Improving Evoked Potential Brain-Computer Interface Design Using Mutation Based Genetic Algorithm

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***Abstract*—The performance of Evoked Potential Brain-Computer Interface design is improved using mutation based genetic algorithm (GA) method that extracts stimulus related evoked component from the averaged electroencephalogram. GA is conducted with the fitness function given by the negentropy values of the extracted independent components. The method was tested on artificially generated signals and signals from the Wadsworth dataset available as part of the BCI competition III. The results indicate the improvement of evoked potential extraction using the proposed method.**

Keywords-brain-computer interface; electroencephalogram; independent component analysis; genetic algorithm

I. INTRODUCTION

Brain-computer interface (BCI) is very useful for paralysed individuals to communicate with their surroundings. It is also useful for hand-off control of devices like computers or in virtual reality applications. There are several methodologies for implementing a BCI using electroencephalogram (EEG) signals. The commons ones are based on evoked potentials (typically from visual stimulus) [1], mental activity [2], mu and beta rhythms during imagined movements [3] and slow cortical potentials [4]. The advantage of using the visual evoked potential (VEP) based BCI is that it is easier for the users to adopt and does not require any significant prior training.

However, BCI technology using VEP signals suffers from one serious drawback. The recorded EEG signal consist of the stimulus related VEP and unrelated spontaneous EEG. As VEP based BCI technology commonly uses P3 (also known as P300) parameters, it requires signal averaging from many trials to reduce the random effects of spontaneous EEG, which is many times higher in amplitude than VEP.

In this study, a pilot attempt is made to increase the separation of the VEP component from the spontaneous EEG to improve the performance of the BCI system using mutation based genetic algorithm (GA) method. It is basically a blind source separation (BSS) of VEP and spontaneous EEG components but unlike the existing independent component analysis (ICA) methods that use neural network architecture [5], the method here uses a computationally simpler GA approach. ICA based infomax method has been used to enhance the P300 wave for BCI [6] but the use of GA and related evolutionary algorithms is novel and has not found any applications related to BCI.

Though kurtosis is the common maximising Gaussianity criterion used in ICA, the GA method here utilises negentropy [5] as it is more robust to noise.

The validity of the method is first shown using artificially generated VEP and spontaneous EEG signals. Next, EEG signals available in the Wadsworth P300 VEP BCI competition III are used. It is shown that the inclusion of GA method further reduces EEG from VEP beyond that capable by signal averaging and thus improves the detection of the focused character in the BCI design.

II. FUNDAMENTAL CONCEPT

The fundamental concept of ICA is that a mixed signal will have more Gaussian behaviour that it's independent components [5]. Therefore, by using some measure such as kurtosis, negentropy, etc. as a measure of Gaussianity, we could separate the mixed signals into the independent components. Here, negentropy is used as it is simpler yet more robust than kurtosis. Mutual Information (MI) is yet another good measure of independence but is more computationally expensive as compared to negentropy.

Negentropy is a measure that could be obtained from differential entropy. It is always non-negative and is zero for a Gaussian variable unlike kurtosis, which could take positive or negative values for super-Gaussian and sub-Gaussian signal, respectively. Though the computation of negentropy is difficult as it involves probability density function, it can be approximated by using cumulants to give the approximation as [5]:

$$Negentropy(x) \approx \frac{1}{12} E[x^3]^2 + \frac{1}{48} kurt(x)^2 \quad (1)$$

where x is the zero-mean signal and $kurt(x)$ is the kurtosis of signal x.

The mixing matrix that mixes the original source components is iteratively improved for source separation using increments in negentropy as a measure of non-Gaussian

behaviour. The negentropy is used as the fitness function to be maximised by the GA. The method will work as long as one of the signals is non-Gaussian, i.e. with non-zero negentropy.

The mixing matrix is represented by real-valued chromosomes that iterate through the GA operators: selection and mutation to maximise the fitness function given by the negentropy of the independent components. The method relies only on GA, which is simple as compared to existing ICA techniques that use complicated neural learning algorithms.

III. BLIND SOURCE SEPERATION SETTINGS

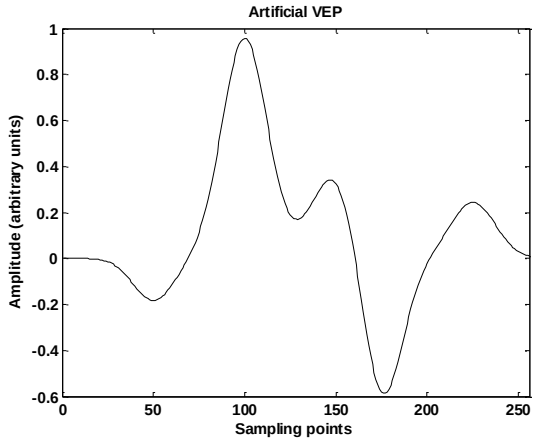
Consider the two artificially generated signals as shown in Fig. 1. Fig. 1(a) shows an artificially generated VEP signal using a combination of Gaussian shaped waves with different mean and variances while Fig. 1(b) shows the artificially generated spontaneous (ongoing) EEG signal generated with an 8^{th} order autoregressive model.

Assume that both these signals are mixed with a random mixing matrix, *[W]:*

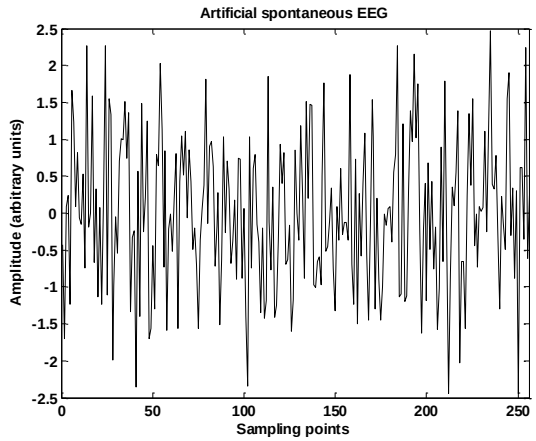
$$[Y] = [W][X],$$

$$[Y] = \begin{bmatrix} Y_1 \\ Y_2 \end{bmatrix};\ [X] = \begin{bmatrix} VEP \\ EEG \end{bmatrix};\ [W] = \begin{bmatrix} w_{11} & w_{12} \\ w_{21} & w_{22} \end{bmatrix}, \tag{2}$$

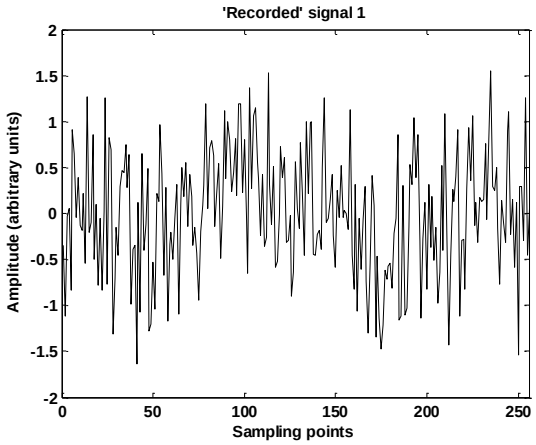
where *[X]* is the matrix containing VEP plus EEG signals, while *[Y]* is the matrix of the hypothetically observed (i.e. recorded) signals. Fig. 1 (c) and (d) shows these 'recorded' signals.



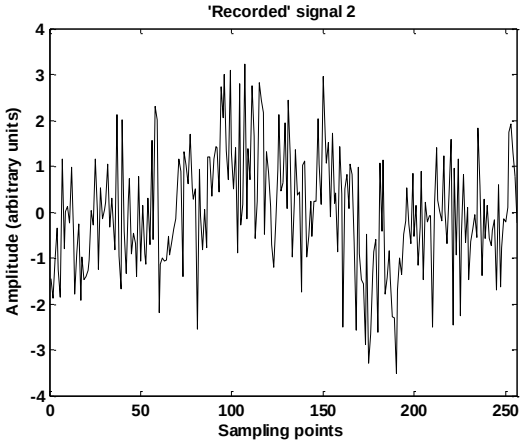
(a)



(b)



(c)



(d)

Figure 1. (a) artifical VEP, (b) artificial spontaneous EEG, (c) 'recorded' (mixed) signal 1, (d) 'recorded' (mixed) signal 2.

In BSS methods, the task is to obtain the inverse of matrix *[W]* to reconstruct the original matrix *[X]*. Assume

$$inv[W] = [A] = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}, \quad (3)$$

Then

$$VEP = a_{11} * Y_1 + a_{12} * Y_2 ;$$
$$EEG = a_{21} * Y_1 + a_{22} * Y_2 \quad (4)$$

As could be seen from (4), if GA could be iterated using negentropy to give the coefficients a_{21} and a_{22} (or a_{23} and a_{24}), then these could be used to reconstruct the VEP signal.

IV. Genetic Algorithm Methodology

GA [7] is a computational model inspired by evolution and is based on genetic processes of biological organisms. It is an adaptive method, which may be used to solve search and optimisation problems. Over many generations, natural populations evolve according to the principles of natural selection and "survival of the fittest". GA requires fitness or objective function, which provide a measure of performance of the population individuals.

GA operate on the coding of parameters rather than the parameter itself. These parameters or genes, which are known as chromosomes, are a string of values representing potential solutions to a problem.

These certain number of genes will be used to represent each of the coefficients in *[A]* as in (3). Assuming that there are 2 recorded signals, 4 genes would be necessary as in (4). A population of size 20 is generated randomly in the range [0,1]. That is there would be 20 chromosomes with 4 genes each. The range [0,1] is suitable as the independent component outputs are likely to be scaled anyway. An example of the population is shown in Fig. 2.

Next, these 4 real-valued gene values are used in (4) to generate 20 independent signals and the negentropy of each signal is computed. The fitness of each of the 20 chromosomes will be set to these negentropy values.

Selection (reproduction) operator is performed next based on these fitness values. During this reproductive stage of GA, chromosomes are selected from the population and recombined, producing offspring chromosomes that will comprise the population for next generation. Selection is applied randomly from the initial population using a scheme that favours the more fit chromosomes (evaluated using the fitness function) to create the intermediate population. Good chromosomes will probably be selected several times in a generation while the poor ones may not be selected at all.

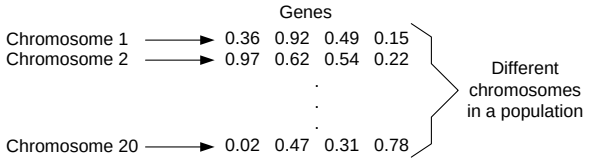


Figure 2. Genes and chromosomes in a population.

There are a number of ways of performing the parent selection process. The common methods are roulette wheel selection and rank based methods such as tournament selection. Both these selection operators are used here. In tournament selection, certain chromosomes are picked randomly (in this case 5) and the best chromosome (i.e. with the highest fitness) is stored. Since 50% of the new population will be selected here using this method, this procedure is repeated for 10 times (with the entire population) to obtain 10 chromosomes, where there maybe more than one similar chromosome.

The rest half of the new population will be selected using the roulette-wheel method. In this method, the fitness values of each chromosome are cumulatively added onto a roulette wheel and when the wheel spins, there are higher chances for the higher fitness chromosomes to be selected. Here, a random number is used to represent the wheel spin and the particular chromosome with the cumulative fitness range denoted by the number will be selected. This is repeated 10 times to add to existing 10 chromosomes from tournament selection.

Mutation works by changing the value of all the genes in all the chromosomes. The new genes are obtained by

$$g_{new} = g_{old} + \alpha * (\beta - 0.5), \quad (5)$$

where α is the learning rate (a value of 0.01 is used for this study here) and β is a randomly generated number in the range [0,1]. The whole procedure is then repeated for 100 generations. The chromosome that gave the highest fitness value (i.e. the highest sum of negentropies of the independent components) is used with (4) to obtain the VEP and EEG. Later, a method will be shown on how to detect VEP automatically from the two independent components. It should be noted here that crossover operation, a common GA operation is not used here as preliminary simulations indicated that its use did not improve the fitness value significantly.

Fig. 3 shows a block diagram of the GA method.

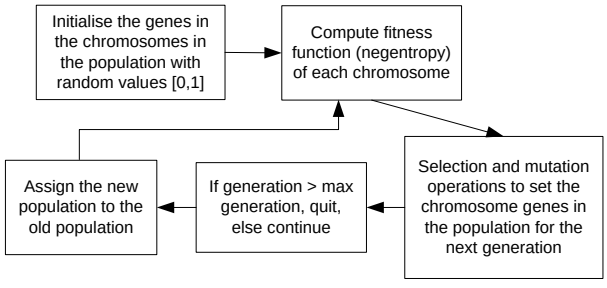


Figure 3. GA methodology.

V. ARTIFICIAL DATA RESULTS

The GA method is tested out on the artificially generated data as discussed earlier. Fig. 4 shows the output of the application of the proposed method. There were two output signals and VEP was identified as the one that gave the higher low frequency spectral energy. Specifically, the VEP was identified as the one that gave a higher 0-8 Hz spectral energy as most P3 components encountered in VEP is limited to 8 Hz and spontaneous EEG generally has a white spectral distribution.

From the figure, it is clear that the proposed method has successfully separated the VEP from the spontaneous EEG. The obtained VEP signal was a scaled version of the original VEP and this is a common issue encountered in ICA methodologies[1]. The VEP could be standardised to a fixed standard deviation value to avoid this problem.

VI. BRAIN-COMPUTER INTERFACE DATA

EEG data from one subject from the dataset II available on the BCI Competition III website: (http://ida.first.fraunhofer.de/projects/bci/competition_iii) were used here. The EEG data was recorded using 64 electrodes sampling frequency of 240Hz. The subject's task was to focus the attention on a six by six matrix (as shown in Figure 1) that consisted of alphanumeric characters formed in a matrix of six rows and six columns. The objective was to detect the focused target character when the rows and columns were intensified randomly. Two (i.e. the specific row and column) out of 12 intensifications will contain the specific character. The evoked responses for the rows and columns that contain the target character will be different from the other 10 responses, which do not have the target character.

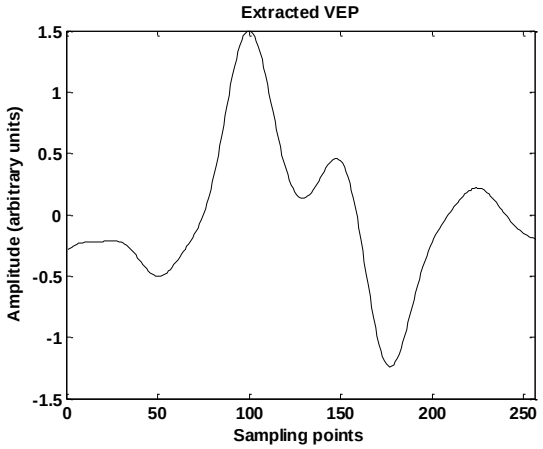


Figure 4. Extracted VEP.

[1] Sometimes, the extracted signals will be inverted. This is also another issue in ICA methodologies.

Figure 5. Spelling paradigm matrix for the BCI data [8].

There were 15 random intensifications in every column and row in the character matrix when the subject focused on a single character. This lead to a total of 180 intensifications (i.e. 12 times 15) for a single character. Data for one character were used here.

A. Standard method

The standard method used in [8] to analyse this data will be explained. Only EEG data from channel Cz were used. The EEG signals were averaged from 15 trials to reduce the spontaneous EEG. After averaging, only 12 VEP signals will remain (one for each row and column).

The six row and six column VEPs were further averaged to give 36 VEP signals. From these, ideally only one VEP signal (that was averaged from the target row and target column) should have a high P3 component as compared to the rest 35 VEP signals. Fig. 6 shows these 36 VEP signals. The target row and column VEP signal is in bold and it could be seen that there are other VEP signals (either from non-target row and non-target column or target row and non-target column or non-target row and target column) have higher P3 component (around 300-400 ms, equivalent to 125-167 sampling points). Therefore in this case, the character would have been misidentified using the standard method.

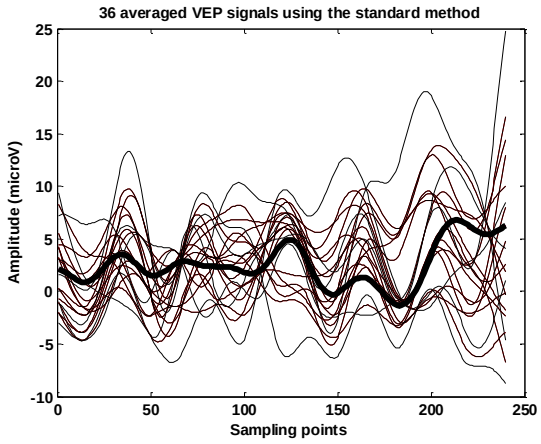


Figure 6. 36 further averaged VEP signals using the standard method. The target row and column VEP signal is in bold.

B. *BCI data results using proposed method*

Each row and each column VEP signal was fed into the GA method to give one output, i.e. instead of averaging as in the standard method, GA was used to obtain the VEP. The 36 output VEP signals from the GA method are plotted in Figure 7. It is clear that the target row and column VEP signal in bold exhibit a higher P3 component from the other VEP signals that contain a row and/or non-target column and as such, the character that is focused by the subject is identified correctly.

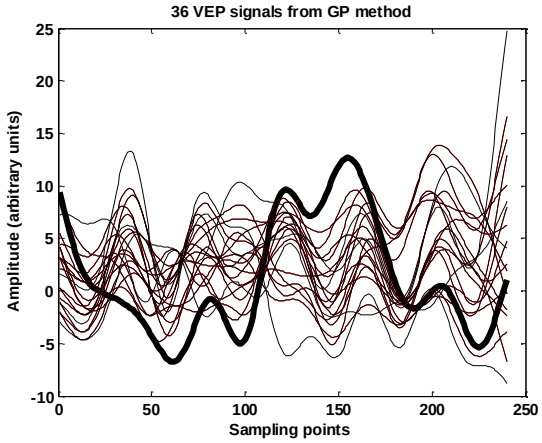


Figure 7. 36 VEP signals from GA method. The target row and column VEP signal is in bold.

VII. CONCLUSION

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 P3 component that properly indicated the focused character in the BCI system. Further work is in progress on determining the quantitative improvement that could be obtained by using the GA method in the P3 VEP based BCI design. Since the method does not assume any property (i.e. completely blind), it could be equally applied to extract/separate any type of mixed signal.

ACKNOWLEDGEMENT

The author wishes to acknowledge the Wadsworth Center, New York State Department of Health, Albany, NY, USA for their P300 evoked potential data set IIb that was placed in the BCI Competition III website.

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