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VOG-ENHANCED ICA FOR REMOVING BLINK AND EYE-MOVEMENT ARTEFACTS FROM EEG

Mohammad Reza Haji Samadi, Zohreh Zakeri and Neil Cooke

***Abstract*— The steady-state visual evoked potential (SSVEP) is reliable for many paradigms such as clinical neuroscience and brain computer interfaces (BCI), providing high information throughput with minimal between-person variations. However, Electrooculogram (EOG) artefacts in Electroencephalography (EEG) signal limit applications with dynamic SSVEP stimuli due to eye movement and blinks. Independent Component Analysis (ICA) is a successful method for removing EOG artefacts. We propose 'Blink VOG-ICA' (BVOG-ICA) - an enhanced ICA algorithm that uses eye tracker video-oculography (VOG) eye movement and blink detection information. It demonstrates improved performance compared to ICA variants Plöchl and our previous VOG-ICA when evaluated on matched VOG and EEG data. SSVEP classification accuracy for the post-ICA clean EEG consequently improves 7% and 4% for static and dynamic SSVEP stimuli respectively, suggesting BVOG-ICA as a potentially reliable automatic EOG artefact removal method for SSVEP paradigms.**

I. INTRODUCTION

Electroencephalography (EEG) is the recording of electrical activity of brain over the scalp using a set of electrodes [1]. The Steady-State Visual Evoked Potential (SSVEP) is the electrical response of the brain which is synchronised in the frequency and phase to a flickering visual stimuli at a frequency greater than $6Hz$ [2]. SSVEP is a popular technique for many paradigms in cognitive and clinical neuroscience [3], [4], [5] as well as Brain-Computer Interface [6], [7], because it requires less user training and provides minimal between-person variation. EEG signals are usually contaminated by artefacts which may hinder correct interpretation of EEG. Electrooculogram (EOG) artefacts - artefacts arising from eye movements and blinking - are particularly prevalent.

The blind source separation method Independent Component Analysis (ICA) has been successfully applied on EEG data to remove artefacts and avoid unnecessary intervention [8]. ICA assumes the observed EEG signal is a linear combination of several independent (artefact and non-artefact) sources and attempts to estimate the sources. The main limitation of ICA is its inability to label the estimated sources. Consequently, automatic labelling of artefactual sources then removing them from the EEG signal before its reconstruction is an active topic of research [9], [10], [11], [12].

In this work we combine the problem of reliably detecting SSVEP for dynamic stimuli with that of removing EOG artefacts. Eye blink is inevitable in EEG recordings and dynamic stimuli elicits eye movement artefacts - specifically pursuit eye movement - which can degrade SSVEP detection accuracy further. In section 2 we review previous studies for EOG artefacts removal. Section 3 includes our proposed method to use optical information (VOG) for EOG artefact detection and SSVEP detection. In section 4 we describe the evaluation method and the experimental paradigm. Results are reported in section 4 following by a discussion in section 5.

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II. RELATED WORK

Several studies attempt to identify artefactual sources (including eye-related artefacts) by exploiting the spatial, temporal and frequential characteristics of artefacts. In recent years, use of optical information to remove eye-related artefacts from EEG gained interest. Plöchl et. al. [10] and our previous work VOG-ICA [11] use matched Video-oculography (VOG) and EEG data to detect eye movement artefacts when rapid (saccade) and smooth pursuit eye movements occurred, respectively. Neither of these methods explicitly consider sources associated to eye blinks. In this work we propose 'Blink VOG-ICA' (BVOG-ICA), a fully automated method to label eye-related artefacts corresponding to blink, pursuit and rapid eye movements.

III. APPROACH

A. Optical Information

VOG data gives the time-variant signals $x(t)$ and $y(t)$ representing the horizontal and vertical gaze position at time t, respectively. In VOG recordings, there are times when eye-tracker does not detect the pupil due to occlusion i.e. blinking. This results in gaps of several hundred milliseconds in $x(t)$ and $y(t)$. From these gaps we derive a boolean valued blink trigger signal $b(t)$ representing blink occurrence at time t. The gaps in the $x(t)$ and $y(t)$ signals are filled by linear interpolation between the first values before and after the gap.

B. BVOG-ICA for EOG artefact removal

To separate eye-related sources from EEG recordings, we apply the Extended-Infomax [13] ICA algorithm. The cross-correlation [14] of the first order derivative of the i_{th} Independent Component (IC), S_i, with the first order derivative of $x(t)$, $y(t)$ and $b(t)$ is calculated. ICs are scored according to the maximum absolute values of their cross-correlation with $b(t)$:

$$\gamma_{b,i} = \max(|(\frac{dS_i}{dt} * \frac{db}{dt})(t)|) \tag{1}$$

where $\gamma_{b,i}$ refers to the maximum absolute values of cross-correlation between the first order derivative of i^{th} IC, $\frac{dS_i}{dt}$, and the first order derivative of the blink signal $\frac{db}{dt}$. The Z-Scores of the ICs in the scoring $\gamma_{b,i}$ is calculated:

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

where $E[...]$ and $\sigma(...)$ refer to the expected value and standard deviation of the $\gamma_{b,i}$, respectively. ICs with Z-scores above the threshold, $Z\gamma_{b,i} = 2.0$, are highly correlated with eye blinks and are detected as blink artefacts. The same procedure is applied for obtaining ICs which are associated with horizontal and vertical eye movement sequences, $x(t)$ and $y(t)$, respectively following our VOG-ICA algorithm [11]. All detected artefacts are removed and artefact-free EEG data is reconstructed from the remaining ICs.

C. SSVEP response detection

To detect SSVEP frequencies, the EEG signal recorded at each electrode is split into $2000ms$ windows with 60% overlaps. The power spectral density (PSD) of each window is estimated using Welch's method [15]. The amplitude of the stimulation frequencies ($7Hz$, $10Hz$ and $12Hz$) and their second harmonics (i.e. $14Hz$, $20Hz$ and $24Hz$) obtained from PSD are extracted as features. A k-Nearest Neighbour (kNN) classifier ($k = 1$) with Euclidean distance metric distinguishes different SSVEP stimulation frequencies. The classifier performance is evaluated by 10-fold cross validation.

IV. Evaluation

A. Method and Apparatus

Five healthy subjects having normal or corrected-to-normal vision participated in the experiment. A 19 inch liquid crystal display (LCD) with $60Hz$ vertical refresh rate is used as the SSVEP stimulator and subjects are seated at a distance of about $100cm$ from it. All participants are instructed to relax and avoid moving their body to prevent the contamination of EEG signals with muscle artefacts. Each subject conducts two tasks, *Fixed SSVEP* and *Dynamic SSVEP*, each approximately 9 minutes duration. Trials start with the presentation of a fixation cross in the centre of the screen. After 5 seconds a $10x10$ checkerboard, flickering in $7Hz$, $10Hz$ or $12Hz$, overlays the fixation cross for another 14 seconds.

In *Static SSVEP* the checkerboard is remained fixed in the centre of the screen. In *Dynamic SSVEP* the checkerboard moves from centre towards different locations on the screen. Each task consist of 8 trials for each frequency.

Two consumer-grade recording apparatus capture EEG and VOG. The EEG signal is recorded using a 14 electrodes wireless EEG headset (Emotiv EPOC), sampling at $128Hz$. The slow drifts and high-frequency noises are removed from EEG recordings by band-pass filtering (1_40Hz). VOG is captured using a head-mounted monocular eye-tracker (Tobii Glasses), sampling at $30Hz$, which enables recording a subjects focus of gaze within his field of view (with $56° \times 40°$ visual angel). The VOG is up-sampled to $128Hz$ with linear interpolation in order to match the EEG sample rate. Timestamps displayed on the LCD and recorded by the eye-tracker's scene camera are used to synchronise the EEG and VOG recordings. Further details of the data captured can be found in our paper detailing the VOG-ICA algorithm [11].

B. SSVEP response detection tests

The SSVEP detection accuracy before and after removing EOG artefacts is compared. If the EOG artefacts are labelled and removed correctly, an increase in the accuracy of SSVEP detection is expected. Results are compared with the state-of-art VOG-based EOG artefact removal methods proposed by [10] (named Plöchl) and our VOG-ICA method [11].

V. Results

A. BVOG-ICA for EOG artefact removal

Fig. 1 illustrates the VOG gap interpolation procedure described in section III-A. Additionally, Fig. 1.b depicts the blink signal $b(t)$, derived from the missing samples in VOG data. The gap filling method avoids the occurrence of false saccadic (rapid) eye movement by providing a smooth transition between the last data sample before start of a gap and the first data sample after the end of that gap.

Fig. 2 shows the distribution of the blink, horizontal and vertical eye movement Z-Scores of ICs of all subjects in *Static SSVEP* (Fig. 2.a) and *Dynamic SSVEP* (Fig. 2.b). The ICs with Z-Scores higher than 2.0 are considered as EOG artefacts. This value is determined empirically. Fig. 3 shows a typical sample of the blink and saccade ICs derected using the proposed method. During Dynamic SSVEP the BVOG-ICA ICs considered as EOG artefacts are better separated from the mean distribution of all other ICs compared to the *Static SSVEP* where subjects make minimal eye movements. This suggests that BVOG-ICA performs a better EOG source separation because there are more eye movement signals to convey EOG information.

Considering both Static and Dynamic SSVEP, there are 8 ICs detected as blink, 8 ICs detected as horizontal eye movement and 8 ICs detected as vertical eye movement artefacts. The 8 ICs detected as horizontal eye movements are the same ICs detected as vertical eye movements. This suggests that both types of eye movements are in the same ICs. Additionally, there are three ICs mutually detected as blink and eye movement artefacts. In total, BVOG-ICA detects 13 unique ICs as EOG artefacts.

B. SSVEP detection

Table I summarises the SSVEP detection accuracy. It is highest for BVOG-ICA in both tasks (i.e *Static SSVEP* and *Dynamic SSVEP*). The SSVEP classification accuracy increases by 7% in Static SSVEP, and by 4% in Dynamic SSVEP. There is also an increase in the average SSVEP classification accuracy when our previous VOG-ICA method [11] is applied - a 4% increase in Static SSVEP and a 3% increase in Dynamic SSVEP. However,

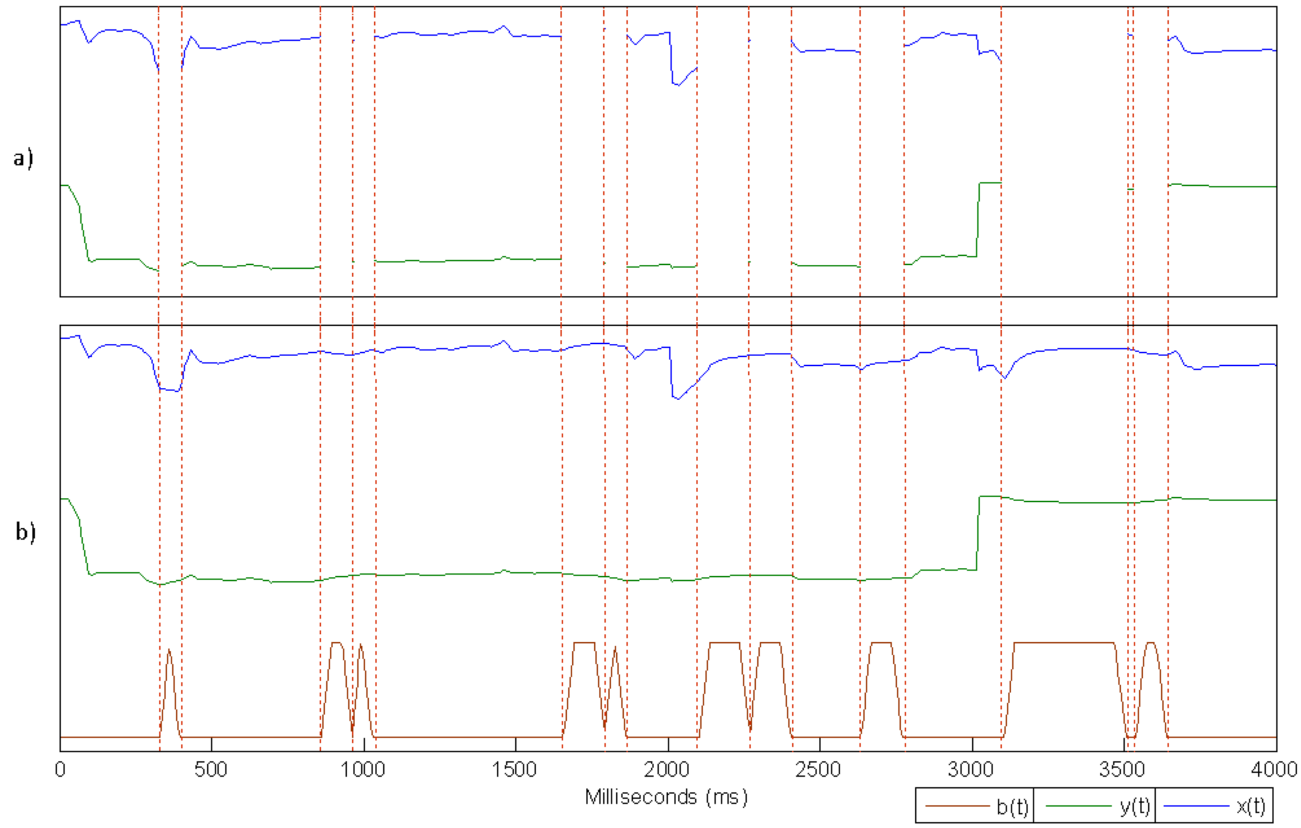

Fig. 1. Sample processed VOG data where missing values in (a) are substituted using linear interpolation; (b) shows the interpolated VOG data and the blink component derived from the missing values.

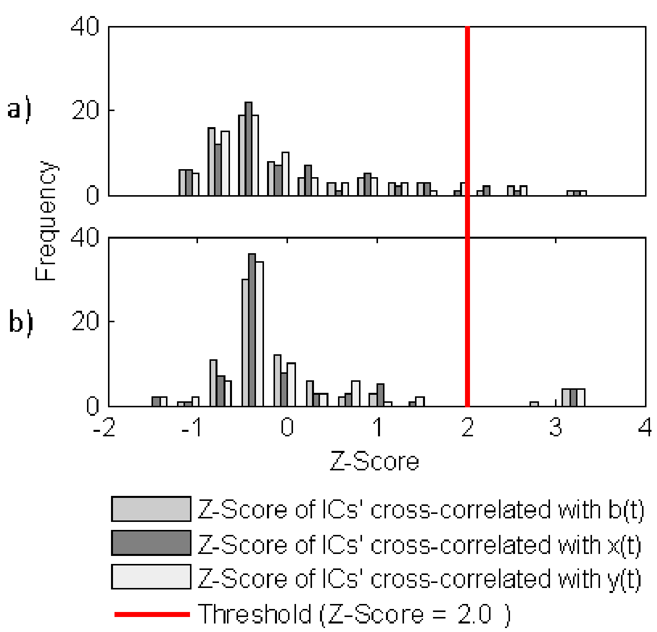

Fig. 2. Distribution of the Z-Score values obtained by cross-correlation of each single IC with $b(t)$, $x(t)$ and $y(t)$. Scores belong to all subjects in a) the *Static SSVEP* and b) the *Dynamic SSVEP* task. Red lines indicate the selected threshold ($Z\gamma_{b,i}$,$Z\gamma_{x,i}$ or $Z\gamma_{y,i} = 2.0$).

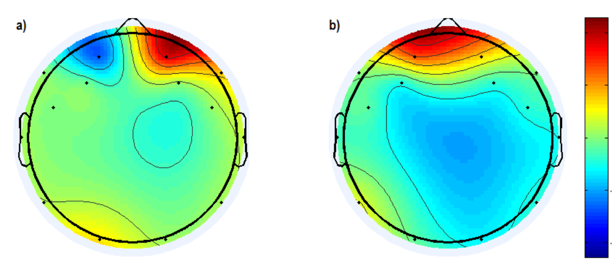

Fig. 3. Typical scalp topography maps representing distribution of the a)saccade and b) blink artefact sources.

when comparing the SSVEP classification accuracy of the subjects individually for VOG-ICA, there are some cases where SSVEP classification accuracy decreases. The lowest averaged SSVEP classification accuracy is obtained using Plöchl, falling below raw data by approximately 6%. This could be due to false detection of ICs as EOG sources which contain SSVEP information.

Overall, SSVEP classification accuracy increases when VOG-ICA and BVOG-ICA are applied. However, BVOG-ICA achieved better results because VOG-ICA does not remove the artefacts arising from eye blinks. Additionally, between all three EOG artefact removal methods BVOG-ICA achieved less between-person variations (last row of Table I).

TABLE I

PERFORMANCE OF SSVEP CLASSIFICATION FOR EACH SUBJECT IN *Static SSVEP* AND *Dynamic SSVEP*; WHEN THERE IS NO EOG ARTEFACT REMOVAL (ORIG) COMPARED TO WHEN PLÖCHL, VOG-ICA AND BVOG-ICA ARE APPLIED FOR EOG ARTEFACT REMOVAL. THE BEST OBTAINED RESULT IS HIGHLIGHTED IN BOLD.

Subjects	Static SSVEP				Dynamic SSVEP			
	Orig(%)	Plöchl(%)	VOG(%)	BVOG (%)	Orig (%)	Plöchl (%)	VOG(%)	BVOG(%)
S01	**82.98**	68.36	81.6	**82.98**	89.14	–	93.47	**93.98**
S02	88.99	89.24	**94.02**	**94.02**	88.65	64.55	91.24	**92.34**
S03	80.38	76.1	90.65	**93.02**	89.8	83.79	**85.86**	**85.86**
S04	85.27	72.99	82.00	**94.01**	83.85	83.29	95.01	**96.00**
S05	81.76	–	90.55	**90.56**	81.54	–	80.12	**81.88**
Ave	83.88	77.69 *	87.76	**90.91**	86.60	80.46 *	89.14	**90.01**
std	3.37	8.08	5.62	4.65	3.68	9.33	6.11	5.92

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

VI. DISCUSSION

In this work, we propose ‘Blink VOG-ICA’ (BVOG-ICA), a VOG-based automatic method for the detection and removal of EOG artefacts from EEG. We detect eye blinks in the VOG and use this information in addition to VOG eye movement information to improve SSVEP classification accuracy. BVOG-ICA outperforms [10] and our previous method [11] which does not consider explicit blink detection from the VOG signal. Although we claim favourable performance compared to Plöchl et. al, our evaluation was conducted using consumer grade EEG and VOG equipment designed for Human-Computer Interaction where SSVEP paradigms have greatest potential. This equipment typically has fewer channels, lower signal to noise ratio and lower sampling rates compared to laboratory grade apparatus. Future studies considering clinical EEG with larger sample sets to evaluate BVOG-ICA would be beneficial, as would the performance of artefact rejection algorithms against a wide range of grades of apparatus to demonstrate field potential.

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