Development of Activity Generation and Behavior Observation Systems for Distance Learning

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ABSTRACT: Distance learning and e-learning are popular and widely used technology in today's teaching environment; monitoring systems allow teachers to assess the learning state of their students. This study proposes a development of activity generation and behavior observation systems that allows teachers to assess the learning activities of their students. We use the concept of deterministic finite automaton to define learning activities. In the proposed system, teachers only need to click the drop-down list items to manage learning activities. The proposed system also generates an activity recognizer after defining the activity. The activity recognizer can parse student-learning logs allowing teachers to get the real-time learning activities of students. When students are in abnormal learning states, teachers can immediately provide them with active guidance. The experiments in this study demonstrate the feasibility and effectiveness of the proposed system. Experimental results show that students received higher grades and exhibited less abnormal learning with the proposed monitoring system. These results demonstrate that the proposed system provides teachers with a convenient interface for assisting their students. The proposed monitoring system improves the learning outcomes of students. Comput Appl Eng Educ 22:52–62, 2014; View this article online at wileyonlinelibrary.com/journal/cae; DOI 10.1002/cae.20528

Keywords: distance learning; monitoring system; active guiding; learning activity; learning portfolio

INTRODUCTION

To increase the quality of instruction and address the limitations of traditional learning to enable learners to learn at any time and from anywhere, e-learning studies and applications have become increasingly popular. Researchers have designed and implemented various learning platforms [1–3] that serve as interfaces for students to access e-learning systems. The literature focuses on the establishment of learning platforms and environments. These e-learning systems provide learners with more comfortable learning environments to complete the learning process [4]. The interaction between teachers and students is another important aspect of the learning process. Student learning activities are an important way for teachers to interact with students [5]. An e-learning system should not only promote the learning process, but also allow teachers to interact with students in a better learning environment.

In the traditional education environment, teachers provide the guidance necessary to improve student-learning performance. To assist students during the learning process in the e-learning environment, teachers observe students' learning activities [1,6–11]. The information contained in any learning portfolio is a convenient way for teachers to analyze the learning activities of students using online learning systems. Teachers assess learning activities using learning portfolio variables, including the number of times students log in to system, their frequency of accessing materials, and the number of messages they post. Learning portfolios provide personal learning histories, encouraging student self-reflection. It may take teachers a long time to analyze learning portfolios before they can recognize the problems or situations of students. Teachers may not be able to guide students in an efficient manner. When students lose their direction in the learning procedure for a long time, it takes more time and effort to lead them back to the right direction in learning. Teachers must manually define the rules or policies for analyzing learning portfolios are for a specific course. It is difficult to reuse these rules or policies for different courses. The rules or policies for learning activities are described in human language, making it difficult to understand their meaning without a translation for the tutoring system [12,13].

In many countries [6], students are often passive about the learning process. If those students encounter problems in their

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learning procedure, they will not relay these problems to the teacher. Even if a teacher asks students if they are experiencing learning problems, many students are too introverted or afraid that other students will laugh, and respond. They are often embarrassed to ask questions in front of other students. Students may ask questions when the teacher shows particular concern for them on an individual basis. Teachers need to know if students are experiencing any problems during the learning process. A real-time and adaptive learning activity monitoring system should be provided to allow teachers to counsel their students efficiently.

This study designs and implements an activity generation and behavior observation system. The proposed system uses the real-time learning events of students to recognize their learning activities. The teacher can then monitor these real-time learning from the learning platform. The proposed system supports an interface for teachers to manage the activities that they want to monitor in the course. After defining or modifying the activities, the system generates an activity recognizer. Using the proposed activity recognizers, teachers can determine students' learning activities and actively provide real-time guidance when students experience abnormal learning states.

The rest of this paper is organized as follows. The background and related work of our research are described in the next section. The method of the proposed system is presented in the third section. The research design is described in the fourth section. The system implementation and prototype are presented in the fifth section. The evaluation and discussion are presented in the sixth section. Conclusions are made in the seventh section.

RELATED WORK

The interactions between teachers and students are the basic activities of the learning process. A learning portfolio provides the learning state logs of students. Teachers use the information contained in a learning portfolio to analyze students' learning behaviors [14,15] or activities and increasing their learning performance. Previous studies [1,8–11,16–19] examine ways to increase learning performance through learning behaviors or activities. Sun et al. [11] proposed a grouping method for teachers to improve group learning efficiency in e-learning. These groups are established with rules based on data mining of the following four categories: learning period, region, age, and value type. Teachers can use this grouping methodology to facilitate student interaction in Web-based courses. Students with different learning behaviors have unique learning periods, and interact with one another at times determined by their preferences in working time. Students come from different regions with different customs, cultures, and cognitive modes. These regional differences cause students to have different learning behaviors. The different lifestyles, attitudes, and economic interests between generations also lead to different learning behaviors. Sun et al. developed a questionnaire to survey personal data. This questionnaire is used in testing personalities. Sun et al.'s study develops an online interaction monitor to allow teachers to produce effective groups based on these four attributes. This study conducts a field experiment with student groups formed with and without the proposed method. Experimental results show that groups adopting the proposed method performed better in all measures.

Cooperation is an important part of training in laboratory-based courses [20,21]. Several types of interaction emerged during the cooperative learning experiment in following study. Bermejo [22] demonstrated how to design cooperative learning activities over the Internet using basic principles derived from contemporary pedagogical research. Bermejo suggested two improvements to the system, including learning objects and Web-based forums. Learning objects should be implemented using HTML pages with links to introduction slides, theoretical documents, and simulations. The Web-based forum is an ideal e-learning platform for students and teachers. Students accessed the course of Java-based experiments in this study through a Web page. Students were required to write reports of their personal contributions for other students. This approach allowed them to reflect on issues before adding their contributions through asynchronous Web-based forums, and encouraged group discussion. The experiment in this study examined the same course in two different years. During the first year, students could not interact with the Web-based forums, while students in the second year course could interact with each other. Experimental results show that group interaction during the second year was greater than that during first year, and group processing improved as the course progressed. Student questions could be answered quickly via a Web-based forum.

A Web-based course is a kind of asynchronous learning environment that learning time distribution is the primary guideline for student learning behaviors. Hwang and Wang [7] proposed the learning time patterns to diagnose the learning state in asynchronous learning environments of students. Teachers often use the learning time intensity, burst evaluating equations, and state denotation approaches to evaluate the learning time characteristics of their students. Burst state and diligence state are two variables of asynchronous learning time patterns. The inter-arrival time and duration variables from student learning portfolios represent these two states. The Web-based course in this study includes three phases: prior, middle, and posterior phases. Combining these three phases with the burst rate variables produces six burst styles and three diligence styles. With these styles and learning portfolios, teachers can help students learn in the proper sequence and encourage students to exercise self-discipline for better learning outcomes. Experimental results reveal that students have burst- or diligence-learning characteristics.

Jong et al. [10] proposed a learning behavior diagnosis system to analyze the learning behaviors of students in Web-based learning. Their system obtains students' learning states from learning logs. This system must collect learning logs long term, such as half a semester or more, to diagnose student-learning behaviors. This learning log explorer diagnoses the behavior of students and consists of four layers: the linking layer, learning log database definition layer, feature definition layer, and behavior description layer. The linking layer enables the diagnosis of student learning states on different platforms. The definition layer uses the SQL condition character string to filter the learning logs in the database. The main function of the feature definition layer is to assign defined parameters with specified scope values. The behavior description layer refers to logical combinations (such as AND, OR, and NOT) of the definitions in the feature definition layer. Using these four layers, the proposed system allows teachers to set up and observe students' online learning activities. The proposed system also transmits warning messages to students to recommend that they pay attention during the online course. Teachers can provide appropriate guidance and assistance to students. The learning log explorer system uses the student's learning state and interaction between students to conduct the experiment. Experimental results show that students who learned with the learning log explorer system were more likely to pass their final examinations.

LEARNING ACTIVITY MODEL AND BEHAVIOR OBSERVATION

Student learning activities provide important information for the proposed system. The following section presents the learning activity model and behavior observation.

Learning Activity Model

Figure 1 shows a use case of the proposed system. The management system allows teachers to identify student-learning activities. As students study the learning materials, the learning activity recognizer obtains their learning activities and responds to the assistant agent and the teacher. The assistant agent provides basic guidance for students, while the teacher provides advanced guidance. The proposed learning activity model is a deterministic finite automaton (DFA)-based model [23], and describes the process of learning activity. The greater learning environment or course determines these learning activities. The adaptive learning activity model is as follows:

Definition 1: The learning activity is a five-tuple, $L_A = (S, A, I, F, P)$, where

(1) $S = \{S_1, S_2, \ldots, S_i\}$ is a finite set of activity states. Each learning activity has a set of states that is dependent on the learning environment. This set includes all the learning activity states.
(2) $A = \{A_1, A_2, \ldots, A_j\}$ is a finite set of actions for the learning activity. The normal actions for the activity are used to transform activity states. To complete the conversion from initial state(s) to final state(s), a series of actions are accomplished and the learning activity is performed. The proposed learning system detects and records all of the actions and events.
(3) $I \subseteq S$ is the set of initial states of the activity. A learning activity could have one or more initial states, and the activity should begin with one of these initial states. Thus, all the states that can potentially trigger the learning activity will be in the set.
(4) $F \subseteq S$ is the set of final activity states. These final states are necessary to determine if an activity is accomplished. Until the initial state transforms into the final state, the activity is not accomplished. Therefore, a teacher can identify which students have accomplished an activity based on the states they occupy.

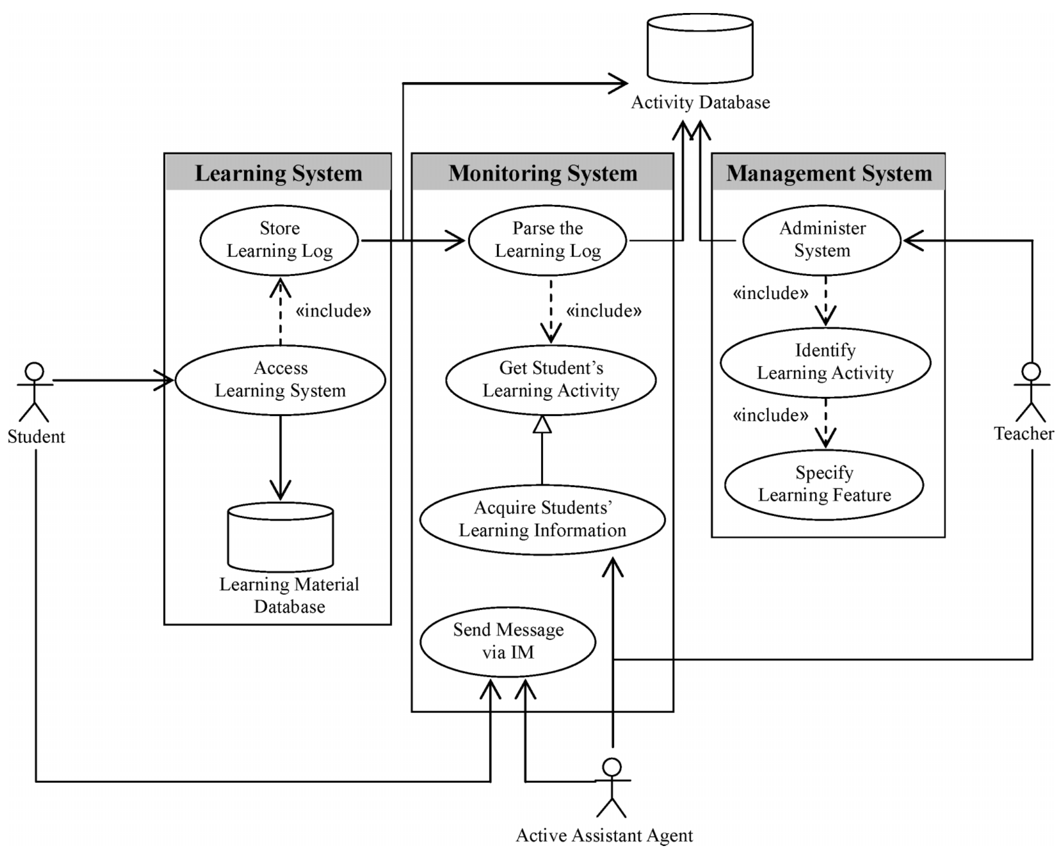

Figure 1 The use case of the proposed system.

(5) $P \subseteq S \times A \times S$ is the transition relation of the learning activity. Each learning activity has a specific transition relation. This transition relation describes all the relations among the states for a learning activity. Using these transition relations, teachers can trace their student's learning logs to determine their learning activities.

The learning actions and learning states are the edges and nodes of the learning activity, respectively. Learning actions are the detectable events in the learning system. The learning states indicate the status of students as they use the learning system to study. According to the learning materials or environments, we can design and analyze various learning activities in the learning system. Each learning activity can be expressed as a graph $G = (V, E)$, where V denotes the set of nodes and E represents the set of edges. The nodes and edges are the learning states and actions defined in Definition 1. The node is indexed by a finite set I, where I is the set $\{1, 2, 3, \ldots, |V|\}$. For any two nodes V_x, $V_y \in V$, an edge $E_{x,y} \in$ E, implies that the student can change states from V_x to V_y with the action of $E_{x,y}$.

According to the above definitions, the reading and assessing activities can be presented as follows. In some learning environments, Web pages present the learning materials. We get the DFA of reading activity when students read the learning materials on the Web pages in this learning environment, as Figure 2a shows. Figure 2b shows the DFA of assessing activity.

To increase the adaptability of learning activities, the proposed system uses learning features and learning activities to determine the progress of students. The main function of the learning feature is to determine the scope of parameters for each situation. Parameters divisions are determined by the environment or course of the learning system. The system can be used to detect and check whether a student is in the abnormal state or not.

The changing of active states means the time transfer. The time sequence diagram in Figure 3 depicts the order of activities in the proposed system. This figure shows that the primary student learning activity involves reading the teaching materials. When a reading loop has not been completed, or has repeated too many times in a period of learning time, it indicates an abnormal state. This indicates that students may have left the learning system and started another task, or simply become distracted. It is abnormal for students to change states quickly in a short time. In this case, students may not understand some parts of the learning process, and are looking for answers.

When students exhibit abnormal behavior, they might need some help from the teacher. Providing guidance is an important activity for teachers in traditional education. The proposed monitoring system can recognize whether a student needs assistance in the learning process based on the results of behavior observation, and reminds the teacher to provide guidance.

Behavior Observation

According to the previous section, time is an important factor for evaluating students' learning situations. This study considers two situations for students' behaviors:

Situation 1: The abnormal activity of *Idle* is when the student stays in the learning system for time $t_n - t_l$ or when $t_{j+1} - t_j$ is higher than the threshold of θ_ι, where t_n is the current time of system, t_l is the time that the student enters the current state, and t_j is the time when the student enters the jth state. Thus, $t_n - t_l$ denotes the current idling time of the student and $t_{j+1} - t_j$ denotes the idling time of the student in the jth state. θ_ι Each activity can have different threshold values of idle time.

These students should be noticed and guided to go back to the normal learning status. The algorithm to detect students locating in the *Idle* situation is defined as follows:

Algorithm 1: Abnormal Activity Checker for *Idle* Situation.
Input: The learning portfolio of the student.
Output: The *Idle* situation of the student.
S_s = the state of the student logins the learning system
T_s = the time that the student enters S_s
while the student studying in the learning system **do**

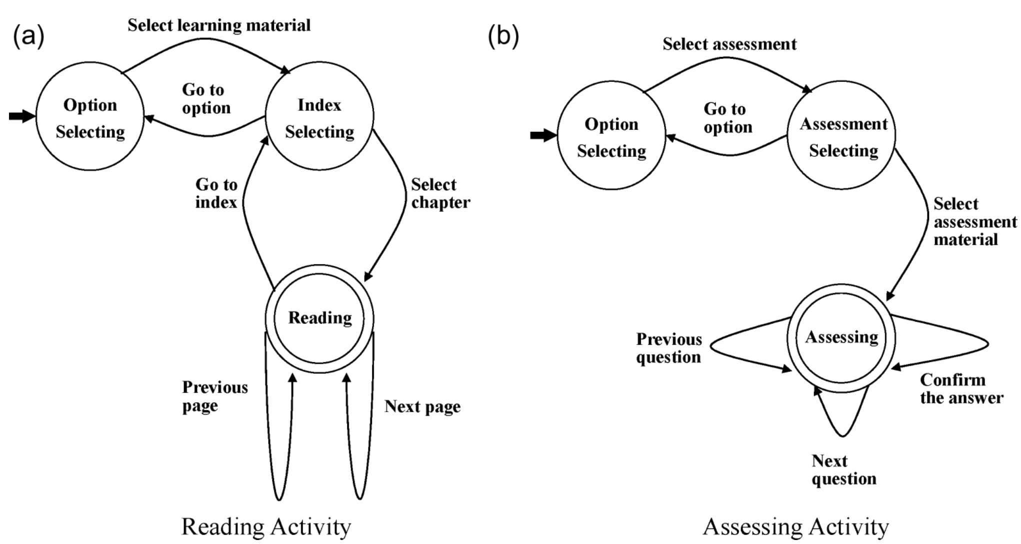

Figure 2 (**a**,**b**) The examples of learning activities.

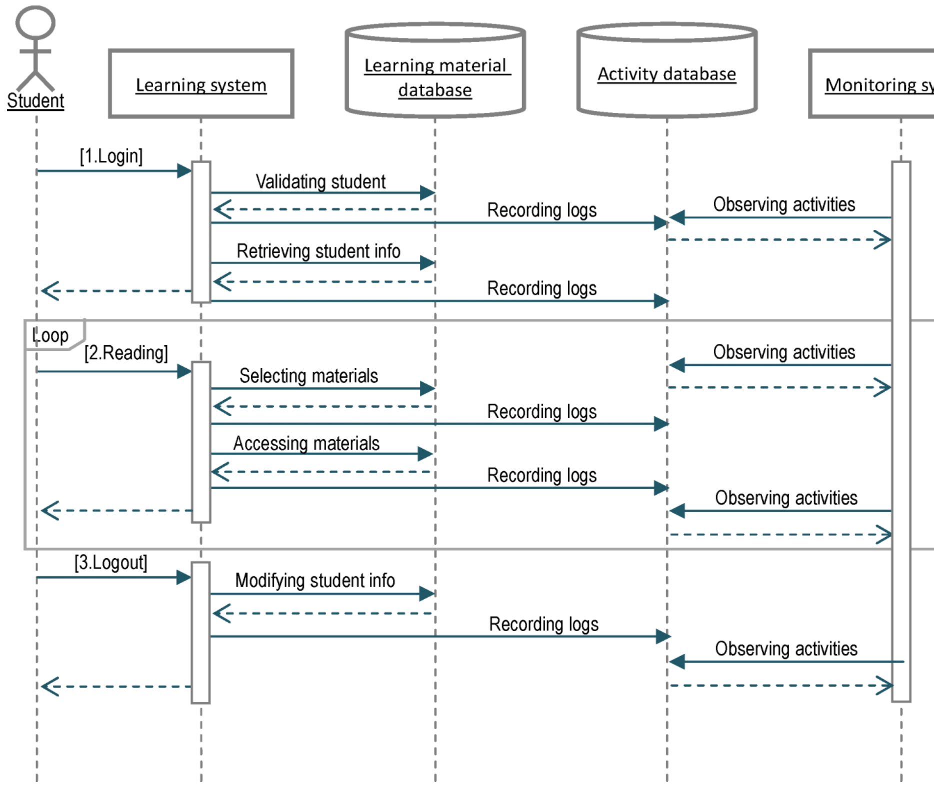

Figure 3 Sequence diagram of reading learning activities.

if T_r is expired then
S_c = the current state of the student
T_c = the current time
if $S_s = S_c$ then
if $T_c - T_s > \theta$ then
send the *Idle* alarm message
endif
else
$S_s = S_c$
T_s = the time that the student enters S_s
endif
endif
endwhile

Situation 2: The abnormal activity of *Rush* is when the student in the learning system and the frequency of transition among the states is greater than f_α, where f_α is the threshold of the system that determines if the student is rushing or not. $(T(k,i))/t_k{-}t_i$ is the frequency of transitions from the ith state to the kth state, and the kth state is the locating state of student. The term $T(k, i)$ denotes the number of transition times from the ith state to the kth state, and t_i and t_k are the times at which the student enters the ith and kth states, respectively. Different activities could have different thresholds for the frequency of transitions among states.

Algorithm 2: Abnormal Activity Checker for *Rush* Situation.
Input: The learning portfolio of the student.
Output: The *Rush* situation of the student.
while the student studying in the learning system **do**
if the student changes the learning state **then**
T_c = the current time
if Queue_T is full **then**
pop T_n from Queue_T
push T_c into Queue_T
if $\frac{T_c - T_n}{n} > f_\alpha$ **then**
send the *Rush* alarm message
endif
else
push T_c into Queue_T
endif
endif
endwhile

The proposed adaptive learning activity model can define the learning activities and conveniently design learning actions and learning states. Teachers can use one learning activity for several courses, and define the specified learning features for each course.

SYSTEM ARCHITECTURE

Figure 4 shows that the proposed system has both management and guiding phases. In the management phase, the teacher defines new learning activities or modifies the defined learning activities to obtain the desired learning objective. In the guiding phase, the teacher uses the activity recognizer to determine students' learning activities and prove appropriate and timely assistance.

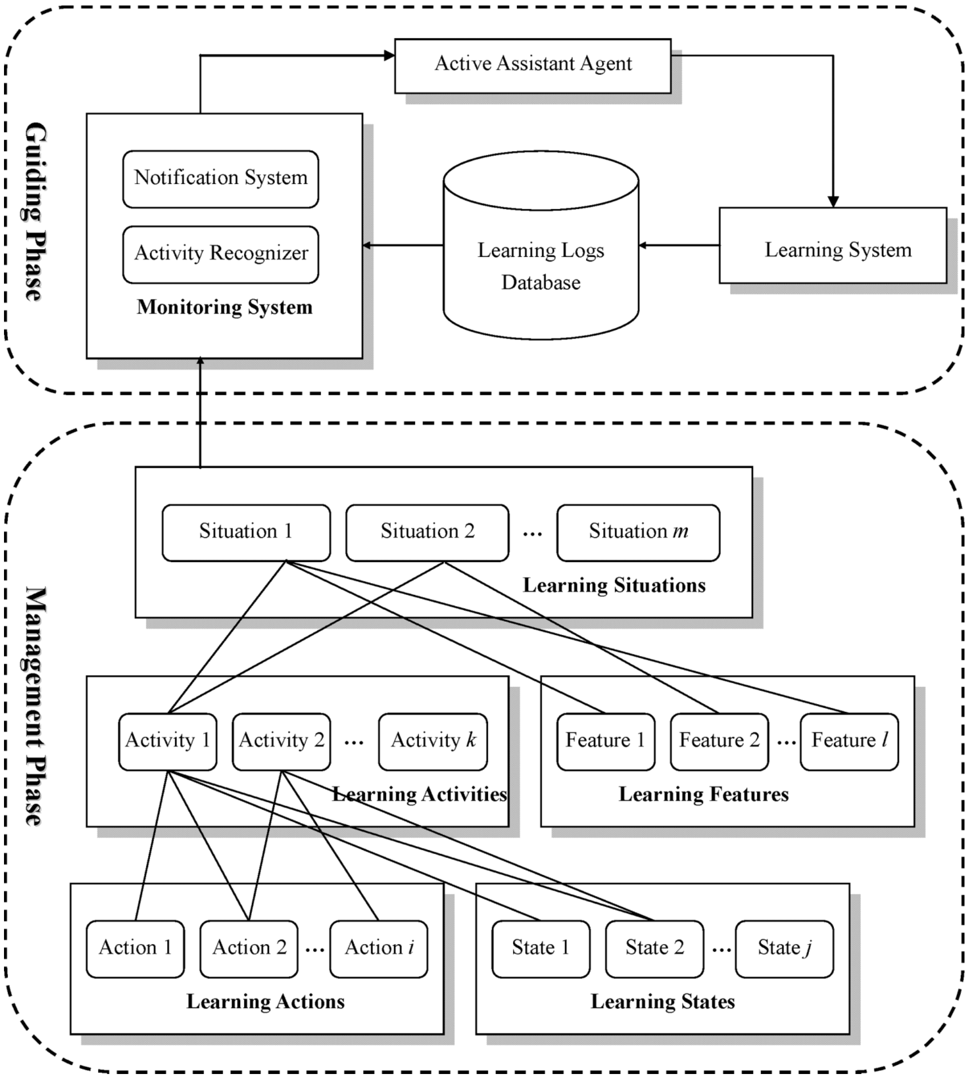

Figure 4 The system architecture.

Management Phase

Learning actions in the management phase include the event types that occurred when students studied the online learning materials. All the event types can be used to define the learning activities. The teachers defined the learning states. The learning activities in the proposed system adopted the definition of the DFA. The learning actions and learning states represented the edges and nodes of the DFA. The learning activities consisted of the learning actions and learning states. This made it possible to design normal learning activities to meet course requirements.

To increase the adaptability of learning activities, the learning features and learning activities together identify the status of students in the proposed system. The main function of learning features is to assign the scope of parameters for each situation, while the teacher determines the parameter divisions. Teachers can use one learning activity for several courses and define the specified learning features for each course. This learning activity model can not only recognize the learning activity states of students, but also record their learning progress. The defined learning activities and learning situations can detect and check whether a student is in the abnormal learning activity or not in the guidance phase. When the monitoring system detected a student is in the abnormal learning activity, it notified the active assistant agent and teachers to give appropriate assistance.

Guiding Phase

The guiding phase consists of the learning system, monitoring system, learning log database, and active assistant agent. The learning system is the learning platform, which allows students to access online learning materials. The learning log database stores all events that occur as students study the learning materials. The monitoring system analyzes this log information to determine student-learning activities.

The monitoring system consists of an activity recognizer and notification system. The activity recognizer analyzes a student's learning logs and determines which learning activity the student is performing. The teacher creates a learning activity that generates an activity recognizer. The learning log database provides the events that the activity recognizer uses to identify student activities. The notification system provides an interface allowing teachers to determine which students need assistance. The learning feature in the management phase defines the notification system policy. The learning system delivers the alarm messages to the students via the assistant agents, demonstrating that the abnormal learning activities occurred during the learning process. When the students received the alarm messages, they can immediately communicate with the assistant agent or ask the teachers for additional guidance. The proposed system automatically detects abnormal learning activities and provides active guidance for students.

The management phase allows teachers to define the learning activities that students will experience while using the online learning platform. The activity recognizer in the guiding phase uses the definitions in the management phase to analyze student-learning logs immediately. Using this notification system, teachers can guide students when they experience abnormal learning situations.

SYSTEM IMPLEMENTATION AND PROTOTYPE

The proposed system was implemented with PHP using Ajax scripts coupled with a MySQL database. The system consists of two parts, including a learning system and a management system. The learning materials were obtained from the Cisco networking academy. All the events that students studied using the online learning system were recorded in the database. The activity recognizers used these event logs to notify teachers of the states of their students. The main function of the management system is to provide an interface for teachers to define the learning activities and learning features, as Figure 5 shows. Definition 1 describes the learning activities of the proposed system. The learning activity management page allows teachers to create or modify the activities that they want to obtain in the class.

Figure 6 shows that the teacher defines the reading material activity used in this experiment. The teacher can add, delete, and modify the activity rules that they want for the class. The teacher can also identify the abnormal statuses of *Idle* and *Rush* with Algorithms 1 and 2, respectively. In the proposed system, the definition of θ in the *Idle* situation and the

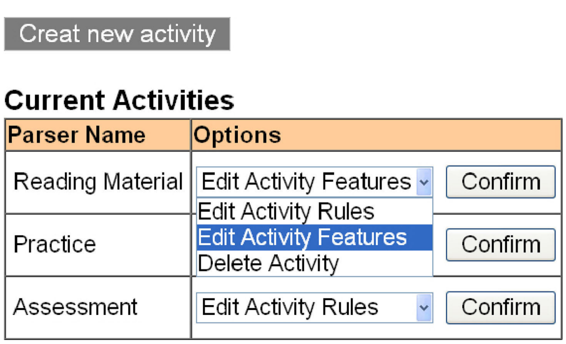

Figure 5 Create or edit the learning activities. [Color figure can be viewed in the online issue, which is available at wileyonlinelibrary.com.]

frequency of transition among the states in the *Rush* situation is as Figure 7 shows. In the experiment, θ is 3 min in the *Idle* situation. The threshold of frequency for students to switch Web pages is 10 pages in 5 min.

With the activity recognizer and the definition of learning feature, the proposed system provides a monitoring system that allows teachers to determine their students' learning states immediately. Teachers can assess student activities using the activity recognizer by identify if students are experiencing normal or abnormal activities. After teachers gather the information of the learning states for students, teachers can decide the appropriate policies to help these students. Teachers can provide guidance to the students who need help while studying the learning materials.

EVALUATION AND DISCUSSION

This study presents the results of experiments involving undergraduate students to demonstrate the feasibility and effectiveness of the proposed guidance system. This section describes and analyzes experimental results.

Experiment Environment

Experiments involving undergraduate students were conducted to test the feasibility and effectiveness of the proposed learning activity recognition system. The experimental subjects were undergraduate students from two computer networks classes. Fifty-seven and 58 students were assigned to the experimental and control groups, respectively. Students in the experimental group were required to study the learning materials 1 h before they took the test. In this experiment, students read the assigned learning materials. Students could press "Next Page," "Previous Page," or "Index" buttons to select learning materials. The teacher identified the abnormal statuses of *Idle* and *Rush* using Algorithms 1 and 2, respectively. Thus, the assistant agent and the teacher can obtain students' learning activities via the monitoring system. Thus, the assistant agent and the teacher can obtain students' learning activities via the monitoring system. If the assistant agent detected that students were experiencing abnormal learning situations, those students received basic guidance from the agent's alarm messages. The teacher provided advanced guidance to those students who needed further help via instant messages.

Data Collection

This experiment contained two phases of self-study for students: the pre-test and test phases. In the pre-test phase, students in both groups studied the learning materials without the teacher's guidance. Table 1 shows the grades for the pre-test phase. In the test phase, students in the control group continued to study the assigned learning materials without guidance from the teacher or teaching assistant. The teacher and teaching assistant provided active guidance for the students in the experimental group when students were online self-studying the learning materials. Table 2 shows the grades for the test phase. In the test phase, if a student exhibited an abnormal status, the teacher promptly provide the student with assistance.

Table 1 shows that the average score of the experimental group was 5.3 points higher than the average score of the control group during the pre-test phase. The standard deviation in

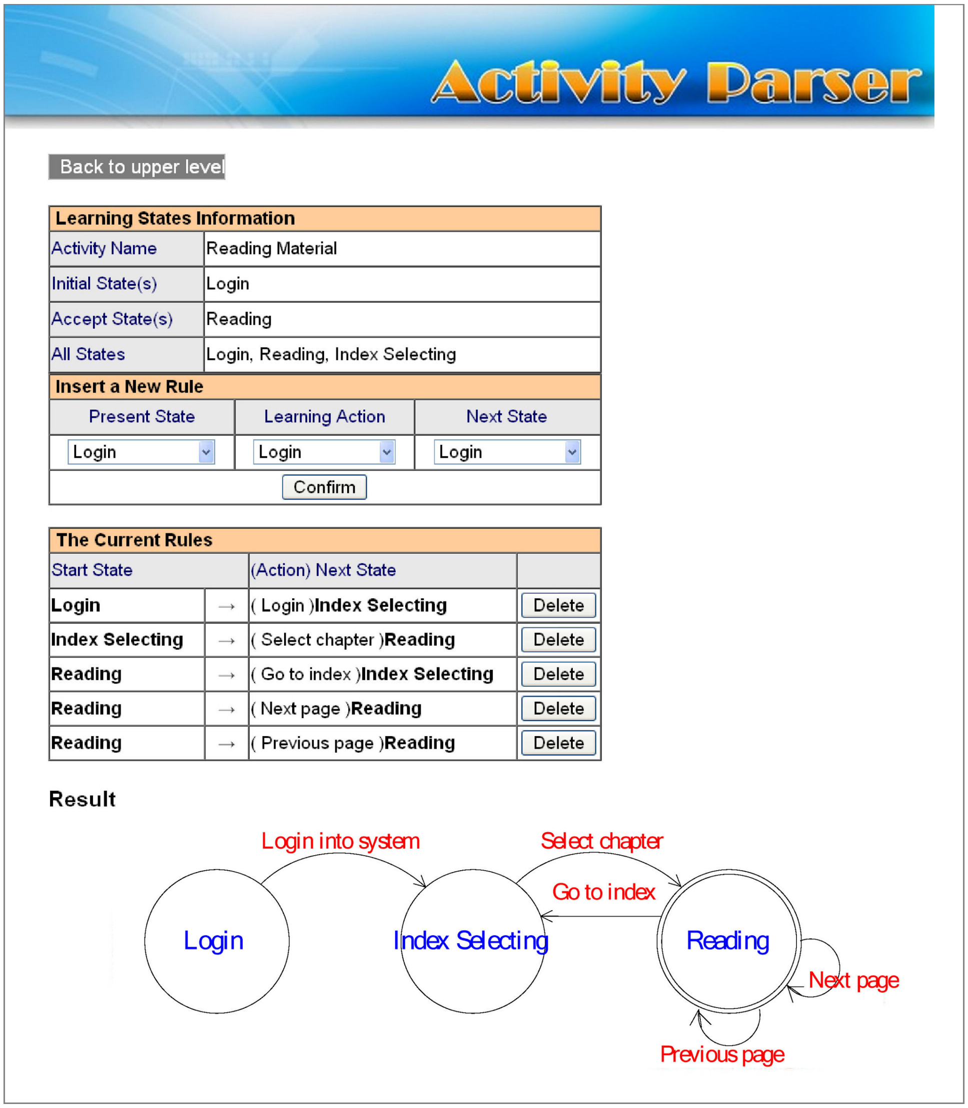

Figure 6 The snapshot of learning activity management page. [Color figure can be viewed in the online issue, which is available at wileyonlinelibrary.com.]

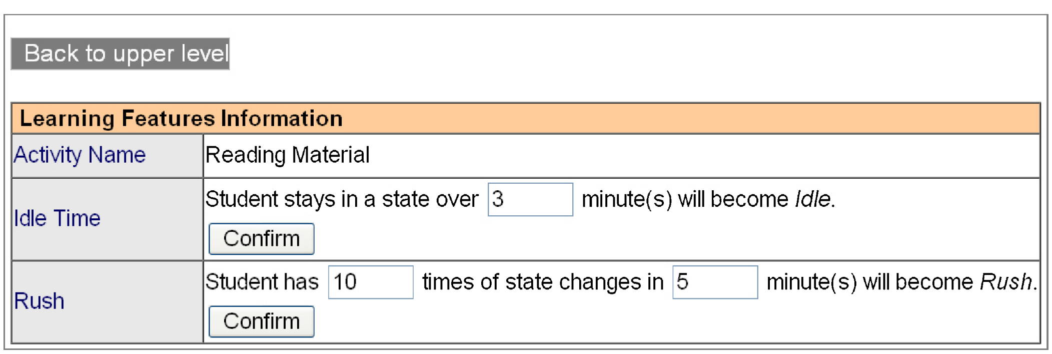

Figure 7 The learning features of reading material activity. [Color figure can be viewed in the online issue, which is available at wileyonlinelibrary.com.]

Table 1 The Grades of Pre-Test Phase

	Experimental group	Control group
Number of students	57	58
Average score	68.9	63.6
Standard deviation of score	14.7	14.0
Average number of idle times	6.0	5.5
Average number of rush times	2.5	2.0

the scores of the experimental group was higher than that of the control group. Students in the experimental group got the higher average numbers for the abnormal learning states of *Idle* and *Rush*. In the pre-test phase, however, students in the experimental group had grades similar to students in the control group.

Table 2 shows the grades of the test phase, during which students in the experimental group received guidance from the teacher and students in the control group did not. The average scores of the experimental group and control group improved 27.9% and 16.8% points from pre-test to test, respectively. As for the standard deviation in scores, the experimental group had the lower standard deviation during the test phase. The control group had almost the same standard deviation in scores during test phase and the pre-test phase. Besides, the frequency of abnormal learning state in the experimental group was lower than that in the control group. These experimental results show that the proposed real-time guidance system increased the learning efficiency and decreased the frequency of the abnormal learning state.

Discussion

The students in this experiment tried to familiarize themselves with the use of the online learning system during the pre-test phase. Therefore, they had a higher frequency of abnormal learning states in this phase. After using the online learning system several times, the students became accustomed to the online system. Both the experimental and control groups had better scores than the pre-test scores. Furthermore, the abnormal learning states of *Idle* and *Rush* decreased during the test phase. The improved average scores from the pre-test phase to the test phase for the experimental group and control group are 19.2 and 10.7, respectively. The experimental group receives increased scores and has the lower standard deviation of scores. The frequency of abnormal learning states of *Idle* and *Rush* in the experimental group decreased 26.7% and 68%, respectively. The frequency of abnormal learning states of *Idle* and *Rush* in the control group decreased 7.3% and 40%, respectively.

Table 2 The Grade of Test Phase for Experimental Group With Guiding

	Experimental group	Control group
Number of students	57	58
Average score	88.1	74.3
Standard deviation of score	12.2	14.1
Average number of idle times	4.4	5.1
Average number of rush times	0.8	1.2

Table 3 The Grade of Test for Students in Experimental Group

	Students	
	Advanced guiding	Basic guiding
Number of students	12	45
Average scores of pre-test	66.4	71.2
Average scores of test	88.0	88.1
Average number of idle times	5.0	3.6
Average number of rush times	1.5	0.8

Students in the experimental group knew that the teacher was monitoring them, which helped them pay attention on their learning. The monitoring system in the experimental group effectively decreased the abnormal learning states. In this experiment, only 12 students in the experimental group received advanced guidance from the teacher in the test phase. Table 3 shows the grades of the students in the experimental group. The students who were guided by the teacher had a higher frequency of abnormal learning states. After receiving advanced guidance, they improved their scores from the pre-test to the test grade. These experimental results show that the proposed monitoring system can improve the learning efficiency of all students even if the teacher only provides advanced guidance to some of them.

Figure 8 presents the distributions of the scores in the control group, showing no obvious differences in the distribution trend between the pre-test and test phases. The distributions of scores shifted to higher grades from the pre-test to the test. Without real-time guidance from the teacher, the proposed system cannot effectively improve student-learning outcomes.

Figure 9 presents the distributions of the scores in the experimental group, showing an obvious difference in the pre-test and test distribution of scores. The grades of the experimental group not only exhibit an increasing trend from the pre-test to the test, but also show that most of the students got scores higher than 90. This is because some students could not concentrate on the learning without teacher monitoring. Some students also had a passive attitude toward learning. Thus, it is important for teachers to pay attention to students when students are learning. The experiment in this study shows that the proposed system helps teachers monitor students' learning states and provide timely guidance.

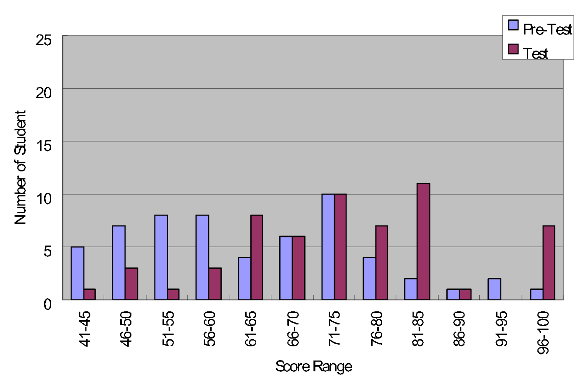

Figure 8 The distributions of the scores in the control group. [Color figure can be viewed in the online issue, which is available at wileyonlinelibrary.com.]

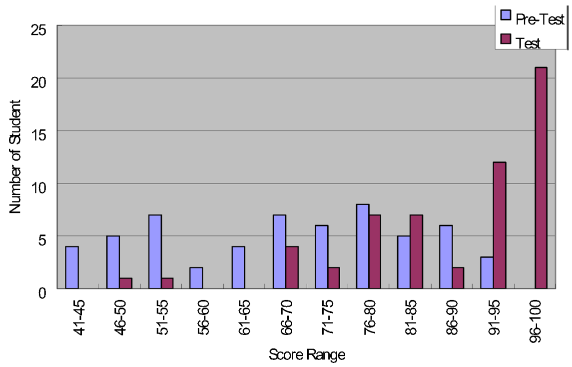

Figure 9 The distributions of the scores in the experimental group. [Color figure can be viewed in the online issue, which is available at wileyonlinelibrary.com.]

CONCLUSIONS

The learning process requires teachers to spend time assessing the learning states of their students. Some students are passive in the learning process. If teachers want to identify which students need assistance, then they must devote more time and attention to monitoring and observing the students' learning activities. This study proposes a monitoring system that helps teachers define the activities they want to conduct in the class. The proposed system can automatically generate an activity recognizer based on the activities defined by teachers. Teachers can specify the learning features for each learning activity. Using the proposed activity recognizers, teachers can monitor the real-time learning activities of their students. The system detects students who need assistance, allowing teachers to provide the appropriate assistance to the students immediately. The teachers can reuse activity definitions for different courses. The activity recognizer automatically adjusts itself based on the teacher's modified activity definitions.

Experimental results indicate that students earned better grades when their teachers provided them with guidance using the proposed system. When students knew that the teacher was monitoring them through the system, they were better able to concentrate on the learning materials. The amount of abnormal learning activities in the experimental group decreased significantly. Only a few students received advanced guidance from the teacher. Future research will attempt to improve the guiding ability of the active assistant agent, allowing it to provide advanced guidance for all students.

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