EEuGene: Employing Electroencephalograph Signals in the Rating Strategy of a Hardware-Based Interactive Genetic Algorithm

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Abstract We describe a novel interface and development platform for an interactive Genetic Algorithm (iGA) that uses Electroencephalograph (EEG) signals as an indication of fitness for selection for successive generations. A gaming headset was used to generate EEG readings corresponding to attention and meditation states from a single electrode. These were communicated via Bluetooth to an embedded iGA implemented on the Arduino platform. The readings were taken to measure subjects' responses to predetermined short sequences of synthesised sound, although the technique could be applied any appropriate problem domain. The prototype provided sufficient evidence to indicate that use of the technology in this context is viable. However, the approach taken was limited by the technical characteristics of the equipment used and only provides proof of concept at this stage. We discuss some of the limitations of using biofeedback systems and suggest possible improvements that might be made with more sophisticated EEG sensors and other biofeedback mechanisms.

1 Introduction

Genetic Algorithms (GAs) are a well-established evolutionary computing approach to problem-solving, whereby a set of candidate solutions is generated, individually evaluated for fitness (proximity to a desired outcome) by an evaluation function and then used to generate a new set of potential solutions using techniques analogous to natural genetics, this process being repeated until a candidate meets the desired criteria. Interactive Genetic Algorithms (iGAs) are a variation of this, in which the evaluation function is replaced by the conscious decisions of a human user. We have developed this concept further, using biofeedback in the

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form of EEG signals to make these human decisions subconscious. The chosen domain for initial proof of concept was that of music synthesis, where the evaluation of short sequences of notes where the parameters of the sound used was generated by the iGA over successive generations, with rating of the sounds carried out by taking EEG measurements from subjects. The aim was to identify if the sounds generated converged on sounds that were "liked" by the subjects. Using an EEG approach to rate responses could be used in other domains such as image synthesis.

2 Background and related work

2.1 Genetic Algorithms

Genetic algorithms [1] are a category of evolutionary algorithm used in optimisation and search strategies, which loosely parallel Darwinian evolutionary theory. The GA process begins with an initial population of solutions, each of which is represented by the values of a given set of variables. In a traditional GA, a fitness function is then used to rate each individual on a scale according to the closeness of its characteristics to those of the desired outcome. In an iGA [2] the fitness function is the user, who similarly rates the individual solutions on the appropriate scale. In both the GA and the iGA, this rating is proportional to the probability of the individual being chosen as a parent for the next generation. Pairs of parents contribute variables (genes) to the new population, using a crossover. A mutation factor may be used to introduce some further random changes into the new population. This process is repeated until it converges to a solution that, in the opinion of the user, represents a desirable final state. Naturally, the number of individuals in a given generation for an iGA will be lower than that for a GA, as a human evaluator will be subject to such factors as the time it takes to observe or listen to the stimuli and also to fatigue, which are not an issue for the GA evaluation function.

It may be argued that, unless the solution space of an iGA is appropriately mapped to the cognitive space, users are not effectively supported by the system in terms of making good choices [3]. It is also difficult to measure the usefulness and usability of iGAs as tools without evaluating them on the basis of whether they reach a defined goal. It is possible to have fuzzy goals, where the user explores the solution space until they find a candidate that they find acceptable. This is an approach often taken in evaluating iGAs, but it is less rigorous than a goal-based approach [4] Furthermore, as Bauerly [5] points out, there is an assumption that users are consistent in their assignation of ratings across multiple generations, but we cannot be sure of the impact of user concentration changes and fatigue on the consistency of their judgement.

These possible inconsistencies in the behaviour of human evaluators seem to be a disadvantage of iGAs when compared to the traditional GA. However, there are some problems for which it is difficult to formalise the evaluation process. These might include evaluating the artistic merit of machine-generated images or sounds [7, 8, 9], the quality of music [10] or the stylishness of a machine-generated dress or suit design. Such evaluations require the judgement of a human being. Of course, these judgements are always going to be subjective to some degree, and to design a dress that will appeal to a large section of the population, it might be necessary to combine the opinions of a number of human individuals in generating each rating. This approach has been taken by Biles with 'GenJam Populi'. [11] The point is that, as long as the judgements are accurate enough to facilitate the required convergence, absolute precision is not required.

2.2 Biofeedback

The idea of using Electroencephalograph (EEG) data as a means of interfacing to a computer system is not a new one. Applications have included gaming, enabling technologies, and emotional response to valence and cognitive workload recognition. Brain Computer Interfaces (BCIs) are often problematic in practice. For example, in an application where a BCI is used by a subject to actively control a system, it can be difficult to identify when a signal is supposed to be associated with the system under control, and when it has been generated by some unrelated mental activity of the user. There is therefore a requirement for the users themselves to learn how to use such systems properly. Evidence suggests that not all users can be trained [12].

Bradley et al [13] exposed subjects to images for six seconds while gathering data using a range of biofeedback readings such as skin resistance and Electromyographic measurement. Similar work by Franzidis et al [14] only allowed a 1 second exposure, with 1.5 second breaks between images, while collecting EEG readings. Clearly, exposure times and choice of reading technique are parameters that must be optimised by experimentation. Franzidis's work [14] also explores the day-to-day variation in neurophysiological responses to the same stimulus and considers neurophysiological profiles.

There has been a substantial amount of work exploring more general biofeedback approaches for managing stress and relaxation, although these will not be explored here. There has also been a significant amount of work on the use of neural networks to identify emotions from EEG signals, when giving subjects specific stimuli. For example, Murragapen et al [15] took this approach and found a 10.01% improvement with an audiovisual stimulus over a visual stimulus alone.

One of the difficulties with more complex EEG systems is setting them up, as they may have in excess of 100 electrodes. However, simpler EEG systems can still be effective. For example, Lee and Tan [16] claimed a 93.1% accuracy in distinguishing between which of two tasks were being carried out, using a relatively low cost EEG setup.

There has been an increased use of EEG signals from gaming headsets [17] in the research community. These are often easy to configure and almost all of the signal processing is carried out onboard using proprietary Integrated Circuits, in the case of the Neurosky MindWave Mobile it is a Think Gear ASIC Module. This is responsible for noise filtering (in particular from muscular and skeletal movement signals and power cable interference). These headsets are often supplied with development kits that facilitate using the EEG data in custom applications or research [18]. The associated games are often limited to simple activities that rely on the user being able to focus or relax. One research application of such technologies is the measurement of cognitive workload and attention [19, 20]. Cernea et al [21] and Moseley [22] used gaming headsets to measure emotional states/facial expressions and to induce specific user target states (i.e. meditative) respectively. We chose to use such a device to measure users' subconscious reactions in response to sound sequences, mapping these to quantified evaluations of the candidate solutions in an iGA. This represents a kind of 'halfway house' between a pure GA and an iGA; there is user interaction, but it is not consciously carried out.

3 Methodology

The Eugene system, described in [3] and shown in Fig.1, is an Arduino based hardware controller with MIDI output, allowing the preview and rating of six individual candidate solutions in any given generation of an iGA using slider potentiometers set by the user.

Fig. 1. The original Eugene interface with 6 sliders for rating [3]

The system has been adapted so that the data previously taken from the conversion of the potentiometers' voltage output is now taken from an EEG reading. The MIDI output (31250 baud) now utilises the Software Serial library and pin 11 of the Arduino, which is necessary because the Bluetooth board uses the transmit and receive pins. One advantage of this is that when updating code, the MIDI adaptor does not have to be disconnected. The six button switches in the original Eugene are also no longer required, as the sounds are played automatically after a successful EEG reading, rather than under user control. A design decision was made to keep the population to six individuals, as too many individuals might lead to user fatigue. The hardware used included a Neurosky MindWave mobile [17] EEG headset, with a single dry electrode. The on-board processing circuit outputs values over a Bluetooth data stream (57,600 baud). A BlueSmirf Gold [23] Bluetooth transceiver board was used to receive the signal from the Mindwave. The BlueSmirf uses the RX pin on the Arduino Uno. The signals that can be obtained from the Mindwave include an attention and meditation signal, which are parsed by the Arduino.

The initial experiments were based on simple observation of the EEG signals captured when the users were listening to music that they "liked". A pilot study then explored how the development platform behaved and if the output of the iGA was converging. Finally a smaller experiment was carried out to identify if the output converged on sounds that were "liked" by the subjects in the context of the given musical sequence.

We recorded at the attention and meditation signals of 20 subjects listening to music they "liked".

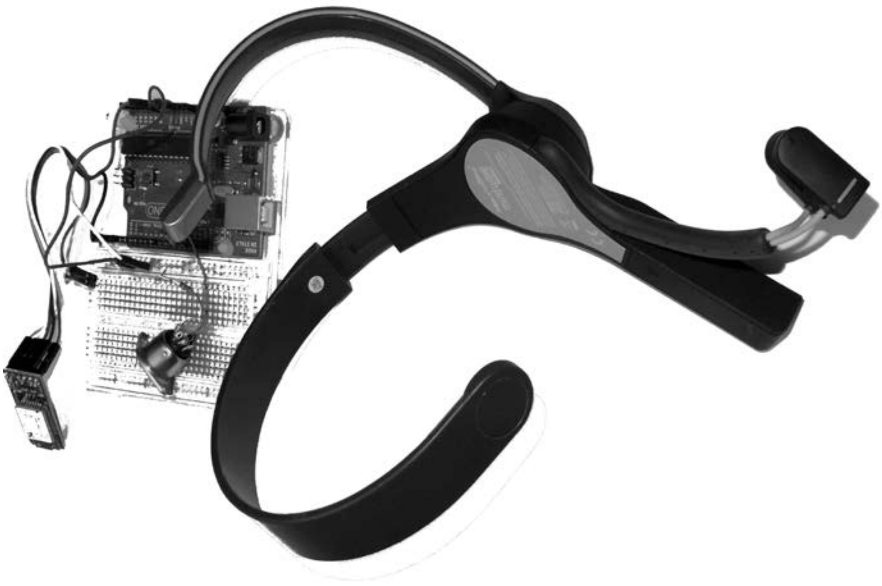

Fig. 2. The equipment used, Arduino, Bluesmirf and Mindwave.

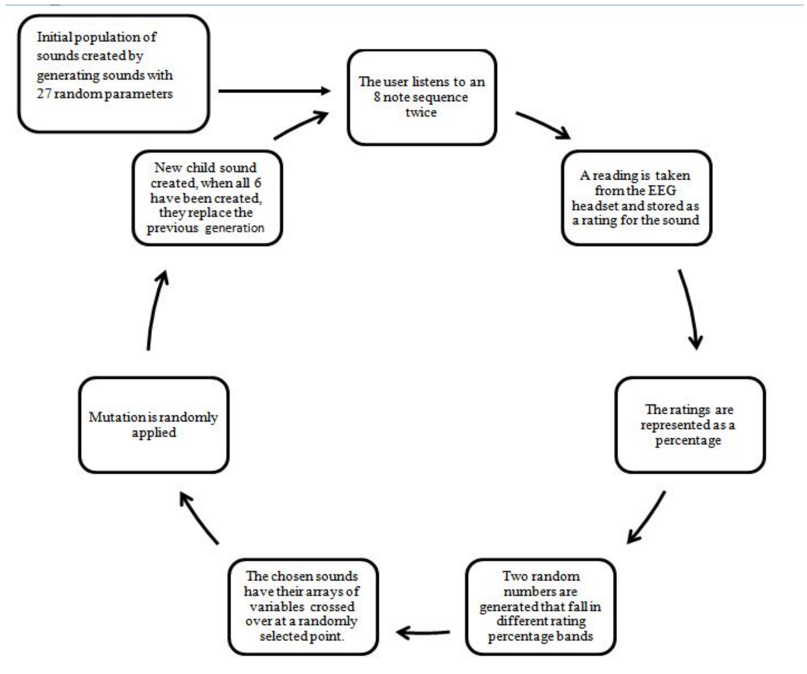

Fig. 3. The iGA process in the context of this work

We found that for 19 of them, the levels of both of these signals increased and the levels of both fell when the subjects listened to music they did not like. The sum of these two signals was then chosen to rate the sounds. Alternative possible strategies are considered in the discussion below, but these require further evaluation.

The initial population of sounds is generated randomly and selection of the parent sounds in each generation is by means of a roulette approach based on the sum of the two EEG ratings as stated above. In the original Eugene controller elitism was used to keep the best sounds for the next generation, this has not been adopted here.

For each sound, 27 MIDI Continuous Controller (CC) values (genes) are assigned to the values of parameters that control a simple two-oscillator software synthesiser built in SynthEdit [24]. These parameters included attack, sustain, decay and release for two envelope generators, filter parameters of cut-off frequency and resonance, choice of oscillator waveforms and modulation parameters. The CC numbers used were from 5 to 28. SynthEdit is flexible in the mapping of CC values to the synthesiser parameters and also in the range of each parameter.

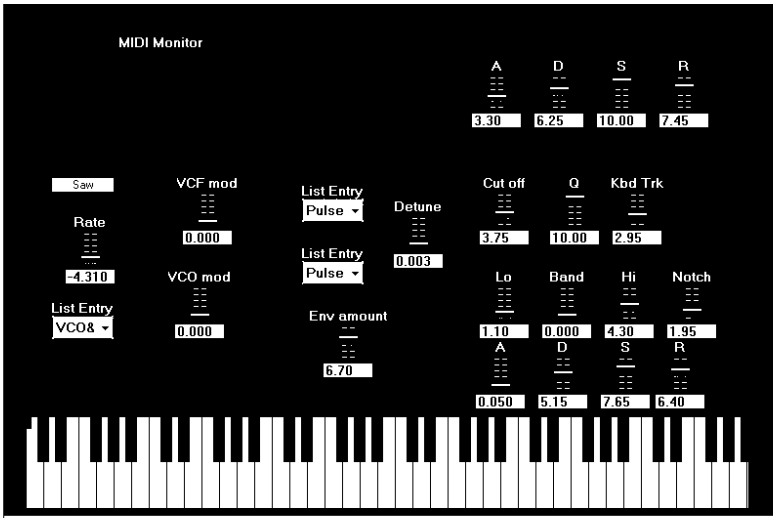

Fig. 4. The software synthesiser used

4 Pilot Study

A pilot study was conducted with two subjects, in which an 8 note sequence (C2, D#2, F2, G3, A#2, C3, D3) was repeated 4 times and the EEG data was read at the end of the sequence. It was possible to monitor the EEG data from the headset using the Arduino Serial Monitor. Although care had to be taken to ensure that the Serial Monitor was running at the start of the process as launching it caused the iGA process to start from the beginning.

A number of issues were identified:

- The sequence should only be repeated once or twice to reduce the time between generations and the effect of user fatigue, as the entire process of reviewing each generation was taking too long (over 30 seconds).
- The MindWave headset and headphones (for listening to the sounds) were not very comfortable to wear together, but in-ear headphones were not considered suitable to be shared by users.
- A warning needed to be generated when the signal quality was low, which happened occasionally (especially when headphones were adjusted) and interfered with the results.
- When a sound was very quiet or indeed inaudible, the EEG readings were no longer related to the sound, but were still used by the iGA in rating, this led to poor convergence.
- Some of the initial populations sounded similar and users did not think afterwards that there was much to choose between them.

The pilot study did not produce data about generating sound the user might like, but did identify a number of issues with the setup of the experiment.

5 Experiment

Following the pilot study, the following changes were made:

- The sequence was only repeated twice before an EEG reading was taken.
- Smaller headphones were used that provided more comfort when the two headsets were used together.
- An LED indicator was programmed to respond to any loss of signal quality. Tests ascertained that the Bluetooth connection was very reliable and that any loss of signal was normally the result of movement of the electrode. Dampening (not wetting) of the forehead with water increased the reliability of the headset.
- The mutation rate was set in software to 2%, which is high, but seemed to allow better exploration of the solution space.
- The MIDI CC values could be restricted in their ranges, but this would increase the setup time and require uploading of the sketch (program) to the Arduino, every time there was a change. Using SynthEdit, it was possible to adjust the range of the parameters and mapping to CC values and this allowed many of

those parameter interactions that produced no, or very low level audio output to be removed from the solution space. The remapped parameters were:

- Amplifier Attack
- Amplifier Sustain
- Filter Attack
- Filter Sustain
- Filter Cutoff Frequency
- Keyboard Filter Tracking

The experiment looked to identify if there was any convergence to a sound that was "liked" by the subject, in the context of the musical sequence of notes.

Three subjects took part in the test and each ran the controller three times. The subjects had no identified hearing difficulties. The results converged differently for each subject, with two of the subjects converging on variations of white noise based sounds in one of their trials. Monitoring indicated that this sound was producing a high meditation state reading from the subject, leading to a higher probability of selection. The subjects felt that the output after 5 to 7 generations had led to possibly viable solutions that they "liked", but not necessarily optimal ones. However, this was an improvement on the pilot study. Observation of the MIDI data and EEG readings showed that the iGA was working properly. Users also felt that this was a fairly time-consuming exercise, which was an interesting perception as the tests were only running for about 5 minutes for each.

6 Discussion

Interactive Genetic Algorithms traditionally ask the user to consciously rate each of the candidate solutions in each generation, and these ratings are used in the selection of parents for the next generation. Our approach involves the measurement of a subconscious response, which does not require any active decision making by the subjects. However, the results may be affected by the impact of the environment on the user; this was found to be the case when very low levels of sound, or no sound, were produced by the synthesiser. It might be reasoned that, because the data from the user is subconscious, it is not subject to distortion by factors such as the user second-guessing what those conducting the experiment might be expecting. However, the results can be manipulated by a user consciously choosing to relax or focus or by the user being distracted. A good example is counting backwards; this type of activity will distort the results obtained. A possible way to reduce distractions would be to conduct the experiments in a darkened room. A user's view on what may be a good output may change over time (even as the iGA is running) and possibly as they become aware of the solution space, we do not know the extent of this or its possible effect on the results.

The choice of notes in the sequence and the tempo would also have an impact on the results and users' choice of sounds. It is possible to make these into variables as part of the gene sequence or even as a second gene, but this would have significantly added to the complexity of the evaluation. Given that with some existing research, using very short exposure to stimuli before taking EEG readings, it might be possible to only use a 4-note sequence played once, which would speed up the process and produce results more quickly.

The strategy of adding together the meditation and attention signals was based on limited observation and the results, whilst improving the sound by removing sounds that did not suit the sequence or were unmusical, did not always converge to values that the users considered to be optimal, although they did generally converge to more desirable sounds. It seems that better algorithms for ascertaining rating values might be required. It is possible that some of the gaming headsets with more electrodes would perform better, as these have been used in other research successfully. When using gaming headsets, we are dependent on trusting the manufacturers' signal processing techniques and their software, but the loss of control over these things is offset by the gains in terms of portability, user acceptability and low project costs.

One of the issues identified by many researchers in the iGA area is that of user fatigue. The use of EEG and other biofeedback may provide some insights into this. More accurate rating systems will also allow us to explore the differences between conscious and subconscious rating, by capturing the EEG ranking and comparing it to conscious ratings using sliders.

The Arduino platform has limitations in terms of processing power, memory and speed, but these factors are not significant in this application. The Arduino also has the ability to connect to a wide range of low cost analogue and digital sensors, thus allowing other biofeedback rating strategies to be evaluated.

7 Conclusion

We have presented a novel approach using EEG signals for rating candidate solutions in an interactive Genetic Algorithm. This approach is highly appropriate for problem domains that are difficult to evaluate using a goal-based approach, due to the subjective nature of the evaluation. Our work so far has been with sound, but we have previously applied iGAs to visual media and the use of biofeedback data would be equally valid for this or indeed for any problem where the evaluation relies on the users' subjective satisfaction with the output.

The platform was developed from our original Eugene hardware-based iGA system [3], augmented with the necessary hardware and software necessary to capture and process the relevant EEG signals. The experiments conducted with this platform have established proof-of-concept for this system. This will also enable further research and we have suggested possible future directions for that research, including more sophisticated EEG capture and other biofeedback mechanisms. Our choice of using the sum of meditative and attention EEG signals to drive our evaluation was justified above, but nevertheless, experiments with more robust and tested signal processing algorithms and richer EEG data might produce a more optimal system, notwithstanding the extra costs in time and money associated with more sophisticated EEG capture. While the research has many limitations, it does enable us to explore the ways in which humans can interact with evolutionary systems and will hopefully lead to further useful insights in this area.

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