Adaptive Hypermedia System: A Design Proposal and a Case Study

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Abstract - Adaptive hypermedia is a new and promising area of research at the crossroads of hypermedia and adaptive systems. One of the most important fields where this approach can be applied is the e-Learning. In this context the adaptive learning resources selection and sequencing is recognized as among the most interesting research questions. This paper addresses the design problem of an Adaptive Hypermedia system by the definition of original user and adaptation model. The proposed adaptive hypermedia system was integrated in an e-Learning platform and an experimental campaign was conducted. In particular we used the proposed approach in three different blended courses (Introduction to Computer Science, Computer Networks and Web Design) and a comparison with traditional approach was conducted. The obtained results are very promising.

Index Terms – Adaptive Hypermedia System, e-Learning, User Model, Intelligent Tutoring System

INTRODUCTION

Distance education is becoming one of the most interesting topics in scientific literature. In particular the real interest of researchers is in the definition of techniques and methodologies able to create new value-added services. It is common opinion that e-Learning environments should not only be limited to transfer didactic units to the student but also to support a new concept of “teaching” whose final objective is to increase the quality and effectiveness of the traditional teaching thanks to the Information and Communication Technology. In this scenario one of the most interesting contributes is furnished by the use of Adaptive Hypermedia System and more in particular from the student activities tracking service. In fact one of the main criticisms to e-Learning approach is the lack of interaction between teachers and students: in particular the main criticisms regard the poor control of student progresses and attitudes in the learning process by teachers. On the other hand, new e-Learning platforms can collect a large size of data concerning the student’s learning process but this huge quantity of information often can bewilder teachers. In fact a teacher in order to evaluate the student’s learning workflow uses few information: in general the student’s results at the final or end-unit tests and the time that they spent on the various learning object. Obviously, this information can not explain all the aspects of student’s knowledge process and teachers can not support effectively them. In this context an effective contribute can be given by the integration in an e-Learning environment of an adaptive hypermedia system and in particular of an effective tracking module. In general an Adaptive Educational Hypermedia is defined by the introduction of four main components: the Knowledge Space, the User Model, the Observations model and the Adaptation Model. In literature, many papers deal with this argument and offer several models whose target is the identification of the main parameters to track in an e-Learning process [1]. Some of them are based on the formalism of the graphs where the nodes estimate the student’s knowledge [2]. Other approaches analyze the actions of the student during his learning process furnishing a detailed report to the tutor [3],[4],[5]. An interesting approach is proposed in [6]. This paper describes a model that builds the best students’ learning path starting from the analysis of some features outlining the main pedagogical characteristics. This approach is student-centred and students’ parameters are selected according to three main factors: Test performance, Time performance, Reviewed topics. The above factors, by an opportune mathematical model, indicates to teachers the learning level achieved by students. By analyzing these indexes, moreover, it is possible to establish if students may attend the next subject of the course or more in general support them during the learning phase. This kind of approach is the starting point of this paper. In fact the real aim of this paper is the definition of a tracking strategy able to obtain information about the status of students during the learning path. At this aim some indexes able to describe the students’ attitude during the learning process have been selected. At the same time a student profile, described according the IMS LIP standard, was introduced. In this way the proposed Adaptive Hypermedia System can easily update the user profile and adapt, in an automatic way, the learning path. At the same time a detailed report on students’ activities and main difficulties has sent to the teacher. In particular the system can underline to the teacher the main criticisms for each student and the main actions that can be undertaken. The paper has the following organization: first of all a brief description of Adaptive Hypermedia System is introduced and a more detailed discussion on the student’s tracking question is faced. Then the various indexes and the tracking approach are described. So the rules used to build the best learning path are analyzed. In the last section of the paper some experimental results are showed.
ADAPTIVE EDUCATIONAL HYPERMEDIA SYSTEM

An Adaptive Educational Hypermedia System (AEHS) [7][8] is an approach whose target is to personalize the learning experience for the learner. In this way, by improving the learner satisfaction, it could be possible to enforce the learning experience. A general definition of an AEHS, reflecting the current state of the-art, is so described:

- Knowledge Space (KS), subdivided into the Media Space, containing the educational resources and associated descriptive information (e.g. metadata attributes, usage attributes etc.) and the Domain Mode, containing graphs that describe the structure of the domain knowledge in-hand and the associated learning goals.
- User Model (UM), that describes information and data about an individual learner, such as knowledge status, learning style preferences, etc. The User Model contains two distinct sub-models, one for representing the learner’s state of knowledge, and another one for representing learner’s cognitive characteristics and learning preferences (such as learning style, working memory capacity etc.). This distinction is made due to the fact that the first model (Learner Knowledge Space) can be frequently updated based on the interactions of the learner with the AEHS. On the other hand, learner’s cognitive characteristics and learning preferences are more static, having the same property values during a significant time period.
- Observations (OBS) which are the result of monitoring learner’s interactions with the AEHS at runtime. Typical examples of such observations are: whether a user has visited a resource, the amount of time spent interacting with a given resource, etc. Observations related with learner’s behaviour are used for updating the User Model.
- Adaptation Model (AM), which contains the rules for describing the runtime behaviour of the AEHS. These rules contain Concept Selection Rules which are used for selecting appropriate concepts from the Domain Model to be covered, as well as, Content Selection Rules which are used for selecting appropriate resources from the Media Space. These rule sets represent the implied didactic approach of an AEHS.

USER MODEL: A PROPOSAL

From the definition, in the previous paragraph it is clear that in order to define the runtime behaviour of the AEHS, the definition of how learner’s characteristics influence the selection of concepts to be presented from the domain model (Concept Selection Rules), as well as the selection of appropriate resources (Content Selection Rules), is required. The design of the student model that we will adopt in this paper is carefully described in [9] where a quintuple of characterization is provided. This model takes into account the learner’s learning style, his background knowledge, and his preferences, so represented:

- Format (f): type of media the learner prefers to study a learning resource
- Bandwidth (b): the type of link used by the learner to connect to the internet
- Interactivity (i): the level of interactivity used by the learner to interact with the learning resource
- Difficulty (d): the level of preparation of the student
- Time (t): the time of study the learner spends to study a lesson

Each parameter assumes values in the range [1,10] coherently with the IMS-LIP metadata fields. In order to have an objective starting point we propose a change in the initialisation of the model. In particular in this paper we propose a matching between the results obtained by the use of ILS questionnaires and the proposed model. ILS is an instrument used to assess preferences in four dimensions (active/reflective, sensing/intuitive, visual/verbal and sequential/global) of a learning style model and was designed by Richard M. Felder [10]. The ILS approach furnishes information about the learning style by the use of four dimensions. The first dimension is sensing/intuition. Sensing learners tend to like learning facts and to be patient with details and good at memorizing facts and doing hands-on (laboratory) work. Intuitive learners often prefer discovering possibilities and relationships and may be better at grasping new concepts and are often more comfortable with abstraction and mathematical formulation than sensing users. The second dimension is active/reflective. Active learners tend to retain and understand information best by doing something active with it—discussing or applying it or explaining it to others. Active learners tend to like group work more than reflective learners, who prefer working alone. Reflective learners prefer to think about it quietly first. “Let’s try it out and see how it works” is an active learner’s phrase; “Let’s think it through first” is the reflective learner’s response. The third dimension is sequential/global. Sequential learners tend to gain understanding in linear steps, with each step following logically from the previous one. Global learners tend to learn in large jumps, absorbing material almost randomly without seeing connections, and then suddenly “getting it.” The fourth dimension is visual/verbal. Visual learners remember best what they see - pictures, diagrams, flow charts, time lines, films, and demonstrations. Verbal learners get more out of words - written and spoken explanations. Starting from ILS information, an accurate analysis has been done in order to adapt them to the metadata standard. In particular, from the active/reflective dimension the interactivity level of the student has been extracted. Then, from the visual/verbal dimension the type of media the learner typically uses has been extracted. In order to complete the student model, further information is necessary. In particular, it could be necessary to know which is his/her level of preparation on a particular argument, how much time he/she usually spends to study a lesson, how many times he/she usually repeats a
In depth account the difficulties that the student meets when he faces more useful and concrete way in order to help the docent in necessary to design a method for tracking the student in a student during his learning activity. To this aim, it is In this section we describe an approach for tracking the topics are very difficult for him and how it is possible to approach is able to watch how much he is learning, which represents a particular aspect of the resource and gathers the description of the user and learning object model in the next paragraph we will describe in details the tracking strategy and the adopted approach.

LEARNING CONTENT MODEL: A PROPOSAL

The opportunity of better defining a resource by using its didactic and pedagogical characteristics through the description standard fields induces us to represent it with a model. The idea is to generate, a “digest” of learning objects. Our aim is to better qualify the resource, making it clear to the software module, which interacts with the contents, the knowledge domain to which it belongs and its more peculiar characteristics. At the same time, an opportune modelling allows quantifying the resource, making it possible to establish a relationship among metadata by using appropriate metrics. The objective quantification makes it possible for an intelligent software tool to propose the contents that are suitable to the student needs. We have therefore implemented a software module able to model the single described training resource through a string vector so defined:

Didactic Resource ={Typology, Ontology, Pedagogical educational properties, Technical requisites, Rights}.

Each component of this vector is still a string vector, and represents a particular aspect of the resource and gathers the most important information obtained combining standard description fields. We have chosen to use a vector since this structure better organizes the information associated with the resource allowing its easier retrieval. It is clear that the possibility of presenting this vector representative of learning object semantic content to an intelligent software module, which is able to semi-automatically infer decisions concerning the training contents utilization improves and allows quantifying the resource, making it possible to establish a relationship among metadata by using appropriate metrics. The objective quantification makes it possible for an intelligent software tool to propose the contents that are suitable to the student needs. We have therefore implemented a software module able to model the single described training resource through a string vector so defined:

Didactic Resource ={Typology, Ontology, Pedagogical educational properties, Technical requisites, Rights}.

The tracking module observes the student activity during his period of a learning resource study. The two main targets of this methodology are:

- to maintain up-to-date information about student model’s parameters. The information observed during learner’s activity studying are:
  - the studying time
  - the level of preparation
  - the interest for determined kind of media
- to provide an evaluation of the learner action related to his entire learning path by using information acquired during the observation activity. In this way it is possible to evaluate the learner performance by providing a global assessment usually based only on the final test mark.

By denoting with the subscript \( u \) information related to the student and with \( r \) those related to the learning resource, it is supposed to know some parameters the tutor initially sets:

- time of studying of his learning resource, \( t_r \)
- a time parameter \( t_t \), generally a percentage of \( t_r \), that measures the maximum moving from the \( t_t \) defined by the teacher
- the fair mark \( v_r \) for that learning resource.

In this way, once the student learning time, \( t_u \) is acquired, it is possible to compare it by using the evaluation function:

\[
G_{t_u}(G_r, v_r) = \begin{cases} 
G_r & \text{if } t_u \leq t_t \\
\frac{v_r}{t_u} & \text{if } t_u > t_t
\end{cases}
\]

The goal of \( G_r \) is, by setting opportunely its parameters, to give the right weight if the student has spent a lot of or little time in the making use of a lesson. Moreover, the mark student \( v_r \) is matched with the reference mark \( v'_r \), the docent has a priori assigned for that Learning Object by using an appropriate rational function \( G_v \). In this way, if the student has obtained a good mark, his profile is updated and the successive adapted didactic unit is located, otherwise a unit with the same content but less difficult is chosen for him. In this case it is necessary to update the student profile. The proposed strategy is depicted in the following figures:

**Table 1: User Model**

<table>
<thead>
<tr>
<th>Type of media</th>
<th>Interactivity level</th>
<th>Bandwidth</th>
<th>Difficulty level</th>
<th>Study Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>ILS (Visual/Verbal)</td>
<td>ILS (Active/Reflective)</td>
<td>Further Information</td>
<td>IP fields</td>
<td>IP fields</td>
</tr>
</tbody>
</table>

where the third parameter, the bandwidth, takes into account which device the student typically uses to connect to the internet and to download the lessons.

**DEVELOPING A TRACKING STRATEGY**

In this section we describe an approach for tracking the student during his learning activity. To this aim, it is necessary to design a method for tracking the student in a more useful and concrete way in order to help the docent in an effective evaluation. The proposed approach takes into account the difficulties that the student meets when he faces a didactic unit and furnishes to each student the most adapted didactic unit to his actual knowledge. The proposed approach is able to watch how much he is learning, which topics are very difficult for him and how it is possible to give to him the appropriate feedbacks. From this point of view, the system helps the docent by furnishing the best pedagogical contribution for the learning process of each student. How it is possible to choose the best learning path for each student? It is supposed to know the time the student spends when he faces a k-th Learning Object \( T_k \) related in a certain topic and the final mark obtained in the evaluation test \( v_k \) of the same topic. The time student \( T_k \) is matched with a reference learning time that the docent has a priori assigned, \( T'_k \), for the k-th Learning Object. This matching is made by using an appropriate rational function \( G_v \). The goal of \( G_v \) is, by setting opportunely its parameters, to give the right weight if the student has spent a lot of or little time in the making use of a lesson. Moreover, the mark student \( v_k \) is matched with the reference mark \( v'_k \), the docent has a priori assigned for that Learning Object by using an appropriate rational function \( G_v \). In this way, if the student has obtained a good mark, his profile is updated and the successive adapted didactic unit is located, otherwise a unit with the same content but less difficult is chosen for him (also in this case it is necessary to update the student profile). The proposed strategy is depicted in the following figures:

**Figure 1: Learning Scenario**

The tracking module observes the student activity during his period of a learning resource study. The two main targets of this methodology are:

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G_r & \text{if } t_u \leq t_t \\
\frac{v_r}{t_u} & \text{if } t_u > t_t
\end{cases}
\]
\[ G_i = 1 + N + \frac{(T^u_i - T^k_i)^2 - T^r_i^2}{(T^u_i - T^r_i)^2 + T^r_i^2} \]

The minimum value (i.e. 1) is assumed when the estimated time student corresponds with that expected, that is \( t_u \in [t_r - t_x, t_r + t_x] \) while the maximum value is \( 2 + N \) where \( N \) is a parameter related to the difficulty of the resource. Moreover the tracking module is able to take into account how many times the student repeats the same lesson. This occurrence is considered by evaluating the function:

\[ T_k(i) = \frac{1}{1 + a(i-1)} \in [0,1] \]

where \( i = 1, 2, 3, \ldots \) counts the number of repetitions of the same lesson and in this way \( T_k(i) = T(u) \). The function has a hyperbolic progress that assumes the maximum value when \( i = 1 \) and decreases when \( i \) increases. The parameter \( a \) sets the decrement rate and is equal to:

\[ a = \frac{d}{2d} \]

In this way, if the resource is more difficult than the learner preparation level, the decrement rate does not heavily penalize the learner, and vice versa. The second target of the tracking module is providing a student evaluation by using information acquired during his studying activity. The purpose is to assess the learner performance focusing attention to his complete studying activity. To this aim, the learner assessment is a weighted average that takes into account the previous activity and a term relative to his past learning activity. The student assessment evaluation is then:

\[
\text{Score}_k = \frac{\mu}{\nu} \left( \frac{\text{Sign}(G(v_k) + 1)}{2} \right) + \alpha \left( \frac{T_k(i)}{G_i} \right) \left( \frac{1 + \text{Sign}(D^v_k - D^r_k)}{2} \right) + (1 - \mu) \left( 1 + \log_{10} \left( S_p(Q_k) \right) \right)
\]

The first term:

\[ A = \frac{\nu}{\nu_{\max}} \left( \frac{\text{Sign}(G(v_k) + 1)}{2} \right) + \alpha \left( \frac{T_k(i)}{G_i} \right) \left( \frac{1 + \text{Sign}(D^v_k - D^r_k)}{2} \right) \]

With \( G_i = v_k - v_k' \in \left[ 1 - v_{\text{max}}, 1 + v_{\text{max}} \right] \) and

\[ v_k' = \left( - \frac{1 + \text{Sign}(D^v_k - 3)}{2} \right) + \left( \frac{1 + \text{Sign}(D^v_k - 7)}{2} \right) \]

Where \( v_k \) is a term relative to the student grade \( v_k \) obtained in the final test. The term \( A \) represents the results obtained in the study of the last learning object.. In particular \( A \) is equal to 0 when the student has a very low result and 1 when the student has a very good result. The other term

\[ B = 1 + \log_{10} \left( S_p(Q_k) \right) \]

takes in account the previous results of the student. In particular

\[ S_p(Q_k) = \frac{Q_k}{1 - \sum_{q=1}^{k-1} Q_q} \in \left[ \frac{1}{v_{\text{max}} D^r_k}, v_{\text{max}} D^r_k \right] \]

where \( Q_k = D^v_k \in \left[ v_{\text{max}}, v_{\text{max}} \right] \).

In particular this term measures the mark obtained for the actual learning object with the marks obtained in the past. The value \( \mu \) is a weight able to emphasize the A or the B term. In general we fixed \( \mu \) to the value 0.8. So the score value assumes the following form:

\[
\text{Score}_k = \mu \left( \frac{\text{Sign}(v_k - v_k') + 1}{2} \right) + \alpha \left( \frac{1 + \text{Sign}(D^v_k - D^r_k)}{2} \right) + (1 - \mu) \left( 1 + \log_{10} \left( \frac{D^v_k}{D^r_k} \right) \right)
\]

By analyzing each single element of the Score\_k term, we can realize that if Score\_k assumes a low value, learner assessment is not fair, and the learner is forced to repeat the same lesson. Otherwise, score value near to 1 he can approach to the following learning resource. In any case, the student profile parameters are updated as we will show in the next paragraph.

**LEARNER DIFFICULT LEVEL UPDATE**

If the learner has a preparation level greater than the \( k \)-th learning resource’s difficulty one, his score assessment is not fair and he failures the final test twice, his preparation level is decreased. If the threshold for the score function is 0.5 we can say that:

\[ D^v_k = \tilde{D}^v_k \cdot \frac{1 - \text{Sign(\text{Score}_k - \text{Score}^{\text{thres}}})}{2} + \tilde{D}^v_k \cdot \frac{1 + \text{Sign(\text{Score}_k - \text{Score}^{\text{thres}}})}{2} \]

and if

\[ \tilde{\text{Score}}_k > \text{Score}^{\text{thres}} \Rightarrow D^v_k = \tilde{D}^v_k = \frac{1}{k} \sum_{i=1}^{k} D^v_i \]

Otherwise

\[ \tilde{\text{Score}}_k < \text{Score}^{\text{thres}} \Rightarrow D^v_k = \tilde{D}^v_k = \frac{1}{k} \sum_{i=1}^{k} D^v_i \]

**LEARNER STUDYING TIME UPDATE**

The learner’s learning time is so updated:

\[ T^v_k = \tilde{T}^v_k \cdot \frac{1 - \text{Sign(\text{Score}_k - \text{Score}^{\text{thres}}})}{2} + \tilde{T}^v_k \cdot \frac{1 + \text{Sign(\text{Score}_k - \text{Score}^{\text{thres}}})}{2} \]

and if

\[ \tilde{\text{Score}}_k > \text{Score}^{\text{thres}} \Rightarrow T^v_k = \tilde{T}^v_k = \frac{1}{k} \sum_{i=1}^{k} T^v_i \]
In particular, the proposed module is developed in three steps: starting on learner and learning resource information profile. The information updated in the IMS-LIP metadata fields are showed in table 2.

<table>
<thead>
<tr>
<th>Learner metadata fields</th>
<th>Semantic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Activity.evaluation.result.result[i].fielddata</td>
<td>Assessment value relative to the j-th learning resource</td>
</tr>
<tr>
<td>Activity.evaluation.result.score</td>
<td>Assessment value relative to the complete learning path</td>
</tr>
<tr>
<td>Goal.status = completed</td>
<td>Overcoming relative to a learning resource</td>
</tr>
</tbody>
</table>

### Table 2 IMS-LIP Metadata fields updating related to the assessment information

#### THE ADAPTATION MODEL

In [6] two distinct areas of adaptation are distinguished: content level adaptation or adaptive presentation and link level adaptation or adaptive navigation support. This work is focused on the design of an adaptive presentation model by starting on learner and learning resource information profile. In particular, the proposed module is developed in three steps:

**Step 1: matching of parameters profiles:** the learners profile’s and learning resource’s parameters are considered. For each homonym parameter a matching function is considered. The minimum value corresponds to the best matching for that parameter, otherwise the resource parameter is very distant from learner. The function s are:

- **Interactivity:** \( M_I = 1+ | I_1 - I_2 | \in [1,10] \)
- **Difficulty:** \( M_D = 1+ | D_r - D_o | \in [1,10] \)
- **Type of Media:** \( M_F = 1+ | F_r - F_o | \in [1,10] \)
- **Time of Studying:** \( M_t(T_r,T_o) = 1 + \text{Int}\left(\frac{(T_r - T_o)^2 - 10^2}{(T_r - T_o)^2 + 10}\right) \in [1,10] \)
- **Bandwidth:** \( M_B = 5(1 - \text{Sign}(B_r - B_o) + 2) \)

**Step 2: Evaluation of the characteristic functions:** once the matching functions are evaluated, the educational \( (C_e) \) and technical \( (C_t) \) characteristics can be considered. To this end a normalized weighted average mechanism is considered:

\[
C_e = \sqrt{M_F(F_r,F_o)^2 + M_B(B_r,B_o)^2} \in [1,10\sqrt{2}] \\
C_t = \sqrt{M_I(T_r,T_o)^2 + M_D(D_r,D_o)^2 + M_T(T_r,T_o)^2} \in [\sqrt{3},10\sqrt{3}] \\
\]

**Step 3: Evaluation of the global matching index:** the final step consists in the evaluation of the distance between the learner and the learning resource in term of educational and technical characteristics. To this end, the global index \( Ind \) is so calculated:

\[
Ind = \sqrt{C_t^2 + C_e^2} \in [2,10\sqrt{5}] \\
\]

In this way, the minimum value of \( Ind \) defines the nearest learning resource to the learner characteristics, namely:

\[
Ind_{OPT} = \min Ind_i \\
\]

In figure 2 the complete schema of the proposed tracking and adaptation model.

### EXPERIMENTAL RESULTS

In our experimentation we have considered three different blended courses Introduction to Computer Science (about 50 students), Computer Networks (about 20 students) and Web Design (about 100 students) belonging to the faculty of Engineering and a comparison with traditional approach was conducted. For each of this course we used a dataset composed by one hundred descriptions, according the model previously described, of learning objects that we created or retrieved in internet. Obviously the learning objects belong to various modules according to the ontology model described by teacher. At the same time teachers described the profile of their classes. The proposed AEHS was introduce, as plug-in, in the E-Learning Platform named Moodle. At this point we started the courses and the end of each learning object we submitted an evaluation test. In particular the course model was the following: traditional lessons and support by the use of modified Moodle platform. At the end of the courses we measured the average knowledge level of students. At the same time we compared the values with the other ones obtained one year before with the same courses. In particular the courses used the same datasets and a course model based on traditional lessons and by the use of a normal Moodle platform. The obtained results are depicted in table 3.

<table>
<thead>
<tr>
<th></th>
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<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Starting Knowledge Level</td>
<td>4.3</td>
<td>4.1</td>
<td>4.7</td>
<td>4.3</td>
<td>4.8</td>
<td>4.2</td>
</tr>
<tr>
<td>Final Knowledge Level</td>
<td>7.2</td>
<td>7.8</td>
<td>5.9</td>
<td>6.8</td>
<td>5.7</td>
<td>6.1</td>
</tr>
<tr>
<td>Increase (percentage value)</td>
<td>67%</td>
<td>90%</td>
<td>26%</td>
<td>58%</td>
<td>19%</td>
<td>45%</td>
</tr>
</tbody>
</table>

### Table 3 Obtained results

The obtained results show as the proposed approach increase the knowledge level and improve the learning approach of students.

#### DISCUSSION ABOUT THE ADOPTED METHODOLOGY

In this paper we presented a novel model to model user and learning contents. This modelling strategy allows to better...
building the learning path of students. In particular this approach introduces many useful applications such as the continuous adaption of student’s learning path or a more accurate assessment phase. In particular this framework can be easily integrated to an open source e-Learning platform as Moodle in order to improve its performances. In particular the proposed approach allows a real tracking of students and answers to a hoary problem in the e-Learning field: how we can use at the best the very huge quantity of data that an e-Learning platform collects. By the use of the proposed approach each data coming from student’s interaction with the learning contents, and more in general during his interaction with the learning paths, contributes to the building of a personalized and effective learning experience. The proposed approach, besides, gives back the student as main character of his knowledge process and helps him in the search of most effective learning objects. The proposed methodology transforms the static approach of e-Learning platform in a dynamic experience where at the centre of the process there is the student.

CONCLUSION

In this paper we showed an AEHS based on the definition of a set of features related to the concepts, skills and attitudes the student is expected to assimilate by the end of a unit. Each feature is represented by means of appropriate mathematical functions, which are combined in a mathematical model devised to facilitate the course characterization and comparison and to provide support for diagnostics. In the paper we showed the design and implementation of a software module for deducing the representative “vector” of a given student starting from the standard description of various resources (student profiles, content descriptions and so on). We discussed experimental results in using the quoted vectors to find the most suitable set of contents for each student profile and we proved its effectiveness in some real cases.

References
