An Adaptive Learning Based on Ant Colony and Collaborative Filtering

Bourbia Riad, Seridi Ali, Hadjeris Mourad, and Seridi Hamid

***Abstract*— One of the most prominent stakes of the online learning is learner's autonomy. Adaptive e-learning will permit frameworks use improvement by suggesting courses adapted to results, behaviors, preferences, tastes,… learners, without any awareness of it that can be noticed by them. In the present paper, we have proposed a hybrid approach based on the Ants colonies' optimization algorithm to recommend a learning course which fit in the best manner into learner's profiles. These courses are dynamically built using elementary pedagogical objects which can be organized in a graph. The filtering algorithm is used to arrange learners into groups based on similarities to accelerate the proposal process. The method will be adaptive and robust at the same time. The innovative approach is helpful in improving both the learning achievement and learning efficiency of individual Learners.**

***Index Terms*— Adaptive learning, ants colonies, collaborative filtering, learning objects, personalization parameters**

I. Introduction

Information and communication technologies, particularly the internet, have prevailed this last decade our everyday life, personal's as professional's. After been interfered within many domains such as E-learning, the internet is being to be the vault key to a new way of teaching. In fact, E-learning sites are increasing because of the interest which they bring: time, transport and accommodation saving, use flexibility, interactivity… etc. Since few years, a new current is interested to adapt pedagogic contents to learners. Hence, it will be most appropriate to offer a tailored contents, and more adapted courses based on preferences and learners abilities, to effectively master the management of knowledge to be transmitted. In the reality, most learners cannot find most suitable pedagogical objects because each one has different attributes and each learner has different characteristics. Thus, adaptive learning has gained more attention in recent years. Several intelligent proposals have been developed: dynamic learning recommendation [4], intelligent learning contents suggestions [8], Adaptive pedagogical path [13], and adaptive learning [3]. The establishment of the learning path for learners was certainly not a new approach as indicated above, but learner's characteristics and their learning behaviors lead to the elaboration of adaptive systems.

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Kolb [10], Felder and Silverman [6] indicated that students learn in different manners: some of them learn best when visualizing contents, others when listening…etc. Thus, a learning style can be considered as a general predisposition to process information, in particular manner. Learning styles have to be considered when elaborating the dynamic learning environment [9]. Our approach is different from many existing models and brings some contribution, especially when using together algorithms such: Ant colonies (adaptive courses) and filtering (similarities' treatment) for optimization reasons, and at the same time without reducing the Unified Learning Model Style (ULSM) interest, gathering a height number of psychological features derived from various learning style models which we find in literature. The following sections include: the literature review of the related studies (section 2), a description of our designing system (section 3); an introduction to optimization algorithm (section 4), some screenshots (section5), and finally, the concluding remarks of the study (section 6).

II. Related Work

Adaptive educative systems (Fig.1) try to offer an alternative to non-individualized approach, by providing several services adapted to learner's profile. The goal of such adaptation is to maximize the subjective learner's satisfaction, the progress of learning and evaluation results. Learner's features identification is the first phase of adaptation, called learner's modeling. Decision making of adaptation is the second one, in which particular adaptation measurements are made, based on the collected information of the first phase. The user's model have to be modeled with a given number of parameters, which can be determined by the requirement diagnosis, learners interests and difficulties, and as result, the system have to be adapted automatically.

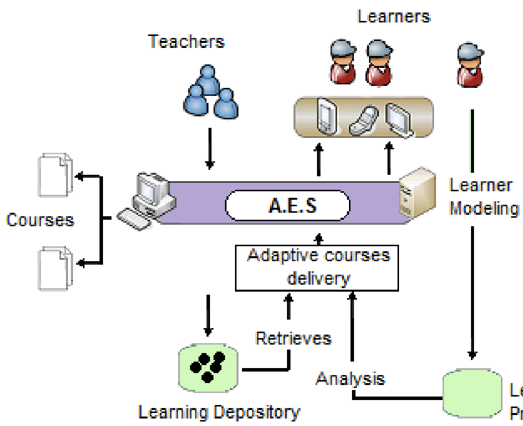

Fig. 1. Adaptive Educational Systems

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The personalization of the human learning raises from works on interaction between aptitudes and treatments that prone instruction adaptation to person's characteristics. For this goal, several researches to have focused on identification of dimensions of person's differences. These researches have led to the birth of learning style theory. This theory is translated by the different manner in which a given person can learn. Table I summarizes the all-important of Adaptive Educational Systems (AES) that came out in the last decade and personalization parameters that underlie.

TABLE I
ADAPTIVE EDUCATIONAL SYSTEMS CLASSIFIED ACCORDING TO THE PERSONALIZATION SETTINGS.

AES	Personalization Parameters
PERSO [5]	Learner's Level knowledge, media preference
TANGOW [12]	Based on two dimension of FSLSM: sensation/intuitive and sequential /global.
AHA [15]	Felder-Silverman learning style, media preference, navigation preference
Milosevic[11]	Kolb leaning cycle, motivation level
WELSA [13]	Unified learning style model (ULSM), which integrates characteristics of several models, relative to: perception methods, treatment mode, information organization and also motivation and social aspects.
SACS [16]	Based on VARK learning style (Visual / audio, read/writing, kinesthesia) and an optimization approach (Ants Colonies) to personalize learning.
SAAD [1]	Learner's Level knowledge, Language preference, media preference

Each of these systems employs, at most, three personalization parameters. Most of them use a learner's knowledge level. Many of them grant importance to media choice made by learners. For example, PERSO [5] employs RBC approach (case based reasoning) to determine which courses to suggest to learners based on their knowledge level, and their media preferences.

TANGOW is based on two dimensions of FSLSM (Felder-Silverman Learning style Model): deductive/ intuitive and sequential/ global. Learners are invited to fill ILS (Index of Learning Styles) assessment when they connect to the system for the first time, the learner's model is initialized by consequence. Afterword, learner's actions are monitored by the system, and if they controvert the expected behavior for these learning preferences, the model is updated [12].

AHA [15] systems based on the notion of "education's meta strategies," by which pedagogic content authors can choose learning styles that have to be used as well as adaptation strategy. This way, the system is free from any other particular model of learning style. However, there exists a limitation in strategy's styles that can be defined and as a result, in the set of learning styles that can be used. Another model of learning style that has been adopted by other educational systems is VARK [7] which deals with the preferred perception modality of the learners (Visual, Aural, Read/write, Kinesthetic).

SAAD [1] was designed to allow authors to develop adaptive learning contents based on IMS learning design. A standard used to ensure content's interoperability. The adaptation holds on the account learner's knowledge level, learning language and perception's modality. WELSA (Web-based Educational with Learning Style adaptation [13]) adopts the unified model of learning style which embeds characteristics of several models proposed in literature, to adapt courses to learners.

III. DESIGNING THE SYSTEM

The system named "FORMATION PATH" is a compound of a convivial set of tools, eased to use, well adapted to users who manipulate the system, to know: teachers, learners and administrator (Fig.2). The content generator who through his three modules (profiling, filtering and learning path generator) allows dynamic adaptation of pedagogic contents based on learner's profiles.

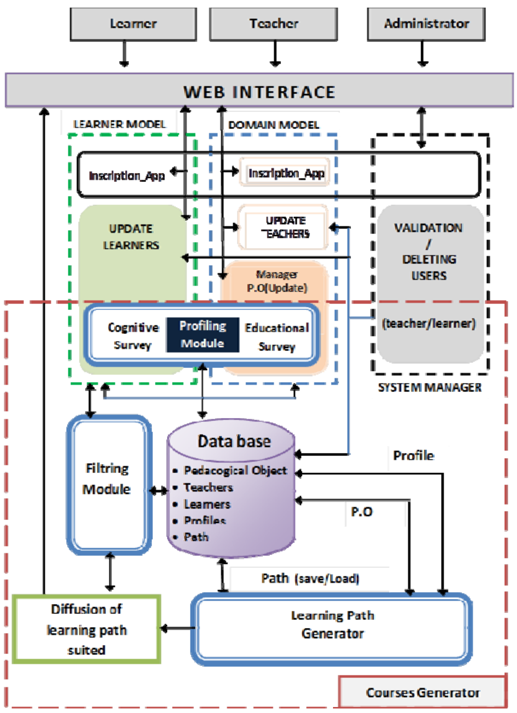

Fig. 2. System's Architecture « FORMATION PATH » [2]

A. Profiling Module

One distinctive feature of any adaptive system is the user model that represents essential information about each learner. For the learner's psychological aspect, the emphasis is put on an under-set of ULSM (see Table II) Model attributes. This model integrates characteristics of learning style, the most relevant using several models proposed in literature.

TABLE II
UNIFIED LEARNING STYLE MODEL [13]

ULMS – Learning Style			
Perception modality	Visual	vs	Verbal
Information processing	abstract	vs	concrete
Reasoning	Deductive	vs	Inductive
Social Aspects	Individual work Competitive	vs	Team work Collaborative

Following the educational test, knowledge level attribute allows learners to divide into four categories: apprentice (novice), beginner, intermediate, expert (see Table III). Educational contents of a domain model are partitioned on elementary units called granules (Learning Object), which are indexed using LOM model (Learning Object Metadata). These granules, enormously promote share and reuse, and they are well suited to form adaptive contents by a diverse assembling of those fragments (combinatory problem).

TABLE III
LEARNER'S ATTRIBUTES AND LEARNING'S OBJECTS ATTRIBUTES [16]

Learner's attributes	Pedagogical objects attributes	
Knowledge level	Object type	Object level
Apprentice	Graphic (image, graphe, symbole)	Easy
Beginner	Video (animation, audio)	Intermediate
Intermediate	Texte (texte, Word, Power Point)	Advanced
Expert	XML (Web, SCORM, LOM)	Expert

Additionally, the course is structured by block (Fig.4) analogically to what happens in face to face course, that is to say: each block contains a certain amount of learning objects (LO) of different natures and different levels. The fourth block incidence (tutorials, practice works) is optional for a given particular module.

B. *Filtering Module*

Filtering paradigm allows learners looking for learning to be able to profit of what has been already found, used and perhaps evaluated. Filtering module is charged of comparing the newly registered learner's profile with those who are registered, to suggest him the most appropriate learning path without calling the adaptive course generator module (Fig.3). This important step allows recommendation time optimization in the case where profile's similarities among learners population set existed.

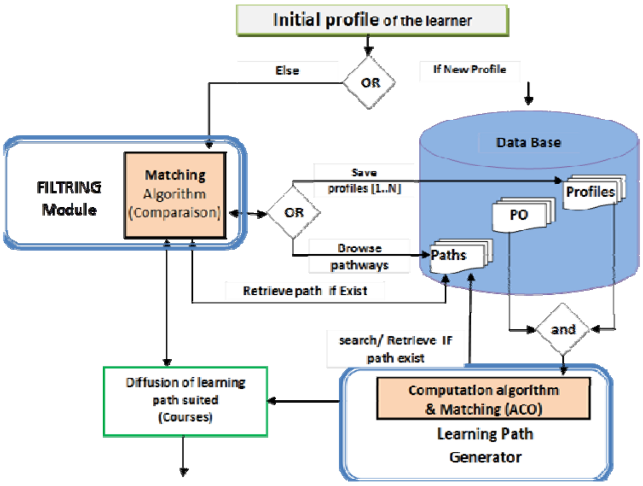

Fig. 3. Filtering Module

C. *Learning Path Generator Module*

The pedagogic content of our educational site can be modeled using a browsing graph (Fig.4) where nodes represent pedagogical objects (granules), and arcs are learning activities. Thus, the training path of a particular learner is obviously different from another path of another Learner with different interests. In the next section, we present the optimization method using ants colonies algorithm employed to recommend adapted training courses (paths).

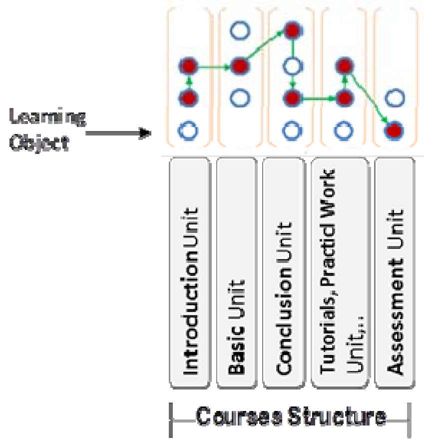

Fig. 4. Browsing graph

IV. OPTIMIZATION USING ANTS COLONIES ALGORITHM

This Meta heuristic is inspired from collective behavior of storing, and paths tracking observed within ant's colonies. Ants communicate indirectly through dynamic modification of their environment (pheromone's paths) and build by this way, a solution to one problem by taking on account their collective experience. Dorigo [17] proposed the ant colony optimization (ACO) algorithm inspired by ant colonies behavior to search the shortest path. The proposed algorithm is as follows:

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***Procedure** ACO algorithm*
Set parameters, initialize pheromone trails
***While** (termination condition not met) do*
Solution construction
Location search
Pheromone update
End
***End** ACO algorithm*

A. Solution description

We use pedagogical object attributes and attributes of learners (see Table III) to build a solution. Let be an agent «ant» having an **S** style and knowledge level **N**, produces a fixed amount of pheromone when it moves across a node. If attributes of the agent ant match in total or in a partial manner with the node attributes (pedagogical object), then, nodes, which are on the path crossed by the ant agent can obtain a supplement of pheromone (increasing their selection probabilities), and therefore the pheromone trail on such a path will grow faster and attract more ants to follow.

V. Application

FORMATION PATH has been implemented with PHP and MySQL. The educational web site contains three actors, to know: Learner, Author/ Teacher and Administrator. Learner is prompted with a double questionnaire, in order to determine his or her profile. The following figures describe the process of learning objects recommendation.

Fig. 5. Home page

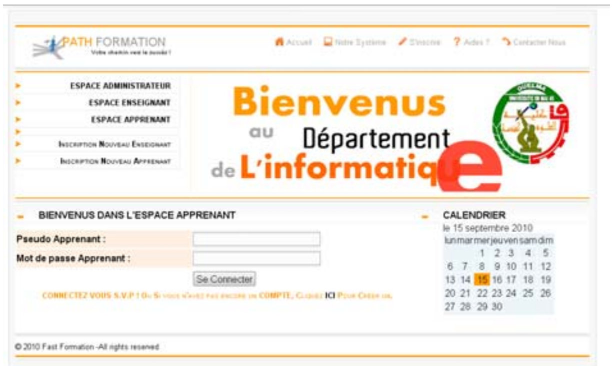

Fig. 6. Learner's login: Once the learner is registered, it is sufficient to enter their password and username to access his own space.

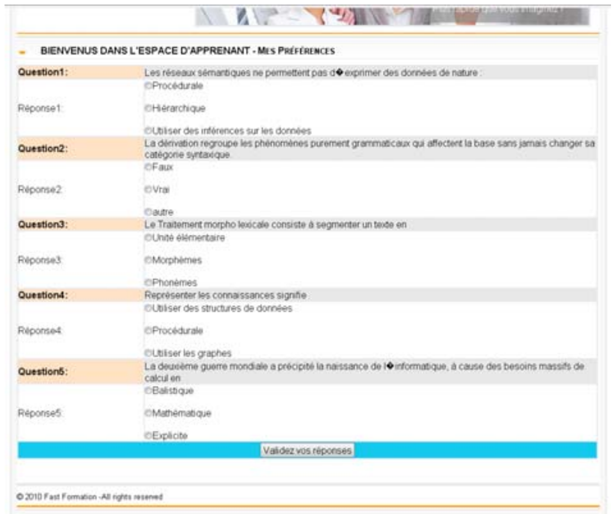

Fig. 7. Pedagogical survey: the learner must answer all the questions to know his educational level.

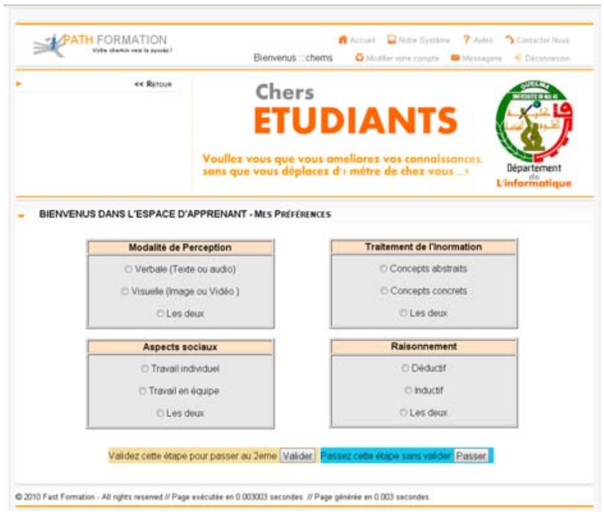

Fig. 8. Cognitive survey: assist the system to know the learning style of the learner.

Fig. 9. Learning objects and courses recommendation

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VI. CONCLUSION

In this paper, we propose an adaptive learning platform, FORMATION PATH, which takes multiple sources of personalization information into consideration, including individual educational level and learning styles.

FORMATION PATH is an environment that can assist teachers to develop web-based courses and provide learners with suitable educational objects to improve their learning performance.

In this work, we used a hybrid method based on ant colony algorithm and the collaborative filtering algorithm. Ants Colonies Algorithm remains a fine tool to solve combinatory problems. Data sharing on pheromones is the highlight of such technique, which can be combined with distributed artificial intelligence where each agent comes over to enrich the collective knowledge. Its implementation in conjunction with ULSM learning style model, learner's domain knowledge level and learning objects attributes can provide an adaptive solution to learners. Collaborative filtering algorithm allows recommending a learning path to a new learner with the same profile without triggering the calculation process. The experiment conducted in a Computer Science Department is only at its beginning. Now, we work to optimize all parameters, the first results will be discussed in our future work.

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