Interactive Evolutionary Computation with Adaptive Mutation for Increasing the Effectiveness of Advertisement Texts

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***Abstract*— Interactive evolutionary computation systems can be used to evolve advertisement texts. Google AdWords was used as the interface that users can use to see the advertisement texts, and have a chance of being persuaded by the text into clicking them. Interactive evolutionary computation systems use humans to perform fitness evaluation in the evolutionary process, which can be applied on a genetic algorithm. This work presents a comparison between two variations of the genetic algorithm: one that uses a fuzzy inference system to dynamically adapt the mutation rate, and another that uses a fixed mutation rate. The results show that the dynamically adapted genetic algorithm in the interactive evolutionary computation system has the potential to have a better performance and lead to smaller costs in advertising campaigns.**

***Keywords*— Interactive Evolutionary Computation, Fuzzy Logic, Genetic Algorithm, Advertisement Text Optimization.**

I. Introduction

Although communication channels, such as the television, the radio, and video transmitted through the Internet are popular at the moment, text-based communication channels are still prevalent, and they can greatly impact an individual in terms of persuasion [1]. This idea also applies to textual advertisements, which can still be found in, for example, newspapers and on the Web. In the case of the Web, many advertisement services, such as Google Adwords or Bing Ads, play a major role in how websites can be monetised. These services enable its clients to create advertisements based on video, image or textual content. The created advertisements are then eligible to be displayed on a variety of websites that are participating in the corresponding ad publishing programs (such as Google Adsense), which are chosen depending on the keywords they are targeting (e.g., an advertisement about dog food should be displayed on a pet store website). Other mediums that can display the advertisements exist, such as mobile applications and search result pages in search engines.

M. Guerini et. al. [2] state that accurate wording is paramount to correctly and clearly express ideas in verbal communication, and the statement has been extended to textual communication as in the work by S. Demir [3]. This implies that in order to achieve a successful advertisement campaign, having the correct idea is not enough: the correct words must also be selected. This can turn out to be an overwhelming task for a human being, as there can be thousands of word combinations that can express the same idea, even in a small text (e.g., around 100 characters, as the limit in most online advertisement programs). This process of changing some words of a block of text, while retaining its original meaning receives the name of valence shifting in the literature. S. Demir [3] states that "valence shifting is the task of rewriting a text towards more/less positively or negatively slanted versions."

In order to find a good combination of words, the authors of this work have previously [4] developed a method which uses an interactive evolutionary computation (IEC) based on genetic algorithms to find individuals who represent these combinations of words. Users rated the advertisements through the Google search engine, by using the Google Adwords advertisement program. The advertisements with higher fitnesses (in this case, the fitness is represented by the number of clicks divided by the number of times the advertisement was presented to the users) were used to participate in a traditional evolutionary process, giving as a result offspring that should, in theory, perform better than their parents. This method should be an effective tool to complement the work of an expert in advertising campaigns, and should lower the time and effort needed to obtain the desired performance. Nevertheless, the authors of the present work believe that better results can be obtained faster by dynamically adjusting the mutation parameter of the genetic algorithm in the method proposed in Section IV, instead of fixing the value of that parameter during every generation in the evolutionary process. The idea behind this process is that the genetic algorithm should start with a high mutation probability, producing high exploration; and then, gradually, the algorithm should change its mutation probability to a lower rate in order to produce a lower exploration and higher exploitation. The implementation of this dynamic adjustment of the mutation is performed by using a fuzzy inference system.

To test the presented method, an experiment was conducted where the proposed method in [4] is compared against its dynamically adjusted counterpart. Several works related to the proposed method are presented in Section II. In Section III, the method is described, and Sections IV and V present the experiment and the results, respectively. Finally, a conclusion is given in Section VI and a short discussion about the future work is presented in Section VII.

II. Related Work

A. Interactive Evolutionary Computation

As mentioned in Section I, the present work involves a technique called valence shifting. This is achieved by using an IEC system that treats the advertisement text as a chromosome that can swap words or full sentences (that are represented as genes) with other chromosomes in the population. This approach is based on the method proposed in [5], which uses an IEC system to evolve animations: all the parameters that determine how the animation should behave, like the colors, the speed, and the shapes, are represented by numbers in the chromosomes of the genetic algorithm's population. Other works that use a similar approach to evolve objects exist, as in the case of Picbreeder [6], an online service that allows users to collaboratively evolve images; EndlessForms.com [7], a website that allows its users to collectively explore the space of CPPN-encoded objects via interactive evolution by selecting the objects they are interested in, which serve as parents to create offspring for the next generation.

B. Voting Interfaces

In a previous work [4], the evolved advertisement texts were evaluated by asking people how persuasive they thought the texts were. As a comparison work, Guerini et al. [8] propose using Google AdWords to have users evaluate the advertisement ads: they measure the persuasiveness of a text based on how many clicks it receives during its exposure to the public on the Google search engine result pages and the websites that are participating on the Google AdSense online advertisement program. The previous work used two platforms: EvoSpace [9], a database based on the tuple space paradigm that was designed to hold populations of diverse evolutionary algorithms; and EvoSpace-Interactive [10], a web platform that is able to translate the chromosomes held in EvoSpace into Processing.js (a programming language designed to show images, and animated and/or interactive content) animations. EvoSpace-Interactive presents these animations to its users, provides an interface that allows the users to vote negatively or positively the animations, and uses these votes as a performance metric for an implementation of a genetic algorithm that evolves the animations. For this previous work, EvoSpace-Interactive was modified to be able to show advertisement texts to its users. The present work opted for discarding the previously described method, and using Google AdWords for its "voting interface," as in [8].

C. Valence Shifting

Valence shifting is used in order to change the persuasiveness of advertisement texts (as was mentioned in Section I). Several works exist which prove the effectiveness and validity of valence shifting, but two notable examples are the work by Gardiner and Dras [11], and the work by Gatti et al. [12]. Additionally, some example works that show methods that perform valence shifting effectively are the one by Demir [3], and the one by Guerini et al. [2].

D. Dynamic Adaptation of Parameters

Finally, the present work compares the performance of two IEC systems working with genetic algorithms, but one has a fixed mutation rate, and the other has a dynamically adapted mutation rate. Several bio-inspired optimization algorithms have previously been modified to have a dynamically adapted parameter, with the idea of improving its performance in finding a solution in less iterations or generations. In the particular case of the present work, a fuzzy type-1 controller is used to perform this dynamic adaptation. This approach has been used in other works, such as in the works by Olivas et al. [13], where they modify the particle swarm optimization (PSO) algorithm; the work by Castillo et al. [14], where the differential evolution algorithm is compared against a dynamically adapted version using a fuzzy controller, and several mathematical functions are used as benchmarks to compare their performances; Valdez et al. apply the mentioned approach for PSO [15] and genetic algorithms [16]. These dynamically adapted optimization algorithms have already been successfully used in applications, as in the works by Melin et al. [17] and Neyoy et al. [18]. The reader can find a survey on the approach in the work by Valdez et al. [19].

III. Preliminaries

A. Interactive Evolutionary Computation

An IEC system is basically an implementation of an evolutionary algorithm where the fitness function is replaced by the subjective evaluation of human beings. IEC is useful in situations where the objects being evolved cannot be evaluated by a formal method (or it would be too difficult to model such fitness function). Some common examples of these situations are the evolution of musical pieces, 3D sculptures, animations, static images, and, as in the case of the present work, text.

B. Article Spinning

Article spinning is a technique that involves changing parts of a block of text in a way that preserves its coherence and cohesion, but its meaning is expressed with different words. These parts that can be changed can range from single words to full sentences and paragraphs. Fig. 1 depicts an example of a text that follows a syntax that enables article spinning. In this example, a single word can be chosen from the group: great, good, and perfect, and another one from the group: method,and technique. The latter could be changed to: awesome method, or incredible technique, in order to demonstrate to the reader that several words can be placed in each position of the group of texts. This example would represent a total of six different texts that express a similar meaning.

This is a {great | good | perfect} example of the article spinning {method | technique}.

Fig. 1. Example of a Template for Article Spinning.

C. Dynamic Adaptation of Parameters in Bio-Inspired Algorithms

Most of the bio-inspired algorithms have parameters that can be adjusted by the user before their processes begin. Certain combinations of these parameters are going to provide better results than other combination of parameters, due to their heuristic nature. It is often indicated by the creator of these algorithms that these parameters can be adjusted in a dynamic manner, and that it should provide better results than their fixed parameters counterparts. This dynamic adjustment is provided by a controller, and this controller can be as simple as an if-else statement, which changes the value of certain parameters depending on the current environment the algorithm is experiencing at a certain time. More robust controllers can be used, as in the present work, where a fuzzy type-1 controller is used.

IV. Proposed Method

The present work proposes a method to increase the effectiveness of an advertisement text. In order to achieve this, an IEC system is used to evolve the texts, with the objective of gradually increasing their persuasiveness. The IEC system is necessary, as the persuasiveness of the texts cannot be measured with a formal method, as this is a subjective metric which varies depending on the person who is reading the text. Google AdWords is used to gather the performance information for each of the advertisement texts, and these texts are generated from a single template by using the article spinning technique explained in Section III-B

The IEC system is based genetic algorithms: one which has a dynamically adapted mutation rate (see Section III-C), and another genetic algorithm which works with a fixed mutation rate. This work compares the performances of these two genetic algorithms in the IEC system, and helps in empirically proving that using an IEC system helps in increasing the effectiveness of advertisement texts.

In Section IV-A, an explanation of how Google AdWords was used as a voting interface where users can help deciding which advertisement texts are better is discussed. In Section IV-B, article spinning is described, and how it was used for the genetic algorithm in the IEC system. Section IV-C explains the configuration used in the genetic algorithm for the IEC system. Finally, Section IV-D explains how a fuzzy controller was used to dynamically adapt the mutation chance of the genetic algorithm in the IEC system.

A. Google AdWords and Interactive Evolutionary Computation

As was mentioned in Section III-B in a previous work the authors of the proposed method decided to ask human beings what was their perception about the different advertisement texts that were being evolved in the IEC system. This was a tedious task, and it was not very reliable, as people could get biased by the presence of the interviewer, they could get confused by the task they were being asked to accomplish, and other factors that could possibly lead to unreliable results. A more reliable and convenient method is to use Google AdWords, as this tool allows a publisher to create an advertisement text to be published on the Google search engine result pages, and websites that are participating on the Google AdSense program. This method is more reliable, as the evolved texts are presented to the users just like any other web advertisement, and the user experience is not changed by any other external factors. The users click on the advertisement if they felt persuaded by it, and the number of clicks this advertisement text receives is used as a metric to measure the performance of the text (in reality, a measure called Click-Through Rate, or CTR, is used, which is simply the number of clicks divided by the number of times the advertisement was shown to users).

To effectively use Google AdWords as a voting interface, the authors leveraged the Google AdWords API. By using the programming language Python, and a module called googleads, extraction of the metrics and management of the advertisement campaigns in an automated manner was possible.

Certain number of advertisement texts were created (the population of the genetic algorithm), which are represented by chromosomes. These texts are sent to Google AdWords, and are used to create a new advertisement unit. After the advertisement has received a number of clicks, it is paused. When all of the advertisement texts are finished collecting a minimum of clicks and are paused, their CTRs are collected. These CTRs are used as their performances, and the crossover process begins to create new individuals that use genetic material from the more fit individuals (the advertisements that got a higher CTR). This process is further explained in Section IV-C.

B. Article Spinning Template for the Genetic Algorithm

The article spinning technique was briefly explained in Section III-B and the Fig. 1 gives a basic example of an article spinning template. Fig. 2 shows a more generalized template. In this template, A1 ... A6, B1 ... B3, and the other groups enclosed in curly braces and separated by bars, represent blocks of text. These blocks of text can range from simple words, to full sentences. In the A group, any block of text can be randomly chosen, and the same applies for the other text groups. As examples, this template could generate the following texts: “A1 text B3, text D2 text, text E4. Text F1 text, text, text. G1.” and “A2 text B2, text D1 text, text E3. Text F2, text, text. G3.” As can be noted the text parts in bold represent fixed texts, i.e., these blocks of text will not change in any resulting combination.

These templates can be translated to chromosomes in a convenient manner. The groups of blocks of text can be represented as numbers of a chromosome. Fig. 3 shows how the “A group” from FiG. 2 can be translated to a gene of a chromosome, and how all the groups of text from the Fig. 2 are translated to a full chromosome.

C. Genetic Algorithm

The IEC system evolves its population of chromosomes by using a simple genetic algorithm. This genetic algorithm creates an initial population of individuals, and the chromosomes that represent these individuals are randomly generated by using the total number of blocks of text from each group in the article spinning template as the maximum number each gene can represent (e.g., the “A group” in Fig. 2 has six possible blocks of text, which means that the gene that represents this group can hold numbers from 0 to 5, as the implementation of the genetic algorithm is 0-indexed).

The initial population is converted to advertisement texts that can be read by Google AdWords, and are sent to it. The genetic algorithm needs to wait until a minimum number of clicks is achieved (read Section V for a particular implementation of the method described) for every advertisement, and when an advertisement reaches this number of clicks, it is paused. When all the advertisements complete this requirement and all are paused, their CTR (number of clicks divided by the number of times the advertisement was shown to users) is retrieved from Google AdWords, and it is stored as the performance of that advertisement text.

The crossover process takes place after the CTRs are collected. This process involves taking two randomly selected samples of individuals from the population: one representing a group of possible “fathers,” and the other group representing possible “mothers.” The best chromosomes from each group are selected as the final father and mother, and they are recombined to form offspring. The recombination method is randomly chosen between one-point and two-point crossover operators. The result of the crossover yields two offspring that have genetic material from their parents. The least fit individuals from the father and the mother groups are removed from the population, and the offspring take their place, i.e., the population always remains constant in size. As the evaluation process in Google AdWords can (and should) be performed in parallel (evaluating several advertisements at the same time), the crossover process can be performed several times to generate a considerable amount of offspring.

After the creation of the offspring, there is a chance for them to suffer a random alteration, i.e., a mutation. If the mutation process is triggered, a randomly selected gene is changed to a random number from 0 to the total number of possible options for that gene, minus one (because of the implementation being 0-indexed). To clarify, following the example from Fig. 2, if the E group was selected, that means that the fifth gene was randomly selected, and the possible values range from 0 to 4, as there are five blocks of text in that group. As is explained in Section IV-D two genetic algorithms were used separately in the IEC system: one with a fixed mutation chance, and another one with a dynamically adapted mutation chance. For a particular case of an implementation of these two systems, see Section V.

The newly generated individuals are then translated to advertisement texts that can be read by Google AdWords, and the process is repeated until certain number of iterations is fulfilled.

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{A1 | A2 | A3 | A4 | A5 | A6} text {B1 | B2 | B3}
{C1 | C2 | C3}, text {D1 | D2 | D3 | D4 | D5}
text, text {E1 | E2 | E3 | E4 | E5}.
Text {F1 | F2 | F3 | F4 | F5} text, text, text.
{G1 | G2 | G3}.
```

Fig. 2. Generalized Template for an Advertisement Text.

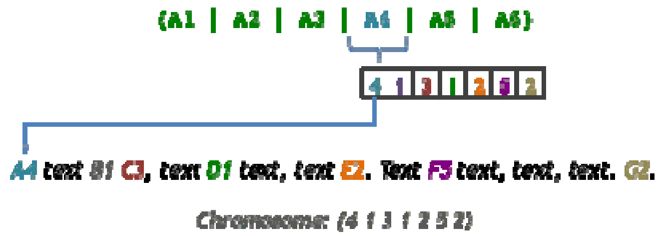

Fig. 3. Translation of an Advertisement Template to a Chromosome

D. Fuzzy Controller for Dynamic Adaptation

It is common that the authors of parameterized algorithms mention that some of these parameters can, and should, be adapted according to the environment where the algorithm is running. One way of achieving this is by using a fuzzy controller that, by using variables from the environment as input, it can compute a new value for one or several parameters of these algorithms. In the case of the proposed method, a Mamdani type-1 fuzzy inference system is used, which uses the number of iterations as its input, and the mutation chance is its output.

The idea behind this controller is that the mutation chance should be high at the beginning, so the genetic algorithm is exploring the solution space, more than exploiting it. And as the evolution process advances, the mutation chance is decreased so the genetic algorithm starts exploiting more. This behaviour, as a hypothesis, should increase the overall performance of the genetic algorithm in the IEC system.

V. Experiments

The experiments in this section describe two implementations of the proposed IEC system: one that uses a fuzzy controller to dynamically adapt the mutation chance of the genetic algorithm in charge of the evolutionary process in the IEC system (as explained in Section IV-D), and another version that uses a fixed mutation chance. The dynamic IEC system uses the fuzzy controller to change the mutation chance from 0 to 0.2, or a mutation chance of 20%. In the case of the fixed IEC system, a mutation chance of 5% was used. These two systems were compared in order to see if a dynamic adaptation of the mutation chance would yield significantly better results for an IEC system, than one that uses a fixed mutation chance.

The IEC systems were initialized with a population of fifty individuals, and these individuals were generated by using the template presented in Fig. 4. This template generates advertisements about a food website, and all the advertisements that can be generated by this template comply with the character limits that Google AdWords establish. After the fifty individuals are generated, they are translated to Google AdWords advertisements, and are exposed to the public to start receiving clicks. In the case of these experiments, every advertisement needs a minimum of two clicks before being paused. After all the advertisements receive the minimum of two clicks and are then paused, the IEC system extracts the CTR they obtained during their exposure. For example, if an advertisement was shown 1,000 times, and received 5 clicks, its CTR will be 5/1,000, or 0.5%.

The rated advertisements are then used in a crossover process, as described in Section IV-D. The number of iterations in the case of both experiments, is twenty iterations. The low number of iterations is due to the high cost of publishing the advertisements (each of the experiments costed around $50 USD).

The genetic algorithm with a dynamically adapted mutation rate uses a Mamdani type-1 fuzzy inference system, as described in Section IV-D. The input linguistic variable is granulated into three fuzzy adjectives: low, medium, and high. The output linguistic variable is granulated into three fuzzy adjectives: high, medium, and low. These variables can be seen in Fig. 5 and 6. These fuzzy adjectives are represented by Gaussian membership functions. In the case of the input variable, all Gaussian membership functions have a standard deviation of 4.0, and the input variable ranges from 0 to 20 iterations. Low iterations has a mean of 0, medium iterations has a mean of 10, and high iterations has a mean of 20. In the case of the output variable, all Gaussian membership functions have a standard deviation of 0.052, and the input variable ranges from 0 to 0.2. High mutation chance has a mean of 0, medium mutation chance has a mean of 0.1, and low mutation chance has a mean of 0.2. Fig. 5 depicts an example of the fuzzy inference process with an input of 2 iterations, which gives an output of 0.059 as the mutation chance. Fig. 6 depicts another example, but with 17 iterations as its input, which gives an output of 0.130. As can be seen in these two Figures, the results are obtained by calculating the centroid of the aggregation of the alpha-cut output membership functions.

The fuzzy rules for the fuzzy inference system controller are the following:

- If number-iterations is low then mutation-chance is high
- If number-iterations is medium then mutation-chance is medium
- If number-iterations is high then mutation-chance is low

Each of the IEC systems was run for 20 iterations, were each of the iterations produced 10 new individuals. The results of these experiments are presented in Section VI.

{Hot | Tasty | Superb | Juicy | Great | Good } { tacos | hot dogs | pretzels | donuts | pies | pizzas }, {5% | 10% | 15% | 20%} off Check {here | this link | this ad } {immediately | promptly | urgently | now | pronto | right now | this minute | this hour | today } to {enjoy | make effective | make use of} this {offer | discount | deal}

Fig. 4. Article Spinning Template Used in the Experiments.

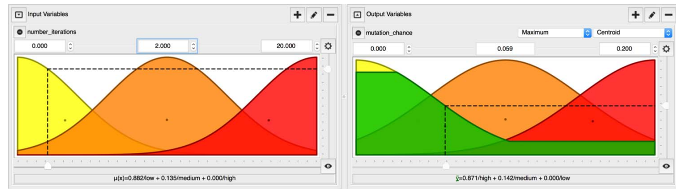

Fig. 5. Example of the Fuzzy Controller with Input of 2 Iterations.

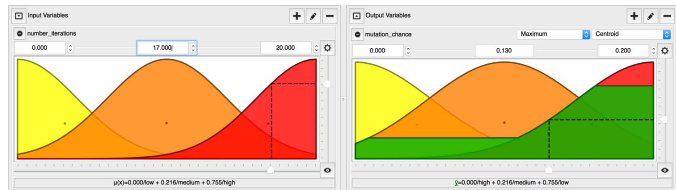

Fig. 6. Example of the Fuzzy Controller with Input of 17 Iterations.

VI. Results

Fig. 7 and Fig.8 show two plots each: the blue line shows the best chromosome that was achieved until that iteration, and the red line shows the best chromosome in that particular iteration. The reader can notice that the IEC system with the dynamic mutation chance performed better, but only because at iteration 3 a good chromosome was found.

For a more reliable conclusion, the results from the red line (the progress, or the best chromosome in each iteration), were used in a hypothesis test. In the case of the dynamic mutation chance, the average of the performances is 1.202, and the standard deviation is 1.002, while in the case of the fixed mutation chance, the average of the performances is 0.862, and the standard deviation is 0.748. Using t-student, the results yield a test statistic of 1.3596, meaning that the results of the dynamic mutation chance IEC system are better with at least a confidence interval of 80%.

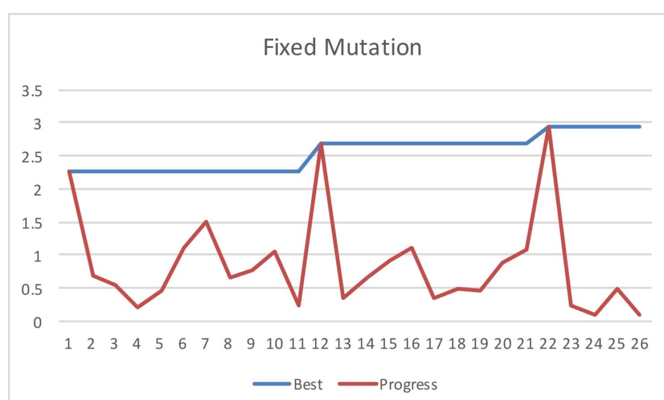

Fig. 7. Fixed Mutation Performance Over Time.

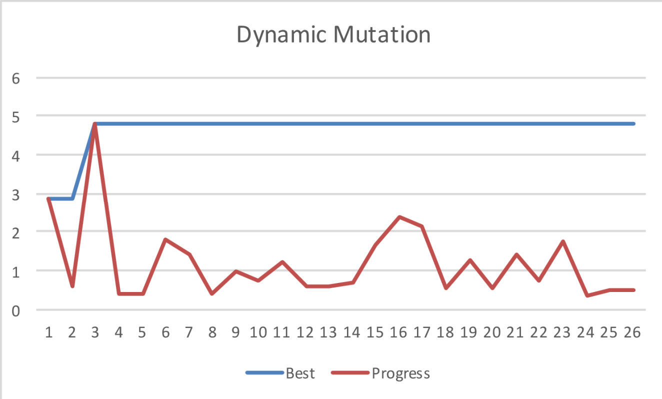

Fig. 8. Dynamic Mutation Performance Over Time

VII. Conclusion

A more exhaustive study needs to be done in order to achieve conclusive evidence that a dynamically adapted mutation chance in the IEC system is going to provide better results. Nevertheless, the results obtained in this work demonstrate that the approach could lead to an important increase in performance for the advertisement texts, which is directly translated into smaller costs in advertising campaigns.

Introducing a Mamdani type-1 fuzzy inference system as a controller for the mutation chance in the IEC system does not impact in a significant manner the performance of the system in terms of computational resources, and its implementation is trivial. This means that there is a low cost of implementation and it has a high possibility of producing better results in the advertising campaigns, which should be a profitable decision for a marketing organization.

VIII. Future Work

A lower cost niche for the experimental campaigns must be found. This would enable running more advertising campaigns, and lead to achieving more reliable conclusions. This also implies that more experiments must be performed in order to achieve a conclusive result of whether using a dynamically adaptive mutation chance in a genetic algorithm in the proposed IEC system is going to yield better results.

Another possibilities are to try with a broader range of mutation chance for the fuzzy inference system as output, and to extend the fuzzy controller to Mamdani interval type-2 and Mamdani generalized type-2 fuzzy inference systems.

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