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Intelligent web-based learning system with personalized learning path guidance

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Abstract

Personalized curriculum sequencing is an important research issue for web-based learning systems because no fixed learning paths will be appropriate for all learners. Therefore, many researchers focused on developing *e*-learning systems with personalized learning mechanisms to assist on-line web-based learning and adaptively provide learning paths in order to promote the learning performance of individual learners. However, most personalized *e*-learning systems usually neglect to consider if learner ability and the difficulty level of the recommended courseware are matched to each other while performing personalized learning services. Moreover, the problem of concept continuity of learning paths also needs to be considered while implementing personalized curriculum sequencing because smooth learning paths enhance the linked strength between learning concepts. Generally, inappropriate courseware leads to learner cognitive overload or disorientation during learning processes, thus reducing learning performance. Therefore, compared to the freely browsing learning mode without any personalized learning path guidance used in most web-based learning systems, this paper assesses whether the proposed genetic-based personalized *e*-learning system, which can generate appropriate learning paths according to the incorrect testing responses of an individual learner in a pre-test, provides benefits in terms of learning performance promotion while learning. Based on the results of pre-test, the proposed genetic-based personalized *e*-learning system can conduct personalized curriculum sequencing through simultaneously considering courseware difficulty level and the concept continuity of learning paths to support web-based learning. Experimental results indicated that applying the proposed genetic-based personalized *e*-learning system for web-based learning is superior to the freely browsing learning mode because of high quality and concise learning path for individual learners.

Keywords: Genetic algorithm; Personalized learning path; Intelligent tutoring system; Web-based learning

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1. Introduction

Traditional teaching resources, such as textbooks, typically guide the learners to follow fixed sequences to other subject-related sections related to the current one during learning processes. Web-based instruction researchers have given considerable attention to flexible curriculum sequencing control to provide adaptable, personalized learning programs (Brusilovsky, Eklund, & Schwarz, 1998; Jih, 1996; Lee, 2001; Lin & Hsieh, 2001; Mia & Woolf, 1998; Papanikolaou & Grigoriadou, 2002; Tang et al., 2000; Tang & Mccalla, 2003). Curriculum sequencing aims to provide an optimal learning path to individual learners since every learner has different prior background knowledge, preferences, and often various learning goals (Brusilovsky & Vassileva, 2003; Chen, Lee, & Chen, 2005; Roland, 2000; Weber & Specht, 1997). In an educational adaptive hypermedia system, an optimal learning path aims to maximize a combination of the learner's understanding of courseware and the efficiency of learning the courseware (Roland, 2000).

Moreover, as numerous web-based tutoring systems have been developed, a great quantity of hypermedia in courseware has created information, and cognitive overload and disorientation (Berghel, 1997; Borchers, Herlocker, Konstanand, & Riedl, 1998), such that learners are unable to learn very efficiently. To aid more efficient learning, many powerful personalized/adaptive guidance mechanisms, such as adaptive presentation, adaptive navigation support, curriculum sequencing, and intelligent analysis of student's solutions, have been proposed (Chen et al., 2005; Papanikolaou & Grigoriadou, 2002; Tang & Mccalla, 2003; Weber & Specht, 1997). Nowadays, most adaptive/personalized tutoring systems (Lee, 2001; Papanikolaou & Grigoriadou, 2002; Tang & Mccalla, 2003) consider learner/user preferences, interests, and browsing behaviors when investigating learner behaviors for personalized services. However, these systems neglect the importance of learner ability when implementing personalized mechanisms. On the other hand, some researchers emphasized that personalization should consider levels of learner knowledge, especially in relation to learning (Chen et al., 2005; Chen, Liu, & Chang, 2006; Papanikolaou & Grigoriadou, 2002). That is, the abilities of individuals may be based on major fields and subjects. Therefore, considering learner ability can promote personalized learning performance.

Over the years, designers of web-based learning have evolved several common lesson structures for different learning occasions. These lesson structures include the classic tutorial lessons, active-centered lessons, learner-customized tutorial lessons, knowledge-placed tutorial lessons, exploratory tutorial lessons, and generated lessons (Horton, 2000). Among the six kinds of lessons, the generated lessons aim to customize learning for those who have very specific needs and not much time or patience to complete topics they have learned (Horton, 2000). The generated lessons tailors a learning sequence based on the learner's answers to questions on a pre-test or questionnaire at the start of the lesson (Horton, 2000). To construct a personalized learning path based on simultaneously considering courseware difficulty level and learning concept continuity during learning processes, a genetic-based curriculum sequence scheme is here presented to customize personalized learning path. The proposed approach is based on a pre-test to collect incorrect learning concepts of learners through some randomly selecting testing items (Hsu & Sadock, 1985), then the genetic algorithm is employed to construct a near optimal learning path according to these incorrect response patterns of pre-test. The goal of this study aims to help learners learn more effectively and efficiently by skipping the learning concepts that learner has given correct responses for the corresponding testing items in a pre-test process. Since the fitness function of genetic algorithm is determined by the difficulty parameter of courseware and the concept relation degree between two successive courseware in a generated learning path, the proposed curriculum sequencing scheme can generate high quality learning paths for individual learners. Experimental results indicated that the proposed genetic-based personalized *e*-learning system with curriculum sequencing mechanism generates appropriate course materials to learners based on individual learners' requirements, and help them learn more effectively and efficiently in a web-based learning environment.

2. System architecture

This section describes the system architecture, system components, and details of the learning procedures for the proposed genetic-based personalized *e*-learning system.

2.1. System architecture and components

A personalized *e*-learning system based on the proposed genetic-based curriculum sequencing scheme, which includes an off-line courseware modeling process, six intelligent agents and four databases, is presented herein. The six intelligent agents are the learning interface agent, pre-test process agent, learning path generation agent, adaptive navigation support agent, post-test process agent and courseware management agent, respectively. These four databases include the user account database, user profile database, testing items and courseware database and teacher account database. The learner interface agent aims at providing a flexible learning interface for learners to interact with the pre-test process agent, adaptive navigation support agent and post-test process agent. The pre-test process agent aims to generate randomly a testing item for the corresponding learning courseware in order to identify the incorrect learning concepts of individual learner according to the incorrect testing responses for personalized curriculum sequencing. In the meanwhile, the pre-test process agent will pass these incorrect testing responses of individual learner to the learning path generation agent to plan a personalized learning path based on the proposed genetic-based curriculum sequencing scheme. Moreover, the adaptive navigation support agent is in charge of guiding the learner's learning process based on a learning path generated by the learning path generation agent and storing learning records into the user profile database. In addition, the post-test process agent provides a final test while the learner finishes the whole learning process. The courseware management agent with authorized account management mechanism provides a responsive testing items and courseware management interface, aiding teachers to create new testing items and course units, upload testing items and courseware to the testing items and courseware database and delete or modify testing items and courseware from the testing items and courseware database. The system architecture is shown as Fig. 1.

To implement the proposed genetic-based personalized *e*-learning system by agent techniques, interaction is one of the most important features of an agent-based system (Nwana, 1996). Agent-based systems recurrently interact to share information and to perform tasks to achieve their goals by agent communication language. There are two main approaches including procedural and declarative schemes to designing an agent communication language (Genesereth, 1997). The procedural approach, where communication is based on

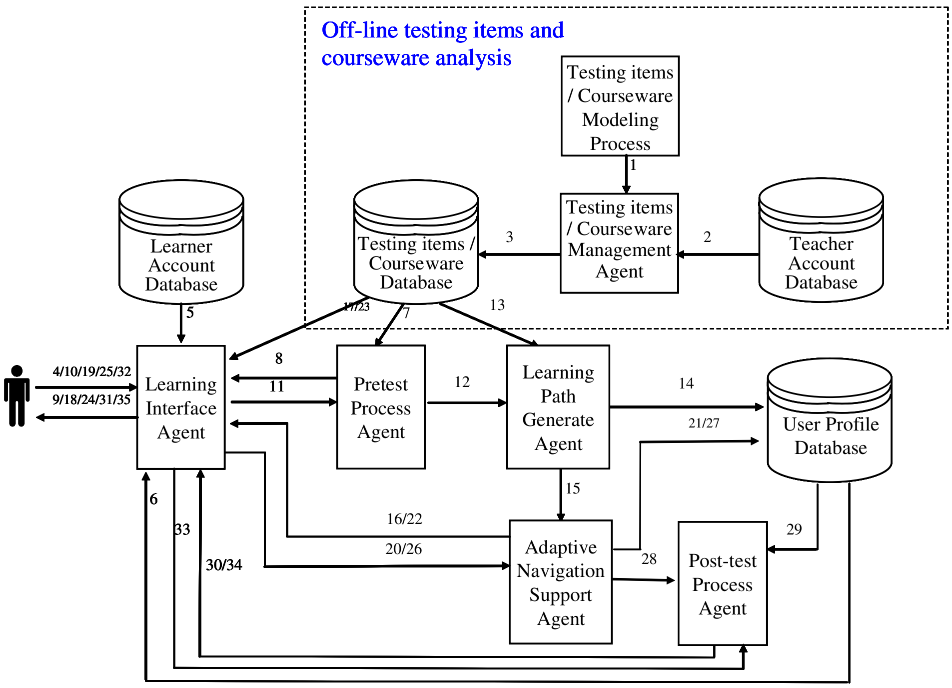

Fig. 1. The system architecture of the genetic-based personalized *e*-learning system (the numeral marked in this figure represents the system operation procedure).

executable content, could be accomplished using programming languages. The declarative approach is based on declarative statements, such as requesting or commanding, to accomplish agent communication. One of the more popular declarative agent languages is Knowledge Query and Manipulation Language (KQML). To avoid implementing complicated message format and a message handling protocol defined in the declarative-based agent communication language, this study used the procedural approach to implement the proposed genetic-based personalized *e*-learning system.

2.2. System operation procedures

Based on the system architecture mentioned-above, the system operation procedures are briefly described as follows:

- *Step* 1. The testing items were designed by courseware experts based on the course materials stored in the testing items and courseware database. According to Item Response Theory (IRT) (Baker Frank, 1992), the difficulty parameters of these testing items can be determined through statistical method based on testing results of learners. After that, courseware with web page type can be designed according to the conveying concept of the corresponding testing item. The detailed courseware modeling process is described in Section 3.
- *Step* 2. Teachers login the system to upload, delete or revise testing items and courseware in the testing items and courseware database by the legal teachers' accounts.
- *Step* 3. The designed courseware are maintained and stored into the testing items and courseware database through the courseware management agent.
- *Step* 4. Learners login the system through the learning interface agent by the legal learners' accounts.
- *Step* 5. After a learner logs in the system, the learning interface agent checks whether his/her account stored in the user account database.
- *Step* 6. If the learner has already owned a registered account, the system will get his learning profile from the user profile database and guide the learner to perform the previous unfinished learning courseware; otherwise, the proposed system will treat the learner as a beginner who must accept a pre-test.
- *Step* 7. For a beginner, the proposed system will randomly generate a test sheet based on the testing items stored in the testing items and courseware database for the learner and guide the learner to perform a pre-test.
- *Step* 8. The generated test sheet is transformed to the user interface agent for a learner to conduct a pre-test.
- *Step* 9. The learner performs the pre-test through the user interface agent.
- *Step* 10. The learning interface agent transfers the pre-test results to the pre-test process agent.
- *Steps* 11–12. The pre-test process agent analyzes the pre-test results and conveys the incorrect testing responses to the learning path generation agent for personalized curriculum sequencing.
- *Steps* 13–14. The learning path generation agent plans a learning path according to the incorrect pre-test results of an individual learner transformed from the pre-test process agent based on the proposed genetic-based curriculum sequencing approach. Simultaneously, the generated learning path is also stored into the user profile database and conveyed to the adaptive navigation support agent for the courseware learning of individual learner.
- *Steps* 15–16. The adaptive navigation support agent takes charge of guiding the learning path of individual learner according to the generated learning path through the designed control mechanisms in the proposed genetic-based personalized *e*-learning system.
- *Steps* 17–21. The adaptive navigation support agent communicates with the learning interface agent to guide the learning contents according to the planned learning path for individual learner. Meanwhile, the learning processes of individual learner are also recorded into the user profile database.

Steps 22–27. The learner repeats the same learning procedures mentioned in Steps 15–21 until the learner finishes all courseware planed by the learning path generation agent.

Steps 28–29. After the learner finishes the entire courseware planed by the learning path generation agent, the adaptive navigation support agent will notice the post-test process agent to randomly generate a testing sheet to the learner for performing a post-test in order to evaluate the learning performance.

Steps 30–35. The generated testing sheet in a post-test will be transformed to the learning interface agent, and then displayed to the learner. The post-test results are also provided to the learner for self-examination and stored into the user profile database. So far, the learner finishes the entire learning process for a learning course unit.

3. Courseware modeling process

The courseware modeling process presents a detailed courseware design procedure to establish the difficulty parameters of courseware and courseware contents for personalized courseware generation. This study presents a statistics-based method derived from computerized adaptive testing (CAT) theory (Hsu & Sadock, 1985) through a conscientious test process to determine the difficulty parameters of courseware. The detailed flowchart of the courseware modeling process is illustrated as Fig. 2.

To design a course of the course unit "Fraction" of elementary school mathematics in Taiwan as an example, several experienced teachers were invited as courseware experts to analyze the primary concepts for the course unit "Fraction" in the courseware modeling process. The courseware experts designed the corresponding testing item for each learning concept. That is, the testing items are regarded as key characteristic of the corresponding learning content. Additionally, about 500 elementary school examinees who had majored in the course unit "Fraction" were invited to join the exam, which contains 17 testing items to cover those learning concepts. According to the Item Response Theory (Baker Frank, 1992; Hsu & Sadock, 1985) in CAT, their testing data was analyzed by the statistics-based BILOG program to obtain the appropriate difficulty parameters for these testing items. After that, the web page of courseware was designed following the conveying content of the corresponding testing item. Since the content of courseware is derived from the concept of the testing item, it is assumed the difficulty of courseware equals the difficulty of the corresponding testing item. That is, each testing item in the testing item database has a corresponding courseware that conveys the learning concept of the corresponding testing item.

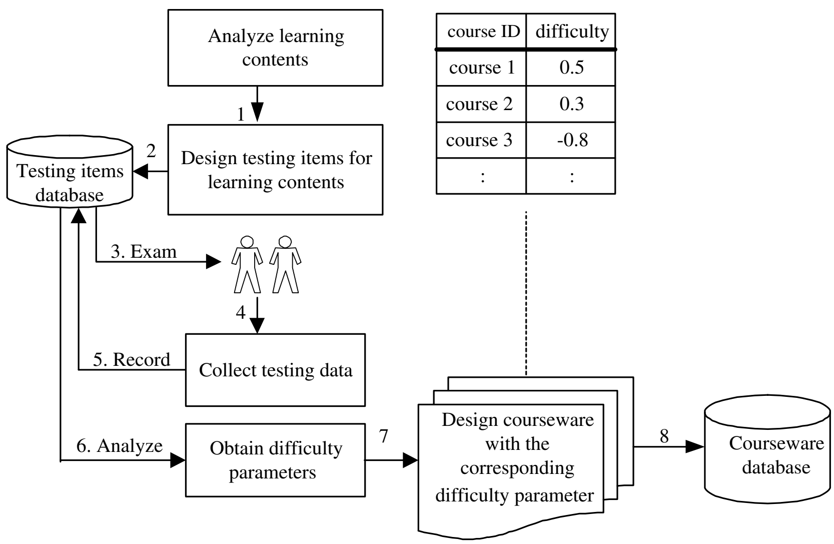

Fig. 2. Courseware modeling process.

4. Evaluating concept relation degrees among courseware

In order to facilitate easier courseware concept relation analysis, all courseware in the courseware database has followed the standard of the metadata information model of Sharable Content Object Reference Model (SCORM) 1.2 (SCORM version 1.2-The SCORM Content Aggregation Model, 2001). Restated, each courseware in the courseware database has a corresponding XML binding file to record important SCORM metadata, which conveys the main courseware concept. In the meanwhile, this study also developed an interface for teachers to maintain the SCORM metadata for the relevant courseware. In order to generate a near optimal learning path for a learner based on the results of pre-test, these SCORM metadata are applied to calculate the concept relation degrees among courseware by using Chinese natural language processing (An Extension Chinese Lexicon Scanner, 2006) and information retrieval (Frakes & Baeza-Yates, 1992) methods. Fig. 3 illustrates the maintained interface of SCORM metadata. Next, how to compute the concept relation degrees for personalized courseware generation will be explained in detail.

4.1. Metadata preprocessing

First, two metadata fields of the corresponding XML binding file of courseware are selected to represent the conveyed learning concept for a courseware. They are keyword and description fields in the SCORM 1.2 metadata information model shown as Fig. 3, respectively. In order to calculate the concept relation degrees for personalized courseware generation, metadata preprocessing is required because the description field in the SCORM 1.2 metadata information model is described by Chinese natural language in this study. Thus, the first phase of metadata preprocessing aims to perform Chinese word segmentation by an ECScanner (An

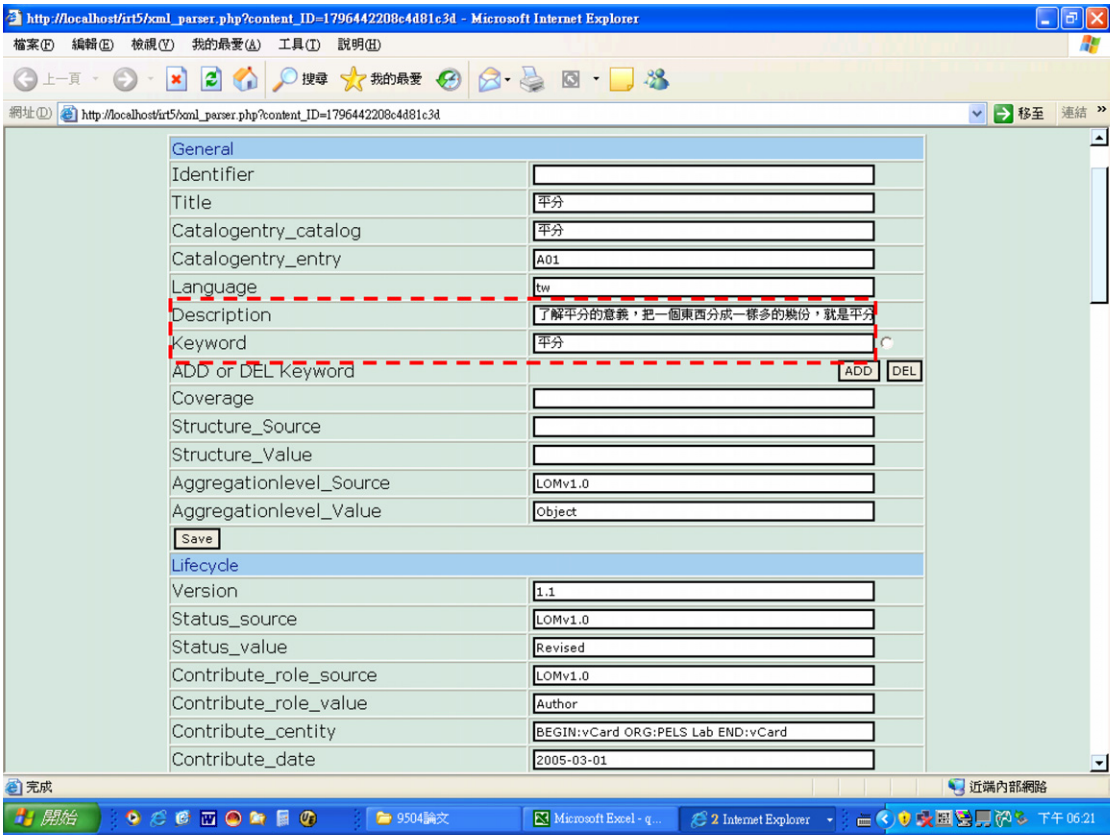

Fig. 3. The maintained interface of SCORM metadata in our system.

Extension Chinese Lexicon Scanner, 2006) in order to describe the metadata field of the corresponding XML binding file of courseware so that separated linguistic terms can be obtained. The second phase of metadata preprocessing filters out non-textual words (e.g. numeric data, symbols, notation and ASCII drawings) and one-word terms because they do not carry any usable information for calculating concept relation degrees. Fig. 4 shows the details of the metadata preprocessing procedure.

4.2. Estimation of concept relation degree

To estimate the concept relation degree between two courseware, the vector space model (Frakes & Baeza-Yates, 1992) is applied to represent each courseware as vectors in a multidimensional Euclidean space. Each axis in this space corresponds to a linguistic term obtained from Chinese word segmentation process. The coordinate of the ith courseware in the direction corresponding to the kth linguistic term can be determined as follows:

$$w_{ik} = tf_{ik} \times \log \frac{N}{\mathrm{df}_k} = tf_{ik} \times \mathrm{IDF} \tag{1}$$

where w_{ik} represents the importance/weight of the kth term in the ith courseware, tf_{ik} is term frequency of the kth term, which appears in the ith courseware; N denotes the total number of courseware in a course unit, df_k is the document frequency of the kth term, which appears in a course unit.

Assume that there are total m terms under union of all linguistic terms of the ith courseware and jth courseware. The concept relation degree for the ith and jth courseware can be found by using the cosine-measure, and formulated as follows:

$$r_{ij} = \frac{\sum_{h=1}^{m} w_{ih} w_{jh}}{\sqrt{\sum_{h=1}^{m} w_{ih}^2 \sum_{h=1}^{m} w_{jh}^2}} \tag{2}$$

where $c_i = \langle w_{i1}, w_{i2}, \ldots, w_{ih}, \ldots, w_{im} \rangle$ and $c_j = \langle w_{j1}, w_{j2}, \ldots, w_{jh}, \ldots, w_{jm} \rangle$, respectively, represent the vectors in a multidimensional Euclidean space for the ith and jth courseware, r_{ij} denotes the concept relation degree between the ith and jth courseware.

Assume that there are totally n courseware in the courseware database, the concept relation matrix for all courseware can be expressed by the matrix $\mathbf{R}$, and listed as follows:

$$\mathbf{R} = \begin{array}{c} \\ c_1 \\ c_2 \\ \vdots \\ c_n \end{array} \begin{array}{c} \begin{array}{cccc} c_1 & c_2 & \cdots & c_n \end{array} \\ \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ r_{n1} & r_{n2} & \cdots & r_{nn} \end{bmatrix}_{n \times n} \end{array} \tag{3}$$

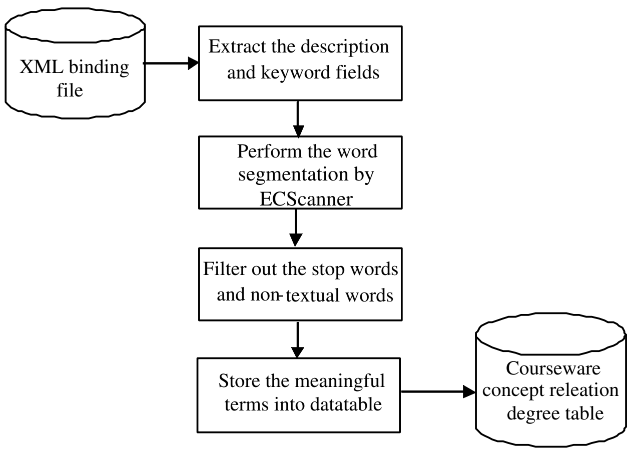

Fig. 4. Metadata preprocessing procedure.

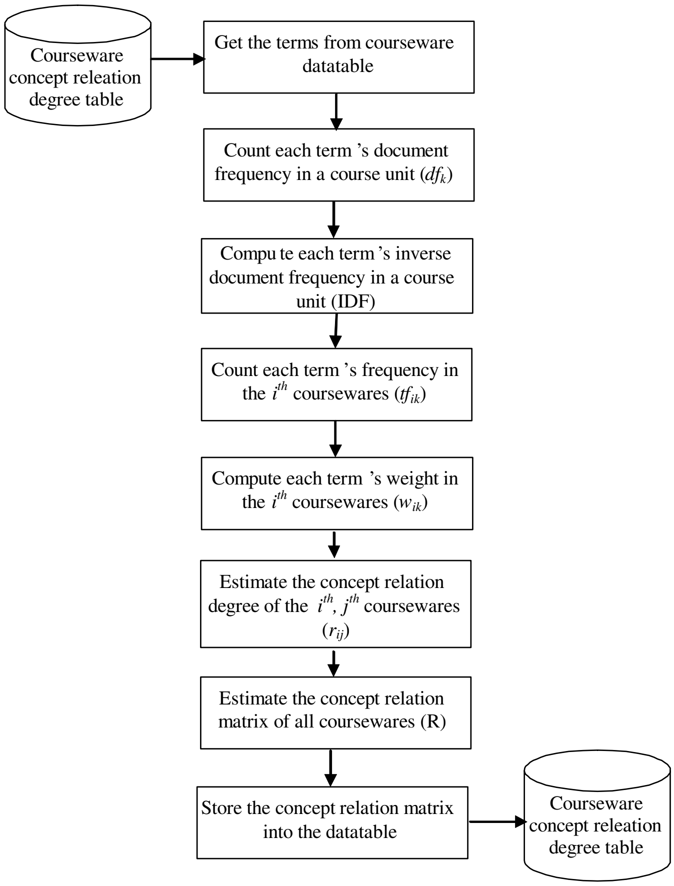

Fig. 5. The procedure of estimating the concept relation degree.

In summary, the entire procedure of estimating the concept relation degree based on SCORM 1.2 metadata information model can be displayed as Fig. 5.

5. Personalized learning path generation based on genetic algorithm

This section explains how to generate a personalized learning path for an individual learner utilizing the genetic algorithm (Rothlauf, 2002).

5.1. Generated courseware for web-based learning

Generated courseware tailor a courseware to each learner based on answers to a pre-test before at the start of the learning course unit. Fig. 6 displays the architecture of generated courseware for web-based learning. Generated courseware are helpful to individual learners for performing more efficient learning specially when learners have different needs, varying desires, and different levels of knowledge background. The details of the proposed genetic-based curriculum sequence scheme are presented in the next subsection.

5.2. Genetic algorithm for personalized learning path generation

5.2.1. Definition of individual strings

First, a serial number is assigned to each courseware from 1 to n if there are totally n courseware in the testing items and courseware database for personalized learning path generation. The integer-coded scheme

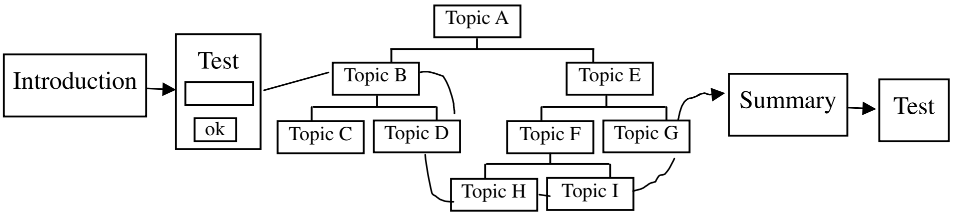

Fig. 6. The generated courseware for web-based learning (Horton, 2000).

was employed to represent an individual string herein, i.e. a potential solution for the genetic algorithm. Thus, the assigned serial number of each courseware combined with the serial numbers of other courseware forms a chromosome to represent a generated learning path for personalized curriculum sequencing. That is, an individual consists of a single chromosome herein. The whole individual consisted of the genes of all courseware serial numbers for the genetic algorithm is illustrated as Fig. 7. In Fig. 7, the assigned serial number of each courseware is viewed as a gene in the chromosome.

5.2.2. Initial population size

Generally, the initial population size can be determined according to the complexity of the solved problem. A larger population size reduces the searching speed of genetic algorithm, but it could increase the probability of finding high quality solution. To plan a learning path with high quality for an individual learner, the initial population size was chosen as one hundred for personalized learning path generation in this study.

5.2.3. Selecting fitness function

Fitness function is a performance index that it was applied to judge the quality of a generated learning path for the genetic algorithm in the study. In order to generate a personalized learning path with high quality for an individual learner based on the pre-test results, the difficulty parameters of courseware and the concept relation degrees of courseware are simultaneously considered to determine the fitness function. In our method, a learning path constructed by the genetic algorithm only considers the mapped courseware that learner gives incorrect pre-test results. Moreover, the courseware with the smallest difficulty parameter is always selected as the first courseware ranked in a generated learning path. The proposed fitness function is formulated as follows:

$$f = \sum_{i=2}^{n}((1-w)\times r_{(i-1)i} + w\times(1-b_i)) \tag{4}$$

where f is the proposed fitness function for personalized learning path generation by the genetic algorithm, $r_{(i-1)i}$ represents the concept relation degree of the $(i-1)$th courseware with the ith courseware in a generated learning path, b_i is the difficulty parameter of the ith courseware, w is a adjustable weight, and n stands for the total number of courseware considered for personalized learning path generation.

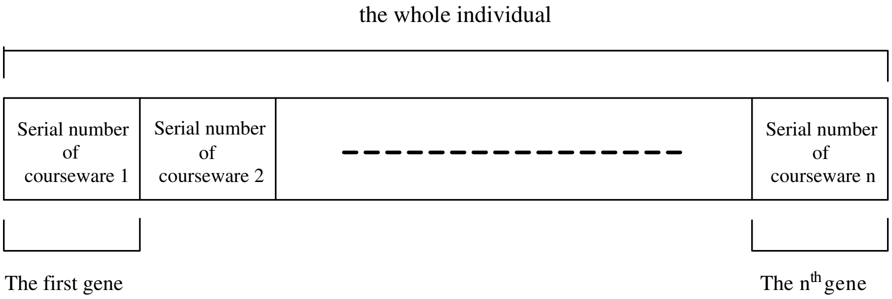

Fig. 7. The individual strings combined by the serial numbers of courseware for the genetic algorithm.

5.2.4. Reproduction operation

In the reproduction operation, the individuals with large fitness function value have a relatively higher probability to reproduce next generation. This operation aims to choose good individuals to achieve the goal of gene evolution. The most common used method of reproduction operation is the weighted roulette selection scheme (Rothlauf, 2002) and the scheme was also employed to perform reproduction operation in this study.

5.2.5. Crossover operation

This operation aims to combine two parent individuals to evolve better child individuals. In this study, the uniform crossover scheme (Rothlauf, 2002) was employed to perform the crossover operation and the probability of crossover is set to be 0.9. Meanwhile, to avoid generating illegal learning paths while performing the crossover operation, i.e. a learning path contains duplicate serial number of courseware or a learning path contains any serial number of courseware that is over the total number of courseware, two randomly selected serial numbers of genes in two individuals exchange genes to each other by probability decision. Fig. 8 illustrates an example of the proposed crossover operation. Restated, using the proposed crossover operation can guarantee to obtain a logical learning path.

5.2.6. Mutation operation

In the proposed mutation operation, two randomly selected genes in an individual are forced to exchange the gene to each other under probability decision. The proposed mutation operation is similar to the mutation operation of swapping two-points implemented in the standard genetic algorithm. The only difference is that the binary-coded scheme is employed in the standard genetic algorithm, but the integer-coded scheme was employed to represent an individual string, i.e. a potential solution for the genetic algorithm, in the study. This scheme can avoid generating illegal learning paths mentioned in the previous subsection. The mutation operation can evolve some new individuals that might not be produced by the operations of reproduction and crossover to avoid that the solution traps into the local optimum. Generally, a low probability of mutation can guarantee the convergence of genetic algorithm, but it may lead to poor quality solution. By contrast, a high probability of mutation may lead to the phenomenon of random walk in the genetic algorithm, thus reducing convergence speed. In this paper, the probability of mutation is set to be 0.001. Fig. 9 illustrates an example of the proposed mutation operation.

5.2.7. Stop criterion

The genetic algorithm repeatedly runs the reproduction, crossover, mutation and replacement operations until it meets an assigned stop criterion. In this study, the stop criterion is set to be 200 generations because this criterion can obtain satisfied learning paths for personalized learning path generation.

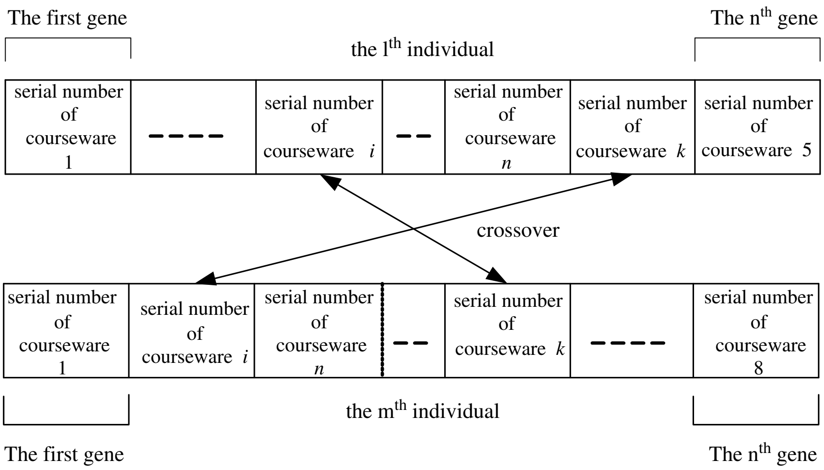

Fig. 8. Crossover operation.

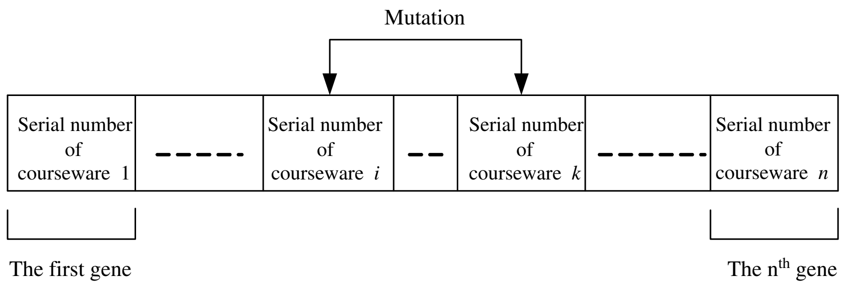

Fig. 9. Mutation operation.

5.3. Procedure of personalized learning path generation

In summary, the procedures of the proposed genetic-based personalized learning path generation scheme are detailed as follows:

Step 1. A learner performs a pre-test based on randomly selected testing items in a course unit for personalized learning path generation.
Step 2. The proposed system collects the incorrect testing items in the pre-test and their corresponding courseware in the testing items and courseware database.
Step 3. The corresponding courseware with the smallest difficulty parameter among the incorrect testing items is selected as the first courseware for personalized learning path generation.
Step 4. The system generates a near optimal learning path for an individual learner utilizing the genetic algorithm according to the incorrect response testing items.
Step 5. A learner performs personalized web-based learning according to the generated learning path.
Step 6. Terminate the learning process if the learner finishes courseware learning of the generated learning path; otherwise, return *Step 1* for next learning cycle.

6. Experiments

Currently, the proposed genetic-based personalized *e*-learning system is available on the web to simultaneously provide both the freely browsing learning mode and the learning mode of curriculum sequencing recommendation. To verify the quality and effectiveness of planned learning path in the learning mode of curriculum sequencing recommendation for personalized web-based instruction, some elementary school students who were majoring in the course unit of "Fraction" of elementary school mathematics were invited to test this system. The detailed functions of this system and experimental results are described as follows.

6.1. The developmental environment of software and hardware

In this study, AppServ package (AppServ Open Project, 2007) was employed as the development tool to implement the proposed genetic-based personalized *e*-learning system. The software package can simultaneously support to install the development tools including apache server, PHP analyzer, MySQL database, and MySQL database management system to promote the development speed of web applications. It is suitable to be employed to develop web-based learning system with client–server architecture. The designed genetic-based personalized *e*-learning system contains a server side for learning content services and client side for learner learning. The detailed specifications of software and hardware in both the server and client sides are listed in Table 1.

6.2. The implemented genetic-based personalized e-learning system

To explain how to perform the learning processes using a generated learning path for an individual learner, this section briefly introduces the learning procedure on the implemented genetic-based personalized

Table 1
The specifications of server and client sides

Server side		
1	Host	Middle-level server HP ML-370
2	Operating system	Windows server 2000
3	Web server	Apache 1.3.29
4	Database	MySQL 4.0.16
5	Language	PHP 4.3.4
Client side		
1	Host	Multimedia personal computer
2	Operating system	Windows XP
3	Browser	IE 6.0
4	Other peripheral equipment	Speaker or earphone

e-learning system. Fig. 10 shows the entire layout of the user's learning interface. As a learner logins this system, he/she must conduct a pre-test if he/she is a beginner; otherwise, the system will guide the learners to learn the courseware according to the previous unfinished learning procedures. Fig. 11 shows the interface of performing a pre-test for a beginner. After a beginner finishes a pre-test, the system will analyze the results of pre-test, then the system will generate an appropriate learning path based on the incorrect testing responses of individual learner in a pre-test process. Fig. 12 displays a generated learning path with learning priority according to the incorrect testing responses of an individual learner. The system will guide the learner to perform the learning process according to the learning path generated for the learner. Particularly, a learner must follow a learning path planned by the genetic-based personalized *e*-learning system to learn the corresponding courseware with incorrect testing responses. The genetic-based personalized *e*-learning system will temporally disable the courseware that their ranking priorities are less than the priority of the current learning courseware until the current learning courseware has been acquired. Fig. 13 displays the learning courseware with the first learning priority that has not been acquired by the learner in the generated learning path. Currently, course material organized on web pages with flash animation and synchronous voice comments is the course element in the proposed system. Moreover, one randomly selected testing item related to the current learning

Fig. 10. The user interface with user account identification.

Fig. 11. A pre-test for a beginner.

Fig. 12. The generated learning path according to the incorrect testing responses of an individual learner in a pre-test.

courseware is arranged in the bottom-right window to help system get the learner's comprehension degree for the learning courseware. When a learner can pass the corresponding test question of some learning courseware, this indicates that the learner has acquired the learning courseware. If a learner cannot pass two randomly selected testing questions for some learning courseware, the genetic-based personalized *e*-learning will guide the learner to conduct the remedy learning. In this work, the courseware database contains course materials with easier difficulty level than the current learning courseware used for supporting remedy learning.

Fig. 13. The courseware with first learning priority in the generated learning path.

The remedial course materials convey similar learning concepts with the current learning courseware, but they contain different learning content. The remedy learning mechanism aims at improving the learning performance of individual learners for the courseware that they cannot acquire well through the standard courseware. Fig. 14 reveals the learner interface of the freely browsing learning mode. In the freely browsing learning mode, no any learning path is planned for an individual learner and no any course material is disabled to forbid browsing, thus learners can freely click any course material for learning.

Fig. 14. The learner interface of the freely browsing learning mode.

6.3. An example for personalized learning path generation

This section gives an example to show how to plan a learning path for an individual learner according to the incorrect testing responses in a pre-test. First, the course modeling process mentioned in Section 3 is used to determine the difficulty parameter of each courseware. Restated, courseware organized on a single web page is the smallest course element in the proposed personalized courseware generation approach. In our experiments, the course unit "Fraction" of elementary school mathematics in Taiwan is used to generate personalized learning path, which includes many courseware with various levels of difficulty to convey the concept of the "Fraction". Assume that a pre-test in the course unit "Fraction" is performed by a learner, and totally occurs 17 incorrect testing items. Assume that Table 2 illustrates the concept relation degrees of corresponding courseware that learner gives incorrect testing item responses. Table 3 lists the titles of corresponding courseware and their difficulty parameters that the learner gives incorrect testing item responses.

Based on the corresponding concept relation degrees and difficulty parameters listed in Tables 2 and 3, the genetic algorithm was employed to construct a personalized learning path with high learning quality according to the proposed fitness function. Table 4 illustrates the generated learning path by the genetic algorithm. This study found that the generated learning path recommends learning path with smooth learning concept to a learner under simultaneously considering the difficulty parameters of courseware and concept continuity. Restated, the learning concepts with high concept relation degree will be successively recommended during a learning process under simultaneously considering the difficulty parameters of courseware. This is very beneficial to a learner because it can guide the learner to achieve more effective and efficient learning. Additionally, Fig. 15 shows the convergence curve of the proposed fitness function using the genetic algorithm with the adjustable weight 0.7. This result demonstrates that the proposed genetic-based personalized learning path generation scheme can indeed generate a learning path with high quality for an individual learner to support personalized learning service.

6.4. Experiments

This section explains how to employ statistics method to assess the learning performance for the proposed genetic-based curriculum sequencing scheme.

6.4.1. Experimental design

To evaluate whether the proposed learning mode of curriculum sequencing recommendation is superior to the freely browsing learning mode, 220 three-grade elementary school students who were majoring in the "Fraction" unit in a mathematics course were invited to participate in the experiment. Table 5 displays the statistics information for assessing learning performance in the experiment. Among 220 elementary school students, there are 92 students who were served as the control group to perform the freely browsing learning mode, and the remaining students were served as the treatment group to perform the proposed learning mode of curriculum sequencing recommendation only for the courseware with wrong answer responses in a pre-test. Both the learning modes simultaneously perform a pre-test and post-test for comparing the difference of learning performance before and after learning.

In the experiment, teacher first detailed the system operation procedures for all participators in the first hour, and then all participators logged in the system to perform the planned learning process according to two different experimental groups from the following two to four hours. Each participator must follow three learning stages to complete the entire learning process, i.e. pre-test process, learning process, and post-test process, no matter what learning modes were used. Fig. 16 exhibits the actual teaching scene at Hualien County Jiamin Elementary School in the experiment.

6.4.2. Experimental analysis

Since a part of participators had not completed the entire learning processes, this study thus filtered out these learning records. Table 6 lists the number of the participators who finished the entire learning processes or filled out the satisfaction investigation of questionnaire. Table 7 displays the

Table 2
The concept relation degrees for the incorrect testing items

r_{ij}	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17
C1	1	0.0118	0.1685	0.0173	0.0173	0.0760	0.0339	0.0509	0.0567	0.1847	0.0138	0.0329	0.0329	0.0114	0.0114	0.0114	0.0114
C2	0.0118	1	0.2062	0.6572	0.1988	0.0205	0.0091	0.0137	0.0026	0.0026	0	0.0050	0.0050	0	0	0	0
C3	0.1685	0.2062	1	0.1571	0.1571	0.0162	0.0072	0.0108	0.0020	0.0021	0	0.0039	0.0039	0	0	0	0
C4	0.0173	0.6572	0.1571	1	0.5517	0.0301	0.0134	0.0201	0.0038	0.0038	0	0.0073	0.0073	0	0	0	0
C5	0.0173	0.1988	0.1571	0.5517	1	0.0301	0.0134	0.0201	0.0038	0.0038	0	0.0073	0.0073	0	0	0	0
C6	0.0760	0.0205	0.0162	0.0301	0.0301	1	0.5561	0.7492	0.0325	0.0329	0.0286	0.0504	0.0504	0.0237	0.0237	0.0237	0.0237
C7	0.0339	0.0091	0.0072	0.0134	0.0134	0.5561	1	0.4837	0.0207	0.0210	0.0257	0.0413	0.0413	0.0213	0.0213	0.0213	0.0213
C8	0.0509	0.0137	0.0108	0.0201	0.0201	0.7492	0.4837	1	0.0124	0.0125	0.0261	0.0438	0.0438	0.0216	0.0216	0.0216	0.0216
C9	0.0567	0.0026	0.0020	0.0038	0.0038	0.0325	0.0207	0.0124	1	0.7833	0.0940	0.1394	0.1394	0.0780	0.0780	0.0780	0.0780
C10	0.1847	0.0026	0.0021	0.0038	0.0038	0.0329	0.0210	0.0125	0.7833	1	0.1309	0.1929	0.1929	0.1085	0.1085	0.1085	0.1085
C11	0.0138	0	0	0	0	0.0286	0.0257	0.0261	0.0940	0.1309	1	0.4809	0.4809	0.2285	0.2285	0.2285	0.2285
C12	0.0329	0.0050	0.0039	0.0073	0.0073	0.0504	0.0413	0.0438	0.1394	0.1929	0.4809	1	0.4158	0.4342	0.2342	0.4342	0.2342
C13	0.0329	0.0050	0.0039	0.0073	0.0073	0.0504	0.0413	0.0438	0.1394	0.1929	0.4809	0.4158	1	0.2342	0.4342	0.2342	0.4342
C14	0.0114	0	0	0	0	0.0237	0.0213	0.0216	0.0780	0.1085	0.2285	0.4342	0.2342	1	0.3619	0.4380	0.3619
C15	0.0114	0	0	0	0	0.0237	0.0213	0.0216	0.0780	0.1085	0.2285	0.2342	0.4342	0.3619	1	0.3619	0.4380
C16	0.0114	0	0	0	0	0.0237	0.0213	0.0216	0.0780	0.1085	0.2285	0.4342	0.2342	0.4380	0.3619	1	0.3619
C17	0.0114	0	0	0	0	0.0237	0.0213	0.0216	0.0780	0.1085	0.2285	0.2342	0.4342	0.3619	0.4380	0.3619	1

Table 3
The corresponding difficulty parameter for each courseware in the "Fraction" unit

Courseware	Title of courseware	Difficulty parameter
C1	Equal parts	−1.8
C2	Division as sharing	−1.5
C3	Division as separating	−1
C4	Sharing with a remainder	−0.1
C5	Separating with a remainder	0
C6	Parts of a whole	0.1
C7	Improper fractions	0.2
C8	Sequence of fractions	0.4
C9	Compare proper fractions with the same denominator	0.5
C10	Compare proper fractions with different denominators	0.7
C11	Add and subtract fractions	1.2
C12	Adding fractions	0.8
C13	Subtracting fractions	1
C14	Missing addend	1.3
C15	Missing subtrahend	1.5
C16	Missing summand	1.6
C17	Missing minuend	1.8

Table 4
The generated learning path by genetic algorithm with the adjustable weight 0.7

Learning path		Difficulty parameter	Concept relation degree between two successive courseware
C1	Equal parts	−1.8	–
C11	Add and subtract fractions	1.2	0.0138
C8	Sequence of fractions	0.4	0.0261
C6	Parts of a whole	0.1	0.7492
C7	Improper fractions	0.2	0.5561
C12	Adding fractions	0.8	0.0413
C2	Division as sharing	−1.5	0.0050
C3	Division as separating	−1	0.2062
C9	Compare proper fractions with the same denominator	0.5	0.0020
C5	Separating with a remainder	0	0.0038
C14	Missing addend	1.3	0
C10	Compare proper fractions with different denominators	0.7	0.1085
C15	Missing subtrahend	1.5	0.1085
C17	Missing minuend	1.8	0.4380
C16	Missing summand	1.6	0.3619
C4	Sharing with a remainder	−0.1	0
C13	Subtracting fractions	1	0.0073

comparison of learning performance for both the learning modes. The results reveal that the learning scores of 48.15% learners who learnt by the proposed learning mode of curriculum sequencing recommendation are progressive, but only 32% learners have progressive learning scores by the freely browsing learning mode. Next, the statistical information was utilized to further analyze the learning performance by statistical method.

In the work, the Matched-Pairs *T*-Tests was employed to analyze whether the freely browsing learning mode or the proposed learning mode of curriculum sequencing recommendation provides benefits in terms of learning performance promotion based on pre-test and post-test scores. Three cases are respectively discussed as follows:

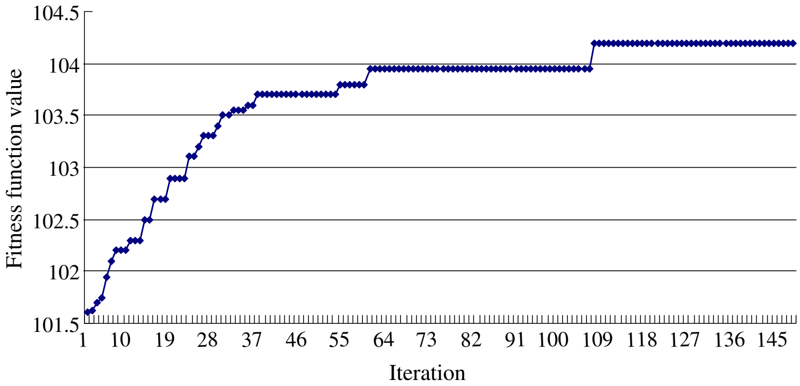

Fig. 15. Convergence curve of fitness function of genetic algorithm with the adjustable weight 0.7.

Case 1: The Matched-Pairs *T*-Tests for assessing the learning performance promotion of the freely browsing learning mode.

Table 8 lists the statistics information for the Matched-Pairs *T*-Tests of the control group to evaluate whether the freely browsing learning mode provides benefits in terms of learning performance promotion. Based on the goal, this study gave two research hypotheses for this case, and described as follows:

H0-Case 1: Suppose the learners who participated in the freely browsing learning mode have the same mean score in both the pre-test and post-test.

Table 5
The statistics information for assessing learning performance

Experimental group	Pre-test	Learning process	Post-test	Number of learners
Control group (learning by the freely browsing learning mode)	✓	Freely browsing a half of courseware in the designed course unit at least	✓	92
Treatment group (learning by the proposed learning mode of curriculum sequencing recommendation)	✓	Only learning the courseware with wrong answer responses in a pre-test	✓	128

Fig. 16. The actual teaching scene at Hualien County Jiamin Elementary School.

H1-Case 1: Suppose the learners who participated in the freely browsing learning mode do not have the same mean score in both the pre-test and post-test.

Table 9 shows the results of the Matched-Pairs *T*-Tests of the control group. The results indicate that the hypothesis H0 is satisfied under the significant level $\alpha = 0.05$ and $P = 0.273 > 0.05$. That is, no any reasons can conclude that the freely browsing learning mode provides benefits in terms of learning performance promotion. Actually, our experiment shows that the mean score of the post-test of learners lowers 2.27 points.

Case 2: The Matched-Pairs *T*-Tests for assessing the learning performance promotion of the proposed learning mode of curriculum sequencing recommendation.

Table 10 lists the statistics information for the Matched-Pairs *T*-Tests of the treatment group to evaluate whether the learning mode of curriculum sequencing recommendation provides benefits in terms of learning performance promotion. Therefore, this study also gave two research hypotheses for this case, and described as follows:

H0-Case 2: Suppose the learners who participated in the learning mode of curriculum sequencing recommendation have the same mean score in both the pre-test and post-test.

H1-Case 2: Suppose the learners who participated in the learning mode of curriculum sequencing recommendation do not have the same mean score in both the pre-test and post-test.

Table 11 shows the results of the Matched-Pairs *T*-Tests of the treatment group. The results indicate that the hypothesis H0 is satisfied under the significant level $\alpha = 0.05$ and $P = 0.602 > 0.05$. In other words, no any reasons can conclude that the learning mode of curriculum sequencing recommendation provides benefits in terms of learning performance promotion. However, our experiment shows that the mean score of the post-test of learners promotes 0.93 points.

Table 6
The statistical information for the participators who finished the planned learning processes and the satisfaction investigation

Analysis item	Control group	Treatment group
Finishing the entire learning process	75	108
Finishing the satisfaction investigation of questionnaire	61	103
Finishing the satisfaction investigation of learning mode	23	

Table 7
Comparison of learning performance for both the learning modes

Comparison item	Learning mode	
	The freely browsing learning mode for the control group	The learning mode of curriculum sequencing recommendation for the treatment group
Number of learners	75	108
Number of learners with progressive score	24 (32.00%)	52 (48.15%)
Number of learners with retrogressive score	36 (48.00%)	36 (33.33%)
Number of learners with constant score	15 (20.00%)	20 (18.52%)

Table 8
The statistics information for the Matched-Pairs *T*-Tests of the control group

Learning mode	Comparison item			
	Mean	Number of learners	Std. deviation	Std. error mean
Pre-test for the freely browsing learning mode	73.80	75	23.20	2.68
Post-test for the freely browsing learning mode	71.53	75	25.86	2.99

Table 9
The results of the Matched-Pairs *T*-Tests of the control group

	Paired differences					*t*	df	Sig. (2-tailed)
	Mean	Std. deviation	Std. error mean	95% Confidence interval of the difference				
				Lower	Upper			
Pair 1: Pre-test of freely browsing learning mode–post-test of freely browsing learning mode	2.27	17.77	2.05	−1.82	6.35	1.105	74	.273

Table 10
The statistics information for the Matched-Pairs *T*-Tests of the treatment group

Learning mode	Comparison item			
	Mean	Number of learners	Std. deviation	Std. error mean
Pre-test for the learning mode of curriculum sequencing recommendation	76.67	108	21.34	2.05
Post-test for the learning mode of curriculum sequencing recommendation	77.59	108	22.98	2.21

Table 11
The results of the Matched-Pairs *T*-Tests of the treatment group

	Paired differences					*t*	df	Sig. (2-tailed)
	Mean	Std. deviation	Std. error mean	95% Confidence interval of the difference				
				Lower	Upper			
Pair 1: Pre-test of the learning mode of curriculum sequencing recommendation–post-test of the learning mode of curriculum sequencing recommendation	−.93	18.41	1.77	−4.44	2.59	−.523	107	.602

Table 12
The statistics information for the Matched-Pairs *T*-Tests of both the control and treatment groups under the learners with the same pre-test score

Learning mode	Comparison item			
	Mean	Number of learners	Std. deviation	Std. error mean
Post-test for the freely browsing learning mode	72.32	69	25.96	3.13
Post-test for the learning mode of curriculum sequencing recommendation	79.49	69	23.08	2.78

Case 3: The Matched-Pairs *T*-Tests for assessing the learning performance promotion of the learners who have the same pre-test score in both the learning modes.

Table 12 lists the statistics information for the Matched-Pairs *T*-Tests of both learning groups to evaluate whether the learning mode of curriculum sequencing recommendation provides

Table 13
The results of the Matched-Pairs *T*-Tests of both the control and treatment groups

	Paired differences					*t*	df	Sig. (2-tailed)
	Mean	Std. deviation	Std. error mean	95% Confidence interval of the difference				
				Lower	Upper			
Pair 1: Post-test of freely browsing learning mode–post-test of the learning mode of curriculum sequencing recommendation	−7.17	17.94	2.16	−11.48	−2.87	−3.323	68	.001

benefits in terms of learning performance promotion for the learners with the same pre-test score in both the learning modes. Thus, this study gave the following two research hypotheses for the case, and described as follows:

H0-Case 3: Suppose the learners with the same pre-test score in both the learning modes have the same mean score of post-test.

H1-Case 3: Suppose the learners with the same pre-test score in both the learning modes do not have the same mean score of post-test.

Table 13 shows the results of the Matched-Pairs *T*-Tests of both the control and treatment groups. The results indicate that the hypothesis H1 is satisfied under the significant level $\alpha = 0.05$ and $P = 0.001 < 0.05$. That is, we can logically conclude that the learning mode of curriculum sequencing recommendation is superior to the freely browsing learning mode in terms of learning performance promotion in this case. Actually, our experiment shows that the mean score of the post-test of learners with the same pre-test score who performed the learning mode of curriculum sequencing recommendation is obviously 7.17 points higher than the learners who performed the freely browsing learning mode.

In conclusion, the proposed learning mode of curriculum sequencing recommendation indeed surpasses the freely browsing learning mode because it can guide learners to conduct efficient and appropriate learning paths as well as avoid cognitive overload or disorientation during learning processes.

6.5. Questionnaire analysis

To evaluate learners' satisfaction degree for the proposed genetic-based personalized *e*-learning system, referring to Chen's et al. research (Chen, Hsieh, & Hsu, 2007), a questionnaire which involves 26 questions distinguished six various question types was designed to measure whether the proposed genetic-based personalized *e*-learning system satisfied the real requirements of most learners. The six question types contain the

Table 14
The descriptions of question types

Question type	Number of questions	Description
The services of software and hardware	8	To investigate whether learners satisfy the provided user interface, course materials, and remedy learning mechanism
Learning interests	2	To investigate whether learners are interested in using the proposed genetic-based personalized *e*-learning system for mathematical learning
Learning mode	4	To investigate whether learners can accept the proposed learning mode with personalized learning path guidance
Learning interaction between teachers and learners	3	To investigate whether the proposed genetic-based personalized *e*-learning system affects learning interaction between teachers and learners
Learning attitude	5	To investigate whether learners with computer use the proposed genetic-based personalized *e*-learning system for mathematical learning at home
Learning performance	4	To investigate whether the proposed genetic-based personalized *e*-learning system can promote learners' learning performances and confidence

Table 15
The satisfaction evaluation results of questionnaire

Question type	Question	Satisfaction degree (%)									
		The freely browsing learning mode (there are totally 61 valid questionnaires)					The learning mode of curriculum sequencing recommendation (there are totally 103 valid questionnaires)				
		Very approved	Approved	No opinion	Disapproved	Very disapproved	Very approved	Approved	No opinion	Disapproved	Very disapproved
The services of software and hardware	1. I agree that the proposed system has provided a friendly user interface to support learning mathematics via web-based learning	52	33	13	0	2	61	26	13	0	0
	2. I agree that the learning contents with flash animation provided by the proposed system can deepen my impression of learning mathematics	54	28	15	2	2	63	23	13	0	1
	3. I agree that the learning mathematics by the proposed system with interactively learning interface is a very interesting learning mode	51	31	18	0	0	59	25	12	3	1
	4. I can completely understand the meaning of all designed course materials in the proposed system	44	31	15	2	8	53	29	15	2	1
	5. I can completely understand the meaning of the corresponding test question of the learned courseware in the proposed system	59	23	13	5	0	57	28	11	3	1
	6. I agree that using the proposed system for mathematical learning is very interesting because I can operate all system functions as well as control self-learning time	74	18	5	3	0	65	26	7	1	1
	7. I agree that the immediate test function provided by proposed the system can help me understand whether I have acquired the learned courseware or not. Meanwhile, I like the learning mode very much	56	26	8	2	8	57	26	9	4	4
	8. I agree that the remedy learning mechanism provided by the proposed system for unfamiliar learning concepts is very helpful to my learning	46	31	16	3	3	57	19	15	6	3
	Average	82		13	5		85		12	4	

Learning interests	1. I feel that using the proposed system for mathematical learning is very interesting	70	21	3	3	2	71	23	4	1	1
	2. I agree that the learning contents provided by the proposed system can promote my interests of learning mathematics	61	23	10	5	2	60	21	17	2	0
	Average	88		7	6		88		10	2	
Learning mode	1. I agree that using the freely browsing learning mode for mathematical learning is a very good learning mode because I can freely click any course materials by myself for learning	64	26	8	0	2	–	–	–	–	–
	2. I agree that directing learners to enter the post-test process after they learnt one half of course materials by the freely browsing learning mode is a good learning mode	54	26	13	5	2	–	–	–	–	–
	3. I agree that using the learning mode of curriculum sequencing recommendation is a very good learning mode because I only need to learn unfamiliar courseware based on a planning learning path under skipping acquired courseware	–	–	–	–	–	51	27	13	2	7
	4. I agree that the learning mode of curriculum sequencing recommendation provides a reasonable learning path because it simultaneously consider courseware difficulty level and the concept continuity of learning path to plan the learning order of courseware	–	–	–	–	–	64	19	13	1	3
	Average	85		11	4		81		13	6	

(*continued on next page*)

Table 15 (*continued*)

Question type	Question	Satisfaction degree (%)									
		The freely browsing learning mode (there are totally 61 valid questionnaires)					The learning mode of curriculum sequencing recommendation (there are totally 103 valid questionnaires)				
		Very approved	Approved	No opinion	Disapproved	Very disapproved	Very approved	Approved	No opinion	Disapproved	Very disapproved
Learning interaction between teachers and learners	1. I agree that I do not need to rely on teacher instruction if I can use the proposed system for mathematical learning	49	28	13	7	3	49	26	12	4	10
	2. I agree that I can learn better if I can get assistance from teacher except learning mathematics by the proposed system	64	26	8	0	2	68	18	8	3	3
	3. I feel that using the proposed system for mathematical learning will reduce interactive chance with teacher	41	20	28	8	3	46	22	22	7	3
	Average	76		16	8		76		14	10	
Learning attitude	1. I would like to reply once again for the test question that I cannot give correct answer when I learnt mathematics by the proposed system	56	23	16	5	0	60	20	11	4	5
	2. I feel that time always passes very quickly when I use the proposed system for mathematical learning	48	16	23	7	7	52	28	15	3	2
	3. I feel so happy when I think of using proposed system for mathematical learning	56	31	10	2	2	63	23	10	2	2
	4. I feel that using the proposed system for mathematical learning is very convenient because I can learn at any time and any place by Internet. Therefore, I have a strong willing to learn mathematics by the proposed system once again	49	28	11	8	3	50	25	15	5	5
	Average	77		15	11		76		12	10	
	5. Do you have any computers that can be used at home?	Yes	87	No	13	–	Yes	87	No	13	–
	5.1 Can you surf Internet at home?	Yes	69	No	31	–	Yes	77	No	20	–

	5.2 Have you ever logged into the proposed system for mathematical learning by Internet at home?	Yes	66	No	33	–	Yes	53	No	42	–
Learning performance	1. The remedy learning mechanism provided by the proposed system can help me acquire the courseware that I could not understand in the past, thus promoting my learning confidence	52	21	18	7	2	57	27	12	1	3
	2. I feel that learning mathematics by the proposed system is superior to the conventional classroom learning	44	23	26	5	2	51	19	22	6	1
	3. I agree that the learning process followed by the pre-test, learning and post-test is a very efficient learning mode	54	26	8	7	5	54	20	17	5	4
	4. I agree that the proposed system is an effectively assisted learning tool for mathematical learning	56	31	8	2	3	61	21	12	0	6
	Average	77		15	8		78		16	6	

Table 16
The questionnaire for assessing satisfaction degrees of learners who conducted both the learning modes

Question	Number of learners who selected the first item	Number of learners who selected the second item
1. The personalized *e*-learning system provides two learning modes. I prefer (1) the learning mode of curriculum sequencing recommendation. (2) The freely browsing learning mode	16 (70%)	7 (30%)
2. Based on the aspect of curriculum sequencing, I prefer (1) the learning system help me plan a logical learning path only for the courseware that I have not acquired. (2) To learn freely for all courseware by myself	16 (70%)	7 (30%)
3. In two evaluated learning modes, I feel that (1) only learning the courseware that I have not acquired is enough. (2) Learning all courseware can let me learn much more	7 (30%)	16 (70%)
4. In two evaluated learning modes, I feel that (1) only learning the courseware that I have not acquired can learn more efficiently than learning all courseware. (2) Learning all courseware can let me learn more efficiently than only learning the courseware that I have not acquired	13 (57%)	10 (43%)
5. In two evaluated learning modes, I think that (1) only learning the courseware that I have not acquired can improve my learning performance. (2) Learning all courseware can enhance my learning performance	7 (30%)	16 (70%)

services of software and hardware, learning interests, learning mode, learning interaction between teachers and learners, learning attitude, and learning performance. Table 14 gives a summarization of question types with brief descriptions. There are totally 164 effective questionnaires filled out by learners who participated in this experiment. Among 164 effective questionnaires, 61 learners adopted the freely browsing learning mode and 103 learners used the proposed learning mode of curriculum sequencing recommendation for mathematics learning. The evaluation results of satisfaction degree are detailed in Table 15. To conveniently observe the evaluating results, the investigation results of ‘‘strongly agreed’’ and ‘‘agreed’’ are merged as ‘‘approved’’, and the investigation results of ‘‘strongly disagreed’’ and ‘‘disagreed’’ are merged as ‘‘disapproved’’.

The evaluating results listed in Table 15 indicate that over 76% learners are satisfactory in terms of the services of software and hardware, the promotions of learning interests, learning attitude and learning performance for both the evaluated learning modes. Most learners agreed that both the evaluated learning modes provide satisfied software and hardware environments and are very helpful to their mathematical learning. Moreover, both the evaluated learning modes can attract learners to learn mathematics using leisure time by Internet at home. Most learners also agreed that both the evaluated learning modes help them conduct efficient learning. Particularly, the remedy learning mechanism provided by both the evaluated learning modes can help learners acquire the courseware that they could not understand well in the past, thus promoting their learning effectiveness and confidences. Additionally, 81% learners agreed that the learning mode of curriculum sequencing recommendation provide an appropriate learning path for aiding mathematical learning because they only need to learn unfamiliar courseware, but skipping acquired courseware. Similarly, 80% learners also agreed that using the freely browsing learning mode for mathematical learning is a good learning mode because they can freely select any course materials by themselves for learning. Encouragingly, 77% learners agreed that they do not need to rely on teacher instruction if they can use any one of both the learning modes for mathematical learning, but up to 90% learners agreed that they can learn better if they can also get assistance from teacher except learning by any one of both the evaluated learning modes.

The satisfaction evaluation results of questionnaire mentioned-above show that both the evaluated learning modes obtain very high satisfaction degree for mathematical learning. To further compare the difference of satisfaction degree between both the learning modes, this study invited 23 learners who had adopted any one of both the learning modes for mathematical learning to conduct another learning mode, then they were invited to fill out another questionnaire for assessing satisfaction degrees of learners who simultaneously conducted both the learning modes. Table 16 presents the evaluation results of questionnaire containing 23 effective samples. The results indicated that 70% learners felt much more prefer the learning mode of curriculum sequencing recommendation than the freely browsing learning mode because it can help them plan a logical learning path only for the courseware that they have not acquired. In the meanwhile, 57% learners felt that only learning the courseware that they have not acquired yet can learn more efficiently than learning all courseware. However, there are up to 70% learners to think that learning all courseware can enhance their learning performances. The phenomenon shows that most students of Taiwan's elementary schools are facing a very competitive learning environment among schoolmates, such that they cannot adequately trust to conduct more efficiently learning like the proposed learning mode of curriculum sequencing recommendation even they prefer it than the freely browsing learning mode.

7. Conclusion

This study proposes a genetic-based personalized learning path generation scheme for individual learners to support personalized web-based learning. The proposed personalized learning path generation scheme can simultaneously consider courseware difficulty level and the concept continuity of successive courseware according to the incorrect testing responses in a pre-test while implementing personalized curriculum sequencing during learning processes. Compared to the freely browsing learning mode used in most web-based learning systems, experimental results indicated that the proposed learning mode of curriculum sequencing recommendation can precisely plan a personalized learning path for the courseware that a learner has not acquired yet based on a difficulty parameter and concept continuity of successive courseware, and moreover can promote learner's learning effectiveness during learning processes. In the meanwhile, the investigation results of questionnaire revealed that most learners agreed the learning mode of curriculum sequencing recommendation is superior to the freely browsing learning mode in terms of learning efficiency. An important advantage is that the learning mode of curriculum sequencing recommendation customizes learning for those who have very specific needs and not much time or patience to complete topics they have learned.

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References

An Extension Chinese Lexicon Scanner (2006). Available from http://dlll.nccu.edu.tw/rank/ecscanner/.

AppServ Open Project (2007). Available from http://www.appservnetwork.com/.

Baker Frank, B. (1992). *Item response theory: Parameter estimation techniques*. New York: Marcel Dekker.

Berghel, H. (1997). Cyberspace 2000: Dealing with information overload. *Communications of the ACM, 40*(2), 19–24.

Borchers, A., Herlocker, J., Konstanand, J., & Riedl, J. (1998). Ganging up on information overload. *Computer, 31*(4), 106–108.

Brusilovsky, P., Eklund, J., & Schwarz, E. (1998). Web-based education for all: A tool for development adaptive courseware. *Computer Networks and ISDN Systems, 30*, 291–300.

Brusilovsky, P., & Vassileva, J. (2003). Course sequencing techniques for large-scale web-based education. *International Journal of Continuing Engineering Education and Lifelong Learning, 13*(1–2), 75–94.

Chen, C.-M., Hsieh, Y.-L., & Hsu, S.-H. (2007). Mining learner profile based on association rule for web-based learning diagnosis. *Expert Systems with Applications, 33*(1), 6–22.

Chen, C.-M., Lee, H.-M., & Chen, Y.-H. (2005). Personalized *e*-learning system using item response theory. *Computers and Education, 44*(3), 237–255.

Chen, C.-M., Liu, C.-Y., & Chang, M.-H. (2006). Personalized curriculum sequencing using modified item response theory for web-based instruction. *Expert Systems with Applications, 30*(2), 378–396.

Frakes, W. B., & Baeza-Yates, R. (1992). *Information retrieval data structures and algorithms*. Englewood Cliffs: N. Prentice Hall.

Genesereth, M. (1997). An agent-based framework for interoperability. In J. M. Bradshaw (Ed.), *Software agents* (pp. 317–345). Menlo Park, Calif.: AAAI Press.

Horton, W. (2000). *Designing web-based training: How to teach anyone anything anywhere anytime?* John Wiley & Sons, Inc.

Hsu, T. C., & Sadock, S. F. (1985). Computer-assisted test construction: A state of art. TME report 88, Princeton, New Jersey, Eric on Test, Measurement, and Evaluation, Educational Testing Service.

Jih, H. J. (1996). The impact of learners' pathway on learning performance in multimedia computer aided learning. *Journal of Network and Computer Applications, 19*, 367–380.

Lee, M.-G. (2001). Profiling students' adaptation styles in web-based learning. *Computers and Education, 36*, 121–132.

Lin, B., & Hsieh, C.-T. (2001). Web-based teaching and learner control: A research review. *Computers and Education, 37*, 377–386.

Mia, K., & Woolf, B. P. (1998). Curriculum sequencing in a web-based tutor. In *Proceedings of intelligent tutoring systems*.

Nwana, H. S. (1996). Software agents: An overview. *The Knowledge Engineering Review, 11*(3), 205–244.

Papanikolaou, K. A., & Grigoriadou, M. (2002). Towards new forms of knowledge communication: The adaptive dimension of a web-based learning environment. *Computers and Education, 39*, 333–360.

Roland, H. (2000). Logically optimal curriculum sequences for adaptive hypermedia systems. In *International conference on adaptive hypermedia and adaptive web-based system*, pp. 121–132.

Rothlauf, F. (2002). *Representations for genetic and evolutionary algorithms*. Heidelberg, New York: Physica-Verlag.

SCORM version 1.2-The SCORM Content Aggregation Model (2001). Advanced distributed learning initiative. Available from http://www.adlnet.org/screens/shares/dsp_displayfile.cfm?fileid = 476.

Tang, C., Lau Rynson, W. H., Li, Q., Yin, H., Li, T., & Kilis, D. (2000). Personalized courseware construction based on web data mining. In *Proceedings of the first IEEE international conference on web information systems engineering*, 2, pp. 204–211.

Tang, T. Y., & Mccalla, G. (2003). Smart recommendation for evolving *e*-learning system. In *11th international conference on artificial intelligence in education, Workshop on technologies for electronic documents for supporting learning, July 20–24, Sydney, Australia*, pp. 699–710.

Weber, G., & Specht, M. (1997). User modeling and adaptive navigation support in WWW-based tutoring systems. In *Proceedings of the sixth international conference on user modeling*, pp. 289–300.