Journal of Theoretical and Applied Information Technology
20th November 2013. Vol. 57 No.2

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

AN INTELLIGENT ARCHITECTURE FOR GENERATING EVOLUTIONARY PERSONALIZED LEARNING PATHS BASED ON LEARNER PROFILES

[1] JABER EL BOUHDIDI, [2]MOHAMED GHAILANI AND [3]ABDELHADI FENNAN

[1,2,3] Department of Computer Science, Laboratory LIST, Faculty of Science and Technology
Tangier, 90000, Morocco
E-mail: [1]jaber.f15@gmail.com, [2]ghalamed@gmail.com, [3]afennan@gmail.com

ABSTRACT

In this paper we present a solution that is a continuation of work done in the field of adaptive educational systems. It is an approach oriented objectives based on ontologies, multi-agent system and Bayesian networks to generate dynamically personalized learning paths. The dynamic aspect is essential for each learning session in the context of this solution, because the learning paths meet the objectives formulated by the learners will be generated to measure and after formulation the specific request. The operation consists of searching, filtering and composing dynamically hypermedia units of learning responding to the learner profile.

For structuring and modeling information managed by our architecture, we used ontologies of Semantic Web. We designed the ontology of learners using the standard IMS-LIP to represent the learner profiles, some fields are added to include, in the model of the learner, learning styles according to the model of Felder and Silverman. And for representation of resources we designed the ontology of resources based on the LOM standard. Furthermore, the architecture is divided into three layers; each layer is managed by a number of agents. Agents exploit the Bayesian model and ontologies to provide learners with personalized learning paths.

Keywords: *Personalized Learning Paths, Learning Styles, Ontologies, Multi-agent system, Bayesian Networks*

1. INTRODUCTION

The adaptation of the learning paths to learner profiles is a subject that concerns the scientific community for many years. Several solutions have been proposed in the literature to reduce the semantic distance between the wishes of learners and paths presented [1],[2],[3], [4] and [5].

Current educational systems do not take into account the educational process dimension in styles and learning methods. Several studies in psychology and science education have shown the positive impact of learning styles on the teaching-learning process and encourage its inclusion in educational strategies to make it easier for learners and improve their results[6]. It is therefore important to include this information in the learner model in order to increase the level of adaptation and performance of adaptive educational systems.

Overcoming the inadequacy of current educational systems to the needs of learners, we present in this article an architecture that attempts to be consistent with high expectations and needs of learners. Our adaptive architecture combines Semantic Web technologies and those of artificial intelligence to help learners acquire knowledge by offering learning paths and assessments in measure. Similarly, it facilitates to teachers, the publication of their courses in a warehouse of shareable resources. Learners can freely formulate the objectives of concepts they want to acquire and teachers can design courses that will be used by the system when the composition of the learning paths. To retrieve the learning styles of learners we used the model of Felder and Silverman [7]. This model classifies learners preferences in four dimensions: Active / Reflexive, Sensory / Intuitive, Visual / Verbal and Sequential / Global.

The semantic web and artificial intelligence is needed more than ever, in the design of adaptive learning systems. The Semantic Web [8] is a current technology based on formal knowledge representations called ontologies. These ontologies represent the information in a particular domain using concepts and relationships between concepts. The ultimate goal is to facilitate the exploitation of this knowledge through programs and software

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ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

agents. About artificial intelligence, it is used to provide the system capabilities automated reasoning imitating the teacher and thus making the most interactive and autonomous educational systems.

The proposed architecture is designed based on multi-agent systems, ontologies and Bayesian networks. To facilitate its management, we have divided the architecture into three layers: UI, adaptation and semantic layer, each layer is managed by a number of agents. The communication and collaboration between different layers of the architecture is assured by the exchange of FIPA-ACL Messages between agents [9,10]. And this, in order to provide learners with a pedagogical tool that, through its intelligent architecture, generate personalized learning paths.

2. DESIGN OF MULTI-LAYERED AND MULTI-AGENTS ARCHITECTURE

To respond to needs of learners in personalization of learning paths, we have developed a multilayer and multi-agent architecture. The architecture is divided into three layers, as shown in the following figure:

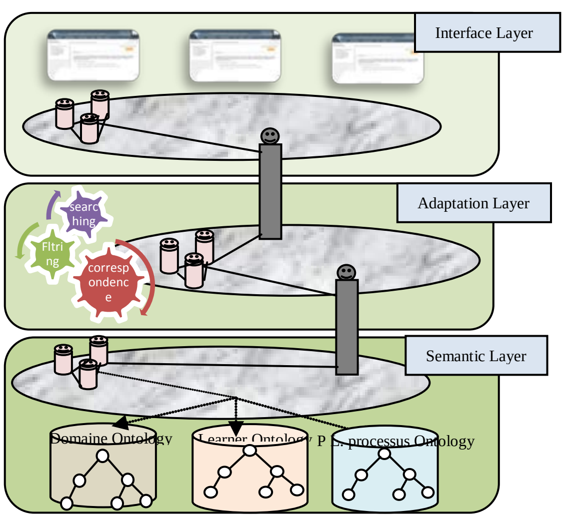

Figure 1: The Main Layers Of The Proposed Architecture

Each layer is managed by a number of agents that interact by exchanging messages in FIPA-ACL format for response to different system actions:

2.1 The User Interface Layer

The UI layer is responsible for various communications between the system and its users. It provides the necessary interfaces to help users interact with the system and perform specific tasks. This layer is managed by two agents whose roles are summarized as follows:

Learner Interface Agent (LIA): It is through this agent that learners can send requests to the system. The LIA capture external requests learners and conveys it's to the Manager Agent of the adaptation layer. We give some actions taken by learners:
-Send responses of learner(Evaluation result…etc)
-Formulation of goals in a training module.
-Presentation of learning paths and evaluation.
- Update a profile …etc.

Teacher Interface Agent (TIA): Same as LIA, TIA acts as a gateway requests from teachers to the system, to perform the actions of teachers and designers-teaching. We give some example of activities of teachers:
-Authentication of the teacher.
-Structuring of the modules according to their objectives specifications.
-Publication and annotation of hypermedia units of learning and assessments…etc.

All these actions are encapsulated in ACL messages and sent to the Manager Agent of the adaptation layer. Of course, there are many agents TIA or LIA as teachers or learners. Each agent is responsible for the user associated with it.

2.2 The Adaptation Layer

This layer is used to implement different pedagogical rules and adaptation mechanisms to dynamically generate personalized learning paths. Algorithms for dynamic composition and Bayesian networks module are implemented and operated at this level by agents. This layer is managed by the following agents:

Manager Agent (MA): ensures the proper functioning of the system, all other agents are in its service and under its responsibility. It is responsible for assigning the different requests that he receives from agents involved in the process of building dynamic learning paths.

Learning Paths Builder Agent (LPBA): This agent is responsible for the generation of learning paths, other agents in its service. It is also responsible for storing the generated paths in a historical basis in order to be able to exploit later.

Evaluation Paths Builder Agent (EPBA): Same as the LBPA agent, this agent is responsible for the generation of evaluations paths that are generated in conjunction with the learning paths. The EPBA mobilizes other agents for this purpose. As LBPA, EPBA stores the evaluation paths generated for later use.

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ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

2.3 The Semantic Layer

The semantic layer reduces the distance between the expression of a need and hypermedia units stored in the warehouse of resources. This is used to model formally and semantically different system information using ontologies. These ontologies are used by agents whose roles are summarized as follows:

Learner Manager Agent (LMA): This agent manages the learner profiles namely the update, search and delete a profile.

Domain Manager Agent (DMA): its role is to respond to various requests sent by the agents of the adaptation layer.

Search and Filtering Agent (SFA): As its name suggests, the SFA search and filter hypermedia units that meet the various search criteria following requests agents adaptation layer.

3. LEARNER MODEL

The learner model is the first brick of our adaptive architecture. It can represent the characteristics of learners, such as: preferences, goals, knowledge, learning styles ... etc. In this article we used the model of Felder and Silverman to identify students' learning styles. Learning styles are essential for the system selects and organizes hypermedia units according to the preferences of learners. The learner model also allows representing the cognitive state of learners in each concept. Research in the field of learner modeling gave rise to two kinds of learner models: Overlay model and disturbance model[11]. In this article we have chosen the Overlay model. This model can be represented by a set of pairs concept- value, each concept is characterized by a degree of control.

3.1 The Learning Styles

Learning styles is one of the individual differences that play an important role in learning. The learning style is anything that is characteristic of an individual when he learns, i.e the specific approach to a learning task, learning strategies activated during performance of a task. Felder defines learning as a process that can be divided into two parts: the receipt of the information and its processing. The Felder-Silverman model classifies learners preferences in four dimensions:

Active/Reflective: Active learners understand and retain information better when they start operating, they like to apply or explain it to others. Reflective learners prefer to work alone and think quietly to information. A student can spend an active periods and reflective periods.

Sensing/Intuitive: Sensing learners have a preference for facts and details and they tend to be practical and cautious. The intuitive learners prefer abstract material, they like to innovate, discover opportunities and relationships. Intuitive tend to work faster than the sensing.

Visual/Verbal: Visual learners remember best what they see (video, pictures, diagrams, etc.). Verbal learners get more words, when they receive written and oral explanations. Learners learn best when they are presented visually and verbally information.

Sequential/Global: Sequential learners tend to understand in linear steps they follow logical paths to find the solutions. Global learners learn in large jumps are not interested in the details of the object.

3.2 Learner Model Management

The learner model is composed of two parts, a static and a dynamic one, the static part can store information fixed, such as: name, discipline, level, date of registration ... etc. The dynamic part is used to store information that evolves over time, we divided it into three facets.

To model the characteristics of learners, we have developed an ontology based on IMS-LIP standard [12] The following figure shows an overview of the ontology *LearnerOnto*:

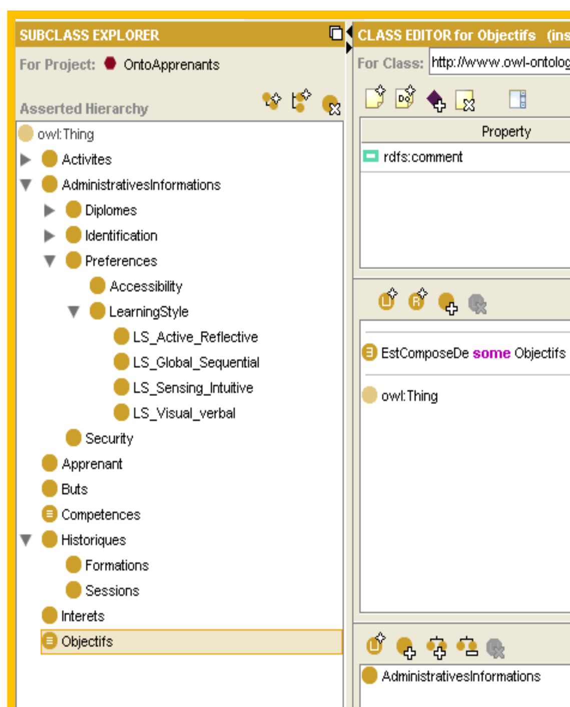

Figure 2: Overview of Learner Ontology Created by Protégé 2000

Journal of Theoretical and Applied Information Technology
20th November 2013. Vol. 57 No.2

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

3.2.1 Facet "Preferences and Learning Styles"

Student preferences are diverse linguistic, technical presentations of content, learning styles ... etc. While these preferences are important in the teaching-learning process, especially in an adaptive educational system on the Internet, however, those relating to learning styles we seem ultra important insofar as they act as indicators essential to the psychological adaptation of content to learners' profiles. To determine this individual characteristic, several models have been proposed in the literature, we chose one of Felder and Silverman. This classifies the preferences of learners in four dimensions: Active/Reflective, Sensing/Intuitive, Visual /Verbal and Sequential /Global.

Therefore students are encouraged to respond with precision to ILS questionnaire of Felder and Silverman[13], [17]. This questionnaire consists of 44 questions, each can have two possible answers (a) or (b). The result of the questionnaire determines the learning style of the learner. This result is described on a scale from -11 to +11 (with a step of + / -2) for each dimension.

3.2.2 Facet "Knowledge"

Knowledge of a learner represents his acquired experiences, training and learning activities he performed. This knowledge influences the acquisition of new knowledge. To include this parameter in the adaptation mechanisms of our architecture, each concept is represented by a pair Concept-Degree of control. The degrees of control proper are eminent for the system to have a clear vision on the level of the learner and offer him the concepts whose difficulty is slightly higher or lower at the prerequisite knowledge the learner.

3.2.3 Facet "History an Activities"

This facet is used to store information of various activities and formations of the learner and their history. The interim results of operations are stored temporarily until the learner conducts its activity, against the final results of each training session must be stored so eternal for the system to come back at any time. We ensure that any learning activity or learning path followed by the learner is stored for later use.

4. DOMAIN MODEL

The domain model is the second brick of our architecture, it is equally important in an adaptive educational system that the learner model presented above. This model is used to represent the concepts to teach in a particular domain. To ensure better adaptation of content, the domain model is designed on the basis of the independence of logical structures of modules that physical resources. With regard to the representation of resources we relied on a fairly fine granularity, modules to teach, based on the concept of hypermedia unit.

4.1 Hypermedia Unit

Representation of resources is based on the concept of hypermedia unit (HU), hypermedia unit is considered the smallest teachable entity, it is an educational component meets an operational objective and characterized by a set of information, it may be such as video, audio, text, image, multimedia ... etc. Indeed, each teaching module is designed to give students a skill, that skill is divided into a number of general objectives that develop specific objectives and operational objectives, hypermedia units meet operational objectives and aim to induce the learner to learn a part of knowledge or expertise. Hypermedia units can be reused in several learning paths, this reuse is achieved by defining three levels of description: Pedagogical level, Educational level and Technical level, as shown in the following figure:

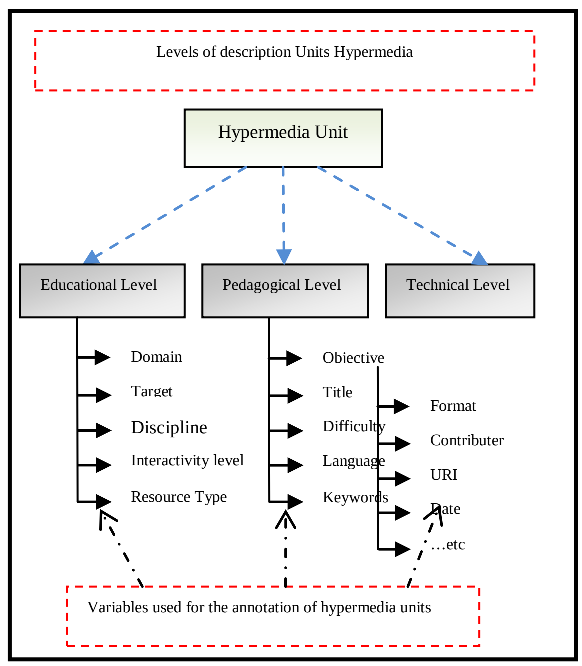

Figure 3: Representation Of Hypermedia Unit

We distinguish two types of hypermedia units: Units Hypermedia Learning (UHL) and Units Hypermedia Evaluation (UHE). Hypermedia learning units are units that fit into the composition of learning paths and Hypermedia Evaluation Unit

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

used to test the achievement of the objectives of the UHL.

4.2 Representation Of The Domain Model

The domain model is represented by ontologies. Each ontology presents the key concepts, attributes, relationships and individuals to model a class of homogeneous information in order to facilitate the work of the adaptation model. The extreme interest to use ontologies in the domain model is to specify the semantic context associated with the use and research of educational resources. First we designed an ontology structures modules operated by instructional designers. To structure modules, we have adopted the pedagogical approach by objectives, because it promotes a three-level hierarchy of educational objectives [14]: General objective, intermediate or specific objectives and operational objectives. Instructional designers specify the competence and objectives of each module to teach. The teaching module is structured according to Bloom's taxonomy [15] and in accordance with the educational activities and orientations of its specifications. A module can contain one or more parts, each part consists of chapters and each chapter is divided into a number of hypermedia units. Parts of modules meet the general objectives, chapters meet the specific objectives and hypermedia units meet the operational objectives.

The following figure shows an overview of the owl file representing the instantiation of the ontology of Structures Modules:

```
<owl:Ontology rdf:about=""/>
   <owl:Class rdf:ID="Module"/>
   <owl:Class rdf:ID="Partie"/>
   <owl:Class rdf:ID="Chapitre"/>
  <owl:Class rdf:ID="UniteHypermedia"/>
   <owl:Class rdf:ID="UniteHypermediaEvaluation">
    <rdfs:subClassOf rdf:resource="#UniteHypermedia"/>
  </owl:Class>
  <owl:Class rdf:ID="UniteHypermediaApprentissage">
    <rdfs:subClassOf rdf:resource="#UniteHypermedia"/>
  </owl:Class>
  <owl:ObjectProperty rdf:ID="Est_Compose_de_Partie">
    <rdfs:domain rdf:resource="#Module"/>
    <owl:inverseOf>
      <owl:ObjectProperty rdf:ID="Est_partie_de_module"/>
    </owl:inverseOf>
    <rdfs:range rdf:resource="#Partie"/>
  </owl:ObjectProperty>
  ..............................
  <owl:ObjectProperty rdf:about="#Est_compose_de_UH">
    <owl:inverseOf rdf:resource="#est_partie_de_chapitre"/>
    <rdfs:domain rdf:resource="#Chapitre"/>
    <rdfs:range rdf:resource="#UniteHypermedia"/>
  </owl:ObjectProperty>
  <owl:ObjectProperty rdf:about="#est_partie_de_partie">
    <owl:inverseOf rdf:resource="#Est_Compose_de_Chapitre"/>
  </owl:ObjectProperty>
  ..................
```

Figure 4: Overview Of The Owl File of Ontology Structure Modules

This ontology is used by instructional designers, the task of instructional designers is central, because they are required to state much more finely the different objectives of a module in order to facilitate to the teachers to publish their courses and the students to express their needs and expectations.

We present in the following figure the structure of a chapter. Each chapter consists of an introduction, a conclusion and a number of hypermedia units of learning and assessment that constitute his paragraphs.

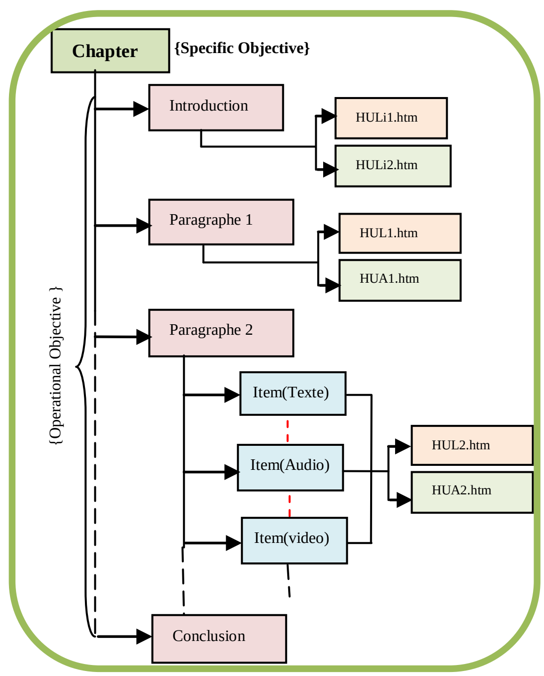

Figure 5: A Chapter Structure

To represent educational resources, to materialize the objectives of each module, we designed an ontology of resources. This ontology defines a vocabulary for describing hypermedia units. Each hypermedia unit responds to an operational objective and is characterized by three levels of

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ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

description, we based on the LOM standard to describe the three levels of description [16]. The following figures show an overview of this ontology edited by Protégé 2000.

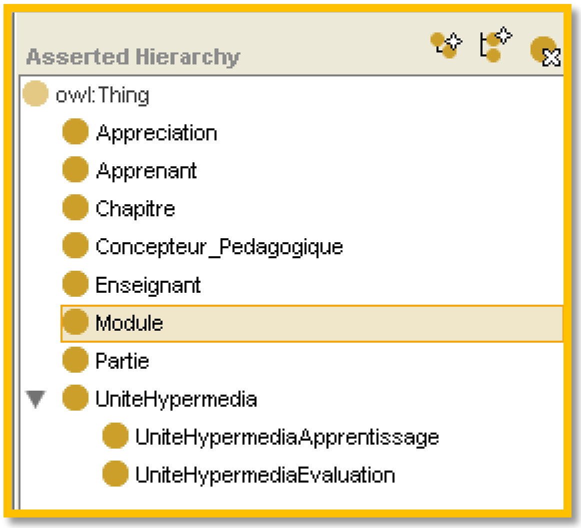

Figure 6-A: The Classes Hierarchy Of Ontology Of Resources

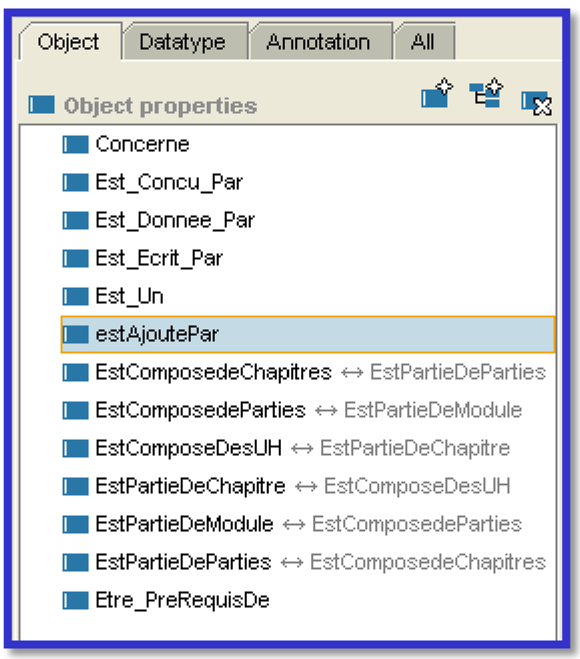

Figure 6-B: The Object Properties Of Ontology Of Resources.

5. ADAPTATION MODEL

We come to the heart of our system, in this section we will focus on the presentation of the principles of adaptation and dynamic composition implemented by our architecture for the generation of personalized learning paths. The adaptation model cleverly mimics the work of teachers in planning learning sessions respecting preferences, learning styles and goals of learners. For this, the adaptation model mobilizes the various components of the system to respond to the requests of students while applying different adaptation mechanisms. In the next sub-section we present the adaptation mechanisms on which this model is based.

5.1 Adaptation According To The Learning Styles Of Learners

Adapting the learning paths according to the learning styles of learners is used to determine the most preferred format of hypermedia units as well as the amount and positioning of the various components of the learning path that will be generated, namely the number of exercises the number of examples, the position summary ... etc.. The system calculates, based on the learning styles of learners the number of exercises, the number of examples, the number of evaluations, indicating their position in the learning path. For the model of Felder and Silverman, the learner does not belong to a single learning style but can learn using a mixture of learning styles, i.e, the learner may be both active, which tend to learn by experience, and sensing that focuses on the facts that require more examples, as it can be visual, who remembers better when he sees videos, pictures, diagrams, patterns, ... etc.. To determine the preferences of learners in terms of the number of exercises and examples, we based on the study conducted by Graf [17].

5.2 Adaptation According To The Cognitive State Of Learners

This second part of adaptation consists in applying the rules of adaptation related to the cognitive state of the learner, the prerequisite knowledge of the learner in a module may unduly influence the acquisition of new concepts. If the level of prerequisite knowledge is above the average, the learner can quietly carry on learning of new concepts. If, however, gaps in pre-requisites have been identified with him, a session of leveling is imposed. Adaptation by cognitive status of a learner is to calculate the degree of control of knowledge prerequisites before exposure learning content. The formulation of the intentions of learners as objectives is already a custom in itself because first, the educational criteria that channel its formation are expressed unnoticed, and then part of the educational criteria is explicitly expressed. Indeed, the student directly target concepts to understand in a module, it is guided by the

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ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

objectives customization, which makes it easier for both the learner and the system. Only hypermedia units serve this purpose will be returned and then passed to the cognitive filter.
To calculate the level of knowledge the system uses the following formula:
DC(C)= $\sum_1^n \frac{DC(Oi)}{n}$, with DC(Oi)=$\sum_{j=1}^m \frac{DC(SOj)}{m}$ and DC ∈ [0..1]

units while applying different levels of filtering. And then, composes dynamically those restituted units while respecting the predefined pedagogical rules. If on the contrary, gaps are identified in the learner, the system offers a path of leveling. Figure 8 shows the flow diagram of dynamic composition of a learning path.

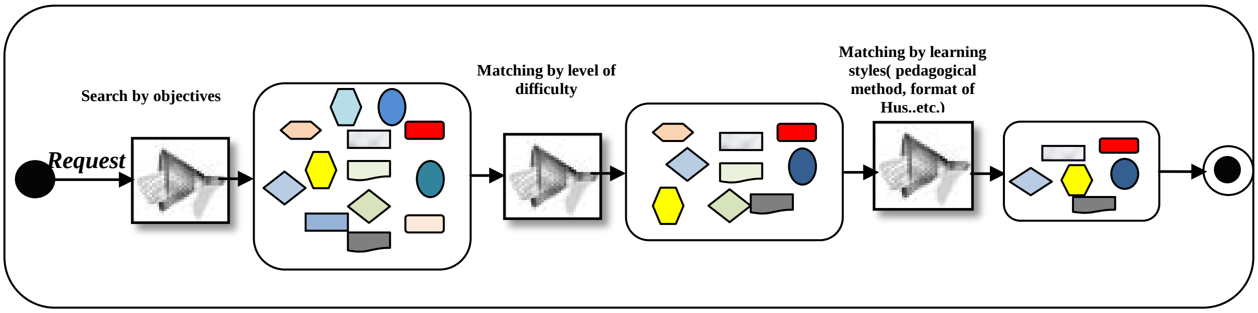

Figure 7: Different Levels Of Filtering Applied By The Adaptation Model

DC(C) : Degree of control of the competence C.

DC(Oi): Degree of control of the objective O*i* component the competence C.

DC(Soj) : Degree of control of the sub-objective SO*j* component the objective O*i*, if O*i* is decomposable.

After calculating the degree of control of prerequisites knowledge, the system performs a pairing between the level of pre-requisites and the difficulty of HUs knowledge to choose the most appropriate UHs. Thus, the process of building adaptive learning paths follows the steps illustrated in the following figure(Figure 7).

6. SCENARIO OF A DYNAMIC COMPOSITION OF A PERSONALIZED LEARNING PATH

In this section we present an illustrative scenario for the dynamic construction of a personalized learning path.
The learner starts with the choice of a teaching module in order to make its intentions. After submitting the request, the system decomposes the objective formulated in operational objectives before starting the process of search and selection the appropriate hypermedia units. But before, the system provides a validation test of the prerequisites of the concept asked. If the student passes the test, the system begins the process of building learning paths by selecting for each operational objective the appropriate hypermedia

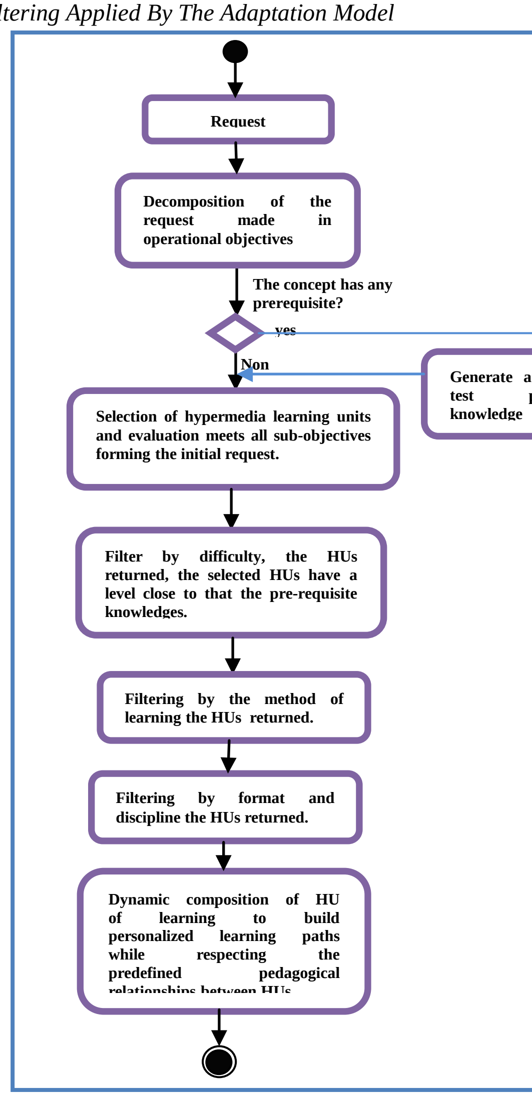

Figure 8: Flow Diagram Of Dynamic Composition Of A Learning Path

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ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

We present in the following figure the algorithm for dynamic composition of personalized learning paths.

```
Input : Formulated Objective (FO), Learner Profile (IDLearner),
        Training Module (IDModule)
Output : Personalized Learning Path (PersLearPath)
Begin
PersLearPath  : Collection {List of Learning paths generated }
List_Test : Collection  {List to store the validation tests prerequisites
        }
List_OO: Collection { List of operational objectives}
List_HULC, List_HUML, List_HUD, List_HULO:Collection {
        List of hypermedia Units}
if IsDecomposable(FO)=True then
{Decomposition of the objective formulated by  the learner in
        Operational Objectives }
List_OO←Decomposer( FO: Objectif)


     endIf ;
     { Browse the list of operational objectives to ensure their
       prerequisites }
     For (ObjectiveOperationnel  Oi : List_OO) Do
      if HasPrerequisites(Oi)=true Then
        { generate a validation test of the prerequisites for each
        operational objective }
        List_Test.add(GenereTestPrerequisites(Oi) )
       EndIf ;
     EndFor ;
     { Search HUs concretizing all the sub objectives of the initial
       objective }
     for (Objective OO: List_OO) do
       List_HULO←Search(OO ); { Search all hypermedia units of
         learning meet the objective OO, the search criteria is the
         learning objective }

     For (HypermediaUnitLearning HUL: List_HULO ) Do
       { This function applies the first level of filtering, filtering
           according to the cognitive state of the learner }
       List_HULC← FilterLevelCognitif(HUL) ;
       IF  List_HULC.Size()>1 Then
       { We apply the second filter, filtering method of learning }
          For (HypermediaUnitLearning HUL: Liste_HULC) do
             Liste_HUML← FilterMethodLearning(HUL) ;
            If  List_HUML.Size()>1 Then
                  { The third filter, filtering is applied by media
           format}
              For (HypermediaUnitLearning HUL: List_HUML) do
               List_HUF← FiltrerFormat(HUL)
               if  List_HUF.Size()>1 Then
                   { We apply the fourth filter, filtering by
           discipline }
                For (HypermediaUnitLearning HUL: List_HUF) Do
                     HULO[k]← FilterDiscipline(HUL); {The
           Hypermedia units of each operational objective are
           stored to perform the dynamic composition }
          PersLearPath←DynamicComposition
           (HULO,IdLearner,IdModule)
                     EndFor ;
                EndIf ;
              EndFor ;
             EndIf ;
          EndFor ;
        EndIf ;
      EndFor ;
     End.
```

Figure 9: Algorithm For Dynamic Composition Of Personalized Learning Paths

The algorithm uses several levels of filtering to generate dynamically learning paths. However, the system is much more flexible, since it does not always apply the four levels of filtering for all learners, but based on the results obtained in a level he decides whether to apply the filtering of the next level. For example, if the HUs returned after the application of level 3 (Filtering by learning method and / or media format), were designed for a single discipline, there is no question to applying the filtering by discipline. Like if HUs returned after the application of level 2 (Filtering by level of difficulty) are the same difficulty level 3 is logically ignored, and so on.

Several learning paths can be offered to the learner based on the number of hypermedia units returned for each operational objective. To refine these learning paths, you should choose the closest path to the learner profile. For this, we need to include features of hypermedia units to define the adequacy of each one. A naive approach is to consider all these features into a single fitness function where each parameter has a weight according to its importance in the function:

$$f(HUL^k)=\sum_{i=1}^{n} w_i * c_i^k$$

with:

- HUL^k is the kth hypermedia unit of learning concretizing an operational objective.
- c_i^k: This is the i^{th} characteristic of HUL^K.
- w_i: The weight of the i^{th} feature, with $\sum_{i=1}^{n} w_i = 1$.

The fitness function will calculate for each hypermedia unit the degree of adaptation to choose the most appropriate. The figure shows the process of application the fitness function for the choice of hypermedia units.

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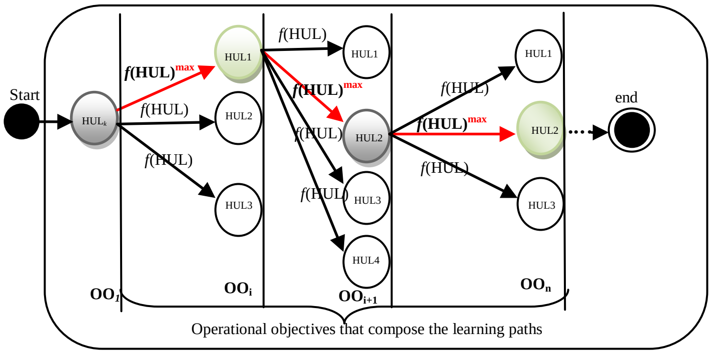

Figure 10: The Process Of Application The Fitness Function

This technique allows choosing the most suitable learning path. In the next section, we present a second method to create evolutionary learning paths based on Bayesian networks.

7. GENERATING AN EVOLUTIONARY LEARNING PATHS BASED ON A BAYESIAN MODEL

To refine the learning paths generated by the system, we chose a technique based on Bayesian networks. This technique is intended to help the system to generate evolutionary adaptive learning paths, i.e gradually as the learner advances in learning, the system chooses, based on the characteristics of the learner and the results of intermediate tests obtained, the most appropriate hypermedia units of learning. Begin, first, by identifying variables and the structure of Bayesian model.

7.1 Structure Of The Bayesian Model

Before identifying the variables of the proposed model, it would be wise to evoke the main types of Bayesian Networks (BN) [18]. The BN can be of two types: causal or non-causal. A causal Bayesian network models formally a set of cause-effect type: each non-root node of the graph is the direct result of his parents in the graph. A non-causal network, however, models of probabilistic dependency relationships between variables, the causal relationship does not exist between its nodes. The model we propose is a causal network structure is defined based on discrete or continuous variables representing the characteristics of the learner, the test results and metadata hypermedia units.

Learner characteristics: Characteristics of learners we have taken into account for the choice of the most appropriate hypermedia unit are:

- The student learning styles represented by four discrete random variable S = {S1, S2, S3, S4}. Each variable represents the projection of the student on one of the axes of the model Felder (Visual-Verbal, Sequential-Global, Active-Reflective, Sensing / Intuitive). Each of the variables $\{S_i\}$ i = [1,4] is an integer between -11 and +11. If ∉1[-9, -7, -5-3, -1,1,3,5,7,9,11] ∀ i ∈{1,2,3,4}.
- The result of the formative evaluation (intermediate test), which occurs at the end of each objective, is stored in a continuous random variable FE ∈ [0 .. 20].
- The degree of control of prerequisite knowledge is represented by a continuous variable DC ∈ [0 .. 1].

Hypermedia Units characteristics: The hypermedia units have the educational and pedagogical features that allow them to distinguish themselves from each other. In the Bayesian model, we identified four heavy characteristics of hypermedia unit, and we have represented by four discrete random variables {HU = HU1, HU2, HU3, HU4}.

- The HU1 variable represents the format of the hypermedia unit. It can take three values HU1 ∈ {T, A, V} (T) text illustrated with pictures and / or diagrams (A) Audio with graphics and / or drawings of illustration and (V) Video or Animation accompanied by textual explanations.
- The HU2 variable represents the difficulty of the hypermedia unit. It can take five values HU2 ∈ {VE, E, Average, D, VD}, with VE = Very easy, E = Easy, A = Average, D = Difficult and VD = Very difficult.
- The HU3 variable represents the appropriate teaching method to present hypermedia unit. It can take three values HU3 ∈ {E, A, I}, with E = Expositive, and A = Active I = Interrogative.
- The HU4 variable is the level of interactivity of hypermedia unit. It can take three values HU4 ∈ {L, M, G}, with L = Low, M = Medium, and B = Good. The following figure illustrates the structure of the proposed with different causal relationships between nodes Bayesian model.

Journal of Theoretical and Applied Information Technology
20th November 2013. Vol. 57 No.2

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

We are used this structure depicted in the figure 10 to define the relationships between different variables in our Bayesian model

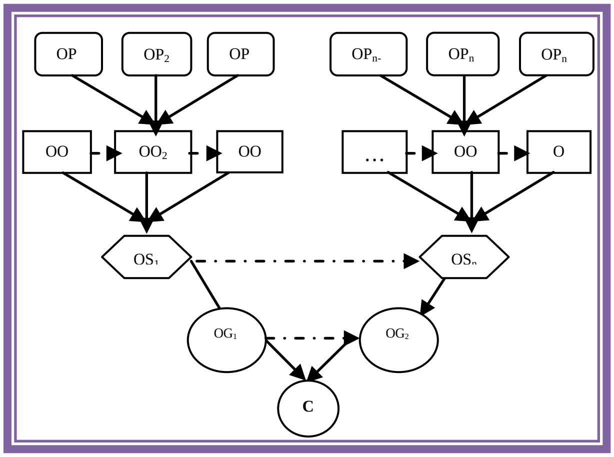

Figure 10: Structure Of Pedagogical Relationships Defined Between The Different Objectives Of A Module

with:

OP: Objective Prerequisites, OO: Operational Objective, OS: Specific Objective.

7.2 Calculation and Validation

The problem is to select among all candidates HULs the one that gets most appropriate HUL^{appro}, ie the one that the probability of his success is the highest. To do this, we will calculate the probability of success of each HULs candidate and choose the one whose probability of success is maximized. The calculation of this probability is based on the following three parameters: the degree of control of the knowledge prerequisites to the objective, results of formative evaluations and learning styles of learner. The degrees of control of all prerequisite objectives OP and results in HULs upstream of the objective OOj have a causal influence on the acquisition of the objective (OOj). In other words, if the level of prerequisite knowledge is good and the results of formative evaluations are satisfactory, the probability that the learner succeeds his objective is high.

So we need to apply the Bayes' theorem:

$$P(A|B)=\frac{P(A|B)\times P(A)}{P(B)}$$

$P(A)$: A priori probability;

$P(A|B)$: Posterior probability;

To calculate the following probabilities:

$HUL^{appro}=Argmax\{P(Success=V|HUL1,HUL2,HUL3,HUL4)\}$

with :

P(HU1| DC, FE, S1,S2,S3),
P(HU2| DC, FE, S1,S2,S3),
P(HU3| DC, FE, S1,S2,S3),
P(HU4 | DC, FE, S1,S2,S3)

To validate our Bayesian model, we adopted an experimental approach with a sample of 100 students. We have collected first learning styles of learners using the questionnaire Felder and Silverman that is posted online. Then we proposed learning activities and assessment of different levels of difficulty and different formats. We then measured the degree of success for each hypermedia unit based on the characteristics of learners and those of hypermedia units of learning. This study allowed us to establish the a priori probabilities to calculate the posterior probabilities to perform inferences.

The following figure shows the different causal relationships between variables in the model. We used a reduced number of variables to facilitate the calculation, three variables learning for s1, s2 and S3 are used styles.

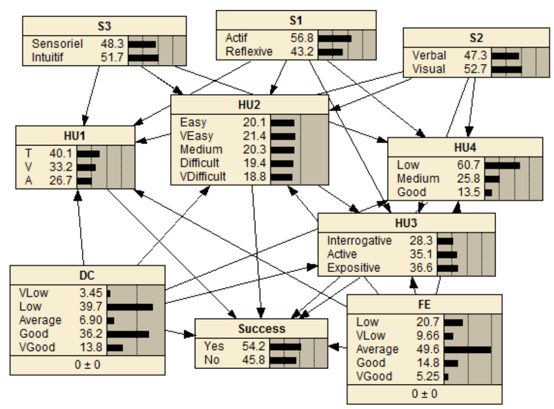

Figure 11: Structure Of Our Bayesian Model

The system uses the Bayesian model to choose in an evolutionary manner the hypermedia unit of learning whose probability of success is high.

8. CONCLUSION

In this paper we presented an adaptive architecture based on ontologies, multi-agent systems and Bayesian networks for the generation of evolutionary personalized learning paths. We based on the model of Felder and Silverman to determine the learning styles of learners. We have designed an ontology to represent the characteristics of learners while integrating their learning styles and degrees of control of each concept, and an ontology of resources to represent hypermedia units of learning and evaluation. Then we established formulas to perform adaptation according to the cognitive state

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

and the learning styles of learners. In addition, we developed a Bayesian model to infer the most appropriate hypermedia unit to succeed in the next operational objective and thus create evolutionary personalized learning paths. This architecture is designed to facilitate to the learners acquire new concepts while maintaining their rhythms and their preferences.

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