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An Interactive Evolutionary Computation Framework Controlled via EEG Signals

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***Abstract*—This paper presents an EEG-based interactive genetic algorithm framework, with the goal of leveraging EEG signals collected from a human expert involved in the evaluation of interactive genetic algorithm as inputs for genetic parameter control. We explain the framework of the system and our cognitive model constructed based on a 19 channel EEG system. An experiment has been performed to test the effectiveness of our framework and our cognitive model. Our work is the first attempt to combine brain-computer interaction with interactive evolutionary computation and parameter control.**

I. Introduction

Bio-inspired evolutionary algorithms have been successfully applied to optimization and learning problems over the last few decades so as to solve complex problems that are not easily solved by classical analytical methods [1]. Among the various types of evolutionary algorithms, genetic algorithm (GA), introduced by Holland [2] which mimics natural selection, is one of the most popular search methods used in practice. Parameter control of the GA is a critical area in any GA, because the success of the optimization process depends largely on the design and selection of appropriate search operators and parameters [3], which comes to be the balance between two cornerstones of problem solving by search - exploration and exploitation [4]. Exploration avoids getting stuck in local optima, and exploitation helps to converge quicker. In GA, exploration and exploitation are balanced by two important genetic operators: crossover and mutation. To obtain a balance of these two genetic operators is an important issue in controlling the degree of exploration and exploitation in problem solving. To ensure the effectiveness of GA for a particular problem, parameter tuning before running of the algorithm and parameter adaptation during the process of problem solving are both common methods used for parameter control [3]. With regard to the challenge of this balance, on-line parameter control has drawn more attention because of its adaptability under various conditions and in non-stationary environments [3]. Human evaluation for the on-line parameter control of interactive genetic algorithm is also suggested [5].

In this paper, we present a new way to model mental states of a human subject as inputs for task controls based on EEG signals. On-line parameter control in genetic algorithm (GA) is selected as an example to demonstrate our work with regard to Brain Computer Interfaces(BCI). The application of BCI in GA parameter control is important for individuals and families of individuals who have physical limitations to use GA based applications. It is as well important in developing future interfaces with better communication quality and larger bandwidth between healthy individuals and machines.

Electroencephalography(EEG), which is an effective measurement of the electrical functions of brains [6], has been widely applied in Neuroscience and Brain-computer Interaction. The source of EEG is the electrical signals which are created when electrical charges move within the central neural systems. The advantage is that it is low cost, compact, flexible and more robust than other non-lesional brain imaging techniques (e.g., PET, fMRI, etc.) [7]. It also provides a reasonable spatial resolution (if sufficient number of electrodes are used) and an excellent temporal resolution. These advantages have led to a wide employment of EEG in non-invasive brain functional mapping when continuous recording is needed [7], or BCIs in virtual environments when real-time monitoring, interpretation and feedback is required.

Real-time EEG has been recognized as a new communication channel between human brains and computer system by human-computer interaction and virtual reality communities. These EEG-based BCIs have been firstly researched in order to help disabled persons in motor recovery and substitution, for example, the control of a wheelchair [6]. More recently this approach has been extended to create an immersive experience for healthy users and have been tested in game environments [8], from simple games like navigation in a maze [9], Pacman [10], to more complex games including flight simulators [11].

However, in classical BCI design, before successfully using the system, the subject needs to learn how to regulate their brain signals in a systematical manner by performing several imaginary tasks. Some researches rely on the subjects' own ability to control their mu and central-beta rhythm by will so as to (for instance) move cursors on screens [12]. Others rely on machine learning algorithms to learn the subject-specific brain pattern before reliable control could be expected in BCIs [13]. This training stage may consist of several or more sessions. Further, the training time varies among subjects, which can last from several hours to many months [14]. The cost is high and the resulting control scheme is always subject-dependent.

Clearly, cost of training is a significant challenge in moving the current BCI research from lab experiments to real world applications. We tackle the problem by 1) avoiding complex mental tasks that require particular ‘skills’ of the subjects to regulate their brain waves, but focusing on simple mental tasks that would trigger certain brain wave patterns which have been long addressed in Cognitive Science; 2) using baseline tasks to overcome between-subject variability in performing these tasks in order to build up a mathematical model. The experiment of our system described herein proves the success of this idea in reducing training time, as compared to traditional approaches to BCIs design. Further, the technique can also be applied in the application of BCIs for other purposes.

Our work is the first attempt to link the EEG-based BCI research and GA parameter control to balance the trade-off of exploration and exploitation in evolutionary computation. This proof of concept opens the doors to extend the work to other applications that require real-time control.

Real-time EEG signals are collected from a human expert as inputs to control parameters in GA, when solving a benchmark problem. We show the results of how the mental tasks performed by the human expert change the crossover and the mutation rate, so as to drive the evolutionary process. The aims of our study are to discover:

- if a framework of using EEG brain signals as inputs to control genetic parameters is feasible;
- if the technique of using baseline tasks in order to reduce training time is applicable in our framework.

The paper is structured as follows: Section 2 presents the methodology of the proposed interactive GA framework, the designed mental tasks, the EEG signal processing, and the parameter control; Section 3 shows the experimental design and procedures; The test results are discussed in section 4, and section 5 concludes our current research with proposals for future work.

II. Methodology

A. Framework

The framework has a human expert involved in the system. The human expert observe/evaluate the problem and control the parameters of the genetic algorithm on-line during the process of problem solving. The system by itself takes care of the GA, the EEG recording and the mental states identification as parameter control inputs. The framework of our purposed system is illustrated in Figure 1.

As shown in Figure 1, the system is composed of 5 main components: the GA, the EEG collection, signal processing, mental states identification and the mapping of mental states to the changes in genetic parameters. We collect EEG signals from the human expert after he/she has evaluated the problem and made a decision for parameter control, process the signal to extract features, identify mental states in real-time using these features, and at last map the mental states to parameter control functions. The functions feedback to the GA main program to process and to display results again for the human expert to evaluate. This loop continues until the GA has provided a satisfactory result.

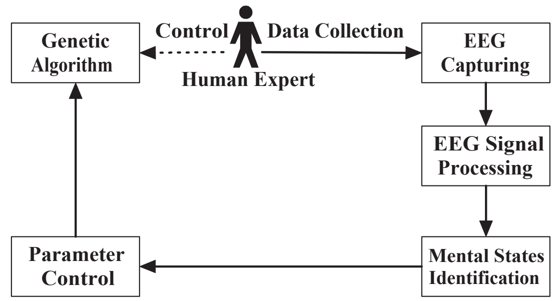

Fig. 1. The Framework of the Interactive Evolutionary System with Parameter Control

This framework of the interactive genetic algorithm system is processed in real-time so as to obtain instant control messages. Besides a quick baseline session that takes just several minutes, no training stage are required as in classical BCIs design. This design makes the framework neither algorithm-dependent in choosing genetic algorithms, nor subject-dependent in choosing the human experts as subjects.

B. Genetic Algorithm and EEG Controlled Parameters

A detailed explanation of the designed interactive GA system is shown in flow-chart 2. The system consists of a standard GA with Roulette wheel selection and an EEG parameter control component.

When EEG parameter control is enabled, the system will collect EEG data, calculate mental states, and control the crossover and mutation rate accordingly by the resulting control functions. If not enabled, the GA will follow the standard way of evaluation, selection, reproduction and mutation without changing parameters.

C. Mental Tasks Design

The mental tasks are designed such that the human expert completing the mental tasks results in the corresponding control changes in the GA - changes of crossover and mutation rate during the problem solving. The control functions are determined by features extracted from EEG signals captured during the tasks. In order to avoid the tedious process of BCI training, these tasks need to be designed to be simple enough for the human expert to identify and remember, but also diverse enough to generate distinguishable brain signal patterns that could be identified by our constructed cognitive model.

We design the mental tasks by reviewing studies on EEG signal patterns under various thinking tasks. The increasing frequency of information transmissions between neurons is an electro-physiological indicator of excitement and activation

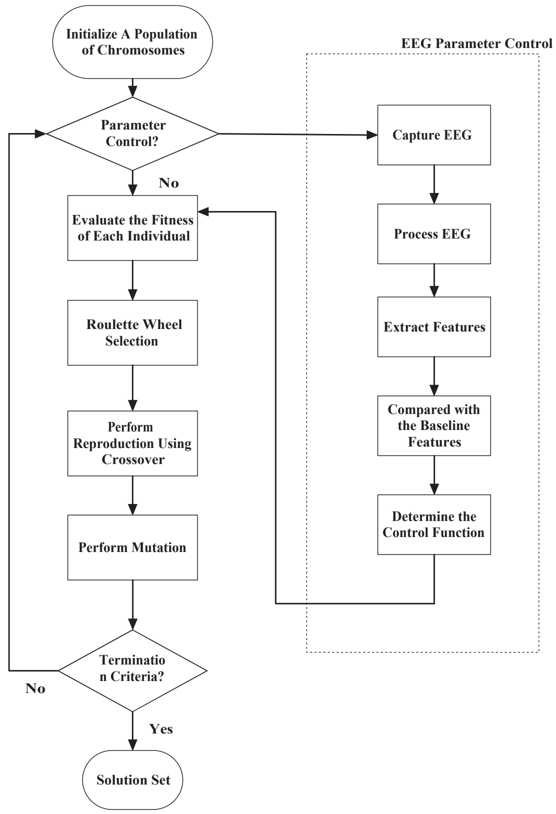

Fig. 2. The Implementation Diagram of Genetic Algorithm with EEG Parameter Control

of the corresponding cerebral functional area. Conversely, decreasing frequency is an index of attenuation and inhibition of the cerebral functional area. This implies the correlation between spontaneous brain activities, which could be shown as relative EEG power, and its corresponding underlying brain functions.

The mean power level of EEG alpha band has long been recognized as an important measure of resting-state arousal under eyes-closed and eyes-open conditions. Recently, the topographic changes between eye-close and eye-open states has also been studied and identified [15]. During eye-close and relaxation stage, the temporal-occipital region is activated with an attenuation of the frontal region. Attenuation of temporal-occipital region and activation of pre-frontal region are observed during eye-open relaxation mode. The dorsolateral prefrontal cortex (DLPFC) is the neural basis of the brain's central executive control function in most of the working memory models. It is one of the cortical association areas in the brain which has neural connections with all parts of cortex. Research has proven the activation of the DLPFC region while doing computational tasks. The function of the DLPFC is to summarize all information for activity planning, to coordinate cerebral motor cortex, and to control and accomplish complex tasks. The more information needed to retained and to processed in working memory, the higher the activities levels observed from DLPFC region will be [16]. Counting backwards is used as a simple and effective method for mental arithmetic in the former research [17] as computational tasks to activate DLPFC region.

We designed 4 mental tasks for the human subject to control genetic parameters, as listed in Table I, based on the EEG features and the brain functions explained above. The tasks are labelled as EC, EO, ECC and EOC.The corresponding genetic parameter changes are also shown. The computational task is to count backwards from 100 at a step of 3.

TABLE I
FOUR HUMAN MENTAL TASKS

Mode	Eye Status	Relaxation /Computation	Period (Sec.)	Parameters
EC	Closed	Relaxation	15	Increase Crossover Rate by 10%
EO	Open	Relaxation	15	Decrease Crossover Rate by 10%
ECC	Closed	Computation	15	Increase Mutation Rate by 2%
EOC	Open	Computation	15	Decrease Mutation Rate by 2%

Before leveraging these mental tasks for parameter control, EEG baseline information needs to be first collected from the targeted subject to overcome individual differences in EEG signals. We also designed 4 baseline tasks to be the same as the 4 control mental tasks with the same durations. The 4 baseline tasks should be performed thoroughly by the subject before the control session starts. The EEG signals collected from the 4 baseline tasks are processed to generate EEG signal patterns from each brain functional region to setup baselines for the control tasks.

D. EEG Signal Collection

The EEG signals are collected using a 19-channel EEG Nexus32 system. 21 electrodes (including 2 reference channels) are integrated in an EEG cap following the international 10-20 system. The recordings of the EEG signal are continuous during the baseline session and the control tasks. The recordings are sent to the cognitive model for EEG data processing once the baseline tasks or control tasks has completed. The data is sent as a 19-channel EEG data stream at the sample rate of 2048Hz.

E. EEG Signal Processing and Cognitive Model

Our designed cognitive model receives and processes the recorded EEG data stream after the subject completed each baseline or control mental task. The model is explained in this section.

First, in order to find the EEG voltage readings which represent the pure electrical activity at the targeted electrode positions on the scalp, the recorded EEG data stream, which is usually called the raw EEG data, needs to be re-referenced to obtain the relative measure between the targeted position and a reference position. We are using the common average referencing method to provide a dereferencing solution for

EEG data analysis, based on the assumption that the same electrical activities across all the sites spreading up the entire head could be considered as artifacts [18]. While we acknowledge that on a theoretical basis this referencing system is suitable for a large number of electrodes, our test demonstrate that it was adequate enough for our task. The common average reference is mathematically represented by subtracting the mean of recordings from all electrodes in each channel.

The EEG signal is then filtered into 8 frequency bands as in Table II by using spectral analysis. An FFT transformation is performed on the re-referenced EEG signals to change the time-domain signal into frequency domain using Equation 1. The relative EEG amplitude $A_{f'}$ and power $P_{f'}$ are also calculated by dividing those at the overall band as Equation 2 and 3. Note that the frequency bands of the signal below 1Hz and higher than 42Hz are filtered out. The process is specifically explained in Algorithm 1, in which amp is the absolute EEG amplitude, $Amplitude$ and $Power$ are relative amplitude and power, $DeltaAmp$ and $DeltaPower$ are relative amplitude and power in Delta band.

$$X[m] = \sum_{n=0}^{N-1} x[n] e^{\frac{-imn2\pi}{N}} \tag{1}$$

where, $m = 0, 1, ..., N-1$, $n = 0, 1, ..., N-1$, $x[n]$ is the n^{th} input sample, and $X[m]$ is the m^{th} harmonic.

$$A_{f'} = \frac{A_f}{\sum_{j=1}^{42} A_j} \tag{2}$$

$$P_{f'} = \frac{P_f}{\sum_{j=1}^{42} P_j} \tag{3}$$

where, $f = 1, 2, ..., 42$, A_f and A_j represent the absolute amplitude, P_f and P_j represent the absolute power.

TABLE II
THE 8 FREQUENCY BANDS OF THE EEG SIGNALS

EEG Bands	Frequencies(Hz)
Delta	1-4
Theta	4-8
Alpha	8-12
low Beta	12-15
Beta	13-21
High Beta	20-32
Gamma	38-42

EEG rhythmic activities can be classified within the bounds of each frequency band that has a particular biological significance. We chiefly focus on the theta/beta ratio (TBR) which has long been studied in the Neurofeedback domain as an indicator of the attention deficit hyperactivity disorder(ADHD) [19] and were used successfully in our research group for an air traffic control context [20], which manifests as hyperactivity and inattention. There is consensus that the elevation of absolute and relative theta activity, together with suppression of beta activity, are likely associated with ADHD [21]. However, for healthy task subjects who do not

Algorithm 1 FFT Implementation, the Calculation of Absolute and Relative EEG Amplitude and Power

$F \Leftarrow \frac{SamplingRate}{2}$
Initial an array: $amp[C][T][F]$ {C is the number of channels, T is the duration of the mental task}
Initial an array: $Amplitude[C][T][F]$
Initial an array: $Power[C][T][F]$
Get $realFFT$ and $imgFFT$ by Fast Fourier Transform with the input of EEG signals according to Equation 1
$amp \Leftarrow \sqrt{realFFT^2 + imgFFT^2}$
for each channel c of EEG channels C **do**
  for each second t of the task duration T **do**
    $sum \Leftarrow \sum_{f=1}^{42} amp[c][t][f]$
    for frequency $f = 1$ to F **do**
      {Normalize the amplitude calculated at each frequency by dividing amplitude at overall band}
      $Amplitude[c][t][f] \Leftarrow \frac{amp[c][t][f]}{sum}$
      $Power[c[t][f] \Leftarrow Amplitude[c][t][f] \times Amplitude[c][t][f]$
    end for
    Calculate amplitude for each EEG band according to Table II {e.g. $DeltaAmp[c][t] \Leftarrow \sum_{f=1}^{4} Amplitude[c][t][f]$}
    Calculate power for each EEG band according to Table II {e.g. $DeltaPower[c][t] \Leftarrow \sum_{f=1}^{4} Power[c][t][f]$}
  end for
end for

TABLE III
THE COGNITIVE MODEL

Indicators	Brain Functional Region	Electrodes' Positions in EEG Recording
Attention	Pre-frontal Cortex	Fp1 Fp2
Planning	Frontal Cortex	F7 F3 Fz F4 F8
Situation Awareness	Parietal Lobe	P3 Pz P4
Language	Wernicke's Area	T5 T6
Emotion	Limbic System	T3 T4
Visual	Occipital Lobe	O1 O2
Motor	Motor Cortex	C3 Cz C4
Flexibility	Precentral Gyrus, Central Sulcus and Postcentral Gyrus	Fz Cz Pz

have ADHD, the TBR value corresponds to high mental activities in the corresponding brain region. The TBR is calculated by dividing activities of the theta band and the beta band. EEG band activity is represented by band power, which is computed by accumulating power spectrum density within the given frequency range.

The cognitive model is constructed as the averaged TBR value calculated within the given time period in the particular brain functional region, which is shown in Table III. The implementation process is explained in Algorithm 2, in which TBR represents the theta/beta ratio.

The EEG Topographic heat maps - which show relative activity by regions of the brain - are computed based on the interpolation of EEG power calculated from each channel. We first present the topographic maps focused on the temporal changes. After detrending, we select topographic maps computed at 5 seconds, 10 seconds, 15 seconds and 20 seconds of each baseline task from one of the conducted experiments, as shown in Figure 3. The results in the figure show that during EC baseline, the visual cortex was shutdown as high power in O1 and O2 positions. During EO baseline, the power at O1 and O2 positions attenuated, while the frontal, prefrontal

Algorithm 2 TBR Model

for each channel c in channels **do**
    for each second t in the task duration of T **do**
        $TBR[c][t] \Leftarrow \frac{ThetaAmp[c][t]}{BetaAmp[c][t]}$
    end for
end for
{Calculate indicators according to the channel position showing in Table III}
$Attention \Leftarrow \sum_{t=1}^{T}(TBR[Fp1][t] + TBR[Fp2][t])/2$
$Planning \Leftarrow \sum_{t=1}^{T}(TBR[F7][t] + TBR[F3][t] + TBR[Fz][t])$
$\quad + \sum_{t=1}^{T}(TBR[F4][t] + TBR[F8][t])/5$
$SA \Leftarrow \sum_{t=1}^{T}(TBR[P3][t] + TBR[Pz][t] + TBR[P4][t]))/3$
$Language \Leftarrow \sum_{t=1}^{T}(TBR[T5][t] + TBR[T6][t])/2$
$Emotion \Leftarrow \sum_{t=1}^{T}(TBR[T3][t] + TBR[T4][t])/2$
$Visual \Leftarrow \sum_{t=1}^{T}(TBR[O1][t] + TBR[O2][t])/2$
$Motor \Leftarrow \sum_{t=1}^{T}(TBR[C3][t] + TBR[Cz][t] + TBR[C4][t])/3$
$Flexibility \Leftarrow \sum_{t=1}^{T}(TBR[Fz][t] + TBR[Cz][t] + TBR[Pz][t])/3$

cortex and parietal lobe (which is associated with attention, planing and situation awareness) began to activate. During ECC baseline, the activation of the frontal cortex was not as much as what we see during EO and EOC baseline, also the visual cortex was activated, but not as strong as in EC baseline. Finally during EOC baseline, the mainly activated areas were pre-frontal and frontal cortex, which indicates high engagement and planning. The results show that the four cognitive tasks are differentiable on the basis of the extracted features.

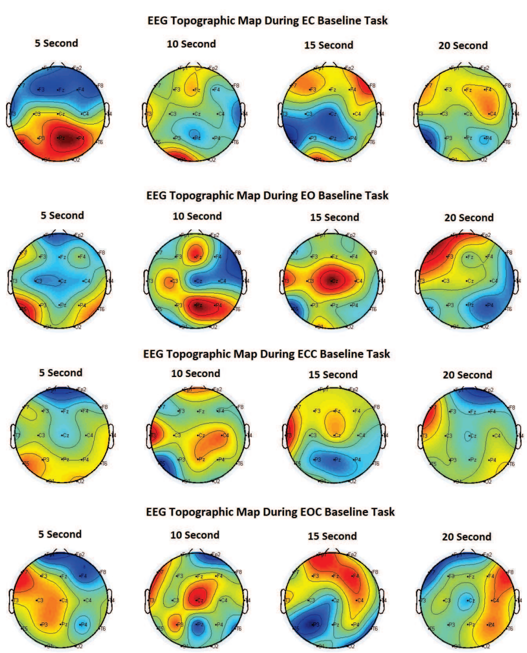

Fig. 3. EEG Topographic Maps Computed on 4 Baseline Tasks

The topographic maps of power at each frequency band are also shown in Figure 4, which are calculated by averaging the EEG power in the frequency bands across the duration of the tasks. The color map is scaled to the data range of each topographic map. The first column shows the total EEG power from 1 to 42Hz. The Delta and Theta Band power are attenuated during eye closed tasks (EC and ECC). During EC task, the visual cortex was activated as high power at O1 and O2 from Alpha to Gamma Bands. During ECC task, the visual cortex was activated as what happened at the EC task, and frontal cortex was also activated as an indicator of the attention and planning during computational tasks. During the eye open tasks (EO and EOC), the EEG power were showing more slow-wave activities compared to eye close tasks, and higher EEG power at frontal cortex was shown during EOC task compared to EO task, which is in accordance with eye close tasks.

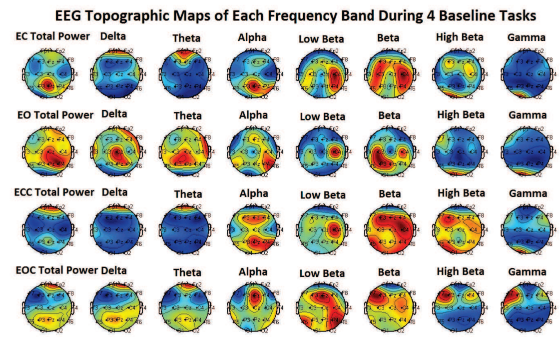

Fig. 4. EEG Topographic Maps During 4 Baseline Tasks

F. Parameter Control

The Euclidean distances of features between a control task and a baseline mode is calculated and then the minimum is found, which shows the maximum similarity between these two tasks. The mental state during the control task is classified the same as the baseline task with the minimum distance. The distance coefficients are calculated as Equation 4 for each baseline task.

$$D_{M,T} = \sum_{b=1}^{8} \sqrt{(I_b - B_{M,b})^2} \tag{4}$$

where, $D_{M,T}$ is the distance coefficient between a mental task T and a given base line of mode M, I_b is the task indicator of band b, and $B_{M,b}$ is the baseline of band b in mode M, as listed in Table I.

III. EXPERIMENTAL DESIGN

A. Experiment Protocol

The experiments are conducted on a voluntary basis, with each participant completing their experiment, before another begins. A background knowledge of genetic algorithms and parameter control are needed for the participants to take part in this experiment.

Before the experiment starts, the researcher briefs each participant on the procedure of the experiment, the baseline tasks and the control tasks. The participant will be given a printed table from the researcher during this stage which shows the relationship between mental tasks and the parameter control results as in the table I, so that he or she does not need to memorize. The EEG sensor setup will be done after the subject briefing. The baseline session would be started if the EEG signal quality is satisfactory after sensor set up.

The baseline session consists of 4 baseline tasks (EC, EO, ECC, and EOC) which need to be performed one by one in sequence. The participant was required to be fully focused on the tasks during this stage. 20 seconds EEG recording were taken from the participant doing each baseline tasks, with 5 seconds for stabilization and 15 seconds used for input to calculate features by cognitive model. The EEG recordings during warm up period is preserved but not calculated. The researcher monitors the process and notifies the participant of which task needs to be performed, the duration and the end of each baseline task. This session takes 2 minutes.

After going through all 4 baseline tasks, the main session starts. The participant is required to observe a test problem with unknown functions but its global maximum position is shown on the screen. After identifying the problem, the GA starts with the generation of an initial population and the first 10 generations by the default crossover and mutation rate. The resulting values are plotted on the screen as colored dots on the contour map of the task problem. The fitness function is also shown on the screen to help the participant to evaluate the problem.

After each 10 generations, the GA stops for the participant to decide if the genetic parameters needs to be changed (increase or decrease). The participant needs to first observe the current state of the problem solving process, evaluate the problem, make a decision (change the parameter or not, which parameter to change, increase or decrease), refer to the corresponding mental control task, clear their mind and relax for 20 seconds, and then start the selected control task for 20 seconds. The researcher will inform the participant of the procedure above during this stage. If the participant decides not to change any parameters, both the relaxation and the control tasks stage would be skipped.

The control tasks are processed as the same as the baseline tasks - the system takes a 20 second EEG recording, also identifies the first 5 seconds as warm up and the next 15 seconds to obtain features in real-time from our cognitive model. The features derived are then compared with the baseline features using similarity metrics, a control decision is made, the genetic parameter of GA is changed accordingly, and the results of the following 10 generations generated under the changed parameters are shown on the screen for the participant to evaluate. If the participant decides not to change any parameters and the above control task stage has been skipped, the GA will take the former parameters and generate 10 generations under the former designated parameter value. The system will be operated in real-time exactly after the participant has finished the control task stage and the EEG recordings have been received.

Once the results of the following 10 generations have been shown, the participant can repeat the process of observe, evaluate, decide, relax and then start of the control tasks. This process could be repeated as many times as needed. In this experiment, we repeat this process 9 times, resulting in a total of 100 generations (the first 10 generations are generated on default value of parameters).

B. Test Problem

We chose a single-objective function as the test problem. The function uses sin to create several local maximum and a global maximum. The definition of the fitness function is described in Equation 5. And the landscape of the fitness is shown in Figure 5.

$$\begin{gathered} f(x,y) = (15xy(1-x)(1-y)\sin(3\pi x)\sin(3\pi y))^2 \\ x \in [0,1], y \in [0,1] \end{gathered} \tag{5}$$

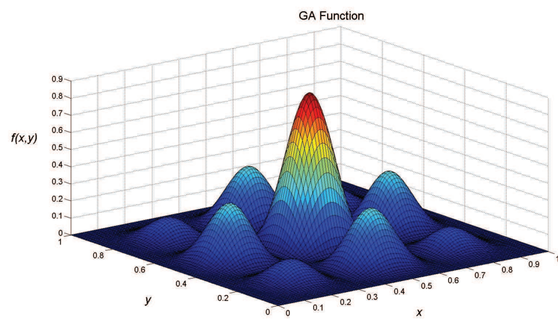

Fig. 5. Experiment Protocol

There are four local optima surrounding the global maximum ($f = 0.8789$) at point [0.5, 0.5]. It is a suitable example function in order to investigate the balance between exploration and exploitation in GA by changing parameters.

Figure 6 shows the results of GA evolutions with a fixed seed but different crossover and mutation rates. As shown in the figure, when the mutation rate is low (0.01), the solutions are stuck at the local optimal.

C. Experiment Setup and Procedure

The experiment was conducted by strictly applying the experiment protocol. The first author participated in the experiment as the subject, and the experimental procedure was controlled by the second author.

The experiment conducted consisted of about 45-minute test procedure. During the experiment, the subject was required to remain seated on a comfortable chair in a closed, bright, and quiet lab environment. The EEG signal was captured using the Nexus-32 EEG system produced by the Mind Media.

IV. RESULTS AND DISCUSSION

In our experiment, we have run the GA functions 10 times, with each function including 100 generations and 9 parameter control mental tasks. The first 10 generations were generated by the default crossover and mutation rate set before the experiment(Crossover Rate (CR) =0.6, the Mutation Rate (MR)=0.01). The mental tasks were performed at the step of 10 generations. The subject did not use the skip function during the experiment. Therefore, a total of 90 mental tasks (10 runs

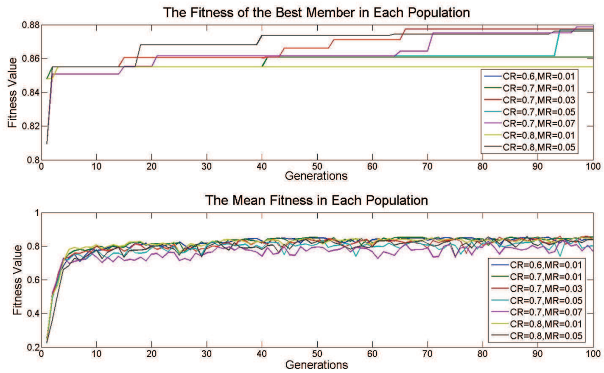

Fig. 6. Fitness Values of the Genetic Algorithm Populations, under EEG Controlled Parameters

TABLE IV
EXPERIMENTAL RESULTS

Tasks	Number	Accuracy	Numbers of Mapped Tasks			
			EC	EO	ECC	EOC
EC	22	81.82%	18	3	1	0
EO	22	77.27%	3	17	2	0
ECC	24	66.67%	3	4	16	1
EOC	22	95.45%	0	0	1	21
Total	90	82.22%				

by 9 opportunities per run to alter a parameter) were processed and identified, and the results are shown in Table IV.

One of the GA processes is shown in Figure 7 and Table V. In this example, the identification of control mental tasks was performed with 100% accuracy.

TABLE V
THE MENTAL TASKS AND CONTROL ACTIONS

Sequence	Mental Tasks	Control Actions	Parameter Values after Operation
0	Initialize	Default	CR=0.6 MR=0.01
1	EO	Increase CR by 0.1	CR=0.7 MR=0.01
2	EO	Increase CR by 0.1	CR=0.8 MR=0.01
3	EO	Increase CR by 0.1	CR=0.9 MR=0.01
4	EC	Decrease CR by 0.1	CR=0.8 MR=0.01
5	EOC	Increase MR by 0.02	CR=0.8 MR=0.03
6	EOC	Increase MR by 0.02	CR=0.8 MR=0.05
7	EOC	Increase MR by 0.02	CR=0.8 MR=0.07
8	ECC	Decrease MR by 0.02	CR=0.8 MR=0.05
9	EO	Increase CR by 0.1	CR=0.9 MR=0.05

The member values (x,y) for the test problem from generation 1 to 100 are shown in Figure 8. The global optimal is at (0.5,0.5) and the color of the scatter map is drawn based on the fitness value of each member in the population. The member values are drawn at the step of 10 generations after each mental task. The figure shows a convergent result for our EEG-based interactive GA system.

As in the example, the test problem is a single-objective easy function, so the best, mean and median fitness increased quickly during the first 10 generations under the default value CR=0.6, MR=0.01. The CR value increased up to 0.9

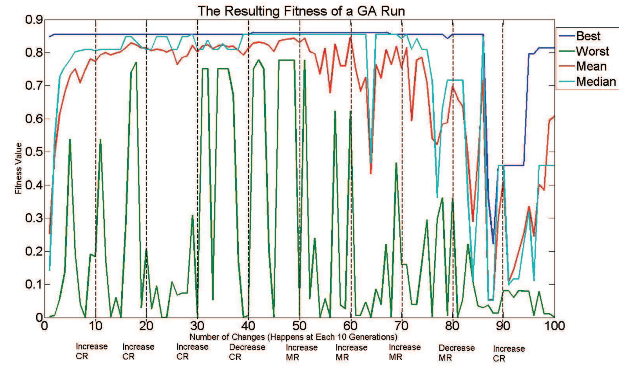

Fig. 7. The Best, Worst, Mean and Median Fitness Value With On-line EEG-based Parameter Control.

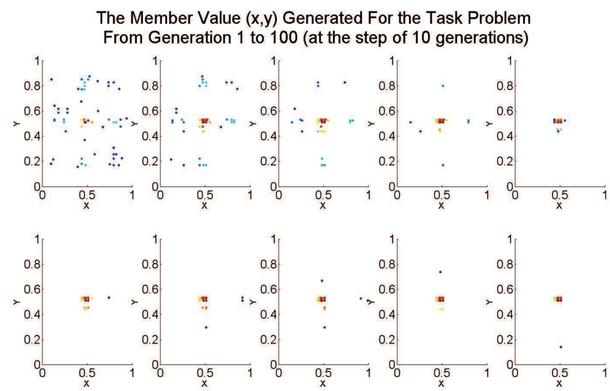

Fig. 8. The Member Values for the Test Problem

to generate the next 30 generations, and the fitness value increased steadily to try to reach the global maximum 0.8789. After 50 generations, the median fitness was close to the maximum. The increase of MR in the following stages added more variations to the population, so that the mean and median fitness value of each population generally decreased until the MR decreased at the end of 80 generations. There were sharp decreases of all the best, mean and median fitness values from generation 80 to 90 after the mutation rate decreased. That was probably because after the global maximum was almost reached, the mutation process in the population deteriorated the results. After increasing the CR at the end, the fitness value started to increase again.

All experiment results with mental task parameter control are shown in Table IV. The overall identification accuracy of the 90 control mental tasks is 82.22%, with 74 of them correctly identified by the system developed. Among these, the EOC task has the best identification rate (95.45%), which is probably because during the performance of EOC task, most of the brain areas are activated especially the pre-frontal and frontal cortex. The resulting action, planning and situation awareness indicators have significantly higher values than those computed during EC, EO and ECC tasks. In contrast, the ECC task has the worst identification rate of 66.67%, with the mis-identified (confusion) result falling into all the other three categories. There are probably 2 reasons that lead to this results: 1) the ECC task (counting backwards in steps of 3 during eye closed) is hard to control for both the researcher and the participant. For the research it is hard to identify from observation if the participant is faithfully doing the computational tasks or not. And the participant may find it hard to focus when their eyes are closed; 2) The ECC task is hard to classify especially when using the indicator of attention, since the participant is both mentally engaged in computational tasks as well relaxed because of the eyes being closed.

To obtain a better identification rate, one of possible improvement of the methodology is to perform a thorough study on the most appropriate duration of the mental tasks, and the ratio of the warm-up stage to the EEG recording stage. A longer time duration of EEG recording during mental tasks will likely provide more robust results. Further obtaining more than one baseline sample of each task would likely lead to an improvement. Similarly, more sophisticated classification algorithms (than Euclidean distance to a single reference sample) could be used. This is one area that will receive work in the coming year.

V. CONCLUSION

This paper focused on developing the new concept of an EEG based interactive genetic algorithm. To sum up, we have first presented the framework of our system is based on, but not limit to, the current progress in both brain-computer interaction and evolutionary computation. The system has been implemented and a thorough experimental protocol has been designed to conduct the experiment. A preliminary experiment has been conducted and the classification accuracy is satisfactory. This shows the effectiveness of the concept and the implemented system.

We will be doing more experiments to prove the effectiveness of our system with detailed discussions for our future research. Further, the EEG signals that has been collected during the experiments will be used for detailed off-line studies.

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