w}_v = \mathbf{Y}_v$ and $\mathbf{X}^\top \mathbf{w}_h = \mathbf{Y}_h$. Since there is not an a priori guarantee that an exact solution will always exist, the solution is obtained by means of a regression problem, e.g., calculate the $\mathbf{w}_v$ and $\mathbf{w}_h$ that are able to reliably reconstruct the $\mathbf{Y}_v$ and $\mathbf{Y}_h$, according to the two different optimization approaches presented in the following subsections.

1) Linear Least Squares (LLS): Here, the goal is to find the $\mathbf{w}_v$ and $\mathbf{w}_h$ that minimize $||\mathbf{X}^\top \mathbf{w}_v - \mathbf{Y}_v||_2^2$ and $||\mathbf{X}^\top \mathbf{w}_h - \mathbf{Y}_h||_2^2$ respectively. Since typical EEG recordings contain much more samples in time than their channels, it is guaranteed that $rank\{\mathbf{X}\} = rank\{\mathbf{X}\mathbf{X}^\top\} = C$. Therefore, the solutions can be obtained as $\mathbf{w}_h = (\mathbf{X}\mathbf{X}^\top)^{-1}\mathbf{X}\mathbf{Y}_h$ and $\mathbf{w}_v = (\mathbf{X}\mathbf{X}^\top)^{-1}\mathbf{X}\mathbf{Y}_v$.

2) Least Absolute Shrinkage and Selection Operator (LASSO): LASSO was developed in order to perform not only robust regression analysis but to also serve as a variable selection and regularization in order to enhance the prediction accuracy and interpretability of the resulting predictor [9]. In our case, since we need to find a spatial filter that linearly combines the EEG channels so as to reconstruct the EOG channels, LASSO will allow us to uncover the particular EEG channels that carry significant information on EOG. In a more rigorous formulation, LASSO is expressed as the following minimization problem with respect to $\mathbf{w}$: $||\mathbf{X}^\top \mathbf{w} - \mathbf{Y}||_2^2 + \lambda||\mathbf{w}||_1$. It becomes apparent that the loss function is the same as in the Linear Least Squares accompanied by a penalty term. The constrained region defined by the $\mathscr{L}_1$ norm is a rhombus that its corners lie on the axes that consequently tends to lead to a sparse solution $\mathbf{w}$.

III. Results

In this section we present the results obtained by each of the corresponding reconstruction method. The main score that is employed to evaluate the performance of the adopted methodological framework is the Root Mean Square Error (RMSE). Two validation methods were employed so as to estimate the performance of each spatial filter. The first concerns personalised spatial filters, specifically tailored to each recording (we note that we hold one recording per subject). In this case, the recordings were split into a 60-40% for train and test, respectively, and one spatial filter was estimated for each recording. The second validation approach, Leave One Subject Out (LOSO), concerned a more generic approach where the spatial filters were calculated so as to reconstruct the EOG activity by exploiting previously recorded EEG signals. In order to enable a fair comparison between the two different approaches, namely the LLS and LASSO, we note that the methodologies were validated on the same test set (e.g. the same 40% of each recording as in the personalised case). In both validation schemes three different electrode montages were tested: i) using three prefrontal electrodes, ii) using seven frontal and prefrontal electrodes and iii) using the whole electrode array (e.g. 62 channels). Tables I and II present the average RMSE values, across all subjects. As expected, the generic spatial filters learnt across subjects lead to less accurate EOG representations. However, such an approach is not limited by the need to perform a calibration recording containing EOG at the start of each session.

TABLE I: Average (across participants) RMSE for LLS-based spatial filter for each validation approach under the three employed electrode montages.(Prefrontal - Fpz, Fp1, Fp2; Frontal - Fpz; All - 62 EEG channels)

LLS	60-40 personalized			LO Subject Out (40% test)		
	Prefrontal	Frontal	All	Prefrontal	Frontal	All
Horizontal	0.2036	0.1191	0.1011	0.3420	0.2561	0.2133
Vertical	0.1059	0.0964	0.0844	0.4256	0.4440	0.4945

As we already pointed out previously, LASSO may serve as a channel selection process. Therefore, by using an appropriate λ value to enforce a sparse solution on the whole electrode array we uncovered two rules of thumb, which were consistent across all subjects, for EOG approximation through EEG signals: i) electrode Fpz alone is a reliable estimation for vEOG and, ii) the difference F7-F8 is a reliable estimation for hEOG. These rules of thumb enable EOG estimations when no-particular approximation performance is required or the process of estimating a spatial filter may induce an unsuitable time-delay.

TABLE II: Average (across participants) RMSE for LASSO-based spatial filter for each validation approach under the three employed electrode montages (Prefrontal - Fpz, Fp1, Fp2; Frontal - Fpz; All - 62 EEG channels).

LASSO	60-40 personalized			LO Subject Out (40% test)		
	Prefrontal	Frontal	All	Prefrontal	Frontal	All
Horizontal	0.2126	0.1271	0.1151	0.35	0.2537	0.1999
Vertical	0.1055	0.0990	0.0833	0.4317	0.4990	0.4489

Alongside the quantitative evaluation presented above, we also provide qualitative evidence in Figures 1 and 2, which depict two indicative examples so as the reader may obtain an intuitive interpretation of the presented RMSE values. As it can be noticed, the EOG reconstruction, which is specifically tailored to a subject/recording, is almost identical to the actual EOG signal. In the case of a more generic spatial filter, suitable for all subjects, although the approximation captures the most evident dynamics, it may fail to imprint their exact intensity and accurately approximate the micro-saccades. This is possibly attributed to the fact that a recording-specific filter is capable to consider the small alternations in electrode placement and the possible differences in impedance, hence, adjust its weights accordingly.

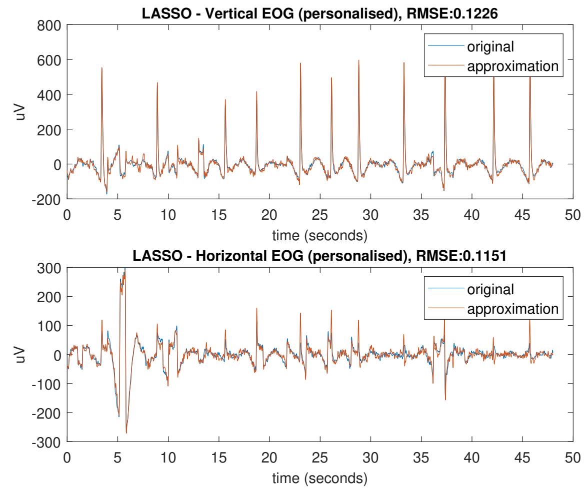

Fig. 1: An indicative example of the actual EOG (blue) and the approximation from EEG (red) achieved by a spatial filter that operates on the three prefrontal electrodes (Fpz, Fp1, Fp2), as obtained through LASSO, tailored to this subject, accompanied by the corresponding RMSE values.

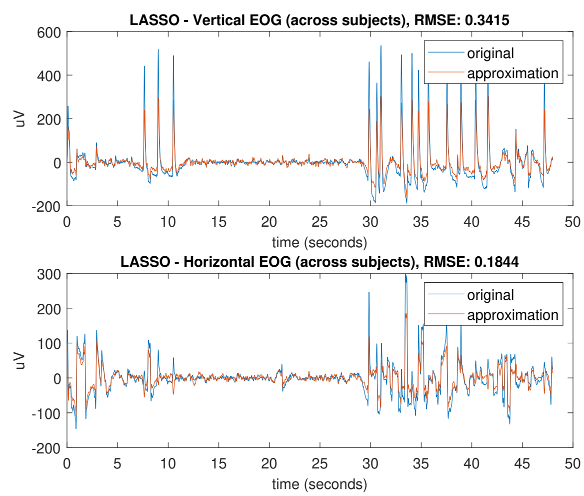

Fig. 2: An indicative example of the actual EOG (blue) and the approximation from EEG (red) achieved by a subject-independent spatial filter that operates on the three prefrontal electrodes (Fpz, Fp1, Fp2), as obtained through LASSO accompanied by the corresponding RMSE values.

In order to provide further indications about the validity of our approach, a probabilistic algorithm [10] for blink and saccade detection from EOG signals is employed. In essence, the employed EOG-event recognition approach estimates the parameters of the Gaussian likelihoods using an expectation maximization algorithm, hence, allowing to consider the uncertainties in the detected events. Figures 3 and 4 present the operation of the aforementioned EOG event detection algorithm on a sample of original and the corresponding reconstructed EOG signal, as obtained by our subject-independent spatial filter method, that operates on the three prefrontal electrodes (Fpz, Fp1, Fp2). By means of visual inspection, it becomes apparent that the obtained results are almost identical. This fact indicates that the proposed spatial filter method allows mechanistic approaches to address the EOG-event detection with similar performance on both original and reconstructed data.

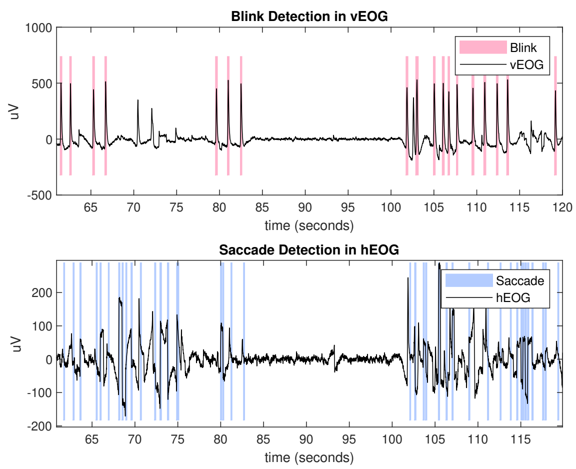

Fig. 3: EOG activity detection on the original EOG signal.

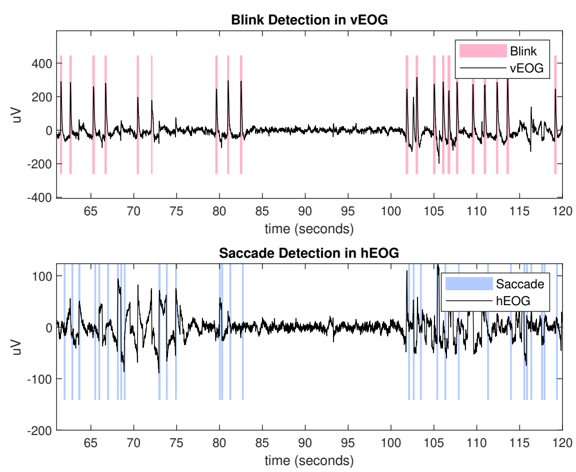

Fig. 4: EOG activity detection on approximated EOG signal.

IV. Discussion

The current study aimed to develop a robust approach for accurately and reliably reconstructing EOG signals from EEG timeseries. The proposed approach is motivated by the increasing interest in unobtrusive characterization of human mental states using a variety of neurophysiological signals. Recent brain computer interface (BCI) applications in areas such as neurorehabilitation, neuroergonomics and neuromarketing have pointed to the need of using reduced sensor setups capable of seamlessly providing a variety of neurophysiological signals simultaneously [11].

Our approach demonstrates that, first, it is possible to reconstruct with high accuracy horizontal and vertical EOG from EEG timeseries using two slightly different approaches, LLS and LASSO. The accuracy of estimated EOG events (blinks and saccades) is comparable to that of a method based on dedicated EOG sensors. Second, we show that is is possible to employ a reduced number of EEG sensors, located on the frontal non-hair-bearing areas, to reliably reconstruct EOG. This is highly relevant in the context of using wearable unobtrusive EEG sensors incorporated into clothing items (such as headbands or caps) for "out of the lab" applications. Third, we demonstrate that our approach works both in a personalized manner (in which the spatial filters are learned from individual subjects), as well as in the subject-independent manner (albeit with a trade-off in accuracy), in which generic spatial filters are learnt across subjects.

V. Conclusions

In this paper we propose an approach based on spatial filters to reconstruct EOG signals using EEG signals exclusively. We show that the linear least square (LLS) and Least Absolute Shrinkage and Selection Operator (LASSO) methods can be used to derive both personalized and generic spatial filters for accurate EOG reconstruction. Our approach proves that spatial filtering represents a computationally efficient framework for reconstructing the EOG activity from EEG signals.

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