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Building a Personalized Multidimensional Intelligent Learning System

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***Abstract*—**Currently, most of distance learning courses can only deliver standard material to students. Students receive course content passively which leads to the neglect of the goal of education – "to suit the teaching to the ability of students". Providing appropriate course content according to students' ability is the main goal of this paper. Except offering a series of conventional learning services, abundant information available, and instant message delivery, a complete online learning environment should be able to distinguish between students' ability and provide learning courses that best suit their ability. However, if a distance learning site contains well-designed course content and design but fails to provide adaptive courses, students will gradually loss their interests and confidence in learning and result in ineffective learning or discontinued learning. In this paper, an intelligent tutoring system is proposed and it consists of several modules working cooperatively in order to build an adaptive learning environment for distance education. The operation of the system is based on the result of Self-Organizing Map (SOM) to divide students into different groups according to their learning ability and learning interests and then provide them with suitable course content. Accordingly, the problem of information overload and internet traffic problem can be solved because the amount of traffic accessing the same content is reduced.

***Keywords*—**Distance Learning, Intelligent Tutoring System (ITS), Self-Organizing Map (SOM)

I. Introduction

THE promotion of distance education has encountered two major drawbacks. First, the course content offered by the distance education provider can not suit individual students' learning ability. Second, the delivery of massive multimedia course content has lead to lower transformation speed. Moreover, information available on line has been massively distributed, duplicated, and restored in computers located all over the world. Internet users have encountered the problem of information overload and disorientation [1]. Despite of providing abundant learning material, efficient resources searching ability, interactive interface, a complete distance learning system should be able to distinguish students' individual learning ability and set up differentiate teaching strategy in order to increase students' learning performance and learning efficiency. Thus, how to find just right bit of information that users need from the web is a big challenge in distance education [2]. Intelligent tutoring system (ITS) has offered a solution to that problem. With the help of ITS, distance learning presented in 3D form has overcome the problem of information overload [3]. In this paper, an effective ITS framework accompanied by the concept of recommendation for online learning is proposed and applied to the establishment of an online course presented in 3D form.

The rest of this paper is organized as follows: In section 2, we briefly describe others' work that touches on ours. In section 3, we introduce the infrastructure of our proposed personalized learning system. The application of the system is shown in section 4. Section 5 contains our conclusions.

II. Related Works

Schema theory is a framework for the mental representation of knowledge. Schema, also called the "building block of cognition" [4], is a significant notation in understand the knowledge structure of our brains. According to schema theory, people process information and make judgment in different ways which leads to different learning habit. It is obvious that a patterned relationship exists between content and learners. Thus, in this paper, adaptive learning content is provided by the system for students who have similar learning interests with students in the same group clustered by the clustering analysis [5].

In the early 1970s a few researchers defined a new and ambitious goal for computer-based instruction. They adopted the human tutor as their educational model and sought to apply artificial intelligence techniques to realize this model in "intelligent" computer- based instruction. Personal human tutors provide a highly efficient learning environment [6]. Then, the word of "intelligent" is introduced to the field of distance education.

Moreover, distance education delivers a large amount of information through the Internet. Online learners are not able to filter out unnecessary or uninterested information effectively which results in the reduction of learning interests. The concept of constructing an effective recommendation of course content that can enhance learners' learning interests by providing contents that learners are interested in is widely discussed by

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researchers [7], [8]. An intelligent tutoring system has been introduced to distance education because of that concept.

In the intelligent tutoring system illustrated in Fig. 1, Self-Organizing Map, SOM, is used for the purpose of clustering students with similar learning backgrounds into the same group. SOM is capable of adjusting the distribution of output neurons based on the distribution of input neurons, meaning the output layer can automatically adjust its distribution if the input layer changes. Thus, in the process of online learning, the change of students either in learning interests or in personal background can be detected by SOM and the results of SOM will be modified due to the previous change[9], [10].

III. The Infrastructure of the Personalized Intelligent Learning System

The infrastructure of the personalized intelligent learning system is shown in Fig. 1. The main character of this system is that it can provide adaptive learning material for students with different personal backgrounds and learning interests. Students no longer receive same learning contents.

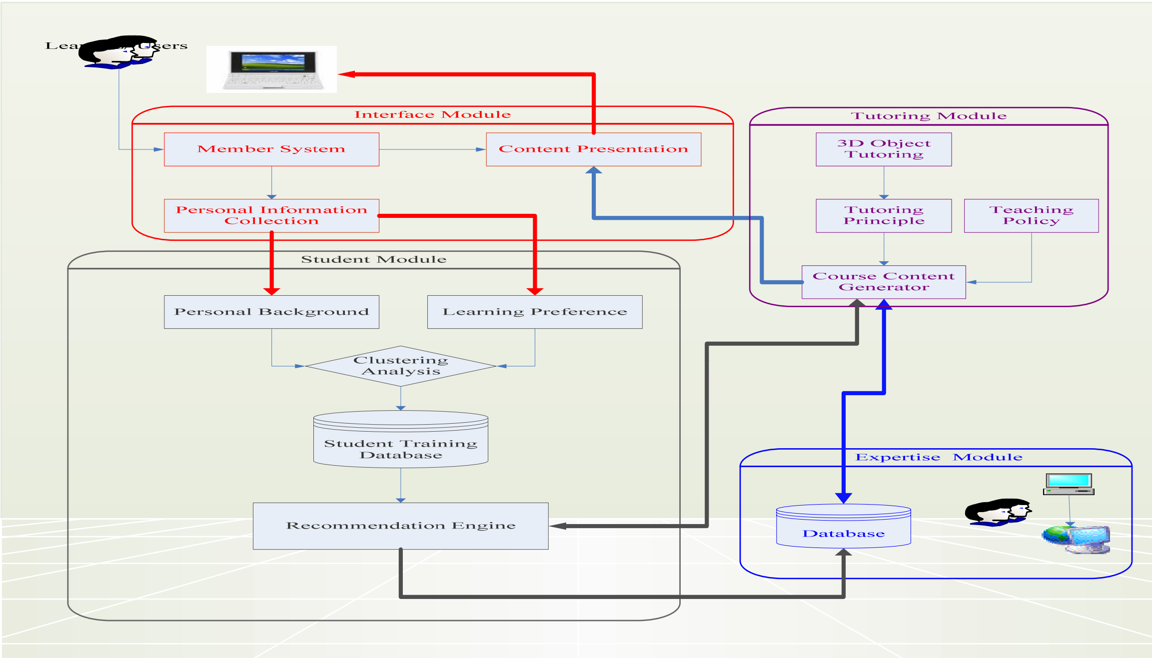

Fig. 1 The infrastructure of the personalized intelligent learning system

A. Introduction of Modules

This system is composed of four major modules: interface module, student module, expertise module, and tutoring module. These four modules interact with each other to produce adaptive learning content for students with various personal backgrounds and learning interests.

Interface module receives inputs from students and displays adaptive learning material produced by the tutoring module to them. Student module processes students' personal information and learning interests and then makes learning suggestions for tutoring module. Tutoring module considers both learning suggestions from student module and instructor's teaching policy to produce adaptive learning material that matches students' various learning interests. Expertise module works mainly with the instructor to generate learning material and the presentation of the learning materials. The presentation of adaptive learning material is through the interface module.

B. Questionnaires in the interface module

The interface module deals with students including receiving information from students and providing learning material to students. Students input their personal information and their preference as the source of training dataset. The training dataset is restored and analyzed in the student module. In the questionnaire, information regarding students' personal backgrounds and learning preference are stored in variables which is used as the input of clustering analysis. Variables are divided into five categories: personal information, cognizance of words and images, willingness of using 3D material, cognizance of 3D platform, and the feeling of multimedia learning.

Personal information includes age, gender, marital status, occupation, education level, and income. The information collected in the variable of cognizance of words and images is used to decide if the presentation of learning material is in the form of word description or image demonstration. The information collected in the variable of willingness of using 3D material and cognizance of 3D platform are used to decide if the presentation of learning is in 3D form. The information collected from the variable of the feeling of multimedia learning is used to analyze students' previous multimedia learning experience.

Students in the training dataset answer all questions. Students who only receive adaptive learning material only answer questions regarding personal background and interests.

C. Clustering analysis in the student module

Students' information regarding personal background and learning preference is restored and analyzed in the student module. Once the collection of the information in a training data set is complete, student module can start analyzing these data.

SOM is used to divide all data samples into several groups in which the similarity among data samples in the same group is the highest and the similarity among data samples in different group is the lowest. Students in the same group have similar personal background and learning preference. Therefore, if there is a student whose learning preference is unknown, the proposed system can provide learning material, that is interested by other students whose personal background and interests are similar to his/hers, to this student.

In the student module, information collected from students through the interface module is used to produce the preliminary recommendation of students' adaptive learning material for expertise module and tutoring module, and then the student module interacts with both modules in order to produce the final adaptive learning material for students. The questionnaire used in the interface module is shown in Fig 2.

D. Learning material generation

The generation of learning material is built upon the output of clustering analysis. The output of clustering analysis is used to classify a student whose learning preference is unknown into one cluster. The system assumes that this student's learning preference is similar to the learning preference of those sample data in the same cluster. The output of the student module is the prediction of this student's learning preference and is sent to the tutoring module as the input of matching strategy. Matching strategy in the tutoring module integrates the prediction of this student's learning preference and the teaching policy or principle of the tutor into one matching strategy. Then, the presentation of the learning material that complies with the matching policy is extracted from the expertise module and then is delivered to students through the interface module.

IV. A PROTOTYPE SYSTEM OF THE PROPOSED STRUCTURE

Based on the modules illustrated in Fig. 1, a prototype system was implemented and it shows a desirable result.

A. The presentation of 2D and 3D images

In the proposed prototype system, a personalized intelligent learning system is constructed and aimed at providing adaptive learning material either in 2D or in 3D form for students. In the system, there are four modules that interact with each other to produce adaptive learning content to suit individual student's need.

Fig. 2 User interface questionnaires

This personalized multidimensional learning system can be used to demonstrate 2D and 3D images which are selected by preferred students. The difference between 2D and 3D images is the amount of information delivered. For 2D images, only one side of the image appears. However, if the system presents different sides of the mage, this image has to be processed from lots of angles. If the system fails to present images from all angles, students will be less interested in learning. A 3D simulation software called Autodesk 3ds Max that integrates with Quest3D^{TM} platform to demonstrate the object in 3D format from all angles. Therefore, images of the object from all angles can be prepared by this software instead of preparing 2D images from all angles which is a time consuming task. However, if the system delivers all images in 3D format, it will case system overload. Thus, a personalized multidimensional learning system is proposed and allows students to choose 2D or 3D images based on students' personal interests. In the mean time, the problem of system overload can be solved.

B. The steps of designing the system and the final results

The construction of the personalized multidimensional learning system is divided into two phases. In the first phase, input of the training data is required for the classification process in the student module. More than two hundred students' information regarding personal background, interests, and learning preference are collected in the Web through the interface module. Students answer questions in questionnaires shown on the Internet. Questions are composed of two types of questions: personal background and learning preference. In the beginning of the entire process, information regarding personal background are asked and restored in Web through a questionnaire. Then, students start answering every question regarding their learning preference. Once the collection of information of all training data is complete, information are transmitted to the student module as the input of clustering analysis that divides these training data into several groups. The input of clustering analysis using Kohonen's Self Organizing Maps (SOM) as analyzing tool is illustrated in Fig. 3. The first phase of the construction of the personalized system is stopped when the clustering analysis yields a result.

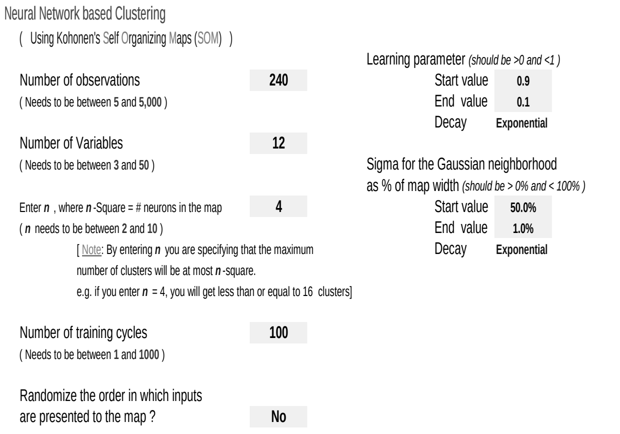

Fig. 3 The input of clustering analysis using SOM as analyzing tool

The second phase starts from transmitting the result of clustering analysis to the tutoring module that uses the online content from the expertise module and the result of clustering analysis from the student module as the input of matching strategy. The matching strategy selects appropriate online content matching online students' learning preference. Online content that is adaptive to online student's learning preference is delivered through the interface module. Thus, an online student whose learning preference is unknown is required to enter personal information regarding background and interests that are sent to the student module to find a belonged group in which people's personal background are similar to him/her. Their interested items of people in the same group are regarded as this student's interested items. The final presentation of items that might be interested by this student is shown through the interface module online. An example of the presentation of the adaptive results is shown in Fig. 4 which shows selected results to an online student whose learning preference is unknown.

V. CONCLUSIONS

The purpose of establishing a personalized learning system is to provide adaptive learning material for students who have different preferences or needs. Students receive learning material recommended by the system through the interface module. After a period of learning, the system can provide learning material which is more suitable to each student's needs.

In the first phase of constructing the system, training data containing personal backgrounds and learning preference is restored and clustered in the student module using clustering analysis. In the second phase, this system presents adaptive contents to an online student whose learning preference is unknown. The first phase is established offline and the second phase is operated online. Through the operation of the proposed system, students are more willing to learn and the problem of system overload can be reduced.

Fig. 4 The presentation of adaptive results

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