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

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Abstract: 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 system, which incorporates learning objects, and is based upon a learning style theory as the foundation for its adaptivity. In this paper, we describe the design and implementation 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 and report the results of an experiment to assess the appropriate granularity of learning object classification.

1. Introduction

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, programming introduction 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 *et al.* 2000), and a specific framework to support the change process is often lacking (Nune & McPherson 2002). Currently, many of the courseware and software resources used in higher education are unstructured and are isolated from each other.

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 tertiary 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 *et al.* 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 have developed a multi-agent based integrated pedagogic system architecture that is student-centred, adaptive, able to learn, and dynamic. Our solution takes a multi-disciplinary approach, combining learning 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 pre-built 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 and strategies about learning objects designing and categorizing, 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 reusablity. 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 under investigation. One of the contributions of our research is to answer these two research questions in the multi-agent education system that we have developed.

2. Introduction of Related Technologies

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

2.1. 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" (AADL *et al.* 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 organized as a variety of learning paths to present to different students.

2.2. 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 paper, 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 (Vernal/Linguistic), questions (Logical/Mathematical), pictures (Visual/Spatial), music (Music/Rhythmic), moving (Body/Kinesthetic), socializing (Interpersonal), and alone (Intrapersonal) (Gardner 1993).

The Felder-Silverman Learning Style Model, which we have chosen to adopt, 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)

2.3. Agent Technology

Depending on the roles that agents take in their deployed environments, their abilities may vary significantly. However, we still can identify essential and 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 communicate with each other. Each agent has control over certain parts of the environment, so they are designed and implemented as a collection of individual interacting agents. Luck *et al.* remark that, "Multi-agent systems provide a natural basis for training decision makers in complex decision making domains [in education and training]" (Luck *et al.* 2003). Furthermore, multi-agent systems can substantially contain the "spread of uncertainty", since agents typically process information locally (Georgeff *et al.* 1999). In the context of our education system architecture, agents provide a means to manage the complexity and uncertainty of the domain.

2.4. The Pedagogic Foundation of Learning Objects and Learning Styles

Some systems have adopted learning style theories, and explored the delivery of learning materials adapted to students' learning styles. The system developed by Carver *et al.* presents a list of links to each student based on their learning style, leaving the individual student to select the material to use (Carver *et al.* 1999). Paredes and Rodriguez use two dimensions of the Felder-Silverman Learning Style theory (Paredes & Rodriguez 2002), and progress has been made on the mechanism elsewhere (Specht & Oppermann 1998, Gilbert & Han 2002, and Hong & Kinshuk 2004). They have incorporated learning style theory into their system and learning material design; however, the pedagogies and technologies are not suited to dynamic adjustment to students' learning styles. The 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.

3. Pedagogic Incorporation of Learning Objects and Learning Style

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, and is discussed in section 3.5. A repository, which provides the learning objects, is under charge of the Learning Objects Management Layer (one of the three layers) in the Learning Object Agent. In order to deliver the learning objects according to different learning styles, the implementation has been divided into three parts: accommodating students into the learning style scheme, categorizing learning objects according to the learning style scheme, and delivering Learning Objects. From a highly abstract level, the method can be laid out as in (Figure 1).

The learning style theory we have adopted in the system is the Felder-Silverman Learning Style Model. Several learning style theories have been considered, including those mentioned above, and the Myers-Briggs Type Indicator (McCaulley 1990). The reasons we has 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.

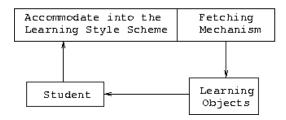


Figure 1: The Abstract Method of the Pedagogy

3.1. 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 for 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 (Soloman & Felder 2004). A Spearman's rank correlation coefficient statistical analysis has been performed on the normalised data, and indicates a strong correlation between the two data sets, and this suggests that our current algorithm is sufficient to categorise a student's learning style.

3.2. Categorizing Learning Objects according to the Learning Style Scheme

The learning objects we use are also organized 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 the other open sources.

In addition to basic information such as author, date, etc., the learning object metadata incorporates a *dimension description*, suggesting for each of the four learning style dimensions the extent of each object's suitability on a five-point scale. For instance, the visual/verbal dimension contains the following descriptors: strongly visual, weakly visual, neutral, weakly verbal, and strongly verbal.

Input a binary number (up to 32 bits): RECONCENTITIOEC					
Select Input Type. © Base-ten Integer © Real Number		Binary Number Hexadecimal Number ASCII Text			
All.Zeros	All Ones	Random	UseInput		
Binary 000000000000000000000000000000000000					
Base-ten Integer: 35313					
Hexadecimal: 891					
Real Number: 4.9484E-41					
ASCI Test: <#0><#0><#137><#241>					

Figure 2: Data Representations Learning Object from (Eck 1997)

As an example, consider the learning object from (Eck 1997) in (Figure 2), which is a data representation applet, which shows six different interpretations for the same string of thirty-two bits. The user can set the type of the

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

The granularity of the categorization, i.e. the location of every learning object in the five-point scale, is pragmatically determined, and seemed appropriate for the learning objects available to us. Samples of users have classified the available learning objects according to the five-point scale category, and the results have been compared and analysed. The evaluation shows that at this stage, the granularity scale we are using is practical for learning object classification.

3.3. Delivering Learning Objects for Different Learning Styles

The multi-agent intelligent tutoring system we have developed 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):

	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

Table 1: Location of Students' Learning Styles

The system will then search 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 realize the algorithm and implement 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.

The possible ways of organizing the learning objects for individual student, are the combinations of the five points values on the four dimensions, for example, strongly sensing, strongly visual, strongly active, and strongly sequential. It should be stressed that both the categorization 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 system. The simulation has covered all of the possibilities — four dimensions, each with four levels, as in figure 3, $(5^4 = 625)$, and the evaluation indicates that our approach is capable of delivering different learning objects to different students according to the learning style category.

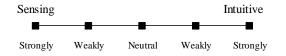


Figure 3: Example of four levels on one dimension

3.4. The Multi-Agent Education System

Learning style theory is the pedagogic foundation of our system, and learning objects provide a way of organizing learning materials for individuals. From a technical aspect of the system, 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.

Agent technology has been used in education systems to facilitate autonomy and adaptivity, decoupled from the pedagogic foundations of the system (Razek *et al.* 2002, Norman & Jennings 2002, Shang *et al.* 2001, Beer & Whatley 2002). Each such system emphasizes a particular aspect, such as training, group work, or human resources requirement. Each has its individual ways of organizing the learning materials, and few have considered the effect of different learning styles or the adoption of learning objects.

Our proposed multi-agent based pedagogic system is functionally constructed by five agents, as shown in (Figure 4), and comprises 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 to actualize the service purpose of the education system, namely to provide dynamic and adaptive learning materials to individual users.

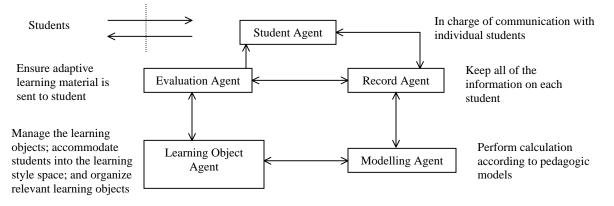


Figure 4: The Multi-Agent Education System

The Student Agent is responsible for communicating with students; the Record Agent maintains information about each student; the Modelling Agent creates models of students' skills and learning objectives; the Learning Object Agent manages the set of learning objects; and 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 will update their knowledge frequently, so any change of students' learning style preferences will be reflected dynamically. We discuss briefly the Learning Object Agent, and refer the reader elsewhere for a more extensive technical discussion (Sun 2005b).

3.5. Learning Object Agent

The Learning Object Agent manages the learning objects, which are organised according to the learning style scheme. In response to instructions from the Modelling Agent, the Learning Object Agent provides different learning style students with relevant learning objects.

The Learning Object Agent is a hybrid agent, and has an architecture in which its subsystems are arranged into a hierarchy of layers as shown in (Figure 5). The results from the Modelling Agent are transferred to the learning path layer by the communication layer, which in turn maps them to an appropriate learning path for a student. The Learning Object Agent communicates with the other agents through its communication layer. Decisions are sent to the learning object's management layer, which is in charge of managing all of the learning objects in its repository. In the learning object repository, learning objects are organised in different levels, according to the learning style scheme. Finally, the learning objects management layer selects a series of learning objects, which are transmitted to the Evaluation Agent through the communication layer. The learning path layer adopts the Felder-Silverman

Learning Style Model to organise learning objects to fulfil different students' requirements. The learning objects in the repository are categorised using the learning style model.

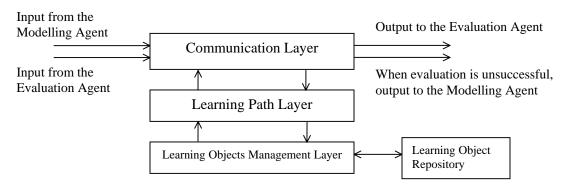


Figure 5: Learning Object Agent

4. Conclusions and Future Work

We have described a novel pedagogical use of learning objects and learning styles in a multi-agent intelligent education 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. A prototype of the multi-agent system has been developed, including the Learning Object Agent, which implements the learning style scheme and learning objects. The method of incorporating learning objects and the learning style scheme is currently being evaluated. In addition to the implementation of the complete system, future work also includes optimising the architecture, and an evaluation of the system effectiveness and efficiency.

5. References

Academic ADL Co-Lab (AADL), University of Wisconsin System (UWS), & Wisconsin Technical College System (WTCS), (2002). What are Learning Objects? <u>http://adlcolab.uwsa.edu/lo/what.htm</u>. Accessed Dec 2003.

Aroyo, L. & Kommers, P. (2001). Special issue preface, Intelligent Agents for Educational Computer-aided Systems. *InteractiveLearning Research*, 10(3/4), 235–242.

Beetham, H. (2002). Understanding e-learning. http://www.ics.ltsn.ac.uk/pub/elearning/. Accessed Nov 2002.

Beer, M. & Whatley, J. (2002). A Multi-agent Architecture to Support Synchronous Collaborative Learning in an International Environment, *Proceedings of the first International Joint Conference on Autonomous Agents and Multiagent Systems*, 505-506.

Blackmore, J. (1996). Learning Styles. *Telecommunications for Remote Work and Learning*, <u>http://www.cyg.net/~jblackmo/diglib/styl-a.html</u>. Accessed May 2004.

Boyle, T., et al. (2004). Learning objects for Introductory Programming, <u>http://www.londonmet.ac.uk/ltri/javaobjects/</u>. Accessed Feb 2004.

Carver, C. A., Howard, R. A., & Lane, W. D. (1999), Enhancing Student Learning Through Hypermedia Courseware and Incorporation of Student Learning Styles, *IEEE Transactions on Education*, 42(1), 33-38.

Eck, D. (1997). Data Representations Applet. *Labs and Applets for The Most Complex Machine*, <u>http://math.hws.edu/TMCM/java/DataReps/index.html</u>. Accessed Sept 2004.

Felder, R.M. & Spurlin, J.E. (2005). Applications, Reliability, and Validity of the Index of Learning Styles, *International Journal of Engineering Education*, 21(1), 103-112.

Gardner, H. (1993). Multiple Intelligences: The Theory in Practice. Basic Books.

Georgeff, M., Pell, B., Pollack, M., Tambe, M., & Wooldridge, M. (1999). The Belief-desire-intention Model of Agency. J. M[°]uller, M. P. Singh, and A. S. Rao (Eds.), *Proceedings. of the 5th International. Workshop on Intelligent Agents V : Agent Theories, Architectures, and Languages*, 1–10.

Gilbert, J. E. & Han, C. Y. (2002). Arthur: A Personalized Instructional System. *Journal of Computing in Higher Education*, 14(1).

Honey, P. (2001). Honey and Mumford Learning Styles Questionnaire. *PeterHoney Learning*, <u>http://www.peterhoney.com/product/learningstyles</u>. Accessed Apr 2004.

Hong, H. & Kinshuk (2004). Adaptation to Student Learning Styles in Web Based Educational Systems, *ED-MEDIA 2004*, 491-496.

Jenkins, T. (2002). On the Difficulty of Learning to Program. Proceedings of the 3rd Annual Conference of the LTSN Centre for Information and Computer Sciences, 53-58.

Jennings, N. R. and Wooldridge, M. (1998). Applications of Intelligent Agents. Agent Technology Foundations, Applications and Markets. Springer-Verlag.

Kolb, D. A. (1984). *Experiential Learning: Experience as the Source of Learning and Development*. Englewood Cliffs, NJ, Prentice-Hall.

Luck, M., McBurney, P. & Preist, C. (2003). Agent Technology: Enabling Next Generation Computing A Roadmap for Agent Based Computing. AgentLink.

McCaulley, M. H. (1990). The MBTI and Individual Pathways in Engineering Design. Engineering Education, 80, 537-542.

Norman, T. J. & Jennings, N. R. (2002). Constructing a Virtual Training Laboratory using Intelligent Agents. *International Journal of Continuous Engineering Education and Life-Long Learning*. 12(1-4), 201-213.

Nunes, M. B. & McPherson, M. (2002). Managing Change in Continuing Professional Distance Education through Action Research. *Proceedings of the 3rd Annual Conference of the LTSN Centre for Information and Computer Sciences*, 20–25.

Paredes, P. & Rodriguez, P. (2002). Considering Learning Styles in Adaptive Web-based Education. *Proceedings of the 6thWorld Multiconference on Systemics, Cybernetics and Informatics*, 481-485.

Razek, M. A., Frasson, C. & M. Kaltenbach. (2002). Toward More Cooperative Intelligent Distance Learning Environments. *Software Agents Cooperation Human Activity*, <u>http://www-perso.iro.umontreal.ca/~abdelram/</u>. Accessed Feb 2003.

Shi, H., Shang, Y. & Chen, S. (2000). A Multi-agent System for Computer Science Education. *Proceedings. of the 5th annual SIGCSE/SIGCUE ITiCSE Conference. on Innovation and Technology in Computer Science Education*, 1–4.

Soloman, B. A. & Felder, R. M. (2004). Index of Learning Styles, <u>http://www.ncsu.edu/felder-public/ILSpage.html</u>. Accessed April 2004.

Shang, Y., Shi, H. & Chen, S. (2001). An Intelligent Distributed Environment for Active Learning. *Proceedings of the tenth International Conference on World Wide Web*, 308-315.

Specht, M. & Oppermann, R. (1998). ACE – Adaptive Courseware Environment. The New Review of Hypermedia and Multimedia 4,141-161.

Sun, S. (2005). Incorporation of Learning Objects and Learning Style - An Investigation of Metadata to Support Adaptive Pedagogical Agent Systems, *Proceedings of the 12th International Conference on Artificial Intelligence in Education - AIED 2005, Young Researcher Track.*

Sun, S., Joy, M., and Griffiths, N. (2005). An Agent-Based Approach to Dynamic Adaptive Learning, *Proceedings of Agent Based Systems for Human Learning (ABSHL) Workshop, the Fourth International Joint Conference on Autonomous Agents and Multi Agent Systems (AAMAS).*

Zywno, M. S. (2003). A Contribution to Validation of Score Meaning for Felder-Soloman's Index of Learning Styles, *Proceedings of the 2003 American Society for Engineering Education Annual Conference & Exposition*, session 2351.