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Learning with an active e-course in the Knowledge Grid environment

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SUMMARY

An active e-course is an open, self-representable and self-organizable media mechanism. Its kernel idea is to organize learning materials in a concept space rather than in a page space. The tailored content and flexible structure of the e-courses can be dynamically formed to cater for different learners with different backgrounds, capabilities and expectations, at different times and venues. The active e-course can also assess learners' learning performances and give appropriate suggestions to guide them in further learning. An authoring tool for constructing course ontology and a system prototype have been developed to support an active e-course, enabling a learner-centred, highly interactive and adaptive learning approach. The results of an empirical study show that the system can help enhance the effectiveness and efficiency of learning. Copyright © 2005 John Wiley & Sons, Ltd.

KEY WORDS: e-learning; constructivist learning; ontology; hypertext; semantic link network; Knowledge Grid

1. INTRODUCTION

Γ With the popularity of the Web, there is a growing need for effective Web-based learning in both academic and industrial settings. The Web-based learning systems make learning much more convenient by stretching the spatial and temporal barriers. However, learners usually act as passive recipients of instruction rather than being engaged in active exploration of the learning content and

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creating their own knowledge. Thus, the learners feel inactive and often drop off, so learning efficiency and learning outcome are relatively low. The literature in education research suggests that learners who are actively engaged in the learning process will be more likely to achieve success [1–4]. So, how to motivate learners to actively learn knowledge becomes an important issue with respect to Web-based learning.

The approach of constructivist learning process has its emphasis on engaging learners in the learning process, which encourages free exploration of the learning materials and enables a greater level of interactivity. So far, a number of research teams have implemented different kinds of Web-based education systems to support learner-centered, interactive and active learning. The Web is used not only as a delivery medium but also to foster free exploration of learning materials and to allow the learners to interact with materials, instructors as well as other learners. Almost all of the systems fall into one of two categories: intelligent tutoring systems (ITSs) and adaptive hypermedia systems. The goal of various ITSs is to use the knowledge about the domain, the learner and about teaching strategies to support flexible individualized learning and tutoring. Examples are DCG [5] and ELM-ART-II [6]. Adaptive hypermedia systems aim to adapt the content and links of hypermedia pages to the learners, such as AHA [7], InterBook [8] and Hypadapter [9].

The current Web is challenged by complex, intelligent, geographically dispersed and heterogeneous-resource-based applications. The Semantic Web (http://www.semanticweb.org) is an effort towards the next-generation Web by using markup languages and building ontology mechanisms. The Grid (http://www.gridforum.org) is used to share, manage, coordinate and control distributed computing resources, which could be machines, networks, data and any types of devices. The ideal of the Grid is that any compatible device could be plugged in anywhere on the Grid and be guaranteed the required services regardless of their locations, just as in the power grid. The Semantic Grid (http://www.semanticgrid.org) is used to absorb the advantages of the Semantic Web and the Grid. The next-generation Web will provide the ideal support to realize complex, intelligent, geographically dispersed and heterogeneous-resource-based applications.

The Knowledge Grid (http://www.knowledgegrid.net) is an intelligent and sustainable Internet application environment that enables people and roles to effectively capture, publish, share and manage explicit knowledge resources. It also provides on-demand services to support innovation, cooperative teamwork, problem-solving and decision-making. It incorporates epistemology and ontology to reflect human cognition characteristics; exploits social, ecological and economic principles; and adopts the techniques and standards developed during work toward the next-generation Web [10]. It will be an ideal support platform to realize effective cooperation and learning across regions and cultures.

By incorporating the intelligent agent and adaptive hypermedia technologies, this paper proposes an active e-course mechanism that focuses on the dynamic organization of learning materials with various semantic links to better support the learner-centered, highly interactive and adaptive learning approach. By separating the concept structure from the learning materials, the generic knowledge structure can be reused by a wide range of people to easily develop educational systems for different domains, and the maintaining and indexing of the learning materials become easier and more flexible. In addition to the authoring assistance provided to the instructors, the e-course effectively supports learners in active study with pleasant interaction facilities, dynamically organizes and provides adaptive learning content, automatically evaluates the learners' learning performances and gives appropriate suggestions.

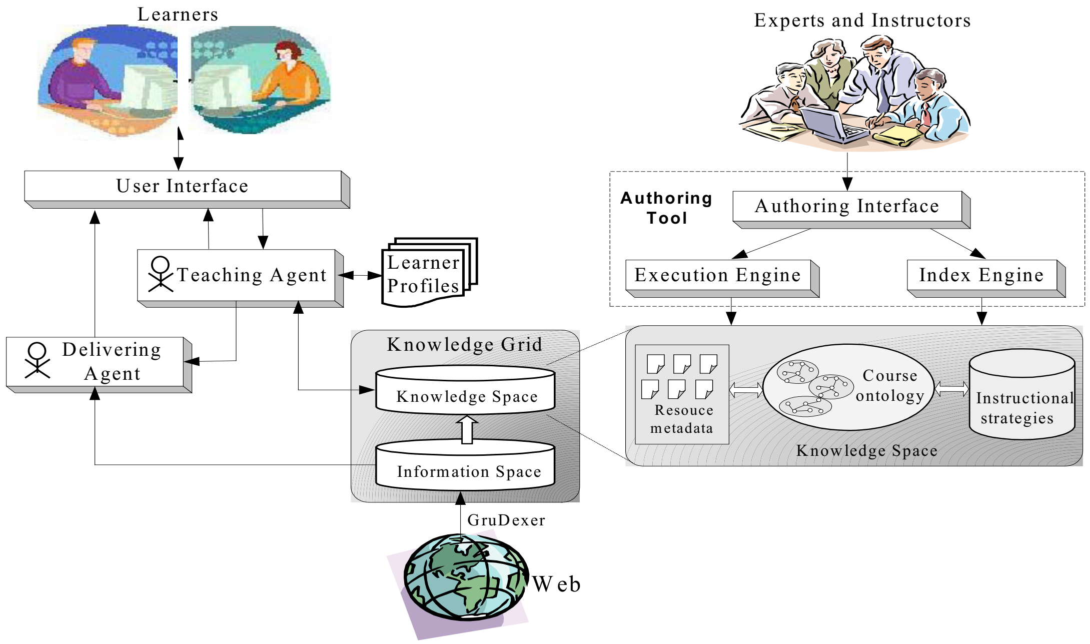


Figure 1. The general architecture.

2. GENERAL ARCHITECTURE

The proposed learning architecture illustrated in Figure 1 includes the following core modules.

- *User interface*, which allows the geographically distributed learners to access the system via a friendly interface. Meanwhile, the user interface controls both the registration and login processes. After successfully logging in, the learners can read a course, take a test or discuss with other learners via the interaction facilities.
- *Knowledge Grid*, which shares and manages distributed heterogeneous knowledge resources in a uniform way [10]. It herein comprises two resource spaces: *knowledge space* and *information space*. The former stores the course ontology, resource metadata and instructional strategies, while the latter stores the learning resources composed of learning materials repository and question bank. The learning materials can be any of the media files: Web pages, PDF documents, animations, audio files and others. We have developed a collection tool GruDexer to continuously collect relevant documents with three methods [11]. First, instructors can manually upload documents with corresponding semantic annotations (e.g. content description, pedagogical information) through the upload interface. Secondly, instructors can specify the potential Web sites in which they have constant interests, so the GruDexer periodically searches

for new relevant documents from the specified destinations. This customized method enables instructors to keep track of the latest information from particular experts or educational institutes. Thirdly, GruDexer acts as a meta-search engine based on general and professional search engines, which provides an easy-to-use interface where instructors can input the key words to search for relevant documents. The found documents are downloaded, classified and then stored in the Knowledge Grid. The question bank is a warehouse of questions that support the generation of tests.

- *Teaching agent*, which serves as an intelligent tutor by interacting with learners. It consists of three function components: plan component, evaluation component and update component. The plan component is responsible for generating the course syllabus by referring to the learner profiles and knowledge space. The evaluation component is in charge of evaluating the test results and giving suggestions to learners. The update component fulfills the task of recording the information gathered through interacting with learners and accordingly updates learner profiles.
- *Delivering agent*, which searches for corresponding resources in the information space, composes them to form a tailored course and finally presents it to the learners in the appropriate context once that received a syllabus from the teaching agent. It also generates personal test papers with different questions at different difficulty levels based on learners' knowledge backgrounds, testing goals and learning status.
- *Learner profile*, which is used as the adaptive learner model representing the needs and knowledge of individual learners [12,13]. Each learner is equipped with a profile to describe his personal information and learning history [11]. The personal information includes learner name, age, background and preferred learning style, which can be manually edited and updated by learners through the system's interface at anytime. On the other hand, the system keeps track of learners' activities and makes inference to obtain learning-related information, such as learned knowledge objects, review times, learning performance, etc.
- *Authoring tool*, which provides support for course structural modelling. In the easy-to-use authoring environment, instructors and experts are able to construct course ontology and define the generic instructional strategies as well as metadata of learning materials. The execution engine is responsible for executing the authoring operations. The index engine fulfills the task of searching the course concept that matches the metadata of learning materials.

3. STRUCTURAL MODELING FOR ACTIVE E-COURSE

3.1. Course ontology

Ontologies are specifications of the conceptualization and corresponding vocabulary used to describe a domain, which enables the organization of learning materials around small pieces of semantically annotated learning objects [14]. Course ontology defines course knowledge and structure within a specific domain, which includes course concepts and roles.

A course concept represents a composite or atomic knowledge object with a unique object identifier, and a structure that includes attribute-value pairs and link anchors. The concept attributes include name, difficulty level, importance level, synonym and classification level. The importance level indicates the importance degree of a concept, such as basic, optional and supplemental. The synonym refers to a list of synonyms and other word forms, such as plurals, abbreviations and commonly used forms. There are three classification levels (i.e. category, sub-category, topic), which define a granularity hierarchy within the non-hierarchical structure of the domain ontology; that is, each concept is divided into sub-concepts corresponding to smaller grained units that allow the system to reason at a finer level, and the topic-level concept represents an atomic knowledge object.

The roles represent the binary relationships among knowledge objects, which is denoted as $K \xrightarrow{\alpha} K'$, where α is a type of semantic relationship while K and K' are knowledge objects. The relationship can be one of the following types.

(1) *Subtype*, denoted as $K \xrightarrow{\text{st}} K'$, which describes the relationship between general knowledge object K and specific knowledge object K', i.e. K' belongs to K.
(2) *Sequential*, denoted as $K \xrightarrow{\text{seq}} K'$, which defines that K should be learned before K', i.e. K is the prerequisite to K'. A single knowledge object may have multiple prerequisite knowledge objects and can also be a prerequisite to multiple knowledge objects.
(3) *Cause–effect*, denoted as $K \xrightarrow{\text{ce}} K'$, which means that K is the cause of K' and the K' is the effect of K.
(4) *Implication*, denoted as $K \xrightarrow{\text{imp}} K'$, which states that the semantics of K' implied to that of K.
(5) *Similar-to*, denoted as $K \xrightarrow{(\text{sim},\text{sd})} K'$, which defines that K' is similar to K to some extent, *sd* is the similarity degree between K and K'. The *similar-to* link is intransitive.
(6) *Reference*, denoted as $K \xrightarrow{\text{ref}} K'$, which means that K' is related to K, e.g. K' can be an annotation of K.
(7) *Part-of*, denoted as $K \xrightarrow{\text{par}} K'$, where K' is a part of K, e.g. K' describes an attribute (such as definition, elaboration, property, operation, application, etc.) of the knowledge object K.
(8) *Corequisite*, denoted as $K \xrightarrow{\text{cor}} K'$, which means that K and K' should be learned in parallel. The corequisite relationship is symmetric.
(9) *Supplement*, denoted as $K \xrightarrow{\text{sup}} K'$, which means that K' serves as the supplementary or additional content to K.
(10) *Contrast*, denoted as $K \xrightarrow{\text{con}} K'$, which means that K' is in contrast to K. Unlike from the similar-to link, this contrast link emphasizes the differences between K and K'. The contrast link is intransitive.
(11) *Inhibitor*, denoted as $K \xrightarrow{\text{inh}} K'$, which means that after studying K it is no longer desirable to study the knowledge object K'.
(12) *Other*, which refers to the other concrete relationships other than the above ten relationships.

A semantic link network (SLN) is a model to intuitively represent the semantic relationships between document fragments or documents [15]. In this paper, we use the SLN to represent the course ontology. That is, a node represents a knowledge object or a network of knowledge objects, and a directed arc (semantic link) represents the semantic relationship between two knowledge objects or networks. The semantic link can be represented as a pointer with a type directed from the predecessor to the successor. Generally, course ontology is modelled as a nested SLN (i.e. a course-SLN is composed of multiple chapter-SLNs, while each chapter-SLN comprises multiple section-SLNs). The three-level structure can be changeable according to the course requirement and the course authors. So, authoring operations refer to manipulating SLN, i.e. creation and modification of SLN, which include reasoning,

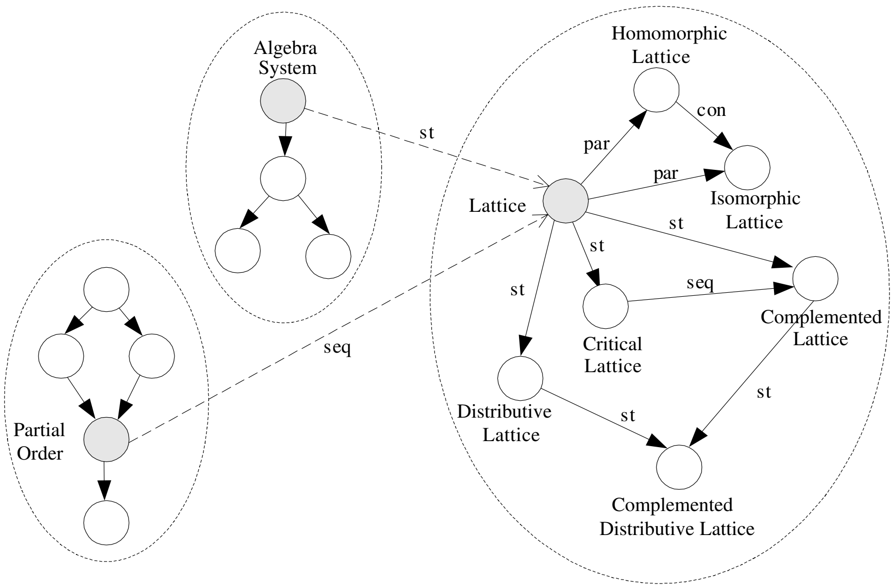


Figure 2. An example of a course-SLN.

consistency check and additional operations on SLNs (such as copy, compare, mapping, merge and extract).

Figure 2 intuitively shows a part of course-SLN on the subject of 'discrete mathematics'. As it illustrates, the ellipse represents a chapter-SLN, the circle represents a knowledge object, the solid arrows with labels represent various relationships between knowledge objects within a chapter-SLN, and the dashed arrows with labels represent various relationships between knowledge objects across different chapter-SLNs. Additionally, the learner profile is represented as a sub-graph of a course-SLN, and each node is attached to several attribute values (such as review times, master level, etc.).

3.2. Instructional strategies

Instructional strategies comprise two parts: reasoning rules and pedagogical expertise. The reasoning rule can be used for chaining the semantic relationships and obtaining the reasoning result from the chaining. A simple case of the reasoning is that all the semantic relationships have the same type, which is called single-type reasoning. According to the transitive characteristic of the semantic relationships, we have the following reasoning rule: $K_1 \xrightarrow{\alpha} K_2, K_2 \xrightarrow{\alpha} K_3, K_{n-1} \xrightarrow{\alpha} K_n \Rightarrow K_1 \xrightarrow{\alpha} K_n$, where $\alpha \in$ {st, ce, imp, ref, par, cor, seq}. Some of the heuristic rules for connecting different types of relationships are presented in Table I. Further discussion on SLNs is available in [15].

Table I. Reasoning rules.

Rule number	Rules
1	$K \xrightarrow{\text{st}} K', K \xrightarrow{\text{sup}} K'' \Rightarrow K \xrightarrow{\text{sup}} K''$
2	$K \xrightarrow{\text{st}} K', K \xrightarrow{\text{st}} K'' \Rightarrow K \xrightarrow{\text{cor}} K''$
3	$K \xrightarrow{\text{par}} K', K \xrightarrow{\text{sup}} K'' \Rightarrow K \xrightarrow{\text{sup}} K''$
4	$K \xrightarrow{\text{par}} K', K \xrightarrow{\text{imp}} K'' \Rightarrow K \xrightarrow{\text{imp}} K''$
5	$K \xrightarrow{\text{par}} K', K \xrightarrow{\text{ce}} K'' \Rightarrow K \xrightarrow{\text{ce}} K''$
6	$K \xrightarrow{\text{par}} K', K \xrightarrow{\text{ref}} K'' \Rightarrow K \xrightarrow{\text{ref}} K''$
7	$K \xrightarrow{\text{par}} K', K \xrightarrow{\text{par}} K'' \Rightarrow K \xrightarrow{\text{cor}} K''$
8	$K \xrightarrow{\text{imp}} K', K \xrightarrow{\text{sup}} K'' \Rightarrow K \xrightarrow{\text{sup}} K''$
9	$K \xrightarrow{\text{imp}} K', K \xrightarrow{\text{par}} K'' \Rightarrow K \xrightarrow{\text{imp}} K''$
10	$K \xrightarrow{\text{imp}} K', K \xrightarrow{\text{con}} K'' \Rightarrow K \xrightarrow{\text{con}} K''$
11	$K \xrightarrow{\text{imp}} K', K \xrightarrow{\text{imp}} K'' \Rightarrow K \xrightarrow{\text{cor}} K''$
12	$K \xrightarrow{\text{ce}} K', K'' \xrightarrow{\text{ce}} K' \Rightarrow K \xrightarrow{\text{cor}} K''$
13	$K \xrightarrow{\text{ce}} K', K \xrightarrow{\text{par}} K'' \Rightarrow K \xrightarrow{\text{ce}} K''$
14	$K \xrightarrow{\text{cor}} K' \Rightarrow K \xrightarrow{\text{seq}} K'$ or $K \xrightarrow{\text{seq}} K$
15	$K \xrightarrow{\text{cor}} K', K \xrightarrow{\text{seq}} K'' \Rightarrow K \xrightarrow{\text{seq}} K''$
16	$K \xrightarrow{\text{ref}} K', K \xrightarrow{\text{ref}} K'' \Rightarrow K \xrightarrow{\text{cor}} K''$
17	$K \xrightarrow{\text{sup}} K', K \xrightarrow{\text{sup}} K'' \Rightarrow K \xrightarrow{\text{cor}} K''$
18	$K \xrightarrow{\text{sup}} K', K \xrightarrow{\text{par}} K'' \Rightarrow K \xrightarrow{\text{sup}} K''$
19	$K \xrightarrow{\text{sup}} K', K \xrightarrow{\text{imp}} K'' \Rightarrow K \xrightarrow{\text{sup}} K''$
20	$K \xrightarrow{\text{sup}} K', K \xrightarrow{\text{st}} K'' \Rightarrow K \xrightarrow{\text{sup}} K''$

Pedagogical expertise specifies how content is sequenced, what type of feedback to give, when and how to hint, explain, remedy, summarize, etc. A variety of methods are used to represent pedagogical expertise, including procedures, plans, constraints and rules [16]. Some example pedagogical expertise are as follows: (1) the learning material that explains some content must precede the learning material that is an example of the same content; (2) if a learner wants to study a knowledge object, then provide him with the prerequisites that are not studied or not well comprehended; (3) if a learner is a novice on a course, then present the simple introduction and example to them; and (4) each time a learner reviews a course, the teaching mode is subject to the learner who can choose the uniform teaching style or adaptive teaching style (the course is taught in a different way according to the learner's previous performance).

3.3. Ontology-based metadata

Metadata enables organizations to describe, index and search their resources with a set of common tags and this is essential for reusing them. In the learning community, several metadata standards are emerging to describe learning resources, such as IEEE LOM (http://ltsc.ieee.org/doc/wg12/LOM3.6.html), ARIADNE (http://ariadne.unil.ch/Metadata/), SCORM (http://www.adlnet.org/), and IMS (http://www.imsproject.org/metadata/imsmdv1p2/imsmd_infov1p2.html). However, these standards introduce the problem of incompatibility between disparate and heterogeneous metadata descriptions across domains, which might be avoided by using ontology as a conceptual backbone in an e-learning scenario [17].

We define resource metadata based on the course ontology that provides a shared meaning of the vocabulary used. The metadata falls into three broad categories: structure, content and context. The structural information mainly involves the headings, locations and links. The content description indicates what the learning material is about, which includes a list of weighted key words, short description, etc. As different authors may express semantically identical concepts with different key words, the course ontology is taken as a reference to describe the content of learning materials. Thus, each learning material is linked to one or more concepts with different association degree. The context description indicates when to present the learning material, which includes educational-objective (e.g. comprehension, application, analysis, synthesis and evaluation), difficulty level (e.g. low, moderate and high) and knowledge type (e.g. facts, principles, concepts, and processes). In this way, the learning materials with different context annotations can be used in different scenarios and for different purposes.

There are several systems developed for the automatic extracting of domain specific metadata [18,19]. By referring to the approaches, the metadata of learning materials are semi-automatically specified in our system. On the one hand, the providers of the learning materials can specify the metadata manually through the pre-specified templates. On the other hand, with the assistance of knowledge engineers, the system can automatically extract the metadata from the content or annotations of the media files based on the course ontology. Herein our approach deals with domain-specific metadata that is content descriptive. Firstly, the documents in different formats are transformed into the text files by eliminating the useless information. Secondly, the text files are parsed to extract metadata based on mining techniques and heuristic rules. As for the research documents, they generally include several parts such as title, author, key words, abstract, body and reference. Some metadata (e.g. author and date) can be directly extracted from the specified parts, while others (e.g. content description) can be obtained by processing the documents to extract the feature terms. With respect to the Web pages, several HTML markup tags are used to emphasize important terms or concepts in their documents. Examples of these emphasizing tags include <meta> <h1>, ..., <h4>, <b>, <strong>, <big>, <i>, <u>, <li>, <dt>. Taking the text in the specified parts as input, data-mining technology is used to automatically extract the salient concepts as content description. Additionally, the text in the specified parts may imply pedagogical information, for example '<h1>Example of ... </h1>' indicates that the learning material gives an instance.

4. BUILDING AN ACTIVE E-COURSE

By referring to the course structure, a tailored active course is dynamically generated and adjusted for various learners with different characteristics and learning goals. For example, learners with specific goals can get some parts of the course in more detail, learners with some knowledge of the subject can avoid being taught the already known knowledge objects again, and less-prepared learners can get more examples and more detailed explanation, starting from the very simple.

4.1. Syllabus planning

Syllabus planning is to find an optimal learning path with required knowledge objects for different learners. The delivery order in SCORM is fixed for each item at the design stage, but not based on learner information. In contrast, according to learners' characteristics, the sequencing of knowledge objects is dynamically executed during the learning process, which is more flexible and adaptive for diverse learners. To achieve an individual-oriented learning scheme, two learning modes are provided for learners to choose before starting their learning processes: (1) learners can select a course subject to systematically study the overall content; (2) if a learner is only interested in some specific knowledge objects of a course, then can input the key words to study the focused content. Afterwards, the teaching agent generates an adaptive learning syllabus by the following two-step process.

(1) *Selecting knowledge objects*. Regarding the knowledge-object-focused learning mode, the teaching agent accordingly finds the matching knowledge objects in the course ontology as well as the related knowledge objects with relevance rank. This relevance rank is computed based on several aspects such as hierarchical subsumption weight, path length weight and context weight. Then, a backward navigation algorithm is performed to retrieve the prerequisites to the knowledge objects. As for the systematic study on a course, the learner's learning history is considered to select the required knowledge objects. If a learner has never studied on this course or studied a long time ago, it selects all of the basic knowledge objects. If the learner has studied before, the teaching agent selects the unstudied knowledge objects and those knowledge objects on which the learner's performance was poor or moderate.

(2) *Structuring knowledge objects*. After selecting the required knowledge objects, the teaching agent invokes the inference engine to infer the relationships between the selected knowledge objects according to the reasoning rules, and determines the learning sequence of the knowledge objects by referring to instructional strategies and the preferred learning style of a learner, and finally structures the knowledge objects in a reasonable pattern (such as linear, flat, tree and hybrid patterns). Additionally, some knowledge objects are associated with quizzes to test the learning performance while others are not. Whether there are quizzes attached to the knowledge objects or not depends on the teaching content of the knowledge objects and the course requirements. For example, a knowledge object may not be associated with a quiz because its content only comprises a simple definition, which will be tested by the questions of the subsequent knowledge objects. As another example, a knowledge object should be associated with a quiz to test the learner's mastery of the algorithm if the knowledge object elaborates on the algorithm.

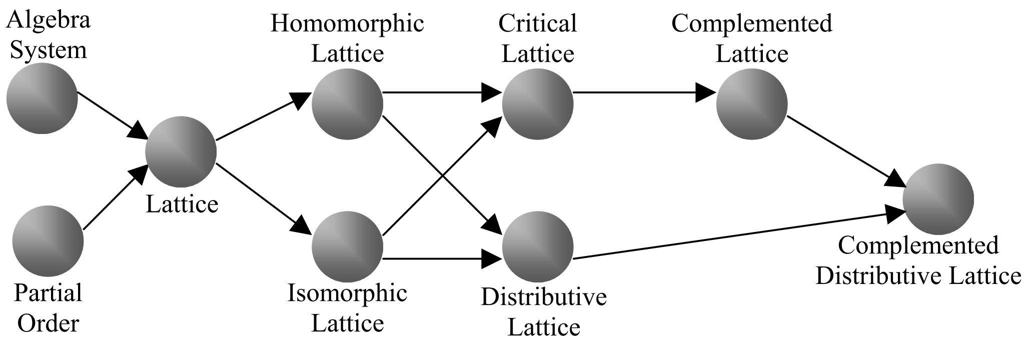


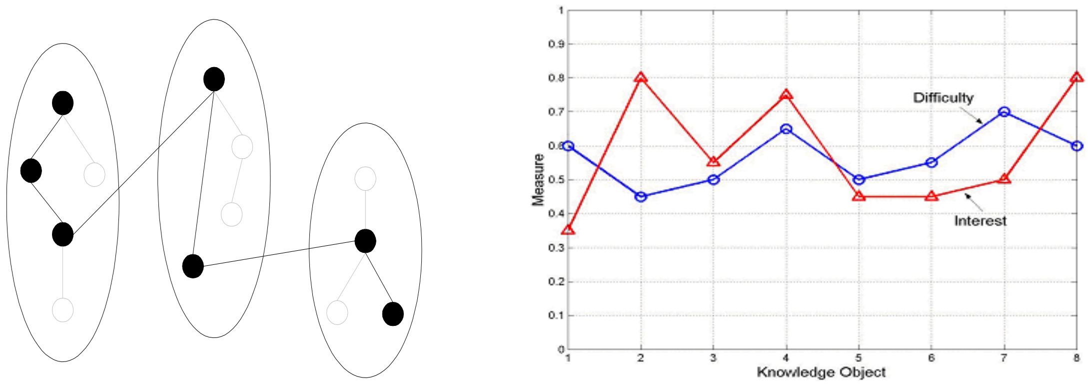
Figure 3. The generated course syllabus.

On the assumption that the constructed course ontology is as shown in Figure 2, we give a simple example to illustrate the process of syllabus planning. When a learner inputs a key word as 'lattice', the teaching agent will first locate the matching knowledge objects in the course ontology, and then select its prerequisites and the related knowledge objects. Obviously, all of the knowledge objects with direct links to the 'lattice' are selected. Specially, although the knowledge object 'complemented distributive lattice' does not directly link to 'lattice', the teaching agent deduces that it is a type of lattice according to the transitive feature of the subtype link. So, the 'complemented distributive lattice' is also selected. It is worth noting that the generated course syllabus is not unique for a learner, and the syllabus can be adjusted according to the learner's preferred learning style. Assume that the learner prefers the deduction learning approach (i.e. study the general knowledge object preceding to the specific knowledge object), the 'algebra system' is sequenced prior to the 'lattice' and the partial content of the 'lattice' is sequenced prior to its sub-objects. Meanwhile, the selected knowledge objects are sequenced according to reasoning rules (rules 2 and 7 in Table I). Figure 3 shows the generated course syllabus with a hybrid structure. As the figure illustrates, the directed arc represents the learning sequence from the predecessor to the successor, and the successor is to be learned until all of its predecessors are learned.

4.2. Course generation

Given the personal syllabus for an individual learner, the delivering agent generates the adaptive course by substantiating each knowledge object of the syllabus with one or more learning materials (such as Web pages, PDF documents, slides, animations and videos). The taxonomy of adaptive hypermedia technologies is given in [20], which mainly includes two technologies: adaptive presentation and adaptive navigation support. By incorporating the adaptive hypermedia technologies, we use a hierarchically organized hypertext to publish the course that can adjust its content and navigation actively in accordance with the learners' characteristics.

The metadata gives a description about the learning materials; in particular, the instructors may specify the quality of materials during the authoring process, such as best, better and normal



(a) (b)

Figure 4. (a) Visualization of learning path; (b) visualization of measure results.

recommendation mark. This kind of metadata is used to directly select the materials with high quality. If there are no manually annotated quality marks, the delivering agent will randomly select the materials with similar metadata annotations, and then track and analyze the learners' feedback to evaluate the materials for later recommendation based on statistics techniques. In this way, based on the metadata, the delivering agent makes use of the heuristic rules to select different materials related to the same knowledge objects so as to adaptively substantiate the syllabus according to the learners' learning goals and learning status. For example, two learners are interested in the same knowledge object, but the advanced learner receives more detailed and in-depth information, while the novice gets more examples and additional explanation. Following that, the presentation pages are generated from the existing materials or assembled from the fragments. On the other hand, versatile semantic links are generated as described in Section 4.3 to support the learners in hyperspace orientation and navigation. In addition to the direct guidance such as 'next' page, different types of semantic links (such as 'cause–effect', 'similar-to', 'part-of') are generated to annotate the knowledge objects. Learners can freely navigate through the hypertext structure, deciding on which knowledge objects to access and the sequence of accessing them. The various associations provided by the semantic links between knowledge objects facilitate the processes of remembering, understanding and knowledge enrichment.

As a complement, a progress-monitoring component is responsible for tracing and analyzing the learning activities (e.g. the learning path, the visit frequency of a certain page, the number of questions proposed) of learners to get an interestingness and difficulty measure of the knowledge objects with statistics methods. As a result, the knowledge objects are annotated with different colors (e.g. red indicates that the knowledge objects are most interesting, blue indicates that the knowledge objects are very difficult) to prompt the learners. Meanwhile, a visualization of the analysis results is provided to instructors. With such a reference, instructors may provide more learning materials as well as useful suggestions, and adjust instructional strategies in the authoring module. Figure 4(a) shows the learning path of a learner within a period and Figure 4(b) gives an illustrative example of the measure results.

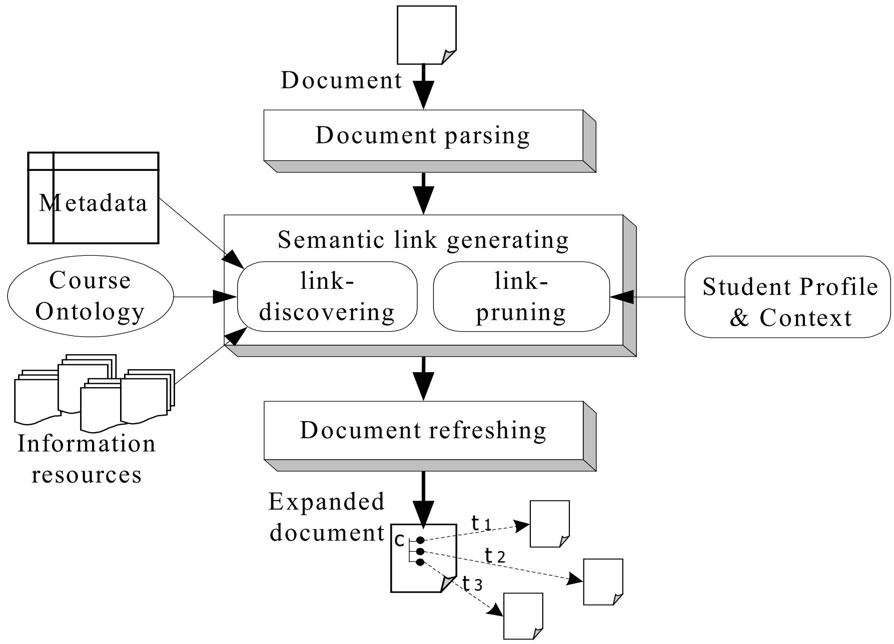


Figure 5. Framework for constructing semantic links.

4.3. Semantic linking

Currently, almost all adaptive hypermedia systems work with closed corpus data. This approach cannot be applied to the non-indexed open corpus cyberspace. To solve this issue, we make use of the information retrieval technology to extract meaning from an open corpus of hyper-documents and create various semantic links between them. In this way, the discrete hyper-documents are associated with various semantic links in a flexible and adaptive manner by referring to learners' different demands and activities. The existing systems used to represent and deploy the adaptive concept linking, such as Ontobroker [21] and SHOE [22], primarily focus on using metadata in formation discovery and have a pre-defined closed linking structure (i.e. the links or associations between resources are hard-wired and fixed by the original author). COHSE [23] is an open hypermedia that allows the addition of extra structures to resources, but has too limited link types. In this paper, we take the advantage of the course ontology with rich semantics and metadata annotations to discover and build various semantic links between documents or document fragments. By using the concepts in the course ontology to choose candidate anchors for creating links, authoring links between documents becomes an activity of authoring with concepts. Figure 5 illustrates the three phases involved.

- *Phase 1: document parsing*. First, the inputted document is parsed to locate the feature key words by eliminating the noises or useless words, which includes individual term identification, stop-wording, and term-phrase formation. A stop-word list is used to remove non-semantic bearing words such as 'the', 'a', 'on', 'in', etc. The term-phrase formation formulates phrases by combining only adjacent words.
- *Phase 2: semantic link generation*. It is composed of two modules: link-discovering and link-pruning. The link-discovering module takes charge of matching the document terms with the concepts in the course ontology. After identifying a corresponding concept in the course ontology, the module searches the information resources to obtain a list of documents that contain instances of this concept. If there is no matching document to the specified concept, it will choose the abstract or specific concepts to find more related documents. Meanwhile, it intentionally selects concepts with different relationships (e.g. similar-to, part-of and subtype) as referenced information. According to a particular context and the learners' learning goals as well as knowledge backgrounds, the link-pruning module is responsible for choosing the appropriate links among many candidate links by referring to the candidate documents' metadata.
- *Phase 3: document refreshing*. Once the set of semantic links has been chosen, the document is refreshed and redisplayed. In this way, the inputted document is expanded with various types of links to the relevant documents or document fragments.

By automatically adding links and annotations into documents as they are delivered from the server to the ultimate client browser, an active e-course dynamically adapts to different learners with an open and flexible structure.

5. LEARNING EVALUATION

The test result is the main factor for determining a learner's learning performance on a knowledge object. Each question may have multiple related knowledge objects with different association degrees that are either directly specified by the instructors through the authoring interface or automatically computed by the system based on the key words and ontology. Herein, three association degrees {weak, moderate, strong} are respectively assigned the association weights {1, 2, 3}. Each question is marked with a difficulty level that is represented with a five-scale rating, that is, the scores {0.1, 0.3, 0.5, 0.7, 0.9} represent the increased difficulty level of questions. The instructors are in charge of defining the difficulty level of questions through the authoring interface. Table II gives an illustrative example of relationship between a set of questions and knowledge objects. d_i indicates the difficulty level of question Q_i, each item (Q_i, K_j) in the table represents the association weight between the ith question and the jth knowledge object and the association weight 0 indicates that there is no relationship between the question and the knowledge object.

Clearly, answering a harder question demonstrates higher comprehension ability than correctly answering an easier question. Similarly, failing to answer a harder question contributes less to the comprehension ability than that of failing to answer an easier question. Thus, we use the following formulae to compute the positive influence (denoted as P_g) and negative influence (denoted as N_g) on

Table II. Illustrate example of the relationship between questions and knowledge objects (K_1, algebra system; K_2, partial order; K_3, lattice; K_4, homomorphic lattice; K_5, isomorphic lattice; K_6, distributive lattice; K_7, critical lattice; K_8, complemented lattice; K_9, complemented distributed lattice).

Question	Knowledge object								
	K_1	K_2	K_3	K_4	K_5	K_6	K_7	K_8	K_9
$Q_1(d_1 = 0.5)$	0	3	0	0	0	0	0	0	0
$Q_2(d_2 = 0.7)$	2	0	1	0	0	0	0	0	0
$Q_3(d_3 = 0.7)$	0	2	2	0	0	0	0	0	0
$Q_4(d_4 = 0.3)$	0	0	0	3	3	0	0	0	0
$Q_5(d_5 = 0.5)$	0	0	3	0	0	0	0	0	0
$Q_6(d_6 = 0.3)$	3	0	0	0	0	0	0	0	0
$Q_7(d_7 = 0.3)$	0	0	1	0	0	3	0	0	0
$Q_8(d_8 = 0.7)$	0	0	2	1	3	0	0	0	0
$Q_9(d_9 = 0.5)$	0	0	1	0	0	0	3	2	0
$Q_{10}(d_{10} = 0.5)$	0	0	2	0	0	1	0	3	2
$Q_{11}(d_{11} = 0.1)$	0	0	2	0	0	0	3	0	0
$Q_{12}(d_{12} = 0.3)$	0	0	1	0	0	2	3	2	1
$Q_{13}(d_{13} = 0.1)$	0	0	0	3	0	1	0	0	0
$Q_{14}(d_{14} = 0.3)$	0	0	1	0	0	2	2	3	1
$Q_{15}(d_{15} = 0.7)$	0	0	2	0	0	3	1	3	1

the comprehension of knowledge object K_g

$$P_g = \frac{\sum_{Q_i \in T} (d_i * a_{gi})}{n} \tag{1}$$

$$N_g = \frac{\sum_{Q_k \in F} ((1 - d_k) * a_{gk})}{m} \tag{2}$$

where d_i denotes the difficulty level of the ith question, a_{gi} denotes the association weight between the knowledge object K_g and the question Q_i. T is a set of questions that are correctly answered by a learner, and the number of the questions in the set is denoted as n. F is a set of questions that are incorrectly answered by a learner, and the number of questions in the set is denoted as m. The following formula is used to compute the error ratio (denoted as ER) of comprehending a knowledge object:

$$ER(K_g) = \frac{N_g}{P_g + N_g} \tag{3}$$

According to the statistics, the learning performance of the learners rationally satisfies the normal distribution, and so does the distribution of the error ratio. Herein we assume that the learners' normal distribution and the corresponding distribution of error ratio (ranges from 0 to 1) are tabulated in Table III.

The larger the error ratio, the worse a learner's learning performance on a knowledge object. According to the above distribution of error ratios, we set the upper boundary and lower boundary

Table III. Distributions of learner and error ratio.

	Learning performance				
	Excellent	Good	Middle	Poor	Very poor
Learner distribution	10%	20%	40%	20%	10%
Error ratio distribution	0.1	0.2	0.4	0.2	0.1

for each learning level, as shown in the following expression:

$$\text{Learning level} = \begin{cases} \text{Very poor} & 1 \geq ER \geq 0.9 \\ \text{Poor} & 0.9 \geq ER \geq 0.7 \\ \text{Middle} & 0.7 \geq ER \geq 0.3 \\ \text{Good} & 0.3 \geq ER \geq 0.1 \\ \text{Excellent} & 0.1 \geq ER \geq 0 \end{cases}$$

The boundary values are not fixed, and can be dynamically adjusted according to the experiment results on a large scale.

Assume that the learner fails to answer Q_2, Q_4, Q_7, Q_9, Q_{12}, Q_{13} and Q_{15}, as indicated in Table II. Formulae (1)–(3) are used to calculate the error ratios of knowledge objects, then we have $ER(K_1) = 0.4$, $ER(K_2) = 0$, $ER(K_3) = 0.37$, $ER(K_4) = 0.77$, etc. By referring to the above expression, we can infer that the learning levels of the learner on the knowledge objects K_1–K_4 are respectively 'middle', 'excellent', 'middle' and 'poor'. In this way, the teaching agent can diagnose which knowledge objects are not comprehended by the learners and give the corresponding suggestions. For example, the learning level of K_4 is 'poor' indicates that the learner fails to comprehend this knowledge object, so the teaching agent suggests that the learner reviews the content related to the knowledge object and recommends more remedial materials for the purpose of reinforcing the learner's understanding of the knowledge object. At the same time, the learning level of the knowledge objects and the reviewed times are recorded in the learner profile for later reference.

6. IMPLEMENTATION AND COMPARISON

An authoring tool has been developed for defining the course knowledge and structure. Figure 6 shows the graphic user interface for constructing the course-SLN. Experts and instructors can click the icons in the top toolbar to add the concepts and relationships, while deleting or editing them in the background graphical interface. Through the dialogues for defining the concept attributes and relationship types, experts and instructors can input the text or select one item from the drop-down list to specify the concept properties and relationship types. Figure 7 gives a graphical view of a part of the course-SLN. As the figure illustrates, the left frame shows a tree hierarchy of the course concepts on a specific subject, the upper part of the right frame shows the constructed course-SLN, and the lower part of the right frame shows the list of properties corresponding to the concepts shown in the

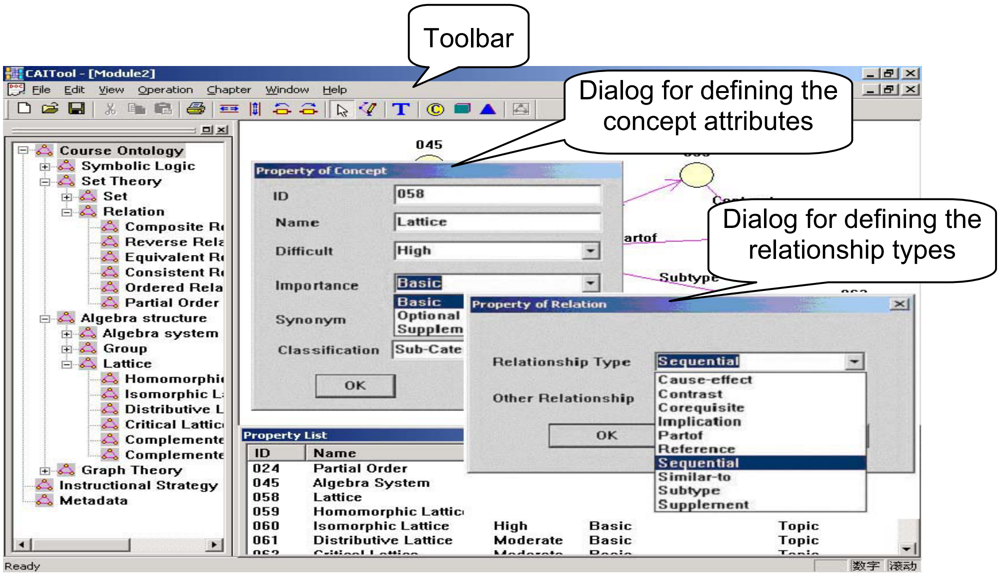


Figure 6. Graphical user interface for constructing the course-SLN.

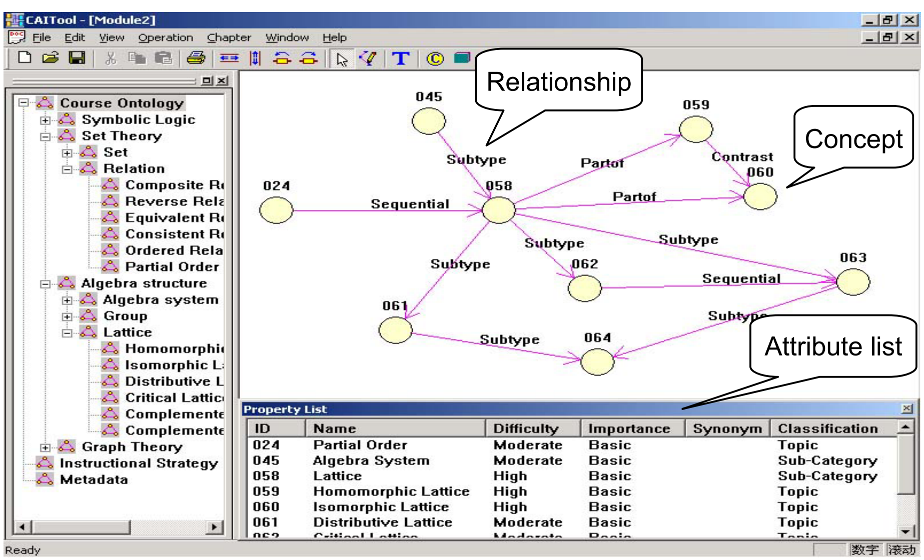


Figure 7. Graphical view of a part of course-SLN.

upper part. The defined course knowledge and structure are finally described in the format of Resource Description Framework (RDF) [24].

Taking the active e-course as core component, we have developed a system prototype KGTutor (available at http://kg.ict.ac.cn/KGTutor/KGTutor.htm) to support adaptive, interactive and collaborative e-learning with the following functions.

- *Course browsing*. Through browsing the friendly interface, learners can freely learn the course at their own paces.
- *Active exploration*. By browsing semantic linked learning materials of different levels, learners can learn more about the specified knowledge objects.
- *Adaptive tests*. Each time a learner takes a test, the system analyzes his past performance and draws questions accordingly. If the learner is less familiar with the content, or has not taken the test before, easier questions are selected to form the test. Otherwise, more difficult questions are provided to the learners. This mechanism keeps track of the standard each individual learner has achieved and accordingly adjusts the difficulty level.
- *Question answering*. A search plug-in is provided to support the question answering function. When learners encounter problems during the learning process, they can input the key words to search for the useful information related to the problems.
- *Progress monitoring*. By viewing the analysis results of the learners' learning activities, the instructors adjust the teaching styles and provide more reference materials as well as useful suggestions. As for those learners who have not been actively accessing the course materials and doing self-tests, the instructors can write emails or post notices to remind them to keep up and prepare for the tests.
- *Automatic evaluation*. After taking a self-test, learners are provided with an evaluation sheet on which the wrongly answered questions are listed and the related knowledge objects with linking guidance are also given. This prevents the learners from wasting time looking for the materials to which the question relates.
- *Knowledge exchange*. As a message forum, the Knowledge Collection Board (KCB) [25] can also collect and refine the knowledge, and finally store the knowledge in the Knowledge Grid to provide reference for other learners. This provides the foundation for the learners to learn collaboratively. Moreover, the system can automatically recommend peers with similar interests to the learners for their private discussion through KCB.

Most of the above-mentioned functions have been implemented. Figure 8 shows the interface for displaying the demo course on 'Object-Oriented Database'. As the figure illustrates, the scalable course catalogue hierarchy is arranged on the left portion of the interface, learners can click the item to read the corresponding content shown on the right portion of the interface. The semantic links are added to the specified terms in the example document. After reading the content, learners can click the rank option to evaluate the quality of this material.

Figure 9 shows an interface for displaying the testing results and evaluations. The learner's answers are clearly itemized while the relevant knowledge objects are attached to the questions.

Table IV compares the KGTutor and other related intelligent educational systems in terms of the adaptive and intelligent technologies.

Furthermore, as the most popular e-learning products, WebCT (http://www.webct.com/) and BlackBoard (http://www.blackboard.com/) provide all-round functions to support e-learning.

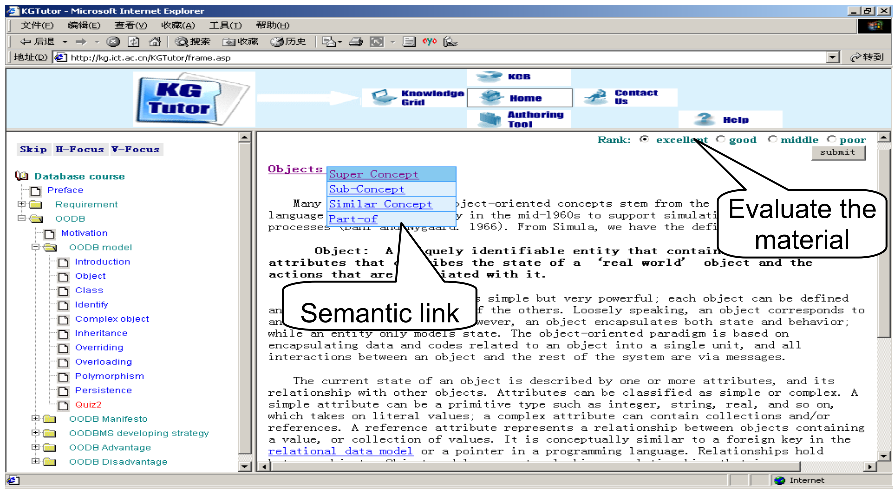


Figure 8. Interface for displaying the course content.

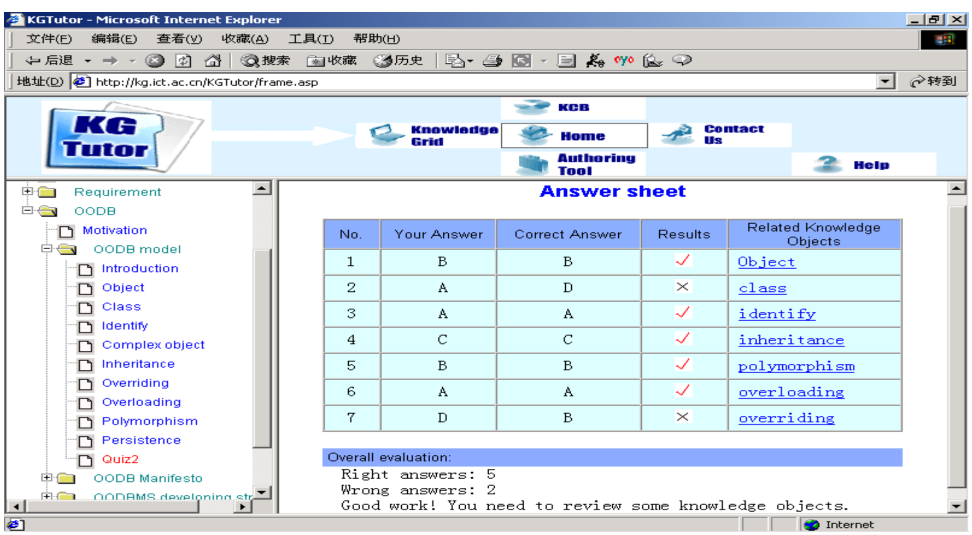


Figure 9. Interface for showing the results of learning evaluation.

Table IV. Comparison between KGTutor and other systems.

System	Knowledge modelling	Adaptive sequencing	Adaptive navigation	Learning evaluation	Authoring support	Underlying platform
KBS [26]	Object-oriented language	Course	Annotation	×	×	Web
CAL-ES [27]	Ontological tree and rules	Teaching materials	×	×	×	Web
ELM-ART [28]	Conceptual network	Course, test	Annotation	×	×	Web
DCG [5]	AND/OR graph	Course	×	×	✓	Web
KGTutor	Semantic link network	Knowledge object	Versatile semantic links	✓	✓	Web and Knowledge Grid

Herein, we give a detailed comparison between the Blackboard system and our proposed system KGTutor in terms of the following aspects.

- *Learning resource management*. Blackboard supports instructors in developing course content, hints and tips in a flexible and friendly manner. It also provides functions for the learners to define the interested links for collecting resources. Constructed on the platform of the Knowledge Grid that supports the resource sharing and management on a global scale, the KGTutor separates the learning materials from the concept-centered knowledge structure, which facilitates the reuse and maintenance of the learning resources. Additionally, the KGTutor provides three methods to collect learning resources by means of GruDexer.
- *Personalized services*. In contrast to the Blackboard system that provides personal page layout, color preferences, calendar for reminding, grades report, and address book, the KGTutor focuses on providing a personal course with different content in a different organization pattern. Additionally, semantic links are semi-automatically added to the learning content with the aim in supporting learners in navigating the course in a more flexible and active manner. As a complement, the KGTutor tracks the learning activities and learning progress of each learner, and accordingly adjusts the course organization and marks the interesting or difficult content with different colors.
- *Cooperation support*. Blackboard supports learners in communicating in several ways, such as e-mail, discussion board, virtual classroom, roster and group pages. KGTutor provides a KCB as the foundation for learners to learn collaboratively. In addition to serving as a message forum, KCB can also collect and refine the knowledge, and finally store the knowledge in the Knowledge Grid to provide a reference for other learners. Moreover, the KGTutor can automatically recommend peers with similar interests to learners for private discussions through the KCB.

- *Learning evaluation*. Blackboard offers self-testing while marking on the test results. In addition to this, KGTutor also itemizes the test results with related concepts, which facilitates the learners in quickly locating the content that needs to be reviewed.

7. EXPERIMENTAL STUDY

To evaluate the functionality and efficacy of the system, we conducted a small-scale experiment with 45 undergraduate students (sophomore) enrolled in a 'discrete mathematics' course. The students are randomly divided into three groups denoted as G1, G2 and G3 (15 students each group). They are required to finish seven lessons over a three-week period, and the students had to take a quiz designed to test their level of understanding of the learning content after each lesson. To encourage the students to perform well, they were told that the best two out of the seven scores obtained would count towards their final grade. Before starting the course, a quiz is used as a pretreatment test of possible group differences in terms of the background knowledge. Group treatments are as follows.

Precondition 1. All of the lessons have a similar level of difficulty and the contents are closely related.

Precondition 2. The quizzes comprise questions related to the knowledge objects learned in the former lessons.

Precondition 3. The experiment is conducted in a closed environment, so students learn independently and can only interact with the system, not other students.

(1) Group 1 (G1). By disabling the interactive and adaptive functions, the system presents the learning materials linearly, and the students have to follow the pre-designed uniform schedule to study the lessons. Thus, students act as passive recipients without being engaged in active exploration of the learning materials.
(2) Group 2 (G2). By presenting the learning materials in a hypertext navigational structure, the system enables students to freely access the learning materials from different perspectives (hyperlinks originating from different nodes). However, students have to study by themselves without any learning guidance from the system.
(3) Group 3 (G3). Students study the course with the full support of the system. According to the pretreatment test results, a tailored course with versatile semantic links is presented to students in a hypertext navigational structure, allowing them to freely explore learning materials at different levels of detail and granularity. Moreover, the system provides evaluations on the students' learning performance and personalized suggestions to guide their further learning.

Figure 10 intuitively shows the comparison between G1, G2 and G3 in terms of the average score of each quiz. The test results of the first quiz (pretreatment) indicate that the students have similar background knowledge before starting the course. During the learning process, the quiz score of the first group is relatively steady, while those of the other two groups both increase with time, but with different velocities. After the completion of the course, a comprehensive quiz is administered to reveal the overall knowledge the students have gained, and Table V displays the distribution of students with different testing scores. According to Figure 10 and Table V, we can see that the third group achieved a higher learning performance than the other two groups, and the second group's learning performance is

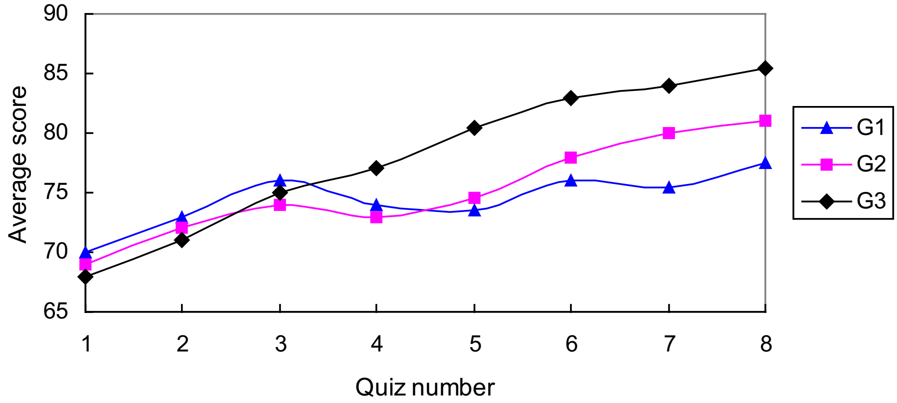


Figure 10. Testing results for different groups studying the same content.

Table V. Students' overall learning performance.

	Excellent ($S \geq 90$)	Good ($90 > S \geq 80$)	Medium ($80 > S \geq 60$)	Poor ($60 > S \geq 40$)	Very poor ($S < 40$)
G1	1	3	7	3	1
G2	1	4	6	3	1
G3	2	6	6	1	0

better than the first group. In addition, by observing the navigation logs of all of the students, we can see that the navigation efforts of the third group students as well as the average time to achieve the learning goal are reduced, and the overall number of navigation steps and the number of task repetitions are significantly smaller with adaptive navigation support. This suggests that the system with interactive and adaptive functions facilitates the learning progresses of students.

In order to have a cross-validation of the experimental results, we conducted a second experiment with one group of students enrolled in three sections of the 'discrete mathematics' course. In this experiment, the students study with three different learning styles and the three sections are of a similar difficulty level. Each section is divided into seven lessons, and the students were required to take a pre-test and seven quizzes after each lesson. Figure 11 intuitively shows the test results for the same group of students with different learning styles.

As Figure 11 shows, the same group of students has different learning performances by adopting the different learning styles. The test results (i.e. change trends of the curves) are similar to those of the first experiment despite a little fluctuation of the curves, which indicates that the learning style with interactive and adaptive function support outperforms the other two styles, while the flexible self-study is better than the passive study in terms of the learning outcome.

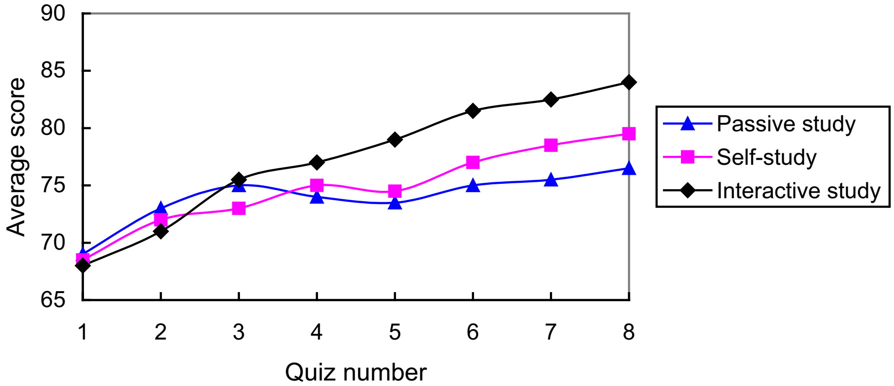


Figure 11. Testing results for the same group with different learning styles.

Table VI. Results from questionnaire survey.

Statements	G1 (average)	G2 (average)	G3 (average)
1. You are satisfied with the course generated for you	2.8	3.5	4.2
2. You feel active during the learning progress	2.5	3.9	4.7
3. You can quickly locate the knowledge objects related to the questions you have failed in the test	1	2.5	4.1
4. This system is effective in supporting your learning	2.6	3.1	4.0
5. You are comfortable with the system interface	×	×	4.1
6. You are satisfied with the hypertext navigation structure	×	×	4.8
7. The semantic links are useful for your learning	×	×	3.9
8. The systematic learning on a course subject is useful	×	×	4.5
9. The knowledge-object-focused learning mode is useful	×	×	4.9
10. The evaluations for the quizzes are useful for you	×	×	4.4
11. The suggestions on your next study are useful for you	×	×	4.5
12. The prerequisite advices for your study are helpful	×	×	4.5

After the completion of the experiments, all of the students are given a survey designed to assess their perceptions regarding the features of the system and the learning effects. All of the students were asked to fill in a questionnaire by rating on a five-point scale (from strongly disagree to strongly agree) to express their level of agreement with the statements. Table VI tabulates the results from questionnaire survey. The first four statements are mainly about the overall impression of the three learning approaches. Compared with G3, students in G1 and G2 give less positive responses, which indicates that the students of the third group have a higher estimation of the system. Statements 5–12 are for the full-scale evaluation of the system, such as interface, options, presentation, etc. The results show that most of the students are satisfied with the system interface, navigation structure and its personalized service as well as interaction functions. It is little surprising to note that not all of the students are very interested in the versatile semantic links as we conceived.

This minority of students prefers sequential navigation, which suggests that the semantic links work in some context, e.g. the learning style and knowledge level of students.

8. CONCLUSIONS

Being separated from the concept-centred knowledge structure, the learning materials can be adaptively organized and reused in a more flexible and interoperable manner. In this way, the active e-course can dynamically organize tailored content and provide intelligent learning services for different learners as well as enable convenient exploration of the learning resources at a learner's own pace. Furthermore, learners' learning effects are automatically evaluated to provide corresponding suggestions. Experimental results demonstrate that the proposed approach promotes the learners' learning performance and learning efficiency.

Ongoing work includes the following aspects: (1) carry out the experiment on a large number of students during a long period to test the effectiveness of the proposed approach; (2) make use of statistical theory and data-mining technology to automatically construct the course ontology; (3) investigate the ontology mapping to support semantic interoperability across courses; (4) conduct in-depth analysis on the roles of learners' cognitive behaviours.

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REFERENCES

1. Bonwell C. Building a supportive climate for active learning. *The National Teaching and Learning Forum* 1996; **6**(1):4–7.
2. Hartman VF. Teaching and learning style preferences. *Transitions Through Technology, VCCA Journal* 1995; **9**(2):18–20.
3. Richards LG. Promoting active learning with cases and instructional modules. *Journal of Engineering Education* 1995; **84**(4):375–381.
4. Rubin L, Hebert C. Model for active learning: Collaborative peer teaching. *College Teaching* 1998; **46**(1):26–30.
5. Vassileva J. Dynamic courseware generation. *Communication and Information Technologies* 1997; **5**(2):87–102.
6. Weber G, Specht M. User modeling and adaptive navigation support in WWW-based tutoring systems. *User Modeling*. Springer: Berlin, 1997; 289–300.
7. Bra PD, Santic T, Brusilovsky P. AHA! meets Interbook, and more. *Proceedings of the World Conference on E-Learning*, Phoenix, AZ, November 2003, Rossett A (ed.). AACE: Norfolk, VA, 2003; 57–64.
8. Brusilovsky P, Eklund J, Schwarz E. Web-based education for all: A tool for developing adaptive courseware. *Computer Networks and ISDN Systems* 1998; **30**(1–7):291–300.
9. Hohl H, Böcker HD, Gunzenhäuser R. Hypadapter: an adaptive hypertext system for exploratory learning and programming. *User Modeling and User-Adapted Interaction* 1996; **6**(2–3):131–156.
10. Zhuge H. China's E-Science Knowledge Grid Environment. *IEEE Intelligent Systems* 2004; **19**(1):13–17.
11. Zhuge H, Li Y. Semantic profile-based document logistics for cooperative research. *Future Generation Computer Systems* 2004; **1**:47–60.
12. Beck JE, Woolf BP. Using a learning agent with a learner model. *Intelligence Tutoring System: Proceedings of 4th International Conference (ITS'98)*, Goettl BP *et al.* (eds.). Springer: Berlin, 1998; 6–15.
13. Murray WR. A practical approach to Bayesian learner modeling. *Intelligence Tutoring System: Proceedings of 4th International Conference (ITS'98)*, Goettl BP *et al.* (eds.). Springer: Berlin, 1998; 424–433.
14. Gruber TR. A translation approach to portable ontology specifications. *Knowledge Acquisition* 1993; **5**:199–220.

15. Zhuge H. Active e-document framework ADF: Model and tool. *Information and Management* 2003; **41**(1):87–97.
16. Murray T. Authoring intelligent tutoring systems: An analysis of the state of the art. *International Journal of Artificial Intelligence in Education* 1999; **10**:98–129.
17. Stojanovic L, Staab S, Studer R. Elearning based on the semantic Web. *Proceedings of the World Conference on the WWW and Internet (WebNet2001)*, Orlando, FL, October 2001.
18. Decker S *et al*. Ontobroker: Ontology based access to distributed and semi-structured information. *Proceedings of DS-8*. Kluwer: Boston, MA, 1999; 351–369.
19. Mao S, Kim JW, Thoma GR. A dynamic feature generation system for automated metadata extraction in preservation of digital materials. *Proceedings of the 1st International Workshop on Document Image Analysis for Libraries*, Palo Alto, CA, January 2004.
20. Brusilovsky P. Adaptive hypermedia, user modeling and user adapted interaction. *Ten Year Anniversary Issue*, Kobsa A (ed.). 2001; **11**(1/2):87–110.
21. Fensel D *et al*. Ontobroker in a nutshell. *Proceedings of ECDL 98* (*Lecture Notes in Computer Science*, vol. 1513). Springer: Berlin, 1998; 663–664.
22. Heflin J, Hendler J, Luke S. Coping with changing antologies in a distributed environment. *Papers from the AAAI Workshop on Ontology Management*. AAAI Press: Menlo Park, CA, 1999; 74–79 (paper WS-99-13).
23. Carr L *et al*. Conceptual linking: ontology-based open hypermedia. *Proceedings of the 10th International World Wide Web*, May 2001; 334–342.
24. Resource Description Framework (RDF). http://www.w3.org/RDF/ [March 2005].
25. Zhuge H, Li Y. KGCL: A knowledge-grid-based cooperative learning environment. *Proceedings of 1st ICWL Conference*, Honk Kong, August 2002 (*Lecture Notes in Computer Science*, vol. 2436). Springer: Berlin, 2002; 192–202.
26. Henze N, Nejdl W. Adaptivity in the KBS hyperbook system. *Proceedings of the 2nd Workshop on Adaptive Systems and User Modeling on the WWW*, May, Toronto and June, Banff, 1999. *TUE Computing Science Report 99-07*, TUE, Eindhoven, The Netherlands, 1999; 67–74.
27. Tsai CJ, Tseng SS. Building a CAL expert system based upon two-phase knowledge acquisition. *Expert Systems with Applications* 2002; **22**:235–248.
28. Weber G, Brusilovsky P. ELM-ART: An adaptive versatile system for Web-based instruction. *International Journal of Artificial Intelligence in Education* 2001; **12**(4):351–384.