行政院國家科學委員會專題研究計畫 成果報告

具個人化學習引導之智慧型教學代理人系統發展與研究 II(2/2)
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行政院國家科學委員會專題研究計劃成果報告

具個人化學習引導之智慧型教學代理人系統發展與研究 II (2/2)

Research on an Intelligent Tutoring Agent System with Personalized Learning Guidance Mechanism II (2/2)

計劃編號：NSC95-2520-S-004-001
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中文摘要

隨著電腦技術及網際網路的蓬勃發展，數位學習已成為當今教與學的另一種趨勢。以網路為基礎的課程順序應該因人而異，能動態安排課程順序以滿足個人化之需求是一重要的技術。因此，近年來有許多研究者著手於發展適性化學習系統，期許能提供個人化的學習路徑；然而大部份的系統僅考慮學習者的興趣、喜好及瀏覽行為，而忽略學習課程的難易度及先後備知識關係，不適當的課程常造成學習者的負擔及學習上之迷失，且降低學習成效。隨著人工智慧技術的快速發展，本體知識論能夠應用來表達課程概念間的學習概念關聯，因此可以用來協助個人化學習路徑的建構。因此本研究在同時考量教材的難易度、先後備知識關係及學習者能力的前提下，提出一個以本體知識概念圖(ontology-based concept map)為基礎之個人化學習路徑產生方法。透過自動產生建構 ontology 的技術，我們能夠以圖型化的方式呈現某一特定領域的重要知識及核心概念關係，據此所產生的學習路徑，可以有效降低學習迷思的問題及認知負載的發生，且可促進學習成效。本研究以國小分數單元作為實驗教材內容，透過資料探勘的方式，將國小分數單元彼此間的關聯利用 ontology 學習概念圖方式來描繪，並配合基因演算法運用在個人化的學習路徑的規劃上，以期引導個人進行符合個人需求之有效率學習。

關鍵字：本體知識為基礎之概念圖、個人化學習路徑、智慧型教學系統、網路學習

Abstract

Developing personalized Web-based learning systems has been an important research issue in the e-learning field because no fixed learning pathway will be appropriate for all learners. However, the current most web-based learning platforms with personalized curriculum sequencing tend to emphasize the learners' preferences and interests for the personalized learning services, but they fail to consider difficulty levels of course materials, learning order of prior and posterior knowledge, and learners' abilities while constructing a personalized learning path. As a result, these ignored factors easily lead to generating poor quality learning paths. Generally, learners could generate cognitive overload or fall into cognitive disorientation due to inappropriate curriculum sequencing during learning processes, thus reducing learning effect. With advancement of the artificial intelligence technologies, ontology technologies enable a linguistic infrastructure to represent concept relationships between courseware. Ontology can be served as a structured knowledge representation scheme, which can assist the construction of personalized learning path. Therefore, this study proposes a novel genetic-based curriculum sequencing scheme based on a generated ontology-based concept map, which can be automatically constructed by a large amount of learners' pre-test results, to plan appropriate learning paths for individual learners. The experimental results indicated that the proposed approach is indeed capable of creating learning paths with high quality for individual learners to greatly reduce their cognitive overloads and to help learners learn more effectively.

Keywords: Ontology-based concept map, Personalized learning path, Intelligent tutoring system, Web-based learning

1 Introduction

With the rapid growth of the Internet, various personalized e-learning platforms were proposed to provide adaptive curriculum sequencing services for individual learners in web-based learning environments. Although information technologies enable learners to easily access a large number of learning materials without geographical boundaries, this phenomenon has caused several serious problems, including learner's self-learning control, learning disorientation, and cognitive overload (Alomyan, 2004; Eppler and Mengis, 2004). In general, learner's self-learning control implies that learners should take the initiative in their learning. However, learners would easily deviate or learn inefficiently when they are receiving unsuitable instruction and scaffold. This phenomenon will result in the great difference with the original teaching goal that the instructors expect (Rasmussen and Davidson-Shivers, 1998). Moreover, the disorientation problems derive from that most of the web-based learning systems flood with complex courseware structure due to over lots of hyperlink-based learning materials, and therefore learners easily trap into learning disorientation and are unable to construct complete and systematic domain knowledge during learning processes (Lin and Davidson-Shivers, 1996; Calvi, 1997). Regarding cognitive overload, it is also a serious problem that affects learners' learning in hypermedia learning systems. This problem emerges from the freedom of navigation that hypermedia systems offer; moreover, it may also be compounded by the vast quantities of easily accessible information, much of which may only be peripherally relevant (Paolucci, 1998). Under the circumstances of overemphasizing the learner's independence, the appearance of information anxiety arises easily when the learner faces cognitive overload. Furthermore, learners have to spend most efforts on deciding what to learn and where to go, which leads to cognitive overload as well.

To deal with these problems, a few researchers brought up an idea to use the learning path as a control way to guide the learning direction for individual learners (Chen et al, 2005; Chen et al, 2006; Lee, 2001). As a web-based learning system with personalized learning guidance is used to aid individual learning, it can increase much learning efficiency and help instructors succeed in achieving their educational goals. In recent years, the property of being adaptive to offer learners appropriate learning resources has been gradually regarded as an important issue in web-based learning field (Federico, 1999). More and more researches attempt to create intelligent learning systems that can arrange the curriculum sequence more flexibly in order to provide learners with more adaptive and personalized learning services (Lee, 2001; Tang and Mccalla, 2003; Papanikolaou and Grigoriadou, 2002; Chen et al, 2005; Chen et al). Among these developed intelligent learning systems with curriculum sequence mechanism, both the e-learning systems ELM-ART and CALAT indicated by Brusilovsky (1998) emphasize the function of curriculum sequencing to support the personalized learning task and provide adaptive guidance for learners. In ELM-ART system, the courseware has been organized in sequence in advance. When learners click in the courseware beyond their ability, the system will warn learners and display the related prior course for them. However, the learning guidance is just provided while learners select the unsuitable courseware, and such a mechanism cannot help each leaner perform personalized guiding learning at any time. In CALAT system, the courseware is displayed by a tree structure and arranged previously in order according to the learning aims. When learners start to learn, the system will consider their understanding levels and the learning aims for showing the learning sequence of courseware webpage. However, these learning guidance mechanisms mentioned-above are not so adaptive to individual learners because all course materials are pre-planned by the system instead of being decided dynamically based on individual learners' progresses and response during learning processes (Alex and Jims, 2000).

Additionally, the genetic-based personalized e-learning system, which can provide a near optimal learning path for individual learners on-line according to the difficulty levels of course materials, concept relation degree between courseware and learners' abilities, was presented by our previous study (Chen, 2007) for personalized web-based learning. However, the concept relation degrees among courseware are served as being symmetric in the study. That is, the curriculum sequence pattern "$A \rightarrow B$" is identical with the curriculum sequence pattern "$B \rightarrow A$". This outcome is inconsistent with the realistic learning situation (Hsu et al., 1998). Generally speaking, prior knowledge that refers to a range of knowledge, skills, and ability should be significantly considered in the learning process. The past researches also indicated that learners with higher level of certain domain knowledge are more competent in terms of understanding, memory, and the effect of cognitive learning (McCormick and Pressley, 1995). In this issue, quite a few researchers have discovered that the related prior knowledge affects the learning performance (Papanikolaou and Grigoriadou, 2002).

Recently, ontology technologies (Gruber, 1993; Song et. al, 2007; Brewster and O'Hara, 2007) have been broadly discussed in the fields of computer science and artificial intelligence. Ontology can be employed to support a great variety of tasks in various research areas such as knowledge representation, natural language processing, information retrieval, database design, knowledge management, digital libraries, geographic information systems, multi agent systems, and e-learning, and so on (Yang et al., 2005; Yang et. al, 2004; Brewster and O'Hara, 2007). Ontology is a hierarchically structured set of terms for describing a domain knowledge that can be used as a skeletal foundation for a knowledge base system. If an ontology is implemented for a specific field well and used to describe the related knowledge such as terminology or associated notions, it can help us find out useful or connected information when we explore under this kind of structured knowledge (Swartout, Knight and Russ, 1996).

Therefore, this research aims to improve the shortcoming of the genetic-based personalized e-learning system presented in our previous study (Chen, 2007), such that the prior and posterior knowledge of learning concept can be considered while planning personalized paths. In this work, the generated ontology-based concept map based on gathering a large number of pre-test results was applied to enhance the construction of the personalized learning path. This study is expected to establish authentic and near optimal learning paths that can help individual learners reduce the effects of cognitive overload and disorientation. Meanwhile, the proposed system can customize learning for those who have very specific needs and not much time or patience to complete topics. Experimental results show that the proposed genetic-based learning path generating scheme based on ontology-based concept map is superior to the genetic-based learning path generating scheme proposed in our previous study in terms of learning path quality because of simultaneously considering the difficulty of courseware and prior and posterior knowledge of learning concept while planning personalized paths

2. System Design

This section is organized as follows: first, an overview of system architecture is introduced in Section 2.1. Section 2.2 aims to explain the proposed concept map generation scheme. Finally, applying the generated ontology-based concept map to personalized learning path generation is described in Section 2.3.

2.1 System Architecture

In our previous work (Chen, 2007), the personalized e-learning system including an off-line courseware and test question construction module, six intelligent agents and four databases was presented for personalized learning path generation based on genetic algorithm. It can conduct personalized curriculum sequencing through simultaneously considering courseware difficulty level and the concept continuity of learning paths to support web-based learning. The experiment results had demonstrated that applying the proposed genetic-based personalized e-learning system with adaptive learning path guidance is superior to the freely browsing learning mode without learning guidance mechanism in terms of the promotion of learning performance.

However, the concept relation degrees among courseware are served as being symmetric in our previous study. That is, the curriculum sequence pattern "A→B" is identical with the curriculum sequence pattern "B→A". In other words, the concept of prior and posterior knowledge had not been considered in the generated personalized learning paths. The result is inconsistent with real learning situations, thus leading to constructing unreasonable learning paths for individual learners. In this study, the previous proposed genetic-based personalized e-learning system is improved to enhance the quality of generated personalized learning paths via an automatically constructing ontology-based concept map. In the refined genetic-based personalized e-learning system, the results of the pretests are first extracted and preprocessed for the needs of constructing concept map and the concept relationships between courseware are constructed through the proposed concept relation measure and fuzzy clustering scheme. After that, the constructed ontology-based concept map is served as the constraint conditions for the employed genetic algorithm to plan an appropriate learning path for individual learner. The entire system architecture is shown as Fig. 1. The function of each component is explained below.

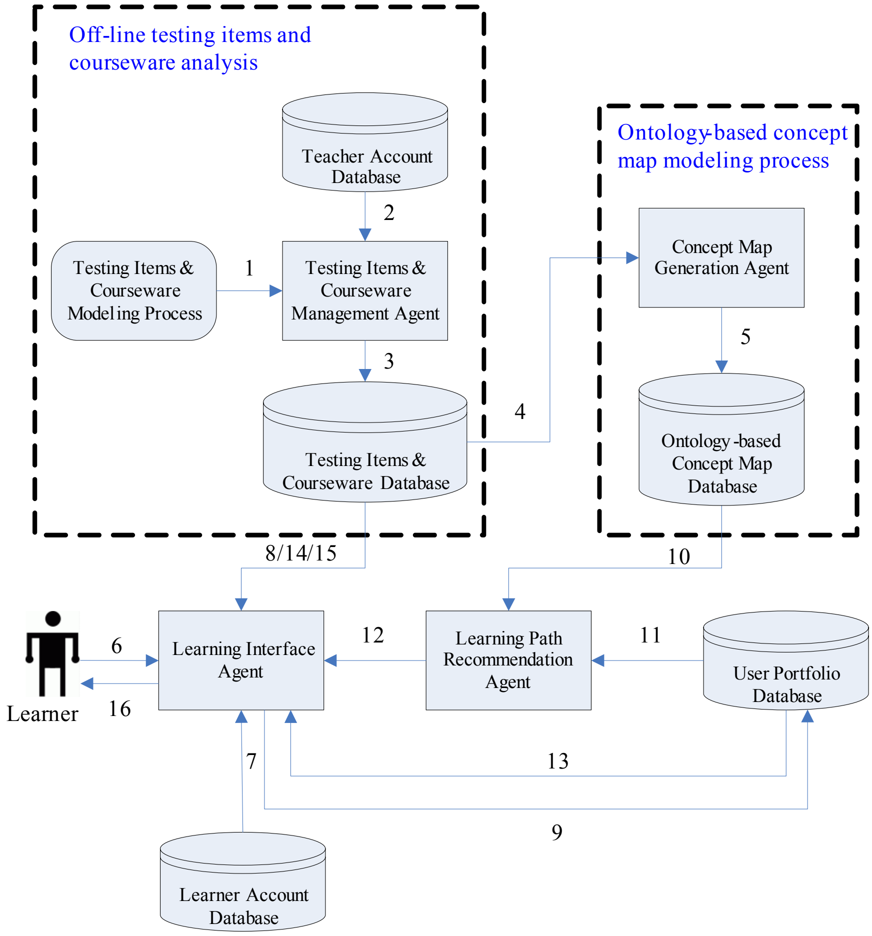

Fig. 1 The system architecture of the personalized e-learning system based on ontology-based concept map

First, the courseware construction module, shown as the left rectangle frame with dotted line in Fig. 1, includes four components: the testing items and courseware modeling process, testing items and courseware management agent, teacher account database, and testing items and courseware database. These four components are detailed as follows:

- **Testing items and courseware modeling process:** The modeling process aims to calculate each corresponding difficulty parameter for each test item according to computerized adaptive testing theory (Horward, 1990). Then, each test item will be transformed into web-based course material with the corresponding difficulty parameter. The detailed processes are explained in Section 2.2.2.
- **Testing items and courseware management agent:** The agent helps teachers to update or maintain the course materials in the testing items and courseware database.
- **Teacher account database:** The database records teacher's account information for checking teacher identification to login the testing items and courseware management agent.
- **Testing items and courseware database:** The database is designed for storing courseware and test items developed by course experts.

The rest system components are detailed as follows:

- **Learner account database:** The database aims to record learner's account information for each learner.
- **Learning interface agent:** The agent's functions include: (1) checking learners' accounts and monitoring learners' learning states. (2) offering friendly learner learning interface with personalized learning path guidance to individual learners. (3) accessing the user portfolio database for personalized learning services and storing learners' learning processes into the user portfolio database.
- **User portfolio database:** The database is in charge of storing tracks of all the detailed learning processes for each learner.
- **Concept map generation agent:** The agent mainly focuses on two parts. One is to handle the results of the exam and to pre-process testing responses. The right testing answers are marked as ones, and the wrong testing answers are marked as zeros. Then, a formula of computing concept correlation mentioned later is employed to calculate the relationships between courseware. Finally, this agent makes use of the fuzzy clustering method and the computing

correlation between courseware to automate the construction of the ontology-based concept map.

- **Ontology-based concept map database:** The database stores totally 17 designed courseware and their corresponding concept correlations to each other for supporting personalized learning path generation based on genetic algorithm.
- **Learning path recommendation agent:** The agent utilizes genetic algorithm supported by the generated ontology-based concept map to construct adaptive learning paths for individual learners and receive learners' testing responses from the learning interface agent.

Next, the system operation procedure based on the system architecture is described as follows:

Step 1:

The course experts first design test items for each corresponding course material, and then the testing items and courseware modeling process follows to estimate the difficulty parameter of each corresponding course material according to computerized adaptive testing theory. After that, each test item is transformed into the web-based course materials according to the conveyed concept of each test item and the authorized teachers can update or maintain the courseware materials through the testing items and courseware management agent.

Step 2:

Teachers can manage test items and courseware using the user interface of the test item & courseware management agent via the legal accounts stored in the teacher account database.

Step 3:

These constructed courseware and test items are stored into the testing items and courseware database.

Step 4:

More than 600 records of elementary school examinees who participated in the exam of the unit "Fraction", including 17 testing items covering those learning concepts, are pre-processed for constructing ontology-based concept map. In this work, the right testing answers are marked as ones and the wrong testing answers are marked as zeros. After that, the concept correlation measure mentioned later is adopted to find out the asymmetric relation among the 17 fraction-related mathematical courseware.

Step 5:

The ontology-based concept map of the "Fraction" unit is constructed by the employed fuzzy clustering method and concept correlation measure, which can group courseware with high correlation into the same cluster. After that, the generated concept map will be stored into the ontology-based concept map database for supporting personalized learning path generation

Step 6:

A learner logs in the system via a legal account for personalized learning services.

Step 7:

Once the learner logs in the system, the learner account database will offer legal account information for checking his/her identification.

Step 8-9:

The learning interface agent checks the learner's identification to determine whether the learner is a beginner or an experienced learner. If the learner is a beginner, the testing items and courseware database will provide a pre-test for the learner to evaluate which concepts that the learner has still not learned well based on incorrect testing responses. If the learner is an experienced learner, then go to the **Step 13** for unfinished learning processes; otherwise, go to the next step. Meanwhile, each learner's learning states are also stored into the user portfolio database during learning processes.

Step 10-12:

The generated ontology-based concept map in **Step 5** is used to support the learning path recommendation agent to plan a near optimal learning path based on the outcome of the learner pre-test, and then the generated learning path is transmitted to the learning interface agent to provide adaptive learning guidance for individual learner.

Step 13-14:

If the learner is identified as an experienced learner, his/her learning portfolio is first downloaded from the user portfolio database. And he/she has to learn all the unfinished courseware recorded in the download learning path before performing the post-test.

Step 15:

Once the learner finishes all courseware learning, the proposed system will provide a post-test to evaluate learner's learning performance.

Step 16:

Complete all the learning procedures and log out the system.

2.2 The Proposed Concept Map Generation Scheme

2.2.1 The designed course materials in the course unit "fraction" for exploring ontology-based concept map

Currently, under the course category, "Mathematics of elementary school", the proposed system contains one course unit "Fraction" and includes 17 course materials designed by several mathematical teachers. Moreover, each course material has a corresponding difficulty parameter, initially determined by statistics analysis, and each courseware corresponds to several testing questions which can be employed to exanimate whether the learned courseware can be understood. In this study, there is a learning portfolio database storing testing records of more than 600 elementary school students who participated in the exam in the "Fraction" unit. In the exam, the learned courseware with wrong answer will be served as "focused concept" to evaluate the correlation with the other courseware with wrong answer as well for the proposed ontology-based generation scheme. All designed course materials for the learning process and their corresponding difficulty parameters are listed in Table 1.

Table 1. The contents of the designed course materials and the difficulty levels of the corresponding course materials in the course unit "Fraction"

Course material	Concept description	The difficulty level of course material
C1 (Equal parts)	To understand the meaning of "equal parts" is to divide a unit into n equal parts	-1.8
C2 (Division as sharing)	To use the concept of "equal parts" solves the problem of "division as sharing". Division as sharing means that a given set is partitioned into a specified number of groups to determine how many partitions are in each equal group.	-1.5
C3 (Division as separating)	To use the concept of "equal parts" solves the problem of "division as separating". Division as separating means that a given set is partitioned by a specified amount to determine how many equal groups.	-1
C4 (Sharing with a remainder)	To use the concept of "equal parts" solves the problem of "division as sharing with remainder"	-0.1
C5 (Separating with a remainder)	To use the concept of "equal parts" solves the problem of "division as separating with remainder"	0
C6 (Parts of a whole)	Identifying the numerator and denominator of a fraction and expressing improper fractions as whole	0.1
C7 (Improper fractions)	Identifying proper and improper fractions	0.2
C8 (Sequence of fractions)	Order the fractions and find the fractional value on a number line	0.4
C9 (Compare proper fractions with the same denominator)	To compare fractions with the same denominator, look at their numerators. The larger fraction is the one with the larger numerator.	0.5
C10 (Compare proper fractions with different denominators)	To compare fractions with different denominator	0.7
C11 (Add and subtract fractions)	Adding and subtracting fractions when the denominators are the same	1.2
C12 (Adding fractions)	Adding fractions with the same denominators	0.8
C13 (Subtracting fractions)	Subtracting fractions with the same denominators	1
C14 (Missing addend)	Perform missing addend fractions problems with the same denominators	1.3
C15 (Missing subtrahend)	Perform missing subtrahend fractions problems with the same denominators	1.5
C16 (Missing summand)	Perform missing subtrahend fractions problems with the same denominators	1.6
C17 (Missing minuend)	Perform missing minuend fractions problems with the same denominators	1.8

2.2.2 The computing method of concept correlation for exploring ontology-based concept map

According to the result of the testing question exam, the right answers would be marked with ones, and the wrong answers would be marked with zeros. Next, this study proposes a computing formula of correlation to calculate the concept relationships between courseware. And the adopted formula is formulated as follows,

$$R_{C_i,C_j} = \frac{N(C_i \cap C_j)}{N(C_i)} \tag{1}$$

where R_{C_i,C_j} represents the concept relation between the i^{th} learning concept and the j^{th} learning concept, $N(C_i)$ is the number of the learners who gave wrong answer for the corresponding testing question that conveys the i^{th} learning concept, and $N(C_i \cap C_j)$ stands for the number of the learners who gave wrong answer for the corresponding testing question that conveys the j^{th} learning concept as well under learners had given wrong answer for the corresponding testing question that conveys the i^{th} learning concept.

In Eq. (1), we can figure out the concept relationships between courseware obtained via calculating correlations based on learners' responses in the testing question exam. All correlations among the 17 designed course materials in the unit "Fraction" can be represented as a concept correlation table, listed in Table 2. Moreover, to simplify the generated ontology-based concept map mentioned later, the concept correlations with weak correlation value will be first filtered out, and these concept entries with weak correlation are set to zeros. These weak concept correlations mean that their correlation values are less than a given threshold. Table 3 illustrates the revised concept correlation table of the 17 designed course materials after filtering out the weak concept correlations.

Table 2. The concept correlations between the 17 designed courseware

Courseware	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17
C1	1	0.23	0.153	0.153	0.192	0.269	0.346	0.423	0.192	0.653	0.307	0.23	0.307	0.461	0.307	0.269	0.384
C2	0.162	1	0.108	0.108	0.189	0.351	0.243	0.297	0.297	0.54	0.243	0.189	0.162	0.189	0.108	0.162	0.135
C3	0.307	0.307	1	0.23	0.538	0.384	0.384	0.538	0.307	0.846	0.23	0.307	0.307	0.384	0.153	0.23	0.153
C4	0.058	0.058	0.044	1	0.161	0.161	0.117	0.132	0.235	0.294	0.058	0.058	0.147	0.132	0.058	0.058	0.058
C5	0.172	0.241	0.241	0.379	1	0.241	0.206	0.31	0.275	0.517	0.137	0.172	0.172	0.206	0.137	0.103	0.137
C6	0.063	0.117	0.045	0.099	0.063	1	0.063	0.171	0.189	0.333	0.108	0.099	0.054	0.153	0.072	0.072	0.072
C7	0.2	0.2	0.111	0.177	0.133	0.155	1	0.244	0.311	0.466	0.177	0.155	0.111	0.311	0.133	0.155	0.177
C8	0.189	0.189	0.112	0.155	0.155	0.327	0.189	1	0.31	0.465	0.206	0.155	0.137	0.155	0.224	0.172	0.137
C9	0.045	0.1	0.036	0.146	0.073	0.192	0.128	0.165	1	0.284	0.165	0.082	0.073	0.1	0.045	0.073	0.036
C10	0.098	0.115	0.063	0.115	0.086	0.213	0.121	0.156	0.179	1	0.127	0.098	0.115	0.208	0.086	0.098	0.092
C11	0.153	0.173	0.057	0.076	0.076	0.23	0.153	0.23	0.346	0.423	1	0.153	0.25	0.326	0.192	0.23	0.211
C12	0.193	0.225	0.129	0.129	0.161	0.354	0.225	0.29	0.29	0.548	0.258	1	0.225	0.483	0.29	0.225	0.258
C13	0.235	0.176	0.117	0.294	0.147	0.176	0.147	0.235	0.235	0.588	0.382	0.205	1	0.382	0.294	0.382	0.441

C14	0.166	0.097	0.069	0.125	0.083	0.236	0.194	0.125	0.152	0.5	0.236	0.208	0.18	1	0.166	0.208	0.222
C15	0.258	0.129	0.064	0.129	0.129	0.258	0.193	0.419	0.161	0.483	0.322	0.29	0.322	0.387	1	0.354	0.387
C16	0.233	0.2	0.1	0.133	0.1	0.266	0.233	0.333	0.266	0.566	0.4	0.233	0.433	0.5	0.366	1	0.4
C17	0.322	0.161	0.064	0.129	0.129	0.258	0.258	0.258	0.129	0.516	0.354	0.258	0.483	0.516	0.387	0.387	1

Table 3. The revised concept correlations between the 17 designed courseware after setting the weak concept correlations as zeros

Courseware	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17
C1	1	0.23	0.153	0.153	0.192	0.269	0.346	0.423	0.192	0.653	0.307	0.23	0.307	0.461	0.307	0.269	0.384
C2	0.162	1	0	0	0.189	0.351	0.243	0.297	0.297	0.54	0.243	0.189	0.162	0.189	0	0.162	0.135
C3	0.307	0.307	1	0.23	0.538	0.384	0.384	0.538	0.307	0.846	0.23	0.307	0.307	0.384	0.153	0.23	0.153
C4	0	0	0	1	0.161	0.161	0	0.132	0.235	0.294	0	0	0.147	0.132	0	0	0
C5	0.172	0.241	0.241	0.379	1	0.241	0.206	0.31	0.275	0.517	0.137	0.172	0.172	0.206	0.137	0	0.137
C6	0	0	0	0	0	1	0	0.171	0.189	0.333	0	0	0	0.153	0	0	0
C7	0.2	0.2	0	0.177	0.133	0.155	1	0.244	0.311	0.466	0.177	0.155	0	0.311	0.133	0.155	0.177
C8	0.189	0.189	0	0.155	0.155	0.327	0.189	1	0.31	0.465	0.206	0.155	0.137	0.155	0.224	0.172	0.137
C9	0	0	0	0.146	0	0.192	0	0.165	1	0.284	0.165	0	0	0	0	0	0
C10	0	0	0	0	0	0.213	0	0.156	0.179	1	0	0	0	0.208	0	0	0
C11	0.153	0.173	0	0	0	0.23	0.153	0.23	0.346	0.423	1	0.153	0.25	0.326	0.192	0.23	0.211
C12	0.193	0.225	0	0	0.161	0.354	0.225	0.29	0.29	0.548	0.258	1	0.225	0.483	0.29	0.225	0.258
C13	0.235	0.176	0	0.294	0.147	0.176	0.147	0.235	0.235	0.588	0.382	0.205	1	0.382	0.294	0.382	0.441
C14	0.166	0	0	0	0	0.236	0.194	0	0.152	0.5	0.236	0.208	0.18	1	0.166	0.208	0.222
C15	0.258	0	0	0	0	0.258	0.193	0.419	0.161	0.483	0.322	0.29	0.322	0.387	1	0.354	0.387
C16	0.233	0.2	0	0.133	0	0.266	0.233	0.333	0.266	0.566	0.4	0.233	0.433	0.5	0.366	1	0.4
C17	0.322	0.161	0	0	0	0.258	0.258	0.258	0	0.516	0.354	0.258	0.483	0.516	0.387	0.387	1

2.2.3 The proposed concept map generation scheme based on the computing concept correlations and fuzzy clustering scheme

2.2.3.1 Concept map generation based on fuzzy clustering scheme

In this section, how to use the clustering algorithm to group courseware with high correlation into the same clusters will be introduced. The adopted method in this study is the fuzzy clustering analysis scheme (Zimmermann, 1991). For the purpose of getting more meaningful clusters, as the above-mentioned consideration, the weak concept correlations are first filtered out, and these concept entries are set to zeros. In the employed fuzzy clustering analysis scheme, the clustering result will be affected by different α-cuts (Zimmermann, 1991). To optimize the clustering result, the concept correlations within the same cluster are expected as high as possible, but the ones between different clusters are expected as low as possible. Thus, the cost function, which integrates maximizing the concept correlations in the same cluster and minimizing the concept correlations among different clusters, was employed to determine best appropriate number of clusters under considering different α-cuts in the employed fuzzy clustering analysis scheme. In other words, the used cost function aims to consider that the courseware within the same cluster should be as similar as possible, but the courseware of different clusters should be as dissimilar as possible. The final clustering outcome under considering optimal number of clusters is listed in Table 4.

Table 4. The result of concept clustering by the fuzzy clustering scheme

The clustering results based on concept correlations among courseware	The clustered set of courseware
Cluster 1	C4 (Sharing with a remainder)、C5 (Separating with a remainder)、C9 (Compare proper fractions with the same denominator)、C1 (Equal parts)、C17 (Missing minuend)、C12 (Adding fractions)
Cluster 2	C6 (Parts of a whole)
Cluster 3	C3 (Division as separating)
Cluster 4	C8 (Sequence of fractions)
Cluster 5	C2 (Division as sharing)
Cluster 6	C7 (Improper fractions)
Cluster 7	C10 (Compare proper fractions with different denominators)
Cluster 8	C11 (Add and subtract fractions)、C15 (Missing subtrahend)、C13 (Subtracting fractions)
Cluster 9	C16 (Missing summand)
Cluster 10	C14 (Missing addend)

The ontology-based concept map can be depicted according to the clustered courseware by the fuzzy clustering algorithm and the asymmetric concept correlation table listed in Table 3. The following descriptions will detail how to construct a concept map:

Step 1: Constructing the inner correlations

Here we only need to consider the clusters that contain more than one courseware, such as Cluster 1 and Cluster 8.

Taking Cluster 1 as example, we can first find out all correlations between the 6 courses and draw connections where their weights can be indicated based on the asymmetric concept table listed in Table 3. To simplify the generated ontology concept map, this study only considers connecting the concepts with top five high correlation values. Thus, the drawing ontology concept map of the Cluster 1 can be shown as Fig. 2. The same method can be applied to construct the ontology concept map of the Cluster 8.

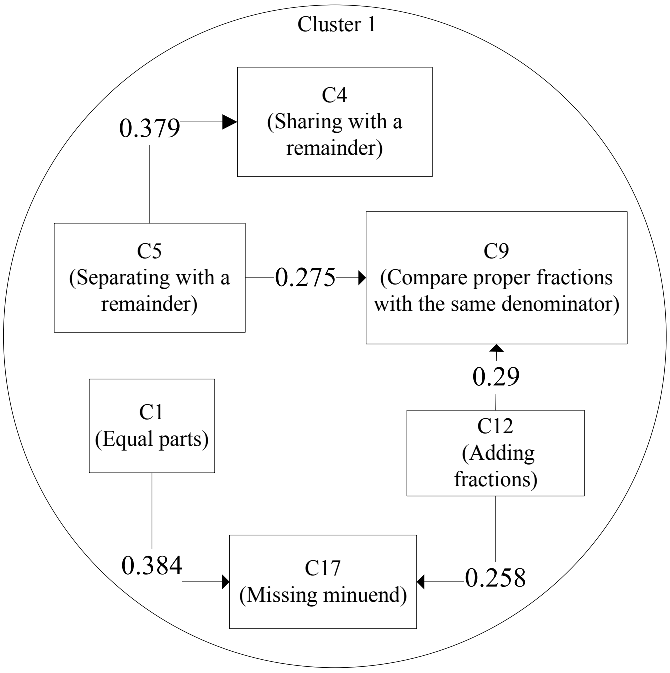

Fig. 2 The generated ontology concept map of the Cluster 1

Step 2: Constructing the outer correlations

In this step, the main idea of constructing ontology concept map is similar to Step 1. Based on the clustering results of Table 4, the total needed number of connections to link each cluster is 9 since 10 concept clusters are grouped by the employed fuzzy clustering scheme. However, how to denote the weight of correlations between any two clusters is a needed consideration issue.

Step 3: Calculating the weights of correlations between any two clusters.

This study employed a similarity measure to estimate the weights of correlations between two clusters, and formulated as follows:

$$weight_{i,j} = \frac{\sum_{p=1}^{n_i}\sum_{q=1}^{n_j} rel(A_{ip}, A_{jq})}{n_i \times n_j}, \quad where\, 0 \le weight_{i,j} \le 1,\ 1 \le i, j \le n \tag{2}$$

where $weight_{i,j}$ is the correlation between the i^{th} cluster and the j^{th} cluster, n_i , is the number of courseware in the i^{th} cluster, n_j is the number of courseware in the j^{th} cluster, $A_{i,p}$ is the p^{th} courseware in the i^{th} cluster, $A_{j,q}$ is the q^{th} courseware in the j^{th} cluster, and $rel(A_{ip}, A_{jq})$ is the correlation between the p^{th} courseware in the i^{th} cluster and the q^{th} courseware in the j^{th} cluster.

For example, the procedure of calculating the cluster correlation weight between the 7th cluster and the 8th cluster is detailed as follows:

$$weight_{8,7} = \frac{rel(C11, C10) + rel(C15, C10) + rel(C13, C10)}{3 \times 1} = 0.498 \tag{3}$$

The final complete ontology-based concept map is displayed as Fig. 3.

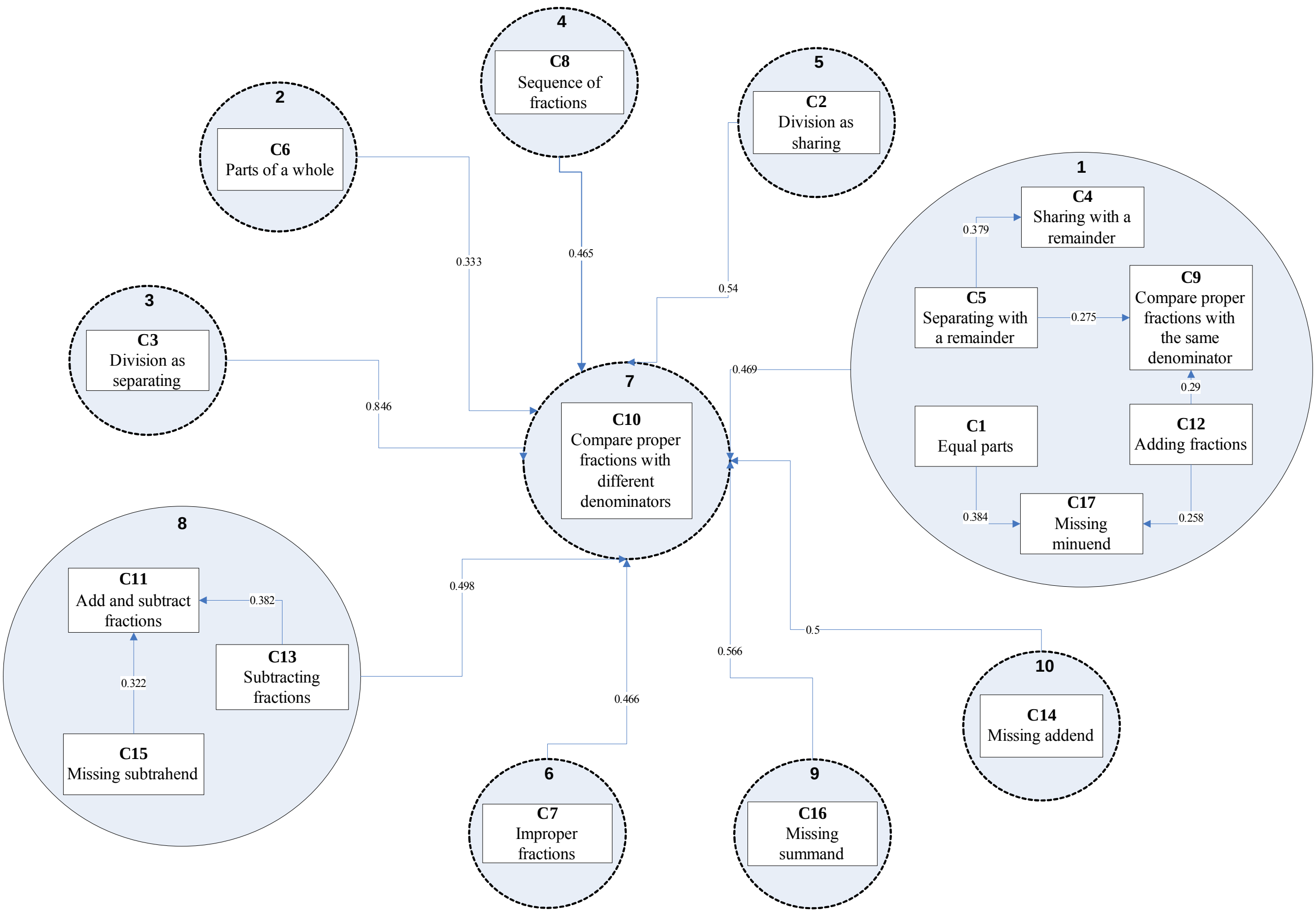

Fig. 3 The generated ontology-based concept map for the 17 designed courseware

2.2.3.2 Courseware teaching sequence pattern derived from the ontology-based concept map

Based on the generated ontology-based concept map shown as Fig. 3, 23 courseware teaching sequence patterns are summarized and listed in Table 5. In each courseware teaching sequence pattern, premise part can be viewed as prior knowledge of conclusion part. This property is beneficial to planning a logical learning path while providing curriculum sequencing for personalized learning services.

Table 5. The courseware teaching sequence pattern derived from ontology-based concept map

No.	Courseware teaching sequence pattern	No.	Courseware teaching sequence pattern
1	C1(Equal parts) → C10 (Compare proper fractions with different denominators)	13	C11 (Add and subtract fractions) → C10 (Compare proper fractions with different denominators)
2	C1 (Equal parts) → C17 (Missing minuend)	14	C12 (Adding fractions) → C9 (Compare proper fractions with the same denominator)
3	C2 (Division as sharing) → C10 (Compare proper fractions with different denominators)	15	C12 (Adding fractions) → C10 (Compare proper fractions with different denominators)
4	C3 (Division as separating) → C10 (Compare proper fractions with different denominators)	16	C12 (Adding fractions) → C17 (Missing minuend)
5	C4 (Sharing with a remainder) → C10 (Compare proper fractions with different denominators)	17	C13 (Subtracting fractions) → C10 (Compare proper fractions with different denominators)
6	C5 (Separating with a remainder) → C4 (Sharing with a remainder)	18	C13 (Subtracting fractions) → C11 (Add and subtract fractions)
7	C5 (Separating with a remainder) → C9 (Compare proper fractions with the same denominator)	19	C14 (Missing addend) → C10 (Compare proper fractions with different denominators)
8	C5 (Separating with a remainder) → C10 (Compare proper fractions with different denominators)	20	C15 (Missing subtrahend) → C10 (Compare proper fractions with different denominators)
9	C6 (Parts of a whole) → C10 (Compare proper fractions with different denominators)	21	C15 (Missing subtrahend) → C11 (Add and subtract fractions)
10	C7 (Improper fractions) → C10 (Compare proper fractions with different denominators)	22	C16 (Missing summand) → C10 (Compare proper fractions with different denominators)
11	C8 (Sequence of fractions) → C10 (Compare proper fractions with different denominators)	23	C17 (Missing minuend) → C10 (Compare proper fractions with different denominators)
12	C9 (Compare proper fractions with the same denominator) → C10 (Compare proper fractions with different denominators)		

2.3 Applying Ontology-based Concept Map to Personalized Learning Path Generation

To plan more appropriate learning path than our previous study (Chen, 2007), the curriculum structure contained in the generated ontology-based concept map is used as the constraint conditions of the employed genetic algorithm to plan personalized learning paths for individual learners. In other words, a planning learning path by the genetic algorithm must be evaluated whether it satisfies the curriculum sequence implied in the generated ontology-based concept map. If a planning learning path by the genetic algorithm conflicts with the order of prior knowledge between courseware, it will be treated as an inappropriate learning path. To measure the qualities of planning learning paths, this study proposes a penalty term α to calculate the violated value by comparing the rules of prior and posterior knowledge derived from ontology-based concept map with the generated learning path, so that those learning paths which conflict with the order of prior knowledge decline the corresponding fitness function value. Thus, a high quality learning path should get a penalty value as less as possible. The proposed penalty term is defines as the following formula:

$$\alpha = \sum_{k=1}^{n} MAX \ (P_{k1} - P_{k2}, 0) \tag{4}$$

where α is the proposed penalty term, n is the total number of prior and posterior knowledge rules, P_{k1} and P_{k2} are the corresponding position index values in a planning learning path which violates with the antecedent and consequent parts of the k^{th} rule of prior and posterior knowledge derived from ontology-based concept map, respectively.

Next, an example is illustrated to explain how to calculate the α value. Suppose that "1→2→15→13→3→12→9→16→7→17→6→11→4→5→8→14→10" is a generated learning path by the employed genetic-algorithm. To compare the teaching sequence of the planning learning path with the 23 rules of prior and posterior knowledge listed in Table 5, only the rule "5→9" violates with the teaching sequence listed in Table 5. The corresponding position index value of the antecedent and consequent parts of the violated rule in the generated learning path are 14 and 7, respectively. Thus, the values of and in the penalty function are 14 and 7, respectively. The calculated penalty value of α is equal to 7 in this case.

In order to combine the penalty term with the difficulty parameter into the fitness function, the penalty function value and difficulty parameter are normalized between 0 to 1. To do so, the planning learning path will simultaneously satisfy the difficult levels of courseware, and the curriculum sequence based on the order of prior knowledge as possible. Finally, the proposed fitness function for planning personalized learning path is formulated as follows:

$$f = (1-w) \times (1-\alpha) + w \times \sum_{i=2}^{n} (1-b_i) \tag{5}$$

where f is the proposed fitness function, α is a penalty term for evaluating the violated value of a generated learning path with the rules of prior and posterior knowledge derived from ontology-based concept map, b_i stands for the difficulty level of the i^{th} courseware, and w is an adjustable weight.

3. Experiments

The study aims to revise the personalized learning path generation scheme proposed by our previous work (Chen, 2007) to construct a near-optimal learning path based on ontology concept map and the results of the pre-test in hopes of aiding learners to learn efficiently. Therefore, the experimental analysis mainly focuses on the performance comparison of the genetic-based learning path generation scheme with the proposed genetic-based learning path generation scheme supported by ontology concept map.

3.1 Parameter Setting of Fitness Function

The research adopted the genetic algorithm assisted by a generated ontology-based concept map to construct personalized learning paths according to the pre-test results for personalized learning of individual learners. In the process, the parameter setting for the proposed revised fitness function will affect the qualities of the generated learning paths. Particularly, the adjustable weight in Eq. (7) is an important parameter affecting the quality of the generated learning path. To determine an appropriate weight for planning personalized learning path, several parameter combinations were evaluated by setting different ratio combinations of the difficulty level of courseware to the penalty level of measuring violated degree of the teaching sequence with the sequence of prior and posterior knowledge obtained from the constructed ontology-based concept map. That is, the adjustable weight determines the importance degree of the difficulty level to the penalty level when evaluating the quality of a generated learning path. In our experiments, the termination condition for the genetic algorithm is set to 150 generations, the population size is set to 50, the mutation rate is set to 0.1, and the duplication rate is set to 1. Moreover, the research adopted the ratio of 3:7 to construct the personalized learning paths for individual learners because this ratio can obtain the best quality learning path as well as fast convergence speed.

3.2 Quality Evaluation of the Personalized Learning Path Generated by the Proposed

Scheme

To measure the quality of the generated learning path planned by the proposed ontology-based learning path generation scheme, two methods were used to measure the quality of learning path under the ratio of the difficulty level to penalty level is set to 3:7. First, the teaching sequence of the learning path generated by the proposed novel scheme in the "Fraction" course unit is compared with the teaching sequence of four version textbooks used in Taiwan elementary schools. Additionally, the teaching sequence of generated learning path is also compared with the teaching sequence suggested by 3 experienced mathematical teachers to examine the validity of the planned learning path.

How to obtain the teaching sequence of four version textbooks for evaluating the quality of the personalized learning path generated by the proposed scheme is detailed as the following steps:

Step 1:

Finding out the teaching sequence of 17 courseware designed for the "Fraction" unit in the selected four textbooks used in Taiwan elementary schools.

Step 2:

The 17 courseware related to the "Fraction" unit are ranked as a sequencing learning path according to teaching order in the four textbooks.

Step 3:

An integrated learning path is obtained based on ranking the average teaching order in the selected four textbooks, and listed as Table 6.

Table 6. Summarization of teaching orders of the designed 17 courseware in the "Fraction" unit in the selected four textbooks for obtaining the integrated learning path

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
Han Lin	1	3	2	5	4	6	16	8	7	17	15	9	10	11	13	12	14
Nani	1	2	4	3	5	6	11	7	9	17	16	8	10	12	14	13	15
Jenlin	1	3	2	4	5	6	12	7	8	13	11	9	10	14	16	15	17
Kang Hsuan	1	2	4	3	5	6	15	7	16	17	10	8	9	11	12	13	14
Total ranking value	4	10	12	15	19	24	54	29	40	64	52	34	39	48	55	53	60
Average teaching order in the four version textbooks	1	2.5	3	3.75	4.75	6	13.5	7.25	10	16	13	8.5	9.75	12	13.75	13.25	15
The integrated teaching order for the designed 17 courseware	C1→C2→C3→C4→C5→C6→C8→C12→C13→C9→C14C11→C16→C7→C15→C17→C10																

Next, the integrated learning path sequence was extracted from the four version textbooks are served as target learning path and compared with the planned learning paths generated by the proposed scheme in our previous study and the proposed novel genetic-based learning path generation scheme supported by the ontology-based concept map. To evaluate the quality of the generated learning path, the total violated distance of teaching sequence is defined and formulated as follows:

$$\gamma = \sum_{i=1}^{n-1} \sum_{j=(i+1)}^{n} MAX\,(P_i - P_j, 0) \quad (6)$$

where γ is the total value of violated distance for a planned learning path, n is the total number of course materials in the course unit "Fraction", P_i is the corresponding position index value in a planning learning path which violates with the antecedent part of the i^{th} rule of prior and posterior knowledge derived from ontology-based concept map, P_j is the corresponding position index value in a planning learning path which violates with the consequent part of the j^{th} rule of prior and posterior knowledge derived from ontology-based concept map.

Table 7 shows an example to illustrate how to compute the total violated distance of the learning path generated by the proposed genetic-based learning path generation scheme supported by ontology-based concept map with the teaching sequence of Han Lin version textbook. In Table 7, the courseware ID is marked with parentheses when the planned learning path violates the teaching sequence of the compared textbook. Finally, the total violated distance in the generated learning path can be obtained by calculating the summation of all violated distance values.

Table 7. An example for computing the total violated distance of the learning path generated by the proposed genetic-based learning path generation scheme supported by ontology-based concept map with the teaching sequence of Han Lin version textbook

The teaching sequence of the generated learning path in Han Lin version textbook	The violated status of the generated learning path with the teaching sequence of the Han Lin version textbook	Computing violated distance by comparing the learning path sequence of the Han-Lin version with the sequence of the generated learning path
[3]→[2]	(2)→(3)→17→9→16→8→14→4→10	2－1=1
[4]→[8]	2→3→17→9→16→(8)→14→(4)→10	8－6=2
[4]→[9]	2→3→17→(9)→16→8→14→(4)→10	8－4=4
[4]→[14]	2→3→17→9→16→8→(14)→(4)→10	8－7=1
[4]→[16]	2→3→17→9→(16)→8→14→(4)→10	8－5=3
[4]→[17]	2→3→(17)→9→16→8→14→(4)→10	8－3=5
[8]→[16]	2→3→17→9→(16)→(8)→14→4→10	6－5=1
[8]→[17]	2→3→(17)→9→16→(8)→14→4→10	6－3=3
[9]→[17]	2→3→(17)→(9)→16→8→14→4→10	4－3=1
[14]→[16]	2→3→17→9→(16)→8→(14)→4→10	7－5=2
[14]→[17]	2→3→(17)→9→16→8→(14)→4→10	7－3=4
[16]→[17]	2→3→(17)→9→(16)→8→14→4→10	5－3=2
The total of violated distance in the generated learning path		29

Next, two main experiments for evaluating the quality of the generated learning path are introduced as follows.

I. Comparing the generated learning path with the teaching sequences of four version textbooks to examine the quality of the planned learning path

In this work, 20 learning paths randomly generated by the genetic algorithm based learning path generation scheme supported by the ontology-based concept map, and then are compared with the teaching sequence of four version textbooks. Table 8 displays the comparison results of the total violated distance between both the personalized learning path generation schemes with the teaching sequence of four version textbooks under the adjustable weight is set to 3:7. In addition, a further experiment was designed to compare the qualities of the learning paths generated by both the personalized learning path generation schemes with the integrated learning path from four version textbooks. Table 9 shows the comparison results.

Table 8. Comparison of the qualities of the learning paths generated by both the personalized learning path generation schemes with the individual teaching sequences of four version textbooks

Running times	Genetic-based personalized learning path generation scheme (Chen, 2007)				Genetic-based personalized learning path generation scheme supported by ontology-based concept map			
	The total violated distance of the generated learning path with the teaching sequence of the Han Lin version textbook	The total violated distance of the generated learning path with the teaching sequence of the Nani version textbook	The total violated distance of the generated learning path with the teaching sequence of the Jenlin version textbook	The total violated distance of the generated learning path with the teaching sequence of the Kang Hsuan version textbook	The total violated distance of the generated learning path with the teaching sequence of the Han Lin version textbook	The total violated distance of the generated learning path with the teaching sequence of the Nani version textbook	The total violated distance of the generated learning path with the teaching sequence of the Jenlin version textbook	The total violated distance of the generated learning path with the teaching sequence of the Kang Hsuan version textbook
1	459	491	535	477	200	154	221	172
2	503	497	563	513	229	216	280	187
3	383	438	467	420	153	129	192	151
4	471	466	539	477	224	182	250	200
5	449	486	529	468	240	174	240	230
6	463	458	531	471	152	146	129	69
7	453	491	541	474	207	187	218	180
8	452	490	535	471	223	235	287	184
9	459	431	487	465	234	180	239	183
10	459	491	535	477	144	113	145	152
11	471	466	539	477	252	191	284	197
12	383	438	467	420	214	249	307	237
13	449	486	529	468	237	213	303	216
14	459	431	487	465	245	249	345	240
15	373	433	461	411	239	244	278	184
16	459	431	487	465	202	180	259	209
17	469	436	493	474	222	198	353	316
18	459	491	535	477	287	240	317	274

19	373	433	461	411	216	200	260	234
20	449	486	529	468	231	198	249	175
Total violated distance	8895	9270	10250	9249	4351	3878	5156	3990
Average violated distance	470				217			

Table 9. Comparison of the qualities of the learning paths generated by both the personalized learning path generation schemes with the integrated learning path from four version textbooks

Running times	Genetic-based personalized learning path generation scheme	Genetic-based personalized learning path generation scheme supported by ontology-based concept map
1	509	146
2	496	119
3	318	256
4	496	216
5	434	240
6	478	209
7	344	228
8	353	181
9	434	263
10	282	145
11	496	158
12	519	167
13	504	211
14	486	137
15	504	237
16	478	284
17	506	117
18	508	248
19	544	179
20	357	185
Total violated distance	9046	3926
Average violated distance	452	196

Based on the experimental results mentioned-above, we can find that the quality of the learning path planned by proposed genetic-based personalized learning path generation scheme supported by ontology-based concept map is superior to the genetic-based personalized learning path generation scheme presented by our previous work (Chen, 2007). Therefore, this study logically inferred that the learning paths generated by the proposed novel scheme match the learning sequence of the textbooks much more than the scheme proposed by our previous work. It means that the proposed novel scheme can plan a more accurate learning path for individual learner. And those generated learning paths can also be adopted as a valuable reference for planning teaching sequence of the textbooks.

II. Comparing the generated learning path with the teaching sequences from course expert's suggestion to examine the validity of the planned learning path

In order to further evaluate the quality of the learning path generated by the proposed novel scheme, this study invited three experienced mathematical teachers who came from Kuan-Hua elementary school in Hualien of Taiwan to ask for their suggestions on the learning sequence of the 17 designed courseware related to the "Fraction" unit. Table 10 reveals the learning sequence of the 17 designed courseware in the "Fraction" unit suggested by 3 experienced mathematical teachers of Kuan-Hua elementary school and the integrated learning path sequence from the three mathematical teachers.

Table 10. The integrated learning path sequence suggested by 3 experienced mathematical teachers of Kuan-Hua elementary school for the 17 designed courseware in the "Fraction" unit

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
Course Expert A	1	2	3	4	5	6	9	10	7	8	13	11	12	14	16	15	17
Course Expert B	1	2	3	6	7	4	8	9	5	10	14	11	12	13	17	15	16

Course Expert C	1	2	3	4	5	6	9	8	7	17	16	10	13	11	14	12	15
Total ranking value	3	6	9	14	17	16	26	27	19	35	43	32	37	38	47	42	48
Average teaching order from three course experts	1	2	3	4.6	5.6	5.3	8.6	9	6.3	11.6	14.3	10.6	12.3	12.6	15.6	14	16
The integrated teaching order for the designed 17 courseware	C1→C2→C3→C4→C6→C5→C9→C7→C8→C12→C10→C13→C14→C16→C11→C15→C17																

Next, 20 learning paths randomly generated by both the learning path generation schemes are compared with the learning paths suggested by 3 experienced mathematical teachers of Kuan-Hua elementary school for the 17 designed courseware in the "Fraction". Tables 11 and 12 respectively show the comparison results of the quality of the learning path generated by both the personalized learning path generation schemes with the individual learning path and the integrated learning path suggested from three experienced mathematical teachers.

Table 11. Comparison of the qualities of the learning paths generated by both the personalized learning path generation schemes with the individual learning paths from three experienced mathematical teachers

Running times	Genetic-based personalized learning path generation scheme			Genetic-based personalized learning path generation scheme supported by ontology-based concept map		
	Course Expert A	Course Expert B	Course Expert C	Course Expert A	Course Expert B	Course Expert C
1	542	562	501	300	308	217
2	219	207	279	310	277	204
3	538	556	508	300	294	224
4	484	505	437	288	298	228
5	539	558	498	469	449	350
6	458	436	426	212	187	173
7	212	205	270	227	240	181
8	415	393	377	359	331	252
9	511	508	467	348	350	278
10	216	203	276	258	265	183
11	535	552	505	228	222	148
12	483	503	447	289	281	204
13	480	499	444	279	294	210
14	461	440	429	197	189	118
15	535	552	505	252	233	153
16	247	212	299	203	219	190
17	506	502	449	288	267	210
18	514	512	470	307	297	228
19	535	552	505	249	240	167
20	516	520	485	309	298	231
Total violated distance	8946	8977	8577	5672	5539	4149
Average violated distance	441			256		

Table 12. Comparison of the qualities of the learning paths generated by both the personalized learning path generation schemes with the integrated learning paths from three experienced mathematical teachers

Running times	Genetic-based personalized learning path generation scheme	Genetic-based personalized learning path generation scheme supported by ontology-based concept map

1	540	193
2	532	223
3	270	423
4	532	323
5	477	296
6	435	341
7	268	321
8	365	336
9	477	388
10	213	291
11	532	198
12	539	198
13	535	335
14	438	185
15	535	325
16	435	361
17	491	159
18	536	373
19	541	310
20	276	261
Total violated distance	8967	5840
Average violated distance	448	292

Based on the experimental results mentioned-above, we can also find that the quality of the learning path planned by proposed genetic-based personalized learning path generation scheme supported by ontology-based concept map is superior to the genetic-based personalized learning path generation scheme presented by our previous work. The results can also confirm that the learning paths generated by the proposed novel scheme match the learning sequence suggested by course experts much more than the scheme proposed by our previous work.

In order to compare the entire quality of the learning path generated by the proposed novel personalized learning path generation scheme with our previous proposed scheme, the experimental results mentioned-above are summarized in Table 13. Based on the results, this study confirms that the proposed learning path generation scheme satisfies the criterion of course experts and various versions of textbooks much more than the learning path generation scheme proposed by our previous study. Thus, the learning paths planned by the proposed genetic algorithm based personalized learning path generation scheme supported by the ontology-based concept map are more accurate and reliable than those constructed learning paths by our previous proposed scheme.

Table 13. The entire quality evaluation of the learning path generated by both the personalized learning path generation schemes

Learning mode / **Comparison items**	Genetic-based personalized learning path generation scheme	Genetic-based personalized learning path generation scheme supported by ontology-based concept map
The average violated distance of the generated learning path with the individual teaching sequences of the four version textbooks	470	217
The average violated distance of the generated learning path with the integrated teaching sequence of the four version textbooks	452	196
The average violated distance of the generated learning path with the individual teaching sequences of the three course experts	441	256
The average violated distance of the generated learning path with the integrated teaching sequence of the three course experts	448	292

3.3 The Implemented System for Personalized Learning Service

In this section, the implemented system is introduced in detail. Fig. 4 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 learner to learn the courseware according to the previous unfinished learning procedures.

Figure 4. The logon user interface

Fig. 5 shows the interface of performing a pre-test for a beginner. After performing the pre-test, the system will plan a near optimal learning path based on those learning materials that the learner fails to give correct answer responses in the pre-test to support the adaptive learning guidance for the learner. Fig. 6 displays the user interface of courseware recommendation learning mode. In the left frame of Fig. 6, those course materials will be ordered according to the learning sequence of the planned learning path. Next, when learners click in the courseware with first learning priority in the left frame of Fig. 6, the proposed learning system will bring out the corresponding learning content for individual learner learning. Fig. 6 shows the courseware with first learning priority in the generated learning path. Moreover, one randomly selecting testing item related to the current learning courseware is arranged in the bottom-right window to help system get the learner's comprehension percentage for the learning courseware. When a learner can pass a test question of the current learning courseware, he/she is served as has acquired the learned courseware. If a learner cannot pass two randomly selected testing questions for the current learning courseware, the proposed system 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 for supporting remedy learning. 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 performances of individual learners for the courseware that they cannot acquire well through the standard courseware. Once learners complete all of the course materials, the system will provide the post-test for learners to assess their entire learning effects.

Figure 5. The user interface of pre-test

Figure 6. The user interface of courseware recommendation learning mode

Figure 7. The courseware with first learning priority in the generated learning path

4. Conclusions

This study presents a novel genetic-based personalized learning path generation scheme supported by an automatically generated ontology-based concept map to improve the shortcoming of planning a personalized learning path proposed by our previous study that concept relations of prior and posterior knowledge between courseware has not been considered. The proposed personalized learning path generation scheme, which can simultaneously consider courseware difficulty level and the concept relations of prior and posterior knowledge between courseware according to the incorrect testing responses in a pre-test, thus it is capable of creating higher quality learning paths than the previous proposed genetic-based personalized learning path generation scheme for individual learners. Compared to the freely browsing learning mode used in most web-based learning systems, our previous study had indicated that the proposed learning mode of curriculum sequencing recommendation based on planning personalized learning path can promote learner's learning effectiveness during learning processes. Meanwhile, the proposed personalized learning path generation scheme can effectively reduce learner cognitive overload or disorientation during learning processes, thus promoting learning performance. Particularly, 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.

Although the proposed ontology-based personalized learning path generation scheme can provide high quality curriculum sequencing for individual learners in a web-based learning environment, there are several critical issues that need to be further investigated in the future. First of all, to record the ontology-based concept map more flexible, the database design for storing ontology-based concept map can be replaced by RDF with XML syntax in the future. The improvement is not only to easily extend the number of courseware, but also make the ontology-based concept map conveniently applied to other web-based educational systems in hopes of supporting adaptive learning materials. Secondly, to integrate the proposed personalized learning path with SCORM (Sharable Content Object Reference Model) curriculum sequencing standard for developing an e-learning system with adaptive learning guidance is also a valuable research issue.

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行政院國家科學委員會補助國內專家學者出席國際學術會議報告

96 年 9 月 26 日

報告人姓名	陳志銘	服務機構及職稱	國立政治大學圖書資訊與檔案學研究所副教授
會議 時間 地點	96 年 7 月 18~20 日 日本新瀉市 Toki Messe, Niigata Convention Center	本會核定補助文號	NSC95-2520-S-004-001 計劃補助
會議名稱	(中文)2007 年 IEEE 先進學習科技國際研討會 (英文)2007 IEEE International Conference on Advanced Learning Technologies		
發表論文題目	（中文）基於 Ontology 概念圖建立之個人化網路學習系統 （英文）Personalized E-learning System based on Ontology-based Concept Map Generation Scheme		

一、 參加會議經過

本次會議旅程是經由天喜旅行社代為訂購機票及安排住宿事宜，經由旅行社安排，個人於七月十七日上午 08:50 搭乘長榮航空班機飛往日本成田機場，抵達成田機場後即搭乘捷運至東京車站，再由東京車站轉搭新幹線前往日本新瀉市住宿之 Hotel Niigata。接下來即為為期將近五天的參加會議及參訪行程。會議結束後，個人於當地時間七月二十一日晚上 20:00 由日本成田機場搭乘長榮航空班機返國，過程相當順利且圓滿的完成整個會議的相關行程。

二、 與會心得

(一)深入了解國際間學習科技領域之發展近況

此次大會由日本 University of Electro-Communications 主辦，國際電機電子工程學會贊助，論文發表涵蓋世界各國，其中台灣發表的論文佔整個大會論文的五分之一，無論在質與量上都獲得國際上的重視。此外，日本學者所發表的論文水準在質與量上也相當高，可見日本學術界在這個領域的研究正蓬勃發展，這次參與的人數受到地震的影響頗大，與會人數因此而減少，但參加會議人士討論熱絡，堪稱一次學習科技學術界的盛會，內容涵蓋極廣，本人參加會議所獲取之新知對個人之未來研究幫助極大。

(二)結交國際學者

經由參加會議吸收許多新知識，並於 Coffee Break 時間，結交許多國際學者，有的係邀稿，有的係吸收會員，有的純粹作學術交流，也有的則閒話家常。在會議其間也遇到許多國內在資訊教育學門領域的學者，例如中央大學的陳國棟教授、楊鎮華教授、楊接期教授等，以及中山大學的陳年興教授，也與芬蘭及英國等地學者互動熱絡，收穫頗多

。

(三)訓練英語聽講能力及體驗加拿大文化及風土民情

個人已累積多次出國發表論文經驗，但此次個人帶領四個碩士班研究生一起出國發表論文，也由研究生以英文報告自己接受國科會出國補助發表的論文，每個人都是第一次以英文在國際場合發表論文，但是表現非常良好，算是一次非常成功的經驗，也有助於提昇學生的國際視野。另外也藉由此次會議的空閒時間，參訪日本新瀉市、左度島及輕井澤各地的風景名勝及瞭解當地人文歷史，是一次成功且難得的經驗，個人覺得獲益良多。

三、 建議

(一)國際間在學習科技相關領域的研究發展與應用進步快速，例如結合生理資訊與學習關聯及遊戲式學習等領域的研究，國內學界與業界應加強緊密之結合，以產學合作模式，以達相輔相成之效。

(二)國內宜加強英語聽講之教學，或者在校園內建立更好的的英語學習環境，如此則未來學人參加國際會議即可得心應手，也增加台灣的國際能見度。此外，在國外也感受到近幾年中文越來越受到重視，因此國內有必要充份運用我們在中文上的優勢，發展中文相關的數位學習內容。

四、 攜回資料名稱及內容

此次參加會議，大會準備了大會議程表、論文集及許多明年相關國際研討會的 Call for Paper 資料，個人也攜回台灣作為明年參加會議的參考。例如 2008 年的 IEEE International Conference on Advanced Learning Technologies 及 2008 年 International Conference on Intelligent Tutoring Systems 等。這些即將舉辦的國際研討會將作為個人明年出國發表論文的目標。

Personalized E-learning System based on Ontology-based Concept Map Generation Scheme

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Abstract

With the great advance in semantic web, more and more studies focus on the importance of ontology and its applications. Through the graphical representation of ontology, the whole courseware structure and core knowledge about a subject domain can be clearly revealed, thus reducing the problems of learning disorientation for learners. This paper thus presents a personalized e-learning system based on ontology-based concept map for personalized learning. The constructed ontology-based concept map can depict the concept correlations between courseware. Moreover, the generated concept map was applied on the personalized learning path generation in order to promote the learning performance and efficiency in this study.
Keywords: *Concept map, Ontology, Personalized learning, Learning path*

1. Introduction

In our previous study [1], a personalized e-learning system based on genetic algorithm had tried to consider the difficulty level of courses, and the curriculum continuity in order to provide personalized learning path for individual learners. However, the concept relation degrees among courseware are served as being symmetric in this study. That is, the curriculum sequence pattern "A→B" is identical with the curriculum sequence pattern "B→A". The result seems to be inconsistent with the realistic learning situation [2]. Moreover, despite the concept of curriculum continuity being considered while planning a personalized learning path in the study, the concept of prerequisite knowledge has not been significantly involved. This fault may lead to planning an illegal learning path for individual learners. In other words, if the courseware A is the prerequisite knowledge of the courseware B, then the courseware A should be taught before the courseware B is taught. In this paper, an ontology-based concept map, which can be used to plan reasonable learning paths for individual learners, was proposed.

2. The Proposed Concept Map Generation Scheme

This section presents the proposed automatic generation scheme of ontology-based concept map. First, this study collected the testing data including 600 elementary school students who participated in the testing question exam in the "Fraction" unit. The exam includes 17 testing questions, and each testing question corresponds to one courseware concept. Second, the computing method of concept correlation was employed on the analysis of the wrong-rate of testing questions in order to find out the pre/post-requisite relationships between courseware. Restated, what is the probability that the question B will also occur wrong answer under the question A has occurred wrong answer? By computing the probabilities, the initial asymmetric concept correlation matrix can be obtained. After that, this study adopted the fuzzy clustering algorithm [3] to group the courseware with similar concept into the same cluster. Finally, a graphical ontology-based concept map can be constructed based on the clustered courseware and the concept correlation matrix.

2.1 The designed course materials for exploring ontology-based concept map

All designed course materials for the learning process and the their corresponding curriculum sequencing orders in the Han-Lin version textbook used in Taiwan elementary schools for the course unit "Fraction" are listed in Table 1.

2.2 The computing method of concept correlation for exploring ontology-based concept map

According to the result of the testing question exam, the right answers would be marked with one, and the wrong answers would be marked with zero. Next, this study first presents a computing formula of correlation to calculate the concept relationships between courseware. And the adopted formula is as follows:

$$R_{x,y} = \frac{N(X) \cap N(Y)}{N(X)} \qquad (1)$$

where $R_{x,y}$ represents the probability as a student gives wrong answer in the testing item X and he/she will also give wrong answer in the testing item Y, $N(X)$ is the number of wrong answers in the testing item X for all learners, and $N(Y)$ is the number of wrong answers in the testing item Y for all learners.

Table 1. The contents of the designed course materials and the curriculum sequencing order of the Han-Lin version textbook used in Taiwan elementary schools for the course unit "Fraction"

The designed courseware and curriculum sequencing in textbook	
(1) Equal parts	(10) Missing addend
(2) Parts of a whole	(11) Missing summand
(3) Division as sharing	(12) Subtracting fractions
(4) Division as separating	(13) Missing subtrahend
(5) Sharing with a remainder	(14) Missing minuend
(6) Separating with a remainder	(15) Improper fractions
(7) Sequence of fractions	(16) Compare proper fractions with different denominators
(8) Adding fractions	(17) Add and subtract fractions
(9) Compare proper fractions with the same denominator	

2.3 The proposed concept map generation scheme based on the computing concept correlations and fuzzy clustering scheme

2.3.1. Concept map generation based on fuzzy clustering scheme. The adopted method for grouping courseware with high correlation into the same clusters is the fuzzy clustering analysis scheme [4] in this study. Besides, the clustering performance will be greatly affected by the parameter "Lambda" in the employed fuzzy clustering analysis scheme [4][5]. To optimize the clustering result, the concept correlations within the same cluster are expected as high as possible, but the ones between different clusters are expected as low as possible. Thus, the cost function for evaluating optimal number of clusters can be formulated as following:

$$\sum_{c}\Big(\sum_{n_k,n_l\in c_i}\mu_{n_k,n_l}\Big)+\Big(\sum_{c,c_i\in c,c_j\in c}(1-\delta_{c_i,c_j})\Big) \qquad (2)$$

where c implies the sets of all concept clusters, c_i is the i^{th} cluster in the set c, n_k is the k^{th} member concept in the i^{th} cluster c_i, μ_{n_k,n_l} is the concept correlation between the k^{th} member concept and the l^{th} member concept in the i^{th} cluster, and δ_{c_i,c_j} is the concept correlation between the i^{th} concept cluster and the j^{th} concept cluster.

To calculate the concept correlations between different concept clusters, this study adopted the formula as follows:

$$\delta_{c_i,c_j}=\frac{\sum_{p=1}^{n_i}\sum_{q=1}^{n_j}rel(C_{i,p},C_{j,q})}{n_i\times n_j},\quad 0\le\delta_{c_1,c_2}\le 1 \qquad (3)$$

where δ_{c_i,c_j} is the concept correlation between the i^{th} concept cluster and the j^{th} concept cluster, n_i is the number of courseware in the i^{th} concept cluster, n_j is the number of courseware in the j^{th} concept cluster, $C_{i,p}$ is the p^{th} courseware in the i^{th} concept cluster, $C_{j,q}$ is the q^{th} courseware in the j^{th} concept cluster , and $rel(C_{i,p},C_{j,q})$ is the concept correlation between the p^{th} courseware in the i^{th} concept cluster and the q^{th} courseware in the j^{th} concept cluster.

2.3.2. Ontology-based concept map verification. Next, this study tried to verify the authenticity of the generated concept map. In this work, the generated ontology-based concept map was compared with the curriculum sequencing order of the Han-Lin version textbook used in Taiwan elementary schools. Table 1 illustrates the curriculum sequencing order of the Han-Lin version textbook for the 17 designed courseware in the "Fraction" unit. This study found that the generated ontology-based concept map is similar to the curriculum sequence order listed in Table 1 based on the order of prerequisite knowledge excluding the curriculum sequence patterns "missing subtrahend → subtracting fractions" and "separating with a remainder → sharing with a remainder". In this study, the curriculum sequence pattern "missing subtrahend → subtracting fractions" implies that the courseware "missing subtrahend" is prerequisite knowledge of the courseware "subtracting fractions". However, Table 1 shows that the courseware "subtracting fractions" should be taught before the courseware "missing subtrahend" is taught, but the generated ontology-based concept map indicated completely inverse curriculum sequence in this case. Similarly, the courseware of "separating with a remainder" and "sharing with a remainder" is also discovered that the curriculum sequencing conflicts with the generated ontology-based concept map like the previous case. However, these two cases are actually very close to the teaching order in the Han-Lin version textbook. Based on the generated ontology-based concept map, course experts may have to reconsider whether the curriculum sequence in the textbook is appropriate or not. Moreover, most courseware grouped in the same cluster shown in Fig. 1 has neighbor or successive teaching orders arranged in the Han-Lin version textbook.

3. Conclusions

This paper presents an ontology-based concept maps for planning an appropriate learning path for individual learner. The proposed concept map can provide much more meaningful information to describe courseware structure. In particular, the knowledge inside the concept map can not only make learners realize the relations of pre/post learning concepts among courseware, but also supply learners with effective scaffolds and guidance for learning. It is also beneficial to reduce the occurrence of disorientation and to enhance the learning effectiveness. Due to the clustering algorithm, some courseware with high concept correlation can be grouped together. It thus makes learners learn in a systematic way and provides them with better and complete courseware structure information. As for teachers, they can apply the concept map to arrange their curriculum sequencing, and even to assist some learners who has difficulty in learning for learning diagnosis.

4. References

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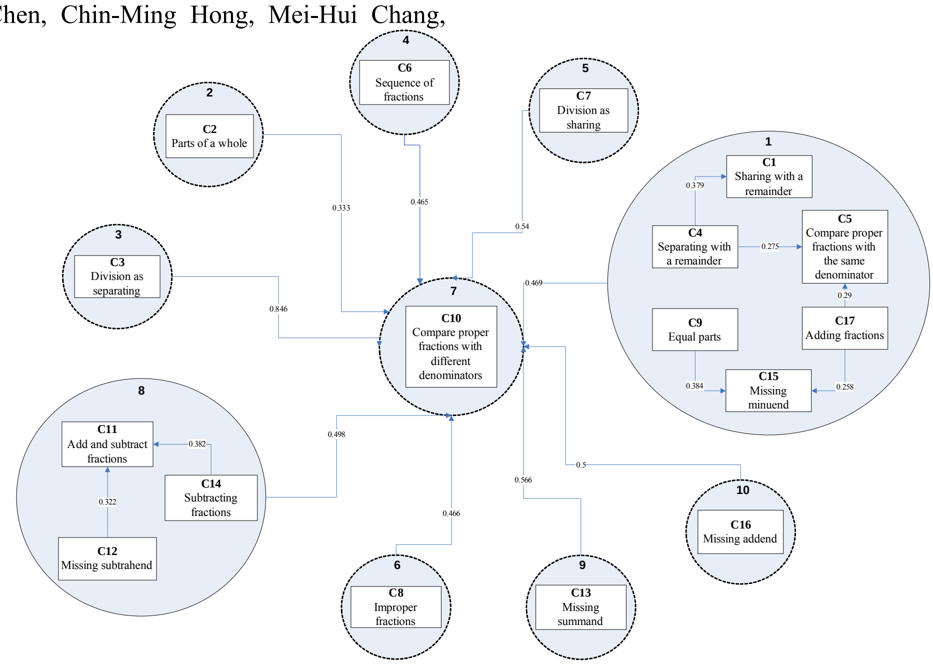

Figure 1. The generated ontology-based concept map for the 17 designed courseware