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ANT COLONY ALGORITHM AND NEW PHEROMONE TO ADAPT UNITS SEQUENCE TO LEARNERS' PROFILES

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The use of new information and communication technology is increasingly common nowadays. Content adaptation of learner's profile is an issue that concerns many researchers in education field. Several studies have been conducted to achieve high quality learning and adapt the content to learners' profiles.

Some researchers have properly applied the ant colony algorithm to the field of e-learning.

In this work we are interested in the improvement of ant colony algorithm for scheduling units of courses (e.g., a Java course). We follow a pedagogical way to establish units. We define five concepts to maintain learners' motivation and adapt the algorithm behavior to our context. So our contribution is a new pheromone that influences the algorithm to choose the right unit in a pedagogical sequence. Many changes are taken into consideration to implement the new version of ant colony algorithm. The trainers apply weights to each arc that are linking two units of the course. The profile definition is a part that was preliminary defined in previous work using fuzzy logic method.

Method Roulette Weel is applied for the selection part. This method is interested in finding the final state. It is used in addition to the ant colony algorithm for the path exploration and optimal learning path.

Keywords: ant colony algorithm, fuzzy logic method, content adaptation, e-learning adaptive, schedule units.

1. Introduction

In the underlying work, we establish pedagogy to follow. It is to maintain learner's motivation. We define a pedagogy that is based on five fundamental concepts: Awareness, exposure, appropriation, assimilation, production.

In this way, it captures the interest and masters more what is offered to the learner. This pedagogy can be applied to any discipline or course. Even for courses in learning programming languages. We applied this logic to Java courses. This view leads us to add a new pheromone Cp which will influence and improve the behavior of the algorithm. We take into account the changes in parameters of the algorithm. Concerning fitness value, pheromone quantity and the allocation of weight by trainers, it is now easier than if we did not have those educational concepts.

In the second section, we review the system conception of Ant Colony Adaptive E-Learning (ACAEL). In the third section we will establish a state of the art of some works in the application of ant colony algorithm, and explaining concepts of the algorithm. We then apply it to our context, explain changes, namely the fitness formula (personal and collective factors), and we present the formula of pheromone quantity in the fourth section. After that, in the fifth section, we make our implementation, we propose in this section, class diagram that groups both of learner profile definition system and adapted ant colony system, and we show after that some results. In the sixth section we discuss some points that have been done and other may be treated in the future to improve the mechanism. In conclusion we share some questions that we have asked during the design of the mechanism.

2. ACAEL system

ACAEL system is a content adaptation that uses a hybrid method. The Fuzzy logic method is to define learners' profile. The ant colony algorithm is process to search for the next unit to the appropriate profile of the learner.

The system aims to invite learners of different levels to develop their skills. That is to say, the system offers to learners the possibility to identify their level first time as: beginners, familiar with a course or experts. If a learner judges himself as an expert on a course, the sequence of the course dedicated to him is displayed. If the learner says, that he is a beginner or familiar with the course then the system proposes a Global test. The test is arranged by several questions from easiest to the most difficult. These questions are composed by different types: multiple choices, single choice...We note that in learning course, the learner takes a mini test after each unit [Benabdellah N. C. et al.; 2013].

The definition of learner profile is based on four criteria. Before starting the adapted course, three criteria are considered: the score obtained after global test, the time elapsed during this evaluation and the number of attempts. After studying each unit, the criteria taken into consideration are four: the score after a test corresponding to the unit, the time spent in learning it, the number of attempts to take the mini test and finally the elapsed time to fill in the test. Thanks to fuzzy logic we can calculate the level of the learner and rank him to establish a logical sequence of units' course that corresponding to his profile [Benabdellah N. C. et al. 2013]. We choose to implement the ant colony algorithm. This is the part that we undertake in this paper.

3. Ant Colony Algorithm

We cannot apply an optimization algorithm to find the optimal path without explaining the logic of its functioning.

According to Steels in 1991, the model of ant colony algorithm is presented by an agent, who walks freely to find a pheromone. If the agent takes food, it will release a pheromone, and follows the path that contains the most pheromones. If the agent does not retain food found, he will release a negative pheromone and follows the path that contains the most pheromone. If the agent has a food and he never obtained it before, then the agent releases a pheromone. Only the path of ants that have food and deposited pheromones, which leads to the source of food, is the leader path [Hsiang L. et al. 2009].

Over the years, the behavior of agents has evolved through, to more complex calculations than only deposited pheromones. More details to understand [Giluon S. and Dras M. 2005].

According to Dorigo in 1992 each agent moves through cities and stores the visited city and the distance between them. We named theses distances arcs. Once the round of cities is completed then we set the amount of pheromone q/l, q is the parameters and it is the total distance of the entire cities in the round. The agent selects the arc which has the largest value of pheromones as other arcs. This is the key to balance between exploitation and exploration. But the method cannot work without the decay of pheromones that will lead to the amplification of the initial fluctuation. That is not necessarily optimal. So the value of pheromone deposited must decrease with time [Hsiang L. et al. 2009].

Work has been conducted on the application of the algorithm in e-learning and especially the adaptation of courses to learners' profile. We present a state of the art of adaptive e-learning specially using ant colony algorithm. Class diagram and use cases of adaptive e-learning are proposed, and the technique of adapting the path is presented [Allach S. et al.2012].

There are tasks that contribute to the modeling of the learning path by combining a planning prescriptive rules and schedule optimization of ant colony inductive rules. Ant colony is used to schedule objects of the course to the learner according to his profile. Sequencing content to a learner is proposed according to its level. Stochastic mechanism is proposed to involve learners in selecting the route and actual performance. These objectives conduct to adapt the algorithm and come away another DYLPA [Hsiang L. et al. 2009].

Some works proposes a new pheromone to improve the behavior of ant colony algorithm as: one new pheromone is used to optimize ACO (ant colony optimization) in solving the traveling salesman problem [Yoshikawa M. et al.2008] shop scheduling problem (JSP) is one of the most difficult NP-hard combinatorial optimization problems due to the "combination explosion" effect. An implementation of ant colony system on JSP by proposing a novel combination of path-construction and pheromone-representation is detailed in reference [Zhuo X. I. et al.2007]. An ant colony optimization approach is applied for the satellite control resource scheduling problem. Two pheromones have been proposed, the reinitialize-guidance-updating and current-guidance-updating methods. The objective is to avoid the trapping in local optima [Na Z. et al.2010]. Another pheromone is used to optimize ACO (ant colony optimization) in solving the traveling salesman problem. This new pheromone trail of each edge is set with a lower limit at the beginning iterations of the algorithm, and the worst ant judged by its tour length like the best ant used in ACO is allowed to perform global trail updating [Sun J. et al 2004]. There is an application on Multi-level Ant System (MLAS) as an improved version of Max-Min Ant System. The improvement is done using a novel pheromone updating scheme [Huy K. D. et al. 2006]. An ant colony algorithm is applied for unwheighted Total Tardiness Problem, some improvement were made. The ants are guided on their way to good solutions by sums of pheromone values. This allows the ants to take into account pheromone values that have already been used for making earlier decisions Merkel D. and Middendorf M. 2000]0.

We had an overview of some applications of the algorithm on adaptive e-learning field. Now we will explain some concepts and parameters of the algorithm.

3.1. *The weight placed on the arcs*

In general, weight is defined by the teaching team. The team decides whether the student should pass in priority by a node. The more the weight's value is important; the passage of the learner by this mode is prioritized. These values are deposited on the arcs. Weights are taken into account initially to make the learning algorithm phase.

3.2. *Pheromone deposited on the road*

We have explained the concept of distance between cities. But, in e-learning field it is about the nods. In practice, if the learner succeeds in node "7", it means that the arc tied to this node is divided by two, and then the next previous arc is divided by "3" until divided by "4". Those are values that represent the deposited pheromone after the success in one node. The same process happens when the leaner failed in node 7, the value of the arc tied to this node, is divided by "2" until it reaches the value of "4" [Allach S. et al.2012]. More the node visited is older, more the value of pheromone decreases.

3.3. *Evaporation of pheromones in time*

In order to not get blocked in local optimum and to perform a dynamic adaptability, we develop the evaporation in the case of failure as well as in the case of success. "T" represents the rate of evaporation. This rate is the key of the simulation tests. X is the period of evaporation. X = 1 day and t = 0999 [Allach S. et al.2012].

3.4. *Store historical weight for each learner*

Ideally, each time, when a learner validates an element, a historical calculation is stored in the database. Initially h1 has the value of 0.5 for success and h2 a value of 0.75 for failure. This factor allows the reduction of the probability to revisit the node a second time. If this happens and the learner revisits a node, h1 and h2 values change. "Ŧ" is a constant to adjust the speed of evaporation. This value corresponds to the volatile memory of the learner [Allach S. et al.2012].

3.5. *Value volatility of the memory of the learner*

The volatility value of the memory of the learner is set according to trainers. For example, to forget an exercise, the trainers estimate 604,800 seconds.

3.6. *The calculation of the fitness*

The calculation of the fitness formula contains all values to learn whether the arc is desirable or not. “F” is the value of fitness. The value of “F” is high when the node at the end of the arc is the last visited a long time ago. In this case, the historical value is close to 1, or the weight defined by trainer is higher. So the trainer recommends visiting this kind of arc, which have higher fitness value, or higher weight value. Many learners succeed in this node therefore the value of Success "S" is high, and the value of failure "F" in a node is small [Allach S. et al.2012]. The calculation of this value will unify the average weight. The most important point of the algorithm is based on calculation of the fitness of an arc. We recall the standard formula that calculates it:

$$F(e,l)=P(e,l)(\omega_w W+\omega_s S-\omega_f F) \qquad (1)$$

When the learner moves from one unit to another, then we calculate the fitness value. Based on the results, the selection algorithm is responsible for choosing the unit to the learner.

- P (e,l) those are the parameters specific to the learner.
- W is the weight deposited by trainers.
- S and F are values corresponded to the success or failure respectively.

4. Use case

Previously we have seen formulas and explanations of algorithm parameters. In this section we explain our contribution from two sides. The first concerns pedagogic side. The second concerns technical side which is how to improve the behavior of the algorithm. We implement the algorithm based on the functions and formulas adapted to our learning model.

We take into consideration the pedagogy as core of all the process of adaptation. “One of the most crucial prerequisites for successful implementation of e-Learning is the need for careful consideration of the underlying pedagogy, or how learning takes place online. In practice, however, this is often the most neglected aspect in any effort to implement e-Learning [Govindasamy T. et al.2001].” This is why, we need to question upstream on learning models to implement [Pemin J.P.2003].

In our case, the design of the units complies with the fundamental concept of motivation for learning sequence. It based on five parts: awareness, exposure, appropriation, assimilation and production.

Trainers apply this logic and educational sequence to teach Java courses. In our case, it represents a set of units in a pedagogical order:

- Awareness of the student to know Java course for example the history of the Java language and platform.
- Another set of units was designed as exposure: it’s represented by some concepts corresponded to Java language, it includes the compilation, programming tools, Run code, comments….
- We design units to use these information exposed in exposure part, and we name this part: appropriation. How we code? How to declare variables? Mathematic operations? ...
- Assimilation part contains how we develop some simple algorithms.

- Production part is an advanced level in programming. It is when a learner masters all notions. We expose to him a complex algorithm with graphical achievement; by using tables, matrix, pile, and tree.

We have an overview of the disposal of java units in pedagogical sequence in Fig. 1.

Fig.1. Overview of units of a Java course for profile1

4.1. *Pedagogical sequence and possible paths*

A learner may move from one unit to another unit that may belong to the first part (awareness). If the learner is initiated then it goes directly to the unit that belongs to the exposure area. Depending on the level of the learner, he can study a few units in this last part or all or at least one to decide his mastery fig.3. And we propose to him units in the third part which is the appropriation. The same reasoning also is applied in the latter. That is to say that a learner can at least study a unit that belongs to any part or some if not all. And he will be able to move to the fourth part in his learning path and the fifth too. Return backwards is also possible if a learner does not master the current unit.

Example of an educational path represented by nodes of different colors: orange represents awareness, gray means exposure, appropriation represents brown, green and blue are assimilation and production, respectively. We judge the mastery of the course, when a learner succeeds in producing a complex Java code at the end of his learning path in Java course Fig.2.

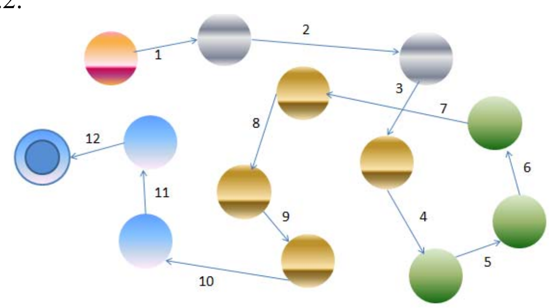

Fig.2. An example of path

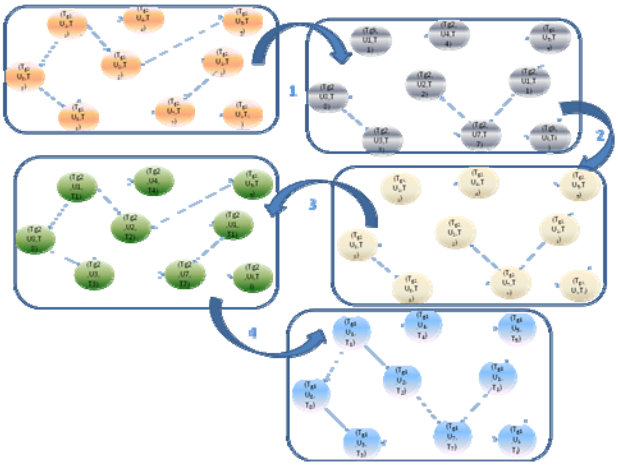
Fig3. Many units in each part

For example, if a learner succeeds in a unit in awareness part and succeeds another unit in exposure, we propose to him a unit in exposure or in appropriation. It means that he is rightly guided. But if he succeeds in exposure and we propose to him a unit in awareness, this is a not logical behavior of the algorithm. We would like to avoid this outcome. The learning path should return backwards only in the case of failure of a learner in a unit that belongs to the exposure, appropriation, assimilation production parts, the algorithm can return to the awareness or exposure area to better control Java concepts. All returns that are allowed are shown in Fig.3.

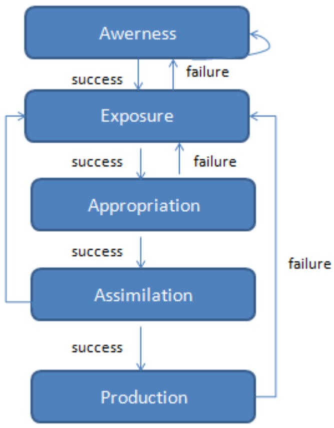

Fig.4. the pedagogic sequence

We see an overview of all the system in fig.5. In the top of the figure, we have the system that define learner's profile using fuzzy method [Benabdellah N. C. et al.2013], end the second part, concern the system that take into consideration the output of the top part to adapt units course using ant colony algorithm adapted.

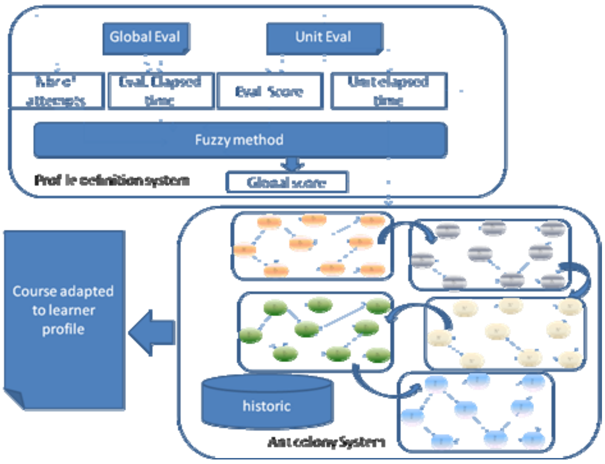

Fig.5 Overview of ACAEL System

4.2. *The calculation of the fitness value*

The standard calculation of the fitness value is mentioned above in (1). Our contribution is to improve the behavior of the ant colony algorithm to lead learners to a more adequate learning path. A new pheromone was added to influence on the choice of the arc. The higher the value of the arc the more likely to the arc is to be used. We take into consideration the historical values stored in the database, the elapsed time spent and the global score result we obtain to define learner profile using fuzzy logic method.

The calculation of the fitness value is based on personal factors "e" and collective "l". The formula for calculating the fitness becomes (2):

$$F(e,l)=(H(n,l)\beta 1+ T(n,l)\beta 2 +P\beta 3)*(\omega wW+\omega pCp +\omega sS-\omega fF) \qquad (2)$$

Such as:

- H: represents the history of a learner during learning.
- T: represents the elapsed time during the consultation unit.
- P: the score obtained to define the learner level
- β_1 and β_2 and β_3 are respectively the weighting factors H and T and P.
- ω_w, ω_p, ω_s, ω_f are respectively the weights weight, educational criteria, success and failure. Values are determined by decision makers to favor one factor over another.
- The calculation of the value of success "S" is represented by $\alpha 1/k$ (k is the number of steps made by one learner).
- The calculation of the value of failure « F » is represented by $\alpha 2/k$ (k is the number of steps made by one learner).
- C_p is pedagogic criteria. It corresponds to unit membership to pedagogic sequence.

In each transit, a learner deposits a positive pheromone that corresponds to C_p value if the unit is defined in the right sequence. If not, the learner deposits a negative pheromone.

If the unit is in the right sequence than Cp value is represented by (3):

$$Cp = Cpc * (\alpha 3/k) \quad (3)$$

$$Cpc \begin{cases} 1 \text{ if unit is in the right sequence} & (4) \\ -1 \text{ else} \end{cases}$$

Cp criterion is a part of collective criteria. The objective to use this criterion is to guide the learner to the right unit, the smooth functioning of the algorithm is based on these criteria personal (history, timing, level) and collective (unit's weight, pedagogic sequence, success, and failure).

4.3. *The pedagogical weight and outranking method*

Initially before finding the suitable path for the learner, the trainers design the course. They initialize the weight of the arcs of the graph. The graph is composed of units. The trainer assigns weight's values. More the value of the arc is high; more it is a recommended path to follow. Before we talk about scheduling unit, the initial state is very important. In general, trainers are responsible for the assignment of values, based on their experiences. This assignment is subjective.

A pedagogic team, which masters the course, can decide about criteria or rules to take into consideration and upgrade units.

"Ranking relationship is a binary relation S defined in A such as aSb if, given what we know about preferences of decision maker and given the evaluation action and problem nature, there is enough evidence to assume that a is at least as good as b, without having an important reason to refuse this affirmation." [Vincke P. 1989].

The teaching team assigns weights to all units of the awareness phase, exposure, appropriation, assimilation, production have values respectively Ws=5, We=4, Wap=3, Was=2, Wp=1.

We should note that initially, we recommend units that have the higher weight in descending order.

4.4. *Updated pheromone*

More a visited unit is old more the pheromone quantity decreases. To encourage or discourage learners to visit a unit, we increase or decrease the pheromone quantity by success value, failure value and Cp value. The pheromone quantity increase by this value of [Naji A. and Ramdani M.2013] (5):

$$\Delta\tau ni,j(t)\alpha n\beta n \quad (5)$$

- n is a learner who succeed in a unit
- β represents the quickness of a learner
- α is the level of knowledge of a learner.

In our case we don't take into consideration the speed of the learner. The elapsed time during unit study is calculated at beginning in personals factors of fitness formula.

We retained the value of pheromones deposited (6).

$$\Delta\tau ni,j(t)\alpha nCp \quad (6)$$

The value of pheromone deposited after one success between unit i and unit j is (7):

$$\tau_{i,j}(t+1) = (1-\rho) * \tau_{i,j} + \sum_{n=1}^{m} \Delta\, \tau n_{i,j}(t) \alpha_n\, C_p \qquad (7)$$

- ρ Represents evaporation rate, we choose x=1 day, which means: ρ =0,999.
- m is the number of learners whom passed through units « i » and « j ».

The learner n deposits the quantity of positive pheromone if he succeeds in a unit and this unit is in the pedagogic sequence (7).

If the learner is not in unit in pedagogic sequence or the learner failed in unit than we decrease the quantity of pheromones deposited on the arc connecting two units (8):

$$\tau_{i,j}(t+1) = (1-\rho) * \tau_{i,j} - \sum_{n=1}^{m} \Delta\, \tau n_{i,j}(t) \alpha_n C_p \qquad (8)$$

4.5. *Learning stage*

The ant colony algorithm can find optimal learning path, if learners complete several passages paths.

4.6. *Historic factor*

This factor allows the storage of visited nodes. With this information you can privilege a node over another. We consider the history H, the value is multiplied by h1 if the learner failed in a unit. If he succeeds in unit H is multiplied by h2. If the node is consider in pedagogic sequence we multiply H by h3.

We have: h3> h2> h1 (9)

We consider those values of: h1, h2 and h3.

h1=0.4, h2=0.6, h3=0.8 (10)

The objectives is to reduce the probability that the node or unit previously visited will be proposed a second time, especially if it doesn't in pedagogic sequence.

4.7. *Selection procedure*

The role of the selection procedure is to decide which arc to follow. When a unit leads to several arcs, the most appropriate one to the learner will be chosen.

Roulette-wheel selection, ranking based and stochastic tournament are the most popular selecting methods used in [Semet Y. et al2003]. In our system we use Roulette-wheel. The formula is (11).

$$p(a_{i,j}) = \frac{f(a_{i,j})}{\sum_{n_k \in E} f(a_{i,k})} \qquad (11)$$

"a" represents an arc that link "I" and "j". "k" is all nods.

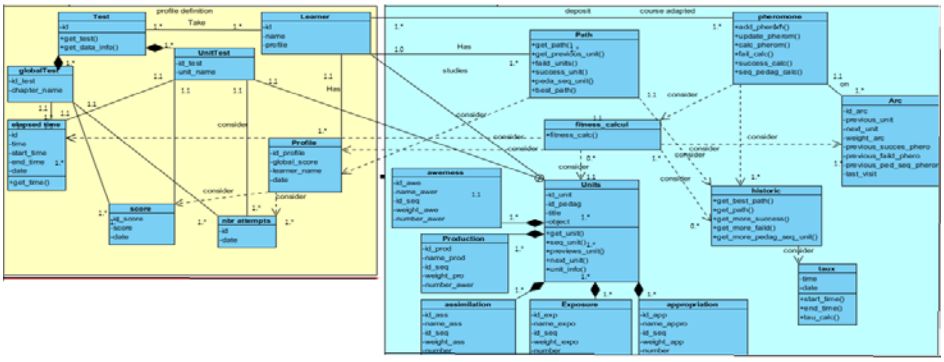

Fig.6. Class diagram

5. Implementation

Class diagram gives all details of how it is implementing classes are defined with functions and links are shown in fig.6.

The code is tested in a console to monitor the implementation step by step fig.7. The objective is to reach the optimal path fig.8.

The function that recognizes, if a unit is in a pedagogical sequence or not with conditions is implemented:

U_i represent current unit and U_{i+1} is the next unit in learner path.

U_{awer}, U_{expos}, U_{appro}, U_{assim}, U_{prod} are respectively sets of units in pedagogical sequence awareness, exposure, appropriation, assimilation and production.

- If U_i and U_{i+1} are both into U_{awer} or U_{exposi} or U_{appro} or U_{assim} or U_{prod} than Yes
- If U_i is a success and is a part of U_{awer} and U_{i+1} belong to U_{exposi} than Yes
- If U_i is a success and is a part of U_{exposi} and U_{i+1} belong to U_{appro} than Yes
- If U_i is a success and is a part of U_{appro} and U_{i+1} belong to U_{assim} than Yes
- If U_i is a success and is a part of U_{awer} and U_{i+1} belong to U_{prod} than Yes
- If U_i is a success and is a part of U_{awer} or U_{expos} or U_{appro} or U_{awer} or U_{prod} and U_{i+1} belong respectively to U_{awer} or U_{exposi} or U_{appro} or U_{assim} or U_{prod} than Yes
- If U_i is a failed and is a part of U_{prod} or U_{ass} or U_{app} and U_{i+1} belong to U_{expos} than Yes
- If Ui is failed and in a part of Uawer or Uexpo and Ui+1 belong respectively to Uawer or Uexpo than Yes
- Else no

In the implementation of this function, we declared the whole units and specified sets of units by discrete integers.

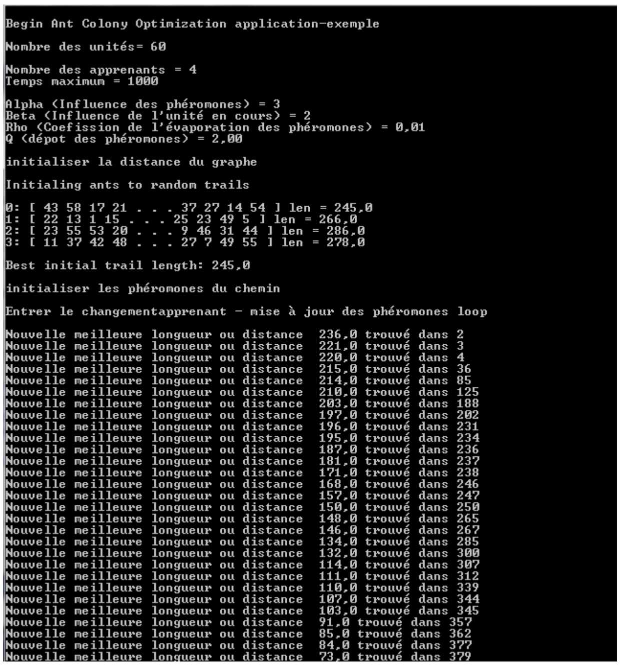

Fig.7. Learning path serach process

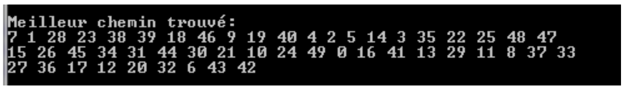

Fig.8. An example of one best path found

6. Discussion

In this work, we adapt the algorithm to our ACAEL system. We proposed a new pheromone that improves algorithm behavior, towards the best path. This new pheromone influences on the choice of the node. It represents the educational criterion that is very important and must enter into consideration in the decision to propose the best unit to the learner during ant colony process. This unit is good only if it conforms to a pedagogical sequence with taking into account historical factors to give a chance to other node be seen by learners.

The teaching staff has a difficulty to lay down adequate suitable weight initially to favor a node over another. We classify units in a pedagogical and sequential order, that facilitates the task and using a method of upgrade, we will move away from subjectivity and external influences such as halo effect, effect of stereotype order effect…

In e-learning adaptive system Paraschool [Gutiereez S. et al. 2002], a new personnel pheromone is proposed. This pheromone gives the information which is whether the exercise was seen twice before in one week. The system did not lead to better results than results with free navigation. In our case, we have the good results and we conclude that this pheromone improve the behavior of the algorithm.

The length of the learning path for a session affects the execution time of the algorithm. To remedy this problem, the session is divided into reasonable number of sub levels. The short learning paths to reach elementary objectives also improve the performance of the algorithm [Wang F. H. 2012].

The best way is not found optimally because learners keep exploring the environment, even when they found their path. The solution is to remove the space that is not necessary during the research process, the search space will be reduced quickly [Wang F. H. 2012].

It is true that the three methods have been implemented but the tests have not been done to conclude which method is the best. Which method of selection we have to choose [Semet Y. et al.2003]. Local selection can be implemented too as another method of selection. Roulette-Weel that we used in our implementation responds to our need for the moment.

7. Conclusion

During this work, some questions we have asked some of them are listed here.
Is the choice of personal settings to the learner and factors are realistic to determine human behavior?

We need to make several passages, to take the learner to the best arc. How many turn we need to judge whether the implemented algorithm is conclusive?

The choice of the teaching staff is not objective. Much time is devoted to decide on the weight of an arc. Methods of decision-making exist to meet this need. We can use decision trees to approach the right decision. How to choose the rules and criteria to consider when making a decision to assign weights? Are these selected criteria will also have weights? The compensation between the criteria is it existing? If so how is it represented? How to manage the independence between those criteria?

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