Two Brains Guided Interactive Evolution

Ahmed Kattan*, Faiyaz Doctor†, and Muhammed Arif‡
*‡Computer Science Department, Faculty of Computing and Information Systems, UQU, Saudi Arabia
Email: ajkattan@uquedu.sa, mahamid@uqu.edu.sa
† Department of Computing, Faculty of Engineering and Computing, Coventry University Coventry, United Kingdom
Email: aa9536@coventry.ac.uk

***Abstract*—In this paper, we show that it is possible to use electroencephalography (EEG) and multi-brain computing with two humans to guide an Interactive Genetic Algorithm (IGA) system. We show that combining neural activity across two brains increases accuracy to guide evolutionary search more effectively. The IGA system involves a simple task of evolving a polygon shape to approximate the shape of a target polygon. Two candidates visually inspected the evolved polygons and mentally ranked them (independently from each other) from $1-10$ based on their similarity to the target polygon. In parallel, the IGA system evaluated the fitness of evolved polygons using a standard fitness function. The IGA system was run for a few generations, before evolution was paused and EEG signals were collected from the two candidates. The collected EEG signals were used to train a regression model that received unseen EEG as input and mapped this into fitness values. The trained model was then used to guide the IGA solely by using the EEG signals. Off-line experimental results showed that it was possible to build better regression models that are trained using two EEG signals to capture participants evaluation of fitness. This paper demonstrates the possibility of a new domain of applications for interactive evolution where standard fitness calculations can be replaced with multiple EEG signals for guiding an optimisation process.**

***Index Terms*—EEG, multi-brain, Interactive Genetic Algorithm.**

I. Introduction

Our brains have evolved to control complex biological systems within the body [12]. However, the idea of using the brain's abilities to control devices outside the body has been of primary interest to the BCI community over the past few decades [12]. This has been made possible through the ability to read brain activities using different tools such as functional magnetic resonance imaging (fMRI) and electroencephalography (EEG). EEG is the main measurement of the electrical activities of brains. The source of EEG is the electrical signals created when electrical impulses move within the central neural systems [12]. The analysis of EEG signals contain both spatial information about the distribution of brains' activities and temporal information about the sequences of these activities. To this end, many reported trials of using EEG signals in a plethora of real-world applications (e.g., [3], [15], [8]) show the great potential of this technology and the endless possibilities of its practical applications. However, while the EEG-based BCI technology has achieved great successes, moving a BCI system from a laboratory demonstration to a real-life application still poses severe challenges such as the acquisition of precise signals and their processing in real-time to identify features of activations that can be correlated to the context and nature of activities being performed. Most BCI applications, if not all, leverage recent advances in machine learning, signal processing, and neuroscience. Generally, the aim of any BCI application is to translate brain activities into commands to control hardware or software or simulate brain activities to mimic feedback in the body to restore function of disabled or dysfunctional body parts [12]. The steps of processing brain EEG signals usually involve signal recording (while candidates are instructed to do a particular task that stimulate brain activity) after which the EEG signals are pre-processed to clear out noise. A machine learning model is then trained using the EEG signals (where different parts of the EEG are classified) and validated using unseen EEG data.

Generally speaking, current BCI applications are very limited. The main reason is the difficulty of getting pure EEG signals directly correlated with the given task. To overcome this problem, recently, researchers presented the idea of combining the signals from neural activity across multiple brains (e.g., see [4], [17], and [10]). The advantage of this is that the chances of getting noisy EEG signals at all times is slim. In principle, it is impossible that all EEG signals will have identical level of noise at all times. Hence, one can build models to switch between different signals at different time slots or perhaps it is possible to build a model that combines EEG signals from different brains to reduce overall noise. One main challenge is that models that will deal with this type of data will probably be complex and demand heavy computations. Another challenge is that it is nearly impossible that two brains would precisely align their thoughts to do a particular task. Therefore, the design of any model to deal with multiple brain signals should take this issue into account.

Combining signals from multiple brains is advantageous because it can surpass single brain limitations by allowing learning models to access a wider range of information to map EEG to specific tasks more accurately [16]. Perhaps in the future, it would be possible to build a "super brain" by aggregating information from multiple brains continuously.

In this paper, we leverage recent successes of combining multi-brain signals and try to use EEG signals from two brains to guide an interactive genetic algorithm (IGA) system. In [13], the idea of using EEG to control IGA was presented for the first time. EEG has been used to control crossover and mutation rates where changes of crossover and mutation rates occur during the problem solving process. Before the system started using EEG for parameter control, subjects performed four baseline tasks and the

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corresponding EEG signals were collected as a training set. The four tasks were open eyes while relaxed, close eyes while relaxed, open eyes while thinking of a simple mathematical problem, and finally, close eyes while think of simple mathematical problem. Unseen EEG signals were classified into one of four baseline states using the minimum Euclidean distances. The system could then increase or decrease mutation or crossover rates at certain percentages based on the classification results. Unlike the work presented in [13], in this paper we use EEG to directly infer the fitness values of GA individuals. In our experiments, we found that Genetic Programming (GP) can evolve mathematical expressions that combine the EEG signals in such a way as to increase the correlation to the target events. It should be noted that the aim of this paper is not to improve interactive evolution rather to show the benefits of combining multiple EEG signals.

The contributions of this paper is that, to the best of our knowledge, this is the first attempt to use GP to evolve decision trees that automatically decide how to combine EEG signals from two brains.

The remainder of this paper is structured as follows. Section II describes some works of previous trials to combine multiple EEG signals from different brains. Section III describes the proposed IGA system. Section IV discusses the experimental setup in detail. Section V will present the results. Finally, Section VI presents some conclusive remarks and potential future work.

II. Related works

Wang et. al. [17] used a collaborative BCI to improve overall performance by integrating information from multiple users. Experiments with 15 subjects participating in a Go/NoGo decision-making experiment evaluated the collaborative method. Results showed that the classification accuracy for predicting a Go/ NoGo decision was enhanced substantially when integrating signals from multiple brains. Poli et. al. [10] explored the possibility of controlling a spacecraft simulator using an analogue BCI for 2-D pointer control. In their experiments, users of the simulator were told to pass as close as possible to the sun. The simulator was set in such a way to stimulate the brain to produce $P300$ signals that signify Event Related Potentials (ERPs) which is a measure of brain response to specific sensory, cognitive or motor events. Support Vector Machine (SVM) were then trained with the $P300$ data. The author used two approaches for combining the ERPs of pairs of users. The first approach, simply averaged the ERPs from each subject before they were passed to a single SVM. The second approach, averaged the outputs of each SVM after training them separately for each user. The second approach resulted in a better classification accuracy. In [4], group decisions and aggregation of multiple opinions lead to greater decision accuracy (the author referred to this phenomenon as collective wisdom). Multi-brain computing Experiments using EEG and from 20 humans making perceptual decisions showed that combining neural activity across brains increased decision accuracy. The experiments showed that a simpler neural majority decision rule resulted in achieving a good accuracy. Later, Poli et. al. [11], investigated whether group decisions based on visual perception would be superior to individual decisions. In this work, the response time was considered as sign of confidence. Yuan et. al. [18] proposed an online collaborative BCI to accelerate human response to visual target stimuli by detecting multiple subjects' visual evoked potentials (VEPs). A spatial filtering algorithm which maximised signal-to-noise ratio was used to extract VEP components from multichannel EEG. Experiments involved three subjects' EEG data. The EEG data of each user were passed to a SVM model where the outputs of all SVMs were combined in a single vector and passed to a second layer SVM as input to classify EEG data. In [16], the authors introduce the concept of Multi-Brain Fusion (MBF) technology. An experiment aggregated the information originating in signals from two subjects. The subjects watched a sequence of 25 PowerPoint slides with humorous cartoon-like drawings. Their decoded emotions were fused to indicate a group emotional response, as a collective assessment of the presented information.

III. Proposed IGA system

A. Overall process

Broadly speaking, the proposed process can be divided into two stages as illustrated in figures 1 and 2. In the first stage, the interactive evolutionary system runs to perform a certain task (in this paper we used IGA, however, in principle any interactive evolutionary algorithm can be used). The IGA can solve any task; however, in this paper, the task given to it was simply to evolve a polygons shape and colour to match an image of a target polygon. The IGA system displays each evolved polygon shape on the screen for a fixed period (of 3 seconds, selected to allow an appropriate length time window to capture relevant ERP). Two subjects (independently of each other) visually inspect the evolved polygons and mentally rank them (based on their similarity to the target polygon) from $1-10$ (10 for perfect match and 1 for poor match). In parallel, the IGA evaluates candidate solutions using a standard fitness function. The IGA system runs for a certain number of generations (details are given in section IV) to collect the EEG signals (from the two subjects) and the corresponding fitness values. In the second stage, the system uses the collected information as a training set and trains a regression model H that receives signals from both subjects EEG^{s1} and EEG^{s2} as inputs to return an approximation of the corresponding fitness values. The model H therefore translates unseen EEG signals into fitness values to guide evolutionary process.

B. EEG headtset

To elicit the EEG signals we use two different Emotiv EPOC headsets [1] which reads EEG signals from 14 channels with 2 reference electrodes (see figure 3). The electrodes are placed to follow the international $10-20$ system and labelled as illustrated in figure 3. The headset transmit encrypted data wirelessly via Bluetooth to a Windows-based machine. The headsets are also equipped with a gyroscope that detects the change of orientation of the subject's head, however these were not used for the purposes of our experiments. The headsets read EEG signals of a subject that were generated in response to different solutions presented on the screen (in our case polygons) to stimulate the $14-$channel electrode sensors ($AF3$, $AF4$, $F7$, $F3$, $FC5$,

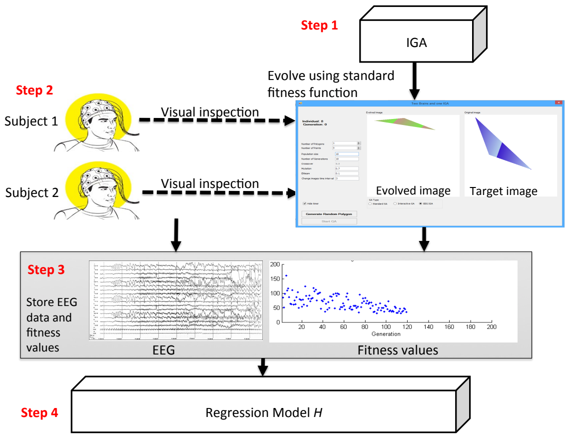

Fig. 1. IGA system stage 1 - generate training data.

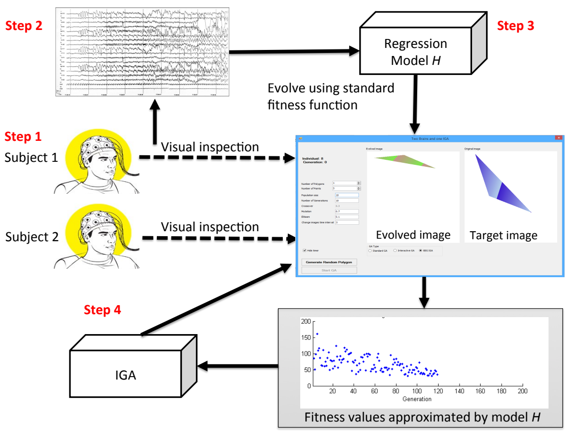

Fig. 2. IGA system stage 2 - guide IGA using EEG.

$T7$, $P7$, $O1$, $O2$, $P8$, $T8$, $FC6$, $F4$, $F8$ in addition to 2 reference electrodes CMS and DRL). The sampling frequency for the signals is $128Hz$ with a bandwidth of $0.2-45Hz$. The signals were filtered with a dual-pass Butterworth filter. Usually, the name of the electrode refers to the region of the cerebral cortex over which they are positioned. Hence, F corresponds to the frontal lobe (usually reacting to thoughts or conscious, deliberated movements), T refers to the temporal lobe (reacting to speech reception) O is positioned over the occipital lobe (related to reception from eye retina), P refers to the parietal lobe (sensory signal reception), and C corresponds to central lobe [9] [7].

C. EEG representation

As mentioned previously, we allow 3 seconds for each evolved solution to be visually inspected by the two subjects. Thus, the amount of data to be collected for each solution (at a sampling rate of $128Hz$ in 14 channels) is $128 \times 3 \times 14$. Each evolved solution will correspond to two matrices $\mathbf{M^{s1}}$ and $\mathbf{M^{s2}}$, where $s1$ and $s2$ refer to subject 1 and subject 2, respectively. The size of each matrix is 14×348 where 348 is the number of samples collected through a headset from each channel (in a 3 seconds time block) and 14 the total number of channels provided by a single Emotiv EPOC headset. To simplify the data representation,

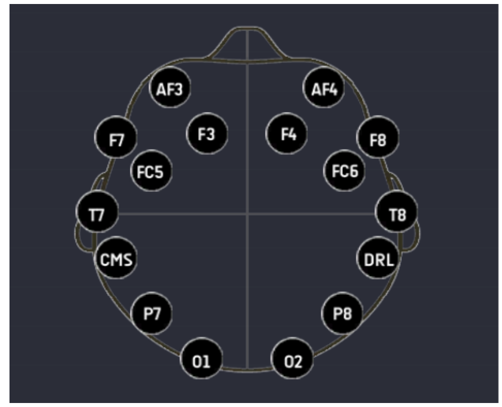

Fig. 3. Emotive headset's electrodes distribution on the scalp.

we collapsed each row in the $\mathbf{M^{s1}}$ and $\mathbf{M^{s2}}$ matrices into a single number which represents the average values from each channel over the each 3 second sample block. Thus, the simplified $\mathbf{M^{s1}}$ or $\mathbf{M^{s2}}$ matrix is of size 14×1. We will refer to the simplified matrices (after averaging their rows) to be X^{s1} and X^{s2}. Now, each evolved solution corresponded to two variables; $\{X^{s1}, X^{s2}\} \in \mathbf{R^{14}}$ and y value which represents the fitness value calculated by the GA system.

Obviously, the main criticism of this abstraction approach is that it may leads to loss of information that is important to understanding and detecting the ERPs. However, we will see in the experimental section that different regression models can map unseen EEG signals to their corresponding fitness values using this representation achieving a good accuracy. In future work, we will explore other representations to model the EEG data.

IV. Experimental Setup

A. EEG collection and GA settings

Our experiments included 6 different subjects (aged $30-40$). All subjects where healthy. They had no history of any known mental or physical illness. The experiments were divided into three sessions. Each session included two subjects simultaneously engaged with the IGA system. The subjects were seated next to each other in front of a screen (see figure 4). The GA software which was written in C# and running under Windows 8.1 OS, shows a window divided into two parts. The left part shows a fixed image of polygon (i.e., target image) the right part shows evolved images. Each image appears for 3 seconds during which the subjects were requested to mentally rank each evolved image from 1 to 10 based on its similarity to the target image (where 1 was for completely dissimilar, and 10 for a perfect match). Subjects were not allowed to talk to each other during the experiments. For the GA settings, we used a population of size 20, number of generations was set to 20, tournament selection of size 2, crossover and mutation rates, 70% and 30%, respectively. Each experiment lasted 20 minutes.

The GA individuals are represented as vectors of 12 real numbers which are used to encode the drawing of the polygon corners at certain coordinates and set it to a certain colour. The first 4 numbers represent the $x1$, $x2$, $y1$ and $y2$ screen coordinate

Fig. 4. Experimental settings - Two subjects seated in front of a screen and requested to mentally rank evolved polygons from 1 to 10 based on their similarity to a target polygon.

to draw the polygon. The second 4 numbers represent code value to set first colour of the polygon. The last 4 numbers represent the second colour of the polygon.

The GA fitness function was simply the Euclidean distance between the evolved polygon and the target polygon. The fitness values were scaled from 1 to 10 to match evaluations of subjects. The target polygon was randomly generated at the beginning of the experimental run. Note that this problem has one global optimum solution and it similar characteristics to the one max problem and the search space is a cone [5]. At the end of each session, data are stored for an offline analysis.

B. Regression models

For the offline analysis we divided the data into two parts; 50% training and 50% testing. The data were represented as pairs of $\{Z_i, Y_i\}$ where $Z_i = \{X_i^{s1}, X_i^{s2}\}$ is the abstracted input vector of EEG signal values from the 14 electrodes, abstracted over 3 seconds of recording and Y_i the fitness value of the corresponding individual (see III-C). Several regression models were trained to predict the fitness values of GA individuals when unseen EEG signals are presented. The aim is to reduce prediction errors and thus, in principle, allow the regression model to guide the GA search. We used four different regression models. Namely, Linear regression, Radial Basis Functions Networks (RBFN), Kriging, and a standard GP [2]. We passed the EEG data to each regression model in 5 different formats. For the standard GP settings used in our experiments, we set the population size and number of generations to 200, elitism rate 1%, tournament selection of size 2, sub-tree crossover and sub-tree mutations rates of 70% and 30%, respectively. The initial population was generated using ramped half-and-half [6]. The function set was limited to arithmetic operators and constants from $0 - 1$.

1) **Data from subject 1 only**: Here we trained each regression model with a training set of inputs-outputs pairs $\{(X_i^{s1}, Y_i)|i = 1, ..., k\}$ and k is the size of the training set.
2) **Data from subject 2 only**: same as previouse format but for subject 2 only.
3) **Data from both subjects 1 & 2**: Here we combined the input variables into one vector. Thus, $X_i^{s12} = \{x_1^{s1}, ..., x_{14}^{s1}, x_1^{s2}, ..., x_{14}^{s2}\}$ the training set is input-outputs pairs $\{(X_i^{s12}, Y_i)|i = 1, ..., k\}$.
4) **The average of subjects 1 & 2**: Here we averaged all corresponding variables from both X^{s1} and X^{s2}. The input variables are $X_i^{AVG.s12} = \{\frac{x_1^{s1}+x_1^{s2}}{2}, ..., \frac{x_k^{s1}+x_k^{s2}}{2}\}$ the training set is input-outputs pairs $\{(X_i^{AVG.s12}, Y_i)|i = 1, ..., k\}$.
5) **The difference between subjects 1 & 2**: Here we calculated the absolute difference between all corresponding variables from both X^{s1} and X^{s2}. The input variables are $X_i^{Diff.s12} = \{Abs(x_1^{s1} - x_1^{s2}), ..., Abs(x_k^{s1} - x_k^{s2})\}$ the training set is input-outputs pairs $\{(X_i^{Diff.s12}, Y_i)|i = 1, ..., k\}$.

The logic of using the first two formats (described above) is to test whether the regression model will make more sense of the EEG data from a single user in comparison to the other proposed data formats. The third format, is used to test whether the regression model will make better predictions when it receives more information. The fours and fifth formats are inspired from [10].

Finally, we added one more technique using GP. Where we used GP to evolve decision trees that receive pairs of $\{Z_i, Y_i\}$ as inputs and return numerical values (we will call it $\hat{Y}$) as outputs (details in IV-C).

In the final system, the GA evolution would be guided by the learnt regression model so inputted live EEG values would be mapped to output fitness values directly without the need to use the fitness function. One may argue that there is no point of using EEG to guide evolution when the fitness function is well defined. However, as mentioned before, the aim of this paper is not to improve IGA itself rather to show the benefits of combining multiple EEG signals. Moreover, one may argue that in many cases the fitness function may be mathematically inexpressible such as evolving art. In these situations using multiple EEG to guide evolution is beneficial.

C. GP evolves decision trees as regression model

One of the advantages of combining multiple EEG signals is that there will always be, in any time window, one signal with the least amount of noise compared to the others. This is because the human ability to concentrate on a given task can fluctuate over time. Thus, to utilise multiple EEG signals one would need to understand how to distinguish noise from ERPs. Also, one needs to know in advance, when the EEG is processed in real-time, which channel (out of the 14 channels from the headset) will provide the least noise, clearest and relevant ERPs. If an ideal multiple EEG processing model exists, this model would receive all EEG signals and decide which one will give the best translation to the given task at a certain time slot (in our case, the given task is to translate EEG signals into fitness values of the corresponding GA individual polygons that appear on the screen). This ideal model will automatically switch between signals at different time slots, or perhaps it will crossover between different EEG channels from different brains to construct a combined brain signals. Also, this ideal model may decide to combine EEG

TABLE I
GP FUNCTION SET

Function	*Arity*	*Input*	*Output*
+, -, /, *	2	Real Number	Real Number
Mean, Median, StD, Variance, Average Div, Kurtosis, Skew	1	x_i^{sj}	Real Number
Constants 0-1	0	N/A	Real Number
IF $<$, IF $>$, IF$\leq$, IF$\geq$	4	Real Number	Real Number

**StD* is Standard Deviation, and *Average Div* is Average Deviation

signals using complex mathematical expressions. Of course, to build such a model we need a deeper understanding of the EEG structure and features.

In this paper, we propose one step toward this ideal model. We use a GP to evolve decision trees that receive all 28 variables (14 from each brain) and returns a translation of the signals as outputs. The use of GP to evolve decision trees for regression problems has been presented previously in [14]. We supplied the GP with a function set as presented in table I. We supplied the GP with two important types of functions 1) statistical features, and 2) IF conditions. Thus, GP will be able to build programs that compare different statistical features from the EEG and executes different blocks of codes based on statistical comparisons. For example, the GP may build a program that compares channel $F7$ from subject 1 against the same channel from subject 2 and execute different block of code based on the comparison. The output of the evolved decision trees will approximate fitness. For the GP settings used in our experiments, we used the same settings as in the standard GP (see section IV-B).

V. RESULTS

Table II presents the results of the experiments. As mentioned previously, we analysed the data offline where the collected data (i.e., abstracted EEG signals and their corresponding fitness values) were divided into two equal parts for training and testing. Once the regression models were trained, we measured their prediction errors on the unseen testing set. Obviously, low prediction errors means that the model can be used to process EEG signals and translate them into fitness values, thus driving the evolutionary search. For the standard GP (referred to as SGP in table II) and the Decision trees GP (referred to as DT-GP), the training set was further divided into two equal parts to construct a validation set. The best solution from each generation was further tested with the validation set and the solution that produced the best results (on the validation set) was selected as the final evolved solution. Each GP system evolved 30 different solutions in 30 independent runs (60 GP runs in total). The results present the mean, median, and best evolved solution across the whole runs. Note that SGP evolves regression functions while DT-GP evolves decision trees.

Clearly, the DT-GP produced the lowest prediction errors in all experimental cases. This is a clear indication of the benefits of combining multiple EEG signals. Remember that the DT-GP can execute different blocks of evolved code at different time slots. The biggest challenge here is to generalise any evolved solutions to work across different brain signals. However, we will not touch on this aspect in this paper.

Looking at the other regression models, we noticed that a simple combination of EEG using average or absolute differences does not always improve predictions. In fact it worsens the results in some cases. The likely reason for this is that the thoughts of participants are most likely not perfectly aligned. For example, at a given moment subject1 may rank an evolved solution as 7 while subject2 may rank it 1 having been completely distracted at that particular point in time. Hence, a simple combination of corresponding variables between 2 EEG signals may not be ideal to match the corresponding fitness value.

Overall, the results are encouraging in the sense that GP managed to evolve decision trees that can distinguish the quality of the EEG signals in a given time slot and decide the best way to translate the given data to match the fitness values of the GA individuals. Note that in this approach, unlike other works, we did not need to extract a baseline EEG for the ranks. We used the collected EEG data as training examples to build regression models. Most previous works require a baseline EEG to compare unseen data against them.

One may argue that actually GP overfit the given EEG signals and therefore it will evolve good mapping between the inputs and outputs anyway. To validate this argument, we did an additional experiment where we asked the last two subjects (in session 3) to close their eyes and relax while, in parallel, the GA system evolved polygons and displayed them on the screen (as described in section III-A). In this case, the EEG data were not related to the GA process. Therefore, we would expect any regression model to give poor approximations since both inputs and outputs are completely independent. Table III, shows the results of this experiments. As can be seen in the table all regression models produced poor predictions. If we then compare the errors of these experiments with those of the previously conducted session (session 3 in table II) we can note the difference margins between prediction errors.

VI. CONCLUSION

In this paper, we used EEG and multi-brain computing with two humans to guide an IGA system. We showed that combining neural activity across two brains increases accuracy and can guide evolutionary search effectively. The IGA system involved a simple task of evolving a polygon shape to approximate the shape of target polygon. Two candidates were requested to visually inspect evolved polygons and rank them (independently from each other) from $1-10$ based on their similarity to the target polygon. The IGA was run for set number of generations after which the system used the generated EEG data. The EEG data was used as a training set to built a regression model that aimed to map unseen EEG signals into the fitness values of the corresponding evolved individuals. Experimental results showed that with the right combination of EEG signals it was possible to build better regression models that can approximate corresponding fitness values well. We used a GP to evolve decision trees that extracted statistical features from the EEG and automatically decided to execute different blocks of code

TABLE II
EXPERIMENTAL RESULTS. NUMBERS REPRESENT THE AVERAGE PREDICTION ERRORS. RESULTS OF EACH GP SYSTEM SUMMARISED FROM 30 INDEPENDENT RUNS.

	Subject 1	*Subject 2*	*Subject 1 & 2*	*Avg. Subject 1 & 2*	*Diff. Subject 1 & 2*
Session 1					
RBFN	2.35	1.68	1.70	1.80	1.72
Linear Regression	0.53	20.06	0.63	1.98	2.05
Kriging	2.15	2.15	2.15	2.15	2.15
SGP (Min,Median,Mean)	1.55 , 2.75 , 2.58	1.64 , 2.72, 2.59	1.12 , 2.70 , 2.57	1.42 , 2.79 , 2.59	1.63 , 2.80 , 2.62
DT-GP (Min,Median,Mean)	**0.42** , 1.46 , 2.00				
Session 2					
RBFN	1.91	1.72	1.73	1.82	1.73
Linear Regression	3.32	5.61	3.02	2.52	2.03
Kriging	2.05	2.05	2.05	2.05	2.05
SGP (Min,Median,Mean)	1.89 , 2.40 , 2.32	1.32 , 2.29 , 2.16	1.37 , 2.26 , 2.16	1.00 , 1.91 , 1.88	2.10 , 2.33 , 2.31
DT-GP (Min,Median,Mean)	**0.54**,1.70,16.30				
Session 3					
RBFN	3.54	2.37	2.94	3.72	2.80
Linear Regression	1.98	10.31	2.47	1.68	1.90
Kriging	2.24	2.24	2.24	2.24	2.24
SGP (Min,Median,Mean)	1.83 , 2.92 , 2.77	1.78 , 2.68 , 2.54	2.41 , 2.95 , 2.85	1.87 , 2.91 , 2.74	1.73 , 2.70 ,2.60
DT-GP (Min,Median,Mean)	**0.65** , 1.53 , 1.66				

TABLE III
ADDITIONAL EXPERIMENTAL RESULTS WITH SUBJECTS WHO PARTICIPATED IN SESSION 3. NUMBERS REPRESENT THE AVERAGE PREDICTION ERRORS. RESULTS OF EACH GP SYSTEM SUMMARISED FROM 30 INDEPENDENT RUNS.

	Subject 1	*Subject 2*	*Subject 1 & 2*	*Avg. Subject 1 & 2*	*Diff. Subject 1 & 2*
Session 3 - Additional experiment					
RBFN	1.27E+134	441.80	1.16E+297	95.46	1.16E+297
Linear Regression	18.95	113.33	122.32	59.06	33.67
Kriging	2.30	2.30	2.30	2.30	2.30
SGP (Min,Median,Mean)	1.37 , 3.7 , 3.4	1.53 , 3.8 , 3.5	1.90 , 3.0 , 2.6	2.02 , 3.4 ,2.8	1.58 , 3.4 , 3.4
DT-GP (Min,Median,Mean)	1.79 , 5.03 , 4.68				

based on the statistical characteristics of the given EEG in any time-slot.

For future work, there are many directions that need further investigation. As a first step, we will increase the number of experiments as well as the number of participating subjects. In addition, since the current experiments were based on offline data, we will apply the system with online data and compare the quality of the evolved solutions against to standard IGA process. Moreover, we will explore the system behaviour when the IGA deals with more complicated tasks. In addition, we will explore other methods for more accurately pre-processing and modelling the EEG signals such fuzzy data granulation and deep learning techniques.

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