Using Semantic Web to support Advanced Web-Based Environment

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***Abstract*—In the learning environments, users would be helpless without the assistance of powerful searching and browsing tools to find their way. Web-based e-learning systems are normally used by a wide variety of learners with different skills, background, preferences, and learning styles.**

In this paper, we perform the personalized semantic search and recommendation of learning contents on the learning Web-based environments to enhance the learning environment. Semantic and personalized search of learning content is based on a comparison of the learner profile that is based on learning style, and the learning objects metadata. This approach needs to present both the learner profile and the learning object description as certain data structures. Personalized recommendation of learning objects uses an approach to determine a more suitable relationship between learning objects and learning profiles. Thus, it may advise a learner with most suitable learning objects. Semantic learning objects search is based on the query expansion of the user query and by using the semantic similarity to retrieve semantic matched learning objects.

Keywords- Semantic Web; Domain Ontology; Learner Profile; Adaptive Learning; Semantic Search ; Recommendation.

I. INTRODUCTION

Learning environment allows learners to access electronic course contents through the network and study them in virtual classrooms. It brings many benefits in comparison with conventional learning paradigm, e.g. learning can be taken at any time and at any place. However, with the rapid increase of learning content on the Web, it will be time-consuming for learners to find contents they really want to and need to study. The challenge in an information-rich world is not only to make information available to people at any time, at any place, and in any form, but to offer the right thing to the right person in the right way [1].

In the context of e-learning [2], adaptive systems are more specialized and focus on the adaptation of learning content and the presentation of this content. According to [3], an adaptive system focuses on how the profile data is learned by the learner and pays attention to learning activities, cognitive structures and the context of the learning material.

In Figure 1, the structure of an adaptive system [5] is shown. The system intervenes at three stages during the process of adaptation. It controls the process of collecting data about the user, the process of building up the user model (user modeling) and during the adaptation process.

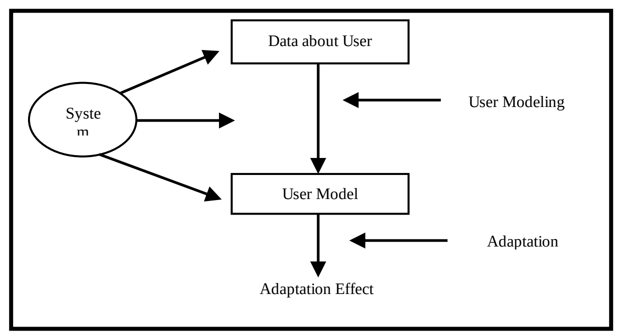

Figure 1: The Structure of an Adaptive System [5]

An advanced e-learning system has to comply with the following requirements [6]:

Personalization: This requirement suggests that the learning process needs to take into account the user's preferences and personal needs. This implies either that the user is in a position to specify explicitly these preferences or that the system has the ability to infer them through a monitoring process. The latter is far more convenient for the end-user and constitutes a highly desirable feature.

Adaptivity: The user's preferences change over time and the system must be able to track them and properly adjust to them. By 'properly', it is implied that the whole history of the user's learning behavior must be taken into consideration, and not just the user's latest (most recent) actions.

Extensibility: An e-learning system has to be extensible in terms of the learning material it provides. The incorporation of new courses and resources must be an easy to accomplish the task.

Interoperability: An e-learning system must be able to both access content from and provide content to digital libraries and other e-learning systems. In this way, the provision of enriched and updated content is feasible.

The semantic web [4] is a space understandable and navigable by both human and software agents. It adds structured meaning and organization to the navigational data of the current web, based on formalized ontologies and controlled vocabularies with semantic links to each other. From the E-Learning perspective, it aids learners in locating, accessing, querying, processing, and assessing learning resources across a distributed heterogeneous network; it also aids instructors in creating, locating, using, reusing, sharing and exchanging learning objects (data and components). The semantic web-based educational systems need to interoperate, collaborate and exchange content or re-use functionality.

Ontology [7] comprises a set of knowledge terms, including the vocabulary, the semantic interconnections, and some simple rules of inference and logic for some particular topic. Ontologies applied to the Web are creating the Semantic Web. Ontologies [8] facilitate knowledge sharing and reuse, i.e. a common understanding of various contents that reach across people and applications. Using ontology in learning environments aims to provide mechanisms to enhance the process of searching and finding learning resources and have the capability to organize and display information that make it easier for learners to draw connections, for instance, by visualizing relationships among concepts and ideas.

Learning environment should not only provide flexible content delivery, but support adaptive content search and recommendation. For better learning experience and effect, search and recommendation of learning content should take into account the contextual information of learners, e.g., prior knowledge, goal, learning style, available learning time, location and interests.

This paper aims to perform the personalized semantic search and recommendation of learning contents on the learning Web-based environments. Semantic and personalized search of learning content is based on a comparison of the learner profile and the learning content description. This approach needs to present both the learner profile and the learning object description as certain data structures. Personalized recommendation of learning objects is based on ontological approach to guide what learning contents a learner should study, i.e. what learning objects a course should have according to learner preference and intention.

II. RELATED WORKS

Personalized search [9] is addressed by a number of systems. Persona [10] uses explicit relevant feedback to update user profiles that are represented by means of weighted open directory project taxonomy [11]. These profiles are used to filter search results. Personalized variants of PageRank, as found in Personalized Google or the Outride Personalized Search System [12]. Authors in [13] re-rank the search results of queries for medical articles profiles keywords, associated concepts, and weights generated from an electronic patient record. In [14], it was filtered search results on the grounds of user profiles obtained from earlier queries. These profiles consist of a set of categories, and weighted terms associated with each category. In their work on personalizing search results, [15] they distinguish between long-term and short-term interests. While aiming at personalization in a broader sense, [16] use click-through data to increase the performance of search results.

In the paper [17], authors have proposed an approach to personalized query expansion based on a semantic user model. They discussed the representation and construction of the user model which represents individual user's interests by semantic mining from user's resource searching process, in order to perceive the semantic relationships between user's interests which are barely considered in traditional user models and to satisfy the requirement of providing personalized service to users in e-Learning systems. They exploited the user model to provide semantic query expansion service in our e-Learning system.

Authors in [18] have shown that extracting the semantic interests of learner profiles can form a reasonable and simple way to represent the learning context, and that semantic learner profile, coupled with a semantic domain ontology that represents the learned content, enhance the retrieval results on a real e-learning platform.

This paper [19] proposed a new method for the personalized search, using click-through data as the personal data. Firstly, uses the semantic statistical of word frequency method to extract the query expansion terms and recommended to the user. Secondly, improves the Naive Bayesian classifier and combines SVM to make users' personalized learning models, then provides personalized re-sort results by user models. After experimental evaluation, it showed that this method has a significant effect, not only provides a meaningful query expansion terms, but also significantly improves the ranking of results.

The study in [20] authors proposed an ontological approach for semantic-aware learning object retrieval. The proposed ontological approach has two significant novelties: a fully automatic ontology query expansion algorithm for inferring and aggregating user intentions based on their short queries.

This paper [21] proposed a personalized e-learning method based on hybrid filtering. Two-level user profiles direct the recommendation process. Group profile reflects the users whose similar learning needs are similar with the current user. Topic profile describes the user's interests with topics that the user has learned. Group profile and topic profile are bases of collaborative filtering recommendation and content-based filtering recommendation respectively.

In the paper [22], the authors introduced the principle and implementation steps of Collaborative Filtering (CF) algorithm. Then a novel CF recommendation algorithm was proposed on the combination of user profile weight and time weight. In this way, on one hand, the improved prediction can discover user's latent demands more precisely. On the other hand, it also can sense the changes of user's preference and then adjust the recommendation promptly.

III. The Proposed System

Personalized service is being paid close attention as a new method of intelligent information service to satisfy the increasing informational demands of the users in different systems. User model plays an important role in providing personalized service by representing the user's identity information and interests. There are many user models which have been adopted in various systems to acquire interests of users. In the e-Learning scenario, the learner model is exploited to represent the interests and background knowledge of individual learners [23]. The key technology of providing personalized learning services is to represent and acquire user's interests that are used in user modeling. User modeling is used to search and recommend content relevant to user interests.

In our proposed approach, personalized search of learning objects in e-learning is based on a comparison of the learner profile and the learning object (resource) description [24, 25]. Because such an approach needs to present both the learner profile and the learning object description as certain data structures, it requires the development of ontological models [26, 9] of the learner and learning object.

The proposed approach has two aspects, first for personalized search of learning objects is generally described in [24, 27], second for personalized recommendation suitable learning objects is proposed in [28, 29].

The key idea of the Semantic Web is to have data defined and linked in such a way that its meaning is explicitly interpretable by software processes rather than just being implicitly interpretable by humans. The Semantic Web can represent knowledge, including defining ontologies as metadata of resources. Ontology is a formal, semantic specification of a conceptualization of a domain of interest. Ontologies are used to describe the semantics of information exchange.

The metadata used in our work, data about data, is to provide structured information that describes, locates and explains information resources making it easier for resources to be retrieved. It is important to remember that data and metadata are different. Data is values, individual parts of information, whereas metadata describes the relationship between the parts and other data. Together data and metadata make information portable, because the relationships among the data values remain separate from their storage. Metadata is a key concept in developing the Semantic Web, to allow computers to share information automatically, data and metadata must be grouped together. Therefore, to ensure metadata can be automatically processed by machines, some metadata standard is needed [46].

The learner model is abstract expression to the learner characteristic. The learner model is not the expression of learner's all characteristics, but to describe and express partial learner characteristics according to the different learning system's needs.

The present research will describe details of building the learner and learning object ontological models to perform personalizes search in learning objects and recommendation suitable learning objects to learners.

In order to implement the proposed personalized search of learning objects according to the created ontological models of the learner and learning object, some IMS Learner Information Package Specification corresponding to some IEEE LOM [30] standard have been chosen, and the criteria to estimate conformity of LOM to the learner personal profile with the coefficients of importance. Our proposed system architecture is shown in figure 2.

Our system aims to perform these objectives:

1. Presenting a technical solution to an approach and methodology for personalized search of learning objects according to criteria that determine the learner's interests.
2. Proposing an approach to adjust a learner's interests. Because different attributes have different importance

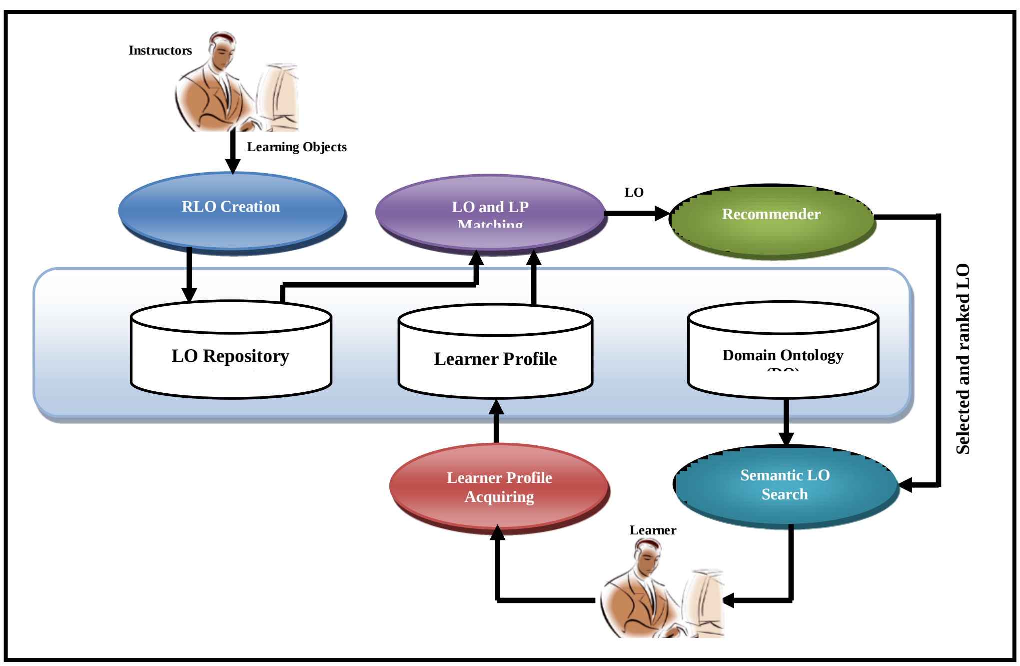

Figure 2: The Proposed System Architecture

to different learners, the system adjusts the weights in comparison to the learner's interests and goals.

3. Proposing personalized learning objects search in E-learning, which is intended to allow a learner (user) to create a learner profile describing his/her personal interests using the IMS attributes [31], and then run a personalized search in a learning object repository on the Web to find relevant learning objects, which match that learner profile.
4. Ranking available learning objects by comparing values of corresponding attributes in the learner profile and learning object metadata (LOM).
5. Using specific ontology to infer what learning objects are needed for a course established for a specific learner requiring a specific subject and how to look for them on the Internet.
6. Recommending suitable learning objects according to a user's preference and intention.
7. Referring to the experiences of similar users and adopting neighbor-interest to look for the learning objects that the user should be interested.
8. Providing adaptive, personalized recommendation for each user (learner).

A. Reusable Learning Objects (RLO) Creating

As mentioned in [32], authors have determined that the reusable learning objects is a reusable chunk of content with the following two fundamental properties: first is instructional sound content with the focused learning objectives. Second property is the facility that allows the learner to practice, learn, and receive assessment. Also, they define the sharable learning objects as RLO with the additional interoperability property that is the metadata or keywords that describe the object's attributes and mechanisms for communicating with any e-learning system. The aim of this methodology is to select and extract as much of the existing raw content into RLO. The methodology is an iterative five step process to select appropriate content for the RLO with opportunities to refine and re-structure as the extraction is taking place. The algorithm for building the RLO is shown in figure 3. A learning object must be modular, discoverable and interoperable, in order to be reused. To achieve these features and improve efficiency many people have dedicated long hours of hard work.

Input: *Learning Material*
Output: *Reusable learning objects of the learning material*.
Procedure:
1. Create detailed table of contents for the material.
2. Define set of learning objectives for some of the topic/subtopic.
3. Select raw content to achieve each identified learning objective.
4. Include the review Question/Answer.
5. Include the examination Question/Answer.

Figure 3: Algorithm for building the RLO

The majority of the efforts focus on the definition of standardization. Organizations such as IEEE [30] have contributed significantly by defining indexing standards called metadata (data about data). Metadata structures [33] contain information to explain what the leaning object is about, how to search, access, and identify it and how to retrieve educational content according to a specific demand.

The IEEE LOM standard specification specifies a standard for learning object metadata. It specifies a conceptual data schema that defines the structure of a metadata instance for a learning object. The IEEE LOM specification consists of nine categories, which includes 60 data elements. Each category has a specific purpose, such as describing general attributes of objects, and educational objectives. Table 1 shows the LOM categories adopted in our work.

TABLE I. THE MAIN CATEGORIES OF IEEE LOM

Category Name	Category Fields	Description
General	Identifier, Catalog, Entry, Title, Language, Description, Keyword, Coverage, Structure, Aggregation Level	general information that describes the learning object as a whole.
Technical	Format, Size, Location, Requirement, OrComposite, Type, Name, Minimum Version, Maximum Version, Installation Remarks, Other Platform Requirements, Duration	technical requirements and characteristics of the learning object.
Educational	Interactivity Type, Learning Resource Type, Interactivity Level, Semantic Density, Intended End User Role, Context, Typical Age Range, Difficulty, Typical Learning Time, Description, Language,	key educational or pedagogic characteristics of the learning object.

One of the chartered activities of the IEEE LTSC is to develop an XML binding for LOM [34]. This activity is ongoing, but the standard XML binding has not yet been approved and published. While the LOM standard defines the structure of a metadata instance, it does not define how a learning technology system will represent or use a metadata instance for a learning object.

The XML Binding defines an exchange format for metadata. With XML, course developers may put semi-structured information, such as the course content or course structure, into a discrete relational field, and then work with this information as with structured blocks of data, not as with a string of bytes. In our research, we describe each Learning Object by means of the XML document validated against an XML Schema defined by the IEEE LOM standard. Figure 4 shows the used LOM category and its fields in our system as relationship diagram of database.

We choose the tags from the standard schema, so every tag in our schema is still meaningful to others. A third-party search engine that can handle the XML metadata documents conforming to the standard schema could also handle ours. Figure 5 shows the part of schema for learning objects metadata (generated by XML Editor [35]) and Figure 6 shows the part of DTD of the XML file of learning objects metadata.

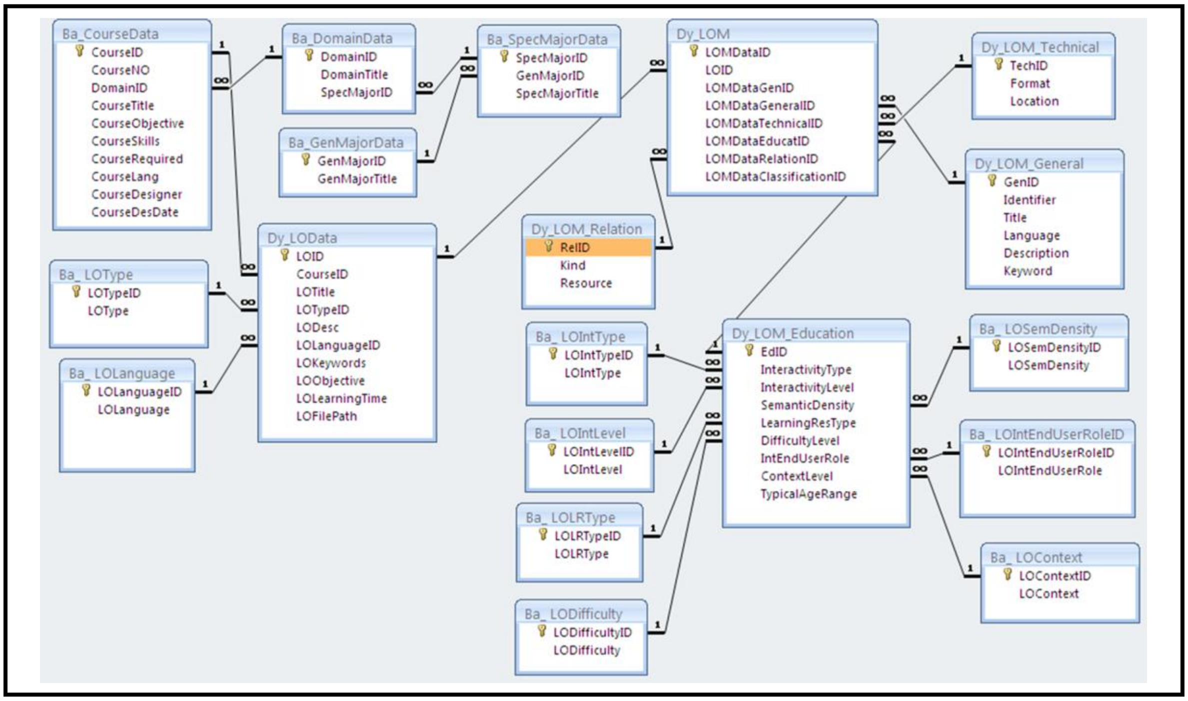

Figure 4: The used LOM category and its fields in our system as relationship diagram of database

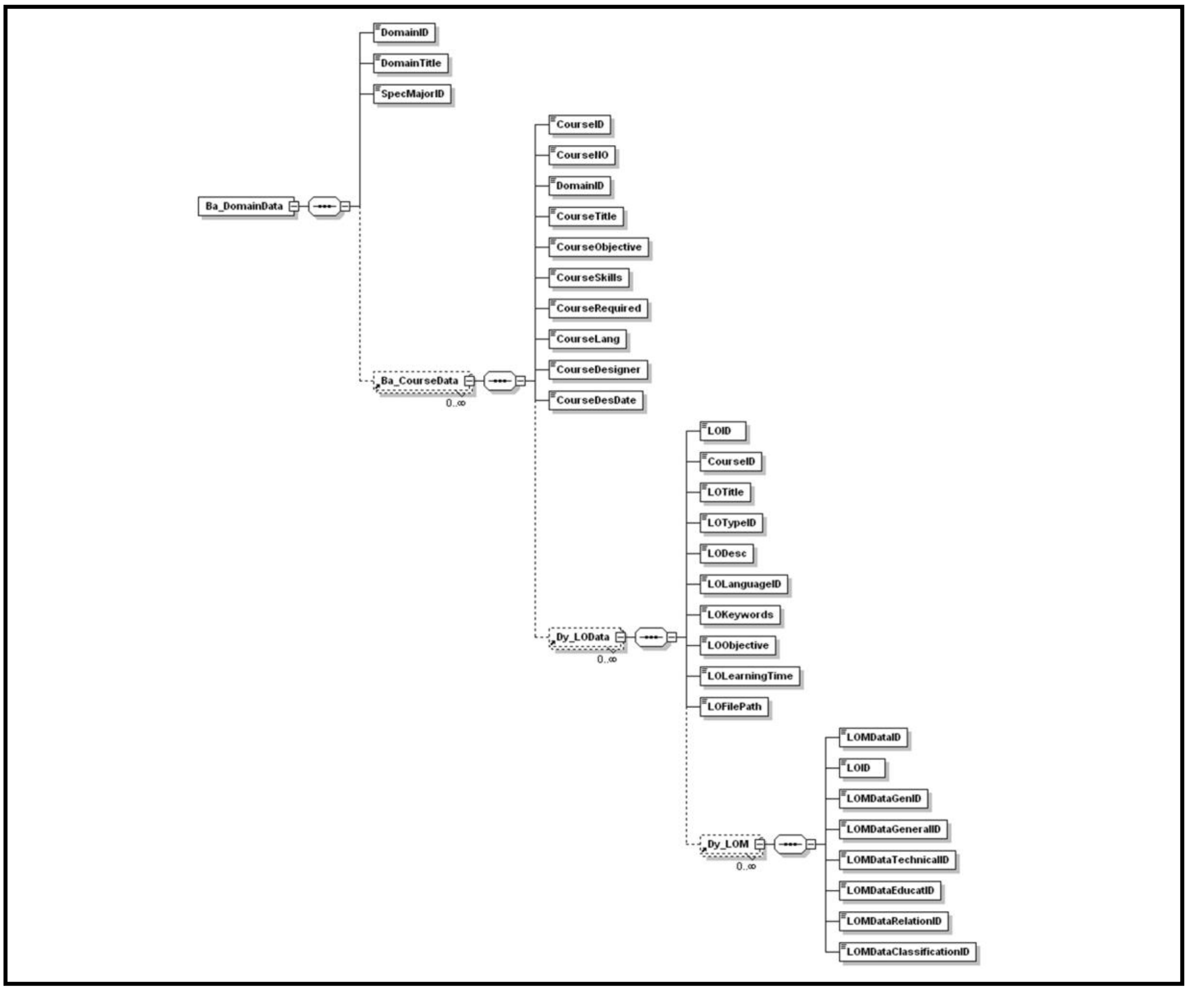

Figure 5: The part of schema for learning objects metadata

```
<?xml version="1.0" encoding="UTF-8"?>
<!ELEMENT Ba_ LOContext (LOContextID, LOContext, Dy_LOM_Education*)>
<!ELEMENT Ba_ LODifficulty (LODifficultyID, LODifficulty, Dy_LOM_Education*)>
<!ELEMENT Ba_ LOIntEndUserRoleID (LOIntEndUserRoleID, LOIntEndUserRole,
Dy_LOM_Education*)>
<!ELEMENT Ba_ LOIntLevel (LOIntLevelID, LOIntLevel, Dy_LOM_Education*)>
<!ELEMENT Ba_ LOIntType (LOIntTypeID, LOIntType, Dy_LOM_Education*)>
<!ELEMENT Ba_ LOLRType (LOLRTypeID, LOLRType, Dy_LOM_Education*)>
<!ELEMENT Ba_ LOLanguage (LOLanguageID, LOLanguage, Dy_LOData*)>
<!ELEMENT Ba_ LOSemDensity (LOSemDensityID, LOSemDensity, Dy_LOM_Education*)>
<!ELEMENT Ba_ LOType (LOTypeID, LOType, Dy_LOData*)>
<!ELEMENT Ba_CourseData (CourseID, CourseNO, DomainID, CourseTitle, CourseObjective,
CourseSkills, CourseRequired, CourseLang, CourseDesigner, CourseDesDate, Dy_LOData*)>
<!ELEMENT Ba_DomainData (DomainID, DomainTitle, SpecMajorID, Ba_CourseData*)>
<!ELEMENT Ba_GenMajorData (GenMajorID, GenMajorTitle, Ba_SpecMajorData*)>
<!ELEMENT Ba_SpecMajorData (SpecMajorID, GenMajorID, SpecMajorTitle, Ba_DomainData*)>
<!ELEMENT Dy_LOData (LOID, CourseID, LOTitle, LOTypeID, LODesc, LOLanguageID,
LOKeywords, LOObjective, LOLearningTime, LOFilePath, Dy_LOM*)>
<!ELEMENT Dy_LOM (LOMDataID, LOID, LOMDataGenID, LOMDataGeneralID,
LOMDataTechnicalID, LOMDataEducatID, LOMDataRelationID, LOMDataClassificationID)>
<!ELEMENT Dy_LOM_Education (EdID, InteractivityType, InteractivityLevel, SemanticDensity,
LearningResType, DifficultyLevel, IntEndUserRole, ContextLevel, TypicalAgeRange, Dy_LOM*)>
<!ELEMENT Dy_LOM_General (GenID, Identifier, Title, Language, Description, Keyword,
Dy_LOM*)>
<!ELEMENT Dy_LOM_Relation (RelID, Kind, Resource, Dy_LOM*)>
<!ELEMENT Dy_LOM_Technical (TechID, Format, Location, Dy_LOM*)>
<!ELEMENT CourseTitle (#PCDATA)>
<!ELEMENT CourseObjective (#PCDATA)>
<!ELEMENT CourseSkills (#PCDATA)>
<!ELEMENT CourseRequired (#PCDATA)>
<!ELEMENT CourseLang (#PCDATA)>
<!ELEMENT CourseDesigner (#PCDATA)>
<!ELEMENT CourseDesDate (#PCDATA)>
<!ELEMENT DomainID (#PCDATA)>
<!ELEMENT DomainTitle (#PCDATA)>
<!ELEMENT SpecMajorID (#PCDATA)>
<!ELEMENT GenMajorID (#PCDATA)>
<!ELEMENT GenMajorTitle (#PCDATA)>
<!ELEMENT SpecMajorID (#PCDATA)>
<!ELEMENT GenMajorID (#PCDATA)>
<!ELEMENT SpecMajorTitle (#PCDATA)>
<!ELEMENT LOID (#PCDATA)>
<!ELEMENT CourseID (#PCDATA)>
<!ELEMENT LOTitle (#PCDATA)>
<!ELEMENT LOTypeID (#PCDATA)>
<!ELEMENT SemanticDensity (#PCDATA)>
<!ELEMENT LearningResType (#PCDATA)>
<!ELEMENT DifficultyLevel (#PCDATA)>
<!ELEMENT IntEndUserRole (#PCDATA)>
<!ELEMENT ContextLevel (#PCDATA)>
<!ELEMENT TypicalAgeRange (#PCDATA)>
<!ELEMENT GenID (#PCDATA)>
<!ELEMENT Identifier (#PCDATA)>
<!ELEMENT Title (#PCDATA)>
<!ELEMENT Language (#PCDATA)>
<!ELEMENT Description (#PCDATA)>
<!ELEMENT Keyword (#PCDATA)>
<!ELEMENT RelID (#PCDATA)>
<!ELEMENT Kind (#PCDATA)>
<!ELEMENT Resource (#PCDATA)>
<!ELEMENT TechID (#PCDATA)>
<!ELEMENT Format (#PCDATA)>
<!ELEMENT Location (#PCDATA)>
```

Figure 6 The part of DTD of the XML file of learning objects metadata

TABLE II. CATEGORIES OF FELDER-SILVERMAN'S LEARNING STYLE

Learning Style Category	Description
Sensing vs. Intuitive	**It represents the abstraction level of the learning material the learner prefers. A sensing learner likes learning facts and needs more practical case studies. An intuitive learner usually prefers innovation and dislikes repetition.**
Visual vs. Verbal	**It indicates whether the learner prefers auditory (textual) or visual documents.**
Active vs. Reflective	**It indicates how the learner prefers to process information: actively (through engagement in activities or discussions) or reflectively (through introspection)**
Sequential vs. Global	**It indicates how the learner progresses toward understanding. Sequential learners prefer sequential explanations while global learners usually prefer an initial overview of the involved topics which possibly shows them the most important steps and relations they are going to study**

B. Learner Profile Acquiring using learning style

There are five popular and useful features when is viewing the learner as an individual, these are: the learner 's knowledge, interests, goals, background, and individual traits [36]. Learning styles are typically defined as the way people prefer to learn. We can represent the learning style in stereotype model according to the Felder-Silverman's learning style categories. From the perception, input processing and understanding four dimensions, the Felder-Silverman's learning style categories are shown in table 2 [37, 38].

The learner actions that can be used to identify learner cognitive traits in learning systems by learner behaviors that can enable to acquire the learning style . Number of these actions is shown in [39]. Example of the actions that can enable to acquire learning styles base on Felder-Silverman model (FSLSM) is found in table 3.

TABLE III. THE RELATIONSHIP BETWEEN LEARNER ACTIONS AND (FSLSM) CATEGORY

Parameter	Value	FSLSM Category
No. of visits/postings in forum/chat	High	Active, Verbal
No. of visits and time spent on exercises	High	Active, Intuitive
Amount of time dealt with reading material	High	Reflective
Performance on questions regarding theories	High	Intuitive
Performance on questions regarding facts	High	Sensing
Amount of time spent on a Test	High	Sensing
No. of revisions before handing in a test	High	Sensing
No. of performed tests	High	Sensing
No. of visits and time spent on examples	High	Sensing
Amount of time spent on contents with graphics	High	Visual
Performance in questions related to graphics	High	Visual
Performance on questions related to overview of concepts and connections between concepts	High	Global
Performance on questions related to details	High	Sequential
Performance on tests in General	High	Sequential
No. of visits and time spent on outlines	High	Global
Navigation pattern	Skipping learning objects	Global
Navigation pattern	Linear	Sequential

Another action that is found in [40] as the number of rules to describe learner learning style by recording the learner behavior in the system as found in figure 7.

IF learner does not know the answer;
THEN
Show learner image/diagram;
…………………………………………………………………………..
IF learner shown image/diagram **AND** learner gives correct answer;
THEN
Increase VISUAL;
…………………………………………………………………………..
IF answer is given in the explanation text **AND** learner does not know the answer;
THEN
Increase INTUITOR **AND** Increase VISUAL;

Figure 7 Example of rules used to adjust learner learning style

C. Learning Content Recommendation and Matching

Personalized recommendation is a widely used application of Web personalized services which alleviate the burden of information overload by collecting information which meets the user's needs. An essential of Web recommendation is how to build user profile, which involves the information and preference of user and has a great impact on the performance of Web personalized recommendation. The Adaptive Systems and Recommender Systems [41] are focused in exploring a certain hypermedia structure in order to help user finding the best way for their interests, while the Recommender Systems are focused on a network of Web resources, bind by existing or virtual relations, aiming to provide users with individual views on Web data.

The Felder-Silverman Learning Style Model is described by the dimensions of Learning and Teaching Styles [42], creating a relationship to learning styles and teaching strategies that could be adopted to support the learner learning style [43].

Zaina and Bressan in [44, 45] proposed an alternative approach that splits the learner learning profile (preferences) into three categories: perception, presentation format and learner participation. Along the text, this altered model is referred to as preference categories; its goal is to detect clusters of preferences that reflect different data perspectives caught during the tracking of learning styles.

Each category has a teaching-method correspondence that defines the matching with the learners' learning styles, as predicted in the Felder/Silverman proposal as found in [45]. According to Felder and Silverman, the teaching-learning style corresponds to the values of LOM category fields. The Example to show the relationship between LOM educational fields and the preferences category is shown in table 4.

By matching the learning objects metadata, that is stored in learning objects repository, with the learner profile in the system, the system can recommend the learning objects based on the learning styles.

D. The Domain Ontology

The main reason for ontology [47] is to enable communication between computer systems in a way that is independent of the individual system technologies, information architectures and application domain.

TABLE IV. THE RELATIONSHIP BETWEEN LOM EDUCATIONAL FIELDS AND THE PREFERENCES CATEGORY

Preference Categories	Features	Learning Styles	Teaching Methods	LOM – Educational Field	LOM – Educational Field Value
Perception	The focus is in the best way through which the learner can obtain information: contents, exercise types, for instance.	Sensing	Concrete	Interactivity	Active
		Intuitive	Abstract		Expositive
Presentation Format	It is related to the input. Content preferences chosen by the learner such as media types.	Visual	Visual	Learning Resource Type	Figure, Video, Film, and others
		Auditory	Verbal		Text, Sound, and Format others
Learner Participation	It represents the learner preferences for the activities participation or observation.	Active	Active		Practical Exercise, Experiment, and others
		Reflective	Passive		Questionnaire and Readings

Ontology includes rich relationships between terms and each specific knowledge domain and organization will structure its own ontology which will be organized into mapped ontology. The domain of our learning content and the ontology we have developed within proposed system is that of computer science. The ontology covers topics like artificial intelligence, communications; computational theory, computer graphics, data structures, database, programming, etc. It is used mainly to index the relevant learning objects and to facilitate semantic search and re-usability of learning objects.

It was proposed in [48] a knowledge engineering approach to build domain ontology. Figure 8 shows main steps of the ontology development process.

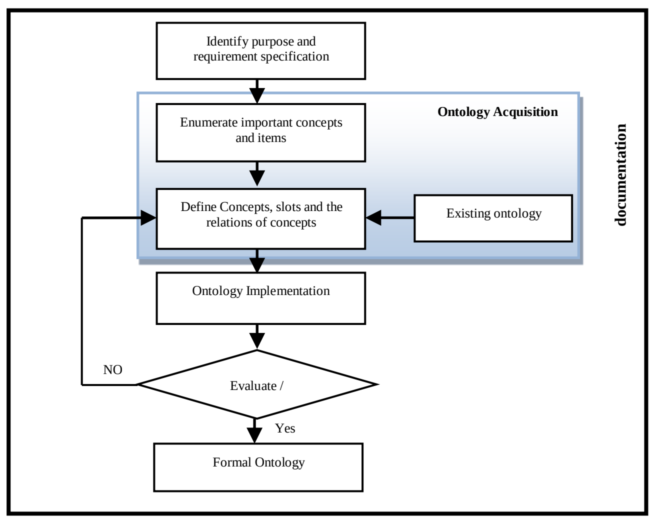

Figure 8 Main steps of the ontology development process

We use protégée [49, 50] as our ontology tool. Since protégée is an open source ontology editor, developed by Stanford Center for Biomedical Informatics Research and coded by JAVA. Protégé interface style is similar to Windows applications' general style, so it is easy to learn and use. Figure 9 shows part of our domain ontology and the extracted.

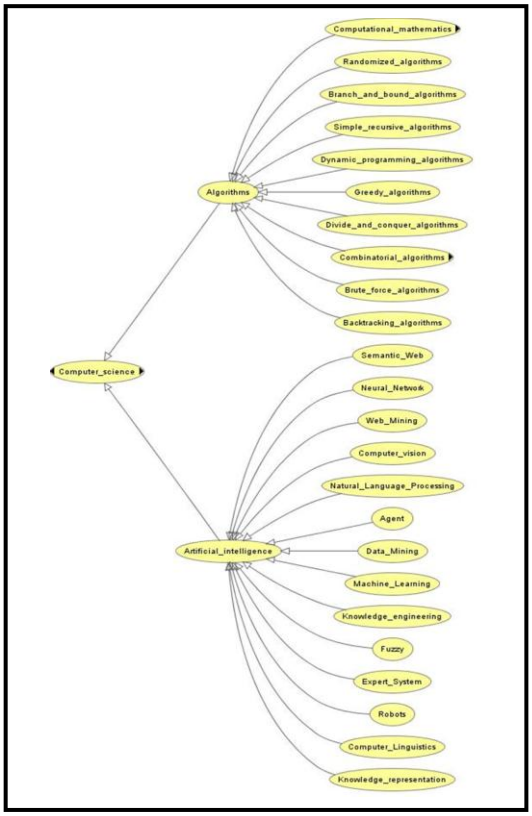

Figure 9 Part of our domain ontology

E. Semantic LO Search

According to keyword-based search present serious problems related to the quality of the search results. It often happens that relevant pages are not indexed by a traditional search; in this case important information can be reached only if its specific internet address is known. Moreover, searches based on keywords are very closely related to the spelling of the word and not to its meaning. One current problem of information search issues is that it is not really possible to automatically extract meaning from the relevant results of a query. One main reason for this is that the web was initially designed for direct human use and thus the documents do not provide machine readable semantic annotations. This work focuses on the first of these items, specifically in the formulation and the user's query processing. We expect to prove that through linguistic processing, the use of dictionaries and domain ontologies, the instructional designer's query terms become more specific.

The Semantic Search process includes the steps, that is appeared in the next algorithm , is shown in the figure 10.

CONCLUSION

The adaptive learning system provides support to the learner according to the individual characteristic. It can provide a learner view adapt to learner personalization characteristic, which not only includes personalized resources, but also includes the personalized learning process and strategy. So we should establish a learner model for each learner, containing the information such as state-of-art of learner, the goal and interest and so on. The system reduces the information spaces for learner browsing according to the learner model in the application, and presents the most interesting information to the learner.

Input: Query of User.
Output: Retrieved Semantic Information
Procedure:

1. Tokenizing query keywords to number of terms.
2. Remove the stop words.
3. Stem the word.
4. Get POS (Part of Speech) of the word in the query.
5. Expand the words by the hypernym and hyponym concepts in the Wordnet.
6. Expand the words by the Domain Ontology (DO) as:
    a. Search the word in the DO.
    b. Check if the word is the root or not.
        i. If Yes
            1. Get the Hyponym, and Get the neighbor node.
            2. Add the two concepts to the expanded query.
        ii. If No and is not the Leaf.
            1. Get the Hyponyms Hypernyms, and neighbor.
            2. Add the two concepts to the expanded query.
        iii. If No and is the Leaf.
            1. Get *Hypernyms*, and neighbor.
            2. Add the two concepts to the expanded query.
    c. Compute the similarity between concepts, put N pre-expansion words that has high relativity as expansion words.
    d. Add Expanded Query to the original query.
7. Use Semantic Similarity between the expanded words and the terms in the LO
8. Rank the LO based on the high semantic similarity weight.
9. Return the ranked LO from LOR.

Figure 10 Algorithm of Semantic Search of LO

This work presented a technical solution to an approach and methodology for personalized search and recommendation of learning objects according to the learner's profile. Adaptive recommendation model is to retrieve and recommend for a learner suitable learning objects.

In this work, we have defined a methodology that links learning objects metadata and learning profiles for automatic content recommendation. To do so, we have used the Felder-Silverman Learning Style Model along with the IEEE LOM standard, a combination that, extending former works, can suitably relate learner profiles and learning objects, automatically, in different fields of learning, and consistently reflecting the intrinsic style of the learners.

The semantic search of the learning objects is based query expansion and using semantic similarity between the learning objects and the query keywords.

REFERENCES

[1] Y. Zhiwen, N. Yuichi, J. Seiie, K. Shoji, and M. Kenji. (2007), Ontology-Based Semantic Recommendation for Context-Aware E-Learning, UIC 2007, LNCS 4611, pp. 898–907, 2007, Springer-Verlag Berlin Heidelberg.

[2] F. Christoph, (2005). User Modeling and User Profiling in Adaptive E-learning Systems, Master's Thesis At Graz University of Technology.

[3] [3] Felix M¨odritscher, (2004). Victor Manuel Garcia-Barrios, and Christian G¨utl. The Past, the Present and the future of adaptive E-Learning. In Proceedings of the International Conference Interactive Computer Aided Learning (ICL2004), 2004. http://www.iicm.edu/iicm_papers/icl2004/adaptive_e-learning/adaptiv_e-learning.pdf.

[4] D. Dicheva. (2008), Ontologies and Semantic Web for E-Learning, In : "Handbook on Information Technologies for Education and Training", 978-3-540-74155-8, Springer Berlin Heidelberg.

[5] B. Peter and T. Mark. (2002) From Adaptive Hypermedia to the Adaptive Web. Communications of the ACM, Volume 45 Issue 5.

[6] K. Yiouli, D. Panagiotis, A. Evgenia, D. Konstantinos, T. Michael, P. Maria. (2008). User Profile Modeling in the context of web-based learning management systems. Journal of Network and Computer Applications 31 (2008) 603–627. Elsevier Ltd.

[7] G. Fayed, D. Sameh, H. Ahmad, M. Jihad., A. Samir, and S. Hosam. (2006). E-Learning Model Based On Semantic Web Technology, International Journal of Computing &Information Sciences Vol. 4, No. 2, August 2006, On-Line. Pages 63 – 71.

[8] Z. Thomas, and V. Juan. (2010). Towards an Ontology for the Description of Learning Resources on Disaster Risk Reduction. WSKS 2010, Part I, CCIS 111, pp. 60–74, Springer-Verlag Berlin Heidelberg.

[9] G. Susan, S. Mirco, and P. Alexander. (2007), Ontology-Based User Profiles for Personalized Search, DOI10.1007/978-0-387-37022-4, Springer US.

[10] F. Tanudjaja, L. Mui. (2002) Persona: A Contextualized and Personalized Web Search. Proc 35 th Hawaii Intl. Conf. on System Sciences.

[11] The Open Directory Project (ODP). http://dmoz.org.

[12] J. Pitkow, H. Schütze, T. Cass et all. (2002), Personalized search. CACM 2002; 45(9):50-55.

[13] K. McKeown, N. Elhadad, V. Hatzivassiloglou.(2003), Leveraging a common representation for personalized search and summarization in a medical digital library. In Proceedings of the 3 rd ACM/IEEE-CS joint conference on Digital libraries 2003; 159-170.

[14] F. Liu, C. Yu, W. Meng. (2002) Personalized web search by mapping user queries to categories. In Proceedings CIKM'02 2002; 558-565.

[15] K. Sugiyama, K. Hatano, M. Yoshikawa. (2004), Adaptive web search based on user profile constructed without any effort from users. In Proceedings 13 th Intl. Conf. on World Wide Web 2004; 675-684.

[16] R. Almeida, V. Almeida. (2004), A Community-Aware Search Engine. In Proceedings of the 13 th International Conference on the World Wide Web, May 2004.

[17] L. Xiaojian, C. Shihong. (2009). Personalized Query Expansion Based on Semantic User Model in e-Learning System. 2009 Sixth International Conference on Fuzzy Systems and Knowledge Discovery. 978-0-7695-3735-1/09, IEEE.

[18] Z. Leyla, N. Olfa. (2008). Semantic Information Retrieval for Personalized E-learning. 2008 20th IEEE International Conference on Tools with Artificial Intelligence. 1082-3409/08, IEEE.

[19] C. Cheqian, L. Kequan, L. Heshan, D. Shoubin. (2010). PERSONALIZED SEARCH BASED ON LEARNING USER CLICK HISTORY. Proc. 9th IEEE Int. Conf. on Cognitive Informatics (ICCI'10). 978-1-4244-8040-1/10, IEEE.

[20] L. Ming-Che, T. Kun, W. Tzone. (2008). A practical ontology query expansion algorithm for semantic-aware learning objects retrieval. Computers & Education 50 (2008) 1240–1257. Elsevier Ltd.

[21] D. Lianhong, L. Bingwu, T. Qi. (2010). Hybrid Filtering Recommendation in E-Learning Environment. 2010 Second International Workshop on Education Technology and Computer Science. 978-0-7695-3987-4/10, IEEE.

[22] D. Chen, D. Xu. (2009). A Collaborative Filtering Recommendation Based on User profile weight and Time weight. 978-1-4244-4507-3/09, IEEE.

[23] L. Xiaojian, C. Shihong. (2009), Research on Personalized User Model Based on Semantic Mining from Educational Resources Searching Process, 2009 International Joint Conference on Artificial Intelligence, 978-0-7695-3615-6/09, IEEE.

[24] B. Yevgen, B. Hamidreza, K. Igor, F.Michael. (2009), An adjustable personalization of search and delivery of learning objects to learners, Expert Systems with Applications 36 (2009) 9113–9120, doi:10.1016/j.eswa.2008.12.038, Elsevier Ltd.

[25] K. Igor, L. Natalya, M. Sergiy, T. Vagan.(2004), Personalized Distance Learning Based on Multiagent Ontological System, Proceedings of the IEEE International Conference on Advanced Learning Technologies (ICALT'04), 0-7695-2181-9/04, IEEE .

[26] Z. Hui, S. Yu, and S. Han-tao, (2007). Construction of Ontology-Based User Model for Web Personalization, C. Conati, K. McCoy, and G. Paliouras (Eds.): UM 2007, LNAI 4511, pp. 67–76, Springer-Verlag Berlin Heidelberg.

[27] K. Igor, R. Victoria, B. Yevgen. (2006), Building Learner's Ontologies to Assist Personalized Search of Learning Objects, ICEC'06, August 14–16, 2006, Fredericton, Canada, Copyright 2006 ACM 1-59593-392-1.

[28] W. Tzone, H. Kun, L. Ming and C. Ti Kai. (2007), Personalized Learning Objects Recommendation based on the Semantic-Aware Discovery and the Learner Preference Pattern, Educational Technology & Society, 10 (3), 84-105.

[29] T. Kun, C. Ti Kai, L. Ming Che, W. Tzone. (2006), A Learning Objects Recommendation Model based on the Preference and Ontological Approaches, Proceedings of the Sixth International Conference on Advanced Learning Technologies (ICALT'06), 0-7695-2632-2/06, IEEE.

[30] Draft Standard for Learning Object Metadata (LOM). IEEE P1484.12.1, IEEE Learning Technology Standards Committee (2004), http://ltsc.ieee.org/wg12/files/LOM_1484_12_1_v1_Final_Draft.pdf.

[31] http://www.imsproject.org.

[32] S. Rajendra, B. Margaret, G. Ross. (2004). Creating sharable learning objects From Existing Digital Course Content. WCAE '04 Proceedings of the 2004 workshop on Computer architecture education.ACM.

[33] A.Prasad and P. Devika. (2009). Metadata for Resource Discovery in Learning Repositories Road to enhanced access to e-learning content. International Workshop on Technology for Education (T4E), Aug 4-6, 2009, Bangalore. 978-1-4244-5505-8/09, IEEE.

[34] M. Pasquale, G. Alfredo, T. Giorgio, U. Domenico. (2007). Personalizing learning programs with X-Learn, an XML-based, ''user-device'' adaptive multi-agent system. Information Sciences 177 (2007) 1729–1770. Elsevier Inc.

[35] Altova XMLSpy® 2012 Enterprise Edition, http://www.altova.com/download/xmlspy/xml_editor_enterprise.html.

[36] B. Peter, M. Eva. (2007). User Models for Adaptive Hypermedia and Adaptive Educational Systems. The Adaptive Web, LNCS 4321, pp. 3 – 53, Springer-Verlag Berlin Heidelberg.

[37] Enver Sangineto. (2008). An Adaptive E-Learning Platform for Personalized Course Generation". In Claus Pahl.(ed) Architecture Solutions for E-Learning Systems. IGI Publishing.

[38] C. Shipin, Z. Jianping. (2008). The Adaptive Learning System based on Learning Style and Cognitive State. 2008 International Symposium on Knowledge Acquisition and Modeling. 978-0-7695-3488-6/08, IEEE.

[39] P. Elvira,T. Philippe and B. Costin. (2007). Adaptive Educational Hypermedia Systems: A Focus on Learning Styles. EUROCON 2007 The International Conference on "Computer as a Tool". 1-4244-0813-X/07, IEEE.

[40] M. Annabel, A. Keeley, A. David, E. Bruce, and S. Karen. (2010). Oscar: An Intelligent Conversational Agent Tutor to Estimate Learning Styles. 978-1-4244-8126-2/10, IEEE.

[41] B. Mihaela, S. Florence, Z. Corinne. (2009). Ontology-Based User Competencies Modeling for E-Learning Recommender Systems. IGI Global.

[42] F. RICHARD, B. REBECCA. (2005). Understanding Student Differences", Journal of Engineering Education, 94, 1, 2005, pp 57-72.

[43] F. Richard, L. Silverman. (1988) "Learning and Teaching Styles in Engineering Education", Journal of Engineering Education, 78, 7, 1988, pp. 674-681.

[44] Z. Luciana, B. Graça. (2008). Classification of Learning Profile Based on Categories of Student Preferences. 38th ASEE/IEEE Frontiers in Education Conference, October 22 – 25, 2008, Saratoga Springs. 978-1-4244-1970-8/08, IEEE.

[45] Z. Luciana, R. Jose, B. Graça. (2010). An Approach to Design the Student Interaction Based on the Recommendation of e-Learning Objects. SIGDOC, September 27-29, 978-1-4503-0403-0, ACM.

[46] Y. Liyang. (2007). From Traditional Web to Semantic Web, In: Introduction to the Semantic Web and Semantic Web Services. Taylor & Francis Group, LLC.

[47] U. Siti, A. Rohiza, M. Shakirah. (2010). Ontology of Programming Resources for Semantic Searching of Programming Related Materials on the Web. 978-1-4244-6716-7110, IEEE.

[48] H. YUN, J. XU, M. J. XIONG. (2009). Development of Domain Ontology for E-learning Course, 978-1-4244-3930-0/09, IEEE.

[49] F. Natalya, S. Michael, D. Stefan, C. Monica (2001) W. Ray, and Mark A. Musen.(2001), Creating Semantic Web Contents with Protégé-2000, IEEE INTELLIGENT SYSTEMS, 1094-7167/01, IEEE.

[50] H. Mike, L. Fuhua, E. Larbi, and Y. Chunsheng. (2005), Constructing Knowledge Bases for E-Learning Using Protégé 2000 and Web Services, Proceedings of the 19th International Conference on Advanced Information Networking and Applications (AINA'05), 1550-445X/05, IEEE.

[51] Khaled M. Fouad , Mostafa A. Nofal , Shehab Gamalel-Din and Nagdy M. Nagdy (2010). Adaptive E-Learning System based on Semantic Web and Fuzzy Clustering.

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