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Adaptive Course Sequencing for Personalization of Learning Path Using Neural Network

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Abstract

Advancements in technology have led to a paradigm shift from traditional to personalized learning methods with varied implementation strategies. Presenting an optimal personalized learning path in an educational hypermedia system is one of the strategies that is important in order to increase the effectiveness of a learning session for each student. However, this task requires much effort and cost particularly in defining rules for the adaptation of learning materials. This research focuses on the adaptive course sequencing method that uses soft computing techniques as an alternative to a rule-based adaptation for an adaptive learning system. The ability of soft computing technique in handling uncertainty and incompleteness of a problem is exploited in the study. In this paper we present recent work concerning concept-based classification of learning object using artificial neural network (ANN). Self Organizing Map (SOM) and Back Propagation (BP) algorithm were employed to discover the connection between the domain concepts contained in the learning object and the learner's learning need. The experiment result shows that this approach is assuring in determining a suitable learning object for a particular student in an adaptive and dynamic learning environment.

Keywords: *adaptive course sequencing, backpropagation, learning path, personalization,Self-organizing map*

1 Introduction

Most of the earliest and typical computer-aided educational system provides the same leaning materials to all learners without dealing of his goal, level of knowledge, learning style and preferences [1]. This situation was contradicting with the nature of traditional one-to-one instructional process which considering the personality of a learner. [2]. Different learner may needs different information and regarding his. Therefore, course sequencing technology which is originated in the area of intelligent tutoring system (ITS) is developed with the goal to provide student with the most suitable and optimal learning path [2]. In contrast to a traditional computer aided instructions, ITS use the knowledge about the domain, the student and teaching strategies to support flexible individualized learning and tutoring [3]. Artificial Intelligence (AI) techniques, are used to simulate activities related to the delivery or tutor, such as coaching learners and/or diagnosing their misconception.

A major disadvantage, however, is that this type of system is more likely 'teacher-centered' rather than 'learner-centered' because the flow of the learning activities and instructions are predefined and determined by the teacher/instructor without giving learners an alternatives to select their own learning resources and activities based on their preferences**.** To overcome this problem, a Web-based Intelligent Tutoring System which offers more freedom to navigate the media space of the subject content was introduced [3]. Considered as a learner-driven system, the hypertext and hypermedia technologies reside in the world wide web (www) enabled learner to go through the learning materials and activities with less guidance from instructor.

However, a disorientation problem arises because student tends to lost in cyberspace due to the information overloading. The cognitive overload occurs when learner overwhelmed with too much information and guides while interacting with the Web. This will result in low efficiency of human to absorb and process useful information which may lead to unsuccessful learning [4]. Learner may found themselves lost in the cyberspace without achieving their goal or learning objectives. Therefore, adaptation and personalization are being very important in the web based educational system**.**

Adaptive educational hypermedia system (AEHS) is one of the approaches toward personalization of e-Learning system. AEHS is a type of educational system that based on the integration of hypertext technology and user modeling (from ITS). A typical AEHS consists of a domain model, user model, and adaptation model. The goal of student model is to represent some characteristics and attitudes of the learner which are useful for achieving the adequate and individualized interaction established between computational environments and students [5], A domain model contains a set of domain knowledge elements along with their relationships. Meanwhile the adaptation model contains the rules for describing the runtime behavior of the AEHS as well as how the domain model relates to the user model to specify adaptation for the personalization task to be accomplished. [6].

In the problem of generating personalized learning path, the rules for adaptive course sequencing are defined in the adaptation model. The content selection rules and concept selection rules are required in order for setting the principles of content selection and instructional planning of the system. They are designed according to the cognitive style or learning preferences of the learner [7]. Though most of these rules are domain independent, there are still an absence of well defined and commonly accepted rules on the selection and sequencing of the content in a way to produce a sense of instructional value in most educational system ([9],[10],[11]). Furthermore, the complexity of dependencies between the content characteristics and learners usually requires a complicated and huge set of rules to be defined. Thus, generating personalized paths to each learner will inflict prohibitive cost because the sequencing process is done manually by instructors. [12].

This research focuses on developing a course sequencing method that imitates instructor’s role in designing the adaptation rules. As an alternative to the tedious work of rules definition, this method will employ soft computing techniques in order to generate and optimize the learning path for a student. This is due to the ability of soft computing technology in approximating solution to an ill-defined problem. In this paper, we addressed the problem of selecting the suitable set of learning objects associated to learner knowledge level as a classification problem.

The rest of the paper is organized as follows: in Section 2 we will give some overview on the soft computing approach to AEHS. Section 3 will explain our approach toward the problem. The experiments that have been conducted will be presented in Section 4. Section 5 will discuss the results of the experiment. We will conclude the paper in Section 6 along with the further works of the study.

2 Soft Computing Approaches to Educational Application

Educational systems especially AEHS have gained benefits from soft computing technologies for few reasons. The ability of soft computing techniques to deal and work with uncertainty makes it possible to model and simulate human decision-making task [13].Teaching and learning are processes that involve very much to human related actions such as interactions, thinking, decision-making, memorizing, and etc. Moreover, in order to provide an effective adaptation, the system should be able to capture some information of the user such as his goal, plan, preferences, knowledge level and etc. In educational systems, user model data provided by those activities and elements are usually imprecise, incomplete and heterogeneous [13]. Therefore, the ability of soft computing to mix different behavior and capturing human decision process has been employed in the AEHS to make the system more adaptive and dynamic.

Basically, there are four types of task involving soft computing techniques and user model of AEHS such as prediction, recommendation, filtering and classification. Among the techniques are fuzzy logic, neural networks, genetic algorithm (GA), fuzzy clustering and neuro-fuzzy systems. Different techniques have different capabilities in manipulating the user model and none of the technique is suitable for all tasks and situations.

The work presented in this paper is an attempt to combine the employment of soft computing technique, artificial neural network (ANN) in both user model and domain model in order to select a set of suitable learning object for a student. ANN is inspired by the way biological nervous system processing information. It is composed of large numbers of highly interconnected neurons which responsible as a processing elements. ANN models have particular property such as ability to adapt, to learn, or to cluster data. For classification problem, the network needs a training corpus of objects with known category membership. New objects with unknown category can be classified after training the network. Intensive employment of ANN has been seen in multiple fields related to classification task such as pattern and speech recognition, non-linear system and control.

In the e-learning area, ANN has been widely used in classification of students based on their preferences or learning styles. In that case, ANN has been used to build the learner model which consists of personal static data, system usage data and his preferences. However ANN rarely been employed in educational system in the classification and modeling of the domain knowledge and learning materials. An attempt has been done by [8] by combining both user modeling and learning object (LO) classification using ANN.

3 Proposed Approach

This section discusses the research methodology that will be used in order to achieve the goal of this study. Works reported in this paper is only a part of overall framework of this research. Basically the methodology is based on the conceptual framework as depicted in Fig.1. The following subsections will explain briefly on the framework.

3.1 User Model

For the design of the User Model, overlay model has been used for representing the student knowledge space. The idea of the overlay model is to represent an individual user's knowledge of the subject as an 'overlay' of the domain model. Profiles of 60 learners are created based on their performance which representing their knowledge level for every concept tested during the pre-test evaluation. The pre-test questions given are corresponding with the learning goal that he has selected. The data for every student is recorded as in Table 1. Table 2 illustrates the classification scheme for student mastery level while Table 3 shows the finalized concept mastery representation that will be an input for the experiment using artificial neural network as discussed in the following subsection.

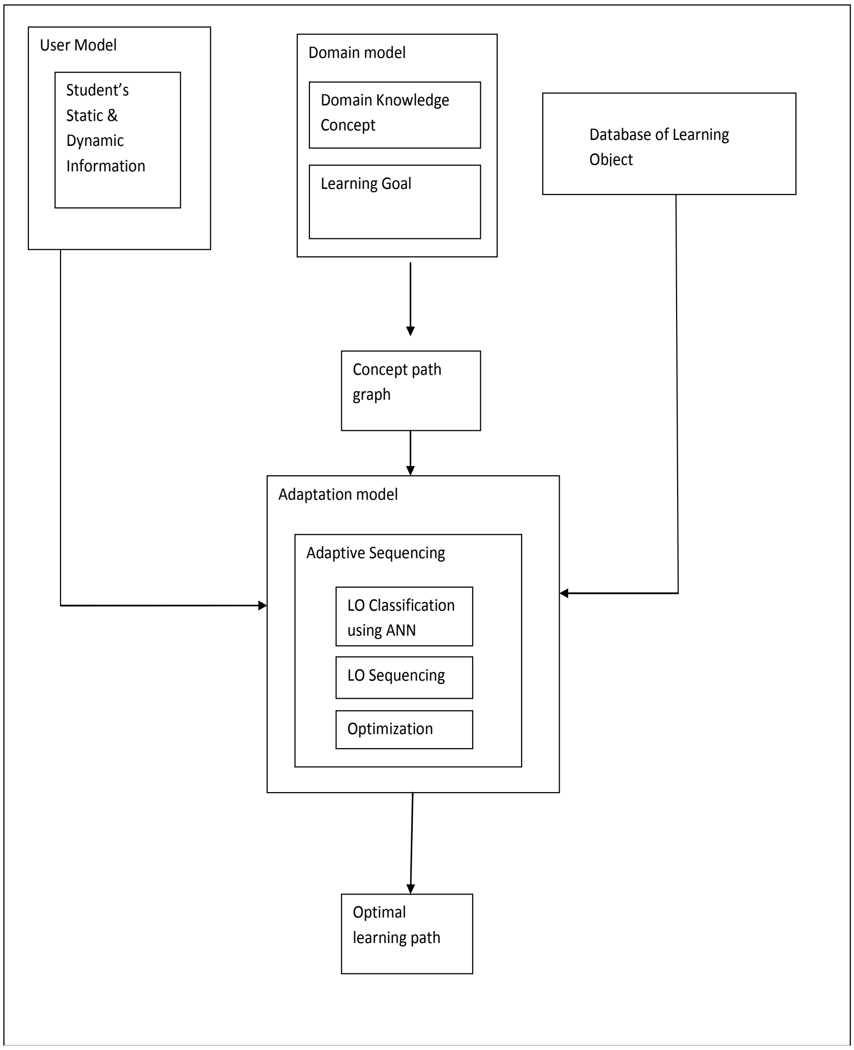

Fig. 1: Conceptual Framework

Table 1: Result of Pre-test (scores for every concept tested)

Concept Id	Concept	Score (Avg)
C1	Primitive data type	80
C2	Array Declaration	60
C3	For- loop	49
C4	Class and Object declaration	35
C5	Initializer list	89

Table 2: Classification of student's mastery level

Score	Level	Representation
80-100	Advance	0
40-79	Normal	0.5
0-39	Poor	1

Table 3: Finalized concept mastery representation

Concept Id	Representation
C1	0
C2	0.5
C3	0.5
C4	1
C5	0

3.2 Domain Model

In this research, the selected domain is Array, one topic of Object Oriented Java Programming course which is currently being taught at FSKSM, Universiti Teknologi Malaysia. We only focused on five learning goals in this topic and to achieve these learning goals, we have identified 25 concepts that must be mastered by the students. Some of the concepts are presented in Table 4. For each learning goal, domain experts have to estimate the weight of each concepts of domain knowledge. The value given to the concept is 1 if the particular concept is important in achieving the learning goal, 0.5 if it is not necessary and 0, if the concept is not relevant.

3.3 Adaptation Model

Adaptation model contains the rules for describing the runtime behavior of the system as well as how the domain model relates to the user model to specify adaptation. In a typical approach to the problem of generating personalized learning path, the rules for adaptive sequencing are defined in this model. In this research, this model will employ soft computing technique in the selection and sequencing of learning objects instead of containing rules definitions.

Table 4: Part of Domain Knowledge Concepts

Learning Goal	Main Concept	Pre-requisite Concept
Declare and create an array of primitive types	• Primitive data type • Array declaration • For-loop • Class and object declaration • Initializer list	• Assignment Stmt • Control Structure • Reference variable • Class and object
Declare and create an array of object	• Creation of array of type class • Creation of object in each/ particular index of the array	• Array of primitive type

4 Experiments

Two experiments have been conducted with the objective to select a group of similar learning object for a particular student regarding to his subject knowledge mastery level.

4.1 Clustering of learning object using Self Organizing Map (SOM)

For the first experiment, a data set comprising of 129 learning objects for the topic have been prepared. Domain expert was then to estimate the weight of each concepts of domain knowledge contained in every LO. The weight value given to the concept is 1, if the concept is very significant or has been described particularly in that learning object, 0.5 if the concept is slightly described and 0, if the concept is not relevant to the LO. There are 25 concepts to be evaluated by the experts for every LO.

The SOM is an unsupervised neural network that maps a set of n-dimensional vectors to a two-dimensional topographic map. The training of an unsupervised neural network is data-driven, without a target condition that would have to be satisfied (as in a supervised neural network). The SOM combines an analytic and graphical technique to group data onto a low-dimensional (typically 2-dimensional) display and organize the data into clusters by this projection[14].

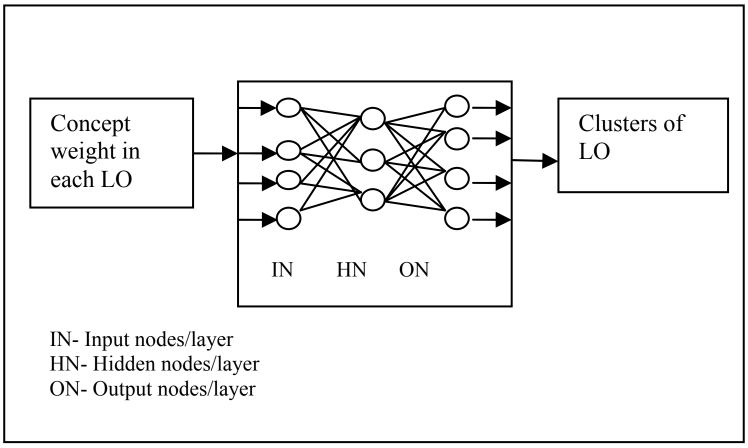

Fig. 2: ANN architecture for LO clustering

In our approach, SOM technique is employed to cluster the collections of LO into groups based on concepts similarity of the LO. A network has been created with 25 input neurons and has been trained with different dimension sizes of the map in order to get the best clustering result. Fig. 2 illustrates the architecture of the ANN for this experiment. From the experiments, using our data, the best result was obtained when the size of the map dimension is 5 x 5. The network managed to cluster the LO into 12 groups based on the concepts of the domain knowledge. The output of this experiment is the LOs with their class ID which later will be trained by the neural network in order to classify each student to any groups of the LO in the second experiment.

4.2 Concept-based classification of learning objects and students using Backpropagation ANN

In the second experiment, profiles of 60 students are created based on their performance in the pre-test evaluation. The input layer represents the concepts of the course, where the input vector is a set of values belonging to the set {0,0.5,1} .The determination of the values is based on the finalized concepts mastery level of the student as in Table 3. For example, if the mastery level for concept C1 is 0 which means that the student is already 'advanced', the value for the concept C1 is set to 0 in the input layer. This concept C1 is not important for the student to be learnt in his learning path anymore. The output layer is assigned to the groups of learning object that have been identified previously. Three steps have been taken in performing this experiment.

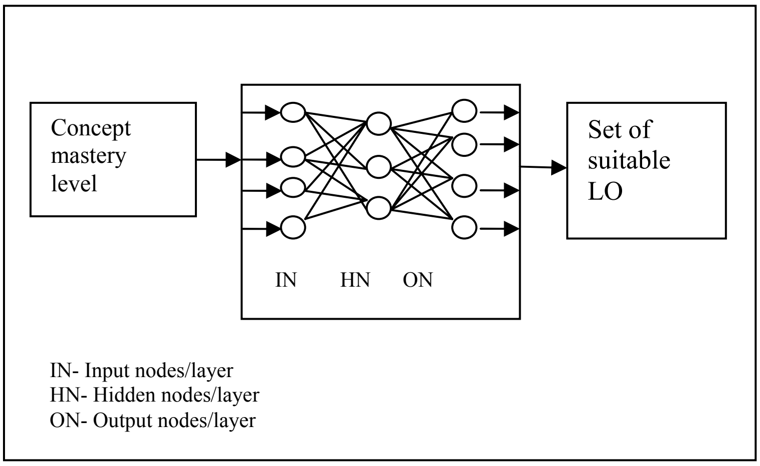

Fig 3: ANN architecture for LO classification

Step 1: Create a neural network to train LO data classification.

The network used for the experiment is constructed of 25 neurons in the input layer which represent 25 domain knowledge concepts that have been identified by the domain expert. Figure 3 illustrates the architecture of the network.

Step 2: Train the network using LO data

The multi layer perceptron (MLP) network in this experiment is trained using a classic Backpropagation (BP) algorithm, Output-Weight-Optimization (OWO). OWO involves solving a set of linear equations using the Conjugate Gradient Technique in order to calculate optimum output weights. Error at each node is calculated and is back propagated to the hidden layer where the hidden weights are calculated so as to minimize mapping error. In our case, the error has been successfully minimized to zero percent (0.000%) after 100 iterations when the hidden layer node is set to 25 neurons.

The weight matrix produced during the training phase will be used for testing the network to classify each student to a suitable LO class.

Step 3: Testing the network using student profiles data

The objective of this step is to determine which class or group of LO that matched the profile of a student. The data to be compared is his mastery level of the domain knowledge concepts. For example, the mastery level for 4 concepts of a student is as in Table 5.

Table 5: Example of student data

Concept	C1	C2	C3	C4
Mastery Level	Advance	Advance	Remedy	Remedy
Representation	0	0	1	1

Therefore, a suitable LO for a student is a LO with same data representation pattern as in Table 6. To identify the LO classes for a student, the created network for training the LO data as well as the weight vector are used.

Table 6: Example of suitable LO

Concept	C1	C2	C3	C4
Significance weight of the concept	Not relevant	Not relevant	High	High
Representation	0	0	1	1

5. Results and Discussion

The neural network has been tested towards 60 students profile. The result shows that the classifier had selected the most matching LOs with the student profiles. Table 7 presents the results of the classification.

Table 7: Classification results

	Hidden Nodes Size	**Mean Squared Error**	**% Correct Classification**
1	13	2.929653	100
2	20	0.779631	100
3	25	0.150094	100
4	50	0.000000	100
5	51	0.000000	100

The result shows that most of the good classifications were the samples with bigger size of hidden nodes. The obtained result shows that ANN were able to select up to 100% of learning objects as selected by the domain expert for each student.

6. Conclusion

Adaptive course sequencing is an approach that aims to provide learner the most suitable learning materials throughout his learning path in a web based educational system. In this paper, we addressed the learning object selection problem based on learner's mastery level upon the domain concepts. Instead of defining a complex and huge set of rules as normally done in a traditional adaptive learning, domain expert only need to give her estimation and decision on selecting the suitable learning objects.

A neural network has been constructed to identify a group of similar learning object as well as to select a suitable learning object for a particular student. The suitability of the learning object here is meant by the similarity of the domain concept data representation pattern between the student's and the learning object's profiles. The result of this preliminary study shows that the computational intelligence approach is assuring in achieving our goal that is to produce an adaptation model that can imitate the rule-based decision making task of an instructor.

The next stage of this research is to generate the learning paths graph for the domain model through the sequencing of suitable learning objects classified before this. Of all possible generated learning paths, we will identify the most appropriate or optimal learning path for a particular student. Some searching techniques such as Beam Search, Partition Search and Simulated Annealing, as well as nature-inspired techniques, ant colony optimization (ACO) will be considered in this further study.

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