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A Comparative Study on User Interfaces of Interactive Genetic Algorithm

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Abstract

This paper provides a review on current developments in the Interactive Genetic Algorithm (IGA). The discussion includes graphical aspects of different applications of IGA. We have reviewed topics like visualization techniques, usage of different machine learning algorithms and mathematical methods in order to get the best solution from IGA. Examples of IGA in this review include the fashion design applications, tree modeling and 3D objects reconstruction. This paper concludes with the current problems and future directions of IGA.

Selection and Peer-review under responsibility of the Program Chairs.

Keywords: User Interface; Interactive; Genetic Algorithm; Visualization; Modeling; Optimization

1. Introduction

IGA is suitable for problems which cannot be easily solved easily by conventional especially where the interference of the user may change the general behavior of GA [1]. This technique is used to solve the problems where the subjective fitness is necessary to assign to the solutions as compare to the objective function [2, 3]. One of the main advantages of this method is that it has the potential to obtain solutions according to the user's desire, and able to produce variations in obtained solutions. The origin of IGA is from 1989, when Interactive Evolutionary Algorithms (IEA) were first demonstrated by Dawkins [4] to create a visualization tool to model an artwork called bimorphs. From last few decades, IGA is successfully used in solving many engineering issues i.e. Aesthetic and artistic problems [2, 3], Image processing applications [5-7], Travelling salesman's problem [8], Chemical optimization problem, Engineering design problems [9, 10], and modeling of artificial scenes or trees [11]. This

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technique also serves as a useful tool for understanding complex architectural designs and civil engineering applications in order to get the solution according to the subjective selection. All of these above mentioned applications are developed using different techniques of IGA to get optimized solutions.

Takagi and his fellows have reported many advantages and limitations of using interactive technique for GA in several research works [12-17]. Takagi [18] in his survey reported categories Interactive Evolutionary Computation with two definitions, i.e. narrow and broad definition. According to the broad definition, the human-machine interface is used to solve different problems using GA. In human-machine interface, the applications are based on a user's preference and selection or it may use some machine learning methods, i.e. Neural Network to approximate the GA parameters, classifier or fuzzy logic to decide the fitness values. According to the narrow definition, the human evaluation is used as the fitness value for an optimized solution. This is the traditional way of using IGA, in which assigning fitness and the selection of the parents for the next generation is based on the human decision [19, 20].

Furthermore, in IGA there are several aspects needs to consider. For example, good visualization and interactive techniques, a good user friendly environment, small population size, less number of generations and an organized presentation are important parameters of GA. In order to address all above aspects the most important part is to improve the interactive interface in order to get good results. User friendly user interfaces will bring a good understanding of the users with the blind searching mechanism of GA. Hence it will help to grasp the cognitive skills of human for the judgment of fitted solutions successfully. The discussion of presented paper is based on the user interfaces, usage of learning methods and mathematical methods categorized for getting best solutions. The presented paper is broadly categorized into three sections i.e. (1) Finding best solution based on human perception , (2) Based on the human machine interactions , (3) Mathematical Or Graphical Methods For IGA.

2. Based on Human Perception for Best Solution

This kind of GA visualization gives a suitable solution for the problem in which inference of the user is necessary to have an opinion for the evaluation and selection of solutions for the next generation [20]. In another sense, human intuition and emotion accordingly, are needed to complete the evolution process. Another advantage of these existing applications is to help the user to draw or select the individuals according to a visual picture of that object in his mind. These applications are mostly used for model representation of individuals. These techniques are applicable to the problems in which computational time is not a critical issue [21].

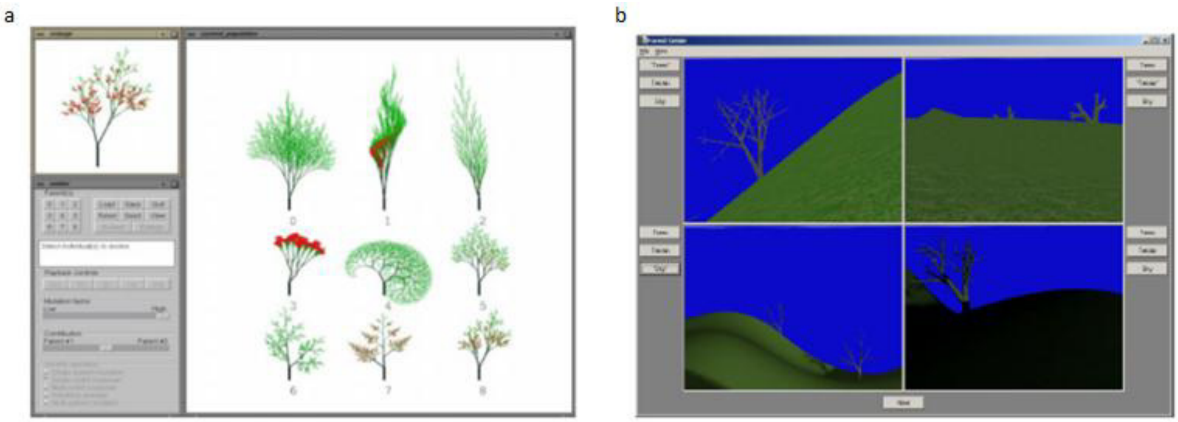

Fig. 1. (a) A user interface for selecting trees for recombination and mutation; (b) User interface for selecting virtual scenes [27]

A variety of solutions can be obtained by exploring the search space. Using these techniques, human selection can bring an optimal solution, in fewer numbers of generations with a smaller population size. This technique has been successfully applied to 3-D modeling of different artistic applications, for example, fashion design [2], 3D geometric shapes [22] and modeling of 3-D flowers [23]. These applications are based on the phenotype or genotype representation of a problem.

In the visualization of 3D geometric shapes [22] and fashion design [2], the evaluation and user selection judge the aesthetic quality of the model to be selected as parents for the next generation. The individuals of the current generation are displayed in genotype form on the screen as a 3D model. In [23], a similar approach is adopted for phenotype representation of 3D flowers with a Structured Directed Graph. In [24], a 3-D graphic model has been created for manufacturing layout designs. Two different phases are used to run GA. During the first phase all individuals are evaluated by the user. Whereas for the second phase, fitness function is used to assign fitness. During the search process, the user may switch to any phase at any time. Another interesting application is developed by [25], for ubiquitous 3-D graphic models using mobile devices. The evaluation and selection of models are done by the user with a mobile device. The drawback of these existing approaches lies in their complete dependence on the user. On the other hand, assigning fitness to each individual in search space create a tiresome environment for the user.

The Traditional IGA technique is also used to do the breeding and recombination for the next generation [20, 26]. A user interface is created which allows the user to selects the models, can manipulate its parameters, and selects the parents for the next generation for breeding. The work done in [26] involved a model visualization of trees (see Fig. 1a). These trees are generated using the L-System. The user involvement is to do the selection of parents for recombination and mutation.

A procedural 3-D model of trees [20] is generated using IGA. Evolution starts with the initial population, generated by random parameters. The IGA technique is also used to model virtual scenes [27, 28] . For these applications, the searching of GA also depends on the user perception. The interface window in [27] (see Fig. 1b) represents four virtual scenes developed by 4 elements namely: terrain surface, clouds, trees and sky. The user interface helps to selects the best scene for the next generation. In this application, it is not necessary to assign a fitness ranking to each scene. Instead, the user selection is based on an element (terrain surface, clouds, trees and sky. In this way, they have contributed to making random virtual scenes for a forest by using TIGA. IGA is used for creating visual scenes for generating a software robot [28]. The genetic representation is based on homologous chromosomes. User involvement is required in each generation that produce the fitter solution for next generation. Numerous works have been done in previous years to present the evolution process using a graphical user interface. All of these systems work with a model of individuals. Up to now, IGA has been applied to solve problems in several fields. These existing applications are based on addressing both optimization problems and the selection of variety of solution for a problem. It has especially enabled production of very attractive solutions for artistic problems such as 3-D CG lighting design support [29], animal and plant evaluation using IEC [30], interactive design for websites [31], traditional or fashion designing [2, 19, 32], 3D modeling for geometrical shapes [33], and optimizing image enhancement filters [5]. A further survey of using IGA for evaluation and user interaction may be found in a survey report by Takagi in [34].

Drawbacks of all above discussed applications are that they need the user involvement in each generation, which create a tiresome environment for user. Due to model representation, the user cannot explore the internal structure and parameters of chromosomes (gene values). Furthermore, the interaction in every generation becomes infeasible for the optimization problems having large search space.

3. Human Machine Interaction

Model based visualization is proposed [29] in which the fitness of an individual is not assigned by subjective or objective function. The fitness is calculated on the base of time spent by a user to make a solution which is satisfied or not satisfied. In this way, the difference of this time while evaluating the solution according to user satisfaction is considered as the fitness value of the individual. The selection of parents for the next generation is done by GA.

In Traditional IGA, the role of user and GA are separated, i.e. the user does the selection and evaluation for individuals and GA performs the search [21]. However, it often creates fatigue and a tedious environment for the user. Since user fatigue is a main problem in IGA, therefore, researchers are taking keen interest in alleviating user fatigue. Several approaches have been proposed to solve this problem and to improve the GA searching ability towards fitter solution with IGA technique [35-37]

A human- machine interaction is introduced to create an interval level between user and system to produce a fitter value. Using this technique, a discrete fitness value is introduced [36] to evaluate the solutions for the next generation. They proposed to assign same fitness value to all individuals having similar features. In this way, they reduce the user fatigue for evaluating and assigning fitness to each individual in the search space. Some approximation approaches have also been used to solve the problem for assigning fitness. A Neural Network has been adopted [37] for assigning fitness values after learning the human selection behaviour for different individuals during the evolutionary process. Feed forward Neural Network is tried for predicting human evaluation and displays the individuals in decreasing arrangement [38]. However, in their work they reported that predications given by the Neural Network were less accurate than fitness function for assigning fitness.

A multivariable problem [35] is addressed to solve the fitness evaluation problem using the Neural Network termed as General Regression Neural Network (GRNN). GRNN approximates the aesthetic intention of the desirable solution by the user with its learning mechanism, whereas IGA is used to evolve the next generation. They applied their proposed approach to designing the cartoon style faces on coffee mugs (see Fig. 2a). These designs are displayed on a grid window for selection by the user. Fig. 2b shows the general flow of their system.

The literature survey shows that, most of the applications developed with the human-machine interface are also based on the user selection or evaluation. Although the fitness is not evaluated by the user, instead; fitness approximation misleads the gradual and fuzzy evolutionary process and restricts it under some fixed parameters. For example, the fitness values are discrete in nature and user select any best option from them [21] or some probability values are taken to evaluate the individuals of each generation. Furthermore, there has been no countable work done in these applications to improve the searching performance of GA using visualization techniques.

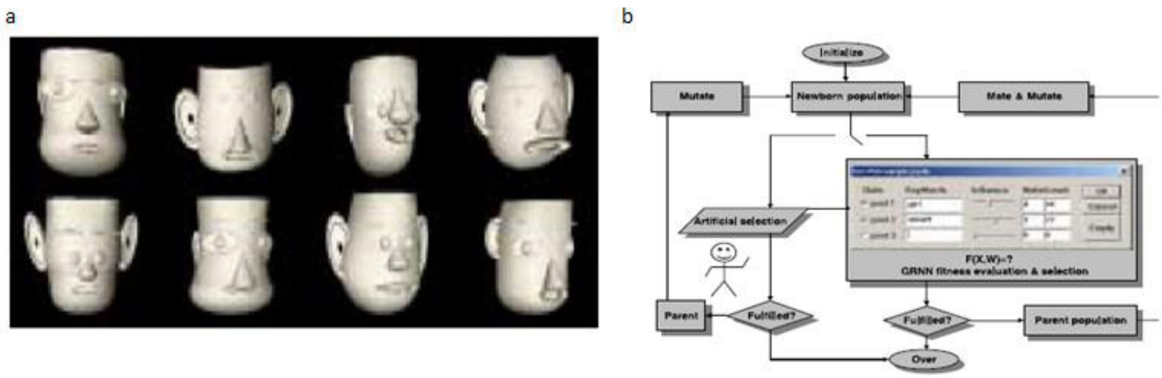

Fig. 2. (a) Cartoon faces generated using GRNN [35] ; (b) General flow of the system [35]

Another idea is to introduce an approach, which involved user in few or pre-defined generations [39]. The advantage of this approach is that it saves the user from the tedious work of selection and evaluation in each generation. The objective function is used to assign fitness to the individuals; hence, a large search space can be used for finding the solutions. An occasional user intervention is introduced to correct the fitness of individuals used for multi-objective optimization [10]. They proposed this approach to solved problems with the large search space. They employed this technique to optimize the parameters for aircraft design. The user interaction was after certain number of generations. Objective function is used to calculate fitness. In their work for representing multidimensional data having different objectives and constraints, different graphs are used. In total, they have 35 design variables separated into 5 groups. The size of the population is 100 - 150. The drawback of their system is in using different graphs for each group. In this way, the overall performance of the system becomes difficult to observe. On the other hand, this technique is helpful to elaborate the usefulness of user interaction to pre-determined generations. In this way, selection or changes in searching becomes easier as it is concerned only with particular generations.

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4. Mathematical or Graphical Methods for IGA

Visualization of multidimensional data on lower dimension is used for comprehensive representation for scientific results, and their interpretation or validation [40, 41]. Besides the modeling and visualization of scientific data, these techniques are also used to visualize the hidden process of algorithms including the biological inspired algorithms such as GA [21]. The visualization of GA searching data is based on different techniques, used to transform multidimensional data to one or two dimensions, i.e. Principal Component Analysis, Biplots [42], Distance Maps [43], Sammon Mapping [44, 45] , Coverage Maps [46] Distance Maps [46], State Space Matrices [47], SOM [21], and Correlation Tours and Grand Tours [48]. Beside these techniques, Tom Routen [49] proposed a distance distribution histogram for calculating distance between chromosomes for population. This technique is only helpful to determine the frequency of chromosomes. There is no information found for the distribution of chromosome in the search space found using this technique. Most of these existing techniques do not have common mapping for all generations. As a result, there is a lack of consistent relationships between the plotted points for subsequent generations. The mathematical complexity of these techniques also makes them impractical to apply for real problems.

Visualization of complicated and multidimensional data of GA may also explore using different techniques that covers in Scientific Visualization (SciVis). For example, in [21], a 2-D map visualization technique is used for GA for improving the searching ability with user interventions. For visualization of GA, they used SOM to map the individuals from n-Dimensional space onto a 2-D space. On a 2-D space, the individuals are represented with different color intensities. For example, an individual with a higher fitness having has a dark color as compared to an individual with a lower fitness, or new selected individuals are represented in different color.

Several computer graphic techniques are used to project the high-dimensional data on one or two dimensions, i.e. scatter plots, parallel coordinates or different color schemes [50]. These visualization techniques give both phenotype and genotype representations of GA data, which is carried out in the form of chromosome or gene values. A pseudo color strategy is adopted in [50] to display all the individuals of the current generation onto one screen(see Fig. 3a). The brightness of individuals change with the fitness value while with the objective value, the hue changes. This approach is applied to solve the knap sack problem. The chromosome encoding is binary; hence, two colors, blue and red, are used to distinguish between gene values 0 and 1 respectively. The user views the individuals of each generation visually and decides the termination condition. Since the color scheme is applicable to individuals having binary coding, therefore, it is not practical to apply this scheme on any other genetic encoding.

A Target Line [50] is projected onto one space for high dimensional data, where all chromosomes are a point on target line as shown in Fig. 3b. The size of the point shows the number of chromosomes projected on it, hence, the larger the size the more chromosomes on it. The color of the target line indicates the number of points on that part of the line which works as a bar; hence, the darker the line more points projected on it. With the selection of any part of bar, a scale shows the percentage of the population in that area. The user may also change the position of the target line in the search space. However, this change will not inform that what position of the target line could be optimal for visualization of a particular run.

Computer graphic techniques are also involved with the visualization of the smallest element of GA (gene values).Visualization of gene values gives a comprehensive overview of chromosome [49]. This technique is used to observe what area of the search space is explored by GA. A travelling sales person [8] is a well known problem in which optimized solution for paths to the cities is obtained. By projecting this data in 3 dimensions, the IGA with user interaction is a suitable idea to solve this problem.

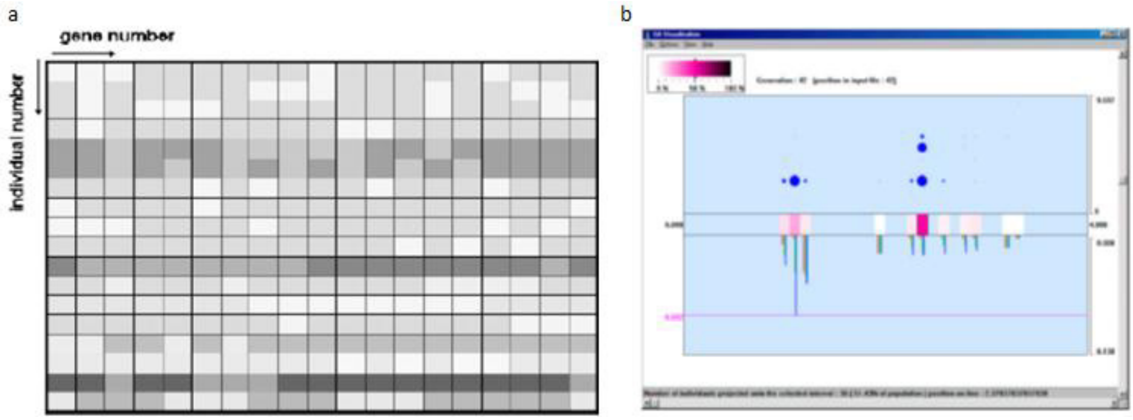

Fig..3.(a) Brightness and Hue [49]; (b) Projecting high dimensional data onto lower projection [51]

5. Major Issues of IGA / Future Directions

This paper provides a survey on existing visualization techniques to improve the performance of GA with an interactive environment and different visualization techniques used for understanding the GA searching mechanism. The discussion includes the review of current literature that has led to highlight the existing techniques for solving problems with IGA. From discussing all this literature, it is concluded that the existing techniques for visualization based on individuals and continue human interventions. These solutions are only feasible for artistic problems with a small number of generations. There is still room for exploring new techniques for solving such problems with large number of generations, to avoid continue user interventions.

Different current approaches are also explored in this paper for assigning fitness using the objective function to show that IGA techniques may also use to visualize the large search space. It was noted, no existing work has been reported to address the problems for improvement in the interfaces designs in term of enhancing the cognitive skills of human. Although a noticeable approaches and techniques had been introduced to overcome the user fatigue, but this problem is still addressable. The future work in this area might be to introduce the techniques to facilitate the user for selection. The cognitive skills of human may effectively use for this purpose. For example, the time spend by a user may be measure by the eye contact, mouse navigation or even with the counting the click times. Another future direction may be to introduce the monitoring of brain activity directly onto the selection area.

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