A Learning Object Approach to Personalized Web-based Instruction

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Abstract

The concept of web-based learning and the use of the Internet in teaching and learning have received increasing attention over the recent years. It is postulated that one of the main problems with e-learning environments is their lack of personalisation (Cristea, 2003; Rumetshofer & Wöß, 2003; Ayersman & Minden, 1995). The concept of extending the learning object metadata to cater for psychological factors has been proposed by Rumetshofer & Wöß (2003). In this article, the latters' approach has been extended in three ways: (1) More factors relating to individual differences are included in the metadata extension as well as fields related to the pedagogical value and level of difficulty of the learning content, (2) The introduction of fuzzy (or belief) values for each aspect that is modelled, (3) A mechanism is provided to adapt to changing attitudes, characteristics and performance of a student both in the student model and in the learning object attributes model. A method is devised to select the most appropriate learning object from a pool of potential objects that exist in the repository and a first evaluation of the proposed algorithm is carried out and reported in the article.

Le concept du e-learning et l'apprentissage par Internet est devenu un domaine très étudié dans le milieu de la recherche en éducation et les technologies éducatives. Cependant une des contraintes de cette nouvelle approche demeure le manque de personnalisation dans ces environnements (Cristea, 2003; Rumetshofer & Wöß, 2003; Ayersman & Minden, 1995). Rumetshofer & Wöß (2003) proposent l'extension des meta-données des objets d'apprentissage (*learning objets*) afin de prendre en considération les attributs psychologiques des apprenants. Cet article décrit une extension de cette approche en trois étapes : (1) L'extension des meta-données contient plus de facteurs ayant trait aux différences individuelles ainsi que des champs sur la valeur pédagogique et niveau de difficulté de l'objet d'apprentissage, (2) L'introduction des valeurs approximatives (*fuzzy*) pour les facteurs qui sont considérés, (3) une stratégie d'adaptation aux attitudes variantes et la performance de l'apprenant. La méthode de sélection des objets d'apprentissage qui sont plus appropriés pour un apprenant spécifique est présentée. Finalement, on décrit une première évaluation de l'algorithme proposée pour la méthode

Keywords

e-Learning, Personalisation, Adaptation, Web-based Learning, Learning Objects, Learning & Cognitive Styles.

Introduction

The concept of web-based learning and the use of the Internet in teaching and learning have received increasing attention over the recent years. One of the main advantages of delivering web-based educational materials is that the same content is delivered to a number of students and can be accessed with no restrictions of time and place. However, there is a wide belief that using the web as only a new kind of delivery medium for educational materials does not add significant value to the teaching and learning process. The integration of technology in learning, needs to address the very important issue of enhancing the teaching and learning process, rather than just being seen as a new flexible delivery medium (Nichols, 2003). It is postulated that one of the main problems with e-learning environments is their lack of personalisation (Cristea, 2003; Rumetshofer & Wöß, 2003; Ayersman & Minden, 1995).

This article focuses on the personalisation issue in web-based learning environments. A brief overview of the concepts of adaptation is presented and a literature review of different related work that has been carried out in the field is made. The paper also discusses on the different factors that are necessary to take into account in attempts to provide personalisation in web-based learning. A method is devised to select the most appropriate learning object from a pool of potential objects that exist in the repository. To achieve this purpose, the learning object metadata extended to contain attributes pertinent for the personalisation process to individual differences. A first evaluation of the proposed algorithm is carried out and reported in the article.

Personalization in Web-based Environments

The concept of Adaptation (adaptability v/s adaptivity)

The concept of 'adaptation' or 'personalisation' is an important issue in research for learning systems. Systems that allow the user to change certain system parameters and adapt their behaviour accordingly are called *adaptable*. Systems that adapt to the users automatically, based on the system's assumptions about the user needs are called *adaptive*. The whole spectrum of the concept of adaptation in computer systems is shown below (Patel & Kinshuk, 1997).

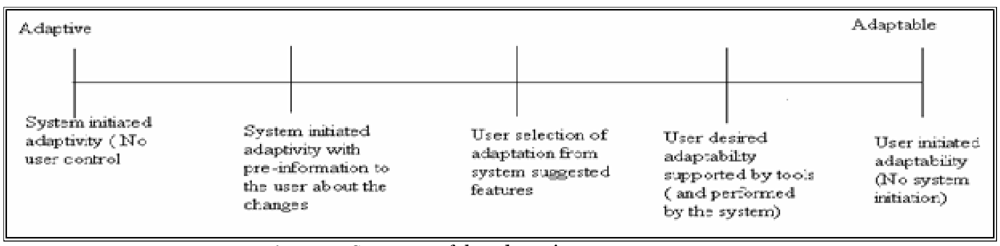

Figure 1: Spectrum of the adaptation concept

Adaptivity in hypermedia systems to personalise the user's experience with the system is not a new concept and Brusilovsky (2001) describes three main types of adaptation that exists in web-based hypermedia systems namely content, navigation and layout. In adaptive hypermedia literature, they are referred to respectively as *adaptive presentation* and *adaptive navigation support* (Brusilovsky, 1996).

Content, navigation and layout adaptivity in Web-based Systems

The goal of the *adaptive presentation* is to adapt the content of a hypermedia page to the user's goals, knowledge and other information stored in the user model. There could be multiple reasons to use adaptive presentation. Two typical cases in the area of education are comparative explanations and explanation variants. The idea of comparative explanations is to connect new content to the existing knowledge of the student. A page can have one or more hidden comparative explanation fragments that comparing some aspects of new topic with relevant aspects of other topic (Fischer et al., 1990).

The goal of adaptive navigation support is to help users to find their paths in hyperspace by adapting link presentation and functionality to the goals, knowledge, and other characteristics of an individual user (Brusilovsky, 1996). The kind of adaptation can take the form of direct guidance, link sorting, annotation, hiding and disabling. These methods involve techniques such as, the visual outline (by the system) of one of the links of a page which is the best link to follow, sorting of links of a page according to the user model or other relevant criteria, annotation of the links by including meta information about the links or preventing the user from viewing links which are not suitable for him at a given instance.

Adaptation to Psychological-Factors

Rumetshofer & Wöß (2003), on the other hand, postulate that, in learning systems, adaptivity needs to cover more that what Brusilovsky (2001) proposes for web-based hypermedia systems, and propose what they call adaptation to psychological factors. These *psychological* factors are cognitive style, learning strategy, learning modality and skills. The system is based on simple adaptation rules that match the students preferences and provide the student with a set of learning objects matching to these preferences. The research at this point in time, does not however, cater for the evolving and changing needs of the learner.

Cristea (2004) highlights the importance of connecting adaptive educational hypermedia with cognitive/learning styles on a higher level of authoring. She briefly reviews some systems and models that address the same issue but with different perspectives. The first system is TANGOW that actually implements the Felder-Silverman dimensions of learning styles. The system includes low-level authoring patterns such as learning material combination in AND, OR, ANY and XOR relations. The second system is AHA!, a low level tool with great flexibility based on IF-THEN rules adaptation model. The aim is to investigate how to incorporate high-level specifications deriving from learning styles, especially those of field-dependent and field-independent styles, into the low-level instances and structures as required by the AHA! system.

Hong & Kinshuk (2004) develop a mechanism to fully model student's learning styles and present the matching content, including contain, format, media type, etc., to individual student, based on the Felder-Silverman Learning Style Theory. They use a pre-course questionnaire to determine a student's learning style or the student may choose the default style and he/she is then provided with material according to his/her style. The efficiency of student learning with the prototype presented has however not yet been tested.

Magoulas et al. (2003) stress on the importance to accommodating individual differences when designing web-based instructions. The authors propose a design rational and guidelines to implement adaptation strategies in such systems. Their model is based on the Kolb learning cycle and the Honey and Mumford (1986) learning styles.

Wolf (2002) proposes *iWeaver*, an interactive web-based adaptive learning environment. *iWeaver* uses the Dunn & Dunn learning style model and the Building Excellence Survey as an assessment tool to diagnose a student's learning preferences. Instead of focusing on student's learning preferences and offering contents matching only a specific learning style of learners, *iWeaver* offers and encourages the trial of different media representations. However, it does not adapt to the changing preferences of the learner.

A major issue in adapting to factors like learning and cognitive styles is that, very often, validity of learning styles instruments has been questioned by researchers. Furthermore, there exist a number of such instruments that categorise learners differently. On the other hand, research demonstrates that both low and average achievers earn higher scores on standardized achievement tests and aptitude tests when taught through their learning styles preferences (Dunn et al., 1995). At the same time, we need to take into account the fact that no single learning preference is better than any other and that preferences for learning styles keep changing over time for the learner. Students become more competent learners if they can have preferences for more than one single learning style. This makes them more versatile learners. This reflection can be sustained by the fact that, gifted learners prefer kinesthetic instruction, but they also have the ability to learn through auditory and visual means (Dunn, 1989). Furthermore, underachievers tend to have poor auditory memory; they learn better through graphics and animations rather than text (Dunn, 1998).

The Learning Object Approach to Instructional Design of Courseware

"Learning Objects are defined here as any entity, digital or non-digital, which can be used, re-used or referenced during technology supported learning. Examples of Learning Objects include multimedia content, instructional content, learning objectives, instructional software and software tools, and persons, organizations, or events referenced during technology supported learning" (LOM,2000)

Learning objects describe any chunk of *decontextualized* learning information, digital or non-digital, such as, an image, text, video, educational game or sound files. The aim of those entities is to provide a tremendous set of learning knowledge that once developed can be exchanged among organisations, and be used to build individual lessons and courses (McGreal & Roberts, 2001). The key factor for this flexibility is not performed by the physical learning object itself but by its standardised description or more precise in metadata specification (Rumetshofer & Wöß, 2003). As cited in IEEE (IEEE, 2002) Learning Object Metadata (LOM) specification:

"A metadata instance for a learning object describes relevant characteristics of the learning object to which it applies. Such characteristics can be regrouped in general, life cycle, meta-metadata, educational, technical, rights, relation, annotation, and classification categories."

Learning objects are often used as components to assemble larger learning modules or complete courses, depending on different educational needs. Assembling of these learning objects is also known as *content packaging* and provides a standardised way (metadata standards) to exchange digital learning resources between different learning systems. Packaging of learning objects of low granularity (for example, a web page) into larger granularity objects (such as a chapter) is similar to the Lego bricks approach that provides children with a set of *decontextualized* small granularity objects. Children assemble (*contextualize*) the relevant bricks to form, say a model of a house. Using learning objects to construct sections, chapters of modules, and eventually curriculums, is analogous to the Lego bricks approach (figure 2). It is worth mentioning here that, the Lego bricks approach has been termed as a too simplistic approach to introducing the concept of learning objects and is, thus, not universally accepted. Wiley proposes the atomic metaphor that departs from the Lego metaphor in some sense.

As it can be seen from figure 2, the learning objects support the principle that multiple representations of the content can be presented. Furthermore, learning objects can be used to represent structured, semi- or ill-structured domains and, therefore, such approaches would support a flexible instructional method for students with individual differences. Since learning objects are normally decontextualized chunks of information, they can be easily reused and applied in different learning contexts such that they support activities centred on the construction of knowledge and not merely the transfer of knowledge.

The particular pedagogical strength of such an approach is that it supports concepts originating from different learning theories such as cognitive flexibility theory, constructivism and learning style theory. It must be noted that this article does not cover the authoring methodology of a learning object itself that is beyond the scope.

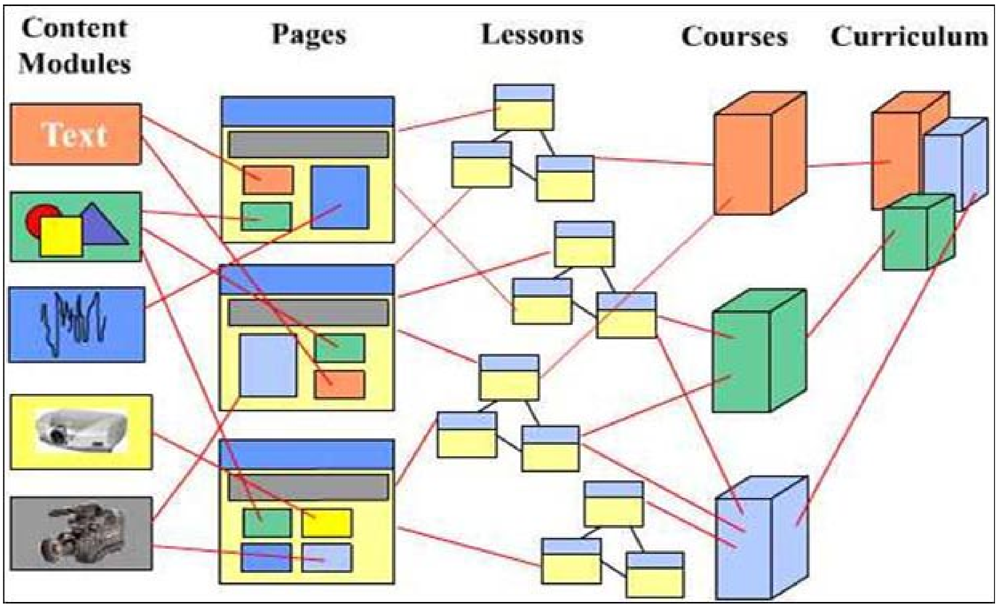

Figure 2: From Learning Objects to complete Curriculum: The Lego Metaphor

Extending the Learning Object Metadata for Adaptation Purposes

The concept of extending the learning object metadata to cater for psychological factors has been proposed by Rumetshofer & Wöß (2003). In this article their approach is extended in three ways: (1) More factors relating to individual differences are included in the metadata extension, as well as, field related to the pedagogical value and level of difficulty of the learning content, (2) The introduction of fuzzy (or belief) values for each aspect that is modelled, (3) A mechanism is provided to adapt to changing attitudes, characteristics and performance of a student both in the student model and in the learning object attributes model.

Cognitive Styles

Information Organising (Serial/holist)

Holists are global by initially creating broad interpretations of their environment while serialists are analytical by focusing on the details involved prior to making broad assumptions about their environment. According to Jonassen and Grabowski (1993), the serialist would prefer combining information linearly, and focusing on small chunks of information at a time. Holists are described as the opposite of serialists as being able to work on several aspects at the same time, having many goals, and working on topics that span varying levels of structure.

Information Gathering (Visual-Auditory-Kinaesthetic)

This instrument has been developed by Barbe & Milone (1980) that describes the learner as visual, auditory and kinaesthetic. Persons with a visual preference tend to show a greater ability to analyse and integrate visual information, mentally convert non-visual information into visual, and show superior retention of mental images (Ayersman & Minden, 1995). An auditory learner, on the other hand would prefer to process information in the form of verbs and, either written or spoken (Jonassen and Grabowski, 1993). Kinaesthetic learners prefer to process information through tactile means such as interactive media.

Cognitive Controls

Field dependence/independence

Field dependent individuals perceive objects as a whole while field independent students focus on parts of the object. The Rod and Frame test is the most widely used measure of field dependence and independence. The test consists of a rod inside a frame, both are moveable and the subject must adjust the rod to a true vertical position as the position of the frame is changed. Degree of error, or the number of degrees away from 90, is the measure used to score the test. The subject is considered field dependent or independent depending on the score on the test. The higher the score the more field dependent the subject is, the lower the score the more field independent the subject (Cognitive Styles: General Experimental Laboratory Cognitive Styles).

Cognitive Flexibility v/s Cognitive Constriction

Cognitive flexibility determines a student's ability to ignore distractions from his environment while he is focusing on some relevant information at hand. An individual high in flexibility would not be as easily distracted as someone who is classified as a constrictor (Ayersman & Minden, 1995).

Learning Styles

People prefer to learn in ways that are different from other people of the same class, culture or religion. This individual preference of how to learn is called the learning style preference. Education research and practice have demonstrated that learning can be enhanced when the instructional process accommodates the various learning styles of students (Buch & Bartley, 2002).

Honey and Mumford Learning Styles

The Honey & Mumford's (1986) Learning Style Questionnaire has four styles- Theorist, Activist, Reflector and Pragmatist. People with Activist preferences, are well-equipped for experiencing. People with Reflector approach, with their predilection for mulling over data, are well-equipped for reviewing and reflection. People with Theorist preferences, with their need to tidy up and have 'answers', are well-equipped for concluding. Finally, people with Pragmatist preferences, with their liking for things practical, are well-equipped for planning (Honey & Mumford, 1986).

Pedagogical Value / Effectiveness

Pedagogy is basically concerned with everything related to method of teaching. The pedagogical effectiveness/value of a learning object is therefore an important factor that can help while selecting a learning object for a student.

Level of difficulty

The level of difficulty value for a learning object is an important factor while deciding whether a student has satisfied the required milestone in terms of performance to move on to a different level. If the student is on a particular level, then it is important that learning objects to be selected are on the same difficulty level that suits the current achievement of the student.

A Method for Instructional Adaptation

The Student Model

The student model is an important part of the system, as it will contain the necessary individual adaptation attributes of the learner. From a recent survey at the University of Mauritius concerning students' learning styles and cognitive styles (Santally & Senteni, 2003), it was found that students can have preferences for one particular style, preference for more than one style and different levels of preferences for the different styles. For example, consider the V-A-K (Visual-Auditory-Kinaesthetic) Survey that was carried out and a sample of the results obtained from the student.

Student (Anonymous)	Visual	Auditory	Kinaesthetic
0200245	44	40	45
0200246	40	40	38
0200247	40	41	33

Figure 3: Table showing Cognitive Preferences

The questionnaire consists of three sections (visual-auditory-kinaesthetic) to determine the student's strength in each field. The minimum that a student could score in any section is 12 and the maximum is 60. In the above cases, the students have more or less varied level of preferences. Furthermore, in the survey, the minimum score was 30 and maximum score 45. The same observation was found in the Honey and Mumford (1986) Learning Style Questionnaire (LSQ) that was used with the students to determine their learning preferences.

It is clear that students would still learn even if they were not given materials according to their preferences, if the range of the scores is taken into account. Therefore, the goal of adaptation is this context is to present the student with the most suitable option in any given learning situation. The values, as shown in the table, would need to be rationalised since these will exist for the different elements that will be taken into account during the adaptation process. The process is simple:

Effective (*Belief*) value for student preference = Actual Value / $\sum$ (Auditory/Visual/Kinaesthetic)

The figure below shows the student entity and the main attributes that will be stored in the student model. There are four main components: (1) cognitive style, (2) cognitive controls, (3) learning style and (4) performance.

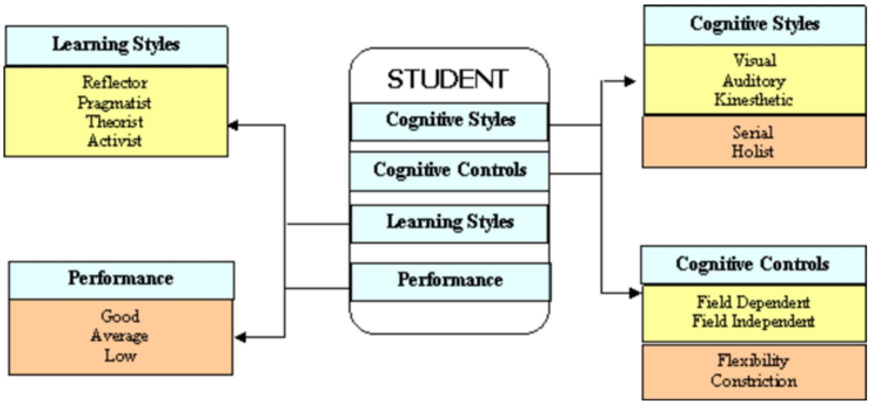

Figure 4: Components of the Student Entity

When a student registers in the system, his profile will also be stored so that this information may be used when he/she starts studying on a particular course. The information to be stored in this profile can be obtained from cognitive style and learning style surveys and diagnostic operations by the teacher or psychological experts.

In an adaptive setting, the values of these attributes may need to change as the student gains more experience with the system and reaches a higher maturity level. The criteria on which the values will be adjusted are three-fold: (1) the student's perceptions history, i.e., the different feedback he gives when a learning object is presented to him, (2) his performance in the different milestone tests, (3) by the teacher who takes a decision based on the students interaction history with the system. Both the system and the teacher, therefore, provide adaptivity to the student's learning.

The Content Model

The learning objects approach to designing e-learning courseware is not new. This is however, a field still under research and the under-utilisation of existing learning object repositories is a major concern for many educators and researchers involved in this area (Santally et al., 2004).

As with the learner's preferences, a learning object may have components that suit visual learners better but that also support kinaesthetic learners up to a certain extent. Therefore, the same mechanism of adding belief values (in the range of 0--1) is applied to the content model to show the extent that a learning object can support a particular aspect.

One constraint with the extension is that, in the current setting, there will be a need to compromise with the reusability of a particular learning object since the belief value for the 'pedagogical value' attribute will be restrictive to the context of utilisation of a particular learning object. A learning object may have a high pedagogical value when used in explaining the concept of *Mechanics* in an elementary Physics course but it might not have the same value if it were to be used in a *Mechanics* course for Maths.

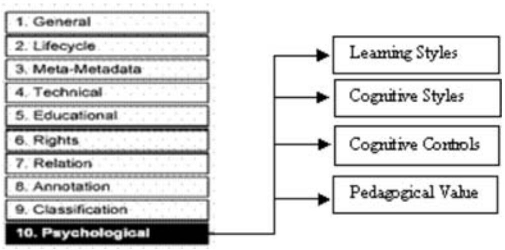

Figure 5: Extension of learning object metadata

A section, for instance, will therefore be represented as a sequencing (in some cases, there may be loops depending on the tutorial strategy) of learning objects. Each concept that will be illustrated in the section will consist of a series of learning objects with varying belief values for each component that has been added to the metadata description (figure 6).

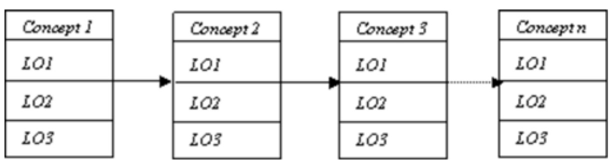

Figure 6: Learning Objects in Multiple Representations for Sequencing

Concept 1 can be taught using *LO1*, *LO2* or *LO3*. However, the selection of a learning object to teach a particular concept will depend on the student model and his current experience in the course. Sometimes, a learning object can be presented more than once depending on the level of understanding of the student or on the tutoring requirements for this section. Different students will therefore have different pathways to reach their learning goals and this brings the required flexibility and personalisation of the learning experience. A possible sequence for student x would be:

[Concept 1, LO1] → [Concept 2, LO3] → [Concept 3, LO1] → [Concept n, LO2]

Algorithm matching Content with the Student Profile

The algorithm, on which the system will decide which is the most appropriate learning object to be presented to the student, will be based on a probabilistic (*fuzzy*) approach. For each learning object that could be potentially presented to the student, the overall belief value or confidence factor (CF) will be computed and the one being closest to the student profile will be selected.

The problem of adaptation in the current context is quite complex since there are a number of parameters to consider for effective personalisation of the learning environment. Furthermore, the list of adaptation parameters is not exhaustive as other parameters can be progressively added. The algorithm reduces the complexity of the adaptation process and ensures that at any particular time the student is provided with the most appropriate learning object available.

1: Consider student profile X (for simplicity reasons, only some attributes are chosen):

In the student model, the following values will be allocated for the different attributes that are actually being modelled. These values will be initially obtained by conducting surveys using the appropriate learning/cognitive styles instruments available. For each student profile and learning object, the dominant attribute for each factor (learning styles, cognitive styles, cognitive controls) considered is in bold characters to facilitate understanding of the algorithm.

X → ***Visual (0.7)*** *Auditory (0.2) Kinaesthetic (0.1);* ***Field Dependent (0.6)*** *Field Independent (0.4);* ***Serial (0.8)*** *Holist (0.2); Flexibility (0.4)* ***Constriction (0.6)***

Now, consider that there are three possible learning objects to be selected for presentation to the student and that each learning object has been initially assigned the values related to the variables being modelled in the student profile. The teacher/instructional designer/instructional planner normally carries out this task:

LO1 → ***Visual (0.4)*** *Auditory (0.3) Kinaesthetic (0.3);* ***Field Dependent (0.2)*** *Field Independent (0.8);* ***Serial (0.6)*** *Holist (0.4); flexibility (0.6)* ***Constriction(0.4)***

LO2 → ***Visual (0.2)*** *Auditory (0.5) Kinaesthetic (0.3);* ***Field Dependent (0.7)*** *Field Independent (0.3);* ***Serial (0.2)*** *Holist (0.8); Flexibility (0.7)* ***Constriction (0.3)***

LO3 → ***Visual (0.5)*** *Auditory (0.2) Kinaesthetic (0.3);* ***Field Dependent (0.1)*** *Field Independent (0.9);* ***Serial (0.2)*** *Holist (0.8); flexibility (0.2)* ***Constriction (0.8)***

From the student profile, it is clear that student X has a visual preference, and is field dependent and is serialist and prefers constriction. Now the task is to identify which of the three available learning objects would be most appropriate for the student.

Step 1: Identify the LO(s) satisfying the most of the student's strengths

- LO1 (Visual [0.4] & Serial [0.6]), LO3 (Visual [0.5] & Constriction [0.8]), LO2 (Field Dependent [0.7])

Step 2: Compute overall belief of the values for each learning object by adding them together.

- LO1 [1.0], LO3 [1.3], LO2 [0.7]

Step 3: If overall belief value of more than one learning objects are equal, then the margin of error for each element is computed with respect to the student's preferences. Otherwise go to step 5 directly.

- LO1 [{0.4-0.7}+{0.6-0.8}] = -0.5
- LO3 [{0.5-0.7}+{0.8-0.6}] = 0

Step 4: If margin of error is equal for the learning objects, then the system selects a learning object based on its previous history. That is, the evaluations and perceptions of other students in terms of its pedagogical relevance and usefulness if any. If relevant statistics do not yet exist for the learning objects, a random selection is made.

Step 5: Select the learning object that has the maximum belief value

- LO3

2: Now consider student profile Y (for simplicity reasons, only some attributes are chosen):

Y → ***Visual (0.4) Auditory (0.4)*** *Kinaesthetic (0.2);* ***Field Dependent (0.6)*** *Field Independent (0.4);* ***Serial (0.8)*** *Holist (0.2);* ***flexibility (0.5) Constriction (0.5)***

The difference with the profile of this student is that he is visual, as well as, auditory and he has no exact preference between flexibility and constriction. It could be either way for him. The algorithm is slightly modified in this case since the student has preferences that are of the same strengths (magnitude):

Now consider that there are three possible learning objects to be selected for presentation to the student:

LO1 → ***Visual (0.5) Auditory (0.3)*** *Kinaesthetic (0.2);* ***Field Dependent (0.6)*** *Field Independent (0.4);* ***Serial (0.6)*** *Holist (0.4);* ***Flexibility (0.6) Constriction (0.4)***

LO2 → ***Visual (0.4) Auditory (0.4)*** *Kinaesthetic (0.2);* ***Field Dependent (0.3)*** *Field Independent (0.7);* ***Serial (0.4)*** *Holist (0.6);* ***Flexibility (0.6) Constriction (0.4)***

LO3 → ***Visual (0.5) Auditory (0.2)*** *Kinaesthetic (0.3);* ***Field Dependent (0.1)*** *Field Independent (0.9);* ***Serial (0.2)*** *Holist (0.8);* ***Flexibility (0.5) Constriction (0.5)***

Step 1: Identify the LO(s) satisfying the most of the student's strengths

- LO1 (Visual [0.5] & Serial [0.6] & flexibility [0.6]), LO2 (Visual [0.4] Auditory [0.4] & flexibility [0.6]), LO3 (Visual [0.5] flexibility [0.5] & Constriction [0.5])

Step 2: Compute the margin of error for each element is computed with respect to the student's preferences.

- LO1 [{0.5-0.4}+{0.3-0.4}+{0.6-0.6}+{0.6-0.8}+{0.6-0.5}+{0.4-0.5}] = -0.2
- LO2 [{0.4-0.4}+{0.4-0.4}+{0.3-0.6}+{0.4-0.8}+{0.6-0.5}+{0.4-0.5}] = -0.7
- LO3 [{0.5-0.4}+{0.2-0.4}+{0.1-0.6}+{0.2-0.8}+{0.5-0.5}+{0.5-0.5}] = -1.2

Step 3: If the margin of error of any two or more LO(s) from step 2 is equal, then compute the margin of error for only the values for which the LO(s) have maximum magnitude:

- LO1 [{0.5-0.4}+{0.6-0.6}+{0.6-0.5}] = 0.2
- LO2 [{0.4-0.4}+{0.4-0.4}+{0.6-0.5}] = 0.1
- LO3 [{0.5-0.4}+{0.5-0.5}+{0.5-0.5}] = 0.0

Step 4: If margin of error is equal again for the learning objects, then, the system selects a learning object based on its previous history, that is, the evaluations and perceptions of other students in terms of its pedagogical relevance and usefulness if any. This will be obtained through the 'pedagogical value' attribute included in the learning object extended metadata. The lecturer/pedagogical designer will initially set the pedagogical value of a learning object and it will be adjusted based on perceptions and extent of use by students. If relevant statistics do not yet exist for the learning objects, a random selection is made. Else go to step 5.

Step 5: Select the learning object that has the maximum belief value

- LO1

Discussion of the Algorithm

A java application has been developed to randomly generate a set of learning objects for a particular concept, values for the variables in the extended learning object metadata and to randomly generate student profiles. At this stage, there is no focus on the content of the learning object and the sequencing mechanism. The mathematical validity of the algorithm is tested since the program will generate a set of values and based on the algorithm, it selects the most appropriate learning object for a particular student profile. On the other hand, a pedagogical expert then checks the learning objects generated with respect to the student profiles. Based on the values generated, the expert will give his judgement on what learning object he would select for the student in question. The degree of coupling of the expert's judgement and the system gives an initial evaluation of the algorithm.

Figure 7 shows the details of some of the student profiles and learning objects that were generated for to test the algorithm. For each student profile and set of available learning objects, the *"Expert belief"* column illustrates the belief of a pedagogical expert/instructional designer while the outcome of applying the algorithm devised is shown in the *"Computed value"* column. The very first observation from the expert's choice is that the learning object, having more variables satisfying the student's strength, was instantly chosen to be the most appropriate. In fact, this approach of the expert is natural and is the first step of the algorithm, i.e., to identify the learning objects satisfying most of the student's preferences. This is illustrated in the figure from all student profiles (SP) except for student profile 6 and 8. For student profile 6, there are two learning objects that satisfy two of the student preferences. The expert therefore has chosen the learning object, which has the higher overall combination value.

For learning object 8, it seems that it is more difficult to choose the most appropriate one as both learning objects have more or less the same attributes. The next step now consists of applying all the steps in the algorithm to see if the final result has some degree of correlation with the expert's choice. Both versions of the proposed algorithm are applied to verify consistency and correctness of the process. The application of the first version of the algorithm shows that except for student profile 8, all the decisions of the expert are matched by the system. The pedagogical value in this case seems to have influenced the expert's decision towards LO2 in that case. Since the student profiles do not consist of attributes having same strengths, the first version of the algorithm is perfectly applicable.

From the table, it is obvious that both versions of the algorithm show consistency with each other. The second algorithm matched all the learning objects that were selected from the first algorithm, except for student profile 2. In this particular situation, LO2 would have been selected with the first algorithm while LO1 would be the choice if the second algorithm were applied. In this particular case, the expert would also opt for LO2 for the principal reason that there are more attributes satisfying the student's preferences. With the first algorithm, the total strength of the belief value is also higher than LO1. However, there is also an arguable case for LO1.

LO1 is preferred using the second algorithm (although in this situation, algorithm 2 would not have been applied) and its pedagogical value is higher than LO2. This is good evidence in support to a fuzzy approach to instructional adaptation. Furthermore, adaptation in educational contexts should not only be just a matter of analysing and comparing numerical values. When the problem is pedagogical, then experience, expertise and intuition of the teacher play a very important part in the process. It is clear that in the case of SP2, the number of attributes satisfying the student's preferences influenced the decision of the pedagogical expert while in the case of SP 8, the pedagogical value was the determinant factor.

	COGNITIVE STYLES					**COGNITIVE CONTROLS**						
	Visual	**Auditory**	**Kinesthetic**	**Serialist**	**Holist**	**FD**	**FI**	**Flexibility**	**Constriction**	**Expert Belief**	**Computed A1 --- A2**	**Pe**
SP 1	**0.15**	**0.6**	**0.25**	**0.1**	**0.9**	**0.18**	**0.82**	**0.1**	**0.9**			
LO1	0.2	0.64	0.16	0.28	0.72	0.55	0.45	0.66	0.34		(1.36) --- (-1.07)	
LO2	0.13	0.32	0.55	0.23	0.77	0.79	0.21	0.34	0.66		(1.43) --- (-1.26)	
LO3	0.3	0.24	0.46	0.3	0.7	0.11	0.89	0.23	0.77		**(2.36)** --- **(-0.62)**	
SP 2	**0.58**	**0.28**	**0.14**	**0.97**	**0.03**	**0.52**	**0.48**	**0.45**	**0.55**			
LO1	0.35	0.51	0.13	0.92	0.08	0.69	0.31	0.94	0.06		(1.61) --- **(-0.60)**	
LO2	0.51	0.37	0.12	0.65	0.35	0.2	0.8	0.43	0.57		**(1.73)** --- (-0.69)	
LO3	0.28	0.42	0.3	0.52	0.48	0.5	0.5	0.85	0.15		(1.02) --- (-1.17)	

SP 3	**0.58**	**0.28**	**0.14**	**0.26**	**0.74**	**0.25**	**0.75**	**0.13**	**0.87**		
LO1	0.57	0.32	0.11	0.67	0.33	0.36	0.64	0.31	0.69		**(1.90) --- (-0.71)**
LO2	0.21	0.67	0.11	0.38	0.62	0.71	0.29	0.95	0.05		(0.62) --- (-1.77)
LO3	0.18	0.67	0.14	0.81	0.19	0.96	0.04	0.22	0.78		(0.78) --- (-1.75)
SP 4	**0.33**	**0.18**	**0.49**	**0.69**	**0.31**	**0.61**	**0.39**	**0.2**	**0.8**		
LO1	0.71	0.14	0.15	0.43	0.57	0.9	0.1	0.1	0.9		**(1.80) --- (-0.21)**
LO2	0.36	0.22	0.42	0.18	0.82	0.49	0.51	0.98	0.02		--- (-1.48)
LO3	0.18	0.6	0.21	0.04	0.96	0.56	0.44	0.56	0.44		(0.56) --- (-0.62)
SP 5	**0.24**	**0.56**	**0.2**	**0.47**	**0.53**	**0.73**	**0.27**	**0.06**	**0.94**		
LO1	0.23	0.38	0.39	0.64	0.36	0.18	0.82	0.24	0.76		(0.76) --- (-1.08)
LO2	0.13	0.23	0.64	0.1	0.9	0.09	0.91	0.84	0.16		(0.90) --- (-1.38)
LO3	0.56	0.18	0.26	0.01	0.99	0.83	0.17	0.8	0.2		**(1.82) ---(-0.56)**
SP 6	**0.4**	**0.23**	**0.37**	**0.68**	**0.32**	**0.3**	**0.7**	**0.9**	**0.1**		
LO1	0.23	0.39	0.38	0.01	0.99	0.12	0.88	0.29	0.71		(0.88) --- (-1.27)
LO2	0.29	0.23	0.48	0.81	0.19	0.22	0.78	0.17	0.83		**(1.59) --- (-0.63)**
LO3	0.39	0.26	0.35	0.63	0.37	0.81	0.19	0.24	0.76		(1.02) --- (-1.23)
SP 7	**0.26**	**0.35**	**0.39**	**0.93**	**0.07**	**0.59**	**0.41**	**0.62**	**0.38**		
LO1	0.28	0.17	0.55	0.95	0.05	0.22	0.78	0.85	0.15		**(2.35)** ---(0.04)
LO2	0.16	0.71	0.13	0.63	0.37	0.05	0.95	0.74	0.26		(1.37) --- (-0.98)
LO3	0.64	0.26	0.11	0.49	0.51	0.57	0.43	0.96	0.04		(1.53) ---(-0.40)
SP 8	**0.61**	**0.17**	**0.22**	**0.43**	**0.57**	**0.18**	**0.82**	**0.1**	**0.9**		
LO1	0.71	0.15	0.13	0.38	0.62	0.23	0.77	0.45	0.55		**(2.65) ---(-0.25)**
LO2	0.41	0.35	0.24	0.5	0.5	0.44	0.56	0.42	0.58		(2.05) --- (-.85)
LO3	0.17	0.35	0.48	0.85	0.15	0.68	0.32	0.52	0.48		--- (-1.78)

Figure 7: Learning Objects/Students Profile Generation & Selection for Presentation

Future Work

Updating mechanism for the student and the content model

Both the student model and the content model need to be updated with time as students use the system. One of the main components that will be used for student model updating will be the performance of the student in different tests given by the system, and other activities as planned by the lecturer. The system will basically log and keep a history of all activities of the student in the system as well as the evaluation/rating a student gives to a learning object. The tutor/pedagogical experts will have access to these history logs in statistical format so that they can make decisions about the updating of both student and content models for each particular student and course. This technique has however a constraint since the complexity of the task will grow exponentially with the increasing number of students and learning objects. In the long run, a reliable method will be conceived and tested that will allow automatic updates of these models.

System Evaluation with a group of Students

The first prototype system will be tested with a group of secondary school students for a Physics class. A first evaluation will be made in terms of the (1) pedagogical efficiency of the approach, (2) student's perceptions of learning with the system, (3) the relationship of student's perceptions with respect to system and tutor approaches to the updating and setting up of the student and content model. These evaluations will help in contributing to the research of personalisation since a good indication of the usefulness of adapting to the individual differences will be hopefully obtained.

Assigning "importance weightage" for each factor

The algorithm devised assumes that all factors that are considered in the personalisation process are equally important to be taken into account. Catering for individual differences may also suggest that there is a need to with the student preferences. Some controls may affect a student learning experience more than another control. Therefore, if these differ in the learning objects metadata, there is a need to adapt the algorithm to cater for the factors that affect the student's learning experience the most.

Conclusion

This paper describes a method for instructional adaptation to individual differences and proposes a simple mathematical algorithm to assign belief values to individual factors that are modelled. The way the algorithm has been designed shows that a fuzzy approach to instructional adaptation is favoured in the process. A simple simulation of student profiles and learning objects shows that the algorithm works well and the results do highly correlate with the choice of a pedagogical expert. This suggests that automation of this process could yield satisfactory results. The next phase of the research will consist of the implementation and testing of a prototype learning environment with students to evaluate the approach. An updating mechanism will finally be worked out, based on an analysis of student's interaction with the system.

References

Ayersman D.J., & Minden A. (1995). Individual differences, computers and instruction. *Computers in human behaviour*, 11(3-4), 371-390.

Cristea, A. (2003). Adaptive Patterns in Authoring of Educational Adaptive Hypermedia. *Educational Technology & Society*, 6 (4), 1-5, Available at http://ifets.ieee.org/periodical/6_4/1.pdf

Barbe, W., & Milone, M. (1980). Modality. *Instructor*, 89(6), 44-46.

Brusilovsky, P. (2001). Adaptive Hypermedia, *User Modeling and User-Adapted Interaction* 11, 87-110.

Brusilovsky, P. (1996). Methods and techniques of adaptive hypermedia. User Modeling and User-Adapted Interaction, 6(2), 87-129.

Buch, K., Bartley, S. (2002). Learning style and training delivery mode preference. *Journal of Workplace Learning*. 14(1), 5-10

Cristea, A. (2004). Adaptive and Adaptable Educational Hypermedia: Where Are We Now and Where Are We Going?, Proceedings of Web-based Education, Feb 16-18, Innsbruck, Austria.

Dunn R (1989). Individualizing instruction for mainstream Gifted Children. in Teaching Gifted & Talented learners in regular classrooms edited by R Milgram. Springfield, ill: Charles C. Thomas

Dunn, R., Griggs, S.A., Olson, J., Gorman, B, & Beasly, M. (1995). A meta analytic validation of the Dunn and Dunn learning styles model. Journal of Educational Research, 88(6), 351-66.

Dunn R. (1998). Commentary: Teaching Students through their perceptual strengths or preferences. *Journal of Reading*. 31(4); p. 304-309.

Cognitive Styles: General Experimental Laboratory Cognitive Styles. Retrieved 10 November 2004 from http://www.ithaca.edu/faculty/stephens/csfinal.html

Fischer, G., Mastaglio, T., Reeves, B., and Rieman, J. (1990) Minimalist explanations in knowledge-based systems. In: Proc. of 23-th Annual Hawaii International Conference on System Sciences, Kailua-Kona, HI, IEEE (1990) 309-317

Hong H. & Kinshuk (2004). Adaptation to Student Learning Styles in Web Based Educational Systems. In L. Cantoni & C. McLoughlin (Eds.) Proceedings of ED-MEDIA 2004 - World Conference on Educational Multimedia, Hypermedia & Telecommunications (June 21-26,2004, Lugano, Switzerland), USA: AACE, 491-496 (ISBN 1-880094-53-3)

Honey P and Mumford A (1986). The manual of learning styles Peter Honey, Maidenhead.

Jonassen & Grabowski, (1993). Individual differences and instruction. New York: Allen & Bacon.

LOM (2000). LOM working draft v4.1 [On-line]. Available: http://ltsc.ieee.org/doc/wg12/LOMv4.1.htm

Magoulas G., Papanikolaou, K., Grigoriadou, M. (2003). Adaptive web-based learning: accommodating individual differences through system's adaptation. *British Journal of Educational Technology*. Vol 34(4). [Online] Available: http://www.dcs.bbk.ac.uk/~gmagoulas/bjet.pdf

McGreal, R., and Roberts, T. (2001). A Primer on Metadata for Learning Objects, http://www.elearningmag.com/issues/Oct01/learningobjects.asp.

IEEE (2002). *Learning Object Metadata*, [Available] http://ltsc.ieee.org/doc/wg12/LOM_WD6_4.pdf. Retrieved 23 June 2002

Nichols, M. (2003). A theory for eLearning. *Educational Technology & Society*, 6(2), 1-10, Available at ttp://ifets.ieee.org/periodical/6-2/1.html

Patel A. & Kinshuk (1997). Intelligent Tutoring Tools in a Computer Integrated Learning Environment for introductory numeric disciplines, *Innovations in Education and Training International Journal*, Vol. 34 No. 3, p. 200-207.

Rumetshofer, H., & Wöß, W. (2003). XML-based Adaptation Framework for Psychological-driven E-learning Systems. *Educational Technology & Society*, 6 (4), 18-29, Available at http://ifets.ieee.org /periodical/6_3/4.pdf

Santally, M., Senteni, A. (2003). Learning and Cognitive Styles Consideration in the Design of Hypermedia Courseware for Distance Learning. International Conference on Open & Online Learning 2003 Proceedings, Reduit, Mauritius. [Online] Available at: http://icool.uom.ac.mu/

Santally, M., Govinda, M., Senteni, A. (2004). Reusable Learning Objects Aggregation for e-Learning Courseware Development at the University of Mauritius. Instructional Technology and Distance Learning. Vol 1(7). pp. 27-34 [Online] Available http://www.itdl.org/Journal/Jul_04/article02.htm

Wiley, D (2000). The Instructional Use of Learning Objects. Bloomington, IN: AECT. Available online at http://reusability.org/read/

Wolf, C. (2002).iWeaver: Towards an Interactive Web-Based Adaptive Learning Environment to Address Individual Learning Styles. European Journal of Distance Learning (EuroDL). [Online] Available: http://www.eurodl.org/materials/contrib/2002/2HTML/iWeaver