EEG Channel Optimization Based on Differential Evolutionary Algorithm for BCI Application

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Abstract. This paper discusses implementation of Differential Evolutionary algorithm for EEG channel optimization. P300 brain-computer interface speller based on the region-based paradigm was used. The EEG signals were recorded from 8 channels from 23 subjects. The results of channel optimization show that the number of channels can be reduced for different subjects without decreasing the accuracy significantly.

Keywords: EEG Channels, P300, Optimization, Differential Evolutianry Algorithm, Region-based Paradigm

1. Introduction

It is usually desirable to record the EEG signals from more electrodes to have a better classification results and decrease the error. However, increasing the number of channels brings more challenges. First of all, it could generate a large size of data which is not necessary useful in adding more information due to the redundancy in EEG data and correlation between channels. Second, increasing the number of EEG channels also increases the computational time and may create limitations for real-time applications. Low speed of brain computer interface (BCI) systems has been one of the main challenges in most BCIs. Therefore, by minimizing the number of EEG channels, a channel optimization method could create a reasonable balance between having a high accuracy and low computational time. Taking a quick look into the literature reminds that lots of efforts have been trying to solve the optimization problem for the EEG signals [Atyabi et al., 2012]. However, there are a few published papers that have applied Evolutionary Algorithms (EV) for channel optimization.

The application of Discrete Particle Swarm Optimization (Discrete PSO) for selecting electrodes from definite regions of the subject's scalp was shown in [Jin et al., 2008] and average classification accuracy of 77% was reported. Multi-Objective PSO (MOPSO) on the motor imagery EEG data was used in [Hasan et al., 2009] where 57% classification accuracy for 3 different classes was obtained. In their next work [Hasan et al., 2010], Multi-Objective Evolutionary Algorithm based on Decomposition (MOEA/D) on the same dataset was implemented and then compared with the MOPSO method. It was shown that 1% improvement was achieved using MOEA/D. The average number of used electrodes with MOPSO and MOEA/D was 4 and 10 electrodes, respectively. It seems that obtaining 1% improvement in accuracy does not worth to increase the number of efficient electrodes from 4 to 10. This paper addresses applying the Differential Evolutionary (DE) algorithm to reduce the number of EEG channels in detecting P300 signals from the region based paradigm [Fazel-Rezai and Abhari, 2009].

2. Material and Methods

Differential Evolution (DE) is a stochastic, population-based search strategy developed by Storn [Storn and Price, 1995]. The DE algorithm is a population based evolutionary algorithm like genetic algorithms using the similar operators; crossover, mutation and selection. The main difference from other evolutionary algorithms is in the reproduction step where offspring is created from three parents using an arithmetic crossover operator. It means that mutation is applied first to generate a donor vector, which is then used within the crossover operator to produce one offspring. The DE does not make use of a mutation operator that depends on some probability distribution function, however introduces a new arithmetic operator which depends on the differences between randomly selected pairs of individuals. Also the DE is defined for floating-point representation of individuals, called the parameter vectors. Our applied DE algorithm is summarized as follows:

Initialize each individual to contain K randomly selected EEG channels.

For t=1 to t_{max}

a. For each two randomly selected individual (x_k, y_k) combinations
    i. Apply the mutation to create the donor vector
    ii. Apply Crossover operator to have offspring (z_k)

iii. Evaluate the fitness function on all $f(x_k, y_k, z_k)$

b. If $e(r) \leq 0.01$, report the best combination of channels and exit.

Here, $e(r)$ is defined as an error function between resulted accuracy from offline data and the new accuracy applying the DE algorithm, while t_{max} is the maximum trail numbers for each K channel selection.

The region-based paradigm [Fazel-Rezai and Abhari, 2009] was used for spelling two words ('PEBBLE!' and 'MX85+Z&') from 23 subjects (6 females) with the approval of the University of North Dakota (UND) Institutional Review Board (IRB). The DE optimization algorithm was applied on the EEG signals recorded from eight channels at FZ, CZ, PZ, OZ, P3, P4, PO7, and PO8 locations according to the international 10-20 system. EEG signals were sampled with a frequency of 256 Hz and filtering was done using a 0.1 Hz high pass, a 30 Hz low pass. Six flashes with a flash time of 100 ms and a blank time of 150 ms were considered. Linear Discriminant Analysis (LDA) was used as the classifier. Also, the experiment was implemented using the g.GAMMAbox and g.USBamp for recording and g.BSanalysis for classification, all of them from products of Guger Technologies (g.tec).

3. Results

The proposed algorithm was implemented on the above dataset for all 23 subjects where $\mathbf{k} = 3, 4, 5$, i.e., the number of selected channels was 3, 4 and 5. Each step yields to different number of combinations of channels as parents as well as offsprings. Table 1, shows the total trial number of search for the chosen **k** values.

Table 1. *Channels combination numbers.*

Combination parameter	Parents Pair	Total trial numbers (t_{max})
k =3	42	1722
k =4	70	2415
k =5	42	861

The DE algorithm starts with choosing 3 channels combination randomly and then shows the convergence with not almost running over the whole trial numbers. The results show that the combination of channels is highly subject dependent and varies from each subject to another one. However, the number of best channels was almost the same for all subjects for $\mathbf{k} = 3$ and $\mathbf{k} = 5$. The results showed a slight improvement in accuracy for $\mathbf{k} = 4$.

4. Discussion

In some trials, the accuracy was suddenly decreased. In close exploration, we noticed that the original EEG channel which was selected randomly had already weak signal, maybe due to not good electrode contact to skin. So it is recommended to double check the EEG recorded signals not only at the starting of experiment, but also during the experiment. In addition, when the accuracy was not close to the target with three channels, increasing the channel numbers resulted to better accuracy almost over the whole dataset. In comparison to other algorithms, DE converges faster and with more certainty than many other global optimization methods through tremendous tests. Meanwhile, it requires only few control parameters, and it is robust and simple in use. The next step is to implement the DE algorithm in real-time mode spelling. This is the advantage of DE method compared to conventional methods that usually are required to be implemented to offline data because of required computational time.

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