Minimising Mutual Information Using Genetic Algorithm For Single Trial P300 Component Extraction

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Abstract. In this paper, genetic algorithm (GA) is used to extract single trial evoked potentials by minimising mutual information (MI) of the independent components (ICs). The proposed method could successfully extract emulated evoked potentials from background electroencephalogram (EEG). When applied for P300 component extraction for single trial speller Brain-Computer Interface (BCI) design, it showed improved results as compared to ensemble averaging, the de-facto standard method for reducing EEG from evoked potentials.

1 Introduction

Speller BCI designs i.e. those that translate brain signals into alphanumeric letters are useful for individuals to communicate with their external surroundings using only signals from the brain. The common technology for speller BCI designs is Visual Evoked Potential (VEP) based BCI [1], which uses P300 parameters extracted from VEP signals.

However, BCI technology using VEP signals suffers from one serious drawback. As it uses P300 parameters, it requires signal averaging from many trials to reduce the random effects of ongoing EEG, which is many times higher in amplitude than the stimulus correlated VEP. This leads to system complexity and higher computational time. There are many proposed methods for analysing VEP on a single trial basis like principal component analysis (PCA) [2] and independent component analysis (ICA) [3]. Single trial approaches reduce time and avoid distortion of the signal caused by inter-trial variation in latency.

ICA seems to be the most successful in extracting the P300 component for use in the VEP based speller BCI but still requiring five trials to achieve good accuracy [4]. Further, ICA uses neural learning methods, which are algorithmically complex and time consuming [5,6]. Here, an IC extraction algorithm based on GA is proposed to extract P300 component from the recorded single trial multi-channel VEP data. The method is proposed as a simpler and efficient alternative to neural learning ICA methods. The use of GA with kurtosis maximisation has been proposed in [7] but never applied for any application. MI minimisation using GA was proposed and applied to speech signal processing [8]. Infomax, a neural learning based ICA method was used to enhance P300 component for VEP based speller BCI design [4].

Kurtosis computation is the simplest and fastest method for use in ICA. However, kurtosis is very sensitive to outliers and has the problem of different signs: positive or negative values for super-Gaussian and sub-Gaussian signal, respectively. Here, MI is used instead as a criterion for ICA representation. It is non-negative and zero only if the variables are statistically independent. MI can be defined as:

$$MI(x_1, x_2, .. x_n) = \sum_{i=1}^{m} H(x_i) - H(\mathbf{x}), \tag{1}$$

where *H(.)* represents the entropy and the vector **x** consists of all the scalar variables, $x_1, x_2, \ldots x_n$.. Here, MI was computed as follows. Each x_i was discretised into 20 equally spaced bins and the entropy computed using

$$H(x_i) = -\sum_{a=1}^{20} P(x_{i,a}) \log P(x_{i,a}), \tag{2}$$

where $P(x_i)$ is the empirical distribution. Therefore, by using MI as a measure of independence, it is possible to separate the mixed signals into the independent components. The mixing matrix is iteratively improved for source separation using MI as the fitness function to be minimised by the GA.

2 Methods

The mixing matrix is represented by binary chromosomes converted to real-value that iterates through the GA operators: selection, crossover, mutation and inversion [9], to minimise the fitness function given by the MI of the ICs. The method relies only on GA, which is simple as compared to existing ICA techniques that use complicated neural learning algorithms. Consider the VEP corrupted with ongoing EEG signal to be represented in matrix form as

$$[Y]=[A]\ [X], \tag{3}$$

where *[A]* is the arbitrary mixing matrix, *[X]* is the matrix containing VEP plus ongoing EEG signals, while *[Y]* is the matrix of the observed (i.e. recorded) signals. In ICA methods, the task is to obtain the inverse of matrix *[A]* to reconstruct the original matrix *[X]*. In this proposed method, signal in matrix *[X]* will be extracted (reconstructed with different scale factors) as GA minimises the MI of the extracted signals. How this works could be understood with the following example.

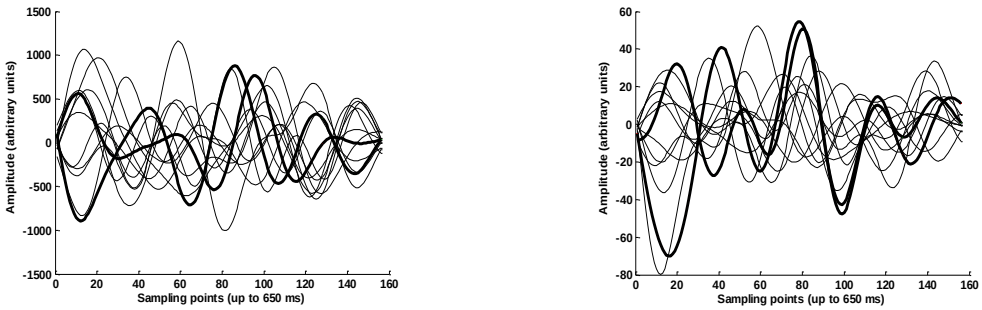
Assume
$$[Y]=\begin{bmatrix} y_1 \\ y_2 \end{bmatrix}, [X]=\begin{bmatrix} EEG \\ VEP \end{bmatrix}, inv[A]=\begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}, \tag{4}$$

Then
$$X_{EEG}=a_{11}y_1+a_{12}y_2 \qquad X_{VEP}=a_{21}y_1+a_{22}y_2\,. \tag{5}$$

As could be seen from (5), GA will iterate to give the coefficients a_{21}, a_{22}, a_{23} and a_{24} to reconstruct the signal that minimises MI.

3 Results

To show the effectiveness of the proposed method, two simulations were conducted. In the first simulation study (not shown here due to space constraints), VEP and ongoing EEG were created and added. VEP was created using different Gaussian shaped waves, while EEG was created using an 8th order autoregressive model based on studies in [10]. The values in the mixing matrix were randomly set in the range [0,1]. The results showed that PCA improved the SNR to 6.33 dB from -5.95 dB. But GA based ICA improved the SNR further to 25.04 dB. It must be noted that the reconstructed signal will be scaled/inverted (just like in other ICA methods). This is caused by the negative/positive coefficients of *inv[A]* given by GA.



(a) (b)

Fig. 1. Results (a) with averaging from 15 trials (channel Cz) (b) with GA based ICA with single trial (note the peaks from sampling points 66-89). Target row and column are in bold.

In the next simulation study, the proposed method was applied to extract VEP from

ongoing EEG using the BCI competition 2003–data set IIb [1]. Signals from 64 channels from a single trial are chosen from this dataset; these represent the recordings when the subject focuses on a character from 6 rows and 6 columns. The data are band-pass filtered from 2-8 Hz, the window of 0-650 ms after stimulus onset is used, and PCA is used to reduce the dimension from 64 to 22; these are based on studies in [4]. Next, GA based ICA method gives 22 independent signals. Only the single independent signal that gives maximum P300 peak in the window 275-370 ms is used. Since the independent signals could be inverted during ICA, the independent signal is inverted before averaging if the P300 peak is a downward curve for any of the independent signal. As a comparison, averaged data from channel Cz from 15 trials are computed. As could be seen from Fig. 1, the P300 component is higher for the target row and column using averaging and GA based ICA method but only one trial is needed for the latter as compared to 15 trials for the former.

4 Conclusions

In the simulation study, the proposed method successfully separated a mixed signal consisting of artificially generated VEP and EEG. To validate the method further, an experiment was conducted with EEG signals from competition 2003 – data set IIb, which also gave good results in extracting P300 component. Since the method does not assume any property (i.e. completely blind), it could be applied to extract/separate any type of linearly mixed signal. For future work, chromosomes with continuous values will be explored instead of binary chromosome converted to real-values as done here.

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