A NOVEL APPROACH FOR SELECTION OF LEARNING OBJECTS FOR PERSONALIZED DELIVERY OF E-LEARNING CONTENT

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ABSTRACT

Personalized E-learning, as an intelligent package of technology enhanced education tends to overrule the traditional practices of static web based E-learning systems. Delivering suitable learning objects according to the learners' knowledge, preferences and learning styles makes up the personalized E-learning. This paper proposes a novel approach for classifying and selecting learning objects for different learning styles proposed by Felder and Silverman The methodology adheres to the IEEE LOM standard and maps the IEEE LO Metadata to the identified learning styles based on rule based classification of learning objects. A pilot study on the research work is performed and evaluation of the system gives an encouraging result.

KEYWORDS

E-learning; Learning Styles; IEEE LOM, Classification;

1. INTRODUCTION

E-learning, regarded as technology package of education has attained significance due to its advantages of learning at any time, any pace and from anywhere. Learning is always a cognitive activity which differs from learner to learner and so raises the need of personalized E-learning. Recent research on the learning process has shown that there is a difference of learning styles among the individual learners and different teaching and learning resources are indispensable to satisfy their learning needs.

Learning Object (LO), a collection of content items, practice items and assessment items for education is an inevitable constituent of any E-learning systems. LOs' metadata need to be recorded in order to classify them according to the style of the learner. The IEEE Learning Technology Standards Committee (LTSC) has prescribed a standard for describing the metadata instance for an LO to facilitate search, evaluation, acquisition, and use of learning objects [2][6][8].

This paper proposes a novel methodology which classifies any LO that adheres to the IEEE LOM standard into different teaching strategies, then mapping these strategies to different learning styles proposed by Felder Silverman catering to learner needs.

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2. RELATED WORKS

Deriving a personalized E-learning environment is a crucial area of research now. Recent research works [1][4][6][7][8][10][11] illustrate the need of personalization of E-learning systems. Adaptation of Learning objects (LOs) is considered as one of the major aspects of personalization [1][4][6][7][11]. The need of customized LO repositories and selection is specified in [8][18]. LO selection problem in intelligent learning systems is addressed in [6] which produce a decision model not compliant with IEEE LOM standard. An architecture based on Semantic Web for E-learning is defined in [1] which understands the learners' preferences and interpreting it as ontology. The use of learning content in different contexts and in different formats most appropriate for an individual learner is presented in [10].

There exists different methodologies to assess learner styles and among those Felder Silverman model plays a significant role [3][9][12][13]. A research work [12] states a way for generation of personalized courses from suitable repositories of learning nodes. A theoretical work is proposed [7] for the definition of learning profiles and classification of the student within a given learning profile. Another work proposed [15] a learning style classification mechanism with k-nearest and genetic algorithm to classify and then identify the learners' learning styles. The study did not refer any proven learning styles. A study [19] used Bloom's taxonomy and Genetic algorithms to personalize e-learning. Franzoni [5] suggested the teaching strategies according to Felder Silverman model and appropriate electronic media.

3. FELDER SILVERMAN LEARNING STYLE

Learning styles are various approaches or ways of learning. Though there are many learning models available, such as David Kolb's, Pask's, Honey & Mumford's, Gregorc's etc., Felder and Silverman Learning style model has been taken frequently by many research works[5][7][12][16][17]. This model classifies students' preferred learning style on four major dimensions [3][9][13] according to their responses for an Interactive Learning Style(ILS) Questionnaire. Table1 shows the four dimensions and two different behaviors of each dimension. This proposed research work uses this model because its ILS Questionnaire gives us the possibility of linking directly its results to automatic adaptive environments.

Table 1. Felder Silverman Model of Learning Style

Dimension	Learning Style	Explanation
Participation	Active (A)	Needs hands on work experiments
	Reflective(R)	Passive and prefer to think things
Processing	Sensory (S)	Believes Concrete facts
	Intuitive (I)	Conceptual and theoretical view
Presentation	Visual (Vi)	Prefers diagrams, pictures, visual presentations
	Verbal (V)	Audio Narration or display of text
Organization	Sequential(Sq)	Needs information in a linear fashion
	Global (G)	Prefers overall view

From Table1, it is inferred there are 16 different combinations of the learner characteristics for eg.{(A,S,Vi,Sq)-1, (A,S,Vi,G)-2,… (R,I,V,Sq)-15, (R,I,V,G)-16}

4. PROPOSED METHODOLOGY

The proposed system consists of two important modules – Learner Profile modeling module, Pedagogical module. The system architecture is given in Figure 1.

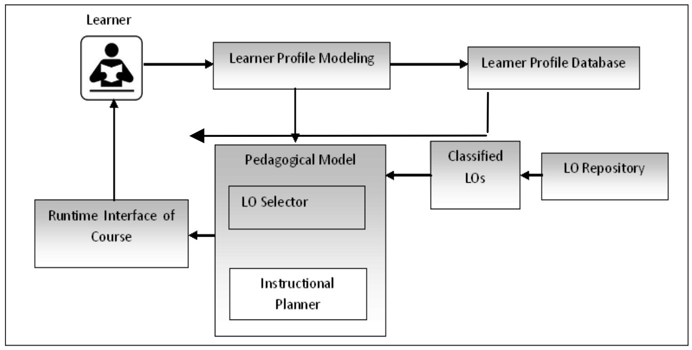

Figure 1 Proposed System Architecture

4.1. Learner Profile Modeling

Initially, the learners are asked to answer Felder Silverman Interactive Learning Style Questionnaire and their preferred style of learning is recorded in Learner Profile Database. Learner Profile model studies the learner and updates his metadata on the preferred learning style. The learner is classified into one of the 16 categories listed above. The learner profile is represented in XML.

4.2. Learning Object (LO) Repository & Classified Los

Each learning objective of the course is designed in multi ways representing the different learner characteristics and stored in LO Repository. The identified learning styles according to the Felder Silverman model are given in Table 1. For a learning objective of the unit, the LOs are designed with the following strategies:

- Unit Overview – Visual(OV)
- Unit Overview Verbal (OVe)
- Theoretical explanations (T) – Lecture materials in the form of narrative text
- Visual Presentations (VP) – Lecture materials along with supporting visuals
- Interactive Demonstrations(ID) – Prompting learners to participate and give answers
- Examples (E) – Illustrations, instances E.g. Pointer increment
- Simulations (S) – Small models of the systems E.g. Navigation of arrays
- Exercise Problems(EP) – Prompting learner to complete small problems
- Case study(C) - A complete explanation of the existing system

Also, the LOs are given a suitability rating (**SLO_{kij}**) which decides the suitability of the learning object j in the topic i for a learner with learning style j.

$$SLO_{kij} = 0 \text{ or } 1 \qquad \text{(Initially 1)} \qquad (1)$$

k = 1..16 reflecting 16 dimensions of Felder –Silverman Learning Style
i = 1..n where n- number of topics in a unit of syllabus
j = 1..m where m – number of LOs for a particular topic i

Table 2 shows the recommended teaching strategies for different learning behavior.

Table 2. Recommended Teaching Strategies

Dimension	**Learning Behaviour**	**Recommended Teaching strategies**
Processing	Active (A)	Interactive Demonstrations, Exercise Problems
	Reflective(R)	Visual Presentation, Examples
Presentation	Sensory (S)	Examples, Case Study
	Intuitive (I)	Theoretical Explanations, Visual Presentations, Simulations
Participation	Visual (Vi)	Visual Presentations, Visual Overview
	Verbal (V)	Theoretical explanations, Verbal overview
Organization	Sequential(Sq)	Visual Presentations, Theoretical explanations
	Global (G)	Visual or verbal overview

The LOs are maintained in XML representation following IEEE LOM standard. It is observed that the classification of the LOs could be made based on metadata elements [5][8][10]. The proposed work takes 6 metadata elements listed as: **Structure (1.7), Aggregation Level (1.8), Technical Format (4.1), Interactivity Type (5.1), Learning Resource Type (5.2), and Interactivity Level (5.3).** Based on the values of the metadata elements of the LOs they are classified into any one of the 8 teaching strategies. LOs are mapped to the respective teaching strategies using rule based classification and Table 3 gives the rule based classification strategy on the metadata elements and their permissible values.

Table 3. Rule based strategy for classifying Learning Objects

Teaching Strategy Classification	**IEEE LO Metadata Elements & values**					
	1.7	**1.8**	**4.1**	**5.1**	**5.2**	**5.3l**
Topic Overview : Visual(OV)	Collection / Hierarchic	2	Video/Mpeg	Expositive	Index	Low
Topic Overview : Verbal (OVe)	Collection / Hierarchic	2	Text/Html	Expositive	Index	Low
Theoretical explanations (T)	Atomic	1	Text/Html	Expositive	Narrative text/ Lecture	Low
Visual Presentations (VP)	Atomic	1	Video/Mpeg	Mixed	Diagram, Figure, Graph, Table	Med
Interactive Demonstrations (ID)	Atomic	1	Application	Active	Questionnaire	Very high
Examples (E)	Atomic	1	Text/Html	Expositive	Experiment	Low
Simulations (S)	Atomic	1	Application Video/Mpeg	Expositive	Simulation	Low
Exercise Problems(EP)	Atomic	1	Text/Html	Active	Self assessment	High
Case Study(C)	Atomic	1	Text/Html	Expositive	Problem Statement	Low

LO classification involves the use of Java code to parse the XML metadata elements of LOs and classify them into one of the teaching strategies.

Eg. A. If Value (5.3) = “Medium” Then LO class = “VP” (Visual Presentations)
B. If Value (1.8) = “2” and Value (4.1) = “Video/Mpeg” Then LO class = “OVe”

4.3. Pedagogical Module

Pedagogical Module comprises two sub modules: LO Selector, Instructional Planner. LO Selector selects all the LOs for a given topic from the metadata element **1.5-Keyword** which describes the topic of the Learning Object. Instructional Planner matches the Learner Profile model with the selected LOs and performs classification and a teaching sequence for a particular topic. Table 4 shows the different learning dimensions of Felder & Silverman and their matching teaching strategies.

Table 4 Learning Styles and their matching teaching strategies

		SUITABILITY OF THE TEACHING STRATEGIES								
		OV	**Ove**	**T**	**VP**	**ID**	**E**	**S**	**EP**	**C**
Learning Style	**Active**	NA	NA	-	-	X	-	-	X	-
	Reflexive	NA	NA	X	X	-	X	X	-	X
	Sensory	NA	NA	NA	NA	NA	X	-	-	X
	Intuitive	NA	NA	NA	NA	NA	-	X	X	-
	Visual	X	-	-	X	NA	NA	NA	NA	NA
	Verbal	-	X	X	-	NA	NA	NA	NA	NA
	Sequential	-	-	NA	NA	NA	NA	NA	NA	NA
	Global	X	X	NA	NA	NA	NA	NA	NA	NA

X → suitable, - → Not suitable, NA → Not applicable for this category

Based on the teaching/learning strategies prescribed in Table4, a combination of the teaching/learning strategies is provided by the Instructional Planner: for eg. Teaching strategies for a category **(A,S,Vi,Sq) : ID,E,C,VP ; (R,I,Ve,G) : T,,S,EP,T,OVe**

Though the pedagogical module recommends the given teaching sequence, it is not enforced on the learner to follow the recommended teaching strategy due to their behavioral changes. The learners are given the choice of following the recommended sequence or navigating between selective LOs of a particular topic in his/her preferred order.

5. IMPLEMENTATION AND EVALUATION OF THE SYSTEM

The proposed system was implemented and tested for a unit of the PG Course “Programming in C”: Arrays & pointers in C. Learning Objects were designed according to the defined teaching strategies and LO repository is created with 72 LOs (8 topics with 9 teaching strategies for each). A web based application was developed with PHP and MYSQL running with Apache Tomcat Web Server where Java Code was used to implement Learner profile modeling and pedagogical module.

A set of 99 PG students were asked to undertake the pilot study of the research work. The students were initially asked to respond to the ILS Questionnaire giving a reasonable amount of time and their profile is recorded. The students were asked to undertake the course by going through all the LOs of a particular topic (i.e.) not restricting them to the recommended teaching sequence. At the end of the delivery of each LO, a short feedback questionnaire on the usefulness of the LO is prompted to the learner. The LO is rated with the user feedback having positive added values for agreement(Strongly agree : 2; Agree : 1) and negative values for disagreement (Disagree : -1 ; Strongly disagree : -2).

Let the feedback value given by a student of learning style **k** for a single LO is $\mathbf{Val_{ij}}$ where **i** is the topic number and **j** is the LO number where $\mathbf{Val_{ij}}$ is the feedback value between 12 and -12. Applying min-max normalization, the normalized feedback $\mathbf{NVal_{ij}}$ is obtained from the given formula:

$$\mathbf{NVal_{ij} = (Val_{ij} + 12) / 24 ; \quad range: 0 \text{ to } 1} \qquad \textbf{(2)}$$

This normalized feedback given by the student of learning style k is used to dynamically adjust the suitability factor (**SLO**) of an LO to a particular learning style. Lesser the feedback value, lesser the suitability of the system is the hypothesis chosen which is universally accepted for evaluating any feedback. The suitability factor is obtained from the given formula which depreciates the suitability factor from 1 to 0 by its uselessness.

$$\mathbf{SLO_{kij} = SLO_{kij} - ((1- NVal_{ij}) / n)} \qquad \textbf{(3)}$$

where n = number of students of style k

The suitability factor of an LO is thus adjusted for n students of learning style k. After evaluating n students of learning style k, the LO is accepted as a part of recommended teaching strategy for the learning style k if $\mathbf{SLO_{kij}}$ value for the LO is above a given threshold, in this case, threshold is chosen as 0.5. Table 7 shows the mean cumulative suitability factors of all LOs in the given topics for all the existing learning styles. From Table 7, the following observations are made.

For a particular teaching strategy **t** (e.g. T – Narrative text), two sets of learners are formed. The first set of learners **(t1)** is with the learning style which has **t** in its recommended teaching sequence and the second set of learners **(t2)** does not have **t** in their recommended teaching sequence. The mean value of suitability factors of both the sets are calculated and represented in graph as Figure 2.

Table 7 Mean of Cumulative Suitability factors of LOs for 11 learning styles

		Learning Styles										
		1	**2**	**4**	**5**	**6**	**8**	**9**	**12**	**13**	**14**	**16**
Teaching Strategies	OV	0.4	0.7	0.4	0.3	0.8	0.4	0.5	0.4	0.4	0.9	0.4
	Ove	0.2	0.3	0.8	0.5	0.3	0.9	0.3	0.8	0.4	0.4	0.8
	T	0.2	0.2	0.9	0.2	0.3	0.8	0.3	0.9	0.3	0.4	0.9
	VP	0.8	0.7	0.4	0.8	0.8	0.3	0.8	0.4	0.9	0.9	0.4
	ID	0.7	0.8	0.7	0.8	0.8	0.8	0.4	0.3	0.5	0.5	0.4
	E	0.8	0.8	0.8	0.4	0.5	0.5	0.8	0.9	0.9	0.9	0.8
	S	0.4	0.3	0.3	0.7	0.7	0.7	0.8	0.7	0.8	0.7	0.6
	EP	0.8	0.7	0.7	0.8	0.7	0.8	0.4	0.5	0.8	0.8	0.8
	C	0.7	0.6	0.7	0.3	0.4	0.3	0.8	0.8	0.7	0.7	0.8

The observation of the graph clearly shows that their preference to the recommended teaching strategy is always higher to the non recommended teaching strategy. And also the standard deviation values of the suitability factors states that there is no significant difference in the rating of an LO of teaching strategy **t** by a particular set of learners whether **t** is recommended to them or not.

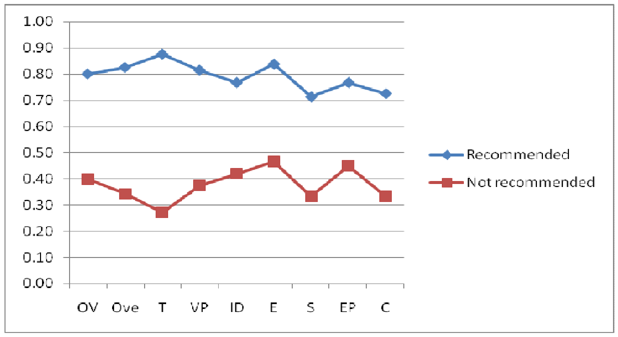

Figure 2 Rating of the recommended teaching strategies

6. CONCLUSION AND FUTURE WORKS

This research work is an experimental effort for approaching personalized E-learning with respect to differing learning styles. It prescribes a way of mapping different learner styles with suitable learning objects. It also provides a means for accessing any learning objects which adheres to the IEEE LOM standard in public repositories to be classified with its metadata information.. The study does not declare the system as a complete alternate to the human teaching system. But it could be a supplementary process in selective topics.

The future work pertains to the extension of the system into a complete prototype which considers the learner knowledge level, specific interests in addition to the learning style. Also, the system would be made to change its decision on knowledge level and learning style dynamically and also considering the learners' interests, time spent with each topic and additional information accessed during navigation.

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