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A Personalized Pedagogical Objectives Based on a Genetic Algorithm in an Adaptive Learning System

Badr HSSINA[a,*], Mohammed ERRITALI[b]

[a]*Faculty of Science and Technology, Mohammedia, University HASSAN II, BP 146, MOROCCO*
[b]*Faculty of Science and Technology, Beni Mellal, University Sultane Moulay Slimane ,BP 523 MGHILA, MOROCCO*

Abstract

The need for e-learning platforms to provide advanced and adapted training requires the introduction of new approaches to the resolution of the problems encountered. In this respect, the adaptability of training systems becomes a desired characteristic.
The use of genetic algorithms makes it possible to automate the search for courses adapted to the profile of the learner. Indeed, we assign different learning paths to learners belonging to the same class.
In this work, we present the approach and the architecture adopted for the development of our adaptive e-learning platform which allows to generate learning paths adapted to the profiles of the learners and according to the pedagogical objectives fixed by the teacher. Thus, we study the problem of adapting the learner's profile to pedagogical objectives as an "optimization problem", using genetic algorithms to look for an optimal path. Finally, we conclude with an experiment and evaluation of our approach based on genetic algorithms.

Keywords: Adaptive e-learning; Educational path; Genetic algorithm; Pedagogical objective.

* Corresponding author. Tel.: +212-662031914; fax: +212-523315353.
E-mail address: badr.hssina@gmail.com

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1. Introduction

Educational systems, learning models and continuing education programs are based on a uniform approach, which may be inappropriate for learners' abilities. Indeed, through research in cognitive science and artificial intelligence, we can migrate to faster learning and more sustainable retention called Adaptive Learning [1].

These proposals are calculated on the basis of the learners' profile, their learning objectives and history, and the content they followed.

Adaptive Learning appeared in the 70s in connection with research work on artificial intelligence; this concept is today very present in the educational world [2].

Technological evolutions and the improvement of user interfaces make it possible to envisage learning that would be able to respond to the acquisition of certain skills. According to [3]: "Adaptive learning is a pedagogical method based on the use of computers as interactive teaching devices. They adapt teaching resources according to the learning needs of students, which are identified through answers to questions, exercises and experiments. This technology is based on different fields of study such as computer science, education, psychology and neuroscience.

It is common knowledge that each learner is unique in their learning process, and in order to reduce the risk of discouragement in the face of only uniform and collective teaching, some digital resources and software can be used to help the learner [4]. In brief, the adaptive learning algorithm can be used to finely exploit the learner's traces and establish a personalized roadmap based on his profile.

2. Adaptive learning and genetic algorithms

Adaptive e-learning is a learning and teaching medium that uses an intelligent tutoring system [5] that can dynamically and systematically adapt e-learning. Fig. 1 illustrates the main components of an adaptive teaching system:

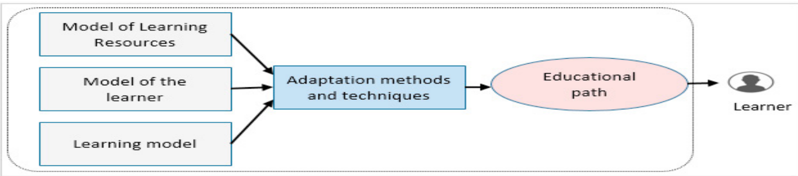

Fig. 1. Adaptation methods and techniques are applied to all three models.

In adaptation methods we can use genetic algorithms that are evolutionary algorithms. The evolutionary algorithms [6] are a family of algorithms that are inspired by the theory of evolution to solve various problems. They thus evolve a set of solutions to find the best results to a given problem. These are stochastic algorithms [7] because they use iteratively random processes.

Historically, three large families of algorithms were developed independently between the 1960s and 1970s. The first methods are the evolution strategies proposed by Rechenberg in [8] to solve problems of continuous optimizations. The following year, Fogel, Owens and Walsh conceived evolutionary programming as an artificial intelligence method for the design of finite state automata [9]. Finally, in 1965, J. Holland proposed the first genetic algorithms for combinatorial optimization [10]. The publication in 1989 of David Goldberg's book on genetic algorithms will make them particularly popular [11].

Genetic algorithms are inspired by the theory of evolution and biological processes that allow organisms to adapt to their environment. They were invented in the mid-1960s by Holand [10]. These were born from Darwinian reflections on the theory of evolution of species [16]. The key idea of this theory is that, under the constraints imposed by the environment, species of living beings have gradually self-modified in order to adapt to their natural environments. Fig. 2 illustrates the general operation of a genetic algorithm. This is to simulate the evolution of a population to which we apply different operations:

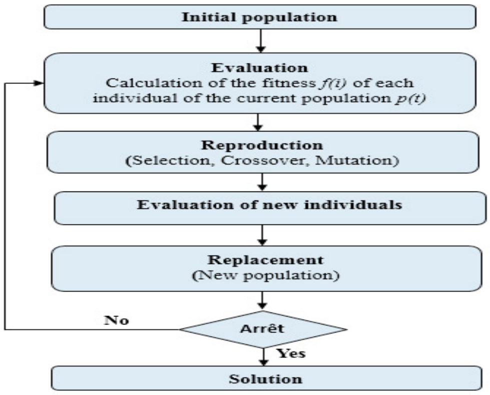

Fig. 2. General operation of a genetic algorithm.

The implementation of genetic algorithms requires several steps to detail. The first is the coding of an individual represented by a chromosome [12]. The second is the calculation of the performance. The third is to define the reproduction operators.

3. Our approach to generating a learning path adapted to the learner profile

Fig. 3 illustrates our adaptive system designed to generate pedagogical pathways that are adapted to the learner's profile and the pedagogical objective set by the teacher. We have studied the problem of adaptation as an "optimization problem", using genetic algorithms. Our system looks for an optimal path from the learner profile through intermediate learning objectives.

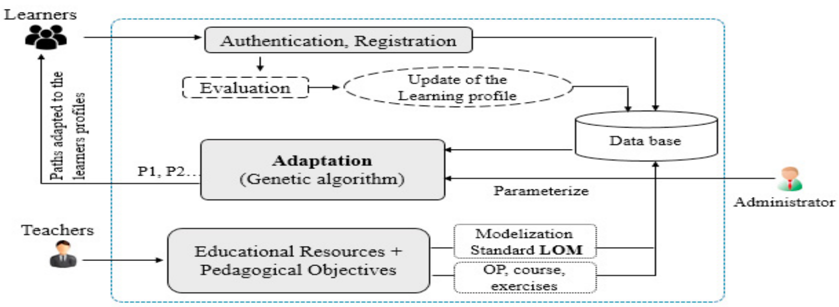

Fig. 3. General architecture of our adaptive e-learning system.

Thus, we focus on the adaptation of course content, and more specifically on the proposal of course unit sequences suitable to the learner profile. This profile is obtained according to the results of an assessment of the learner's achievements. Once the definition of the profile is established, we move on to the personalization of the content (teaching resources).

To prepare the learning resources for adaptation, the system creates a descriptive form for these resources, according to the LOM standard [13] to store them in the database

4. Adequacy of genetic algorithms to our adaptation approach

Genetic algorithms are able to adapt to any search space. They require a measure of the quality of the solution and require the definition of space by coding and operators that allow it to traverse it effectively [14].

The implementation of genetic algorithms in our system requires the definition of the following parameters:

- The size of chromosome n represents the number of concepts of the current training module.
- The probability of crossing Pc used is the probability of acquiring concepts for the learner.

- The probability of mutation Pm is the probability of deducing concepts from others for the learner.

The pedagogical objective defined by the teacher is reformulated using all the concepts to represent the knowledge that the learner must have acquired at the end of this training.

To implement our algorithm, we used the binary representation with a probability of crossing equal to 0.7 and a probability of mutation equal to 0.02. That is to say, the learner gets to acquire all the concepts present in a course or to deduce some concepts from the other concepts.

5. Implementation

The application was designed using free tools in the form of a dynamic website. This makes it easier to use and reduce finances. To integrate genetic algorithms into our system, we used the JGAP package [15]. The latter makes it possible to implement genetic algorithms and genetic programming with the JAVA programming language. It provides the basic genetic mechanisms that can be easily used to solve evolutionary issues. The use of genetic algorithms allowed us to automate the search for courses adapted to the learner.

To understand the value of our solution, imagine a student interested in learning on our platform. After registration, he must pass an evaluation so that we can define his level of knowledge (acquired concept). Then our system provides this learner with a personalized learning pathway to their profile (learning level). This adaptation is based on a genetic algorithm that seeks the most optimal path. That is to say, the list of educational objectives appropriate to the profile of the learner.

Moreover, to follow a training, the learner must have as preliminary knowledge certain concepts defined by the teacher (prerequisite). In order to determine these, a learner must pass a quiz evaluation in order to build his or her initial profile. The latter will consist of concepts deemed acquired from the correct answers.

Adaptability is achieved by implementing genetic algorithms to generate the path adapted to each learner.

6. Experience and evaluation

The starting point is the profile of the learner, the end point is the pedagogical objective of the training, while the intermediate states are the changes in the profile after the monitoring of the available pedagogical activities.

Our experience is conducted with 29 learners.

The module of the training chosen is: Initiation to oracle administration.

The concept number: 15

The number of educational objectives: 12

After the execution of the genetic algorithms. The profile, the objectives and the solutions are presented in the vector format. The representation is binary, which means that if it is equal to 0 then the concept is not acquired, and if it is equal to 1 then the concept is acquired.

The window illustrated in Fig. 4 shows an example of a learning path adapted to the profile of the connected learner.

Fig. 4. Example of a path adapted to the profile of the learner

Through the experience we have realized, we notice that as long as there is a significant distance between the profile and the objective, the error decreases (the percentage of the distance between the solution and the objective). That is, as long as the number of the concepts to acquire is large, the more we are able to find a more suitable solution. If the distance between the objective and the profile is smaller, the solution sometimes exceeds the target.

The evaluation of our genetic algorithm showed its convergence towards the optimal solution from generation 20 in the following figure:

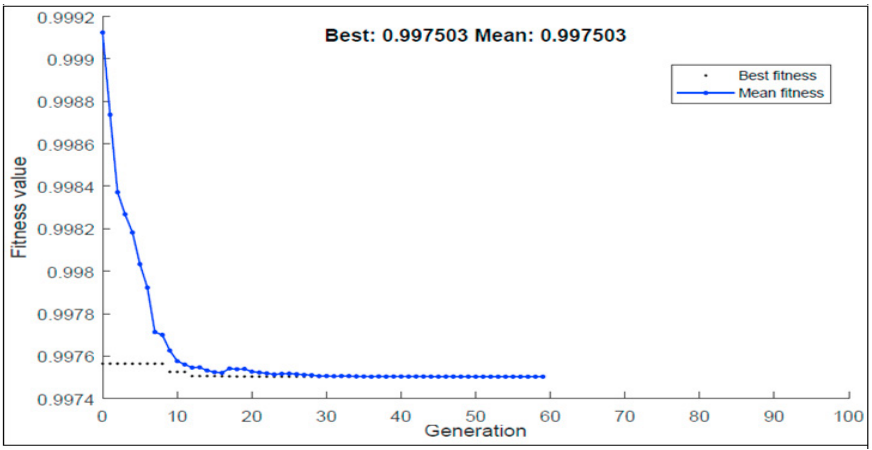

Fig. 5. The convergence of our genetic algorithm towards the optimal solution

Fig. 6 shows the average distance between individuals (educational objectives).

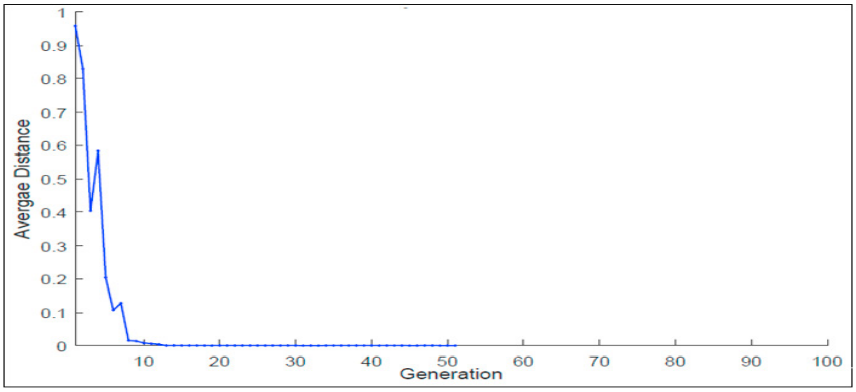

Fig. 6. The average distance between individuals

Fig. 7 illustrates the best and worst scores of the fitness function from generation to generation.

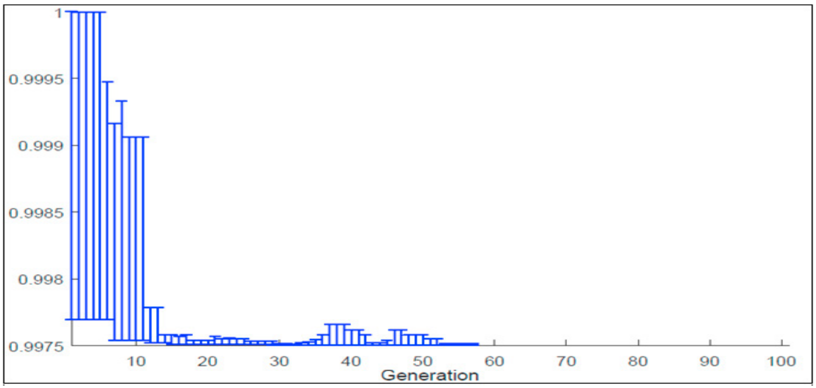

Fig. 7. Best and worst scores of the fitness feature

7. Conclusion

In conclusion, we have created a learning path generation system adapted to the learning profile. The idea is to transform the problem of the adapted course (list of pedagogical activity to follow) in an optimization problem. The use of genetic algorithms allowed us to automate the search for content adapted to the profile of the learner.

Finally, we believe that our system helps to make learning more adaptive, attractive and more effective. In the next section we will add a semantic aspect to this learning environment by proposing a system of semantic recommendation of text documents to learners.

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