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The Use of Learning Objects and Learning Styles in a Multi-Agent Education System

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Adaptive learning and teaching strategies are increasingly demanded in order to improve the efficiency and effectiveness of the education process, but few intelligent education systems exist, which are dynamic and able to satisfy individual students' requirements. In an attempt to overcome these limitations, we have developed a multi-agent education software system, which incorporates learning objects, and is based upon a learning style theory as the foundation for its adaptivity. In this article, we describe the design, implementation, and evaluation of the educational research contribution; in particular we discuss the pedagogical use of the learning objects and learning styles. We present a novel approach to the incorporation of learning style theory. The approach has been evaluated through several experiments to validate particular system functions, and the initial analysis indicates that the approach is able to handle individual students' requirements and improve the dynamic adaptivity in education systems.

Advanced information technologies are increasingly used in higher education to facilitate learning and teaching, but inadequacies exist in current systems, materials, and pedagogy. The application of similar learning strategies to all students in a class can be ineffective. For example, introductory programming modules in Computer Science education are often delivered using a text-based teaching method. However students have their individual preferences of how they can learn programming, and how to make learning programming less difficult is an issue in Computer Science education (Jenkins, 2002). Students often treat a course as a series of mechanical exercises rather than as systemic concepts (Shi, Shang, & Chen, 2000), and currently many of the courseware and software resources used in higher education are unstructured with concepts not being systematically organised and learning resources are isolated from each other. A specific framework to support the changes in the learning process is often lacking (Nunes & McPherson, 2002).

People learn in different ways. It is important to be aware of the differences between learners, and this is especially relevant during the current expansion of higher education to a greater proportion of the population. New delivery mechanisms are required, including online, open, and distance learning (Beetham, 2002). These issues can be partially resolved by providing student-centred, self-paced, highly interactive teaching materials and introducing automatic and asynchronous teaching methods. Although there are many educational technology projects, both stand-alone learning systems and web-based tools using techniques such as multimedia interaction, learning models and asynchronous learning, there is as yet no integrated approach to the design of pedagogic information architectures (Shi et al., 2000).

Such intelligent education systems must be adaptive, able to learn, and dynamic (Razek, Frasson, & Kaltenbach, 2002). Systems should be individualized and able to provide different students with appropriate material, making the learning process more efficient and effective. Agent technology can provide dynamic adaptation not only of domain knowledge, but also to the behaviour of individual learners. Agent technology is influenced by advanced information and Internet technologies, and is a promising approach, which addresses the challenges of modern day education (Aroyo & Kommers, 2001).

We propose a multi-agent based integrated pedagogic system architecture that is student-centred and adaptive (Sun, Joy, & Griffiths, 2005a, 2005b). Our solution takes a multi-disciplinary approach, combining learning style theory with agent-based systems. Thus, at the conceptual level, adaptivity is achieved by the use of learning style schemes to tailor the presentation of learning objects to individual students. Conversely, at the practical level, this adaptivity is achieved by providing a set of agents that uses a combination of prebuilt and acquired knowledge to determine the learning styles and learning objects that are appropriate for individual students.

In contrast to other agent-based pedagogic architectures, learning style schemes form the pedagogic foundation for adaptivity and the use of learning objects. There are many metadata schemes and strategies for designing and categorising learning objects, but research about incorporating real learning objects with learning style schemes into education systems is rare. Learning style theory addresses the issue of adaptivity, and learning objects address the issue of decomposition of learning materials to meet the requirement of reusability. How to incorporate learning style theory into computer-assisted education systems is still a research question, and the suitable granularity of learning object classification is also an education technology research topic. In this article, we report our investigation of these research questions using the multi-agent education system that we have developed.

INTRODUCTION OF RELATED TECHNOLOGIES

Our proposed pedagogic system architecture represents the integration of three key technologies and concepts: (a) agent-based systems, (b) learning objects, and (c) learning style theories. In this section, we give an overview of these foundational aspects of our architecture.

Learning Objects

Many learning materials are distributed using web technologies, and most materials are currently developed for a specific purpose. For example, courseware is usually for a specific module, and its contents will probably not be reused or will only be reused infrequently. To address the issue of reuse, from both the perspective of educators and learners, the concept of a learning object has been proposed.

A learning object is a "self-standing, reusable, discrete piece of content that meets an instructional objective" (Academic ADL Co-Lab [AADL], University of Wisconsin System [UWS], Wisconsin Technical College System [WTCS], 2002). Learning objects may be tagged with metadata so that their identity and content are available to software systems. The decomposition of educational content into learning objects is analogous to the decomposition of an object-oriented program into objects and classes, and permits an individual learning object to be used in a variety of educational contexts. In our multi-agent system, the decomposition of learning materials into learning objects guarantees that knowledge can be organised as a variety of learning paths to present to different students.

Learning Style Theories

People never learn in the same way. The concept of *learning style* has been introduced by educationalists as a "description of the attitudes and behaviours that determine our preferred way of learning" (Honey, 2001). Learning styles depend on a variety of factors, and are individual to different people. Even for the same person, their learning style can change over time. Learning styles may differ between men and women, and between children and adults (Blackmore, 1996). In this article, we restrict our view of learning styles to those applicable for students in higher education.

Learning style theory is the pedagogic foundation of the multi-agent system, however there are several different ways of categorising learning style preferences. Kolb's Learning Style Inventory describes learning styles on a continuum running from concrete experience, through reflective observation, to abstract conceptualization, and finally active experimentation (Kolb, 1984). Gardener's Multiple Intelligences divides learning styles as dealing with words (Verbal/Linguistic), questions (Logical/Mathematical), pictures (Visual/Spatial), music (Music/Rhythmic), moving (Body/Kinaesthetic), socializing (Interpersonal), and alone (Intrapersonal) (Gardner, 1993). After considered several learning styles theories such as these and Myers-Briggs Type Indicator (McCaulley, 1990), the learning style theory we have adopted in the system is the Felder-Silverman Learning Style Model. The reasons we have chosen the Felder-Silverman Learning Style Model are that:

- it has been validated by pedagogy research (Zywno, 2003, Felder & Spurlin, 2005), and
- the number of dimensions of the model is constrained, improving the feasibility of its implementation.

The Felder-Silverman Learning Style Model situates a student's learning style preference within a four-dimensional space, with the following four independent descriptors:

- *sensing* (concrete thinker, practical, oriented toward facts and procedures) or *intuitive* (abstract thinker, innovative, oriented toward theories and underlying meanings);
- *visual* (prefer visual representations of presented material, such as pictures, diagrams, flow charts) or *verbal* (prefer written and spoken explanations);
- *active* (learn by trying things out, enjoying working in groups) *or reflective* (learn by thinking things through, prefer working alone or with a single familiar partner);
- *sequential* (linear thinking process, learn in small incremental steps) or *global* (holistic thinking process, learn in large leaps). (Felder & Spurlin 2005, p.103)

Agent Technology

Depending on the roles that agents take in their deployed environments, their abilities may vary significantly. However, we can identify the commonly agreed properties of agents, which include autonomy, proactiveness, responsivity, and adaptivity. Agents should also know users' preferences and tailor their interactions to reflect these (Jennings & Wooldridge, 1998). It is generally accepted that an agent is an entity that is capable of carrying out flexible autonomous activities in an intelligent manner to accomplish tasks that meet its design objectives, without direct and constant intervention and guidance of humans.

Multi-agent systems contain many agents that interact with each other. Each agent typically has control over certain parts of the environment, so that they are designed and implemented as a collection of individual interacting agents. Luck, McBurney, and Priest (2003) remark that, "Multi-agent systems provide a natural basis for training decision makers in complex decision making domains [in education and training]" (p. 68). Furthermore, multi-agent systems can substantially contain the uncertainty that arises from the interactions of many complex components. In the context of our education system architecture, agents provide a means to manage the complexity and uncertainty of the domain.

Pedagogical Agent Systems

In the context of adaptive education, agent technology can provide a dynamic adaptation not only of domain knowledge but also of the behaviour of individual learners, and has already been used in a number of educational tools. However, most systems incorporating agent technology, such as (Beer & Whatley, 2002; Boicu et al., 2004; Norman & Jennings, 2002; Razek et al., 2002; Shang, Shi, & Chen, 2001), have decoupled the agents from the pedagogic foundations of the system. Existing systems tend to emphasise a particular aspect, such as training, group work, or human resource requirements. Beer and Whatley reported the initial design of an agent-based system to support students undertaking group projects in health care education (Beer & Whatley 2002). For each group of students, a local agent is provided to monitor the project, and enhance the communication between members of the group. The use of agents is emphasised as providing dynamic support for synchronous collaboration.

Each of the current approaches has its individual ways of organising the learning materials, and few have considered the effect of different learning styles. For example, in Shang et al.'s (2001) system, the students' learning styles are stored in personal agents at the beginning of a student's use of the system, and are not changed dynamically during the learning process. However, learning styles will change during the time students are using the system, and students might provide unreliable information about their learning style preferences, since they may misclassify themselves. In our proposed multi-agent system, students' learning styles are updated during the learning process. Shang et al. (2001) organise agents according to different courses, while Boicu et al., (2004) use agents that are implemented according to specific learning topics. In our system, however, the agents are decomposed by their function in the teaching and learning process. The use of learning objects in such systems is rare, although the technology has begun to be used in nonadaptive training software. Garro and Palopoli's (2003) system is designed to assist finding appropriate employees and measuring the skill gaps between the employee and the requirements of the organisation from a human resources perspective.

THE PEDAGOGY OF LEARNING OBJECTS AND LEARNING STYLES

Due to the new requirements for web-based e-learning systems, new intelligent technologies are increasingly incorporated into other technologies (Brusilovsky & Peylo, 2003). Learning objects increase personalization, interoperability, and flexibility (Longmire, 2000). People have their own preferences of how they can learn effectively, and to support a personalized learning strategy the differences between learners must be recognised (Jenkins, 2002).

Customising learning materials as learning objects can support students with different learning styles. Although this idea has been proposed elsewhere (Smith, 2004), the incorporation of learning objects and learning style theories to support adaptivity is still a research problem. Agent technology gives a dynamic support for distributed learning applications, and deals well with crucial issues, such as distance, cooperation among different entities and components and integration of different software system components (Rosmalen et al., 2005). In this article, we present an adaptive e-learning system, which incorporates these advanced e-learning technologies to facilitate achieving adaptivity.

Some systems have adopted learning style theories, and explored the delivery of learning materials adapted to students' learning styles. The system developed by Carver, Howard, & Lane (1999) presents a list of links to each student based on their learning style, leaving the individual student to select the material to use. Paredes and Rodriguez (2002) use two dimensions of the Felder-Silverman Learning Style theory, and progress has been made on the mechanism of incorporating Felder-Silverman Learning Style theory elsewhere (Specht & Oppermann, 1998; Gilbert & Han, 2002; Hong & Kinshuk, 2004). They have incorporated learning style theory into their systems and learning material design; however, the pedagogies and technologies are not suited to dynamic adjustment to students' learning styles. Knowledge is still delivered in a static way and the learning materials are more or less preset for a certain type of learning style or preference, and will not be changed or adjusted according to a change of learning style of the user over time. The pedagogy that incorporates learning objects and learning style, which we have used in the system, is able to dynamically organise and deliver learning materials to satisfy individual learning requirements, and agent technology gives dynamic support.

Incorporating Learning Objects and Learning Styles

In our multi-agent education system, a single agent, the Learning Object Agent, is responsible for incorporating the learning style scheme and the learning objects. A repository, which provides the learning objects, is under the charge of the Learning Objects Management Layer (one of the three layers) in the Learning Object Agent. To deliver the learning objects according to different learning styles, the implementation has been divided into three parts: (a) accommodating students into the learning style scheme, (b) categorising learning objects according to the learning style scheme, and (c) delivering learning objects. From a highly abstract level, this is illustrated in Figure 1.

ACCOMMODATING STUDENTS INTO THE LEARNING STYLE SCHEME

Felder and Silverman use a complex questionnaire (containing 44 questions) to ascertain a student's learning style (Soloman & Felder, 2004). Not only would the use of such a large questionnaire be infeasible in an intelligent tutoring system, but also the information supplied would be more than such a system would require to operate effectively. A simple algorithm that approximates the positioning of a student's learning style in the four-dimensional space can be constructed by using a reduced set of appropriate questions. We have chosen a set of four questions on each dimension, which has been evaluated by comparing the results for a sample of students with those generated by Felder and Silverman's original questionnaire.

The original answers of the 44 questions are on a scale of 11-1 and 1-11 on each dimension such as in Figure 2. "X" is the sample student's score on each dimension.

According to the interpretation of the score,

> If your score on a scale is 1-3, you are fairly well balanced on the two dimensions of that scale. If your score on a scale is 5-7, you have a moderate preference for one dimension of the scale and will learn more easily in a teaching environment which favors that dimension. If your score on a scale is 9-11, you have a very strong preference for one dimension of the scale. You may have real difficulty learning in an environment which does not support that preference. (Soloman & Felder, 2004)

Figure 3 illustrates the normalised scale of the results. The results from the 44 questions are normalised into a five-point scale, for example, the nor-

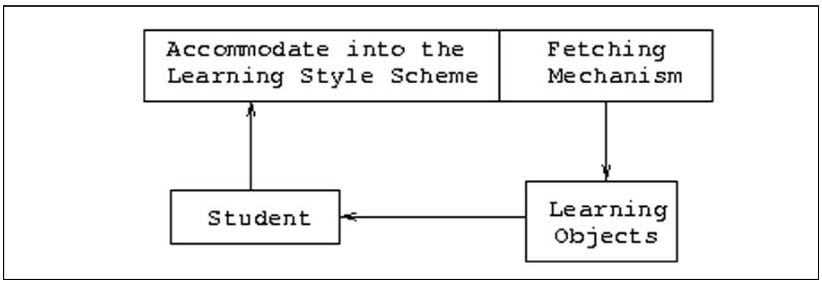

Figure 1. Abstract method for fetching appropriate learning objects

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ACT                                   X                                       REF
     11   9    7    5    3    1    1    3    5    7    9    11
                                    <--  -->

SEN              X                                                            INT
     11   9    7    5    3    1    1    3    5    7    9    11
                                    <--  -->

VIS                                   X                                       VRB
     11   9    7    5    3    1    1    3    5    7    9    11
                                    <--  -->

SEQ                                   X                                       GLO
     11   9    7    5    3    1    1    3    5    7    9    11
                                    <--  -->
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Figure 2. Example result from (Soloman & Felder, 2004)

malised data of Figure 2 is: 0.5, 0.25, 0.5, and 0.5. The results of the reduced set of 16 questions are also based on a five-point scale.

A Spearman's rank correlation coefficient statistical analysis has been performed on the quantified and normalised data (performed in SPSS) – students' answers both for the 44 questions and the 16 questions – and indicates a strong correlation between the two data sets (correlation coefficients are 0.697, 0.904, 0.713, and 0.899, so correlation is significant at 0.01 level, one tailed). This suggests that the reduced set of 16 questions is sufficient to categorise a student's learning style.

CATEGORISING LEARNING OBJECTS ACCORDING TO THE LEARNING STYLE SCHEME

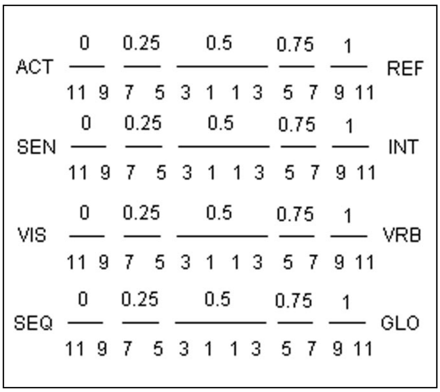

Figure 3. Normalised scale

The learning objects we use are also organised into the four-dimension learning style space, and include learning objects for Introductory Programming (Boyle et al., 2004), as well as some suitable learning objects from other open sources.

In addition to basic information such as author, date, and so forth, the learning object metadata incorporate a *dimension description*, suggesting for each of the four learning style dimensions the extent of each object's suitability on a five-point scale, as illustrated in Figure 4. Each dimension contains the following levels: strongly and weakly on both preferences of the dimension and neutral in the middle.

As an example, consider the learning object from Eck (1997) in Figure 5, which is a data representation applet showing six different interpretations for the same string of 32 bits. The user can set the type of

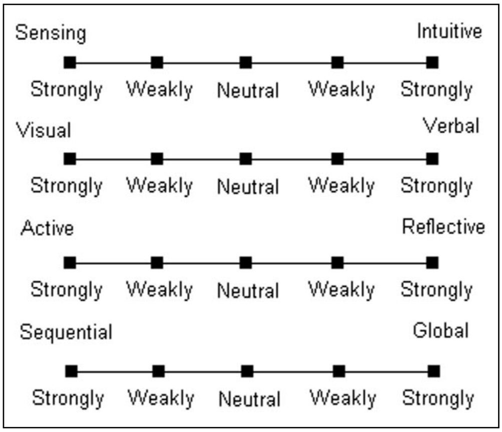

Figure 4. Five-point scale on four dimensions

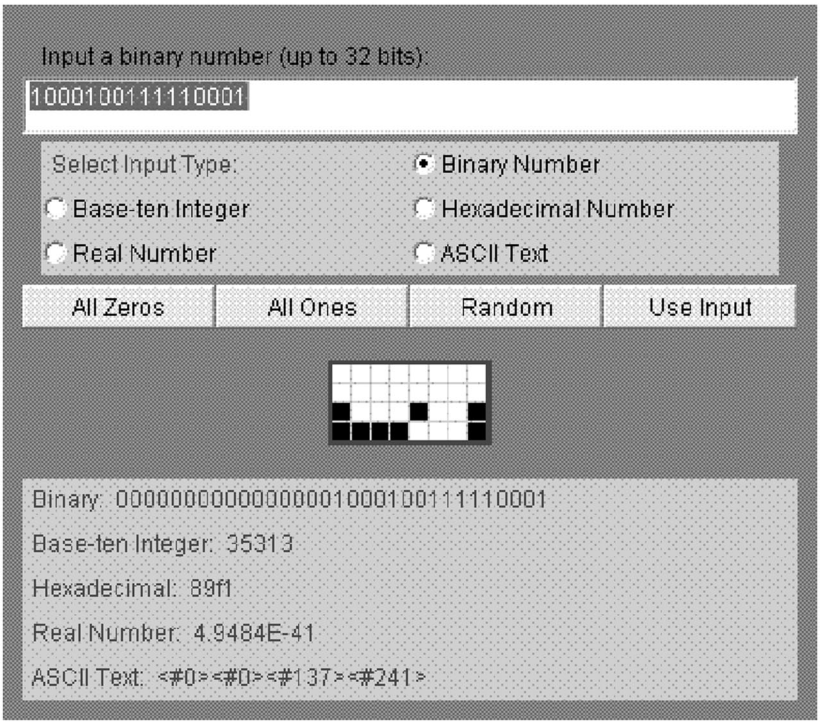

Figure 5. Data representations learning object from Eck (1997)

the number, or have random numbers as input, or specify some numbers, and substantial user interaction is required. The small grid square shows how binary numbers can represent a pixel. The values of the five-point scale of this learning object may be strongly sensing, neutral of visual and verbal, strongly active, and weakly global. For more examples, refer to Sun (2005).

We asked 14 users to rate 11 learning object samples, and at the same time they were interviewed about how and why they made their decisions. On the “Sensing or Intuitive” dimension, the average percentage of the users who rated each learning object on the same half of the direction is 79%, the highest percentage is 93%, the lowest percentage is 64%. To give an example, 93% of the users gave the No. 5 learning object values between –2 to 0 (the normalised scale, which is easier for the users to follow), on the sensing half on the dimension, as shown in Figure 6. Learning object 5 (Figure 7) is “The Animated Internet – Connecting to the Internet” from Michael Lerner Productions (2004). Although all of the learning objects have not been designed following the same standard or guideline, the initial results indicate that it is possible to categorise a learning object on the “Sensing or Intuitive” dimension.

Among the 11 learning objects, eight of them have been rated on one end of the “Visual or Verbal” dimension, the average percentage is 83%, the highest is 100%, and the lowest is 71%. Interestingly, the remaining three learning objects, which have about equal numbers of values on both sides of the dimension, all have a common characteristic, which is that most of the text in each learning object is presented using “frames”, and appears on the screen within the frames. Some of the users also pointed out that they

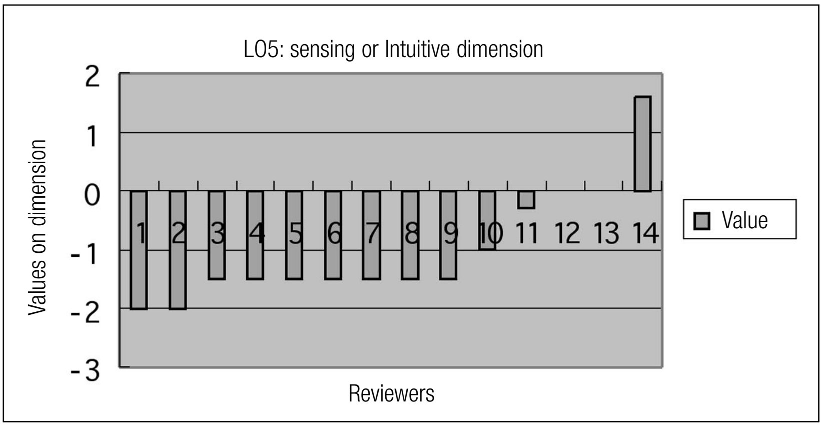

Figure 6. Users’ ratings on “Sensing or Intuitive” dimension for learning object 5

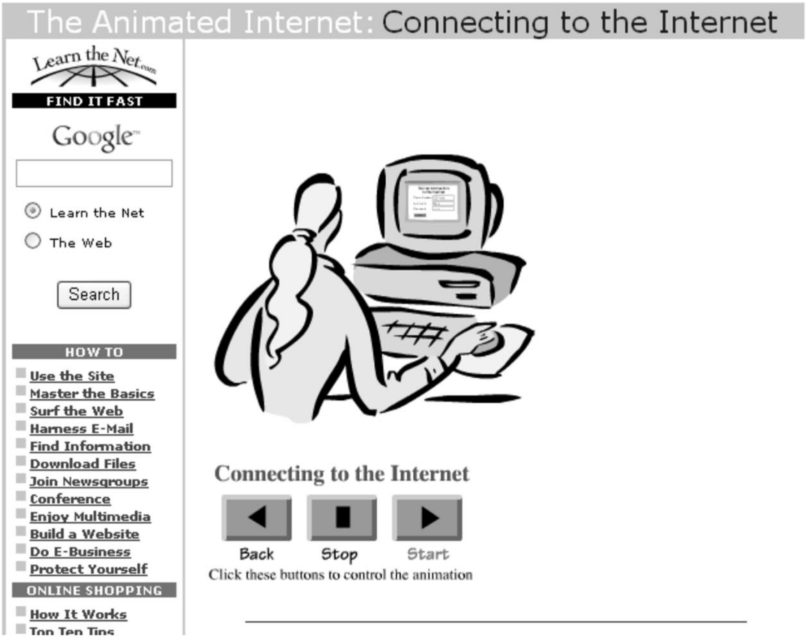

Figure 7. Connecting to the Internet learning project from Michael Lerner Productions (2004)

thought it was quite ambiguous, because these types of texts are presented in a visual way, like a picture, which mostly consists of text, so whether it is text (verbal) or a picture (visual) becomes an unclear definition.

On the "Active or Reflective" dimension, only one learning object has about an equal number of users on both active and reflective sides. The average percentage on one side of the rest of the 10 learning objects is 81%, the highest one is 93%, and the lowest is 64%. The most interesting thing about the remaining learning object is that it is composed of three pages to explain how a computer is been connected to Internet, and all the users have to do is to press a "play" button. Some of the users said they thought that is not really active, because the users have not tried things out, but the other users thought it is like a simulation, which you press the button, then it displays what is happening. Like the "Visual or Verbal" dimension, some clarification will help on this issue.

The "Sequential or Global" dimension is the one for which there is least agreement amongst the users. Eight out of the eleven learning objects are relatively clearly categorised, the average percentage being 78%, the highest is 93%, and the lowest is 64%.

The three learning objects, which are not clearly categorised on the "Sequential or Global" dimension concern backbone networks, the tower of Hanoi, and light spectra. According to the users' comments, some of them think those materials can be used by anybody, because it is not difficult to understand the content, so they should be categorised as "Global." The others think that although anybody can understand the content, it may not be useful for them to relate to their knowledge background – they will be helpful only for the students with significant prerequisite knowledge, and then they should be categorised as "Sequential". To make the category easier and precise, the users suggest a clearer definition of the category scheme.

The initial conclusion from analysis of the results is that all of the learning objects can be categorised on at least two out of the four dimensions. Most of the learning objects can be clearly categorised on three or even four out of the four dimensions, and further investigation of the granularity for the categorisation is underway.

DELIVERING LEARNING OBJECTS FOR DIFFERENT LEARNING STYLES

The multi-agent intelligent tutoring system that we propose stores each student's current learning style (which may change over time), and the style attributes of each learning object, as co-ordinates in the four-dimensional space. The algorithm used to deliver learning objects to students involves matching the style attributes of (appropriate) learning objects to the current style preferences of the individual student. For example, consider the learning styles of students A and B presented in Table 1.

The system then searches the repository of learning objects, to fetch appropriate learning objects with similar (but not necessarily identical) dimensional descriptions. These are supported by agent technology to implement the algorithm and the process. The objects are then presented to the student, and the subsequent interactions between the student and these learning objects may be used to modify the student's learning style attributes.

Table 1
Location of Students' Learning Styles

	Student A	Student B
Sensing or Intuitive	Neutral	Strongly Sensing
Visual or Verbal	Strongly Visual	Weakly Visual
Active or Reflective	Weakly Reflective	Neutral
Sequential or Global	Strongly Sequential	Weakly Global

The possible ways of organising the learning objects for an individual student are the combinations of the five point values on the four dimensions, for example, strongly sensing, strongly visual, strongly active, and strongly sequential. It should be stressed that both the categorisation of a learning object and the assignment of a learning style to a student are necessarily approximate.

Since it is almost impossible to find students with all possible combinations of the learning style scheme, a simulation has been run on the learning object delivery system. The simulation has covered all of the possibilities – four dimensions, each on five-point scale ($5^4 = 625$). The initial simulation succeeded on these combinations, and the evaluation indicates that at this stage our approach is capable of delivering different learning objects to different students with various learning style preferences according to the learning style theory has been used in the system.

THE MULTI-AGENT EDUCATION SYSTEM

Learning style theory is the pedagogic foundation of our system, and learning objects provide a way of organising learning materials for individuals. From a technical viewpoint, the adaptivity requirement suggests that the set of interactions and communications within the system should be dynamic. The use of intelligent agents allows us to abstract the data at a higher level than that which would be appropriate for conventional software technologies, and enables us to conceptualise the system in a natural fashion.

The Multi-Agent Approach

Our proposed multi-agent based learning system is functionally constructed by five agents, as shown in Figure 8, the Student Agent, the Record Agent, the Modelling Agent, the Learning Object Agent, and the Evaluation Agent. Each agent is designed to satisfy a certain functional requirement that contributes to the purpose of the overall learning system, namely to provide dynamic and adaptive learning materials to individual users. Agents allow the system to be functionally divided, since each agent is autonomous and has its own social ability. Agent autonomy (the ability to take charge of its own actions and internal states) also increases system maintainability. The reactivity and proactiveness characteristics give the multi-agent system maximum flexibility in different learning situations and compatibility with different learning style preferences.

The Student Agent is responsible for communicating with students, and provides the interface between the system and human users. The Record Agent maintains information about each student, and it is more than simply a database – it is able to process and draw inferences from the data provided by other agents, and can intelligently provide other agents with informa-

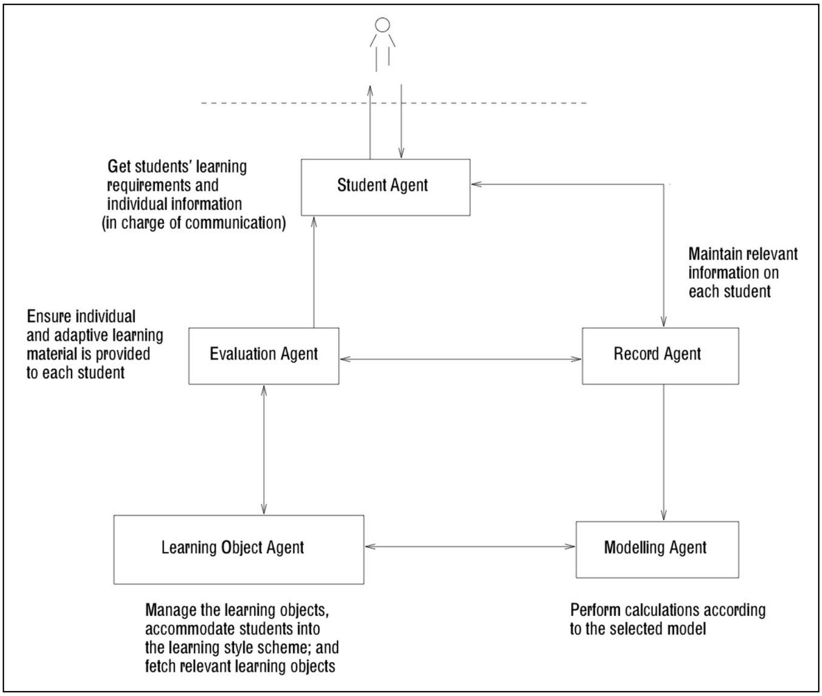

Figure 8. The multi-agent education system

tion in response to its reasoning, even without information being requested. The Modelling Agent is responsible for performing calculations according to a general pedagogical modelling approach (such as Bayesian networks or the fuzzy logic approach), which creates models of students' skills and learning objectives, by which it models each individual student's needs and knowledge background, based on its selection of suitable data for the model from the information provided by the Record Agent. The Learning Object Agent manages the set of learning objects, and provides relevant learning objects for students with different learning styles. The Evaluation Agent ensures that learning objects are presented in individual and adaptive learning paths to each individual student. During the time students are using the system, these agents update their knowledge frequently, so any change of students' learning style preferences are reflected dynamically.

Using the System

When a student first logs in to the system, the Student Agent enters into a dialogue with the student to ascertain the student's learning requirements. The 16-question questionnaire to ascertain the student's learning style preferences will also be sent at this time. After initially analysing the results, the Record Agent is informed of the student's learning requirements together with a suggested knowledge level for the student. These items of information are recorded and then passed to the Modelling Agent, which then sends results and instructions to the Learning Object Agent. This in turn arranges the first batch of learning objects to be sent to the Student Agent according to the results of learning style analysis (which occurs in the learning path layer) and difficulty level of the learning objects, which are also organised according to the learning style scheme. These learning objects are first sent to the Evaluation Agent, which checks the student's data from the Record Agent to evaluate whether the learning objects are suitable for this student. If the evaluation is successful, the series of learning objects is sent to the Student Agent (and then to the student) and recorded by the Record Agent. Otherwise, the Evaluation Agent asks the Learning Object Agent to provide alternative learning objects. After the student has used the learning objects, response data is returned to the Student Agent, which transmits them to the Record Agent. We refer the reader elsewhere for a more extensive technical discussion (Sun et al., 2005a).

CONCLUSIONS AND FUTURE WORK

In this article, we have described a novel pedagogical use of learning objects and learning styles in a multi-agent intelligent education system, and have reported our investigation on the incorporation of learning style theory and learning objects into the system. The way we have incorporated agent technology and learning objects, supported by learning styles, is a new approach for achieving dynamic adaptivity in education systems. The method of incorporating learning objects and the learning style scheme has been evaluated. Ongoing work includes further investigation of the learning objects category granularity. A prototype of the system is being developed using JADE (Bellifemine, Caire, Poggi, & Rimassa, 2003). In addition to completing a full implementation of the complete system, future work also includes optimising the architecture, an evaluation of the system effectiveness and efficiency, and further investigation of the learning objects compatibility.

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