Using Learning Style-Based Diagnosis Tool to Enhance Collaborative Learning in an Undergraduate Engineering Curriculum

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ABSTRACT: In this study, an intelligent learning style aware diagnosis agent for computer-supported cooperative learning is proposed. Learners are first assigned to heterogeneous groups based on their learning styles questionnaire given right before the beginning of learning activities on the e-learning platform. The proposed diagnosis agent then scrutinizes each learner's learning portfolio on e-learning platform and automatically issues feedback messages in case some learner's behavior that is unfitted to his/her learning styles or devious argument on discussion board or wiki is detected. The Moodle, an open-source software e-learning platform, is used to establish the cooperative learning environment for this study. The experimental results reveal that the proposed learning style aware diagnosis agent indeed boosts the performance of the learners. © 2009 Wiley Periodicals, Inc. Comput Appl Eng Educ 19: 739–746, 2011; View this article online at wileyonlinelibrary.com/journal/cae; DOI 10.1002/cae.20359

Keywords: e-learning platform; learning style; computer-supported cooperative learning; diagnosis; feedback; weighted decision graph

INTRODUCTION

In the past few years, developing useful learning diagnosis and assessment systems has become a hot research topic in the literature [1–8]. As the Internet gains wide popularity around the world, e-learning is taken by the learners as an important study aid. In order to help teachers easily analyze students' portfolios in an intelligent tutoring system, many researchers try to transform students' portfolios into some useful information, and hopefully reflect the extent of students' participation in the curriculum activity.

Recently, a lot of e-learning platforms can be used for free on the Internet due to the increasing availability of open-source software. In this work, we incorporate learning parameter improvement mechanisms into an Open Software e-learning platform, Moodle (http://moodle.org/), to verify the feasibility of the proposed algorithms. The most important reason for the choice of Moodle as the pupils' online learning platform is that Moodle is used for free and is designed to support a social constructionist framework of education, such as collaboration, activities, critical reflection, etc. Meanwhile, there are several

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striking features in Moodle that well suit the pupils' online learning in this work:

- It is suitable for 100% online classes as well as supplementing face-to-face learning.
- It supports simple, lightweight, efficient, compatible, low-tech browser interface.
- Most text entry areas, such as resources, forum postings, etc., can be edited using an embedded WYSIWYG HTML editor.
- It allows flexible array of course activities—Forums, Quizzes, Resources, Choices, Surveys, Assignments, Chats, Workshops.
- The teachers can define their own scales to be used for grading forums and assignments.
- It is effortless to proceed with further study and analysis on the learners' profiles as they are comprehensively established.

The synchronous chat tool was used and learners in a small assigned group analyze the problem together. Based on their prior knowledge, they determined the information they already had and what information they were still required to possess and had to learn to solve the problem. During this collaboration, they propose hypotheses to the problem; organize a plan of action required to tackle the generated learning issues; and assign group members to conduct defined tasks. Learning takes place in an active and interactive environment, and the learner constructs knowledge by formulating ideas into words with these ideas built upon the reactions and responses of others.

Traditional techniques for detecting similarity between long texts documents have focused on analyzing shared words [9]. Such techniques are usually effective when dealing with long texts because similar long texts usually contain a degree of co-occurring words. However, word co-occurrence in short texts may be scarce or even nonexistent mainly because of the inherent flexibility of natural language, which enables people to express similar meanings using quite different sentences in terms of structure and content. Since such word co-occurrence information in short texts is very limited, this problem poses a difficult computational challenge. To tackle this challenge, the focus of this paper is primarily on developing algorithms to compute the similarity between very short texts, and then apply the algorithms to detect the relevance degree between the messages posted on discussion board and wiki and the learning topics. Meanwhile, some proper feedback messages will be issued to the learners in case some abnormal behaviors such as idleness are detected.

It has been proven that teaching the learners according to their learning styles could effectively assist the learners in the learning activities. There have been several learner's learning style models proposed in the literature. Kolb/McCarthy learning cycle [10−13] is based on the assumption that learning involves a cycle of four learning stages, but each learner is likely to feel most comfortable in one of the four stages of the cycle based on his/her preferences along two dimensions of Perception (abstract/concrete) and Processing (active/reflective). There are five learning style dimensions specified in Felder− Silverman learning style model [14−19], which are Perception (sensing/intuitive), Processing (active/reflective), Input (visual/verbal), Organization (inductive/deductive), and Understanding (sequential/global). Gee [20] examined the influence of student learning style preference on student achievement in course content, course completion rates, and attitudes about learning in an on-campus or distance education remote classroom. Both distance and on-campus groups were taught simultaneously by the same instructor, received identical course content, and both groups met weekly. The Grasha−Riechmann Student Learning Style Scales (GRSLSS) has been used to identify the preferences learners have for interacting with peers and the instructor in the classroom setting [21−24]. The six social learning styles identified by GRSLSS are the Independent, Dependent, Competitive, Collaborative, Avoidant, and Participant. The inventory is made up of 60 items, including 6 scales, 10 items per scale. Learners are asked to judge themselves using a five-point rating scale that ranges from strongly disagreement to strongly agreement. Among the different learning style instruments, the GRSLSS seems to be ideal for assessing student learning preferences in a college-level distance learning setting. First, the GRSLSS is one of the few instruments designed specifically to be used with senior high school and college/university students. Second, the GRSLSS is a relevant scale that addresses one of the key distinguishing features of a distance class, the relative absence of social interaction between instructor/learner and learner/learner. Third, the GRSLSS promotes a desirable learning environment by helping faculty design courses and develop sensitivity to learner needs. Fourth, the GRSLSS promotes understanding of learning styles in a broad context, spanning six categories. Learners possess all of six learning styles, to a greater or lesser extent, and a rationale for pursuing personal growth and development in the underutilized learning style areas is thereby provided.

A brief discussion of each learning style is enumerated below.

- *Independent* students prefer independent study, self-paced instruction, and would prefer to work alone on course projects rather than with other students.
- *Dependent* learners look to the teacher and to peers as a source of guidance and prefer an authority figure to tell them what to do.
- *Competitive* learners attempt to perform better than their peers do and to receive recognition for their academic accomplishments.
- *Collaborative* learners acquire information by sharing and by cooperating with teacher and peers. They prefer lectures with small group discussions and group projects.
- *Avoidant* learners are not enthused about attending class activities and discussion.
- *Participant* learners are interested in class activities and discussion, and are eager to do as much class work as possible. They have a strong desire to meet teacher expectations.

Cooperative learning [25−31] has received increased attention in recent years due to the movement to educate learners with disabilities in the least restrictive environment. It is a relationship in a group of learners that requires positive interdependence, individual accountability, interpersonal skills, face-to-face promotive interaction, and processing. Computer-supported cooperative learning (CSCL) [25−36] has grown out of wider research into computer-supported cooperative work (CSCW) and cooperative learning. The purpose of CSCW is to facilitate group communication and productivity, and the purpose of CSCL is to scaffold students in learning together effectively. They both are based on the promise that group process and group dynamics are supported and facilitated by computer-supported systems in ways that are not achievable by face to face.

In this work, questionnaire developed by James and Gardner [23] is used to determine students' learning styles. Meanwhile, learners are grouped to facilitate learning based on Kumar's framework, which examines the relationship of instructional process and information technology to students' learning styles [24].

The remainder of this paper is organized as follows. The second section shows the details of the intelligent diagnosis agent. The third section reviews and discusses the experimental results. Conclusions and the future work are made in the fourth section.

ARCHITECTURE OF E-LEARNING PLATFORM

There are three major components in the proposed e-learning platform as shown in Figure 1. They are grouping module, curriculum support module, and learning diagnosis agent. The grouping module is used to group the learners with different learning styles according to the questionnaire of learning styles categorization designed by Kumar [24]. Each learner can be classified into one of the five learning style clusters as shown in Table 1, and each group consists of five members that are selected from the five corresponding learning style clusters. The advantage of grouping the learners this way is because it is expected, for example, that "avoidant" learners can be motivated and pushed forward by "participant" and "competitive" learners; and "collaborative" learners and "independent" learners can be the sources of guidance for "dependent" learners and give timely assistance to "dependent" learners during the progress of the learning activities.

The curriculum support module assists the instructor and the learners in collecting the supplementary learning material and allows the instructor to organize the discussion issues on the discussion board and wiki. The learning diagnosis agent is used to issue the feedback messages to the learners or the instructor in case the transcript posted by the learner is determined to be irrelevant to the designated discussion issues, or some abnormal behaviors of the learner, such as having been idling for some period of time, are detected. Meanwhile, the diagnosis agent will also request the learners who possess collaborative and participant learning styles to pay attention to the learners who stray from the assigned learning activity, and give assistance to the frustrated learners if necessary.

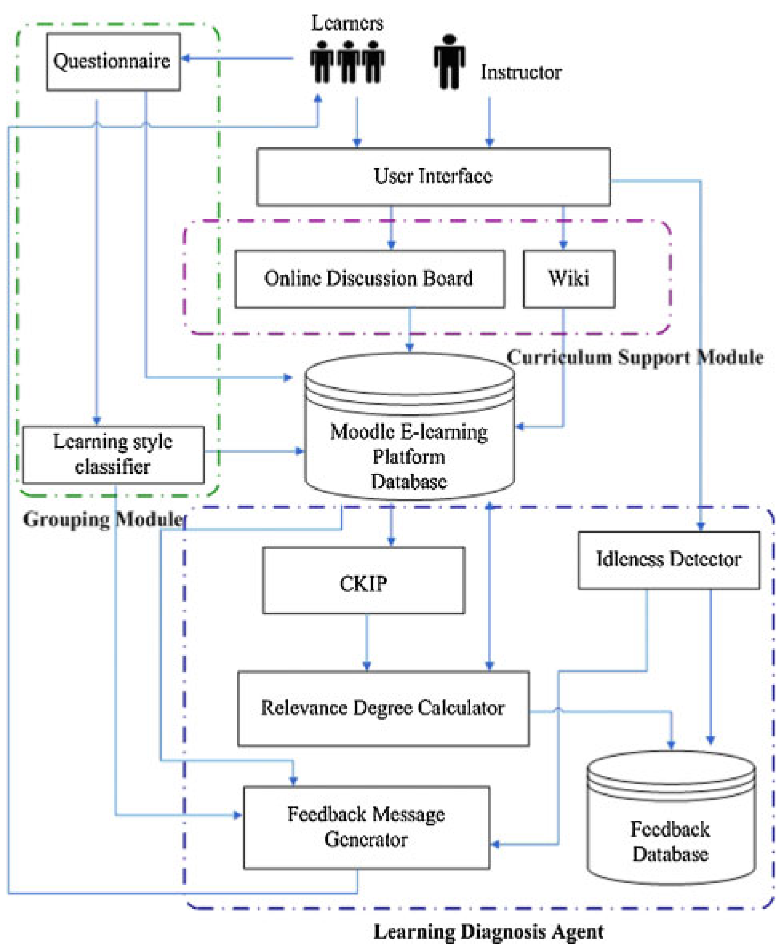

Figure 1 Architecture of e-learning platform.

Table 1 The Five Learning Style Clusters

	Learning styles
Cluster 1	Dependent, Participant, and Competitive
Cluster 2	Participant, Dependent, and Collaborative
Cluster 3	Collaborative, Participant, and Independent
Cluster 4	Independent, Collaborative, and Participant
Cluster 5	Avoidant

Learning Diagnosis Agent

The learning diagnosis agent diagnoses learner's behavior in the e-learning platform, and gives appropriate feedback messages if necessary. The most important function of the learning diagnosis agent is to estimate the relevance degree between the posted transcripts and the learning topics on the discussion board and wiki. As shown in Figure 2, the keyword extractor module is first used to separate and extract the Chinese words. Then a language-independent text analyzer, weighted decision graph, is used to compute the relevance degree between the content of each sample transcript and that of the transcript posted by learner. Idleness detector module is used to report the abnormal behaviors of the learners. Finally, the Feedback Module gathers all available information in the learning portfolio database and gives learners appropriate feedback messages. The above-mentioned modules used in the learning diagnosis agent are elaborated as follows.

Keyword Extractor. Since the learner might use a word that has the same meaning as some word used in the sample transcripts saved in the database, we built a synonym database that can assist us in checking the words used by the learner, and replace them with some appropriate synonym in the database accordingly.

Chinese Knowledge and Information Processing (CKIP) system developed by Academia Sinica in Taiwan is used to separate the Chinese words. Meanwhile, verbosity exclusion module is employed to extract verbs and nouns out of the segmentation results for further processing.

Weighted Decision Graph. Decision graph is an extension of a very well-known decision tree representation. Similar to decision trees, a decision graph contains attribute and decision nodes, where attribute nodes contain some kind of test of attributes' values and decision nodes serve to predict the solution. However, the decision graph principle is more flexible and more general than a decision tree. Since it also contains cycles, additional internal variables can be added to process input in a time-series manner, and makes the decision graphs especially appropriate to deal with signals and continuous data.

Decision graph is used to calculate the similarity between two alphabetical strings S and S'. Each string is separated into ordered sub-strings, and each sub-string corresponds to a node in decision graph, which can assist in determining whether there is a similar sub-string in the original strings S and S'.

A matrix $M_{m,n}$, which is used to describe the decision graph for strings S and S', is first constructed as follows:

$$M_{m,n} = \begin{pmatrix} e_{0,0} & \cdots & e_{0,n} \\ \vdots & \ddots & \vdots \\ e_{m,0} & \cdots & e_{m,n} \end{pmatrix} \quad (1)$$

where m and n denote the length of alphabetical string S and that of alphabetical string S', respectively. Besides, the elements at the first column and the first row in $M_{m,n}$ are initialized to zeroes.

The value of the element $e_{i,j}$ in $M_{m,n}$ is determined by

$$e_{i,j} = \begin{cases} e_{i-1,j-1} + 1 & \text{if} s_i = s'_j \\ \max(e_{i-1,j}, e_{i,j-1}) & \text{if} s_i \neq s'_j \end{cases} \quad (2)$$

where $i = 1, \ldots, m$, $j = 1, \ldots, n$, s_i is the ith alphabetical sub-string in string S, and s'_j is the jth alphabetical sub-string in string S'.

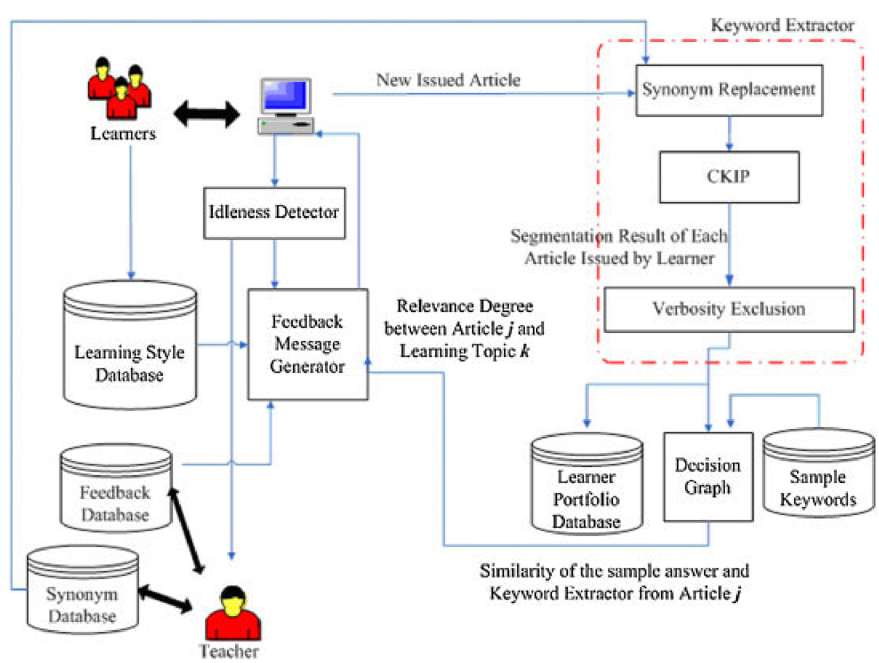

Figure 2 Learning diagnosis system.

In this work, we allow the instructor to grade each sample transcript recorded in the database within the commonly adopted range 0−100. The traditional decision graph should be modified accordingly to accommodate the need for weighting each sample during the process of estimating the relevance degree between the posted transcripts and the expected answers for the discussion issue.We first construct a matrix $W_{m,n}$ which is used to describe the weighted decision graph for the posted transcript T and the sample transcript T' as follows:

$$W_{m,n} = \begin{pmatrix} e_{0,0} & \cdots & e_{0,n} \\ \vdots & \ddots & \vdots \\ e_{m,0} & \cdots & e_{m,n} \end{pmatrix} \tag{3}$$

where m and n denote the length of the posted transcript T and that of the sample transcript T', respectively. Besides, the elements at the first column and the first row in $W_{m,n}$ are initialized to zeroes.

The value of the element $e_{i,j}$ in $W_{m,n}$ is determined by

$$e_{i,j} = \begin{cases} e_{i-1,j-1} + w_j \times \log \frac{\mathrm{NS}}{\mathrm{NK}_j} & \text{if } s_i = s'_j \\ \max(e_{i-1,j}, e_{i,j-1}) & \text{if } s_i \neq s' \end{cases} \tag{4}$$

where $i = 1,\ldots,m$, $j = 1,\ldots,n$, s_i represents the ith keyword in the posted transcript, s'_j is the jth keyword in the sample transcript, w_j is a weighting factor which is used to reflect the instructor's grading on the sample transcripts, NS is the total number of the sample transcripts recorded in the database, and NK_j denotes the counts of the sample transcripts that contains keyword s'_j. The essential functionality of $\log(\mathrm{NS}/\mathrm{NK_j})$ is to filter out the redundant word in the sample transcripts.

Based on Equations (3) and (4), the relevance degree between the posted transcript s and the sample transcript s' is derived by

$$\mathrm{RD}_{s,s'} = \frac{e_{m,n}}{\log(|m-n|+1)+1} \tag{5}$$

where the denominator on the right-hand side of the equation is used to reflect the impact of unequal lengths of the posted transcript and the sample transcript.

Then the relevance degree between the posted transcript and the sample transcript that are most relevant to the posted transcript can be expressed by

$$C = \operatorname*{Max}_i \mathrm{RD}_{u,s_i} \tag{6}$$

where u is the posted transcript, and s_i is the ith sample transcript in the database.

The following example illustrates how weighted decision graph computes the relevance degree between the posted transcript and the sample transcripts. We assume that the discussion topic designated by the teacher is "Why does Token-Ring technique outperform Ethernet when the network is severely congested?" The sample transcripts recorded in the database and their scores given by the teacher are listed in Table 2. Now assume the transcript posted by the learner is "The token passing algorithm adopted by Token-Ring can avoid the collision because the computer must first own the token before they can transmit the packets." Table 3 lists the computation result of Equations (4) and (5). Notably, $e_{m,n}$ represents the cumulative weight for the extracted keywords in the posted transcript that match the keywords in sequence in the sample transcripts, and $\mathrm{RD}_{s,s'}$ computes the relevance degree between the posted transcript and the sample transcripts after taking the lengths of the transcripts into consideration. Based on Equation (6), the second sample transcript as given in Table 2 is determined to be most relevant to the posted transcript as expected.

Idleness Detector. The idleness detector is used to discover whether the learner has not participated in group discussion for some period of time. Figure 3 shows an example of feedback message that reminds or encourages learners to give their opinions on the discussion board or wiki when the idleness detector finds out the learner has been doing nothing for over 5 min.

Feedback Module. The feedback module may issue messages to the learners/instructor if it is activated by weighted decision graph or idleness detector. A set of feedback rules built in the feedback

Table 2 The Sample Transcripts Recorded in the Database and Their Scores Given by the Teacher

Sample transcript	Score given by the teacher
In Ethernet, a computer stops transmitting packets when it observes the medium is busy. No computer can send the packets when the network is congested because the medium is always busy	60
In Token-Ring, a computer can only use the network when it owns the token. This can avoid collisions because only one machine can use the network at any given time	100
The CDMA/CD algorithm adopted by Ethernet introduces some overhead. The computational overhead becomes heavy when the network is congested	0
The token passing mechanism performs better than CDMA/CD when the network is congested	50

Table 3 The Relevance Degree Between the Posted Transcript and the Sample Transcripts

The matched keywords in sequence	$e_{m,n}$	$\mathrm{RD}_{s,s'}$
Computer, stop, transmit, packet	34.9108399549598	19.633222959761
Token-Ring, computer, own, token, avoid, collision	90.3089986991943	61.1385141271519
N/A	0	0
Token passing	15.0514997831991	11.568910657988

Figure 3 An example of the message issued by idleness detector.

message database corresponds to the outputs of weighted decision graph and idleness detector. The feedback message can be used to give advices to the learners if the transcript posted by the learner is determined to be irrelevant to the designated discussion issues or deviated from the expected answers recorded in the database. The instructor is also able to receive the message regarding the occurrence of biased group discussion. Mean-while, different feedback rules for corresponding learning styles are collected in the database with the assistance of the instructor. The example message as given in Figure 4 applauds the learners of cluster 3, who possess collaborative, participant, and indepen-dent learning styles, for their correct answers to the question, and encourage them to keep actively involved in group discussion.

EXPERIMENTAL RESULTS

To verify the effectiveness of the diagnosis agent proposed in this work, a freshman course offered at Computer Science Department, National Hualien University of Education participated in the experiments. There are 32 students enrolled in this class. A pre-test in the form of question and answer was taken after classroom teaching, and nine students passed the test. Notably, short essay questions are given in order to assess students' understanding of and ability to think with subject matter content. Essay questions are chosen over other forms of assessment in this work because essay items challenge students to create a response rather than to simply select a response and thus can reveal students' abilities to reason, create, analyze, synthesize, and evaluate [36]. The 32 students were divided into heterogeneous discussion groups in the e-learning activity according to their learning styles. After their discussion on the learning topics, each student was asked to take a post-test in the form of question and answer again. The post-test is similar in content and difficulty level to the pre-test. It can be seen from the test results, as given in Table 4, that the learners indeed benefited by group discussion held in the e-learning activity.

Table 4 The Comparison of the Experimental Results of Pre-Test and Post-Test

	Pre-test	Post-test
Pass	28.12% (9/32)	96.87% (31/32)
Fail	71.88% (23/32)	3.13% (1/32)

Better student behavior was also observed in the experiment when compared to normal education. For instance, the students were able to develop skills to become active participants in the learning process and to develop collaborative skills with the assistance of the proposed learning diagnosis agent. A change of a learning preference as in the instance of switching from being dependent learners to independent learners was observed. Mean-while, the proportion of the students distracted from group discussion activity substantially lowered down with the aid of the feedback model.

CONCLUSION AND FUTURE WORK

In this work, a learning style aware learning diagnosis agent based on machine learning techniques is proposed. Learners' transcripts on discussion board and wiki were examined to detect whether the learners plan wrong solutions. A feedback rule construction mechanism is used to issue feedback messages to the learners in case the diagnosis agent detects that the learners go in the biased direction or they have not been joining the group discussion for some period of time. The experimental results exhibit that the proposed work is effective in assisting the students with different learning styles in learning the database concepts taught at a freshman course.

In the future work, we plan to employ advanced machine learning techniques to access each individual's performance based on the contents of the learners' transcripts. Meanwhile, we will try to automatize feedback message rule construction mechanism to further reduce the instructor's labor work. In addition, more advanced text mining technique will be adopted in our future work to accurately measure the relevance degree of expected solutions and posted transcripts.

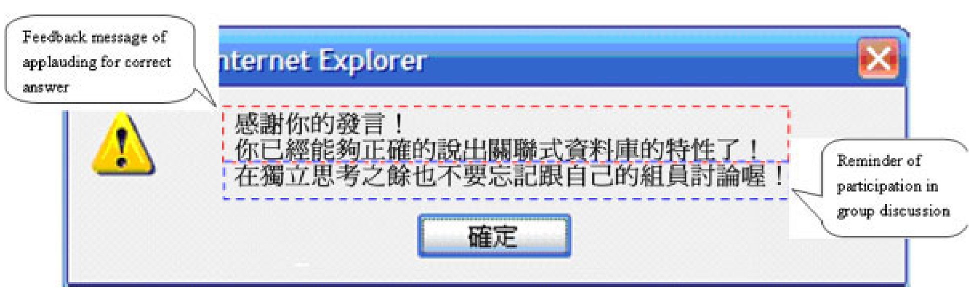

Figure 4 An example of feedback message for the learners of cluster 3.

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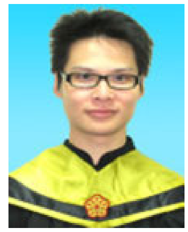

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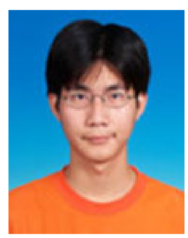

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