Reducing Power Spectral Density of Eye Blink Artifact through Improved Genetic Algorithm

Cota Navin Gupta
School of Computer Science and Electronic Engineering, University of Essex,
Colchester-CO4 3SQ, United Kingdom
e-mail:ngcota@essex.ac.uk

Ramaswamy Palaniappan
School of Computer Science and Electronic Engineering, University of Essex,
Colchester-CO4 3SQ, United Kingdom
e-mail: rpalan@essex.ac.uk

Abstract— **It is a known fact that brain's neurological activity is a source of control in any brain-computer interface (BCI) system and artifacts are undesirable signals. We present a technique to reduce electrooculogram (EOG) artifacts that corrupt electroencephalogram (EEG) signals in BCI applications. The developed genetic algorithm based independent component analysis (GALME-ICA) uses mutual information (MI) as a fitness function to reduce the EOG artifacts, which corrupt the recorded EEG channels. The genetic algorithm using large mutation rates and population elitist selection (GALME) enables local as well as global search to be performed in a balanced way. We tested the algorithm with simulated data and EEG signals corrupted with EOG artifacts from BCI competition IV dataset.**

Keywords- Brain Computer Interface; Electrooculogram Artifacts; GALME-ICA; Genetic Algorithm; Independent Component Analysis, Mutual Information.

INTRODUCTION

A brain computer interface (BCI) system enables a user to control devices using brain activity. BCI systems have been exploited for numerous applications like authentication [1], cursor control [2] and communication [3]. An inherent problem with BCI systems is the occurrence of artifacts, which could be non-physiological (like changes in electrode impedance and power line interference) or physiological signals like eye or body movements. Non-physiological signals could be controlled during the experiment but it is the physiological subject dependent artifacts, which pose a great challenge in BCI system design. Eye movements and blink contamination are especially a serious problem in event related potential (ERP) studies. The electric potential during blinks can be orders of magnitude larger than the electroencephalogram (EEG) and propagates through the scalp to mask brain signals. Higher frequency electrooculogram (EOG) artifacts are caused by blinking of eyes, while low frequency patterns are caused by rolling movements of eye [4]. The EOG activity is most prominent over the anterior head regions and has a wide range of frequencies with the maximum below 4Hz [4].

Numerous methods have been proposed to reduce EOG artifacts. Manual rejection is a common practice which requires human effort and results in considerable loss of data. Overlapping bands of EEG information with that of artifacts prevent a simple filter approach being used. Regression based methods [5] may reduce cortical activity and requires the use of EOG channels, but could be applied to single channels of EEG. Principal component analysis has been used to remove EOG artifacts but it requires the artifacts to be uncorrelated with the EEG signal [6]. ICA is somewhat the most successful method to remove eye blinks [7-8], however most existing ICA methods use complex neural learning algorithms [9]. In [10], we proposed the maximization of kurtosis for the extracting components using a genetic algorithm (GA-ICA), which enabled reduce noise from electrocardiogram (ECG) signals. In this work, we present the application of enhanced genetic algorithm based independent component analysis using large mutation rates and population elitist selection, which enables local as well as global search to be performed in a balanced approach and apply it to reduce eye-blinks from EEG data, which could be applied to applications like BCI design.

MATERIALS AND DATASET

The BCI data corrupted with eye-blinks used for this work was obtained from the BCI competition IV website (Graz data set 2B). A one minute block with eye artifacts, which was recorded at the beginning of each session, was used to test the GALME-ICA algorithm. Three bipolar recordings (C3, Cz and C4) along with three EOG channels were recorded with a sampling frequency of 250 Hz. However the EOG channels were not used in our methodologies. EEG data corrupted with vertical eye movements and eye blinks from randomly selected file B0202T were used for testing the developed algorithm.

METHODOLOGY

Previously, we introduced the basic idea of GA-ICA and applied it to reduce additive noise from biomedical signals using high kurtosis [10]. Following on the idea to develop an efficient GA-ICA framework, which reaches better solutions effectively and hence better performance, we implemented and tested the Genetic Algorithm using Large Mutation rates and population Elitist selection (GALME) [11]. A brief description of GALME is presented here:

(a) The population P(t) *at* t=*0* is initialized randomly with N individuals and evaluated. The mutation rate ρ_m is controlled by a decreasing function of generation t. Type III mutation [11], which involves a two stage reduction was used for this work**:**

$$\rho_{m,t+1} = \beta_1 \rho_{m,t} \quad if \quad \rho_0 \geq \rho_{m,t} \geq \rho_b, \tag{1}$$

$$\rho_{m,t+1} = \beta_2 \rho_{m,t} \quad if \quad \rho_0 > \rho_{m,t} > \rho_{\min};$$

(b) In the selection for reproduction set, all individuals of *P(t-1)* are paired by choosing two individuals without replacement to form *P'(t-1);*

(c) By applying mutation with probability as in (1) and crossover with probability, pcross to individuals of each pair, *C(t)* is produced.

(d) In the selection for survival, *N* individuals based on fitness are chosen from the population obtained by merging *C(t)* and *P(t-1)* to form *P(t)*. The cycle is repeated till maximum number of generations, *Gmax.*

In traditional G-ICA as implemented in [10], low mutation is usually a background operator and it is usually crossover which improves the performance. GALME uses large mutation to produce offspring that are as different as possible from their parents to examine regions of search space not yet explored. Gradually decreasing mutation rates enables GALME to find global optima by performing local search using good solutions obtained so far. According to the study by Hesser [12], optimal mutation rate for GA is a negative exponential function of time. Here, the parameters for GALME were set as in [11]. Thus in GALME, the chance for each individual to become a parent is at least once, regardless of its performance. Also the parents and offspring compete to survive in the next generation. We applied this enhanced GALME-ICA algorithm to reduce eye-blinks from EEG data.

RESULTS

A. Simulated data

To show the improved performance of GALME over GA for noise reduction, we tested both the methods using a mixture of ECG, EEG and electromyogram (EMG) signals and the performances are explained using illustrations (Figure 1-4). Arbitrary noise mixing matrix *A*, as explained in [10], was randomly generated to mix the three signals. Here, mutual information (MI) [13] was used as the fitness function, to be minimized for both GALME-ICA and GA-ICA modules. Given two random variables *X* and *Y*, the mutual information $I(X;Y)$ is defined as follows:

$$I(X;Y) = H(X) + H(Y) - H(X,Y). \tag{2}$$

The parameters used for both GALME-ICA and GA-ICA are tabulated in Table I. It can be observed from Figures 1-4 and Table II that GALME-ICA gives a better performance. Also higher fitness values (inverse of MI) are obtained with fewer generations for GALME-ICA as depicted in Figure 5.

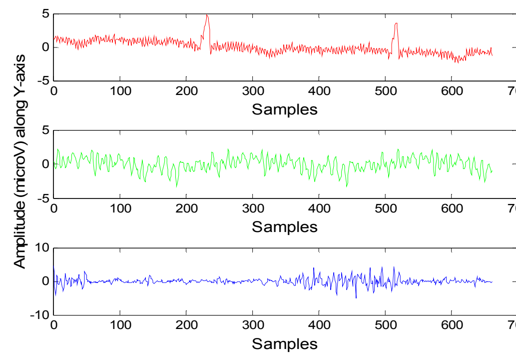

Fig. 1: Original ECG, EEG and EMG signals.

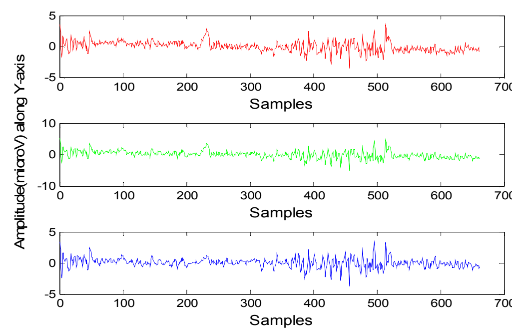

Fig. 2: The mixed signals for GALME-ICA and GA-ICA modules.

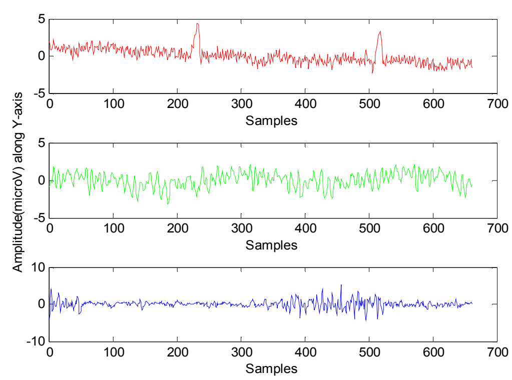

Fig. 3: The unmixed signals using GALME-ICA.

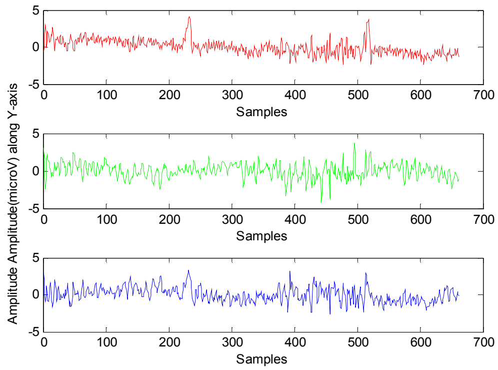

Fig. 4: The unmixed signals using GA-ICA.

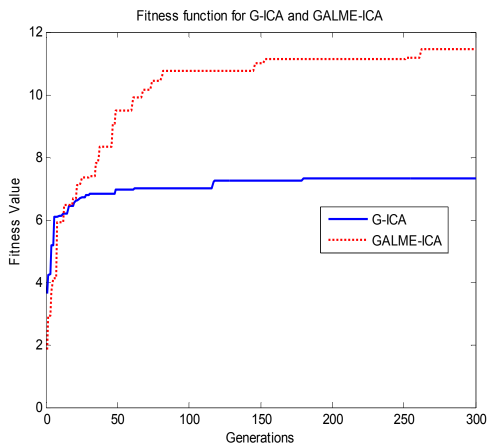

Fig. 5: Fitness functions (inverse of MI) for GALME-ICA and GA-ICA.

TABLE I: Parameters for GALME-ICA and G-ICA

Algorithm	Parameters
GALME-ICA	• No. chromosome = 100 • *Gmax*=300 • Repetitions = 3 • Mutation = Type III • Selection = elitist • ρ_0=0.15, ρ_b=0.06, • $\rho_{\min}$ =0.01, β_1=0.99088, β_2=0.99985, ρ_{cross}=0.6
GA-ICA	• No. chromosomes =100 • *Gmax* = 300 • Repetitions = 3 • Selection = elitist, tournament and roulette (each 1/3 of population) • ρ_{cross}=0.8, ρ_{mutate}=0.01, $\rho_{inverse}$=0.2

TABLE II: Improvements in Signal-to-noise Ratio

GALME-ICA	GA-ICA
ECG=3.65 to 14.72 dB	ECG=3.65 to 4.67dB
EEG=2.70 to 18.10 dB	EEG= 2.70 to 4.90 dB
EMG=5.95 to 18.1 dB	EMG=5.95 to 13.97dB

B. BCI Competition 2008-Graz dataset 2B

We tested the developed GALME-ICA module with BCI competition IV data (Graz dataset 2B) corrupted with EOG artifacts. The three channels and their PSDs are depicted in Figures 6-8. It is known that power of blinks is much higher (more than 100 times) than blink free data [14]. The three components from GALME–ICA methods are illustrated in Figures 9-11. From the obtained three components, the third component depicted in Figure 11 was selected as the EEG component, based on the maximum power spectral density (PSD) reduction, achieved in the 0.5-3 Hz range [14].

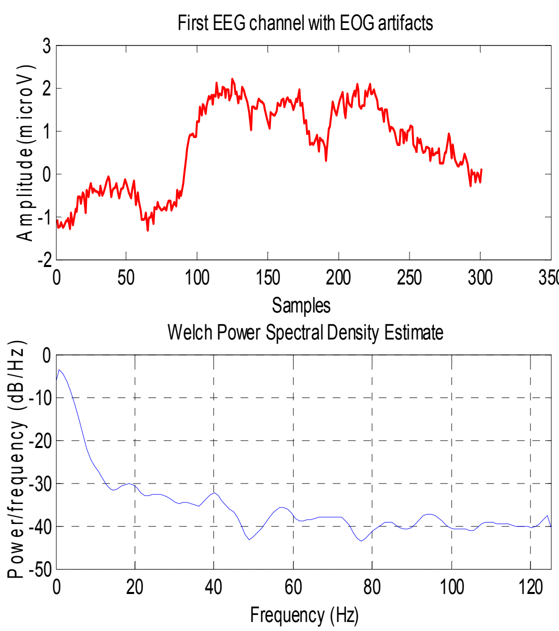

Fig. 6: First EEG channel corrupted with EOG and its PSD.

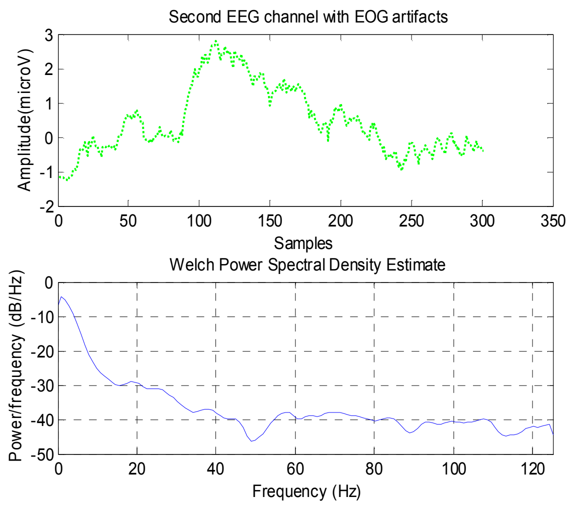

Fig. 7: Second EEG channel corrupted with EOG and its PSD.

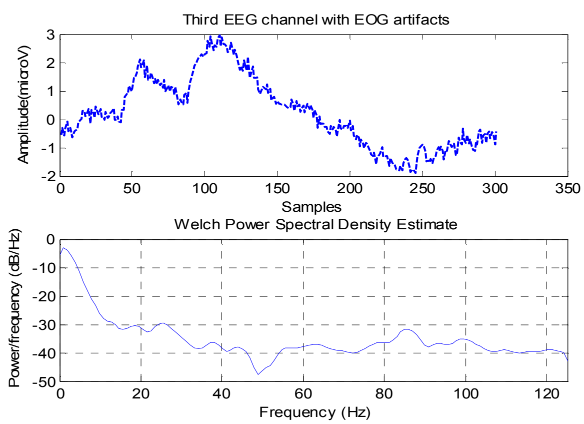

Fig. 8: Third EEG channel corrupted with EOG and its PSD

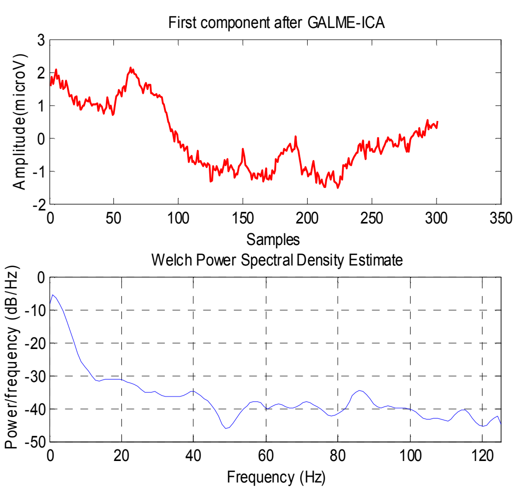

Fig. 9: First component after applying GALME-ICA and its PSD.

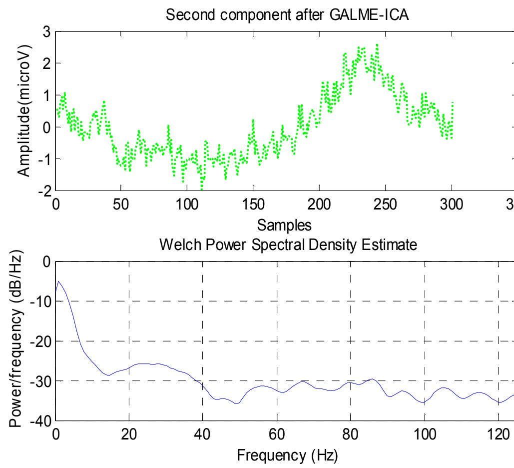

Fig. 10: Second component after applying GALME-ICA and its PSD.

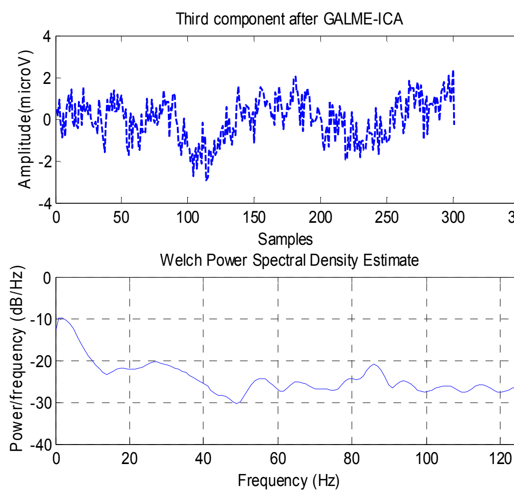

Fig. 11: Third component after applying GALME-ICA and its PSD(EEG component).

DISCUSSION

In this work, we have presented a method to reduce EOG artefacts from EEG signals for applications such as BCI. The proposed technique minimizes the MI (i.e. eye-blinks) between the recorded EEG channels and does not require EOG channels. Further, the method does not require any prior knowledge of signals or artifacts. To validate the method, we mixed three signals (ECG, EMG and EEG), which were then unmixed using GALME-ICA. We also applied the methodology to BCI competition IV data (Graz dataset 2B), which was affected with eye-blinks and obtained motivating results. On the downside, the presented GALME-ICA algorithm might get caught in a local minimum, leading to poor performances. A minimum repetition of three runs is necessary for good solutions. However considering all the facts, the presented framework may be used effectively for offline artefact removal. For future work, we plan to perform classification of the BCI competition IV (Graz dataset 2B) after reducing the EOG and compare the developed framework, with popular ICA methods.

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