Mindfulness Mirror

C James-Reynolds [0000-1111-2222-3333] and Ed Currie [1111-2222-3333-4444]

[1] Middlesex University
[2] Middlesex University
C.James-Reynolds@mdx.ac.uk

Abstract. This paper explores the use of an interactive Genetic Algorithm for creating a piece of visual art intended to assist in promoting the state of mindfulness. This is determined by a Bluetooth gaming electroencephalography (EEG) headset as the fitness function. The visual display consisted of an infinity mirror with over two hundred Neopixels with fade times and colour of zones controlled by two Arduinos running the software. Whilst we have observed some convergence of solutions, the results and user observations raised some interesting questions about how this strategy might be improved.

Keywords: Interactive Genetic Algorithm, Mindfulness, Electroencephelograph.

1 Introduction

This paper describes the development of a piece of interactive art, driven by an interactive genetic algorithm (iGA) powered by the user's subconscious degree of mindfulness as measured by the nature of their brain activity. The purpose was threefold; to produce an interesting piece of art, to explore the extent to which the genetic algorithm converged on any 'optimum' states and to ascertain whether there could be other applications for this or related systems, for example in a therapeutic context.

2 Genetic Algorithms

Genetic Algorithms (GAs) are a specific type of evolutionary algorithm that provide solutions to search and optimization problems through the use of a biologically inspired approach akin to Darwinian evolutionary theory. They were first popularised by John Henry Holland [1] and later developed by David Goldberg [2].

Genetic Algorithms operate by the encoding of an individual's relevant characteristics to represent their genetic makeup. The structure is analogous to a biological chromosome and the attributes correspond to individual genes. The algorithm proceeds by creating an initial population of such structures, each of which represents a potential solution.

These individuals are evaluated using a fitness function and assigned a probability of becoming a parent in proportion to their assigned rating. Those individuals whose characteristics are closest to the desired outcome are the most likely to become the parents of the next generation.

Pairs of parents are selected according to these probabilities and combined to create a population of new individuals. A common algorithm for this combining of parents' genes is crossover, in which each member of the next generation "inherits" variables from each of the two randomly chosen parents. The crossover points are typically randomly selected [3]. Another possible algorithm is co-dominance, in which typically a gene at a given position in the chromosome of the offspring is derived from some kind of averaging of the genes at the corresponding position in each of the parents [4]. This may be applicable where combining the genes of two strong candidate individuals produces a strong offspring.

The strategy adopted in the current work for the choice of parents is the so-called 'roulette wheel' approach [5], whereby each potential parent is assigned a sector of a circle, subtending an angle proportional to that individual's fitness rating. [6] The spinning of the roulette wheel is then simulated, and parents are chosen for breeding according to the ball's position. Alternative selection techniques are discussed in [7].

When the new generation has been created, a small probability of mutation may be introduced whereby the values of some characteristics of some individuals may be changed randomly. [3] The choice of mutation rate is important, because if it is too low, the GA might converge on local, but not optimum, maxima and if it is too high, the GA might not converge at all.

This process repeats, creating successive generations of individuals, and typically ends when an individual is generated that scores higher than some pre-agreed value of the fitness function, or an agreed number of generations have been created.

3 Interactive Genetic Algorithms

An interactive Genetic Algorithm (iGA), as used in our project, proceeds in the same manner as a conventional GA, except that it employs human judgement of the generated individuals as the fitness function. The concept is appropriate where evaluation of individuals is difficult to automate; for example where quality is a matter of aesthetic judgement. Early work on iGAs is described in [8].

The initial population size of an iGA should be large enough to enable effective exploration of the solution space, but not be too large, as this can introduce user fatigue. The deficiencies of smaller population sizes may be compensated for by strategies such as seeding [9] and increasing the mutation rate. The relationship between mutation, crossover and selection are explored in [6]. We adopted a single, randomly chosen crossover point in the current work.

4 Mindfulness

The idea of Mindfulness is derived from Buddhist doctrine, but has been redefined by psychologists in a number of ways. Ryan M. Niemiec presents three different definitions, but favours the following: “Mindfulness is the self-regulation of attention with an attitude of curiosity, openness, and acceptance.” [10].

The Mental Health Foundation website [11] defines mindfulness as “…an integrative, mind-body based approach that helps people to manage their thoughts and feelings and mental health. It is becoming widely used in a range of contexts. It is recommended by NICE (National Institute for Health and Care Excellence) as a preventative practice for people with experience of recurrent depression.”

Mindfulness is now a recognised strategy for helping people to maintain good mental health. With this in mind, it is interesting that there appears to be no universal definition of the term [12].

A review of the neurophysiology of mindfulness concluded that a "co-presence of elevated alpha and theta may signify a state of relaxed alertness which is conducive to mental health" [13]. We therefore chose to adopt this in our work.

5 Bio Feedback and human issues

Bio feedback uses the principle that knowledge about the state of one's body allows the user to learn how to control that state. Informal observations on approximately 1000 people at the New Scientist Live Show [14] and other events indicated that the ability to achieve a state of mindfulness was enhanced by training in a martial art or meditation. In previous work using a simple infinity mirror (without an iGA), indicating meditation state by a change of colour, we found that when subjects became aware of reaching a state of mindfulness, this awareness often then interrupted that state. This also manifested in an experiment with an adapted Scalextric car racing set controlled by a Neurosky MindWave headset [15], whereby achieving the mindful state would cause a car to move. Users would lose focus when the car started moving and it would come to a halt. There are existing apps to assist in developing a mindful state, however, the use of a screen has also been shown to disrupt attention and have an impact on EEG signals [16]. For the infinity mirror project, the user did not have a specific goal to achieve and so in theory, a high degree of mindfulness might be achieved and then maintained if the successive states of the mirror were able to promote this. EEG was used as the rating system, because it allows a reasonable indication of the mindfulness state, without a consciously provided input from the user. The scenario differed from that with the Scalextric cars in that the users did not have a specific goal in mind and therefore no direct feedback to indicate reaching that goal.

It is often claimed that Einstein said that “The definition of insanity is doing the same thing over and over again, but expecting different results”. However, this is precisely what we may appear to get with iGAs and users. Issues such as fatigue, distraction and boredom can all play a part in the subconscious user interaction with the iGA system.

6 Construction of the system

The mirror was constructed from a polystyrene 5mm mirror sheet and a 5mm clear acrylic sheet with a semi-silvered layer, so that the latter acted as a two-way mirror. A gap of 1cm between the sheets was used and the mirrors were cased in a wooden frame. A strip of addressable Neopixel LEDs made up the display. The display geometry consisted of three zones; an outer square, an outer circle and an inner circle.
The Neopixel strip was cut and joined underneath the display with wires, enabling the three zones to be formed from one continuous LED strip which was connected to a single control pin on an Arduino via a 57 Ohm resistor.

The rating strategy adopted for this work, which had previously been deployed in [17], was to employ subconscious rating of the generated individuals by electroencephalogram (EEG) signals derived from a Neurosky Mindwave EEG headset with one electrode. We employed seeding, whereby the initial population was created by hard-coding with a range of different parameter values. The mutation rate was set to 5%. The code enables the use of a crossover approach where each characteristic value comes from either one parent or the other, or a co-dominance approach where the mean of corresponding characteristic values from each parent is used.

Each of the four individuals in the population was genetically coded by an array of 21 elements, which comprised a transition time and RGB values for two 'extreme' colours for each of the three display zones. These values were passed to a method which 'played' the individual on the display. Playing the individual in this context meant that, for each of the three display zones, the pixel colour would cycle gradually between its two extreme colours, that zone's transition time being the time taken to move from one colour to the other. The play method would carry out this activity for some fixed period of time (set for 20 seconds for purposes of testing and demonstrating), then the user's EEG mindfulness reading would be taken and used to score that individual. This was repeated for each of the four individuals, after which the iGA used a roulette wheel approach to breed the next generation. The mutation rate could be varied and parents could be combined using co-dominance or splicing as desired.

The headset was used with a Bluesmirf silver module and an Arduino to capture and parse the data. Although some studies have been quite critical of the Mindwave [18], others [19] find it adequate for capturing simple EEG data. We found that the use of a conductive gel and careful placing of the electrode improved accuracy.

Two Arduinos were used; the first (master) captured and parsed EEG readings using an adaption of software provided by Neurosky [15] and the second (slave) contained the iGA and the display algorithms utilising the Adafruit Neopixel display library [20]. These communicated over an I2C connection.

7 Results and discussion

Some degree of convergence was observed, taking up to 20 minutes. We ran the iGA with a high mutation rate (5%), as the starting population was small (only four individuals). This enables wider exploration of the solution space, but also poses a problem, as when the system approaches good solutions, they are subject to the same high mutation rate, thus moving them away from the “optimal solutions”. The co-dominance approach seems suitable for some variables, but can lead to early averaging of results rather than the best solution if the mutation rate is not sufficiently high.

When running the test on the same subjects on different days we observed convergence, but not necessarily to similar individual solutions. This was anticipated, as we did not expect that there would be one optimal solution for any given user. For the few subjects that were prepared to sit for 30 minutes, once a high level of mindfulness had been achieved, this state tended to be maintained for a period of time before decreasing then rising again with a different individual solution.

It is difficult to quantify the performance of the iGA. However, some convergence was observed and we were able to make subjective measurements of how the users felt about the results. With iGAs, the endpoint is usually considered to be reached when the output meets the user's criteria. However, it has been observed with the infinity mirror that, whilst a specific state might elicit a high rating for a period of time, after a while the EEG output changes and therefore there is no clear endpoint for the running of the algorithm.

Mindfulness has been recognised by the National Institute for Health and Care Excellence as a strategy for maintaining good mental health, which raises the question as whether the artefact could be deployed in this respect; for example as a training tool for awareness of anxiety and stress. Recent work such as [21] shows that effective strategies are available for analysing human emotion and "tastes". We can see the potential for small bio sensors wirelessly connected, where the data might be processed to give information that can be used for feeding iGAs that modify the environment. This might have significant therapeutic benefits in the future as sensors become smaller, more portable and wearable.

8 Conclusion

This work explores the potential of using sensors, in this case an EEG headset with an iGA to promote mindfulness through the manipulation of a physical piece of art. Whilst there are many limitations arising from the choice of platform and hardware, we did see some convergence, although given the nature of the artefact, this is over a relatively long period of time. The main contributions of this work are in exploring the use of sensors for subconscious user interaction with iGAs in place of the traditional approaches and an initial exploration of how iGAs can run continuously to optimize solutions where the nature of the best solution changes according to the changing whims of the user.

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