ADOPT: A Trace based Adaptive System

Henda Belaïd Ajroud[1], Insaf Tnazefti-Kerkeni[2] and Bénédicte Talon[2]
[1]*LIPAH, Faculté des Sciences de Tunis, Le Belvédère, Tunisie*
[2]*LISIC, Université du Littoral Côte d'Opale, Calais, France*

Keywords: Adaptive Learning, Traces, Learner Model, Domain Model, Adaptation Model, Agents.

Abstract: Adaptive learning is learning that tries to get closer to the learner in order to identify his/her strengths and weaknesses and to provide him/her with a learning that best adapts to his/her needs, thereby increasing his/her chances of success. It is in this spirit that this work was carried out. It is interested in adaptation of learning when using a Learning Management System (LMS). To achieve our goal, we designed different models such as the Learner Model and a multi-agents system, ADOPT, which defines intelligent interactive agents. These agents analyze the traces left by the learner, calculate various indicators and propose the most suitable adaptations for the learner.

1 INTRODUCTION

During the past decade, the use of e-learning platforms to supplement or replace face-to-face training has increased. In some situations, the teaching is even 100% distance. Unlike traditional learning where instruction is directed by the teacher and where memorization is very important, modern learning is learner-centered and performance-oriented (Chachoua, 2019). So, some learning systems or platforms consider the learners' needs and adapt to these needs. With these adaptive learning systems, each learner characteristics are considered: strengths, weaknesses, specific learning rhythm and more generally, profile and goal. These parameters are used to in order to maximize their learning outcomes and minimize the risks of abounding. Thus, adaptive learning systems identify the needs and interests of each learner to provide personalized contents and specific learning paths.

Some adaptive learning systems have been set up for specific courses. For example, Yixue is used in China for mathematics courses among middle school students (Wang et al., 2019) and in an after-school english language arts course (Li et al., 2019) and BAGHERA (Pesty and Weber, 2004) is used for geometry proof learning. Other systems, such as AMAS (Gaffney et al., 2014), help users to create adaptive e-learning components but are not open and flexible enough to be used in different learning fields. Other systems adapt presentation such Allegro (Viccari et al., 2007) which supports collaborative learning and MASPLANG (Peña et al., 2002) which supports distance learning via the web.

Therefore, research in the field of adaptive learning systems is still on the agenda.

This paper is organized in six sections. Section 2 presents a literature review. Section 3 presents ADOPT (Adaptation Done On-line through a Process controlled by Tracking), the adaptive e-learning system we propose and highlights its models. Section 4 presents the system architecture and the principle agents used. Section 5 makes a brief comparison of ADOPT with some existing adaptive systems and section 6 concludes the paper and presents our future work.

2 LITERATURE REVIEW

There are three common adaptive e-learning approaches (Ennouamani and Mahani, 2017; Apoki et al., 2019).

The first is a macro-adaptive approach. It takes into account the differences between learners and adapts the learning rate accordingly.

The second is an aptitude-treatment interaction approach. It identifies the learner's main skills by analyzing the behavior. Different levels of control occur during the learning process.

The third approach is a micro-adaptive approach. The learner model evolves according to the learner's

Ajroud, H., Tnazefti-Kerkeni, I. and Talon, B.
ADOPT: A Trace based Adaptive System.
DOI: 10.5220/0010452702330239
In *Proceedings of the 13th International Conference on Computer Supported Education (CSEDU 2021) - Volume 2*, pages 233-239
ISBN: 978-989-758-502-9
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interactions with the system. Identifying the needs allows offering the most appropriate learning process.

The architecture of an adaptive e-learning system is based on three models: the learner model (also named student or user model), the domain model (also named content or expert model) and the learning model (also referred to as tutoring or pedagogical or adaptation model) (Vandewaetere et al., 2011).

The learner model is the pivot of adaptive systems (Kaya and Altun, 2011; M. A. Tadlaoui et al., 2016; Yue Gong, 2014; Ezzat Labib et al., 2017). It contains static and dynamic data related to the learner such as personal properties and behavior when using the e-learning system (Wartiningsih and Surjono, 2019). It is as useful for tutors and learners. Indeed, the tutors can correctly and precisely evaluate learner capabilities and even predict a probable success (or not) during learning activities. Learners can identify nature of the problems they encountered during the learning process, can evaluate skills, etc.

Standards of learner model have been defined: The IEEE standard PAPI learner (Public and Private Information for Learners) (Farance, 2000), IMS-LIP (IMS Learner Information Package) (IMS, 2001) and IMS RDCEO (IMS Reusable Definition of Competency or Educational Objective) (IMS, 2002). (Hlioui et al., 2016) explore these standards, considering parameters such as personal information, preferences, competencies, etc. According to these authors, each standard presents shortcomings. To face these shortcomings, some researches like (Madhour et al., 2006), (Lazarinis et al., 2009) and (Ghallabi et al., 2015), use a combination of IMS-LIP and PAPI standards. But as noted in (Kaya and Altun, 2011), these standards are so detailed that they are complex to use. Moreover, the needs of users can not always be satisfied by these standards. So, some authors proposed specific learner models such as in (El-Kechaïi et al., 2015), (Tack et al., 2016), (Mediani et al., 2015), (Tmimi et al., 2017) and (Heng et al., 2018).

To collect necessary data and build the learner's model in the LMS, it is possible to use questionnaires and quizzes. Felder and Soloman[1] propose a questionnaire that can be filled by the learner in order to identify the learning style (Radwan, 2014). Exploration of traces left by the learner during activities on the LMS is another interesting source of data.

[1] Available at: https://www.webtools.ncsu.edu/learning styles/

The domain model "is a representation of the essential learning content present in the system" (Apoki et al., 2019). It stores expert knowledge and pedagogical digital resources. It contains all information about the courses (Ahmed et al., 2017).

Thanks to the information stored in the learner model, adaptations can be proposed. Indeed, the learning model presents the rules of adaptation and describes instructional strategies and the pedagogical theories (Apoki et al., 2019).

3 PROPOSED ADAPTIVE e-LEARNING SYSTEM

ADOPT follows the aptitude-treatment interaction approach. We track learners' activities during the learning process on the LMS (Tnazefti-Kerkeni et al., 2020; Talon et al., 2013). It uses intelligent agents. In this section, we represent the knowledge that is the basis of our system. This knowledge is contained in models inspired by those conventionally used in an Intelligent Tutoring System.

3.1 Domain Model

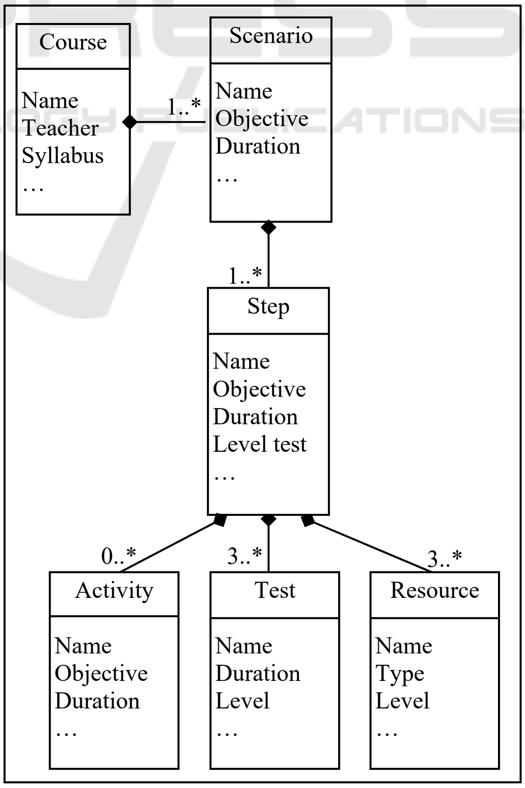

Figure 1: Domain model.

The domain model describes learning objectives, courses, syllabus as well as learning scenarios. The digital learning resources can be text, video, audio, etc. The tutor presents a course as a set of scenarios. Each scenario S is a list of steps given in a certain order.

Each step has an objective and duration and presents three levels: beginner, intermediate and advanced. At the beginner level, only the basic concepts are presented. The intermediate level is more detailed than the first one and the advanced level is an expert level. For each level, the tutor provides visual, auditory, and kinesthetic oriented resources. The tutor also provides tests for each level. A test can be a QCM or an exercise and can eventually plan activities. Figure 1 presents an UML class diagram of the domain model.

We consider that a step is achieved by a learner if at least 90% of the tests are done successfully. A scenario S is acquired if all its steps are done.

3.2 Learner Model

The learner model establishes the profile of the learner by providing his characteristics and the activities done.

When a learner registers on the LMS, he/she enters data such as name, age, gender, and other static data. He/she passes a test enabling to determine his/her personality data. Felder and Soloman questionnaire and Felder and Silverman learning style model (Felder and Silverman, 1988) inspired our test.

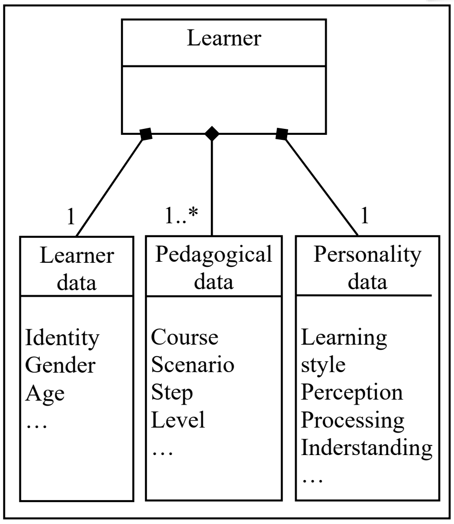

Figure 2: Learner Model.

In addition, each action done by the learner in the LMS is tracked. These traces are analyzed, modeled, and stored. They are used to make real time updates of the learner model.

The learner model used in the proposed adaptive e-learning system is represented in figure 2 as an UML class diagram. It regroups information about the learner. Indeed, we have:

- Learner personal data,
- Pedagogical data which consider the knowledge of the learner in each course and which evolve with learning.
- Personality data which consider his learning style (visual, auditory, kinesthetic) and personality type (perception: sensing or intuitive, processing: active or reflective and understanding: sequential or global).

3.3 Adaptation Model

The adaptation or learning model proposes adaptations according to the learner profiles. The rules of this model are defined using indicators.

When a learner registers in a course, he/she begins with a pre-assessment which identifies the knowledge he/she has mastered in this course according to the course knowledge map (hierarchy which is defined in the domain model). In this way, the system identifies the starting position of this learner for the course and each learner will start the course from his knowledge level. From his starting point and for each step of a scenario, he/she must start by taking a level test. If he/she gets under 50, than he/she has a beginner level in this step. If he/she gets between 50 and 70, then his/her level is intermediate, otherwise it is advanced. The learner gets resources and tests corresponding to the level and when he/she finishes a level, he/she goes to the next level and so on until he/she finishes the step.

3.3.1 Indicators

We note $S=\{s_1, s_2, \ldots, s_n\}$ such as s_i is the i^{th} step of the scenario S. We note respectively R_{ij} and T_{ik}, the j^{th} resource and the k^{th} test presented in the step s_i. Thus, if $l>k$ than T_{il} should be more difficult than T_{ik} and it is proposed to the learner only if T_{ik} is well done.

We consider ΔR_{ij} as the minimum time required by the learner to complete the study of the resource R_{ij} and ΔT_{ik} as the maximum time required by the learner to do the test T_{ik}.

Here are some of the indicators used by the system.

- $I1_{ij}$: Reading or viewing or listening time used by the learner to study the resource R_{ij}.
- $I2_{ik}$: Duration of the test T_{ik} done by the learner.
- $I3_{ik}$: Number of times the test T_{ik} is repeated by the learner before it is well done.

3.3.2 Rules

We present below some of the rules of the adaptation model:

- Rule 1: It is a rule to adapt the resource to the learner style. If the learner style is visual, then the use of video, PowerPoint, picture, etc. resources for the step is proposed. If, contrariwise, it is auditory, then podcast or video resources, etc. are proposed.
- Rule 2: If the learner spends a little time studying a resource ($I1_{ij}<\Delta R_{ij}$) then the system suggests him to review again the same resource and/or to study other resources from the same level.
- Rule 3: If the learner spends too much time to well do a test ($I2_{ik}>\Delta T_{ik}$ and T_{ik} is well done) then the learner is not comfortable with this test and step and the system proposes him to review a resource of this step and to do another test with the same difficulty before continuing.
- Rule 4: If the learner spends too much time to do a test without success or if he/she repeats the test several times before doing it correctly (($I2_{ik}>\Delta T_{ik}$ and T_{ik} is not well done) or $I3_{ik}\geq 2$) than the learner has difficulties with this step and the system proposes to review resources of this step before doing another test with the same difficulty.
- Rule 5: If, after three attempts, the learner still fails to well do the test, he/she is then given its detailed solution with explanations and the system suggests him to review the course resources relates to this part and proposes another test of the same level of difficulty.
- Rule 6: If the learner does the test correctly in a very short time ($I2_{ik}<<\Delta T_{ik}$), then the system suggests that he/she goes directly to the last test of this step.
- Rule 7: If, after a certain number of tries doing a test the learner always fails (T_{ik} is always not well done) then the system suggests to review the resource and to do the lower level test ($T_{i(k-1)}$).

4 SYSTEM ARCHITECTURE

ADOPT is based on traces. Any exchange or interaction between the learner and the system is noted, modeled and stored in a trace model.

ADOPT is a Multi-Agent System. Each model presented above is based on an interactive agent. When interacting, agents update their knowledge and adapt their behavior. They provide the knowledge used to carry out the pedagogical reasoning.

Here is a list of the main agents involved in the system as well as a brief presentation of their main role:

- a-Observer agent tracks the learner's actions when using the LMS. It cleans the raw traces

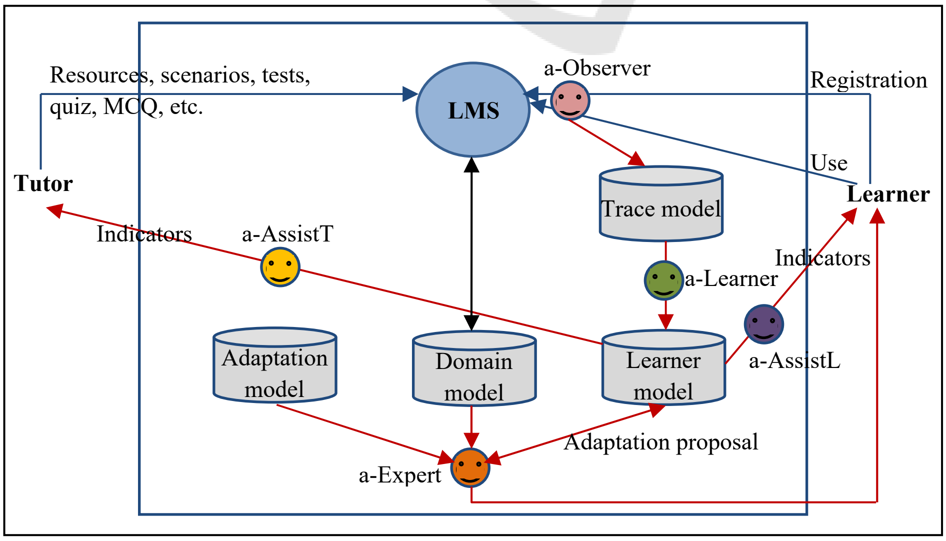

Figure 3: System architecture.

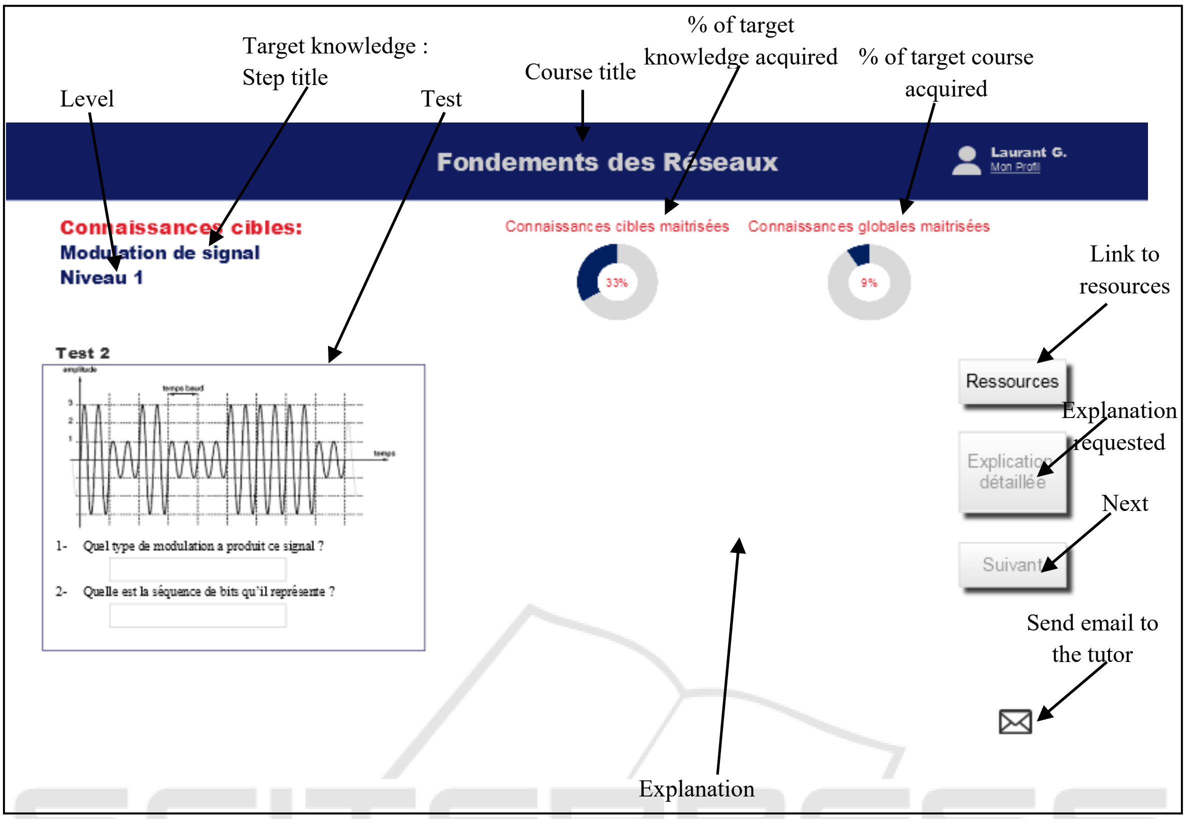

Figure 4: Example of the system interface.

and treats them to get the modeled traces and stores them in the trace model.

- a-Learner agent defines the learner model and updates it in real time to consider the evolution of the learner in his learning.
- a-Expert agent is based on the rules defined in the adaptation model and on the knowledge stored in the domain model and in the learner model to propose adaptations to the learner. It recognizes the knowledge level of the learner and updates the learner model accordingly.
- a-AssistL agent presents some indicators on the dashboard of the learner which help the learner to see his/her difficulties and to get feedbacks regarding his/her learning.
- a-AssistT agent presents to the tutor tables and graphs which help to monitor learners' learning.

Figure 3 presents the system architecture and figure 4 shows an example of the system interface.

5 COMPARISON WITH OTHER ADAPTIVE SYSTEMS

We compare here ADOPT with other existing adaptive systems using agents.

In addition to other criteria, we consider the criteria defined by Brusilovsky (Brusilovsky, 1996) for adaptive hypermedia and which are listed below:

- Direct guidance: Suggesting to the learner what to do next.
- Adaptive sorting: Sorting all the links according to the learner model.
- Adaptive hiding: Hiding links according to the learner model.
- Adaptive annotation: Giving a comment or annotation on the state of a link (for example visited link or not yet visited link).
- Adaptive presentation: adapting presentation to knowledge level and other characteristics of the learner such as his learning style.

As we notice it in table 1, even if ALLEGRO and MASPLANG are not domain dependent, they are only interested by adaptive presentation.

Table 1: Comparison with adaptive Multi-Agents Systems.

System / Criterion	BAGHERA	ALLEGRO	MASPLANG	ADOPT
Direct guidance	-	-	-	X
Adaptive sorting	-	-	-	X
Adaptive hiding	X	-	-	X
Adaptive annotation	X	-	-	X
Adaptive presentation	X	X	X	X
Domain dependent	X	-	-	-
Learner characteristics :				
▪ Knowledge level	X	X	-	X
▪ Learning style	-	-	X	X
▪ Learning progress	-	-	X	X

6 CONCLUSION AND FUTURE WORK

Adaptive learning systems are a family of learning systems that interests in learners' needs and profile learning to increase success. In these systems, the characteristics of each learner are considered and this in order to consolidate the acquisition of learning and to minimize the risk of dropping out and failure. We interest in adaptive learning systems that identify needs and interests of learners to provide personalized contents and specific learning paths. In this paper, after a literature review, we have described the different models integrated in our system and the agent architecture designed to support tracking and personalization. A final comparison of ADOPT (Adaptation Done On-line through a Process controlled by Tracking) with other ones has highlighted innovations it offers. The global architecture allows an in real-time adaptation management. Some features are not completely developed. So the future of our work will consist in a total implementation of functionalities. Then we will be able to test and evaluate ADOPT in a real higher dimensional context.

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