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Personalised learning resources based on learning style

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ABSTRACT: In order to solve the problem of determining personalised learning resources, a strategy is proposed, which includes: building a curriculum knowledge ontology, building a learner model of initial learning style and correcting the learner model. Based on the learning data about the learner, generated through the initial learning style and corrected learning style, the personalised resources recommendation can be built and provided to the learner. The strategy outlined in this article may play an important guiding role in research work into designing and realising personalised learning resources systems.

INTRODUCTION

At present, some common learning management systems (LMS), e.g. Blackboard, WebCT, Moodle and Sakai, provide the learners with an almost identical order of learning activities and learning resources; while, in fact, learners have individual differences and different learning styles [1]. Therefore, it is currently an important issue to realise support for different learners with existing learning resources.

Put forward in this article is a recommendation for personalised learning resources based on learning style. This approach introduces semantics, an ontological description of learning resources and a semantic diagnosis of learning styles. The intent is to display learning resources and teaching strategy dynamically, according to a user model. This will realise the reuse of shared resources and personalised learner support.

CURRICULUM ONTOLOGY

Knowledge in ontology has strong semantic relationships. Through concept attributes, it can not only show the current learning knowledge point, but also prior knowledge, later knowledge, learned knowledge and knowledge relevant to the learner [2].

Thus, it is the precondition of a personalised learning resources recommendation to build a good ontology. This strategy builds a curriculum knowledge ontology, with concept analysis, general indicators and description, as shown by the triad:

$$O = < C, P, R >$$

O indicates the curriculum content ontology; *C* indicates the concept ontology; *P* indicates the property ontology; and *R* indicates the concept ontology. Take *cycle control* in Chapter VI of *C Programming* as an example [3]. First, determine the knowledge points for the concept, i.e.

C (cycle control) = {cycle, goto cycle, while cycle, do while cycle, for cycle, cycle nest, comparison cycle, break statement and continue statement}.

Second, to resolve resource-sharing and reuse properly, set concept property according to the Specification for Learning Object Metadata [4], i.e.

P (concept property) = {title, description, key words, media type and suitable object}, to explain the knowledge points. Then, build the ontology with the ontology editor *PROTEGE*, developed by Stanford University [5].

Figure 1 shows the concept model of knowledge in the chapter. The ontology document is in the Web ontology language (OWL) format [6]. Finally, access the OWL document with Java, Jena Frame and the ontology querying language, SPARQL [7][8].

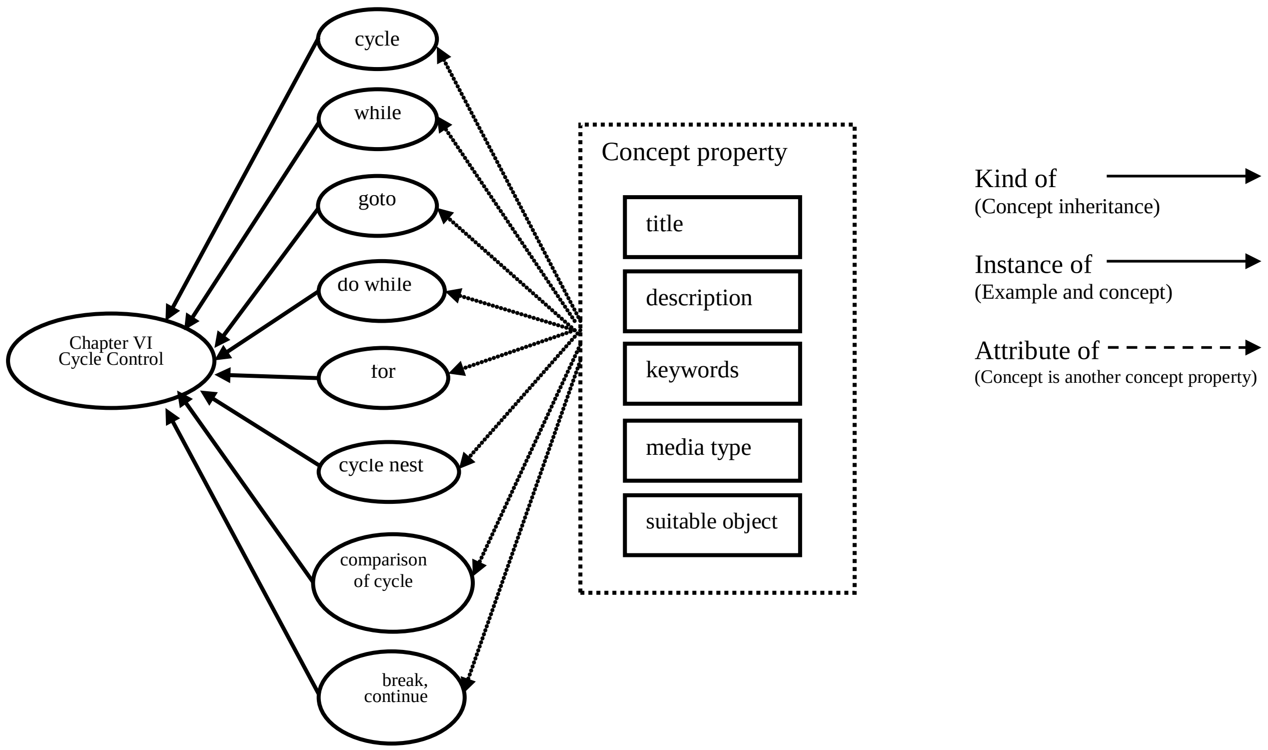

Figure 1: Concept model of knowledge ontology.

BUILDING USER MODELS

At the centre of personalised learning is the personalised learning process and strategy. This requires building a user model for each user. A user model is simply a notation for a user or user group. The knowledge included in the user model is applied to tailoring the interface for a particular user or user group.

Building of user models is based on the Learners' Model CELTS 11, in which, the learner's model should include categories, such as individual information, academic information, relationship information, safety information, predilection information, performance information and showreel information.

Individual information is general information about the learner, e.g. name, gender, date of birth, telephone, e-mail. Academic information relates to the learners' learning, e.g. major, grade and learning plan. Predilection information is the predilection of the learner in respect of learning, e.g. be willing to self-study and have a predilection for learning resource types (picture, animation, audio, video, text).

Performance information includes the learner's learning experiences, e.g. the learner's knowledge and mastery of the learned knowledge. This work built the user models from major factors related to the users' learning style. The process is shown in Figure 2.

First, the user models are initialised through the user registration information (e.g. age, gender, educational background and background knowledge) and using the Felder-Silverman learning style test, which is described below. This produces the initial personalised presentation of knowledge in the system.

In the learning stage, the visited resources types are processed (e.g. video, text, pictures), as well as quantity of postings, visiting times and other data to correct the users' learning style. After the termination of learning, the students' knowledge level is estimated through practice and test, with a concept accumulative-score strategy. Thus, is derived the recommendation of learning content by difficulty degree and whether there should be later learning.

The process of building the user models has three stages, viz. initial user model, corrected user model and perfected user model.

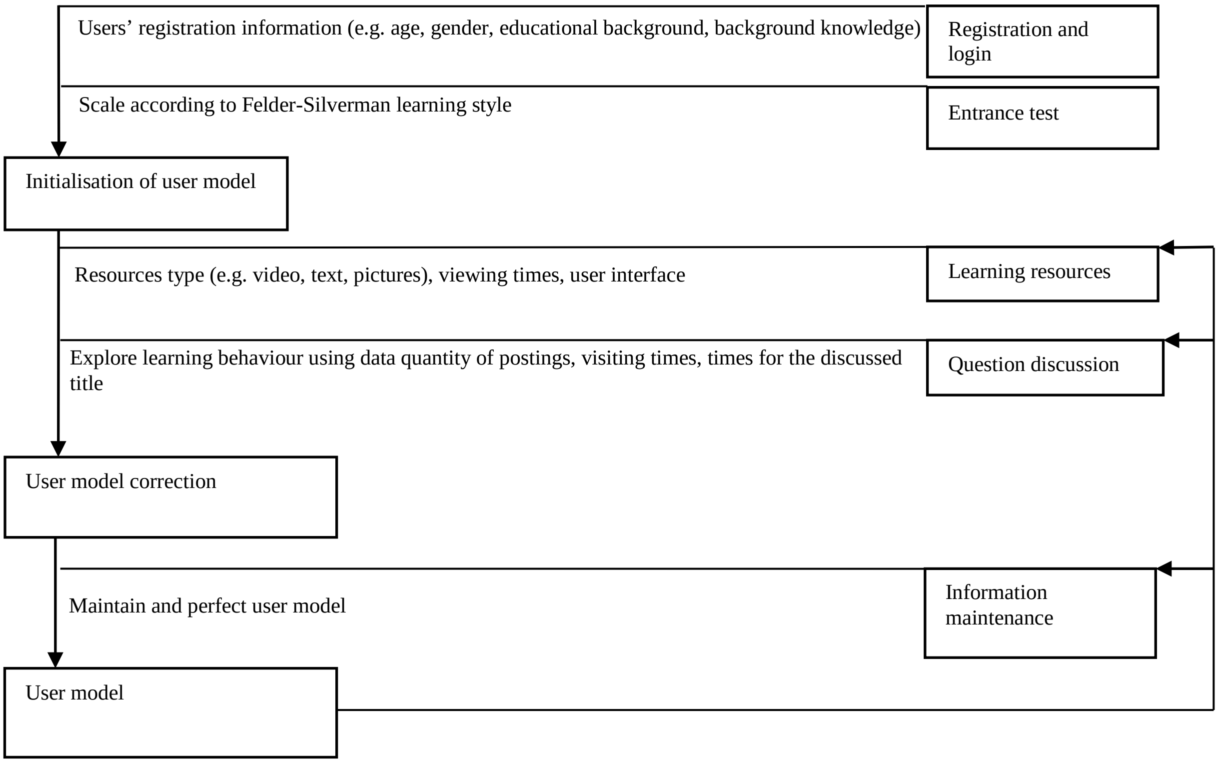

Figure 2: Initialisation and perfection of user models.

LEARNING RESOURCES BASED ON LEARNING STYLE

Initial Determination of Learning Resources Based on Learning Style

A learner's learning style is determined based on the Felder-Silverman learning styles, as shown in Table 1 [9]. The learning activities and learning resources for a learner can be adapted, based upon the initial learning style.

Table 1: Felder-Silverman learning style dimensions.

Learning style dimension	Type	Description
Information processing	Active	Thinking after doing; tends to master information through doing - discusses or applies or explains; tends to work in a team.
	Reflective	Reflects on questions quietly; independent work.
Perception	Rote	Is partial to mechanically memorise; likes learning fact; converts into knowledge, with structuring and intellectualisation; does not like complex conditions and emergency situations; good at memorising fact and redoing existing work.
	Intuitive	Innovate with flexibility; likes the abstract but is careless; does not like repeating; tends to find relationships between things; good at mastering new concepts; can understand abstract mathematical formulae.
Information input	Visual	Good at memorising things seen, e.g. contents of a picture, chart, flow chart, image, video, demonstration.
	Language	Good at acquiring information from words and oral expressions.
Understand contents	Sequence	Likes linear knowledge; logical small steps.
	Comprehensive	Likes acquiring a comprehensive view of knowledge; insight; big leaps of understanding.

- Active and reflective types:

  This refers to whether active or reflective influences the learners' learning activity sequence. Active learners like learning by doing. The learning activity sequence recommended by the system is:

  {participate in discussion (required) - read learning materials (recommended) - case study (recommended) - practice (required) - complete test (required)}.

Reflective learners like thinking about questions, and to learn and work independently. The learning activity sequence recommended by the system is:

{read learning materials (required) - case study (required) - participate in discussion (recommended) - practice (required) - complete the test (required)}.

- Rote and intuitive types:

  Rote and intuitive types are influenced more by the content of knowledge. For rote learners, the system recommends concrete material and concrete data learning resources, while abstract material and abstract data learning resources are recommended for intuitive learners.

  A quantitative assessment of the degree of rote or intuitive behaviour is discussed below. This assessment allows the preponderance of concrete or abstract material to be tailored for the learner.

- Visual and language types:

  These types are influenced more by the media type of the learning resources. For visual learners, the system will recommend learning materials with the property mediatype∈ {picture, chart, flow chart, video}. For language learners, the system will recommend learning materials with the property mediatype∈ {word information}.

- Sequence and comprehensive types:

  These types differ in their learning habits. Sequence learners are partial to linear, step-by-step learning. The system could provide page-up and page-down buttons. Comprehensive learners are partial to non-liner learning. The system could provide a knowledge tree, connecting important points.

Corrected Determination of Learning Resources Based on Learning Style

By using a Felder-Silverman learning style table, the learning style can be measured by suitable metrics. The results can be used to correct the learning style model using the recorded data of learning behaviour, e.g. type of querying, learning time, viewing times, postings in forums, quantity of posts read. Evidence shows that the corrected learners' learning style model is more factual and the system can recommend learning resources, according to the corrected individual learning style model [10].

In Table 2, behaviour model metrics and threshold values are summarised. Each learning style defines a dimension, with the two types of learning style at opposite ends. A high occurrence of a metric will place the behaviour at one or other end of the dimension. For example, the + in t_forum(+) indicates that a high value for this metric implies the left hand type, *active*, whereas the - sign in h_example(-) indicates that a high value for this metric implies the right hand type, *reflective*.

In Table 2, taking the active or reflective type as an example, the longer the forum visiting time t_forum (+), the more the learning style of the learner belongs to the left type, i.e. active; while the higher the viewing number h_example(-), the more the learner belongs to the right, reflective type.

Table 2: Felder-Silverman learning style table with threshold values.

Learning style	Behaviour model	Model description	Threshold values	
			L - M	M -L
Active or reflective	Forum visiting time t_forum (+)	Percentage of the forum visiting time of the whole time to learn the curriculum (t_forum/t_total)*100%	<5%	>15%
	Forum posting quantity n_forum_msg (+)	Posting quantity of each stage of the curriculum cycle (the curriculum cycle is one week) n_forum_msg	<2	>5
	Forum post reading quantity n_forum_read (-)	Post reading quantity of each stage of the curriculum cycle (the curriculum cycle is one week) n_forum_read	<10	>30
	Real example viewing times h_example (-)	Percentage between real example viewing times and learning object viewing total times (h_example/h_LO)*100%	<25%	>50%
Rote or intuitive	Concrete content viewing times h_concrete (+)	Percentage between concrete content viewing times and content object viewing times (h_concrete/h_contobject)*100%	<50%	>75%

	Concrete content viewing time t_concrete (+)	Percentage between concrete content viewing corresponding time and ontology defined concrete viewing corresponding time (t_concrete/t_contobject)/(t_concrete_learning/t_contobject _learning)*100%	<75%	>100%
	Abstract content viewing times h_concrete (+)	Percentage between abstract content viewing times and content object viewing times (h_abstract/h_contobject)*100%	<50%	>75%
	Abstract content viewing time t_abstract (-)	Percentage between abstract content viewing corresponding time and ontology defined abstract viewing corresponding time (t_abstract/t_contobject)/(t_abstract_learning/t_contobject _learning)*100%	<75%	>100%
	Real example viewing time t_example (+)	Percentage between real example content viewing corresponding time and ontology defined real example viewing time (t_example/t_LO)/(t_example_learning/t_LO_learning)*100%	<75%	>100%
	Test time t_test (+)	Percentage between the test time and maximum time allowed for the test (t_test/t_max_test)*100%	<70%	>90%
Visual or language	Text viewing times h_text (-)	Percentage between the test viewing times and content object viewing times (h_text/h_contobject)*100%	<50%	>75%
	Test viewing time t_text (-)	Percentage between text viewing corresponding time and ontology defined text time (t_text/t_contobject)/(t_text_learning/t_contobject _learning)*100%	<75%	>100%
	Video viewing times h_video (+)	Percentage between video viewing times and content object viewing times (h_video/h_contobject)*100%	<50%	>75%
	Video viewing time t_video (+)	Percentage between video viewing corresponding time and ontology defined video viewing time (t_video/t_contobject)/(t_video_learning/t_contobject _learning)*100%	<75%	>100%
	Chart or image viewing times h_graphic (+)	Percentage between chart, image viewing times and content object viewing times (h_graphic/h_contobject)*100%	<50%	>75%
	Chart or image viewing time t_graphic (+)	Percentage between chart, image viewing corresponding time and ontology defined chart, image viewing corresponding time (t_graphic/t_contobject)/(t_graphic_learning/t_contobject _learning)*100%	<75%	>100%
Sequence or comprehensive	Knowledge tree viewing time t_overview (-)	Percentage between knowledge tree viewing time and total time used to learn the curriculum (t_overview/t_total)*100%	<5%	>10%
	Knowledge tree viewing times h_overview (-)	Percentage between knowledge tree visiting time and total navigation time [h_overview/(h_overviwe+h_prevutton+h_nextbutton)]*100%	<30%	>70%
	Times - click page up button h_prevbutton (+)	Percentage between times to click page up button and total navigation clicking times [h_prevbutton/(h_overviwe+h_prevutton+h_nextbutton)]*100%	<30%	>70%
	Times - click page down button h_nextbutton (+)	Percentage between times to click page down button and total navigation clicking times [h_nextbutton/(h_overviwe+h_prevutton+h_nextbutton)]*100%	<30%	>70%

CONCLUSION

Guidance or recommendations are required when a large number of learners want to find learning resources from a huge repository of learning resources. The strategy reported in this article recommends personalised adapted learning resources based on user models. The approach used an initial learning style based on Felder-Silverman learning style dimensions, corrected by data gathered from the actual learning, to recommend the best personalised learning sequence and learning resources for the learner. The next step in this research is to realise the implementation of this strategy.

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