

## Designing and implementing a personalized remedial learning system for enhancing the programming learning

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### ABSTRACT

In recent years, the demand for computer programming professionals has increased rapidly. These computer engineers not only play a key role in the national development of the computing and software industries, they also have a significant influence on the broader national knowledge industry. Therefore, one of the objectives of information education in Taiwan is to cultivate elite talents specializing in computer programming so as to improve Taiwan's national competitiveness. Although programming is a major fundamental subject for students in information sciences, learning to master programming languages is far from easy. Accordingly, this study aimed to establish a personalized remedial learning system to assist learners in remedial learning after an online assessment. The proposed system adopted the fuzzy logic theory to construct an appropriate learning path based on the learners' misconceptions found in a preceding quiz. With concepts of each course constructed in a learning path, the proposed system will select the most suitable remedial materials for a learner in terms of learner preference to facilitate more efficient remedial learning. Finally, the system, proven by several conducted experiments, can offer a comprehensive and stable remedial learning environment for any e-learning programs. The analysis of learners' achievements confirmed that the method of this study has achieved the effects of remedial learning and adaptive learning.

### Keywords

Remedial learning, Intelligent tutoring systems, Fuzzy logic, Learning style

### Introduction

Programming is an important fundamental skill in the fields of information science, engineering, management and education. It is also a basic prerequisite required of students majoring in the disciplines of natural sciences, mathematics, and engineering. Foreman (1988) notes that programming contains knowledge and skills required for the development of computer expertise and is also a key prerequisite for a comprehensive understanding of computer science. Although programming is a major fundamental subject for students in information sciences, learning to master programming languages is far from easy. Winslow (1996) observes that it takes more than ten years of training and experience for a beginning student to become a well-versed programmer. At present, programming languages are taught primarily via a teacher-centered approach, which fails to allow the instructor to identify problems encountered by individual students. A learner who cannot solve problems instantly in the course of learning gradually tends to lose interest in learning. Hence, it is important to find ways of teaching students to solve their own problems in learning a programming language.

In recent years, the learning environment has been changing due to the rapid development of the Internet and information technology. Zhang et al. (2004) note that the Internet and multimedia technologies are reshaping the way knowledge is delivered and that e-learning is becoming a real alternative to traditional classroom learning. The focus of learning has shifted over the past 20 years from an emphasis on traditional classroom learning and paper examinations to greater focus on e-learning and assessment environments, i.e., learning conducted or supported over the Internet. The Internet allows learners to access their learning tools easily at any time and at any place. In addition, e-learning can be used to support teaching in the classroom and also can offer a virtual classroom in which learners can complete their course work. Although several studies have suggested the benefits of developing an e-learning system for instruction, these systems still pose some problems for learners, including learner control, disorientation and cognitive overload (Ausubel, 1968; Conklin, 1987; Alomyan, 2004).

**Learner Control:** Individual learners are able to study independently on the Internet at home or in other places without instructors. Online learning enables a learner to download the learning materials related to a concept that he/she has to learn and to choose or arrange the learning sequence from the collected learning materials. However, some of the learning materials can be too difficult for students who have little prior knowledge or background knowledge. Ausubel (1968) notes that prior knowledge is the most important factor determining the achievements of learners during the learning process. As a result, learners without sufficient prior knowledge may not comprehend the concepts that they need to learn and enhance their learning performance (Gagne & Brown, 1961). **Disorientation:** With a faster, more accessible Internet, people these days tend to search and learn from the Internet for fragmented knowledge. Although they are versatile, these web sites generally follow no standards for content organization and presentation order. When these are posted on the Internet, collected and indexed by robots using keywords, and returned by powerful search engines, a vast number of homepages or learning objects is returned directly to a learner in no particular order. Chiou et al. (2010) note that all the learning materials in a curriculum are sequenced by hyper links in most web-based learning systems, but there is no concrete sequence without navigation support. Even if certain topics are related, a learner who may have little or no experience in the specific domain of study must still move forward and backward among the materials and figure out which page to read first. Thus, an effective way of organizing collected material into systematic and sequenced learning contents would be a great help for learners who are new to a specific domain. **Cognitive Overload:** The most popular tools today for seeking knowledge are the Google or Yahoo keywords-based search engines on the Internet. Learners can easily obtain the information or learning materials they need, but they still have to read and organize those learning materials by themselves. For this reason, learners have to spend a lot of time in browsing and sorting through the information they find. Tsai (2009) notes that the abundance of online information resource could result in anxiety on the part of individual learners over the vast amount of online information. As a result, it is an important challenge to offer the most appropriate learning materials directly to each learner in the online learning environment.

Therefore, in this paper, we have proposed a Moodle-based Personalized Remedial Learning System (MPRLS) that uses fuzzy logic theory to construct an appropriate learning path based on the learners' misconceptions and then to recommend the most suitable materials from the Internet according to the learners' own preferences, to facilitate more efficient remedial learning for the learners.

## Related works

### Adaptive learning environment

In traditional hypermedia education systems, the "one-size-fits-all" approach causes confusion among learners. For example, those traditional education systems provide the same content and the same set of links to all learners. Consequently, the materials may not suit the learners' needs in the learning process (Qu, Wang, & Zhong, 2009). Over the last decade, many e-learning systems have been developed to assist learners in a variety of areas because e-learning systems can be addressed to a maximum number of participants with a maximum diversity of learning style, needs, and preferences (Beldagli & Adiguzel, 2010). There are many advantages of e-learning activities. One of them is the importance of "Adaptive Learning". The learning content can be adapted to each learner's strengths and weaknesses to achieve the most efficient learning experience. That is, by assessing a learner's initial knowledge of a topic and preferred learning style, an e-learning system can decide what learning content should be offered next (Papanikolaou et al., 2002). By offering adaptive content or learning paths, the system enables the learners to study more quickly and more effectively (Bra, Brusilovsky, & Houben, 1999).

Many researchers have developed adaptive e-learning methodologies and platforms. Phobun & Vicheanpanya (2010) proposed an adaptive intelligent tutoring system that combines adaptive hypermedia with an intelligent tutoring system to improving learners' learning achievements. Romero, Ventura, Zafra, & Bra (2009) proposed a web-based adaptive educational system to suggest personalized links based on other students with similar characteristics, using different recommendation techniques and web mining tools. Carchiolo, Longheu, & Malgeri (2002) designed a prototype of a web-based learning environment to provide learners with a dynamically adaptive formative path according to their needs and capabilities. Chen (2008) developed a genetic-based personalized e-learning system to provide a learning path based on the difficulty of the courseware and the results of pre-tests for individual learners.

## Learning style

The concept of learning style can be traced back to the 1970s and has been widely acknowledged in recent years. It is assumed that each learner's personal learning style can enable him/her to achieve optimal learning effectiveness and interest. Though most people learn through a combination of the three primary styles (auditory, visual, and kinesthetic), everyone has a preferred style that works the best for him/her. A learning style is an individual repertoire of preferred learning methods and strategies that are used during the learning process (Beldagli & Adiguzel, 2010).

With the extensive application of adaptive teaching to the digital education in recent years, learning style has drawn a great deal of academic attention, and much relevant research has been published. Keefe (1979) holds that learning style plays a crucial role in learning and enables an instructor to provide an individualized education. An analysis of learning style helps an instructor to understand messages delivered by a learner in response to an external learning situation. Thus, an instructor can provide learners with proper instruction to solve their learning difficulties. Dunn, Dunn, & Perrin (1994) propose that learners will improve their learning performance and attitude when the instruction and resources are compatible with their learning style. Accordingly, helping students develop their learning style and providing proper instruction and teaching materials will improve their learning effectiveness. This paper employs Kolb's theory to evaluate the learning style of each student (Kolb, 1984). Kolb views a human learning activity as a series of processes in which a human being successively acquires a practical concrete experience, form an abstract concept by reflective observation, transform the abstract concept into a general one, apply the general concept to a new situation for verification, and develop a new individual experience and a distinctive learning style.

## The methodology and the system architecture

In this section, several approaches are used to automatically construct a suitable learning path and recommend suitable remedial materials out of a collection of learning materials according to the learners' preferences.

### System modules depiction

The architecture of the proposed system is shown in Figure 1. The four major components of the system are the *Learner Testing Component*, *Inference Module*, *Learning Style Analysis* and *Learning Path and Remedial Materials Recommender*.

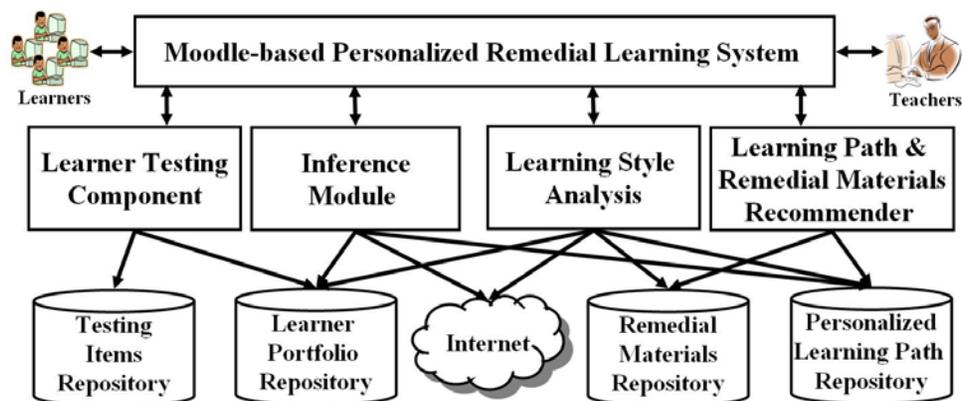


Figure 1. The architecture of the Moodle-based personalized remedial learning system

At first, teachers are able to edit the learning style questionnaire and test items in the testing items repository via the MPRLS interface. Then, a learner logs into the proposed system for learning and testing. For the beginner, the proposed system will provide the learning style questionnaire for the learners to analyze their own learning style. After the learners complete the entire testing process, the proposed system analyzes each of the learners' examination results to identify their misconceptions, and stores them in the learner portfolio repository. The *Inference Module*

uses fuzzy logic to infer an appropriate learning path for each of the learners' misconceptions based on the collected learning material from the Internet. Based on the generated learning path, the *Learning Style Analysis* then retrieves the related remedial materials that satisfy the learners' preferences from the Internet and stores them in the remedial materials repository. Finally, the purpose of the *Learning Path and Remedial Materials Recommender* is to recommend both the most suitable learning paths and the most suitable learning materials for each course unit based on the learners' misconceptions and preferences to facilitate more efficient learning for all the learners. The details of the system components are described as follows.

### Learning testing component

Two major roles are played by the Learner Testing Component. The first role is to support an editor interface that enables instructors to edit the learning style questionnaire and test items. The second role is to analyze the results after the learners complete the entire testing process. Moreover, after the learners complete the entire testing process, the system analyzes the testing results and stores them in the learner portfolio repository. Figure 2 shows the interface of the assisted instruction system on Moodle. The teachers and learners can register for accounts and passwords by hitting the “登入” hyperlink denoted by ①. After they fill in the relevant form with their personal information, the system automatically sends them an e-mail to confirm their registration. As shown in ②, the teachers can design a curriculum that includes the course description, the goals of the course, the test sheets, etc.



Figure 2. The interface of the assisted instruction system

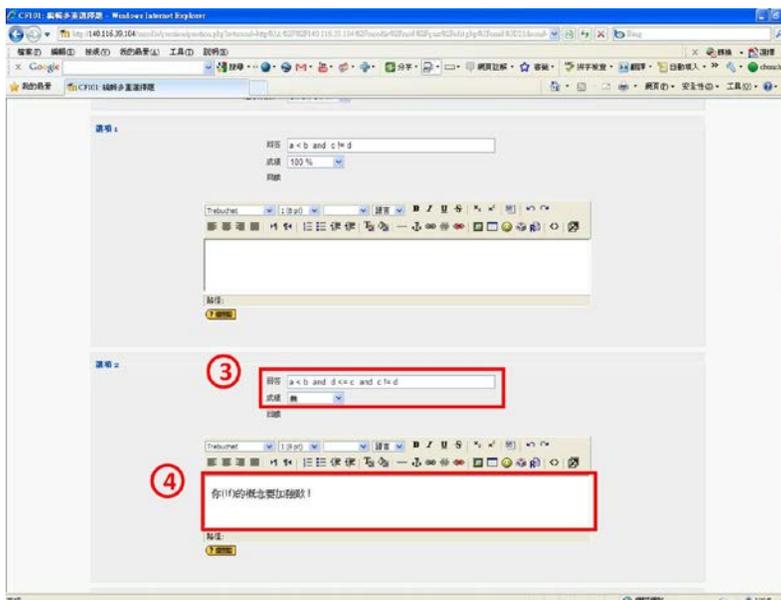


Figure 3. The edit interface of test items and feedback for teachers

Figure 3 shows the test items and feedback edit interface. In ③, teachers can edit the test items, the answers and the score. Furthermore, to help learners to identify which concepts require remedial learning, the teachers edit the feedback message for each test item in ④. After the testing process, the teachers can use the interface to assess learners' learning performances and store the results into the learner portfolio repository. The proposed system also analyzes the testing results to identify the students' misconceptions according to the feedback messages.

### *Inference module*

The concept of fuzzy logic appeared following the definition of fuzzy sets by Zadeh in 1965. The aim of fuzzy logic is to emulate the human reasoning process and to help us make decisions based on imprecise data (Hajek, 2006). The purpose of the Inference Module is to construct a suitable learning path based on the learner's testing results. To identify a suitable learning path according to the learner's misconceptions, we need to consider the degree of relation between two different concepts; if the degree is high, the concept should be recommended as the next one for learning. Hence, the fuzzy inference mechanism computes the relationship degree of each concept pair out of all the candidate concept units by the means of four steps, the *Input*, the *Fuzzifier*, the *Inference* and the *Defuzzifier* (Zimmermann, 1991).

#### **Step 1: The input phase**

The first step is the formation of Input Linguistic Features, which involves computing the three feature values for each concept pair for processing in the next step of the algorithm. The three feature values include the *Concepts' Extension (CsE)*, the *Concepts' Similarity (CsS)* and the *Concepts' Coherence (CsC)*.

- **Concepts' Extension:** In the field of text mining, one of the basic ideas is that two terms that appear together frequently in the same text are likely correlated or connected. In this study, if a document with a theme of Concept  $C_a$  has frequent references to Concept  $C_b$ , it is implied that the two concepts are correlated and that Concept  $C_b$  is likely to be a prerequisite of Concept  $C_a$ . The reason is that any learning is gradually progressive. The concepts frequently appearing in the learning process tend to be those already learned. Accordingly, we adopt a probability model to explore the correlation between the two concepts through a large quantity of online materials. The *CsE* is shown in formula 1.

$$CsE_{A,B} = \frac{\text{Concept}_A \cap \text{Concept}_B}{\text{Concept}_A \cup \text{Concept}_B} = \frac{N_{A,B}}{N_A + N_B - N_{A,B}} \quad (1)$$

where  $N_A$  represents the number of search results obtained by querying the candidate concept  $A$  on the Google search engine,  $N_B$  denotes the number of search results by querying the candidate concept  $B$ , and  $N_{A,B}$  represents the number of search results containing both candidate concept  $A$  and candidate concept  $B$ .

- **Concepts' Similarity:** The *CsS* represents the similarity between a given article and the articles already read by a learner. If the value is high, then presumably the topic of the article is already familiar to the learner, and it should be easy for the learner to comprehend the article. In other words, a concept with a content that is highly correlated to what a learner has already been learning should be more likely to be recommended to the learner. Therefore, a cosine measure is employed to compute the similarity weighting between each article pair. Finally, to calculate the similarity of each concept pair, we sum the similarity weightings of each article for each individual candidate concept by using formula 2.

$$CsS_{A,B} = \frac{\sum_{i=1}^x \sum_{j=1}^y SW_{A_i, B_j}}{x \times y} \quad (2)$$

where  $CsS_{A,B}$  denotes the similarity between candidate concept  $A$  and candidate concept  $B$ , and the parameters  $x$  and  $y$  are constant, where the number of articles chosen out of the search results is set to 10.  $SW_{i,j}$  represents the similarity weighting between article  $i$  and article  $j$ , again with values lying between 0 and 1. The higher the value of  $SW_{i,j}$ , the closer the similarity.

- **Concepts' Coherence:** When recommending a course to a learner with a sequence of learning objects, the continuity between the contents of these articles is very important for the learner to successfully understand the course. To automatically construct suitable learning paths with better content continuity, coherences between articles have must be identified, which are called the coherence weightings and computed from the generated concept lattice derived in (Hsieh & Wang, 2010). After that, we sum up the coherence weights of each article for individual candidate concept, as in the  $CsC$ , by using formula 3.

$$CsC_{A,B} = \frac{\sum_{p=1}^x \sum_{q=1}^y CW_{A_p, B_q}}{x \times y} \quad (3)$$

where  $CW_{p,q}$  is the coherence between articles  $p$  and  $q$ ,  $CsC_{A,B}$  represents the coherence between candidate concept  $A$  and candidate concept  $B$ , and the constants  $x$  and  $y$ , which denote the number of articles selected out of the search results, are set to 10.

### Step 2: The fuzzifier phase

This step computes the degree of membership for the linguistic feature values, i.e., the  $CsE$ ,  $CsS$  and  $CsC$  of each concept pair. We use both the trapezoidal membership function and the triangular membership function for each linguistic term. Each fuzzy input variable has three linguistic terms, namely, *Low*, *Medium*, and *High*, each of which has a membership function to represent its degree of membership.

### Step 3: The inference phase

The third step is the inference step, which contains the *AND* operation and the *OR* operation. It employs a total of  $3^3$  or 27 rules, which are based on the possible combinations of the three linguistic terms and the three fuzzy input variables. All of the fuzzy inference rules are defined by the domain expert's prior knowledge. The output variable of each rule is defined as a fuzzy output variable  $DCR$ , the *Degree of Concept Relationship*, which includes  $DCR\_Low$ ,  $DCR\_Medium$  and  $DCR\_High$  as its three associated linguistic terms. The final three values of the output variable  $DCR$  represent the *Degree of Concept Relationship* between two different concept units; the candidate concept unit with the highest value should be recommended next to the learner.

### Step 4: The defuzzifier phase

This final step involves defuzzification. In this dissertation, we use the discrete *center of area (COA)* computation method, as shown in formula 4. The final step is to perform the defuzzification process to get the  $DCR$  of the concept pair, where  $L$  is the number of quantization levels, such that the finer the level, the more precise the result and the higher the computational complexity.

$$DCR = \frac{\sum_{i=1}^L \sum_{d=1}^D \mu_d(y_i) \times y_i}{\sum_{i=1}^L \sum_{d=1}^D \mu_d(y_i)} \quad (4)$$

In formula 4,  $y_i$  is the  $i$ -th quantization value, and  $D$  is the number of linguistic terms of  $DCR$ .  $\mu_d(y_i)$  is the degree of membership of  $y_i$  in  $d$ . The result of the computation is the degree of relationship between two different concept units based on a quantization value between 0 and 1. The larger the value, the more likely a suitable concept is recommended next to the learner. All of the values of the concept relationship for each concept pair are calculated by formula 4 and are arranged in a *Degree of Concept Relationship Matrix*, the  $DCRM$ , as in formula 5 (Hsieh & Wang, 2010).

$$DCRM = \begin{bmatrix} dcr_{1,1} & dcr_{1,2} & \cdots & dcr_{1,v} \\ dcr_{2,1} & dcr_{2,2} & \cdots & dcr_{2,v} \\ \vdots & \vdots & \vdots & \vdots \\ dcr_{u,1} & dcr_{u,2} & \cdots & dcr_{u,v} \end{bmatrix} \quad (5)$$

For an example of the detail process of inference module, assume a learner’s misconception is the “*For-statements*” in the C++ programming language. By using the Apriori algorithm, two candidate concepts, “*For-statements*” and “*Data types*” are identified (Hsieh & Wang, 2010). The *input phase* then computes the three feature values include the *CsE*, *CsS* and *CsC*, respectively. After that, the *fuzzifier phase* computes the degree of membership for the linguistic feature values. Suppose candidate concept “*For-statements*” and candidate concept “*Data types*” have the following degrees of membership of the linguistic terms low, medium, and high for the three fuzzy variables:  $\{(0,0.4,0.6), (0.3,0.7,0), (0,0.55,0.45)\}$ , as shown in Table 1.

Table 1. Membership degree of linguistic terms of each fuzzy variable.

		Linguistic terms		
		<i>Low</i>	<i>Medium</i>	<i>High</i>
Fuzzy Variables	<i>CsE</i>	0	0.4	0.6
	<i>CsS</i>	0.3	0.7	0
	<i>CsC</i>	0	0.55	0.45

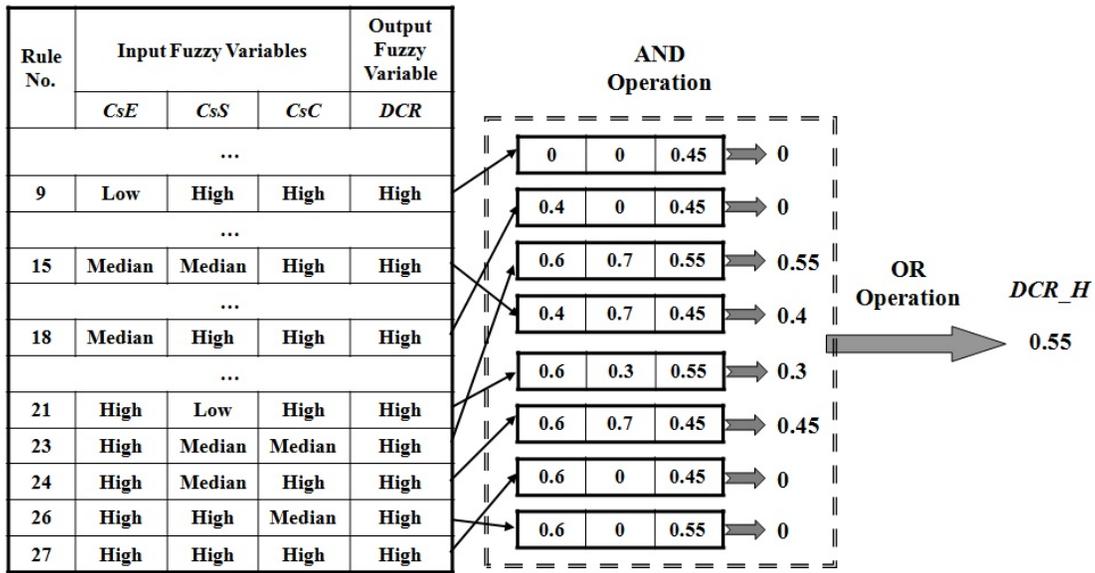


Figure 4. Calculation of the fuzzy rule inference.

Suppose there are eight related rules. The degrees of membership of their linguistic term *DCRs* are the *Hs* in the last column of the left box in Figure 4. The *AND* operation operates on these rules, taking the minimum value of the degrees of membership of fuzzy variables in each rule, and in Figure 4, the values farthest to the right in the middle box comprise the output. The *OR* operation then takes the maximum value of the results of the *AND* operation, and in Figure 4, the value farthest to the right is the final result of *DCR\_H* of *DCR*, which is 0.55. The final values of the other linguistic terms are computed in the same way. Finally, the *defuzzifier phase* computes the relationship degree of each concept pair and the results are in Table 2.

Table 2. An example of the degree of concept relationship matrix.

	For-statements	Data types
For-statements		0.66
Data types	0.11	

### *Learning style analysis*

To analyze learners' learning styles, this study adopted the Learning Style Inventory as modified by Kolb (Kolb, 1984). It is composed of 12 questions describing the four learning stages and serves to measure four types of learning styles, namely, Diverger, Accommodator, Assimilator and Converger. The details of four types of learning styles can be described as follows:

- **Converger:** Those with highest scores in Abstract Conceptualization and Active Experimentation. The greatest strength of a person with a converging learning style is the practical application of ideas. They do best in situations where there is a single correct answer or solution to a problem and they can focus on specific problems or situations. They would rather deal with technical tasks than social and interpersonal issues.
- **Diverger:** Those with highest scores in Concrete Experience and Reflective Observation. The greatest strength of a person with this style is creativity and imaginative ability. They are sensitive. They excel in the ability to view concrete situations from many perspectives and generate many ideas, as in a brain-storming session.
- **Assimilator:** Those with highest scores in Abstract Conceptualization and Reflective Observation. The greatest strength of a person with this style is the ability to understand and create theories. They excel in inductive reasoning and in synthesizing various ideas and observations into an integrated whole.
- **Accommodator:** Those with highest scores in Concrete Experience and Active Experimentation. The greatest strength of people with an accommodating learning style is in constructing plans and experiments and involving themselves in new experiences. They often solve problems and learn by trial-and-error, relying heavily on other people for information.

According to the distinctive characteristics shown by each of the four types of learning style, this study used its system to search online for suitable remedial materials for each type of learners. It has found four sources of remedial materials: Teaching Website, Comprehensive Website, Discussion Website and Applied Website, which can be described respectively as follows:

- **Teaching Website:** A teaching website contains teaching materials focused on instruction in basic syntax and concepts. It is suitable for learners emphasizing theoretical logic with the learning style of Assimilators. The system acquired a portion of the contents of C++ Programming at the website of "Liang-Ge-Ge Learning Notebook" (Lin Hsin-Liang, 2003) for students to learn their desired concepts. This website, constructed with an abundance of information, is recognized in Taiwan as a high-quality teaching website for computer programming.
- **Comprehensive Website:** A comprehensive website contains a variety of teaching materials concerning computer programming and reference documents for relevant techniques. It is suitable for learners who prefer to work on technical problems with the learning style of Convergers. The system has found the website of the MSDN Library for students to learn their desired concepts. The "MSDN Library" website, designed by Microsoft, offers a full spectrum of programming information, including the development of web services, reference documentation, technical articles, software development kits and sample code.
- **Discussion Website:** A discussion website contains discussions on experience sharing and program code and is suitable for learners who prefer to learn actively by brainstorming in an open learning activity with the style of Divergers. Accordingly, the system has found the articles on C/C++ programming on the discussion section of the website of "Study-Area" for learners to learn their desired concepts. This website is a highly interactive discussion website for experience sharing and programming.
- **Applied Website:** An applied website contains application-centered teaching materials that are suitable for learners who prefer practical applications with the learning style of Accommodators. Accordingly, the system has found for students the materials at the website of "YAHOO Knowledge" that receive more than 60% positive ratings from a minimum number of three commentators. YAHOO Knowledge is a social networking website rather than a discussion website. It contains much more information focused on technical exchanges and applications. The website is constructed with a rating function for replies to rule out errors or repetitions and to achieve a high degree of accuracy for its information.

In this study, the system searched and provided suitable teaching materials according to the learning styles of learners. It intended to enable learners to find remedial materials that are interesting to them and to increase their learning effectiveness.

### Learning path and remedial materials recommender

To provide remedial learning resources for a learner, e.g., to satisfy a learner's desire to understand a specific terminology in a given domain, usually requires prerequisite knowledge of the relevant terminology. Some of the concept units associated to the prerequisite knowledge must be prepared for such a learning activity, and they must be taught at the beginning of the learning path, if necessary. This paper constructs a suitable learning path for a learner according to the *Degree of Concept Relationship Matrix*. To build a learning path to correct the learner's misconceptions in a continuous manner, the concept unit that most closely matches the misconception is chosen as the main subject of learning, the candidate concept unit with the highest weight of relationship to the misconception is selected for the prerequisite knowledge, and all the other units are found and arranged subsequently according to their relationship weights. The following algorithm describes the learning path construction.

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#### Learning Path Generation Algorithm

**Input:** Misconception (*MC*), large themeset size (*LTS*) and degree of concept relationship matrix (*DCRM<sub>ij</sub>*).

**Output:** A suitable learning path (*LP*).

**Procedure:**

1:  $LP = \{0\}$

2: Find a concept unit (*CU*) that meets the *MC* from the candidate concept unit set. Add *CU* to *LP*, i.e.,  $LP = \{\rightarrow CU\}$ .

3: While (length of *LP* < *LTS*) {

Find the  $CU_X$  with the highest relation weighting to the Head of *LP* in *DCRM<sub>ij</sub>*

If ( $CU_X \in LP$ )

Do {

Find the  $CU_X$  with the next highest relation weighting to the Head of *LP* in *DCRM<sub>ij</sub>*

} until ( $CU_X \notin LP$ )

else Add  $CU_X$  to *LP*

4: Return *LP*.

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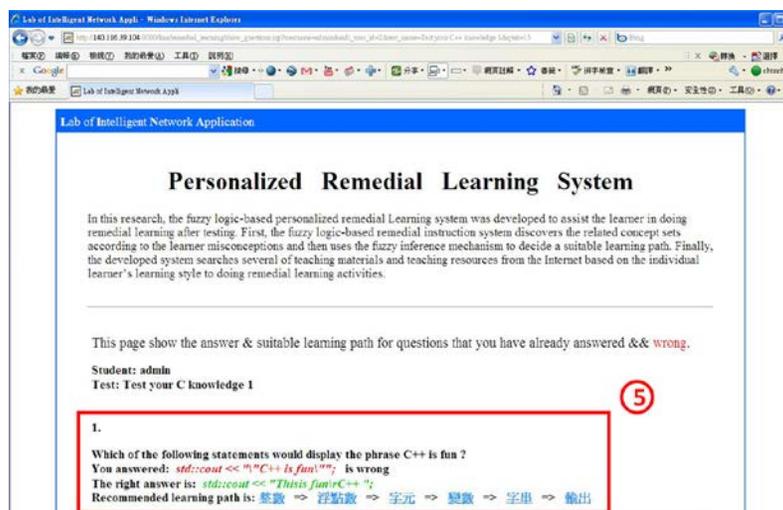


Figure 5. The interface of the constructed learning path for an individual misconception

Figure 5 shows the interface of the constructed learning path with the related remedial materials for an individual misconception. As shown in ⑤, each test item for which the learners chose the wrong answer contains the right

answer and the recommended learning path. A recommended learning path, composed of several concept units, is the suitable learning sequence for the individual learner according to his/her specific misconception. Each concept unit also includes the recommended remedial materials.

After the learner chooses a concept unit to learn, the proposed system then automatically provides the remedial materials extracted from the Internet based on their learning style. As shown in ⑥, those remedial materials that contain four kinds of resources, i.e., teaching websites, comprehensive websites, discussion websites and applied websites, are exhibited in sequence according to the learner's preferences, from top to bottom. Finally, when the learner completes the entire remedial learning process, the proposed system automatically provides a questionnaire to identify their preferences among the different recommended remedial materials, as shown in ⑦.

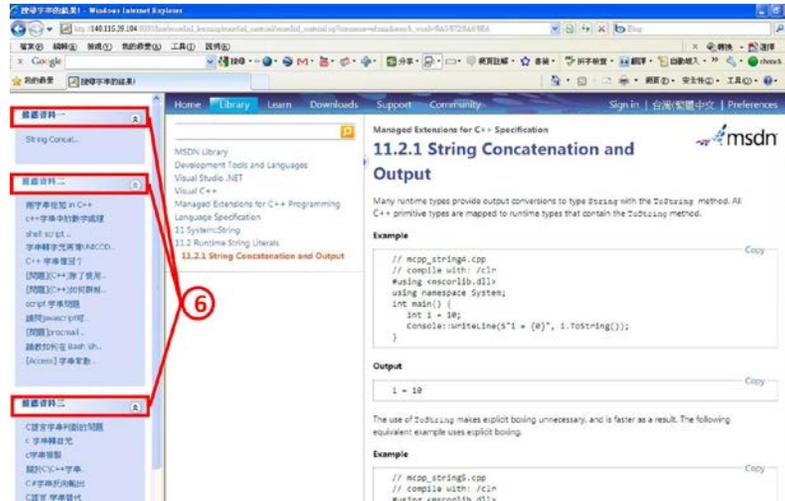


Figure 6. The interface of material contents for an individual concept unit



Figure 7. The interface for a learner's preference feedback after learning

## Experiment results

### Experiment design

Experiments were conducted to evaluate the effectiveness of the method proposed in this paper. A total of 55 sophomore students, 9 females and 46 males, from the Engineering Science Departments of the Nation Cheng Kung University, Taiwan, were involved in the experiments over two months. The C++ programming language is a basic

and important skill for students majoring in the discipline of engineering. It is a required programming language curriculum in the Engineering Science departments of the Nation Cheng Kung University. Therefore, this study uses the C++ programming language as an example. Additionally, most of the participants had no or even minimal prior computer programming knowledge before learning.

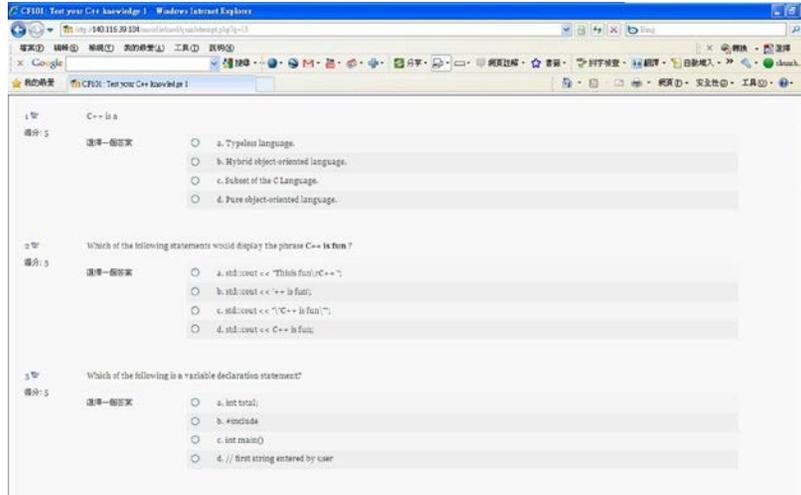


Figure 8. The testing interface for an individual learner

A randomized pre-test–post-test control group design was employed in this paper. The experiments primarily measure the effectiveness of the adaptive remedial learning. All participants were randomly assigned to two groups. A control group (N =28) used the MPRLS without the recommended learning paths and adaptive learning materials. An experimental group (N=27) used the recommended learning paths and adaptive learning materials for remedial learning. In this study, the testing sheets, which are composed of multiple-choice questions, were designed by the teachers for both the pre-test and post-test. The pre-test items are different from the post-test items. Besides, the five experts on the C++ programming language also participate in evaluating the reliability and validity of the measurements. The figure 8 displays the testing interface for the learners. After randomized grouping and pre-testing, participants were engaged in remedial learning processes for two months. The performance of learners in the experimental group, who used the proposed system for remedial learning, was measured. The performance of learners in the control group, who selected learning materials to read on their own, was also measured in the same way. To evaluate their learning performance after the experimental procedure, the participating students were asked to take a post-test.

## Experiment results

This section presents two evaluation results based on the learning performance of learners and the learners' learning style analysis.

### *Learning performance of learners*

An independent sample test was used to verify the differences between the experimental group and control group after the participants finished the pre-test. Table 3 shows the average scores on the pre-test for the experimental group and the control group. According to the analysis results, Table 4 shows that there are no significant differences in pre-test results ( $t = .011$ ,  $*p = .991 > .05$ ) between the experimental group and the control group. In other words, the two groups' abilities in C++ programming were very close. After the two months of remedial learning, the paired samples t-test was used here to assess whether there were statistically significant differences between the performance of the experimental group and control group on the post-test. Table 5 shows the difference in the mean pre-test and mean post-test scores both the experimental group and the control group. The results indicate that there is no significant improvement in learners' abilities after the learning process for the control group ( $t = .657$ ,  $**p = .517 > .05$ ), whereas the improvement for the experimental group is significant ( $t = -2.550$ ,  $*p = .017 < .05$ ). The

results indicate that the participants in the experimental group made significant improvements compared to those in the control group.

To explore whether the remedial system was more helpful to a specific type of learners (low-achieving or high-achieving), students in the experimental group were divided into two categories in terms of their pre-test grades (students with a failing grade and those with a passing grade). The results of the experiment indicated that after using the system, low-achieving students made significant progress ( $t = -5.133, p = .000 < .05$ ) as shown in Table 6, whereas high-achieving students made no significant improvement in learners' abilities ( $t = 1.242, p = .236 > .05$ ) as shown in Table 7.

Table 3. The evaluation results of the pre-test for the experimental group and control group.

	Group	N	Mean	Std. Deviation	Std. Error Mean
Pre-test	Experimental Group	27	55.93	11.688	2.249
	Control Group	28	55.89	10.891	2.058

Table 4. The *t*-test of the pre-test of learning performance.

Equal variances assumed	Levene's Test for Equality of Variances		t-test for Equality of Means					95% Confidence Interval of the Difference	
	F-test	Sig.	t-test	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Equal variances not assumed	.097	.756	.011	53	.991	.033	3.045	-6.074	6.140
			.011	52.395	.991*	.033	3.049	-6.084	6.150

\*  $p > .05$  (confidence interval: 95%)

Table 5. The paired samples *t*-test of the pre-test and post-test for experimental group and control group.

Pair	Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference		t-test	df	Sig. (2-tailed)
				Lower	Upper			
Experimental group (N = 27) Pre-test and Post-test	-6.667	13.587	2.615	-12.042	-1.292	-2.550	26	.017*
Control group (N = 28) Pre-test and Post-test	1.964	15.831	2.992	-4.174	8.103	.657	27	.517**

\*  $p < .05$  (confidence interval: 95%)

\*\*  $p > .05$  (confidence interval: 95%)

Table 6. The paired samples *t*-test of the pre-test and post-test for the learners who failed the exam in the experimental group.

Pair	Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference		t-test	df	Sig. (2-tailed)
				Lower	Upper			
The learners who failed the exam in the experimental group (N = 13) Pre-test and Post-test	-16.538	11.616	3.222	-23.558	-9.519	-5.133	12	.000*

\*  $p < .05$  (confidence interval: 95%)

Table 7. The paired samples *t*-test of the pre-test and post-test for the learners who passed the exam in the experimental group.

The learners who passed the exam in the experimental group (N = 14)	Pair	Paired differences							
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference		t-test	df	Sig. (2-tailed)
					Lower	Upper			
	Pre-test and Post-test	2.500	7.532	2.013	-1.849	6.849	1.242	13	.236*

\*  $p > .05$  (confidence interval: 95%)

### Learners' learning style analysis

Based on the learning style theory of Kolb, this study has classified learners into four types: Accommodators, Assimilators, Convergers and Divergers. For each of the learning styles, the system has found suitable teaching materials from a variety of websites, including discussion websites, applied websites, comprehensive websites, and teaching websites. For instance, for a student identified as a Diverger, the system will have the most suitable teaching materials (from a discussion website) placed at the top of the recommendation list, followed randomly by those from the other three websites. To evaluate whether the teaching materials offered by the system are suitable for each learner, the system conducted a questionnaire survey asking learners to choose the teaching materials in which they were most interested. A total of 27 learners using the system were placed in an experimental group. The analyzed results are as follows:

- Divergers: A learner with the learning style of Divergers is presupposed to have a higher preference for discussion websites. The results showed that six of the nine Diverger-style learners in the experimental group preferred a discussion website.
- Accommodator: A learner with the learning style of Accommodators is presupposed to have a higher preference for an applied website. The results showed that only one of the three Accommodator-style learners in the experimental group preferred an applied website.
- Assimilator: A learner with the learning style of Assimilators is presupposed to have a higher preference for a teaching website. The results showed that seven of the ten Assimilator-style learners in the experimental group preferred a teaching website.
- Converger: A learner with the learning style of Convergers is presupposed to have a higher preference for a comprehensive website. The results showed that three of the five Converger-style learners in the experimental group preferred a comprehensive website.

## Conclusion

This study provides an online learning system that automatically searches for relevant learning concepts and remedial teaching materials for learners to engage in remedial education. Providing guidelines and adaptive teaching materials through a system can help learners improve their learning conditions such as learner control, disorientation and cognitive overload in an online environment and thus improve their learning effectiveness. According to the results of the experiment, this study has the following conclusions:

- There was no significant difference between the experimental group and the control group in the pre-test comparison. Specifically, both groups had the same level of programming ability before the experiment. After using a personalized remedial learning system, the students in the experimental group were able to raise their learning effectiveness and achieve a significant difference in their programming ability. However, low-achieving students could be less effective or less knowledgeable learners who needed to learn gradually and progressively with proper guidance. Hence, given a learning path, low-achieving students progressed to a significantly greater extent.

- With the exception of Accommodator-style learners, more than 50 percent of each type of learners considered that the teaching materials matched learner preference, indicating that the system can provide learners with suitable teaching materials according to their learning styles. However, the results of the evaluation fail to reflect the reality of Accommodator-style learners, with far fewer samples.

The contributions of this study can be described as follows. Many teaching materials are compiled and edited manually. A manually-produced teaching material costs a lot of time and manpower. This study analyzed the characteristics of teaching websites, considered the styles of learners, and obtained online teaching materials automatically. It can provide learners with suitable, diverse teaching materials instantly. Moreover, the questionnaire survey verified that learners take greater interest in the teaching materials recommended by the system. On the other side, the adaptive remedial teaching system developed by this study helps to provide suitable learning access to remedial materials for learners to engage in progressive remedial learning at all times. Therefore, we believe that our research results would support more researchers to follow up such studies in the future.

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