A Novel Approach for Adaptive EEG Artefact Rejection and EOG Gaze Estimation

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Abstract. An adaptive system for Electroencephalography (EEG) artefact rejection and Electrooculogrum (EOG) gaze estimation is proposed. The system inputs optical gaze information, and accuracy of the EOG gaze classification into an adaptive Independent Component Analysis (ICA) algorithm, for improving EEG source separation. Finally two evaluation methods based on EOG gaze estimation are suggested to assess the performance of the proposed system. The work will be of use to researchers considering using BCI and eye-tracking paradigms in real life applications.

Keywords: EEG, Artefact, Adaptive ICA, BCI, Gaze.

1 Introduction

In recent years, there has been a significant increase in the development of assistive technologies and innovative interfaces based on human modalities eye (gaze), touch, speech and brain. This way, traditional computer inputs are supplemented or replaced with others that promise richer and more realistic human computer interaction schemes, for both normal people and people with severe disabilities.

Among the new interaction methods, eye-tracking systems and Electroencephalography-based (EEG-based) Brain-Computer Interfaces (BCI) can be considered as the final frontiers for Human-Computer Interactions (HCI), which are gaining more interests in recent HCI research [1]. This is due to minimum motor control requirement of BCI and eye-tracking systems, which makes the interaction possible for both normal people and people with limited motor control or severe disabilities.

The brain is the centre of human's nervous system and exerts control over the other organs of the body and controls all of human actions and cognitive states [2]. Humans use their eyes to gain information about their environment. As a result, the underlying patterns in both the brain activity and eye movement can distinguish between activities. For example they can be used to reflect the cognitive states of users [3], estimate users' intentions [4], moving a cursor across the screen [5, 6], monitoring visual attention of the drivers [7] and providing an interface for disabled people [8].

One of the main sources of biological artefacts (noise) which contaminate EEG signals is eye related artefact (Electrooculogrum). EEG artefact identification and removal and developing low-cost, consumer grade eye-tracking apparatus for daily life applications are still active topics of the researches [9-12].

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To reap the potential benefits of the BCIs and eye-tracking systems in daily human-computer interactions, the development of a signal processing method for removing artefacts from EEG signals, and development of affordable and robust eye-tracking systems are necessary. Additionally, fusion of brain signals and eye movements has the potential to a more robust method for human activity detection and human intention and/or attention detection.

Here, we proposed an adaptive artefact rejection system, which utilises time-variant optical gaze tracking information to accurately identify Electrooculogrum (EOG) signals from EEG. The aim of this work is to build a system which outputs artefact free EEG and EOG signals, for BCI and gaze-tracking applications, respectively. Moreover it will assess the feasibility of incorporating brain and eye movement signals for human activity and attention detection.

1.1 Independent Component Analysis-ICA

Independent Component Analysis (ICA) is the most widely used method for separating biological artefacts from EEG signals, and cleaning the EEG recordings [10]. ICA assumes that the observed EEG signals from electrodes $X(t)$, are linear mixture of independent source signals (components) $S(t)$, that build them.

$$X(t)= AS(t) \tag{1}$$

where A is the mixing matrix, and source signals $S(t)$, are assumed to be independent, non-Gaussian and stationary. The objective is to estimate a time-invariant invertible mixing matrix A in order to reconstruct original source signals $S(t),$ from only the observations $X(t)$.

Before obtaining the independent sources, first the “unmixing” matrix W should be obtained, so that:

$$S(t) = WX(t) \tag{2}$$

where, $W = A^{-1}$. After obtaining the independent sources, those sources which are attributed to artefact can be identified; therefore EEG signals can be reconstructed without the identified artefact components.

2 Method

2.1 Proposed System

EEG recordings are a mixture of cognitive signals originating from cerebral sources, and artefact signals originating from non-cerebral sources (e.g. EOG artefacts). To recover cognitive signals, the measured voltages $X(t)$ at time t have to be filtered, to remove artefacts which are originated from non-cerebral sources. The prevalent environmental artefact is power line noise (50 Hz Mains hum); and prevalent biological artefacts are EOG and EMG, which have higher amplitude than EEG signals. The primary objective of this work is to propose an adaptive ICA method, for improving the EOG and EEG signal separation, by incorporating time-variant optical gaze information. The idea is to simultaneously record EEG signals and point of gaze, using an EEG headset and an optical eye-tracker, respectively. Therefore, efficiently employing the optical gaze information, $I(t)$, to optimise the estimation of the mixing matrix in the ICA algorithm.

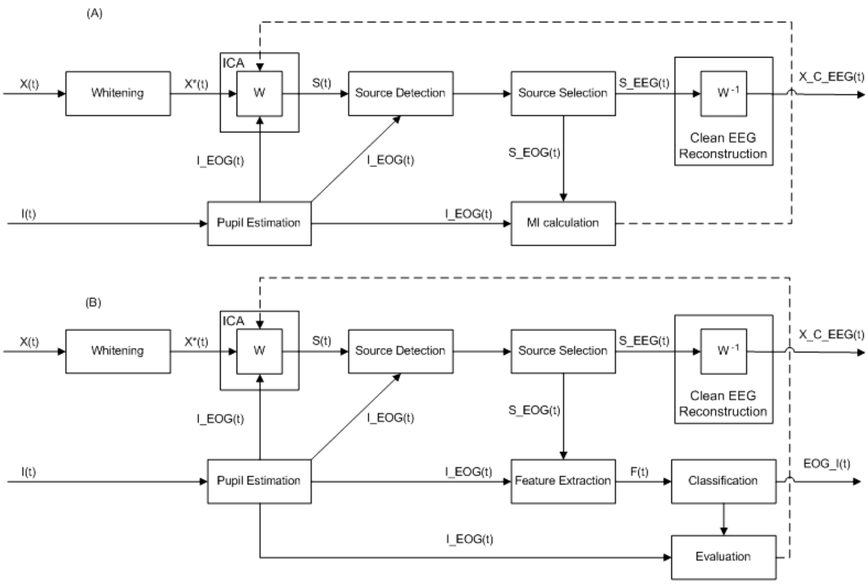

Fig. 1. (A) Proposed system for artefact rejection; use of Mutual Information for evaluation. (B) Proposed system for artefact rejection and gaze estimation; use of classification accuracy for evaluation

The proposed system consists of seven stages (Figure 1.B):

1. Whitening the observation signals $X(t)$, in which, mean values are subtracted from the recorded signals and the covariance matrix of $X(t)$ transforms to an identity matrix (i.e. decorrelation and normalisation to unit variance). This step is undertaken for de-correlating the sources and improving the convergence speed.
2. Exploiting the optical gaze information $I(t)$, for estimating optimal mixing matrix A, in order to recover linear mixture of sources $S(t)$, from the recorded EEG observation $X(t)$at time t.
3. Identifying and labeling eye-related sources $S_{EOG}(t)$, using optical gaze information.
4. Reconstructing cleaned EEG signals for use in BCI. To reconstruct cleaned EEG, the weights of the artefactual sources in the mixing matrix W^{-1} are set to zero. Finally, multiplication of the sources to the unmixing matrix leads to back-projection of the cleaned EEG.

From equation (1) we have:

$$X(t) = AS(t)$$

hence,

$$S_{EEG}(t)W^{-1} = X_{C_{EEG}}(t) \tag{3}$$

where, $S_{EEG}(t)$ is matrix of the sources which are labeled as cerebral activities, and $X_{C_{EEG}}(t)$ is cleaned EEG.

5. After identifying sources related to different types of eye-movements, time and duration of the occurrence of the movements are labeled using optical information. Then temporal features are extracted from the labeled EOG data, and the extracted features are used to train a classifier for gaze detection.
6. Detected movements are validated, and the accuracy of the detections is evaluated, using optical gaze information.
7. An additional step is to feedback the obtained accuracy of EOG gaze detection to the step (2); and use a raw vector optimisation strategy to estimate such mixing matrix that maximises the accuracy of the gaze detection.

Note that in the proposed system, before using optical gaze information; they have to be transformed (modeled) into synthetic EOG data.

2.2 Evaluation

To validate the proposed artefact detection/rejection and gaze estimation approach, it is also demanded to undertake an existing evaluation method or propose an evaluation approach. Generally, there can be two types of evaluation methods; cerebral-based and ocular-based. In the cerebral-based method, the performance of the proposed system can be evaluated using the changes in the accuracy of EEG signal classification during a real BCI paradigm, or changes of the signal to noise ratio on the simulated data. In the ocular-based evaluation method, the performance of the system can be measured using the accuracy of the gaze estimation on the real data or measuring the signal to noise ratio on the simulated data. Due to lack of information about the actual sources of the brain signals, and since, there is available optical gaze information which can be transformed to synthetic EOG data; it is more desired to use the ocular-based method of evaluation. Consequently in the evaluation method the optical information can be considered as the gold standard, and its synthetic EOG information can be used for measuring the performance of the proposed system. Following are two methods that can be employed for evaluating the proposed artefact rejection and gaze detection system.

Method1 (Figure 1.B): Taking the accuracy of EOG gaze classification (which has been measured using optical gaze information) as the performance measure; higher accuracy of EOG signal classification represents higher performance.

Method2 (Figure 1.A): Comparing the Mutual Information (MI) between the synthetic EOG data obtained from optical eyetracker, and EOG data obtained from ICA algorithm. In this method, higher mutual information between optical data and EOG data shows better performance of the system (see Figure 1.A).

3 Conclusion

In this paper, we provided an adaptive EEG artefact rejection and EOG gaze estimation system. The system is based on an adaptive ICA algorithm which uses information coming from an optical gaze tracker for better estimation of EOG sources (eye-related artefacts). The proposed system is not yet applied on real or simulated data. A further study could assess the performance of the proposed system through a real life BCI paradigm.

References

1. Graimann, B., Allison, B., Pfurtscheller, G.: Brain–computer interfaces: A gentle introduction. Brain-Computer Interfaces, 1–27 (2010)
2. Levenson, R.W.: The intrapersonal functions of emotion. Cognition & Emotion 13(5), 481–504 (1999)
3. Marshall, S.P.: Identifying cognitive state from eye metrics. Aviation, Space, and Environmental Medicine 78(suppl. 1), B165–B175 (2007)
4. Asteriadis, S., et al.: Estimation of behavioral user state based on eye gaze and head pose—application in an e-learning environment. Multimedia Tools and Applications 41(3), 469–493 (2009)
5. Pan, S.: Method and apparatus for controlling cursor movement. Google Patents (1994)
6. Wolpaw, J.R., McFarland, D.J.: Control of a two-dimensional movement signal by a noninvasive brain-computer interface in humans. Proceedings of the National Academy of Sciences of the United States of America 101(51), 17849–17854 (2004)
7. Ji, Q., Yang, X.: Real time visual cues extraction for monitoring driver vigilance. Computer Vision Systems, 107–124 (2001)
8. De Santis, A., Iacoviello, D.: Robust real time eye tracking for computer interface for disabled people. Computer Methods and Programs in Biomedicine 96(1), 1–11 (2009)
9. Croft, R.J., Barry, R.: Removal of ocular artifact from the EEG: a review. Neurophysiologie Clinique/Clinical Neurophysiology 30(1), 5–19 (2000)
10. Vigário, R.N.: Extraction of ocular artefacts from EEG using independent component analysis. Electroencephalography and Clinical Neurophysiology 103(3), 395–404 (1997)
11. Kenemans, J.L., et al.: Removal of the ocular artifact from the EEG: a comparison of time and frequency domain methods with simulated and real data. Psychophysiology 28(1), 114–121 (2007)
12. Topal, C., Dogan, A., Gerek, O.: A wearable head-mounted sensor-based apparatus for eye tracking applications. In: IEEE Conference on Virtual Environments, Human-Computer Interfaces and Measurement Systems, VECIMS 2008. IEEE (2008)