

Effective Two-Phase Cooperative Learning on the WWW

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The "conceptual graph" is a conventionally adopted assisted teaching method. Conceptual graphs display the achievements of students. This study proposes a novel learning activity called "Two-Phase Cooperative Learning." The framework of this activity is based on the conceptual graph. The system includes the Dynamic Remedial Instruction Path (DRIP) and the grouping of cooperative learning phases. In phase 1, the DRIP is established and used to analyze the student knowledge structure for self-learning. In phase 2, a grouping cooperative learning subsystem is designed with the help of partners for advanced learning.

The DRIP is composed of systematically guided study activities developed according to the learning status of individual students, and the established Remedial-Instruction Decisive Path (RID path) is used to identify the real misconceptions of students. Study results are kept in the knowledge structure. Phase 2 involves cooperative learning, which uses knowledge structures as a grouping strategy. This study calculates the assistant ability of each student, which represents a homogeneous and complementary relationship. The grouping goal of cooperative learning is based on the heterogeneous knowledge structure. This study adopted two-phase cooperative learning in two courses. The learning evaluation yielded positive experimental results. The evaluation shows that the cooperative learning activities were effective for student learning.

Keywords: conceptual graph, cooperative learning, remedial instruction, knowledge structure, grouping strategy

1. INTRODUCTION

Recently, the continuing development of information technology has ensured the increasingly widespread use of diversified computer applications. Personal computers can display data including not only text, but also graphics, images, voice, video, and animation. Therefore, the potential of the use of personal computers in teaching approaches is enormous. The application of multimedia using computers is useful for teaching in school education, extension courses, and lifelong learning.

Besides continuing hardware development, numerous distance learning systems have been developed by researchers who closely follow teaching theories and completely implement the ideas of such theories. One of these teaching theories, "Cooperative

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Learning,” differs markedly from traditional teaching approaches. In traditional teaching approaches, learners only interact with the teacher in the learning activities, while interaction among learners is unimportant and ignored. In contrast, in cooperative learning activities, learners in the same group exchange their opinions with one another. Generally, learners obtain new knowledge from their discussions. Therefore, cooperative learning emphasizes that all group members should cooperate to achieve the learning goal and, during the learning process, communicate with and help each other.

The “conceptual graph” is another traditional teaching approach which forms learner knowledge as a topology representing the relationships among concepts. A conceptual graph can help students arrange disordered and confused concepts that they have learnt. This study considers that the conceptual graph is useful for learning and diagnosis. This study thus develops a cooperative learning system based on the conceptual graph.

This study proposes a two-phase cooperative learning system based on the conceptual graph for application within virtual reality environments. The learning activities include two phases. In phase 1, student knowledge structure for self-learning was collected and analyzed. Subsequently, in phase 2, the grouping cooperative learning dealt with the help of partners for advanced learning. In class teaching environments with numerous students, teachers have little time to spend on understanding the learning status of every student. However, using the proposed system, teachers can easily obtain the learning situation of each student and observe their learning performance. For lower-performance students, this study supports an optimal cooperative learning grouping algorithm for identifying the best learning partners. Through cooperative learning, students can learn concepts with their partners more easily. Meanwhile, the teacher simply needs to focus on those students with more difficult problems, and can pay attention to their misconceptions. The proposed system is an effective on-line learning system.

This paper is organized as follows. Section 2 introduces the literature on distance learning, cooperative learning, and conceptual graphs. Section 3 then presents some basic definitions to prepare for the main part of this study. Subsequently, section 4 describes the proposed algorithm – Two-Phase Cooperative Learning. The principles and processes applied in the research are also discussed in this section. Next, section 5 performs an evaluation to gather learning outcomes for analyzing and refining the proposed algorithm. This study also demonstrates the evaluation results and statistical analysis. Finally, conclusions and future works are presented in section 6.

2. RELATED WORKS

Because of the development of the Internet and World Wide Web, “Distance Learning” [3, 10, 20] has come to be increasingly widely used. Distance learning has also become a tool used in teaching strategies. Using broadband network transmission, electronic teaching materials and content can rapidly be sent to distant locations. Computer Assisted Instruction (CAI) [1, 9] is another field that combines education with information technologies. Recently, personal computers have provided huge power for dealing with complex and multi-format datum. The use of personal computers increases students learning methods. Besides plain text, CAI also provides pictures, audio and video. Additionally, interactive games and virtual reality allow students to have fun.

From past research, cooperative learning can be extremely helpful to learners. Johnson & Johnson [16, 17] indicated that cooperative learning has five characteristics that distinguish it from traditional teaching methods: responsibility sharing, positive interdependence, individual accountability, interpersonal and small group skills, and group process. Bagley and Hunter [2] noted some essential factors for all cooperative learning activities, namely: active, visible collaboration, sharing of the decision process when formulating group projects, highly structured work groups, and reciprocal commitment among students and teachers. Regarding achievements and abilities, Webb [32, 33] researched learners with different abilities based on different groupings of high, medium and low abilities. Four combinations were identified, that is (1) the group with a mixture of high, medium and low abilities; (2) the group with medium ability; (3) the group with high ability; (4) the group with low ability. Research results demonstrate more cases of mutual help in the mixed and medium ability groups than in the high ability and low ability groups. Webber then divided the groups in another way, that is: (1) the group with high and medium abilities; (2) the group with high and low abilities; (3) the group with low and medium abilities; (4) the group with high, medium and low abilities. The evaluation result demonstrates that mutual help in the mixing group benefits learners with high and low ability more than those with medium ability

Contributing to the success of cooperative learning requires the group to have clear positive interdependence, group members must have face-to-face interaction [7], each group member must possess their personal responsibilities, students must have and use teamwork skills, and students must have good group processing [25, 26]. Whether the activities of a cooperative group can be performed smoothly, depends largely on how participants are grouped. If learners are left to divide into groups themselves, learners with similar characteristics well tend to group themselves together. However, groupings with similar characteristics, for example high or low capability, similar interests or performance, etc, often lead to unsatisfactory cooperative learning results [32, 33]. Therefore, it is more appropriate to attempt heterogeneous grouping. An important consideration when putting individuals together in heterogeneous groups is learner academic achievements, which are mainly evaluated according to their overall academic performance. Learners with different scores are grouped together. However, academic performance alone is inadequate for representing learner knowledge structure. These grouping processes can result in careless mistakes, since learners with the same scores do not necessarily have the same knowledge structure. Consequently, this study proposes a novel grouping method that is supplemented by a conceptual graph. Based on our evaluation, the proposed strategy can effectively help learners achieve increased academic success.

The "Conceptual graph" [22, 27] is a traditional assisted teaching method. Teachers can use the conceptual graph to identify student comprehension levels of certain knowledge themes. The applications of conceptual graphs can be classified into two types. One of these types is concept mapping, in which a student must configure their concept map by themselves. The diagnoses are made by comparing the concept map of each student with that of the instructor [6, 21, 23, 24, 29]. Another type is the diagnostic conceptual graph. In this type, students are not required to configure conceptual graphs, and the instructor creates only one conceptual graph. The learning situation of each student is evaluated using the pre-defined conceptual graph to produce a diagnostic conceptual graph for that student. This diagnostic conceptual graph guides the instructor to focus on

areas in which the students require improvement [13-15]. Chang [5] also proposed a similar approach for diagnosing student performance via a courseware diagram.

Hwang [13, 14] designed a computer-assisted diagnostic system that included concept-effect relationships. The concept-effect relationship is a set of association levels representing the relationship between each concept node and each test item. In his research, instructors must set an association level of each relationship before the start of the course. According to student answers, the algorithm can obtain student learning information with each concept node. Suppose the existence of m concepts and n test items. The instructor then must focus on $m \times n$ association levels. Generally, a learning topic includes around 10~20 concepts and over 200 test items. Maintaining numerous association levels is difficult. To overcome these problems, this study develops a new strategy embedded in a computer-assisted system for diagnosing student learning situations. From student learning records, relevant concepts that students have failed to understand can be obtained and a dynamic remedial-instruction decisive path can be automatically established. If the student still has difficulties with the individual learning, the second learning phase, complementary cooperative learning, is proposed to find some suitable partners for learning together.

This study applies the curricular structure to examine student knowledge structure. Moreover, this study groups students by the complementarity of student knowledge structure. In fact, numerous factors affect learning performance in cooperative learning activities, such as learning achievement, interpersonal relationships [30], cognitive style [28], learning style [11, 19], learning motivation, etc. It is very difficult to simultaneously analyze the effect of every factor in cooperative learning activities. This study focuses on learning achievement and interpersonal relationships, and supports the use of the two factors for grouping student complementally.

3. BASIC DEFINITIONS OF CURRICULAR AND KNOWLEDGE STRUCTURE

In this study all student learning activities are guided by the proposed system. This study adopts curricular structure and knowledge structure as the basis of the proposed algorithm. First of all, the main idea is defined.

Definition 1 Conceptual graph $G(C, R)$ is a direct and finite connected graph, where C denotes a set of concept nodes that indicates student study activities and R is a set of relationships. A relationship, r_{ij} , connects two distinct concept nodes c_i and c_j , where $c_i, c_j \in C$. The relationship represents the studying order, that is, the concept node c_i is learned before concept node c_j . Thus c_i is the prior-concept of c_j . In the algorithm, $r_{ij} = \overline{c_i c_j} \mid \forall c_i, c_j \in C, i \neq j$.

Definition 2 The curricular structure comprises the specialist conceptual graph, teaching materials, and test, where the specialist conceptual graph is defined by experts or teachers, and each conceptual node in the specialist conceptual graph has a related teaching material and test that are designed by teachers.

The conceptual graph can effectively represent knowledge structure. The common method applied in the education field is to allow learners to draw their conceptual graphs and compare them with that of the specialist. The comparison results can be used to obtain the learning performance of every student. However, this study focuses only on the characteristics used to represent the knowledge structure of the conceptual graph. The conceptual graph shows the sequence of learning mainly in our research. Comparing the proposed usage with traditional conceptual graph reveals some slight changes; our conceptual graph is more similar to the courseware diagram [5]. From Fig. 1, a link exists between concepts 1 and 4, and the direction of the arrow represents the learning sequence. In the definition presented here, concept 1 is a prior-concept of concept 4. Similarly, students should learn concept 1 before concept 4 in the learning activities.

Learning activities require several materials and tools, for example teaching materials, tests, quizzes, homework, Web BBS, ICQ, etc. This study only considered specialist conceptual graph, teaching material and test. Any material or tool could easily be embedded into the proposed system as necessary. The curricular structure contained the structure and learning sequence of one course, and it remained unchanged in the learning activities.

Fig. 1 shows the specialist conceptual graph which maps to the knowledge theme of the curriculum arrangement. Each link connects concept c_j and its parent concept c_i , which means that c_i is a prior-concept of c_j . W_{ij} denotes the degree of relationship between the concept c_j and its prior-concepts c_i , and larger W_{ij} represents a closer relationship. From Fig. 1, when concept 4 is determined to be a misconception, there is 50% probability influenced from concept 1, 30% probability influenced from concept 2, and 20% probability influenced from concept 3.

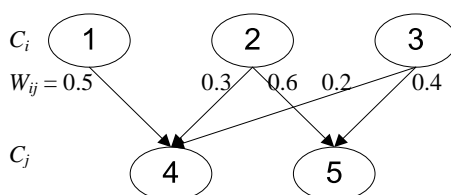


Fig. 1. Conceptual graph maps to the knowledge theme.

The curricular structure is created by the teacher before the start of the course. The architecture of the curricular structure follows the course plan, including course contents and course sequence. To reduce the complexity of the curricular structure design, the teachers can separate whole course into individual units. These units may be chapters, section, or topics. Creating the curricular structure with a unit makes it easier for teachers to create and for students to learn.

SPRT is an assessment test model for examination developed based on Bayes' rules for predicting student proficiency ratio [31]. This study adopts SPRT to diagnose student learning outcome because it is easier to use and does not need to adjust the question accuracy [8, 12]. Using SPRT, this study translates the answers of each concept node into categories that explicitly represent the learning result.

Definition 3 With SPRT, the learning result of a concept node can be a pass node, fail node or partial node.

- (1) **Pass node:** the student gets mastery of the concept represented by the node; that is, they are proficient in that concept. In the proposed algorithm and table, the node is represented by an S symbol. Moreover, the node is expressed as a gray ellipse in the figure.
- (2) **Fail node:** the student has no mastery of the concept; that is, the concept is assumed as a misconception of the student. In the proposed algorithm and table, the node is represented by an F symbol. Moreover, in the proposed figure, the node is expressed as an ellipse with a dotted border.
- (3) **Partial node:** when student proficiency cannot be assessed based on limited questioning, the student may have partly understood the teaching material. Testing thus must be continued. In the proposed algorithm and table, a P symbol represents the node. Moreover, in the proposed figure, the node is expressed as an oblique ellipse.

The student knowledge structure is a no-weight-value conceptual graph, which was built using the curricular structure following the learning activity stage. Each concept node of student knowledge structure records one of three statuses: pass node, fail node or partial node.

Definition 4 The structural score represents the complete degree of student knowledge structure. The full structural score is the structural score of the curricular structure. That is, a curricular structure has complete knowledge structure. Basically, the structural score count the number of pass and partial concept nodes of student.

Definition 5 The direct assistant ability is a helpful ratio which represents the ability of student i to directly assist student j , where for each concept of student knowledge structure, student i can help student j under cooperative learning.

Definition 6 The indirect assistant ability of student i to student j is a helpful ratio, where for each concept C_k of student knowledge structure, there are other concepts with linking relations to concept C_k , which can bring helpful information from student i to student j under cooperative learning.

From Fig. 2, learner X gets a pass in concept A , while learner Y does not. When they were put in one group, learner X can direct help learner Y to study when study materials are related to concept A . This would enable learner Y to learn concept A under supervision.

Additionally, learner X gets a pass in concept A , and concepts $\{B, D\}$ are related to concept A . Learner X also has completely learned concept B , and has partially learned concept D . When learner X instructs learner Y , Learner X can bring information on other concepts ($\{B, D\}$) to learner Y . There will have indirect assistant ability.

Definition 7 The complementary degree of students i and j is calculated by the sum of structural score, direct assistant ability, and indirect assistant ability of both students.

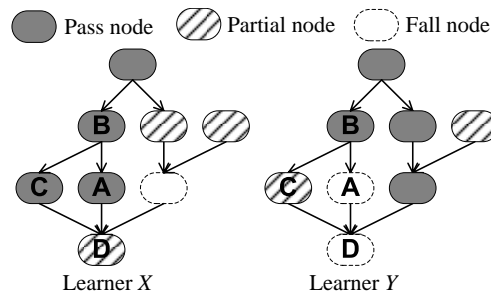


Fig. 2. Direct and indirect assistant ability.

Definition 8 The intragroup complementary degree is calculated by the sum of complementary degree of every pair of members within the group.

How to calculate structural score, direct assistant ability, and indirect assistant ability is discussed in more detail in section 4.2.

4. TWO-PHASE COOPERATIVE LEARNING

This study designed a two-phase cooperative learning system. The novel system includes the “Dynamic Remedial Instruction Path (DRIP)” assisted subsystem and a grouping cooperative learning subsystem, which is a module of the “VRSchool” platform [4, 18]. The system architecture is shown in Fig. 3, and its learning phases are listed in Table 1. The activity of the two-phase cooperative learning system comprises two phases. Phase 1 is applied to establish and analyze the knowledge structure of students for self-learning. Meanwhile, phase 2 is the grouping cooperative learning phase, which deals with the combination of students for advanced learning.

The DRIP assisted subsystem contains the user interface, item bank, teaching material, specialist conceptual graph, student knowledge structure, SPRT, and DRIP components. For convenience, teachers do not need to manage the progress of diagnostic and remedial instruction. Teachers only have to set the parameters of the curricular structure and select the learning material and items based on the user interface. Phase 1 can accurately display student learning status; the DRIP systematically guides study activities based on individual student learning status. Following the end of phase 1, study results are kept in the knowledge structure. This diagnostic process is repeated until the student completes their study of concepts in phase 1.

The complementary degree component of the grouping cooperative learning subsystem indicates the degree of heterogeneousness for every pair of students. Grouping strategy is used to achieve heterogeneous cooperative learning.

Phase 2 comprises cooperative learning with knowledge structure as a grouping strategy. In this stage, student knowledge structure is adopted for more exquisite cooperative learning grouping to obtain more distinguished and efficient cooperative learning results. With the aid of the system and after the self-learning in the first phase, students have fewer learning obstacles, and the remaining complicated or intricate content can learn with partners in cooperative learning in phase 2.

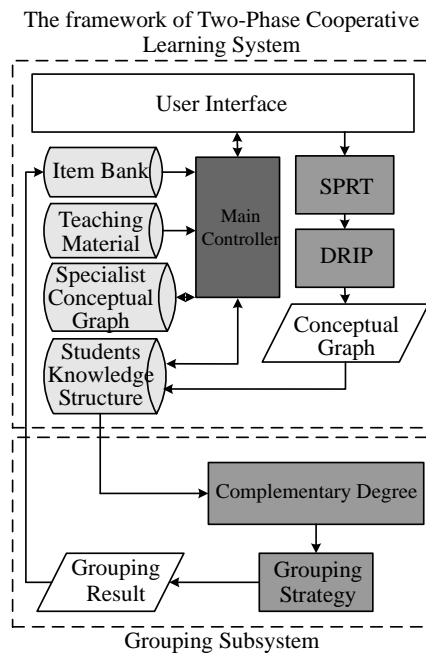


Fig. 3. System architecture of two-phase cooperative learning system.

Table 1. Learning phases of two-phase cooperative learning

| | Phase 1 | Phase 2 |
|------------------------|--|--|
| | | Learning with conceptual graph |
| Number of participants | Individual | Group |
| Psychological process | Validate the contents of their studies by themselves | Validate the contents of their studies with group members |
| | Basic knowledge | Refine knowledge |
| Progress Content | Identifying learners' misconception by <i>basic Q&A with each concepts</i> | The activities are mainly of <i>advanced Q&A</i> , to let the students understand the basic concept as the foundation |
| | The goal of study is achieved through the determination of misses and <i>repeated exercise</i> . | Verifying the learning results by discussing with other students and <i>improving the refinement of the knowledge</i> by assisting each other. |

4.1 DRIP Assisted Subsystem

Fig. 4 displays the flowchart of DRIP assisted subsystem.

- (1) First, experts or teachers should set the weight values and the minimum required value of the right answer rate based on the curricular structure.
- (2) Students log into the system asynchronously to select concepts then answer questions.

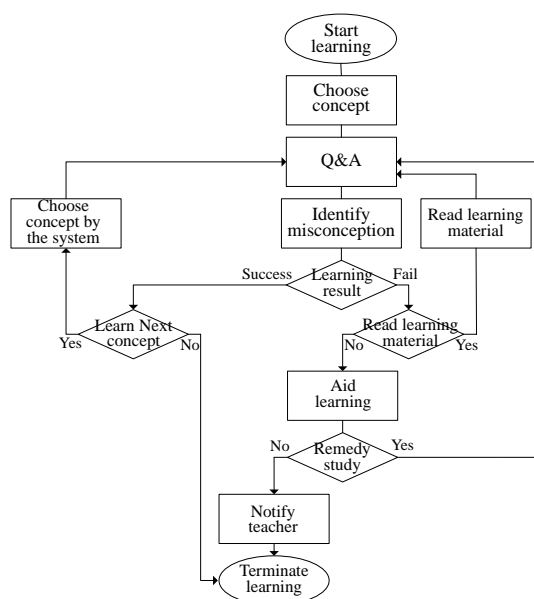


Fig. 4. Flowchart of the DRIP assisted subsystem.

- (3) When a student has finished their questions, the system assesses them for misconceptions. If the result of this assessment is successful, the system selects the next concept for the students to study.
- (4) If the evaluation results in failure, the system will adjust the weight value of the concept and determine whether to require the student to read the teaching materials, establish a RID path for the student, or inform teachers to help that student with their studies.

Fig. 5 shows an example for finding the RID path. The left side of each step represents the curricular structure, the middle represents the student knowledge structure and the right side represents the test stack that stores the prior-concepts of failure concepts. Concepts must be examined to determine whether students understand them. When students begin their learning activities, they have an empty knowledge structure and test stack. Learning activities begin with a starting concept that may be selected by the student or suggested by the instructors. After the student finishes the concept learning activities, they are evaluated using the SPRT. From Fig. 5, the following step-by-step examples are given.

Step A: Before the learning activities, the proposed system includes the curricular structure, empty knowledge structure and empty test stack. The student begins their learning activities with a starting concept 8.

Steps B-C: If concept 8 is identified by SPRT as a misconception, some misconceptions exist in prior-concepts. This study evaluates the prior-concepts of concept 8 in decreasing order of weight values. For the test order, all prior-concepts are placed into a test stack in increasing order of weight values.

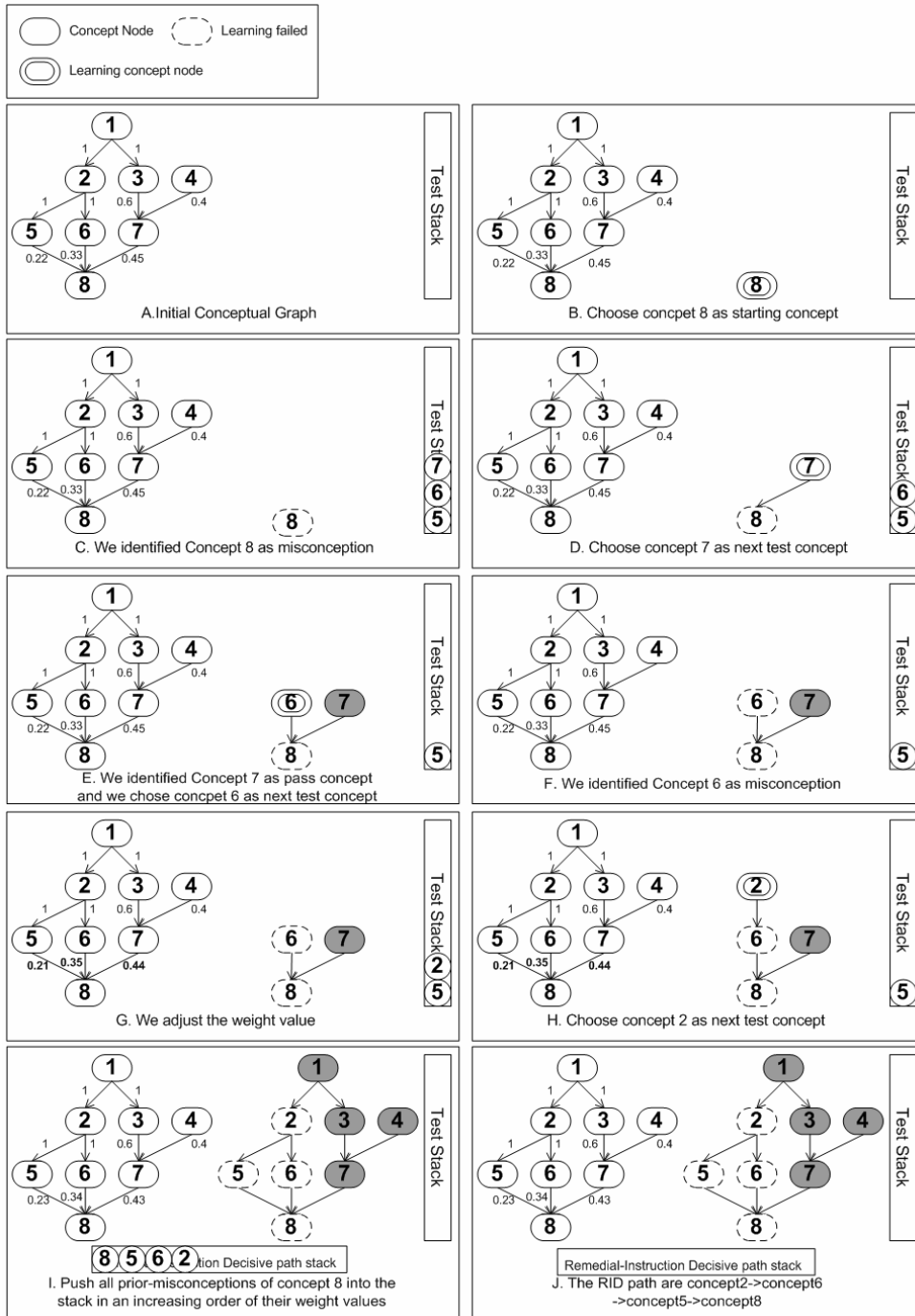


Fig. 5. Example of a DRIP.

Step D: The topmost concept is popped, and thus concept 7 is chosen as the next test concept.

Step E: If concept 7 is identified as a pass concept, the next concept is popped from the test stack. Thus concept 6 is tested.

Steps F-G: If concept 6 is identified as a misconception, the test result represents that concept 6 is one of the reasons why the student failed in concept 8. The correlation between concepts 6 and 8 is increased. To indicate this situation, this study decreased the weight values between concept 8 and its other prior-concepts, and increased the weight value between concepts 6 and 8 by the sum of these decreased values from the curricular structure. In this case, the value of w is assumed to be 0.01 (the teacher can adjust this value by themselves in the proposed system). The weight value between concepts 5-8 and concepts 7-8 thus is decreased by 0.01, and the weight value between concepts 6-8 is increased by 0.02.

Following a series of evaluations (steps I and J), these misconceptions that the student failed in the learning activities are detected. These misconceptions are distributed over the knowledge structure of the students. The RID path is determined during the learning activities. In the present example, the student has a RID path, concept 2 -> concept 6 -> concept 5 -> concept 8.

Although experts preset the weight value in the curricular structure, these preliminary weight values only represent most students or certain types of students in a certain study situation. These weight values cannot match the actual study status of each student. Through dynamic adjustment of weight value, the system can obtain the actual data along with its utilization by students. The relationship between concepts, after numerous adjustments, focuses on improving the ties between important concepts. The preliminary weight value can be reduced or degenerated. Weight values that apply to the status of every student come into being in this way.

In contrast to the traditional learning system, the proposed system can provide more information regarding the understanding of different concepts. This information includes the weight values of curricular structures that represent the learning status of all of the students, and student knowledge structure that represents individual student learning failure and passing concepts.

In this phase, study activities are mainly conducted individually. Students validate the contents of their studies by themselves. Study activities focus on basic and easy concepts. The study goal is achieved by determining misconceptions and performing repeated exercises. DRIP can help students identify their misconceptions quickly and accurately. Students then can find concepts that have not been thoroughly studied and the actual causes of their problems, thus reducing the blindness time in their learning activities.

Since the first phase of this study focuses on individual study, the student may be unable to fully comprehend the teaching materials. The reason is the concept of study failure in student knowledge structure. Besides, more deep knowledge must be learned. Thus some supplements should be made to overcome these weaknesses. Simply providing online teaching material cannot meet the needs. Therefore, this study thinks the supplements must have more advanced. Here, in the second phase, we use cooperative learning to let students conduct further study through interaction with each other.

4.2 Grouping Cooperative Learning Subsystem

Previously, grouping of cooperative learning was based on grade or learning manner. Students may not be able to apply knowledge learned to help other group members in a group. This study strongly analyzed the status of the knowledge structure of each student, and used the new grouping strategy to achieve mutual compensation among students to enhance study effects. Since student interest in a study is relative, students will show full interest in related themes. The learning result shall appear on student knowledge structure and the distributions of well learnt and less well learnt concepts each have their local characteristics. This study thus used the characteristic on cooperative learning, and applied analysis to display the relationship among student statuses in the form of knowledge structure. After finding out the mutualism among students, this mutualism was quantified to find the optimal grouping arrangements. This grouping arrangement was named the “Complementary Grouping method.”

The proposed grouping strategy creates a group comprising student heterogeneous knowledge structure. The main purpose of this step is to enable students to learn new knowledge with the assistance of other group members. Students with a profound understanding of a certain unit can help other students who had failed in the same unit, to improve the study effects of the whole group in cooperative learning activities.

This study refers to and amends the scoring method of Novak and Goin [22] to calculate the structural score. The structural score is calculated by the student knowledge structure. The structural score represents the linking relationship that exists between two concepts. The most direct way of assessing the completeness of the knowledge structure is to think about the learning result of each concept node. The fundamental idea of the structural score describes the number of learning successful concept nodes. Table 2 lists the score-table. The concepts m and n belong to the knowledge structure of one student. The structural score is located between concepts m and n . Moreover, the score of the other six combinations that not exist in the score-table is 0. The structural score can be calculated completely to represent student level of understanding of the overall learning unit.

Table 2. Score-table for calculating the structural score.

| Combination | | Score |
|-------------|-------------|-------|
| Concept m | Concept n | |
| S | S | 3 |
| S | P | 2 |
| P | P | 1 |

Fig. 6 shows an example of how to calculate a structural score. Fig. 6 (a) is a curricular structure, and the structural score of the curricular structure is 27. From Fig. 6 (b), the structural score of Learner X is $3 + 2 + 3 + 3 + 0 + 0 + 2 + 2 + 0 = 15$. The result of calculating the closeness between student knowledge structure and the curricular structure is a closed value between 0 to 1 representing their correlation. Higher closed value indicates increased closeness between the student and specialist map constructions, which signifies better comprehension of the knowledge theme by the student.

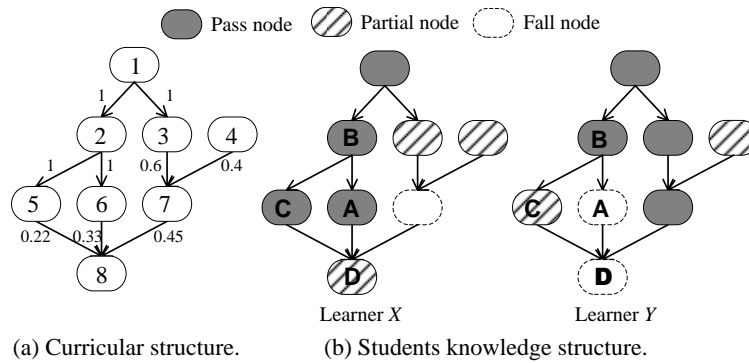


Fig. 6. Example of calculating structural score, direct and indirect assistant ability.

Consider student knowledge structure without a complete structure. When one student in the group instructs other students, ambiguity or incoherence between the concepts may occur, causing negative effects on the students. Therefore, the structural scoring method should be included in the relevant scores.

Table 3 lists the direct and indirect assistant ability for each concept node, which represents the level of assistance provided for a concept. In the present evaluation, the default value of α is 10, and the teacher can adjust this value. The score of the other six combinations not contained in the score-table is 0.

Table 3. Score of direct and indirect assistant ability.

| Combination | | Direct Assistant Ability | Indirect Assistant Ability |
|-------------|-------------|--------------------------|----------------------------|
| Student m | Student n | | |
| S | F | α | $\beta \div U$ |
| S | P | $\frac{1}{2}\alpha$ | $\frac{1}{2}\beta \div U$ |
| P | F | $\frac{1}{2}\alpha$ | $\frac{1}{2}\beta \div U$ |

Fig. 6 shows the direct assistant from learner X to learner Y. The direct assistant ability is 0 for concept B and 10 for concept A (pass node for learner X and fail node for learner Y). Thus from learner X to learner Y, the direct assistant ability is $0 + 0 + 0 + 0 + 5 + 10 + 0 + 5 = 20$. From learner Y to learner X, the direct assistant ability is $0 + 0 + 5 + 0 + 0 + 0 + 10 + 0 = 15$.

From Fig. 6, learner X gets a pass in concept A, and $\{B, D\}$ are adjacent concepts, so that concepts $\{B, D\}$ assist learner Y. Table 3 shows the indirect assistant ability for each concept node, while β represents the assistant level of one concept, and U is the number of adjacent concepts. In the present evaluation, the default value of β is 10, and the teacher can adjust the value of β . Considering concept A of the knowledge structure of learner X in Fig. 6 again, the adjacent concepts $\{B, D\}$ have $(0 + 5)/2 = 2.5$ indirect assistant ability. Thus from learner X to learner Y, the indirect assistant ability is $0 + 5 + 0 + 0 + 2.5 + 2.5 + 1.66 + 5 = 16.66$. Meanwhile, from learner Y to learner X, the indirect assistant ability is $2.5 + 0 + 5 + 10 + 0 + 0 + 1.66 + 3.33 = 22.5$.

Based on the above heterogeneous assistance among students, the complementary degree for every two students is obtained. A fully connected graph is obtained, as shown in Fig. 7, with a complementary degree on every edge. The complementary degree 60 is definitely better than 30, but this does not mean the learning effect of 60 is twice that of 30. This study obtains the characteristics by representing the complementary status.

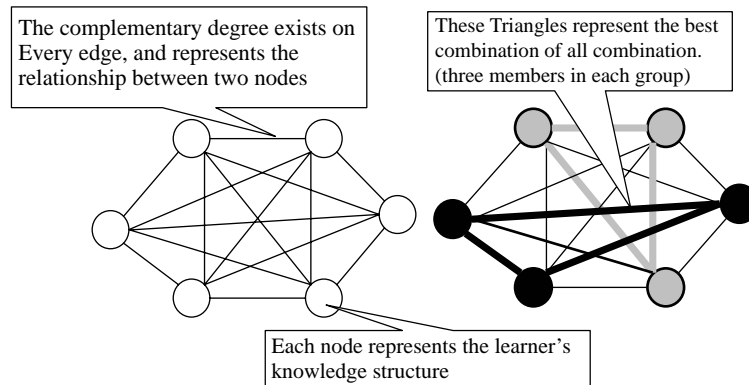


Fig. 7. Degree of complementariness between every two students.

Optimal grouping is designed to optimize the grouping of students for forming the best cooperative combination and achieving the best learning effects in the whole class. This study adopts the grouping method by linear programming to seek the maximization of the total complementary degree. The optimal grouping algorithm is shown as Fig. 8. The object function in this study gets the maximum sum of the intragroup complementary degree for all teams. The constraint thus is that “one student only exists in one team.” The algorithm generates all combinations of cooperative learning groups and then gets the optimal grouping solution.

Interpersonal relationship is an important factor for cooperative learning; the optimal grouping algorithm developed here can be revised to put the learning achievement and interpersonal relationship factors together. Nuisance information was obtained from each student, and these bad relationship combinations were avoided. Discarding these combinations is simple in this study. The optimal grouping algorithm uses possible combinations as inputs, and obtains the grouping results.

The students in the cooperative learning activities are mainly concerned with verifying and refining the learning contents. The activities consist of asking for advanced problems to let the students use the basic and easy concept as the learning foundation and verify the learning results by discussing them with other students. Students also improve the knowledge refinement through mutual assistance. The grouping strategy presented can help students to find the most suitable learning partners, and maximize the effectiveness in both learning activity teaching and learning.

Algorithm Optimum (G, W, N)

Input: $G(V, E)$: a weighted complete undirected graph.
 $W(u, v)$: complementary degree between nodes u and v .
 N : number of students in each group.

Output: The best cooperative learning teammate combination.

Variable: B^m : the set of m -dimensional binary vectors, where the value of 1 represents the student in the team.
 α : the number of complementary degree in each group.
 k_i : the intragroup complementary degree of C_i .
 l_i : binary value that represents the possible teams that student u is grouped into.
 x_i : the optimal grouping result, where student u is arranged in the team C_i .

Step1: Define object function
 Generate all combination of cooperative learning groups by N students, named $C_1, C_2, C_3, \dots, C_m$.

Object function: $Max \left\{ \sum_{i=1}^m k_i x_i : x \in B^m \right\}$, where $k_i = \sum_{j=1}^{\alpha} w_j(u, v)$ and $u, v \in C_i$,
 $\alpha = \frac{N \times (N-1)}{2}$.

Step2: Define constraints
 For each $u \in V$, create a constraint $\sum_{i=1}^m l_i x_i = 1, x \in B^m$, where $l_i = \begin{cases} 1 & \text{if } u \in C_i \\ 0 & \text{if } u \notin C_i \end{cases}$.

Step3: Find solution by Integer Linear Programming.

Fig. 8. The algorithm to solve optimal cooperative learning groups.

5. IMPLEMENTATION AND EVALUATION

The evaluation was conducted to verify the performance of the two-phase cooperative learning system. The evaluation was performed in March 2001, and the evaluation period lasted one month. It was performed at the Department of Information and Computer Engineering, Chung Yuan Christian University in Taiwan. The evaluation examined the usability and acceptability of the proposed algorithm.

The evaluated course was "Introduction and Implementation of RS-232." This course was part of the course "Operating System" taught in the junior class. The course "Introduction and Implementation of RS-232" introduced the theorem and function of RS-232. Students completing the course had to implement a program that transmitted messages via RS-232. The curricular structure in this evaluation was constructed by two professors who had taught the course for many years, and is shown in Fig. 9. The participants were all juniors, and there were thirty-eight students. All participants took a pre-test before evaluation. The pre-test comprised questions that were common sense for students with a background in computer science. The participants were randomly divided into two categories, the experimental and control groups. Moreover, ANOVA was applied to ensure the two categories had an equal degree based on the pre-test score.

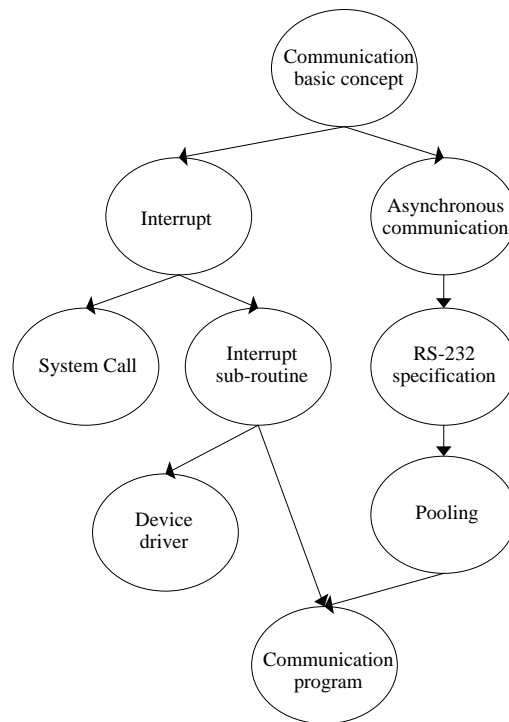


Fig. 9. Curricular structure of the “Introduction and Implementation of RS-232” course.

In the evaluation activities, all participants must participate in the instruction provided by the instructor and complete their assignments. Meanwhile, in extracurricular activities, both the control and experimental groups login to the system and complete some review tests before taking the next course. All participants learned about the curricular structure on the WEB. When the participants had learned a new concept corresponding to a conceptual node, they applied the SPRT to identify their learning outcomes. The different learning arrangements between the two groups are the learning guide method. In extracurricular activities, the DRIP guides the progress of the experimental group members and the control group members learn with their plans. The participants took a post-test on finishing all of their learning activities. The post-test included all content in RS-232. The post-test was designed to evaluate student learning result, and the score in the post-test is included in the final score of the course “Operating System.” Table 4 lists the relationship between the pre-test and post-test results.

Table 4. Summary table of pre-test and post-test (DRIP assisted subsystem).

| Group | Number of students | Pre-test | | Post-test | |
|--------------------|--------------------|----------|------|-----------|------|
| | | Average | SD | Average | SD |
| Experimental Group | 19 | 11.68 | 1.76 | 9.74 | 2.13 |
| Control Group | 19 | 11.58 | 1.46 | 8.37 | 1.74 |

This study applies ANOVA to identify the post-test relationship between the experimental and control groups ($\alpha = 0.05$). Based on this result, the post-test results demonstrate a significant difference between the two groups ($F_{.95(1,36)} = 4.71$), and the average score of the experimental group (9.74) is higher than that of the control group (8.37). Therefore, it can be said that, after finishing remedial instruction activities, the experimental group performs better than the control group.

After evaluation of the DRIP assisted subsystem, a total of six students had scattered knowledge structures, and their structure scores were below the threshold value. These students were discarded from further evaluation, and individual assistance was provided by a teacher and assistant.

To prevent the positive result of DRIP-assisted activity extending to cooperative learning activity, before entering the evaluation of cooperative learning subsystem, the midterm examination score was used as the pre-test, and the students were rearranged into the experimental and control groups. Moreover, this study ensured an equal degree with ANOVA based on the pre-test score. Each group has two students. The experimental and control groups have identical learning activities. The different arrangement between the experimental and control groups are grouping method. The control group was randomly set, and the experimental group was allocated using the optimal grouping algorithm, in which student knowledge structures were constructed in the DRIP assisted subsystem. Every week arrangements were made for the team members to meet at the classroom for half hours to finish some small projects with team members. The complementary degree among team members is important in this study. More communication and interaction among team members is helpful for increasing the effect of the complementary grouping strategy in the cooperative learning. When designing the course learning activities, team assignments, conversation time and team examinations were arranged on a weekly basis. This evaluation also can provide encouragement to students involved in communication and interaction. After the cooperative learning activity, we took the post-test. Table 5 shows the pre-test and post-test results. ANOVA was also adopted for identifying the post-test relationship between the experimental and control groups ($\alpha = 0.05$). From this test result, a significant difference is demonstrated between the two groups in the post-test results ($F_{.95(1,15)} = 6.66$), and the average score of the experimental group (14.87) is found to be higher than the control group (12.68). Therefore, it can be said that, after finishing cooperative learning activities, the experimental group demonstrates better performance than the control group.

Table 5. Summary table of pre-test and post-test (cooperative learning subsystem).

| Group | Number of students | Pre-test | | Post-test | |
|--------------------|--------------------|----------|------|-----------|------|
| | | Average | SD | Average | SD |
| Experimental Group | 16 | 11.44 | 3.22 | 14.87 | 2.09 |
| Control Group | 16 | 11.44 | 3.22 | 12.68 | 2.73 |
| Total | 32 | 11.44 | 3.22 | 13.78 | 2.66 |

6. CONCLUSIONS AND FUTURE WORKS

This study proposed a two-phase cooperative learning system on the Web. The framework was based on the conceptual graph, and the system included the DRIP and the grouping strategy of cooperative learning phases.

In phase 1, DRIP was established to analyze student knowledge structure for self-learning. Meanwhile, phase 2 provided the grouping cooperative learning which was dealt with the help of partners for advance learning. When the students adopt cooperative learning flow, they used a curricular structure to perform the self-test in the first phase, to understand what concepts in the learning contents were obstacles to learning. Particularly, in class teaching environments containing a large number of students, the teachers were unable to spend much time on understanding individual student learning status. As a result, the fast-learning students thoroughly grasped the contents being taught in class, while the slow-learning students fell further and further behind, and eventually the education system gave up on them. Through the analytical and statistical system developed in this study, the teachers could easily understand the learning status of every student in the class, and focused on those concepts where the students have learning obstacles for reinforcement. After the students completed their learning flow, student learning status was shown, and was used to build student knowledge structure and learning model.

When the students failed to complete the whole learning contents by independent learning by themselves, this study raised a new grouping strategy of cooperative learning. Following optimal cooperative grouping, the system assigned students who learned successfully in mutual concepts to the same group, and complemented the learning status of the same group of students. Through maximizing interactive teaching and learning information among the students, the system not only helped students successfully learn the concepts they had previously failed to learn in their independent learning, but also reinforced student understanding of the concepts they had learned successfully and even helped to deepen their learning knowledge by teaching other students. Both knowledge structure scoring and grouping algorithm were processed with the aid of a computer, and the teachers were provided with an excellent user interface. For distance learning system, the proposed strategy were used as grouping tools to aid cooperative learning, and also to effectively upgrade the overall efficiency of cooperative learning.

Possible future research directions include the following:

- (1) Increasing the number of group members to more than three. The two-phase cooperative learning system has got positive experimental results, but the number of group members is two and three. Hopefully the strategy can be extended to more than three students per group. The job is challenging because more assistant tools are required for controlling the experiments;
- (2) Combining knowledge structure and other factors for grouping cooperative learning. The attitudes, behaviors, gender, races, social background and other factors are considered for further heterogeneous grouping;
- (3) Investigating another knowledge structure representation for identifying knowledge genes or patterns in the near future; and
- (4) Improving group strategy. Student knowledge structure can change at any time in the learning activities. This study was only concerned with the situation before coopera-

tive learning, but the variation of the complementary group also needs to be observed. This study plans to improve the group strategy to overcome this issue.

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