Classification of EEG Signals using a Novel Genetic Programming Approach

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ABSTRACT

In this paper, we present a new method for classification of electroencephalogram (EEG) signals using Genetic Programming (GP). The Empirical Mode Decomposition (EMD) is used to extract the features of EEG signals which served as an input for the GP. In this paper, new constructive crossover and mutation operations are also produced to improve GP. In these constructive crossover and mutation operators hill climbing search is integrated to remove the destructive nature of these operators. To improve GP, we apply constructive crossover on all the individuals which remain after reproduction. A new concept of selecting the global prime off-springs of the generation is also proposed. The constructive mutation approach is applied to poor individuals who are left after selecting globally prime off-springs. Improvement of the method is measured against classification accuracy, training time and the number of generations for EEG signal classification. As we show in the results section, the classification accuracy can be estimated to be 98.69% on the test cases, which is better than classification accuracy of Liang and coworkers method which was published in 2010.

Categories and Subject Descriptors

I.2 [**Artificial Intelligence**]: Problem Solving, Search.

General Terms

Performance, Algorithms, Relaibility.

Keywords

Genetic Programming; Emperical Mode Decomposition; Globally Prime.

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1. INTRODUCTION

Electroencephalography (EEG) [1] is the recording of electrical activity which contains information about human brain functionality and the disorders of the nervous system. Although not a brain scan as the term is usually used, the EEG, or electroencephalograph, deserves mention as one of the first ways of non-invasive observing human brain activity. An EEG is a recording of electrical signals from the brain made by hooking up electrodes to the subject's scalp. EEG accurately measures the deviations of electric signals within short period of time through multiple electrodes placed on the human scalp, the changes in these electric signals are measured in terms of voltage fluctuations of brain. The information about the human brain and neurological disorders is found through the output of the electrodes. EEG allow researchers to follow electrical impulses across the surface of the brain. An EEG can show the state of a person such as numb, awake, asleep because the characteristic patterns of current vary for the aforementioned states. One important use of EEGs has been to show how long it takes the brain to process various stimuli.

Epilepsy [3] is a brain disorder in which clusters of nerve cells, or neurons, in the brain sometimes signal abnormally. In epilepsy, the normal pattern of neuronal activity becomes disturbed, causing strange sensations, emotions, and behavior, or sometimes convulsions, muscle spasms, and loss of consciousness. The Epilepsy is characterized by sudden and recurrent malfunction of the brain which is termed *seizure*. Ictal and Interictal [2] are the medical conditions of seizure, where the period of the seizure is represented by *Ictal* and the intermediate period between two seizures is represented by *Intericatal*. However we have to make a note that Interictal differs from that of a non-seizure signal. A prediction of the Ictal from Interictal could make the patient to put away from the next seizure. It is imprecise and erroneous to detect epilepsy by visual scanning of EEG Signals. The detection of epileptic seizures, which are convulsions accompanied by impaired consciousness, in the EEG signal is a vital part in the diagnosis of epilepsy. Nonetheless, Classification between the ictal and interictal is essential for the detection of Epileptic seizures.

A wide range of methods [18] have been proposed to forecast epileptic seizure by classifying seizure and non-seizure EEG signal which employed univariate techniques, eigen spectra of space delay correlation and covariance matrices [20], Hilbert-Huang transform[8], and autoregressive modeling and least-squares parameter estimator [7]. The aforementioned techniques [7],[18] though they exhibit good sensitivity. Yet, their specificity and accuracy are not at expected level.

Genetic programming (GP) [12] is an evolutionary learning methodology that offers a great potential for classification. GP is a very flexible heuristic technique that makes it very convenient to represent complex patterns in the form of trees and graphs, therefore working with various operations and functions becomes easier. Since GP is a search and optimization algorithm, it can be easily employed as the search algorithm for generating a classifier. Since the early 1990s, there have been a number of reports [12, 19, 21] on applying GP techniques to a range of classification problems. In previous research works, many authors came up with classification of EEG signals on basis of Least Squares - Support Vector Machine (LS-SVM) [16],[1]. But the advantage of using GP over LS-SVM is that the objective function can be changed without changing the algorithm, that is instead of the Mean Absolute Error (MAE), the sum of squared errors could be used. For the SVM, such a change requires reformulating the Quadratic Programming(QP) and the optimization algorithm. Similarly, the fitness function of the GP could be defined so as to generate parsimonious [10] solutions. Although parsimony can also be obtained with the SVM [15], this again requires reformulating and re-solving the optimization problem. In short, changing the objective for a GP requires no change to the algorithm; whereas changing the objective for the SVM requires solving a new mathematical programming problem, which effectively defines a new search operator. Though GP shows lots of advantages, but still there is a need to improve the current GP life cycle, because it does not give satisfactory results for classification problems. In GP life cycle, crossover and mutation operators are the most important operator for evolving solutions but it is also considered the most devastating in nature[6]. Further, we focused our work on improving the crossover and mutation operations and demonstrating the improvements in terms of classification accuracy, number of generations and time in later sections.

In this paper, we propose the new Constructive Crossover and Mutation operations (CCM) for Genetic Programming approach and its use for the classification of the EEG Signals. To achieve this goal, we initially extract the intrinsic mode functions (IMF's) from the each EEG Signal using Empirical mode decomposition (EMD) and we use two bandwidth parameters, namely Amplitude Parameter (BAM) and Frequency Parameter (BFM) for the classification purpose. The bandwidth parameters, calculated from the respective IMF's of each EEG Signal is used as the input feature set for the Genetic Programming for the classification of the EEG signals. Finally, we propose constructive crossover and mutation operations to improve the overall GP life cycle.

The remainder of this paper is organized as follows: Section 2, describes the experimental data, and its preprocessing steps Section 3, describes the preliminaries of GP life cycle. Section 4, gives the detail description of the proposed crossover and mutation (CCM) operators. Section 5, gives the experimental results and discussion and finally Section 6 concludes the paper.

2. EXPERIMENTAL DATA

2.1 EEG signal Dataset

An EEG dataset, which is available on-line in [4] is used. It contains three classes: 1) healthy, 2) epileptic subjects during seizure-free interval (interictal), 3) epileptic subjects during seizure interval (ictal). Each case has five datasets named: O, Z, F, N, and S. Sets O and Z are obtained from healthy subjects under condition of eyes open and closed; respectively by external surface electrodes. Sets F and N are attained from interictal subjects. Set F taken from epileptogenic zone of the brain shows focal interictal activity; set N obtained from hippocampal formation of the opposite hemisphere of the brain indicates non-focal interictal activity, and set S is got from an ictal subject. Each set contains 100 single channel EEG segments of 23.6 sec duration. Sampling frequency is 173.61 Hz, so each segment contains N = 4096 samples . These EEG Signals (one from each subset) are shown in Fig 1.

2.2 Data Preprocessing

This section shows how we extract features from EEG signals to use as an input for GP. To extract the features from the EEG signal we have to follow the following steps:

2.2.1 Empirical Mode Decomposition

The empirical mode decomposition (EMD) method was developed by Huang et al. [8] to decompose functions into a superposition of natural modes, each of which could be easily analyzed for their instantaneous frequencies and bandwidths.

EMD is basically a method of breaking down a signal without leaving the time domain introduced for analysis of nonlinear and non- stationary signals. It can be compared to other analysis methods like Fourier Transforms and wavelet decomposition. The algorithm includes the following steps: 1. Calculate the IMF for each iteration using EMD on EEG signals. 2. Calculate two features namely Frequency parameter and Amplitude parameter using Hilbert transform applied on IMF's for each iteration. 3. Generate a Bandwidth parameter by combining Frequency parameter and Amplitude parameter.

2.2.2 Calculation of Intrinsic Mode functions (IMF)

Using the EMD algorithm, we obtain intrinsic mode functions (IMF), which were generated at each scale, going from fine to coarse, by an iterative procedure to locally isolate the modal behavior.

In contrast to the aforementioned Fourier transform and wavelet transform, the EMD decomposes any given data into intrinsic mode functions (IMF) and a residual function that are not set analytically and are instead determined by an analyzed sequence alone. The basis functions are in this case derived adaptively directly from input data. An IMF

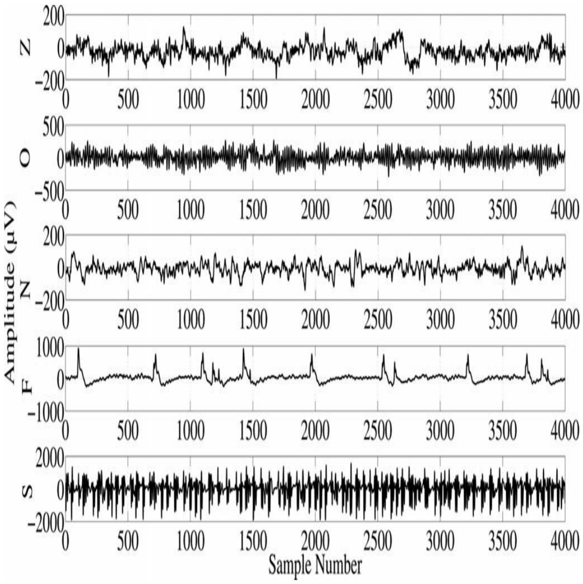

Figure 1: Example of EEG signals from each of the five subsets (Z, O, N, F, and S).

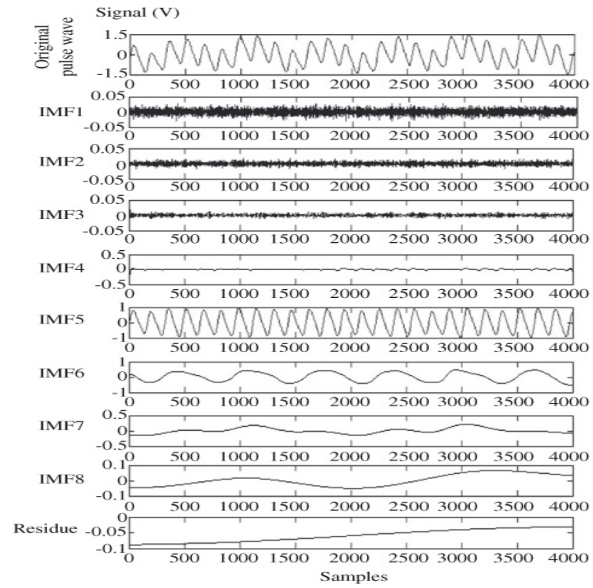

Figure 2: 8 IMF's extracted from EMD of a EEG Signal).

resulting from the EMD shall satisfy only the following requirements: 1. The number of IMF extrema (the sum of the maxima and minima) and the number of zero-crossings must either be equal or differ at most by one; 2. At any point of an IMF the mean value of the envelope defined by the local maxima and the envelope defined by the local minima shall be zero. The algorithm as proposed by Huang requires the identification of all local extrema that are further connected by cubic spline lines to produce the upper and the lower envelopes.

We use a process called sifting [13] to obtain the final IMF. The sifting process is repeated until a certain given stoppage criterion is met. This continues until all IMFs are extracted. The sifting process usually stops when the residue, for example, contains no more than two extrema. At the end of the decomposition, the original EEG Signal is represented as as the sum of IMF's and the final residue. The IMFs generated by EMD process on the 23.6 s EEG signal are shown in Fig 2. Empirical mode decomposition can successively separate the intrinsic oscillatory modes of signals into a finite number of IMFs. At the end of the decomposition, two bandwidth parameters(B_{am} and B_{fm}) are generated for every IMF [5].

2.3 Analytical Representation of EEG signal

Empirical mode decomposition can successively separate the intrinsic oscillatory modes of signals into a finite number of IMFs. At the end of the decomposition, The original EEG Signal is represented as

$$x(t) = \sum_{i=1}^{n} C_i(t) + R(t)$$

where n is the number of IMFs, Ci is the i^{th} IMF and $R(t)$ is the final residue. The analytic signal of any real IMF A(t) is represented as:

$$A(t) = \sqrt{c^2(t) + c_H^2(t)}$$

Where $c(t)$ is the IMF and $c_H(t)$ refer to Hilbert transform of IMF. The instantaneous frequency $\omega(t)$ is defined as:

$$\omega(t) = \frac{d\varnothing(t)}{dt}$$

where $\varnothing(t)$ is instantaneous phase. Then calculate the center frequency which can be defined as:

$$< \omega > = \frac{1}{E}\int \omega |Z(\omega)|^2 \, d\omega$$

where E is the energy of analytic signal and $Z(\omega)$ is the Fourier transform of analytic signal. The amplitude parameter and the frequency parameter are defined respectively.

$$B_{am}^2 = \frac{1}{E}\int \left(\frac{dA(t)}{dt}\right)^2 dt$$

$$B_{fm}^2 = \frac{1}{E}\int \left(\frac{d\varnothing(t)}{dt} - < \omega >\right)^2 A^2(t)\, dt$$

The total bandwidth of analytic IMF x(t) is defined as:

$$B = \sqrt{B_{am}^2 + B_{fm}^2}$$

These Bam and Bfm serve as the input features for our Genetic Programming.

3. PRELIMINARIES OF GP

To build the GP based classifierfor EEG signals classification we had to follow the following steps:

3.1 Multi tree Classifier

In GP every individual is represented in the form of trees. So, for a two class problem a possible classifier or an individual is generally represented by a singletree (T). For a pattern x, the single tree is constructed for two classes as follows:

$$\begin{aligned} &if\ T(x) \geq 0, x \in class\ 1 \\ &else, x \in class\ 2 \end{aligned} \tag{1}$$

The single tree representation of the classifier is sufficient for a two-class problem. This scheme can be extended to a multicategory classification problem. In our design, every chromosome or individual will have a tree for every class. So, a possible solution or an individual for the GP is represented by c trees denoted by $(T_1, T_2, ...T_c)$. For a pattern x, the condition of belongingness corresponding to a class is given as follows:

$$if\ T_i(x) \geq 0\ and\ T_j(x) < 0\ \forall j \neq i, j \in \{1, 2, ...c\}$$
$$then\ x \in class\ i$$

3.2 Initialization

In GP, first we have to generate initial population for performing operations on it. The terminal and function sets are important components for generating the initial population. The terminal set consists of the variables and constants of the programs. The functions are several mathematical functions, such as addition, subtraction, division, multiplication. Trees for each of the individual are initialized randomly using the function set F and the terminal set T. The function set F and terminal set T used here are as follows:

$$\begin{aligned} F &= \{+, -, *, /\} \\ T &= \{feature\ variables of EEG signals, R\}. \end{aligned} \tag{2}$$

Where R contains randomly generated constants in [0.0 to 10.0]. We initialize trees using the ramped half-and-half method [6]. The +, -, and * operators have their usual meanings (addition, subtraction, and multiplication), while / represents protected division, which is the usual division operator except that a divide by zero gives a result of zero. Each of these functions takes two arguments.

3.3 Fitness Measure

The most difficult and most important concept of GP is the fitness function. The fitness function determines how well a program is able to solve the problem. The GP is guided by the fitness function to search for the most efficient computer program to solve a given problem. A simple measure of fitness has been adopted for the classification problem and given as follows:

$$Fitness = \frac{n}{N} \tag{3}$$

where n= Number of Samples correctly classified and

N=Total number of training samples.

The GP is trained with the set of N number of training samples, $X_{tr} = \{x_1, x_2, ...x_N\}$. While training, the response of a tree T_i for a pattern x is expected to be as follows:

$$T_i(x) \geq 0\ if\ x\ \in\ class\ i$$
$$T_i(x) < 0\ if\ x \neq class\ i$$

In other words, a classifier with c trees is said to correctly classify a sample x, if and only if all of its trees correctly classify that sample. If we emphasize that a training sample is from class k than we say that tree T_k correctly classifies x, if $T_k(x) > 0$. On the other hand, the tree $T_{j,j} \neq_k$ is said to correctly classify x, if $T_j(x) < 0$. For each correct classification of a training sample by a classifier, its fitness is increased by 1.

Table 1: COMMON PARAMETERS FOR ALL DATASETS

Parameters	Values
Probability of Crossover Operation (P_c)	50%
Number of individuals selected for Crossover Operation	(N_c)
Probability of Reproduction Operation (P_r)	20%
Number of individuals selected for Reproduction Operation	(N_r)
Probability of Mutation Operation (P_m)	30%
Number of individuals selected for Mutation Operation	(N_m)
Population Size (k)	300
Number of Generations	40
Initial Maximum Depth	6
Initial Minimum Depth	3

3.4 Methods and Parameters

In proposed approach, we used tree structure to represent genetic programs [14]. The ramped half-and-half method [6] is used in generating programs in the initial population. The proposed crossover operator is described in the next Section. The point mutation technique [17] is used. The reproduction operator simply copied the best individuals into the population in the next generation to make sure the best individual programs are not lost during evolution.

Table 1 describes the parameters for the GP process. These parameters values are primarily chosen based on the heuristic guidelines on the choice of parameters [6] and an empirical search through initial experiments on GP with the standard crossover operator. Then, we checked those parameter values on the new approach and found that they also could do a reasonably good job.

3.5 Termination Criteria

In this approach, the learning/evolutionary process is terminated when one of the following conditions is met:

1. The number of generations reaches the maximum generations.
2. The classification problem has been solved on the training set, that is, all objects of interest in the training set have been correctly classified.

4. PROPOSED WORK

In this section, we proposed new constructive crossover and mutation operations (CCM) to improve the overall GP life

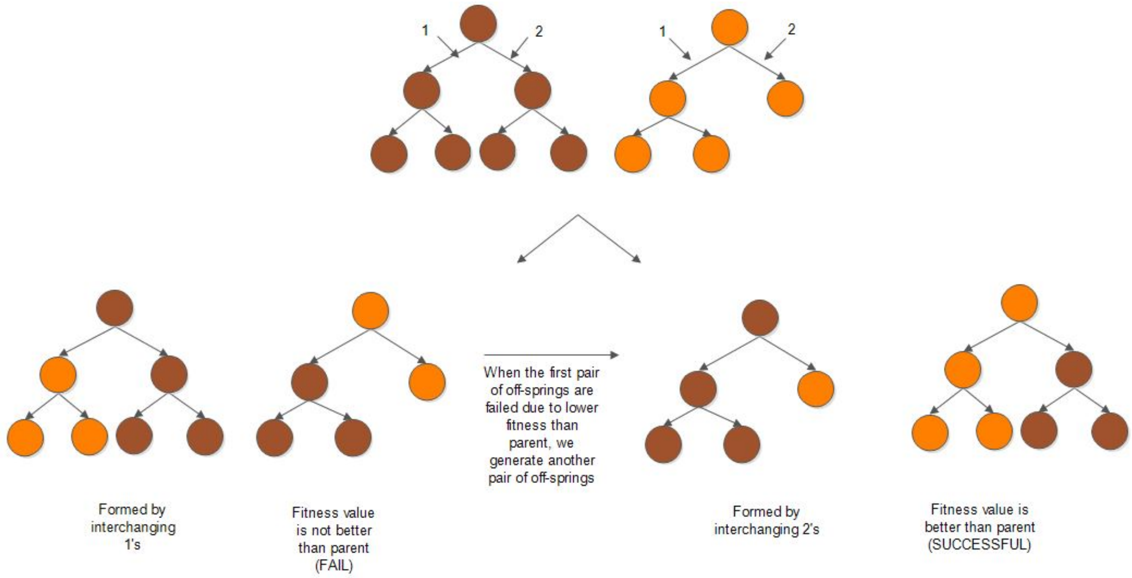

Figure 3: Constructive Crossover operation

cycle. The detailed description of both these operators are described next:

4.1 Constructive Crossover

In our GP process we first transfers the best N_r individuals from the current population to next generation by applying the reproduction operation. Then on remaining individuals we apply the crossover and mutation operation. For selecting the individuals for crossover operations, various authors applied various types of tournament [9]. The idea behind this, is to find the individual which are best for performing the crossover operations. The overall logic of finding the best parent for performing the crossover is little suspicious because of following two reasons. First is that, by just seeing the parent, nobody can guarantee the better off-springs. The second reason is that, even a individual with a lower fitness can produce better off-springs. Therefore, we propose a constructive crossover in which we we select all the individuals for crossover operation (N_c and N_m) which are left after reproduction. We make the pairs of these individuals and perform the crossover operation. We generate the off-springs from selected couple and check whether the off-springs are better than parents or not in terms of fitness. If they are better in terms of fitness, we kept them otherwise reject and repeat this process again till we get two individuals better than parent. We repeat this process for all N_c and N_m individuals. Thus, in this way we had integrated the local hill climbing method in crossover operation. We repeat this process for all the pairs.

Another concept of globally prime off-springs we had introduced in this method. That is selecting the top N_c off-springs on the basis of fitness from all the off-springs generated from crossover operation. The top N_c off-springs in terms of fitness, are present on the top N_c position in the max-heap all the remaining off-springs which are present at lower position in max-heap are deleted. A max-heap is a complete binary tree, in which the value in each internal node is greater than or equal to the values in the children of that node.

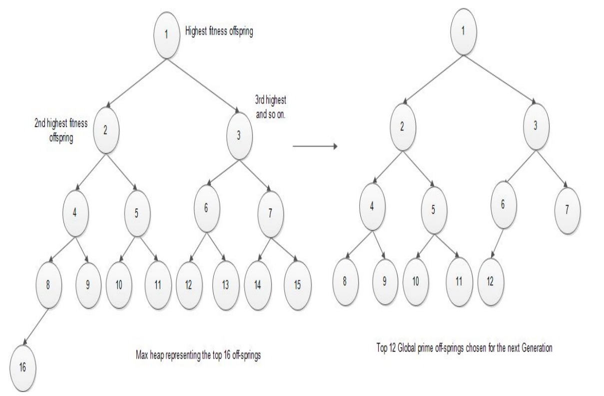

Figure 4: Selection of Global Prime Off-springs from Max-Heap

To explain this approach we are presenting a small example. In this we are taking population size as 10. We are applying reproduction on 2 individuals, crossover on 6 individuals and mutation on 2 individuals. First we transfer the 2 individuals from the population by applying reproduction operator. Than 8 individuals are left, out of which we have to apply crossover on 6 individuals and mutation on 2 individuals. But, rather selecting 6 individuals for crossover we select all the 8 individuals for it and apply constructive crossover. That is, generate 16 individuals from these 8 individuals which are better than parent in terms of fitness and kept in a max-heap. Than from these 16 individuals we select the 12 globally prime off-springs of max-heap (the top 12 off-springs of max-heap). That is, top 12 individuals from these 16 individuals on the basis of fitness and delete the remaining 4 individuals. We select only 12 because the numbers of crossover individuals are 6 only. So, from them only 12 off-springs can be selected. The remaining two parents whose off-springs are not transferred to next generation are automatically selected for constructive mutation operation. The advantage of this method is that we transfer the globally prime off-springs to next generation and the parents which are not able to generate better off-springs are chosen for mutation operation.

Algorithm 1 Algorithm for Constructive Crossover

1: Begin
2: Generate initial classifier population (k).
3: Randomly select fixed percentages of the initial population for crossover crossover (P_c), mutation (P_m) and reproduction (P_r).
4: Group the total population left after reproduction (N_c and N_m) into pairs.
5: Apply Hill Climbing method that is take the parent pair and genrate off-springs from them till we get the better off-springs than parents.
6: Repeat this process for all the pairs and generate the max-heap.
7: Select the top (P_c) globaly Prime offsprings from the max-heap and delete the remaining individuals for the next generation.
8: Repeat steps 2 to 7, until we reach required number of generations or required fitness satisfaction percentage.
9: End

4.2 Constructive Mutation Operation

To further improve the GP life cycle, we propose a constructive mutation operation. In constructive mutation operation, we chose those individuals which are left after reproduction and crossover operations. Then, we apply local hill climbing search on them that is, generate the off-springs till we get the better off-springs than parents. The advantage of using constructive mutation is that we reduce the destructive nature of mutation operation by transferring only the better individuals than parents to next generation. Another advantage is that we chose the mutation parents after crossover and reproduction. So the individuals which are not good for producing better off-springs than parents are changed in our mutation.

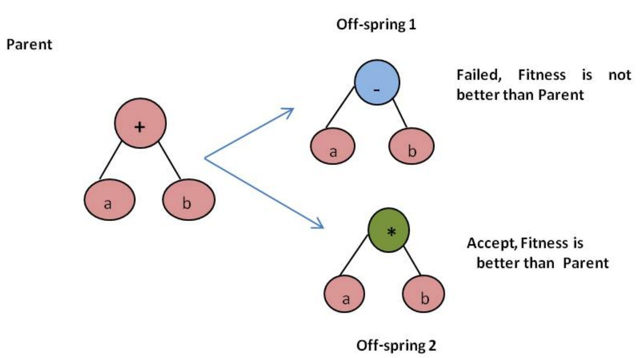

Figure 5: Constructive Mutation Operation

5. EMPERICAL RESULTS AND DISCUSSION

We have used the data described in Section 2, for our experiment. It contains three classes: 1) healthy, 2) epileptic

Algorithm 2 Algorithm for Constructive Mutation

1: Begin
2: Generate initial classifier population (k).
3: Take the individual (N_m) which are left after reproduction and crossover operations.
4: Apply Hill Climbing method that is take the parent pair and generate off-springs from them till we get the better off-springs than parents.
5: Repeat this process for all the pairs and generate the max-heap.
6: Transfer the individual tot he next generation.
7: Repeat steps 2 to 6, until we reach required number of generations or required fitness satisfaction percentage.
8: End

subjects during seizure-free interval (interictal), 3) epileptic subjects during seizure interval (ictal).

5.1 Comparison with Other Approches

To evaluate the generalizability of our approach, we used 10 fold cross-validation [11] scheme (CV). Here, the data are divided into 10 parts of equal size. We use 9/10 of the data to train the GP model, and we use the remaining 1/10 of data to test the model and estimate the classification accuracy, which is how well our approach is able to classify the EEG signals. We performed 10 GP runs, each time leaving out a different 1/10 of data for testing [11]. A classification accuracy is estimated as an average across the 10 cross-validations and standard+ mean deviation of the results are calculated.

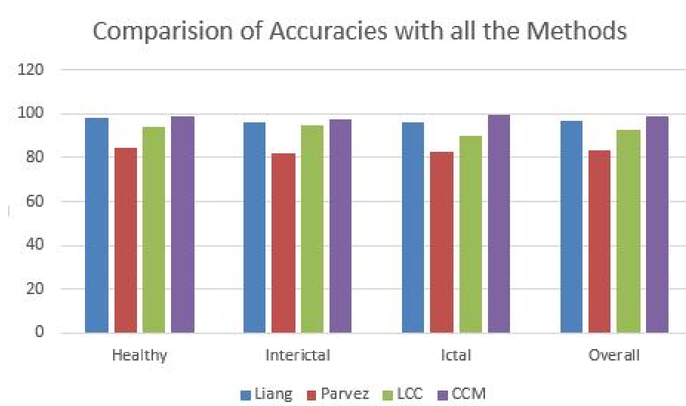

Figure 6: Comparison of Accuracies of all the classes and overall accuracies with all the methods

To compare our work we use the work of Liang et al.[16], Parvez et al.[1] and Zhang et al.[22] because Liang and Parvez had use the same dataset for classification of EEG signals and Zhang had shown the better classification accuracy by improving the crossover operator for object classification problem. Therefore, we found these works more appropriate to compare our work. Liang and Parvez, both used LS-SVM technique for the classification of EEG signals and how ever their accuracies were 97% and 83.25% respectively which is less than the accuracy achieved by CCM which is shown in Table2. The main reason for the improved accuracies is our both constructive crossover and mutation

Table 2: CLASSIFICATION ACCURACY FOR THE TEST SET WITH LIANG; PARVEZ; LCC: LOOSENESS CONTROLLED CROSSOVER; CONSTRUCTIVE CROSSOVER AND MUTATION OPERATION METHODS

Methods	Accuracy of Healthy Class	Accuracy of Interictal Class	Accuracy of Ictal Class	Overall Accuracy
Liang et al.	98.58 ± 1.13	96.43 ± 1.53	96.08 ± 1.43	97.03 ± 1.36
Parvez et al.	84.89 ± 1.18	82.25 ± 1.74	82.61 ± 1.59	83.25 ± 1.51
LCC([22])	94.47 ± 1.22	95.17 ± 1.52	89.87 ± 1.26	93.17 ± 1.33
CCM	99.19 ± 0.14	97.41 ± 1.47	99.47 ± 0.04	98.69 ± 0.55

operation. The Constructive crossover operation finds the better off-springs which help to find the optimal solution fast. The constructive mutation operation brings the diversity on those parents who have not been able to perform well in constructive crossover operation. Therefore, our both these operators work in tandem to bring the improved solution fast.

5.2 Advantage of Classifying the EEG Signals

As the EEG signals are divided into three classes. Each of this class has their properties. If a person is suffering from epilepsy then using our method its 97.41% accurate to say that he/she belongs to the interictal class and suffering from epilepsy of non-seizure and its 99.47% accurate to say that he/she belongs to the ictal class and suffering from epilepsy of seizure and these results shown tremendous improvements as compared to the other methods of Liang et al.[16], Parvez et al.[1] and Zhang et al.[22] as shown in Fig **??**. In this paper, we also improved the GP life cycle by improving the crossover and mutation operations and gives the impressive result for EEG signal classification which is shown in Table 2 and 3. It improves the accuracy of the classifier with a fair amount. We further compared our work with LCC method in terms of number of generation and time required to reach the accuracy because we also uses the hill climbing method to improve the crossover operator as used in LCC method but with further changes. It is found that our method showed improvement in both the departments than LCC method. Our method has removed the issue of selecting the crossover parent by selecting all the parent for crossover which are left after reproduction. This increases the number of fitness evaluation for a single generation, but eventually we got the desired fitness in lesser number of generations than LCC, so the number of fitness evaluation required in our method is almost same as that in LCC. We reach to desired fitness in early generations than LCC because by performing the constructive crossover we transfer the globally prime off-springs which showed tremendous improvement in fitness than parent. The individuals or we can say poor parents poor parents which are not capable of generating good off-springs are used for mutation. This helps in bringing the diversity in poor individuals very early due to which the chances of getting the solution fast is improved which are demonstrated in our result which is shown in Fig 7.

6. CONCLUSIONS

The goal of this paper is to improve the crossover and mutation operations of GP for classification of EEG signals. It is successfully achieved by developing a new constructive

Table 3: COMPARISON OF NUMBER OF GENERATIONS AND TRAINING TIME FOR THE TEST SET WITH LCC: LOOSENESS CONTROLLED CROSSOVER; CONSTRUCTIVE CROSSOVER AND MUTATION OPERATION

Methods	LCC	CCM
Number of generations	22.50 ± 0.76	18.25 ± 0.25
Time(in sec)	12.84 ± 2.39	11.98 ± 0.25

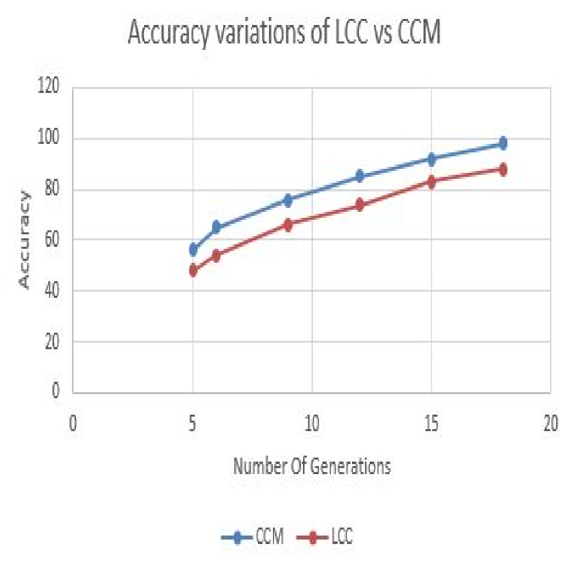

Figure 7: Comparision of Accuracies with Number of generations in LCC and CCM

crossover and mutation operators (CCM). Thus enhance the performance of GP life cycle. In this approach, a local hill climbing search method is used with crossover and mutation operators to generate better off-springs than parent. We choose all individuals which are left after reproduction to perform the crossover operations. Then we generate 2 better off-springs than parent for all the individuals. Then, we compare the off-springs of all the parent and put them in a max-heap. After that we transfer the top off-springs of max heap to next generation. In this way, we ensured that the globally Prime off-springs are transferred to the next generation. The advantage of constructive crossover is that, the best individuals are chosen for crossover and the individuals which does not perform well in crossover are chosen for constructive mutation operation. Thus, we remove the overhead of applying the tournament for selecting the crossover individuals. The constructive mutation operation also apply local hill climbing which helps in bringing the off-springs better than parents. The another advantage of constructive mutation is the poor parents who doesn't generate better off-springs are further improved by providing diversity to them. This approach is experimented and tested with EEG signal dataset and compared with the Liang, Parvez and Zhang methods. Improvements in terms of classification accuracy in the proposed approach is observed when compared with all the methods. The results suggest that this new approach outperformed all the operators in terms of the classification accuracy.

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