Learning case adaptation for problem-oriented e-learning on mathematics teaching for students with mild disabilities

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ABSTRACT

Both problem-oriented learning and case-based learning are effective methods for practical knowledge development. However, an automatic development of learning cases for adaptive learning is still an open issue. To support adaptive case-based learning in a proposed problem-oriented e-learning (POeL) environment and to address the complexity and diversity of the learning problems of students with mild disabilities, this study presents a learning case adaptation framework to support problem-oriented e-learning. This framework provides mechanisms to search and match similar learning cases according to encountered teaching problems by information retrieval techniques and to develop an adaptive learning case by adaptation techniques. Adaptation techniques include a substitution technique, a removal technique, and a composition technique, and utilize cosine-measure and genetic algorithm. In this research, adaptive learning cases were developed for teaching students with mild disabilities so as to assist regular and special education teachers to develop practical knowledge of teaching more effectively.

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1. Introduction

e-Learning has become a newly rising trend in learning as well as an important strategy and direction for promoting the upgrades and reforms of education in all major countries of the world. However, as far as the development of knowledge and competence of pre-service and in-service teachers of regular and special education is concerned, existing e-learning platforms still have the following flaws: (1) failing to provide sufficient guidance on learning concepts or the application of adequate learning strategies; (2) insufficient practical knowledge for solving students' learning problems; and (3) without functions for the management and maintenance of knowledge (Chu, Chen, Lin, & Chen, 2006).

To assist special education teachers in effectively developing knowledge for mathematics teaching for students with mild disabilities, a problem-based e-Learning (PBeL) model and its system framework have been developed (Chu et al., 2006). The PBeL model features situated learning as a theoretical basis to integrate learning theories of social constructivism and case-based learning along a problem-oriented learning approach.

Development of an e-Learning platform requires not only the design of functions and mechanisms for learning activities, but also

the provision of suitable learning materials for teachers' knowledge development. Usually, the knowledge of special education teachers contains both formal and practical knowledge. Formal knowledge is acquired through teachers' formal training program and teaching principles that can be categorized according to different scenarios. On the other hand, most of the practical knowledge is tacit knowledge, which is derived from the application of formal knowledge to real-life teaching situations and the resolution and rumination of teaching difficulties (Fenstermacher, 1994). Therefore, development of learning materials that provides practical knowledge of teaching is one of the major tasks of the development of an e-learning platform for teacher professional development.

Studies have found that the case method, which involves narration of teaching practices based on real teaching cases, does help teachers to link theory with practice (Chin & Lin, 2000; Merseth, 1996; Richardson, 1993) and to stimulate introspections (Richert, 1991) and effective construction of practical teaching knowledge. Therefore, in our research, cases which were developed by expert teachers according to their own teaching narrations and were evaluated through actual teaching, observation, discussion, and assessed by experts are used to provide practical knowledge.

To support cased-based problem-oriented learning, one of the issues is the provision of learning cases that resembles the teaching problems encountered by the teachers as learners. Presently, case-based reasoning (CBR) is a successful artificial intelligence

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methodology, which is employed in retrieval previously solved problems and their solutions from a knowledge source of cases, i.e. case base (Carrascosa, Bajo, Julian, Corchado, & Botti, 2008; Liu & Ke, 2007; Susan, Nirmalie, & Ray, 2006; Yang, Han, & Kim, 2004). However, the solution in the retrieved learning case is not always appropriate for the encountered teaching problem. As far as adaptive learning is concerned, most of the solutions provided by the retrieved cases should be modified for the newly encountered problem (Passone, Chung, & Nassehi, 2006; Roderick & Baden, 2005). Hence, case adaptation becomes an important task for cased-based reasoning.

The rule-based case adaptation is the most common approach to bridge the gap between retrieved cases and a newly encountered problem (Hanney & Keane, 1997). However, knowledge for case adaptation is not easily accessible and available, and is hard to be maintained through updating, changing or substituting the rules. In order to overcome the drawbacks of rule-based approach, several techniques of artificial intelligence, such as neural network (Corchado & Lees, 2000; Zhang, Ha, Wang, & Li, 2004) and genetic algorithm (Huang, Shih, Chiu, Hu, & Chiu, 2009; Juan, Shih, & Perng, 2006; Passone et al., 2006), are utilized for case adaptation in the areas of engineering. In spite of many different methods which have been proposed for performing the task of case adaptation in CBR (Rudradeb & Jayanta, 2005), techniques of case adaptation are rarely utilized in e-learning to develop new learning cases from existing ones. In addition, solutions to case adaptation are knowledge-intensive and remain highly domain dependent, requiring a detailed problem-specific knowledge for cased-based problem-oriented learning.

To assist regular and special education teachers in effectively developing practical knowledge of teaching and improving their teaching quality for teaching students with mild disabilities, this study (1) designed a case adaptation framework based on difference analyses according to types of students disabilities and the mathematical topics of learning difficulties, and then (2) developed a learning case retrieval technique and learning case adaptation techniques where information retrieval techniques, cosine-measure, and genetic algorithm were utilized.

2. Overview of problem-oriented e-learning

This section presents an overview of a problem-oriented e-learning (POeL) model for developing an e-learning platform to promote regular and special education teacher's professional development.

2.1. Problem-oriented e-learning model

By adopting situated learning as a theoretical basis, the problem-oriented e-learning model depicts integrating learning theories of social constructivism and case reasoning along a problem-oriented learning approach. In the spirit of problem-oriented learning, this model includes the stages of analysis, design, development, and practice as discussed below.

The **analysis** stage gauges a learner's (i.e. teacher's) understanding of special education and related knowledge, and assesses her or his student's characteristics to diagnose and analyze the students' learning difficulties. The learning goal for the teacher subsequently transforms into "solving students' learning problems." The **design** stage focuses on identifying teaching objectives based on the characteristics and disabilities of the student, as well as the learner's background and competence to outline a personalized learning plan. The **development** stage retrieves and develops learning contents, such as concepts and cases, for the personalized learning plan. The **practice** stage guides the learner to initiate learning

activities, such as concept learning, case studies, and teaching practice. Finally, the learner shares his or her experiences, thoughts and reflections, thereby expanding and updating the knowledge content of the system.

The learner undertaking case studies may select "individual learning" or "group learning." Selecting group learning takes the learner to a learning mode based on social constructivism, under which, the learner may initiate a group discussion and direct questions to experts or learners with related experiences in any case study phase. During Q&A sessions or online discussions in this forum, an experienced teacher or expert teacher plays the role of an e-consultant, guiding learners.

2.2. Learning case structure

Developing an e-learning platform requires not only designing functional learning activities, but also providing suitable learning materials. This study provides adaptable learning cases as learning contents, which were developed by expert teachers according to their teaching narrations, and were evaluated through actual teaching, observation, and discussion.

Each learning case contains "teaching context" and "teaching narration". The teaching context contains teacher profile, student profile data such as types of disabilities, strengths and weaknesses, a statement of student's learning problems, and teaching setting including the educational, institutional and socio-cultural setting. The teaching narration includes sections of teaching objectives, teaching procedure and learning assessments. A teaching procedure indicates the teaching units involved in the teaching procedure and their sequence. The details of teaching units are represented in terms of teaching cases.

In order to effectively store, organize, manage, and use the content of learning cases, this study defines instances of each class in the case model as learning objects by employing object technology (Bruegge & Dutoit, 2004). Fig. 1 shows the learning case model represented in class diagram of UML (Booch, Rumbaugh, & Jacobson, 1999) notations, where a box represents a class of learning objects and a diamond indicates a composite class, which is composed of its component classes. The bold rounded squares represent retrievable learning objects, while plain squares denote un-retrievable learning objects.

3. Learning case adaptation model

In practice, newly encountered teaching problems may be similar to existing ones, but not exactly the same. Therefore, the differences between them must be identified and the content of solutions should be adjusted to bridge the gape (Susan et al., 2006). This section presents a case adaptation model where a difference analysis between retrieved learning cases and the newly encountered teaching problem is adopted.

3.1. Difference analysis

Most of the special education teachers select teaching strategies and methods according to student's strengths and needs (Ontario Ministry of Education, 2000). Therefore, the teaching problems and the student's disability type are taken as criteria to assess whether a retrieved learning case is appropriate for the newly encountered teaching problem. The differences in between the new teaching problem and the existing teaching problem can be equal, inclusion or relative shown in Fig. 2.

First, the equal relationship means that problem features extracted from problem statements of the retrieved learning case are the same with those stated in the new teaching problem
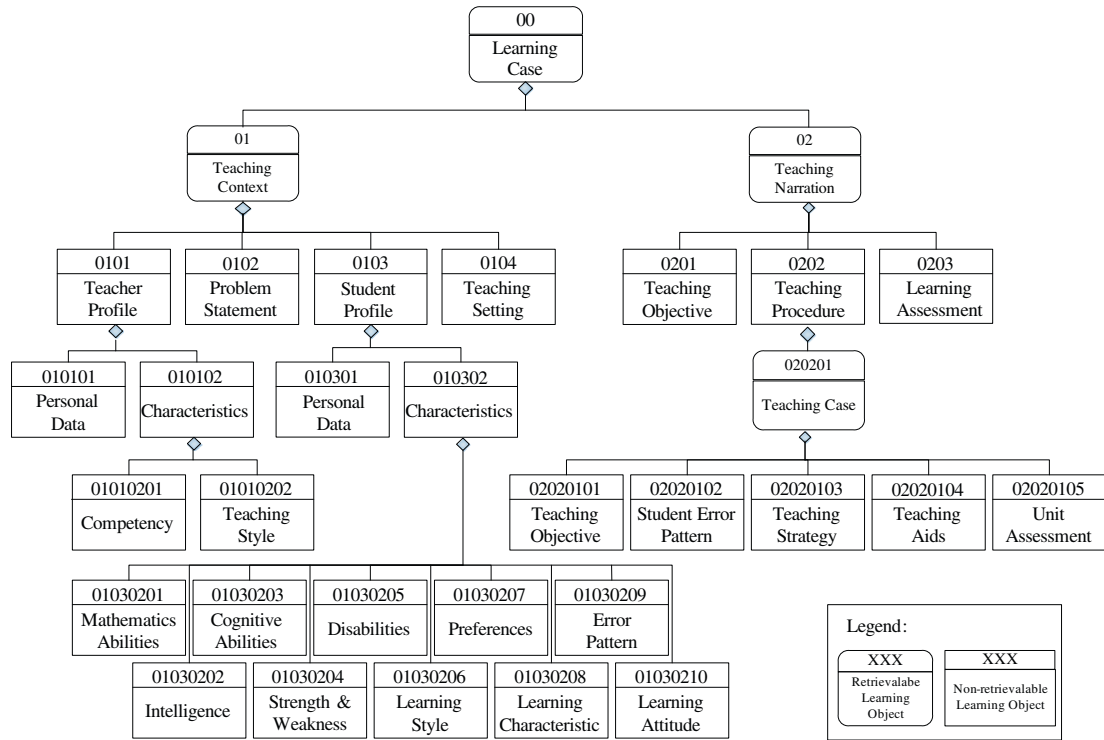
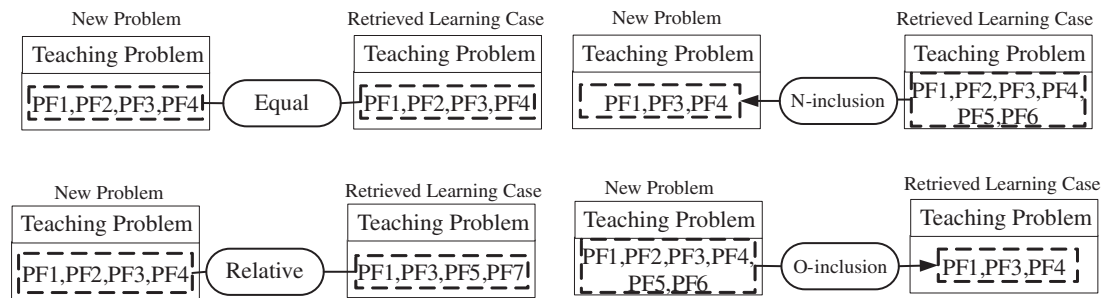**Fig. 1.** The structure of learning case.

Fig. 2. Teaching problem difference types.

statements. Moreover, the inclusion relationship can be the N-inclusion relationship or the O-inclusion relationship. The N-inclusion relationship means that problem features of the new teaching problem statements are the subset of those extracted from the problem statements of the retrieved learning case. On the contrary, the O-inclusion relationship represents that problem features of the retrieved learning case are the subset of those stated in the new teaching problem. Lastly, the relative relationship represents that problem features of both the retrieved learning case and the new teaching problem are overlapping. In the other words, partial of the problem features of the retrieved learning case appear in the new teaching problem, and vise versa.

Another criterion is to measure whether the student's disabilities stated in the retrieved learning case are the same as the new student's disabilities. The relationship in between the disabilities of the retrieved learning case and the newly encountered student can be equal and un-equal as shown in Fig. 3. The equal relationship means that student's disabilities of the retrieved learning case are the same as the newly encountered student's disabilities. Other situations are indicated in terms of un-equal.

3.2. Learning case adaptation model

According to the result of difference analysis, this study further identified three types of learning case adaptations—null adapta-
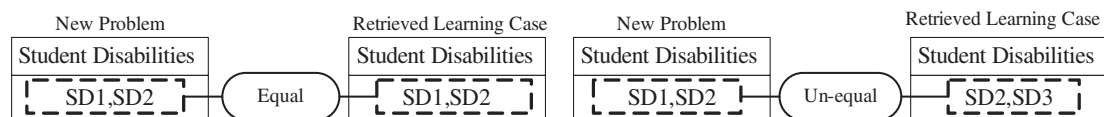

Fig. 3. Student's disability difference types.

tion, teaching case adaptation, and teaching procedure adaptation. Furthermore, the teaching procedure adaptation is classified into a single teaching procedure adaptation and a multiple teaching procedure adaptation. The details of each adaptation model are described below.

3.2.1. Null adaptation

When problem features of both the retrieved learning case and the new teaching problem are the same, the teaching procedure presented in the retrieved learning case can be utilized to solve the new problem. Besides, if the student's disabilities are equal, the teaching cases of the retrieved learning case could be used to solve the new teaching problem. Therefore, it is not required to

adapt the retrieved learning case when the difference relationship of the teaching problem and the student's disabilities between the retrieved learning case and the new teaching problem are both equal.

3.2.2. Teaching case adaptation

When the teaching problems are equal and the student's disabilities is un-equal, the retrieved learning case will be adjusted by using teaching case adaptation, as shown in Fig. 4(A). This case implies that the teaching procedure in the retrieved learning case can resolve the new teaching problem, but teaching cases in the retrieved learning case are not suitable for the new student. Therefore, it should retrieve the suitable teaching cases based on the
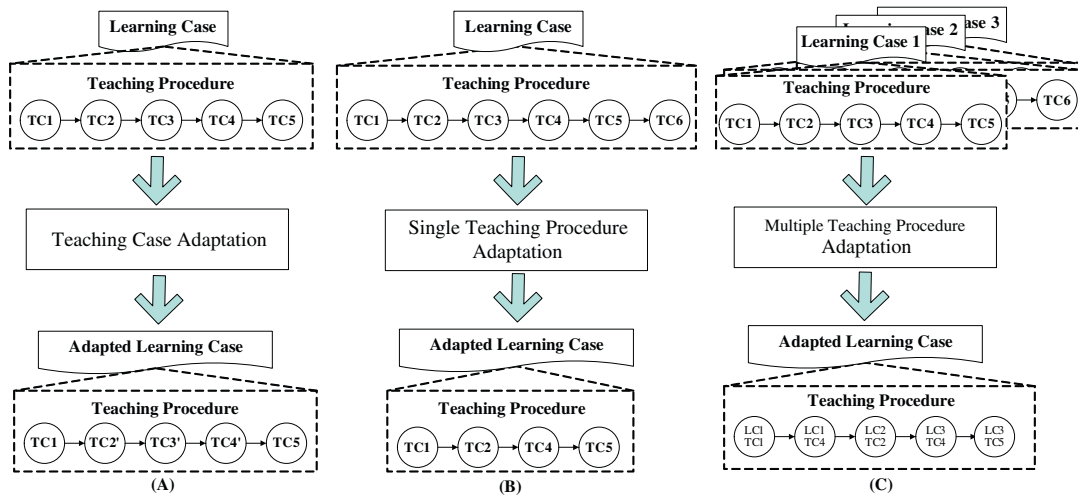

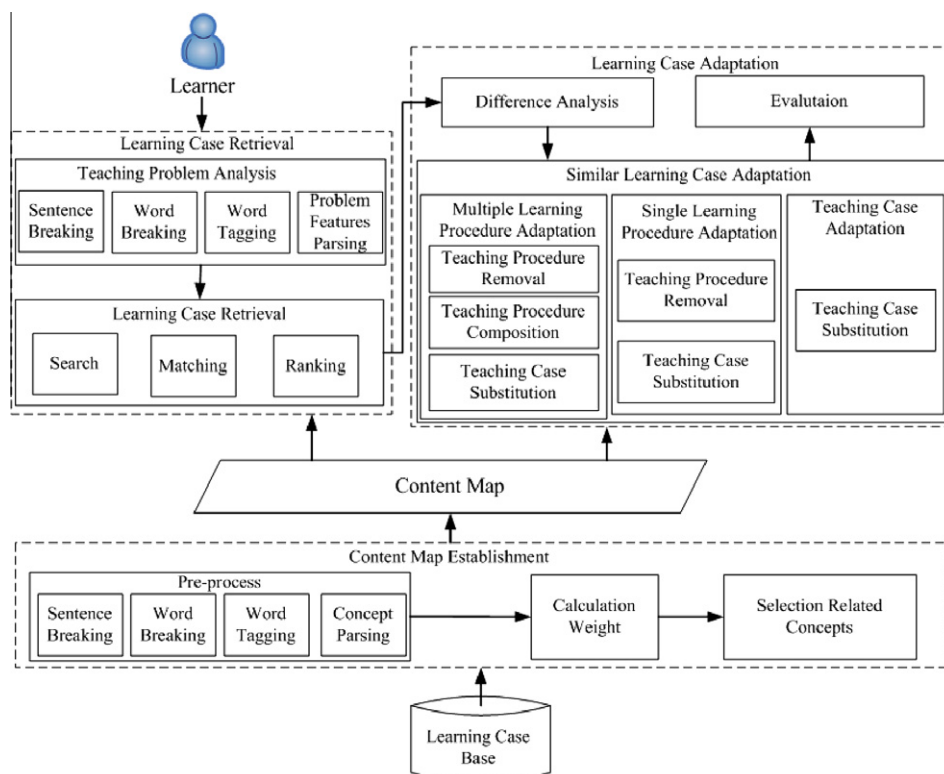Fig. 4. Learning case adaptation model.

Fig. 5. Learning case adaptation framework.

retrieved learning procedure and the new student's disabilities to adapt the retrieved learning case.

3.2.3. Single teaching procedure adaptation

If the problem difference type is N-inclusion, the retrieved teaching procedure consists of the teaching cases that are not related to the new teaching problem. Therefore, the unrelated teaching cases should be removed from the retrieved teaching procedure by a refining adaptation, as shown in Fig. 4(B).

3.2.4. Multiple teaching procedure adaptation

The retrieved teaching procedure would not satisfy the new teaching problem when the relationship type of the problem features is O-subset or relative. In order to overcome this problem, it is required to combine relevant teaching procedures for a new suitable teaching procedure and to retrieve suitable teaching cases according to the new teaching procedure, as shown in Fig. 4(C).

4. Learning case adaptation framework

This section presents the framework of learning case adaptation based on the proposed learning case adaptation model. The purpose of learning case adaptation framework is to provide the most similar learning cases for learners, according to learner's teaching problem and his/her student's disabilities. As shown in Fig. 5, the learning case adaptation framework contains three main modules, the definition and establishment of a content map for historical learning cases, the retrieval of learning case, and the adaptation of learning cases. There are also a learning case base for learning case storage. Each of the three parts is described below.

4.1. Definition and establishment of a content map for learning cases

The content map presents the knowledge structure of the problem statement, the teaching procedure, and the teaching cases in a learning case. Major components of the content map model are the concept, the occurrence, and the association, as is shown in Fig. 6. The concepts are the knowledge concepts of the problem statement, the teaching procedure, and the teaching case. The occurrences of a concept indicate which learning cases the concept appears. The importance of a concept varies with learning cases as well as paragraphs in a learning case, therefore, the weights of an occurrence are specified in terms of W_{PS}, W_{TP} and W_{TC}, corresponding to the problem statement, the teaching procedure, and the teaching case. A learning case may contain more than one teaching cases, thus W_{TC} is a set of weights of concepts in teaching

cases rather than a single value. Beside, association denotes relationships in between concepts.

The content map is established by using a semantic analysis method (Chu, Chen, Lin, Liao, & Chen, 2009). Establishment of knowledge map includes three steps—pre-process, weight calculation, and related concept selection. The purpose of pre-process is to retrieve concepts from learning cases in learning cases repository, which includes sentence breaking, word breaking, word tagging, and concept parsing. After that, the Probability Latent Semantic Analysis (PLSA) (Hofmann, 1999a, 1999b) was applied to calculate concept weights. Last, the correlations between concepts for each other were calculated using the cosine-measure (Gerard, 1989), and association of two concepts were identified as long as its cosine-measure value is higher then a pre-specified threshold. The content map can gauge accurately when learning cases are relevant to a teaching problem feature, even for features that do not appear in a learning case. Thus, the content map enables the case base reasoning to have a semantic search capability to facilitate searching and matching similar learning cases and adapt the retrieved learning case.

4.2. Retrieval of learning cases

This module contains the functions of problem feature analysis and retrieval, and learning case retrieval. The function for problem feature analysis and retrieval aims to transfer the learner's teaching problem in nature language into a problem feature set using information retrieval techniques, including sentences breaking, word breaking, word tagging and problem features parsing. In the learning case retrieval function, similar learning cases are searched and matched according to the learner's teaching problem feature set. They are subsequently ranked in order of degree of similarity.

Let $PF = \{pf_1, pf_2, \ldots, pf_n\}$ denotes a set of n problem features. The learning case similarity, denoted as $Sim(j)$, is defined by

$$Sim(j) = CosSim(C_{PSj}, PF) + CosSim(C_{TPj}, PF) + CosSim(C_{TCj}, PF)$$

$$= \frac{\sum_{i=1}^{t}(w_{PSji} \cdot w_{pfi})}{\sqrt{\sum_{i=1}^{t} w_{PSji}^2 \cdot \sum_{i=1}^{t} w_{pfi}^2}} + \frac{\sum_{i=1}^{t}(w_{TPji} \cdot w_{pfi})}{\sqrt{\sum_{i=1}^{t} w_{TPji}^2 \cdot \sum_{i=1}^{t} w_{pfi}^2}}$$

$$+ \frac{\sum_{i=1}^{t}(w_{TCji} \cdot w_{pfi})}{\sqrt{\sum_{i=1}^{t} w_{TCji}^2 \cdot \sum_{i=1}^{t} w_{pfi}^2}}$$

In the above equation, w_{PSji} is the weight of concept i in the problem statement of learning case j; w_{TCji} is the weight of concept i in the teaching case of learning case j; w_{TPji} is the weight of concept i in
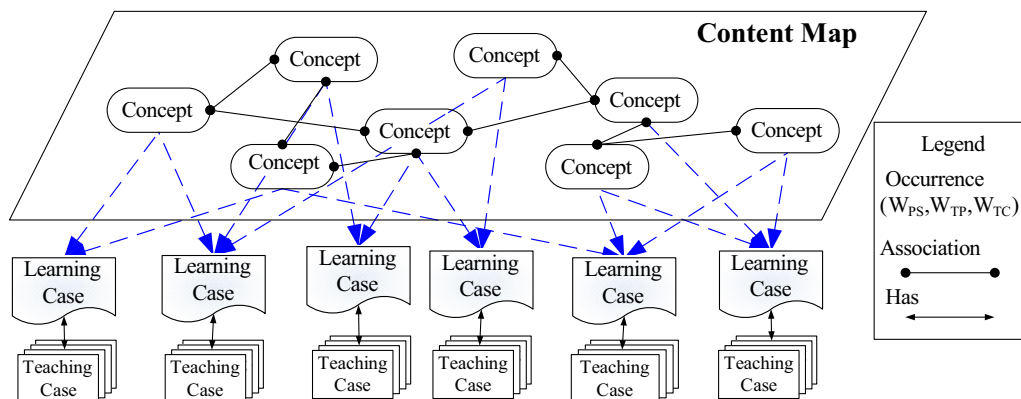

Fig. 6. Content map model.

the teaching procedure of learning case j, and w_{pfi} is the weight of problem feature i in the learner's teaching problem.

4.3. Adaptation of similar learning cases

This module contains functions of difference analysis, learning case adaptation, and evaluation. First, the difference analysis is conducted to identify the difference relationship in both criteria of the teaching problem and the student's disabilities between the retrieved learning case and the new teaching problem. If the teaching problem and the student disabilities are both equal, adaptation won't be required, and the most similar learning case will be recommended. Otherwise, the most similar retrieved learning case needs to be adapted.

Second, learning case adaptation which consists of teaching case adaptation, single teaching procedure adaptation, and multiple teaching procedure adaptation are activated according to the result of difference analysis. Teaching case adaptation and single teaching procedure adaptation only adjust the most similar learning case to make a new learning case. But, multiple teaching procedure adaptation requires more relevant learning cases for new learning case construction.

The teaching case adaptation was implemented by using teaching case substitution technique, which retrieves more suitable teaching cases to replace original teaching cases in the most similar learning case. Moreover, the single teaching procedure adaptation is implemented by using techniques of teaching procedure removal and teaching case substitution, which deletes unrelated steps in the retrieved teaching procedural at first, and then retrieves suitable teaching cases to replace original teaching cases in the most similar learning case. Lastly, the multiple teaching procedure adaptation is implemented by using techniques of teaching procedure removal, teaching procedure composition, and teaching case substitution. At first, this function removes unrelated steps from retrieved teaching procedural in some retrieved learning cases. Then it combines those related teaching procedures to generate a new teaching procedure. Lastly, it retrieves suitable teaching cases according to the new teaching procedures.

After adapting the similar learning case, an assessment is conducted to compare the similarity between the retrieved learning case and the adapted learning case. The most similar learning case is finally provided.

5. Case adaptation techniques

The case adaptation technique consists of a substitution technique, a removal technique, and a composition technique. The details of each technique are described as following.

5.1. Substitution technique

The purpose of the substitution technique is to replace more suitable teaching cases for the most suitable teaching procedure. This technique includes the steps of (i) selecting related teaching case candidates, (ii) calculating similarity of teaching case candidates, and (iii) selecting the most suitable teaching case. Those three steps should be done in order from first teaching case to last teaching case in the most suitable teaching procedure.

5.1.1. Selecting related teaching case candidates

The concept set of the original teaching case, $CF = \{cf_1, cf_2, \ldots, cf_n\}$, is established from content map, and then it is taken as the criterion to filter related teaching cases trough the content map from the learning case repository. After filtering, those related teaching cases are considered as candidates.

5.1.2. Calculating similarity of teaching cases candidates

The second step is similarity measurement, which calculates the degree of similarity between each teaching case candidate and the concept set. The teaching case similarity, denoted as TCS_{ij}, is defined by

$$TCS_{ij} = SDW_j \times \sum_{k=1}^{n} tcfw_{ijk},$$

where SDW_j, the student disabilities weight in the jth learning case, is calculated by Jaccard coefficient which is described as the follow:

$$SDW_j = \frac{|NSD \cap LCSD_j|}{|NSD \cup LCSD_j|},$$

where NSD is the new student's disability set and $LCSD_j$ is the student's disabilities set in the jth learning case. Besides, $tcfw_{ijk}$ is the kth teaching case concept in the ith teaching case of the jth learning case, and n is the amount of concepts in the ith teaching case of the jth learning case.

For example, the concept set, $CF=\{$二 (*two*), 位數 (*digit*), 乘法 (*multiplication*), 運算 (*operation*), 規則 (*rule*)$\}$, which is retrieved from the first teaching case in the retrieved similarity learning case. The new student is diagnosed with mathematics learning disabilities, autism, and nonverbal learning disabilities, $NSD = \{$數學學習障礙自閉症 (*attention-deficit hyperactivity disorder*), 自閉症 (*autism*), 非語文學習障礙 (*nonverbal learning disabilities*)$\}$. And, the teaching case i in the learning case j, TC_{ij}, is a candidate which contains the weight of the concept set, $TCFW_{ij} = \{0.1038, 0.9033, 0.5365, 0.7562, 0.2450\}$, and the set of the student's disabilities in the learning case j is $LCSD_j = \{$非語文學習障礙 (*nonverbal learning disabilities*),
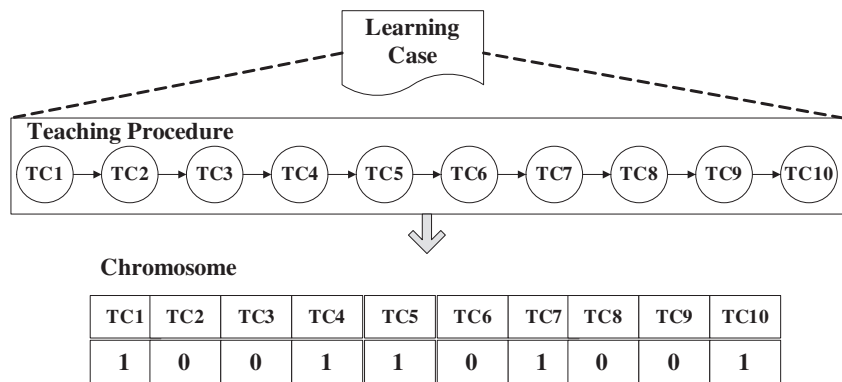

Fig. 7. The chromosome of the removal technique.

TC1	TC2	TC3	TC4	TC5	TC6	TC7	TC8	TC9	TC10
1	0	0	1	1	0	1	0	0	1

情緒與行為障礙 (emotional and behavioral disorders)}. Thus, the student disabilities weight, SDW_j, is 0.25 and the similarity of the teaching case i in the learning case j, TCS_{ij}, is calculated as follow:

$$TCS_{ij} = 0.25 \times (0.1038 + 0.9033 + 0.5365 + 0.7562 + 0.2450)$$
$$= 0.6362.$$

5.1.3. Selecting the most suitable teaching case

The last step selects the most similar teaching case as the most suitable teaching case. That is, if the similarity of the original re-trieved teaching case is lower than other teaching cases, the original retrieved teaching case should be replaced by the teaching case which has the highest similarity.

5.2. Removal technique

The removal technique is utilized in the refine adaptation and the composition adaptation to remove unrelated teaching cases. This study utilized a genetic algorithm to select the suitable teaching case in the teaching procedure according to the learner's teaching problem. The genetic algorithm (GA) is a highly efficient search technique used to find exact or approximate solutions to optimization and search problems (Goldberg, 1989). The genetic algorithm performs the removal process in three stages: initialization, selection and generation, and reiterates the selection stage and the generation stage until the stop criterion is satisfied. Details of each step are described below.

5.2.1. Initialization

The initialization step first represents the problem variable as a chromosome, then chooses the size of a chromosome population, S, the crossover probability, Pc, and the mutation probability, Pm, and finally defines the stop criterion and generates the initial population.

In order to remove unrelated teaching cases in the retrieved learning case, this study takes the teaching procedure as a chromosome. Each chromosome is the Binary string, which consists of a number of genes as shown in Fig. 7. The gene represents a teaching case in this retrieved teaching procedure. Therefore, the number of genes is decided by the number of teaching cases in this retrieved teaching procedure. Moreover, if the value of gene is 0, then the corresponding teaching case should be removed.

Before the process starts, this study sets up the size of a chromosome population $N = 20$, the crossover probability $Pc = 0.9$, the mutation probability $Pm = 0.01$, and the stop criterion is 200 generations. The initial chromosomes are generated randomly based on the population size.

5.2.2. Selection

Selection, also represents reproduction, is a process in which individual chromosomes are copied based on their fitness. In order to evaluate the fitness of each chromosome, this study designs a fitness function according to selected teaching cases which could be utilized to solve the learner's teaching problem. The teaching case is suitable for the learner's teaching problem because the concepts involved in this teaching case relate to teaching problem features. Therefore, if the teaching case has a higher weight of relative concepts and a lower weight of non-relative concepts, then it shows that this teaching case could be utilized to solve the learner's teaching problem. Hence, the fitness function is defined as following.

$$Fitness(C_p) = \sum_{i=1}^{x} G_i \left(\sum_{k=1}^{m} Rtcfw_k - \sum_{h=1}^{n} Ntcfw_h \right),$$

Table 1
The weight of concepts in teaching cases.

Teaching case	乘法 (multiplication)	除法 (division)	解題 (solve)	乘法 (operation)	能力 (capability)	算式 (number sentence)	倍數 (multiple)	過程 (Process)	問題 (Problem)	加法 (addition)	減法 (subtraction)	概念 (concept)	Total weight of related concepts	Total weight of unrelated concepts
TC1					0.2654				0.3451	0.6894			0.2654	1.0345
TC2					0.2368				0.2967		0.7125		0.2368	1.0092
TC3				0.5169			0.4637					0.2138	0.9806	0.2138
TC4	0.6759		0.3378		0.3117								1.3254	0.0000
TC5		0.7351	0.4112			0.4571		0.2314					1.6034	0.2314

where G_i is the value of ith gene; x is the amount of genes; $Rtcfw_k$ is the weight of kth related concept in the ith teaching case, and m is the amount of related concepts in the ith teaching case; $Ntcfw_h$ is the weight of the hth unrelated concept in the ith teaching case, and n is the amount of unrelated concepts in the ith teaching case.

In general, the content of the solution would be more specific than the content of the problem. Thus, concepts retrieved form teaching cases will be more than that retrieved form the learner's teaching problem, and the concepts involved in teaching cases and in the learner's teaching problem might not be the same, although it might be correlated. Thereby, in order to avoid losing suitable teaching cases, this study also takes concepts which have a high correlation with problem features as related concepts. In short, the related concepts may not only be problem features but also be the concepts that have the association with problem features.

For example, the learner's teaching problem is "加強乘法與除法的解題能力(enhance capability of solving multiplication and division problems)". After analysis the state-

Fig. 8. The initial population.

Fig. 9. The crossover operator.

Fig. 10. The mutation operator.

ment, the problem feature set is PF = {乘法 (*multiplication*), 除法 (*division*), 解題 (*solve*), 能力 (*capability*)} and the related concept set is RC = {乘法 (*multiplication*), 除法 (*division*), 解題 (*solve*), 能力 (*capability*), 運算 (*operation*), 算式 (*number sentence*), 倍數 (*multiple*)}. The similarity learning case is then retrieved based on the problem features. The similar learning case contains five teaching cases. The weights of the concepts involved in those teaching cases are shown in Table 1.

In the beginning, this method generates six chromosomes randomly (Fig. 8). The fitness of each chromosome is calculated as following:

Fitness($C1$) = $0 \times (0.2654 - 1.0345) + 1 \times (0.2368 - 1.0092) + 1 \times (0.9806 - 0.2138) + 0 \times (1.3254 - 0) + 0 \times (1.6034 - 0.2314)$ = −0.0056.

Fitness($C2$) = $1 \times (0.2654 - 1.0345) + 1 \times (0.2368 - 1.0092) + 0 \times (0.9806 - 0.2138) + 0 \times (1.3254 - 0) + 1 \times (1.6034 - 0.2314)$ = −0.1695.

Fitness($C3$) = $0 \times (0.2654 - 1.0345) + 0 \times (0.2368 - 1.0092) + 1 \times (0.9806 - 0.2138) + 0 \times (1.3254 - 0) + 0 \times (1.6034 - 0.2314)$ = 0.7668.

Fitness($C4$) = $1 \times (0.2654 - 1.0345) + 1 \times (0.2368 - 1.0092) + 1 \times (0.9806 - 0.2138) + 1 \times (1.3254 - 0) + 1 \times (1.6034 - 0.2314)$ = 1.9227.

Fitness($C5$) = $0 \times (0.2654 - 1.0345) + 1 \times (0.2368 - 1.0092) + 1 \times (0.9806 - 0.2138) + 0 \times (1.3254 - 0) + 1 \times (1.6034 - 0.2314)$ = 1.3664.

Fitness($C6$) = $0 \times (0.2654 - 1.0345) + 0 \times (0.2368 - 1.0092) + 0 \times (0.9806 - 0.2138) + 1 \times (1.3254 - 0) + 1 \times (1.6034 - 0.2314)$ = 2.6974.
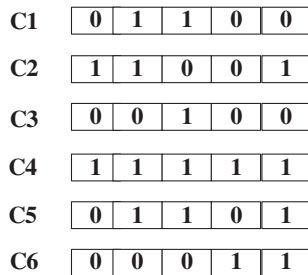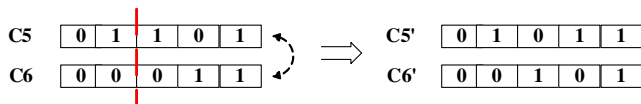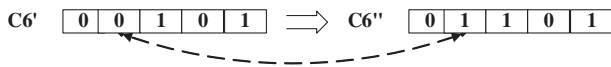
After evaluating the fitness of each chromosome, this study uses the common type of tournament selection—binary tournament selection to select chromosomes which fit highly. Two chromosomes were selected at random from the generation, and then the one which has a higher fitness value will be copied for crossover. According to the above example, supposing the two chromosomes $C5$ and $C2$ are selected and the fitness of $C5$ is higher than the fitness of $C2$, then, the chromosomes $C5$ will be copied into crossover pool. In this example, it has an initial population of six chromosomes. Thus, to establish the same population in the next generation, the tournament selection would be proceeded six times.

5.2.3. Generation

The generation step contains crossover and mutation to generate offspring chromosomes, which are described below.
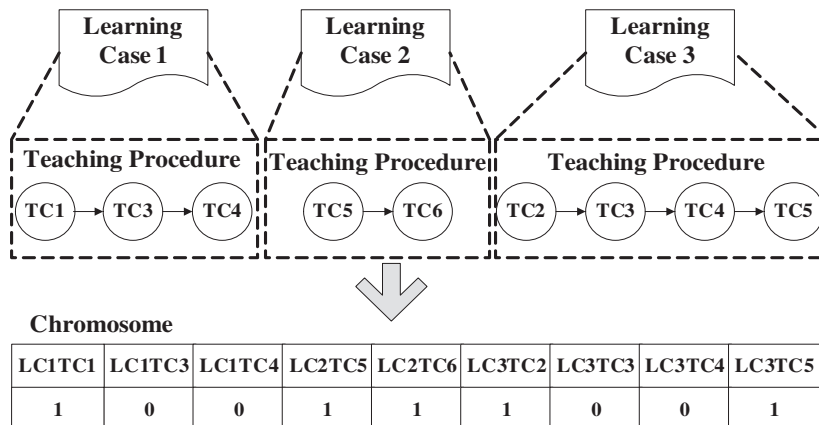

Fig. 11. The chromosome of the selection approach.

Table 2
The weight of related concepts in those teaching cases candidates.

Learning case ID	Teaching case ID	Concept										
		乘法 (multiplication)	除法 (division)	解題 (solve)	進位 (carry)	算式 (number sentence)	倍數 (multiple)	計算 (computation)	符號 (symbol)	加法 (addition)	減法 (subtraction)	概念 (concept)
LC1	TC1	0	0	0	0.4122	0	0	0	0.2159	0.6894	0.5371	0
	TC2	0	0	0.2368	0.4711	0	0	0.2472	0	0.7125	0.7538	0
LC3	TC2	0	0	0.5169	0.3624	0	0	0	0	0.6759	0	0.2138
	TC3	0.6257	0	0.3378	0	0	0	0.4261	0	0	0	0
	TC5	0.5213	0	0	0	0	0.1635	0.3679	0	0	0	0
LC8	TC1	0	0	0	0	0.2216	0	0	0.3657	0.4692	0	0.2110
	TC2	0	0	0.1336	0	0	0	0.2638	0	0	0.3679	0
	TC5	0.3126	0	0	0	0	0.3219	0	0	0	0	0.3116
	TC6	0	0.7351	0.4112	0	0.4571	0	0.2314	0.2117	0	0	0.1238

5.2.3.1. Crossover. This study selects the one-point crossover method to combine two parent chromosomes to generate better offspring chromosomes. At first, two parent chromosomes are selected at random from crossover pool. Next, the crossover operator randomly chooses a crossover point and cuts the pair of parent chromosomes short by a crossover point, and then exchanges the chromosome parts after that point to each other. As a result, two new child chromosomes are generated.

For example, given two parent chromosomes $C5$ and $C6$ from the generation, and randomly chosen crossover point CP = 2. The chromosome parts after that point would be exchanged to each other, as shown in Fig. 9. Thus, the crossover operator produces two new offspring, chromosomes $C5'$ and $C6'$.

5.2.3.2. Mutation. In order to avoid a local optimum, the mutation operator selects one gene as the mutation point in a chromosome randomly, and then reverses the value of the gene. For example, the mutation point MP = 2 was randomly chosen, and then the value of the gene reversed from 0 to 1, which is shown in Fig. 10. Thus, the mutation operator produces one new offspring chromosome $C6''$.

The removal process use genetic algorithm to repeatedly conduct selection and generation operations until it meets the stop criterion.

5.3. Composition technique

The composition technique takes related teaching procedures which have been removed unrelated teaching cases by the above removal technique to construct a new teaching procedure in the adapted learning cases. A teaching procedure involves suitable teaching cases and their sequence. Therefore, this composition technique contains two steps: selection of suitable teaching cases and sorting of those teaching cases as described below.

5.3.1. Teaching case selection

The purpose of teaching case selection is to select a suitable teaching case from teaching cases candidates in related teaching procedures by genetic algorithm. This step first defines two things: a genetic representation of the solution domain and a fitness function to evaluate the solution domain.

5.3.1.1. A genetic representation of the solution domain. In this step, a chromosome denotes all teaching case candidates which are retrieved from learning case patterns in order to select suitable teaching cases. Each gene in a chromosome is defined as the teaching case, which can be easily represented as a one-bit. The value of gene is binary code as shown in Fig. 11. The value 1 represents the selected teaching case, otherwise it is not. The number of gene in a chromosome is decided by the amount of teaching cases candidates.

5.3.1.2. A fitness function. The fitness function needs to capture what makes a teaching procedure either good or bad for the learner's teaching problem. This study defines the fitness function as concerned with the weight of concepts in the teaching case relating to the learner's teaching problem. In general, the more teaching cases are selected, the higher the value of fitness function is. However, the higher number of teaching cases might result in learning overloading. In addition, the same concept may appears in different teaching cases, and thus teaching cases which contains the same concept are selected, which would make duplicated teaching cases. Therefore, the weight of related concepts in teaching cases will be lowered when the number of selected teaching cases that contain the same related concept increases. This study defines the fitness function as:

$$Fit(C_p) = \sum_{i=1}^{k} \frac{\sum_{j=1}^{m} fw_{ij} \times g_j}{n_{fi}^2}, \quad n > 0,$$

where k is the amount of related concepts and m is the amount of genes; g_j is the value of the gene j; fw_{ij} is the weight of the related concept i in the teaching case j; n_{fi} is the number of gene which contains the related concept i and it is value is 1.

For example, this study chooses the top three learning case according to the similarity between the learning case and the learner's teaching problem: LC1, LC3 and LC8. After removing unrelated teaching cases, the weight of related concepts in those teaching cases candidates is showed in Table 2. It is supposed that a chromosome as $C_1 = [110101101]$. The fitness of this chromosome is evaluated as below.

$$
\begin{aligned}
Fit(C_1) = {} & \frac{0.6257 \times 1 + 0.5213 \times 0 + 0.3126 \times 0}{1^2} + \frac{0.7351 \times 1}{1^2} \\
& + \frac{0.2368 \times 1 + 0.5169 \times 0 + 0.3378 \times 1 + 0.1336 \times 1 + 0.4112 \times 1}{4^2} \\
& + \frac{0.4122 \times 1 + 0.4711 \times 1 + 0.3624 \times 0}{2^2} + \frac{0.2216 \times 1 + 0.4571 \times 1}{2^2} \\
& + \frac{0.2472 \times 1 + 0.4261 \times 1 + 0.3679 \times 0 + 0.2638 \times 1 + 0.2314 \times 1}{4^2} \\
& + \frac{0.2159 \times 1 + 0.3657 \times 1 + 0.2117 \times 1}{3^2} \\
& + \frac{0.6894 \times 1 + 0.7125 \times 1 + 0.6759 \times 0 + 0.4692 \times 1}{3^2} \\
& + \frac{0.5371 \times 1 + 0.7538 \times 1 + 0.3679 \times 1}{3^2} \\
& + \frac{0.2138 \times 0 + 0.2110 \times 1 + 0.3116 \times 0 + 0.1238 \times 1}{2^2} 2.4583.
\end{aligned}
$$

5.3.1.3. Running the genetic algorithm. The genetic algorithm includes steps of reproduction, crossover, and mutation as described in the composition step, as well as operators in the removal step. This algorithm uses the tournament selection in the reproduction, and selects the one-point crossover method to combine two parent chromosomes to generate better offspring chromosomes. The mutation operator selects one gene as the mutation point in a chromosome randomly and then reverses the value of the gene. This study sets up the size of a chromosome population $N = 20$, the crossover probability $Pc = 0.9$, the mutation probability $Pm = 0.01$, and the stop criterion is 200 generations. The initial chromosomes are generated randomly based on the population size. The genetic algorithm repeatedly runs above operations, until it meets the stop criterion.

5.3.2. Teaching case sequencing

The composition technique is to sort teaching cases according to the teaching sequence of math curriculum units, which are iden-
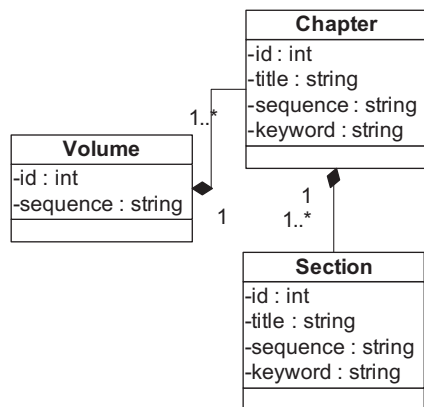

Fig. 12. Math curriculum model.

Table 3
Maximum sequence value of teaching cases.

Learning case ID	Teaching case ID	Maximum sequence value
LC3	TC2	040402
	TC5	050699
LC8	TC2	040403
	TC6	050899

tified in terms of concepts contained in teaching cases. In order to construct a suitable teaching procedure, this study designs the sorting approach containing steps of math curriculum unit matching, sequence value assignment, and teaching case arrangement. Each step is described as below.

5.3.2.1. Math curriculum unit matching. The purpose of this step is to identify chapters or sections which are included in a teaching case based on the math concepts appearing in the teaching case by keyword matching.

At first, this study designed a math curriculum model to represent the sequence of math curriculum units using unified modeling language (UML), as is shown in Fig. 12. This model contains three classes, which are volume, chapters, and sections, based on the structure of math textbook used in Taiwan. The sequence attribute is a two-digit number in all classes to denote the sequence of the math curriculum unit.

5.3.2.2. Sequence value assignment. After matching, each of math concepts has a sequence value which is six-digit number. The first two digits are the number of the math textbook. The third digit and the fourth digit represent the sequence of teaching chapters in the math textbook. The final two digits represent the sequence of sections in a chapter.

However, math concepts may appear in a chapter as well as in a section. If the math concept only appears in the teaching chapter, then the final two digits of the sequence value are set as 99 to indicate that this math concept contains all sections in a chapter.

Besides, the teaching case would contain various math concepts. In order to assign appropriate sequence value, this study takes the maximum sequence value of math concepts appearing in a teaching case as its sequence value.

5.3.2.3. Teaching case arrangement. This step sorts selected teaching cases in an ascending order according to their sequence value. Following the above example, the maximum of fitness value is 3.7932, as the chromosome is $C_{31} = [001010101]$. Therefore, there are four teaching cases need to rearrange. The sequence values of those teaching cases are shown in Table 3. Finally, the teaching procedure of those teaching cases is LC3TC2, LC8TC2, LC3TC5, and LC8TC6 in order.

6. Implementation and demonstration

A learning case adaptation mechanism was implemented in a problem-based e-learning platform based on the proposed learning case adaptation approach. This section presents the implementation details and an example.

6.1. Case representation

To store, organize, manage, and use the case contents effectively, the instances of each class in the case model were defined as learning objects by Extensible Markup Language (XML). XML is a simple, cross-platform, extensible and flexible text-based

standard for representing data (Sun Microsystems, 2002; Zhang, Sheng, & Li, 2002). Practical teaching knowledge can be represented and stored in XML documents by defining tags and the structural relationships among them. The POeL platform can display knowledge content adaptively by enabling the same data to be published in different media.

In this study, a learning case was composed of three XML document classes, i.e. the teaching context, the teaching narration, and teaching cases. Part of the XML schema is shown as following:

<Teaching Case TCID="1" name=" able to say, read, write, and count numbers up to 2000 and compare their values">

Fig. 13. Teaching problem description.

Fig. 14. The teaching procedure of the adaptation learning case.

<Teaching Case Procedure> 1–1 able to say numbers up to 2000 by adding 1, 10, 100 and 1000, and arrange them in a correct sequential order. 1–2 able to read numbers correctly up to 2000. 1–3 able to write numbers correctly up to 2000. 1–4 able to comprehend the correspondence between digits and place values of numbers up to 2000. 1–5 able to operate additions or subtractions for numbers up to 2000. 1–6 able to compare two numbers up to 2000 and to express such a relationship with <, >, or =. 1–7 able to operate additions and subtractions with coins for the sum of monetary values up to 2000. 1–8 able to make correct payment according to prices of the objects concerned. </Teaching Case Procedure>

<Student Error Pattern EPID="1"> (1) Having difficulty counting 10 continuous numbers in the correct sequential order; unable to identify the sequence for 1080–1090-( ) due to problem with numbers from 1090 to 1100. (2) Having incorrect comprehension of place values: missing "thousand, hundred, or '-thy'" when reading numbers, e.g. 1685 was spoken as "one thousand six hundred eight five" and 1035 as "one zero thirty-five," while one thousand and five was written as 105. </Student Error Pattern>

<Student Error Pattern EPID="2"> able to compare numbers but cannot distinguish sign > from sign <. </Student Error Pattern>

<Teaching Approach and Strategy TASID="1"> (1) Hands-on operations with visual aids – using digit table, coins, and place value board for hands-on operations. When student places one more 10 on the digit in tens while counting from 1080 to 1090, teacher must emphasize the digit being added has a "TEN" place value to strengthen student's understanding of place values. Have student add one more "10" to 1090, making "ten 10s," which can be replaced by "one '100'". Through such hands-on operations with the aid of digit table, coins, place value board, student can see clearly the changes in digit in tens, thus facilitating the students' understanding of place values as an abstract concept through physical, visual stimulation. (2) Verbal hints: e.g. teacher says "one thousand 'and' seventy" for 1070, "one thousand 'and' eighty" for 1080, "one thousand 'and' ninety" for 1090, and "one thousand 'and' one hundred" for 1100. The emphasized "and" helps students avoid possible confusions about concepts related to the base-10 number system to 2000. </Teaching Approach and Strategy>

<Teaching Approach and Strategy TASID="2"> Task analysis (1) □ > ○: Have students produce visual cards ⌈ > ⌋ and ⌈ < ⌋, with the hint that A ⌈ > ⌋ B means A is " bigger" than B. likewise, in □ > ○, □ is a bigger and ○ is smaller; then, have students to fill in two numbers of their choosing, one before and the other after the sign, to personally experience the use and concept of ⌈ > ⌋. (2) Have students choose either > or < for a pair of arbitrary numbers, e.g. ⌈8 □ 5⌋. Teacher provides visual cards of both > and < for students to choose from. Based on students' choice, teacher will be able to see if student understands > and <. (3) Teacher gives direct explanations for > and <, and ends with telling students directly that 8 > 5 means "8 is bigger than 5," and ⌈ > ⌋ is read as "is bigger," whereas 5 < 8 means "5 is smaller than 8," and ⌈ < ⌋ is read as "is smaller". </Teaching Approach and Strategy>

<Teaching Aids TAID="3"> digit board</Teaching Aids>

<Objective > Hands-on operations of digit board enhances students' comprehension of place values as a concept, and helps train students for the conversion between numbers and Chinese numerals as well as for the reading and speaking of numbers. </Objective >

Fig. 15. The teaching case of the adaptation learning case.

<Instructional Practice > digit board.jpg </Instructional Practice>
<Explanation > The Chinese character for digits such as ten, hundred, and thousand are made into visual cards. Hands-on operations and arranging these word cards in the correct order improve students' conceptual understanding of place values and strengthen students' interchanging capability in between reading and writing. </Explanation>

</Teaching Case>

6.2. Example

Learners are required to enter their ID and password via the interface to access the POeL platform. If a learner logs into the system at the first time, a user model will be built to contain the learner's demographic data, background information, and the teacher assessment results. The platform then guides the learner to assess his or her student's academic abilities, and analyze the types of disabilities, learning style, and strengths and weaknesses of the students. A student model is then built based on the student assessment results. The learner is then required to describe his/her student's learning problem in Chinese natural language, and chose the matching type as shown in Fig. 13.

After that, the case-based learning module retrieves the most similar learning case according to the learner's teaching problem. Next, the difference analysis function analyzes the gap between the retrieved learning case and the learner's teaching problem. According to the result of difference analysis, the adaptation mechanism will be triggered to generate the adaptation learning case. The teaching procedure of the adaptation learning case is shown in Fig. 14, and the teaching case of the adaptation learning case is shown in Fig. 15. The adaptation learning case will be evaluated by the similarity calculation method of learning case retrieved. The similarity of the adaptation learning case is 8.7319, which is higher than the similarity of the original retrieved learning case, 7.5478. Thus, it shows that the adaptation mechanism could provide a more suitable learning case for the learner.

7. Conclusions and future work

This study designed a learning case adaptation model according to the result of difference analysis between the new teaching problem and existing learning cases, and then developed the learning case adaptation framework to provide adaptive knowledge for learners.

Additionally, in order to implement functions in this framework, this study constructed a content map using PLSA, and utilized information retrieval techniques, cosine-measure, and genetic algorithm to develop learning case retrieval technique and learning case adaptation techniques. The learning case adaptation mechanism can assist the teacher to effectively develop knowledge for teaching students with mild disabilities. Moreover, the knowledge base in the problem-oriented e-learning platform can be continuously expanded and updated.

Although the learning case adaptation mechanism can provide a more suitable learning case for the learner, this mechanism still may provide the learning case which may not fulfill learner's requirements due to the fact that a learner might describe he/her's teaching problem implicitly. This issue may be resolved by developing a user intention retrieval mechanism or an intelligent interactive problem statement function to promote the accuracy of the learner's requirement analysis.

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