VOG-ENHANCED ICA FOR SSVEP RESPONSE DETECTION FROM CONSUMER-GRADE EEG

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ABSTRACT

The steady-state visual evoked potential (SSVEP) brain-computer interface (BCI) paradigm detects when users look at flashing static and dynamic visual stimuli. Electroculogram (EOG) artefacts in the electroencephalography (EEG) signal limit the application for dynamic stimuli because they elicit smooth pursuit eye movement. We propose 'VOG-ICA' - an EOG artefact rejection technique based on Independent Component Analysis (ICA) that uses video-oculography (VOG) information from an eye tracker. It demonstrates good performance compared to Plöchl when evaluated on matched and EEG data collected with consumer grade eye tracking and wireless cap EEG apparatus. SSVEP response detection from frequential features extracted from ICA components demonstrates higher SSVEP response detection accuracy and lower between-person variation compared with extracted features from raw and post-ICA reconstructed 'clean' EEG. The work highlights the requirement for robust EEG artefact and SSVEP response detection techniques for consumer-grade multimodal apparatus.

***Index Terms*—** ICA, SSVEP, EEG, Artefact Rejection, VOG

1. INTRODUCTION

Electroencephalography (EEG) measures the brain's electrical activity from scalp-based electrodes [1]. The Steady-State Visual Evoked Potential (SSVEP) is the brain's electrical response to retinal stimulation by a flickering visual stimuli at a frequency greater than $6Hz$ [2]. It is characterised by an EEG signal oscillation at the same frequency. SSVEP is a popular technique for Brain-Computer Interface (BCI) due to the minimal between-person differences.

Non-biological (e.g. electrical mains) and biological artefacts (e.g. muscle movement) contaminate EEG signals, leading to lower BCI performance [3]. The prevalent biological artefact is Electroculogram (EOG) - eye movements produced by the corneo-retinal dipole, and eyelid movements such as blinks. The Blind Source Separation technique Independent Component Analysis (ICA) has been successfully applied on EEG channel data to remove EOG sources [4] so that a 'clean' EEG signal can be reconstructed. However, ICA does not label sources automatically - a current research topic [5] [6].

In addition to EOG artefacts, SSVEP response detection difficulty arises from people's exposure to prolonged flashing stimuli resulting in a gradual decrease in SSVEP response - the *habituation* effect [7]. Use of static flashing visual stimuli potentially reduces EOG artefacts because slow moving 'pursuit' eye movement is absent. This could improve SSVEP response detection accuracy. However, the SSVEP response is reduced by the habituation effect lowering SSVEP response detection accuracy [8]. Contrastingly, dynamic flashing stimuli may reduce the habituation effect but introduce more EOG artefacts. It is desirable therefore that SSVEP response detection methods should have consistence performance for static and dynamic visual stimuli.

In this work we consider robust field BCI - consistent SSVEP response detection to static and dynamic stimuli from consumer grade, non-clinical wireless cap EEG apparatus and VOG from a portable wearable eye tracker. The EEG device (Emotiv EPOC) has fewer channels and lower sampling rates than clinical versions. The eye tracker (Tobii Eye glasses) is monocular and samples at a low rate compared to laboratory counterparts.

In section 2 we review previous EOG artefact rejection studies. Section 3 outlines our EOG artefact rejection VOG-ICA technique and SSVEP response detection. In section 4 we describe the evaluation method and a VOG/EEG dataset captured. Experiment results are presented in section 5 followed with a discussion in section 6.

2. RELATED WORK

Several studies propose algorithms to identify artefactual sources including EOG from EEG spatial and temporal features [9, 10]. Notably, ADJUST [5] automatically detects different EOG types by considering temporal and spatial features. Recently Plöchl et al. [6] used matched Video-oculography (VOG) and EEG data to discard EOG artefacts when saccades (rapid and large eye movement) occurred.

2.1. Novelty

In this work we use information from VOG to label ICA separated sources as eye movement artefacts arise from pursuit eye movement as well as rapid and large eye movement. In addition, previous studies in EEG for BCI chiefly apply ICA exclusively for artefact rejection rather than feature extraction. We demonstrate that ICA components can be beneficial as features for SSVEP response detection. We evaluate SSVEP response detection on a specifically designed smooth pursuit eye movement VOG/EEG dataset. which itself reduces habituation - a key requirement for the real-world BCI SSVEP paradigm use. We use consumer grade EEG equipment with lower spatial and temporal resolution compared to clinical EEG to demonstrate field potential.

3. APPROACH

3.1. VOG-ICA EOG artefact labelling

To identify eye movement / EOG sources and reject them from EEG, the Extended-Infomax [11] ICA algorithm is applied. A VOG signal is used as an extra information source for artefact detection. It gives the time-variant signals $x(t)$ and $y(t)$ representing the horizontal and vertical gaze coordinates at time t, respectively. The cross-correlation [12] of the i_{th} Independent Component (IC), S_i, with $x(t)$ and $y(t)$, is calculated. ICs are scored according to the maximum absolute cross-correlation values with $x(t)$:

$$\gamma_{x,i} = \max_t(|(S_i * x)(t)|) \tag{1}$$

where $\gamma_{x,i}$ refers to the maximum absolute cross-correlation values between the i^{th} IC, $S_i(t)$, and signal $x(t)$. The ICs Z-Scores in $\gamma_{x,i}$ is calculated;

$$Z\gamma_{x,i} = \frac{\gamma_{x,i} - E[\gamma_{x,i}]}{\sigma(\gamma_{x,i})} \tag{2}$$

where $E[...]$ and $\sigma(...)$ refer to the expected value and standard deviation for $\gamma_{x,i}$, respectively. High scoring IC's are identified as eye movement artefacts.The threshold ($Z\gamma_{x,i}$ or $Z\gamma_{y,i} = 2.0$) for high score is determined empirically. The same procedure is applied to obtain ICs which are correlated with vertical eye movement sequence, $y(t)$.

3.2. SSVEP response detection

To detect SSVEP, the EEG signal channels or ICA components are split into $2000ms$ windows with 80% overlaps. The stimulation frequencies ($7Hz$, $10Hz$ and $12Hz$) amplitude and their second harmonics (i.e. $14Hz$, $20Hz$ and $24Hz$) features are extracted from the power spectral density (PSD) for each window. The PSD is estimated by Welch's method [13]. A k-Nearest Neighbour (kNN) classifier with Euclidean distance metric is trained on a subset of data to distinguish different SSVEP frequencies. k's value is set to 1 (i.e. 1-NN).

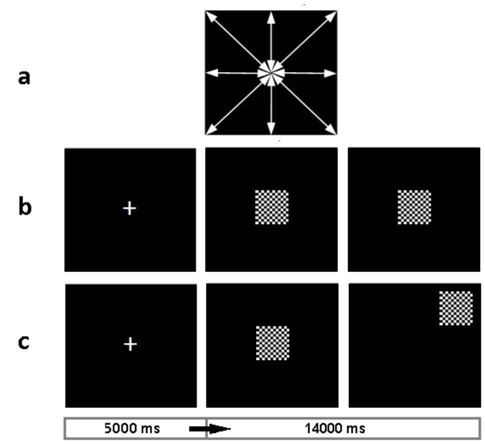

Fig. 1. An illustration of the experimental paradigms: (a) possible trajectories followed by stimuli. (b) *Static SSVEP*: Flickering stimuli are fixed at the screen centre (c) *Dynamic SSVEP*: Stimuli move from the display centre towards locations shown in (a). Subjects follow the stimuli.

4. EVALUATION

4.1. Method

Participants are instructed to perform the tasks illustrated in the Fig. 1: The screen is a black square which is divided into nine possible locations for stimulus presentation (Fig. 1.a). The trials start when a white fixation cross appears in the screen's centre for 5 seconds. Next, a 10x10 checkerboard (the stimulus) covers the fixation cross and flickers at three frequencies ($7Hz$, $10Hz$ or $12Hz$ [14]) for 14 seconds. In *Static SSVEP* the checkerboard is remains fixed in the screen's centre (Fig. 1.b); however, in *Dynamic SSVEP* the stimulus moves from centre towards one remaining location on the screen (Fig. 1.c). Each *Static SSVEP* run consists 8 trials for every flickering frequency. There are also 8 trials for flickering stimulus, moving to different directions, in *Dynamic SSVEP*.

4.2. Participants

Five healthy people participate. All have normal or corrected-to-normal vision and informed consent is obtained. They are positioned in a comfortable chair at approximately $100cm$ distance from a 19 inch liquid crystal display (LCD) with $60Hz$ vertical refresh rate. All participants are instructed to relax and remain as still as possible to avoid the EEG signal contamination with muscle artefacts.

4.3. EEG and eye tracking apparatus

EEG and VOG are captured with two non-intrusive consumer-grade recording apparatus designed for mobile situations. A 14 electrodes wireless EEG headset (Emotiv EPOC) is used for EEG signal acquisition. There are also two reference electrodes located above the subjects' ears. The EEG device has a $128Hz$ sample rate. VOG is captured from a head-mounted monocular eyetracker (Tobii Glasses) at $30Hz$ sample rate . The eye tracker's recording visual angle is $56° \times 40°$ which is sufficient to capture all movement in relation to the LCD. EEG and VOG recordings are synchronised by timestamps displayed on the LCD and captured by the eyetracker's scene camera.

4.4. EEG signal preprocessing and feature extraction

EEG signals are Band-pass filtered to remove the slow drifts and high-frequency noises from the recorded data (1–$40Hz$). To provide synchronization between VOG and EEG recorded signals, the scene camera recordings are visually inspected to label the stimulation start and end. The VOG is up-sampled to match the EEG sample rate with linear interpolation.

Four feature sets are compared for SSVEP response detection: pre-ICA 'raw' EEG channel features (Orig); post-ICA 'clean' EEG channel features from EEG reconstructed from non-EOG IC (ClnEEG); ICA components (ICs); non-EOG ICs identified with VOG-ICA (ClnICs). For each feature set, a 10-fold cross validation method is used to evaluate the kNN SSVEP response detection classifier performance.

4.5. SSVEP response detection tests

To evaluate the VOG-ICA signal processing for EOG artefact rejection, we compare the SSVEP response detection accuracy before and after applying ICA. Results are compared with the state-of-art artefact rejection method proposed by Plöchl et al [6].

5. RESULTS

5.1. VOG-ICA for EOG rejection

Figure 2 illustrates the ICs' Z-Score distribution for all subjects in Dynamic SSVEP. The ICs with Z-Scores higher than 2.0 are highly correlated with VOG, contains eye movement-related activities. Thus, ICs with Z-scores higher than 2.0 are labelled as EOG artefacts.

There is a linear relation between the ICs' Z-scores cross-correlated with eye movement signals $x(t)$ and $y(t)$. The outlying ICs exceed both thresholds, suggesting that the eye-related potentials for vertical and horizontal eye movements are separate ICs (figure 2).

If extracting features from VOG-ICA components for SSVEP response detection, the averaged SSVEP classification accuracy increases by 4% in *Static SSVEP*, and by 3% in *Dynamic SSVEP* (Table 1). All eye-related artefacts are detected.However, when Plöchl is applied, the averaged SSVEP classification accuracy decreases by 6% in both experiments and the EOG artefacts for some subjects are not detected.

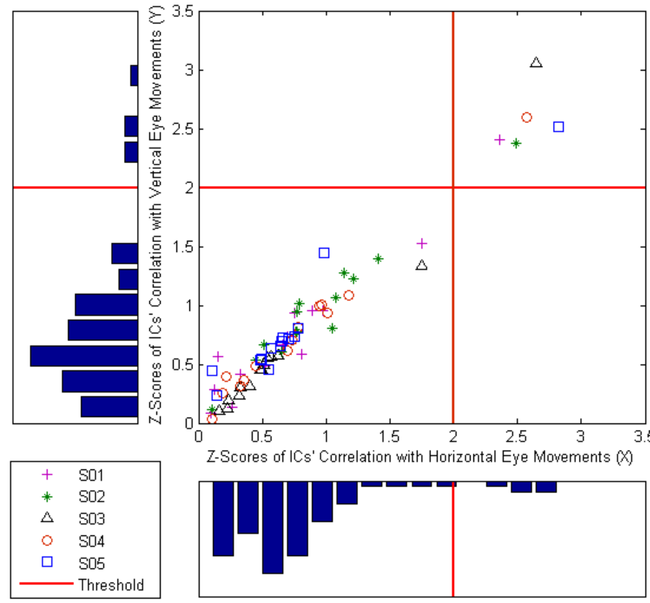

Fig. 2. shows the Z-Score distribution obtained by each single IC cross-correlated with $x(t)$ and $y(t)$. ICs belong to all subjects in the *Dynamic SSVEP*. Z-Score value distribution for each $\gamma_{x,i}$ and $\gamma_{y,i}$ sequences are superposed on the relative axis. Red lines indicate the selected threshold ($Z\gamma_{x,i}$ or $Z\gamma_{y,i} = 2.0$).

5.2. SSVEP response detection from ICA components

SSVEP response detection for all subjects is significantly higher when features are extracted from ICs rather than EEG channels (Table 2 bold figures). This suggests that

Table 1. The percentage ($\%$) SSVEP classification accuracy for each subject in *Static SSVEP* and *Dynamic SSVEP*; when there is no EOG artefact rejection (Orig) compared to when Plöchl and VOG-ICA are applied for EOG artefact rejection. The best obtained result is highlighted in bold.

Subj	Static SSVEP			Dynamic SSVEP		
	Orig	Plöchl	VOG-ICA	Orig	Plöchl	VOG-ICA
S01	82.98	68.36	81.60	89.14	—	93.47
S02	88.99	89.24	94.02	88.65	64.55	91.24
S03	80.38	76.10	90.65	89.80	83.79	85.86
S04	85.27	72.99	82.00	83.85	83.29	95.01
S05	81.76	—	90.55	81.54	—	80.12
Ave	83.88	77.69*	**87.76**	86.60	80.46*	**89.14**
std	3.37	8.08	5.62	3.68	9.33	6.11

* In the cases where there is no IC detected as artefact ("—"), the original accuracy is considered in the averaged accuracy calculation.

Table 2. SSVEP classification performance when SSVEP frequential features are extracted from: the original EEG data (Orig); cleaned reconstructed EEG data (ClnEEG); all estimated ICs (ICs), and ICs detected as non-artefact (ClnICs).

Subjects	Static SSVEP				Dynamic SSVEP			
	Orig (%)	ClnEEG (%)	ICs (%)	ClnICs (%)	Orig (%)	ClnEEG (%)	ICs (%)	ClnICs (%)
S01	82.98	81.60	**96.69**	95.67	89.14	93.47	**96.87**	96.49
S02	88.99	94.02	**96.84**	95.91	88.65	91.24	**95.25**	95.00
S03	80.38	90.65	**96.08**	93.80	89.80	85.86	**95.03**	92.56
S04	85.27	82.00	**96.57**	94.88	83.85	95.01	**96.91**	96.59
S05	81.76	90.55	**95.72**	94.76	81.54	80.12	**96.21**	95.54
Ave	83.87	87.76	**96.38**	95.00	86.60	89.14	**96.05**	95.23
std	3.37	5.62	0.46	0.83	3.68	6.11	0.88	1.63

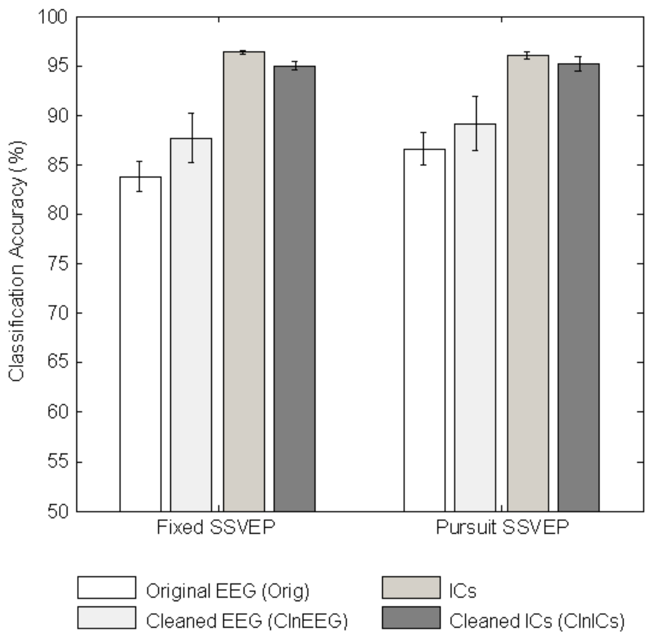

Fig. 3. SSVEP classification performance for *Static SSVEP* and *Dynamic SSVEP*, averaged over 5 subjects. The error bars represent standard errors.

ICA performs well in source separation. Comparing ICs and ClnICs shows detection performance insignificantly decreases 1% in both scenarios, suggesting that EOG ICs may have some SSVEP information due to imperfect source separation. When features are extracted from the original EEG data (Orig), the SSVEP response detection accuracy for *Dynamic SSVEP* is 3% higher than for *Static SSVEP*. This suggests that a gradual decrement in static SSVEP amplitude responses due to the habituation effect which is reduced with the dynamic SSVEP. SSVEP response detection performance improves slightly for reconstructed 'clean' EEG over original 'raw' EEG. In addition to improving detection performance, extracting features from ICs significantly reduces between-person variation (figure 3).

6. DISCUSSION

In this work we demonstrate that static and dynamic SSVEP detection performance is significantly improved by extracting frequential features from source components estimated from ICA rather than EEG signal channels. VOG can assist in the automatic labelling of EOG sources via cross correlation of the eye tracker signal with the independent components.

Five people participated in the evaluation. While this is a small sample set, it is justified because the SSVEP response detection performance from frequential components demonstrates minor between person variation; the reason why the SSVEP BCI paradigm is popular. The good performance of the kNN classifier also suggests a sufficient training data quantity. However, whether or not retaining EOG labelled components for SSVEP response detection is worthwhile given the insignificant performance difference requires further study with more people.

Compared to other techniques, VOG-ICA outperforms Plöchl et al. [6]. The ADJUST [5] method does not detect any EOG artefacts in our data and is omitted. Thus, we cannot claim that VOG-ICA is superior to other methods due to the different dataset characteristics; e.g. non corneo-retinal EOG artefacts such as blinks are accounted for by bandpass pre-filtering in this study rather than explicitly by the algorithm. This highlights that current approaches to artefact rejection and SSVEP response detection evaluated on data captured by clinical grade EEG may under-perform on data captured with consumer grade wireless cap EEG apparatus, which has more utility in field BCI. Future studies considering spatial resolution and temporal precision effects on algorithm performance may therefore be valuable.

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