Development and Evaluation of an Active Learning Support System for Context-Aware Ubiquitous Learning

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Abstract—Situating students to learn from the real world has been recognized as an important and challenging issue. However, in a real-world learning environment, there are usually many physical constraints that affect the learning performance of students, such as the total learning time, the limitation of the number of students who can visit a learning target, and the time needed for moving from one learning location to another. It is essential to guide the students along an efficient learning path to maximize their learning performance according to the current situation. In this paper, an active learning support system (ALESS) for context-aware ubiquitous learning environments is designed and developed. ALESS can provide learning guidance when conducting ubiquitous learning activities. A great deal of context information is used in ALESS, including the location, the current capacity of the learning object, the time available, etc. ALESS is able to actively provide the required learning support to individual students when they approach the corresponding real-world learning targets. To evaluate the performance of ALESS, an experiment was conducted in the National Science Museum of Taiwan. The experimental results showed that, with the help of ALESS, the students learned more efficiently, and achieved better learning performance.

Index Terms—Context-aware ubiquitous learning, learning support system, location-awareness, path optimization, mobile and personal devices

1 Introduction

With the rapid growth in information, how to make learning processes more efficient and convenient has become an important issue. A new learning scenario called context-aware ubiquitous learning has been proposed. Context-aware ubiquitous learning (u-learning) or computer supported ubiquitous learning is defined as a technology-enhanced learning environment supported by ubiquitous computing such as mobile devices, and RFID. In such a scenario, students can learn in any place at any time [1], [2]. Moreover, they are situated in a real-world learning environment with supports from the digital world via mobile, wireless communication and sensing technologies; that is, the students' learning behaviors in the real world can be detected and recorded in the learning system. Mobile devices are very well suited for informal learning scenarios. Due to their small size and high portability, they can be used outside the classroom, e.g., in museums or other informal settings [3], [4], [5].

Several researchers have demonstrated the benefits of context-aware ubiquitous learning for helping students improve their problem-solving ability in the real world [6], [7], [8], [9], [10], [11]. For example, Hwang et al. [12] reported the effectiveness of using Mindtools, such as concept mapping tools, for helping students organize knowledge in context-aware u-learning activities. The experimental results depict that the approach not only promotes learning motivation, but also improves the learning achievements of individual students.

On the other hand, researchers have also identified a common problem which differs from the problems of traditional web-based learning environments; that is, how to provide an appropriate learning path for individual students in the real world [13]. Although several learning path optimization algorithms have been proposed in the literature, most of them only focus on finding a fixed navigation sequence for learners where neither the real-time situation nor the learners' learning behavior is taken into account; that is, they merely provide *a fixed learning path* for all of the learners without considering personal or environmental constraints [13], [14], [15], [16], [17], which might significantly affect students' learning performance. For example, when conducting learning activities without a dynamic guiding mechanism, the learners will be guided to the same learning target simultaneously, resulting in poor learning performance. Thus, it is necessary to provide them with adequate guidance to visit a learning target at the proper time, such that the learning quality for each learning target can be improved.

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Many of the previously proposed systems have employed radio-frequency identification (RFID) tags or quick response code (QR-codes) to obtain location information, but other aspects of the environmental parameters are generally ignored. Moreover, these systems only used passive sensing technologies, such as RFID tags and QR-codes, for identifying the learning targets; that is, the learners still needed to find the specified tags by themselves and then scan the tags at close range. Sometimes, however, it is difficult for learners to find the tags and hence their learning efficiency would be affected or some learning tasks may be bypassed. In order to consider more contextual information and help users identify the learning targets efficiently, we have proposed a navigation mechanism, MONS [18]. In this study, several contextual factors are used in MONS such as the capacity and importance of the learning target, the distance between each learning target, the time needed to complete the learning task, and the concepts related to individual targets. Although the simulation shows that MONS can improve the learning efficacy of learners, the efficiency and effectiveness of the proposed mechanisms have not yet been verified in field experiments.

The objective of this paper is therefore to implement the active RFID technology learning support system, ALESS, and to verify the MONS navigation mechanism. In contrast to the existing context-aware ubiquitous learning systems that usually use passive location-aware technologies such as passive RFID and QR code, active location-aware technology is employed in the developed system for providing instant supports based on the individual learners' real-time status.

Vavoula et al. mentioned that museum visits can offer rich learning experiences facilitated by authentic objects and can be a place to learn across curriculum topic areas in an engaging environment [19]. Many museums are increasingly focused on creating more engaging visitor experiences by using mobile devices and encouraging participation in dialogue and social interaction in the exhibition space. Therefore, Stock et al. also indicated that most visitors come to a museum with limited time available and want to find information related to their area of interest. In such a scenario, where there is an overload of information to be delivered in a relatively short time, technology may play a crucial role in supporting museum visitors and enhancing the overall visit experience [20], [21].

Hence, we chose museum visiting as our experiment scenario. This visiting is also a part of the formal curriculum of the nature science course in the selected school. A large-scale field experiment with ALESS has been conducted in the National Museum of Natural Science located in the center of Taiwan to evaluate the performance of the developed system. The learning activity is concerned with the "Rocks and Fossils" unit of natural science exploration. A total of 46 elementary school students recruited from the fifth grade of a local elementary school participated in the experiment. A posttest was applied to verify the learning effectiveness and efficiency of the activity. We also administered a user satisfaction questionnaire to investigate the students' satisfaction with the developed system and their learning experience. The evaluation results of the field experiment show that, with the help of the active learning support system, the students learned more efficiently and achieved better learning performance.

2 Relevant Works

In a context-aware ubiquitous learning environment, the learning targets are the authentic learning resources around us. In such a learning scenario, the curriculum sequencing can be treated as the visiting order, and is called the learning path of the learning targets [18]. In order to provide the learning path to the learners both properly and actively, several factors should be considered. Because it is difficult for the learners to determine what to visit without any guidance, a navigation mechanism is necessary in a ubiquitous learning environment. On the other hand, the sensing technology should also be applied to achieve the requirements of navigation support [11], [18], [22].

2.1 Navigation Support Mechanisms in a Ubiquitous Learning Environment

The adaptive navigation support problem has been widely discussed, no matter whether in e-learning or u-learning scenarios [23], [24]. Many studies have attempted to apply optimization techniques to identify the optimal learning path [23]. For example, Chen [25] developed a genetic-based personalized e-learning system, which can generate appropriate learning paths according to the incorrect testing responses of an individual learner in a pre-test. The proposed genetic-based personalized e-learning system considers the courseware difficulty level and the concept continuity of learning paths to conduct personalized curriculum sequencing. Fazlollahtabar and Iraj proposed a neuro-fuzzy approach to obtaining an optimal learning path for both instructor and learner [26]. The neuro-fuzzy model allows the creation of knowledge-based decision making, which can be developed on the basis of rules. Salehi et al. [27] applied a learner preference tree (LPT) and genetic algorithm (GA) to deliver suitable learning resources to learners.

When the diagram shifts to a ubiquitous learning environment, more constraints should be considered. Researchers have paid considerable attention to solving the navigation problems in authentic learning environments [10], [13], [18], [28]. Because there are more criteria to be considered in the authentic world, the navigation problem of context-aware u-learning becomes even more difficult than that of a web-based learning environment. In such a case, several approaches have been proposed. For example, Hwang et al. [28] proposed a decision-tree-oriented guidance mechanism for conducting natural science observation activities in context-aware ubiquitous learning. They found that representing knowledge with a decision tree is more suitable than the approaches of neural networks, Bayesian networks, or rule-based engines. Oppermann and Specht proposed a prototype of the nomadic guide Hippie [29], [30], which can be used during a visit to a museum. Hippie consists of three models: the domain model, the space model and the user model, to identify the context of use. The prototype has also been implemented and tested in an art gallery, where the results of evaluations with art experts and real visitors have been encouraging.

However, most of these approaches only determine a fixed learning path for all of the students, without considering the environmental context. In this situation, learners will be guided along the same learning path, such that only a few learners who arrive at the learning targets faster than others have the chance to observe them closely. Moreover, some students might spend more time observing a learning target or moving from one location to another than expected, which would make the previous optimization plan fail. Therefore, the adaptive navigation support problem for u-learning is challenging since it is not only an optimization problem, but also a real-time guidance problem. As Traxler [31] indicated, content can be more context-aware, authentic, and situated in the surroundings where the learning is more meaningful to the learner in the mobile learning.

To cope with this real-time guidance problem, Chiou et al. [18] have proposed an adaptive navigation support mechanism. They considered more contextual information of real-time situations to determine the best navigation path for learning activities. Hence, an adaptive navigation algorithm call MONS (the Maximized Objective Navigation Support algorithm) was proposed. Three kinds of contextual parameters are considered, that is environment-related parameters (including the moving time to the next learning targets, total time limitation, etc.), target-related parameters (including the capacity limitation, the current population density of each learning target, the learning profit and the learning time), and student-related parameters (total consumed learning time). In the MONS algorithm, an objective function was employed for determining the score of each learning target. The objective of MONS was to immediately provide the learning targets with high importance to the learning goal and less learning time, moving time and population density to form a current optimal learning efficacy model for students. The simulation results showed that the proposed mechanism could improve the learning efficiency of students, and outperformed other approaches. However, the effectiveness of the algorithm was not verified by analyzing real data.

2.2 Sensing Technology in Ubiquitous Learning

In order to implement ubiquitous learning platforms, many researchers have employed sensor technologies to acquire context information. Cameras, microphones, accelerometers, gyroscopes, GPS, temperature, light, humidity and pressure sensors, orientation sensors, magnetic sensors and clocks are often used during the learning activities [32], [33]. The quick response code, RFID [12], [13], [34], NFC (near field communication) [37] and GPS senor technologies are usually used for acquiring location information [35].

For example, Hsu et al. [8] used RFID to construct a smart ubiquitous learning environment. They found that the average attitude scores for the experimental group were higher than those of the control group. Hwang et al. [13] proposed a heuristic algorithm to identify the optimal learning path for context-aware u-learning. The relevance of the real-world learning targets and the number of students who visit the same learning targets are taken into consideration. They have attempted to identify and guide a proper learning path for individual learners by employing passive RFID techniques for the learning activities. For example, Chen and Huang [10] proposed a context-aware ubiquitous learning system (CAULS) based on radio-frequency identification. CAULS can guide each student to learn further based on their responses to the pre-designed questions. If they answer the questions correctly, they will be guided to learn the next unit.

Lai et al. [36] employed QR codes to develop an Integrated QR code learning system. The elementary teachers who participated in the experiment expressed significant interest in using the system to conduct outdoor educational activities. The results showed that the integrated QR code learning system is highly acceptable for teaching. The results also showed that using the RFID mechanism to construct the learning activities can help promote better student learning attitudes. Giemza et al. developed a tool called Mobilogue (“MOBIle LOcation GUidancE”) [3] which supports educators and students in authoring and deploying learning support with location awareness and guidance to mobile devices. QR codes are applied to obtain the location information. The guided trips are based on locations and provide information about the particular locations, plus optionally a quiz and/or multimedia data. A recommendation for a next location is also provided.

Moreover, Lee and Kuo [37] proposed an NFC u-learning platform with four interactive teaching scenarios, dynamic grouping, creative scenario-based learning, interactive examination, and gradual learning. NFC reader mode, P2P mode and wireless communication (Wi-Fi, Bluetooth) technologies were applied in the design of the ubiquitous learning.

Li et al. [38] developed a system called SCROLL (system for capturing and reminding of learning log). They attempted to integrate the functions embedded in smart phones, such as photos, audios, videos, location, QR-code, RFID tags, and sensor data to log learners’ learning experiences. They found that SCROLL is helpful for most learners to record and review their learning logs [39].

Although the experiments of the above research show the effectiveness of their approaches, the researchers also found that the interactions between the learning system and the students became another burden. The students needed to find out the exact location of the RFID tags or QR Codes and then use the RFID reader, QR Code scanner or NFC detector to read the corresponding tags for each move. Sometimes, learners waste time finding the identifiers, which, although not related to the learning activities, has become a burden for users.

By reviewing these previous studies, it was found that researchers have paid considerable attention to navigation problems. However, only a few systems have been developed to incorporate a navigation support mechanism which provides active location-aware support, not to mention considering the capacity and importance of the learning target, the distance between each learning target, the time needed to complete the learning tasks, and the concepts related to individual targets. Although MONS has considered several contextual factors, and the simulations show that it outperforms the GA-based algorithm and is more suitable for dynamic learning environments [18], the effectiveness of the algorithm was not verified by analyzing real data. Field experiments which evaluate the effectiveness of navigation

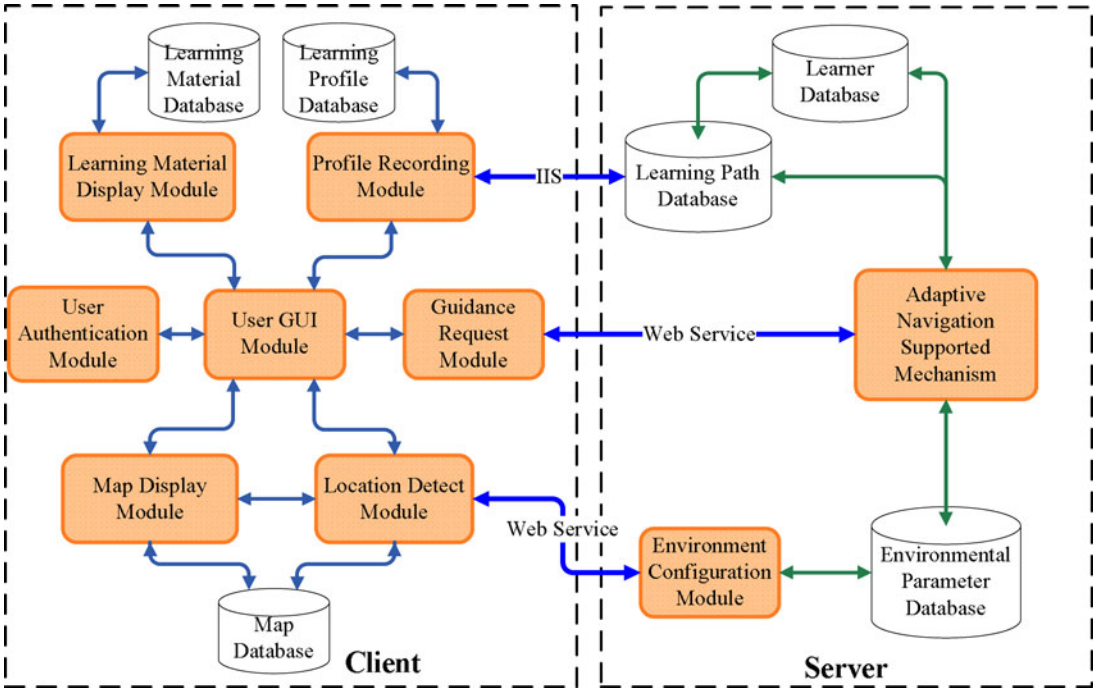

Fig. 1. Illustration of ALESS.

support mechanisms are also lacking. Hence, we implemented MONS in our proposed system and verified it in the field experiment.

3 Implementation of the Context-Aware Navigation Support System

In this paper, a context-aware ubiquitous learning system, ALESS, is developed for guiding students to learn in the real world. In contrast with existing context-aware ubiquitous learning systems that usually use passive location-aware technologies, active location-aware technology is employed in the developed system for more real-time supports. The signal strength of the RFID tags is used to determine the distance between the learners and learning targets. The learning materials can also be retrieved intuitively by approaching the learning targets rather than needing to find the passive RFID tags.

3.1 ALESS Development Environment and System Framework

The development systems and tools for implementing ALESS are separated into server-end and client-end. At the sever-end, a PC with Intel Core2 CPU 2.00 GHz, 2 GB memory, Windows Server 2003 and Microsoft SQL Server 2005 was adopted. The programming environment is Microsoft Visual Studio 2008 C# 3.0. At the client-end, we employed HP iPAQ 212 Enterprise Handheld with Windows Mobile 6 Classic and SQL Server Compact 3.5.

The school where we conducted the in-field experiment is located near the National Museum of Natural Science. The museum visit is a part of the existing curriculum of this school and the available mobile devices in the school are a set of PDAs. Although PDAs are now outdated and have been replaced by smart phones and tablet computers, we still used the PDAs as our development platform to reflect the real situation of the selected school. Moreover, smartphones and Pads do not provide active RFID reader modules, so we used PDAs as our platform base to obtain more detailed contextual information. The mechanism can also be migrated to smartphones and Pads with the Bluetooth solution in the future.

The framework of the system is shown in Fig. 1. ALESS consists of two parts, the server-end and the client-end. The server-end responds to record the environment context and determine the learning paths. The client-end responds to send out the location information and handle requests from learners and the server.

On the server side, there are two modules and three databases. When the system is set up, the *Environment Configuration Module* retrieves the environmental context from the *Environmental Parameter Database*. The information about the learning targets, such as the expected learning profit, the capacity limitations and the expected learning time is loaded according to the learning unit. The number of learning targets, the moving cost of each path between the learning targets and the total time limitation of the learning activity is configured. The learners' location information as well as the current number of visitors at each learning target is also updated by the *Environment Configuration Module*. The environmental context is recorded in the *Environmental Parameter Database*. After learners log into the system, a guidance request is sent to the server-end. The *Adaptive Navigation Support Mechanism* handles the request and calls the MONS Algorithm Module to determine the best learning path. The selected path is recorded in the *Learning Path Database*. All the unvisited learning targets are determined by a fitness function. The fitness function is shown in the following:

$$Score(i,j) = \frac{G_j \cdot ln[S - R_j + 1]}{MT_{i,j} + T_j}, \quad (1)$$

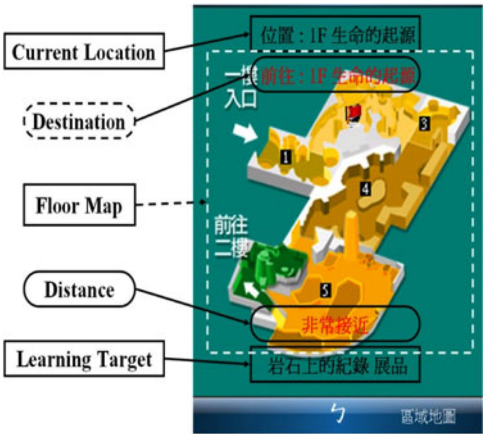

Fig. 2. The navigation information provided in ALESS.

where i represents the index of the current learning target (C_i), and j represents the index of the next learning target (C_j). In this function, a higher score implies that the learning target has higher importance, higher availability and less learning burden. The other notations are listed as follows:

$MT_{i,j}$: Expected time for moving from C_i to C_j
S: Acceptable Saturation ratio, where saturation ratio means the ratio between the maximum allowable number of learners and the capacity.
G_j: The expected learning profit of the learning target C_j (i.e., the importance of C_j to the learning goal), which is designated by the instructor in advance.
T_j: Expected time for learning C_j.
R_j: Current Saturation ratio of C_j

On the client side, there are seven modules and three databases. When the learning process starts, the *User Authentication Module* identifies if the student is valid. Then the *RFID Sensor Module* starts to sense the location of active RFID tags, and the location of the student is determined by the *Location Detect Module* according to the *Map Database*. The map is then provided to the student with the location of the student marked on it by the User GUI Module. The *Guidance Request Module* is called when the system detects that the student is leaving the current location to provide the next suggested learning object to the student. When the system detects that the student is near a specific learning target, the *Information Displaying Module* actively provides the student with the teaching material related to the target. During the learning process, the *Profile Recording Module* records every move of individual students in the *Learning Profile Database.* It is also a kind of non-intrusive observation [5], whereby the behaviors of the visitors in the physical space regarding their models of interest are recorded for future analysis.

3.2 ALESS Interface

In ALESS, two navigation modes are implemented. One is navigation without learning guidance and the other is navigation with learning guidance. In both modes, the *floor map* of the learning scenario is displayed on the student's handheld device. Some information is also provided, including *current location*, *destination*, nearest *learning target* and the *distance* to the learning target. The *destination* information is only provided in the learning guidance mode. The ALESS interface is shown in Fig. 2.

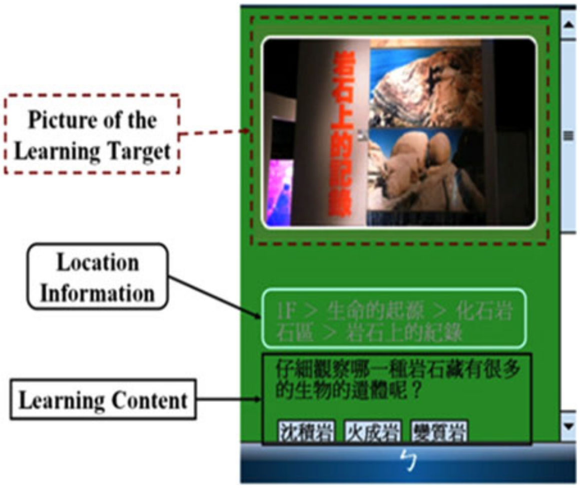

Fig. 3. The detailed content of the learning target.

In the first mode (u-learning without navigation support), the goal of the learning activity, the floor maps and the learning content are provided to the students. During the u-learning activity, the RFID reader on the PDA receives the signals from the active RFID tags; accordingly, the locations of the suggested learning targets are presented on the floor map. If the students' locations are close enough to some learning targets, the learning system will present them with the corresponding learning tasks as well as the supplementary learning materials, which can be found on the Computer Society Digital Library at http://doi.ieeecomputersociety.org/10.1109/TLT.2015.2439683, as shown in Fig. 3. When the students complete the learning tasks of one learning target, they can determine the next target based on their interest or on the information on the floor map.

In the second mode (u-learning with navigation support), not only the learning goal and floor maps, but also the navigation guidance are provided. When the students complete the tasks for a specific learning target, the system will analyze the current contextual information (including distance, importance to the goal, etc.) of each candidate learning target and recommend the next target to them, as shown in Fig. 4.

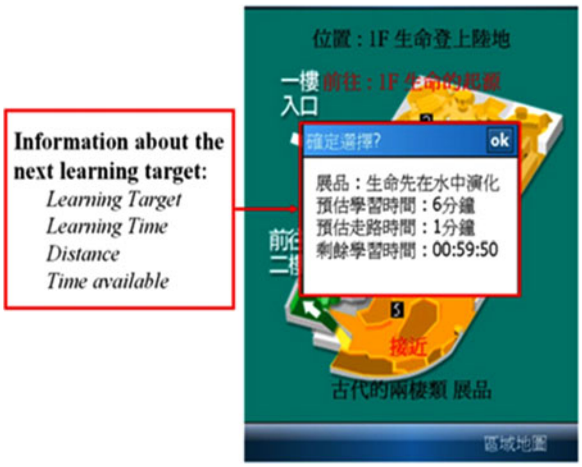

Fig. 4. Navigation guidance to the next learning target.

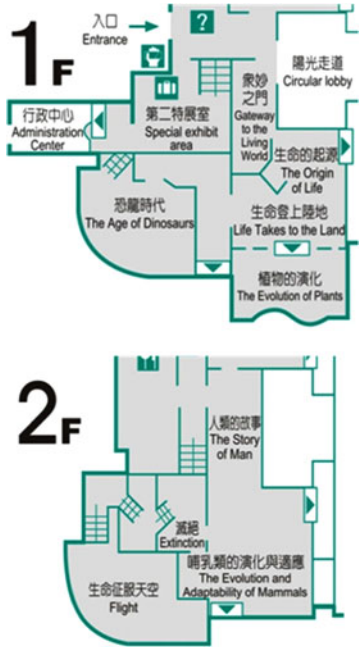

Fig. 5. The location of the rocks and fossils course.

4 Experiment Design

Fig. 5. The location of the rocks and fossils course In order to evaluate the performance of the MONS navigation mechanism, a learning activity was conducted in the National Museum of Natural Science in central Taiwan. This learning activity was concerned with the "Rocks and Fossils" unit of an elementary school natural science course. The in-field activity conducted in the museum was part of the existing curriculum of the selected school. Hence, in order to cater to the requirements of the school, our evaluation focuses on the rationale of schools.

4.1 Participants

A total of 46 elementary school students with an average age of 11.8 years participated in the experiment, including 27 males and 19 females. These students all had previous experience of using PDA devices for ubiquitous learning. The students were divided into two groups, Group A and Group B. Students in Group A used ALESS with no learning guidance. They only received the information about the location and learning targets. Students in Group B used ALESS with the learning guidance. When they left one learning target, they received further instructions about the next one.

4.2 Learning Environment Configuration

The experiment was conducted in the National Museum of Natural Science which is one of the most heavily attended museums in Taiwan. Over 30 permanent exhibit areas cover subjects on astronomy, space science, paleontology, ecology, gems and minerals, Taiwanese Aboriginals, and tropical plants. The Museum is also a major science learning center with over half a million school children visiting annually.

Within the learning activity, students learn about the classification and the formation of rocks and fossils. The learning targets used in the course are scattered across floors 1 and 2; a detailed exhibit map is shown in Fig. 5.

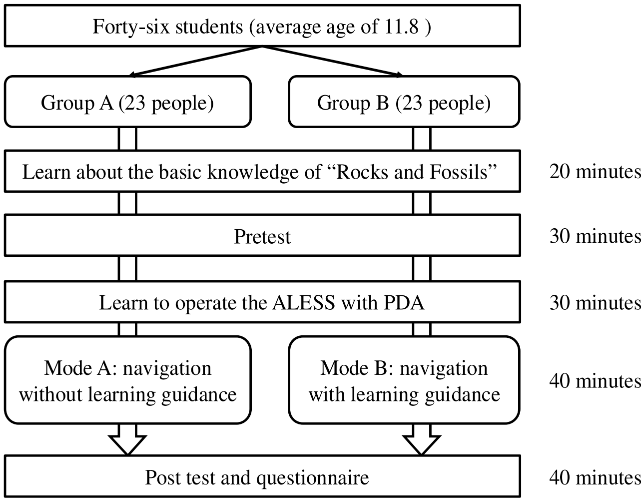

Fig. 6. The experiment flowchart.

Fig. 5. The location of the rocks and fossils course before the experiment, active RFID tags were placed at the corresponding learning targets, and the configuration of the learning environment was completed. The functionality of the navigation system was also verified. The students were trained to use the navigation system in advance.

4.3 Experimental Procedure

The experiment flowchart is shown in Fig. 6. The 46 students were divided into Group A (ALESS with no learning guidance) and Group B (ALESS with learning guidance). Both groups learned the basic knowledge of Rocks and Fossils for 20 minutes in the classroom. After that, a pretest was given to confirm that the prior knowledge of the two groups was equal. The system developer taught the students how to operate ALESS, and then a learning activity was conducted in the museum. The two groups of students learned the learning content using ALESS with the corresponding settings for 40 minutes. After the activity, a post test and a questionnaire were given to measure the difference between the two groups. The experiment scene is shown in Fig. 7.

In order to verify whether or not the navigation guidance can promote learning achievement and efficiency, the students were assigned to one of two groups. Group A used ALESS with no learning guidance. They only received the information about the location and learning targets. Group B used ALESS with the learning guidance. When they left a

Fig. 7. The experiment scenarios.

TABLE 1
T-Test Analysis of the Pre-Test Scores of Two Groups

Group	N	Mean	S.D.	t-vale
A	23	61.30	16.32	0.07
B	23	60.87	23.14	

learning target, they received further instructions about the next learning target. The navigation flow of the two groups is shown in Fig. 8.

4.4 Learning Achievement Analysis

In this section, we discuss the influence of the learning guidance on learning achievement. In order to confirm the knowledge level of the two learning groups, a pre-test of the students' prior knowledge was conducted. The results of the analysis are shown in Table 1, from which it can be seen that there was no significant difference between the two groups ($p = 0.942 > 0.05$).

Since the pre-test knowledge levels of groups A and B were statistically equivalent, a post-test was employed to identify the difference between the two groups after conducting the learning activity. A short course on "Rocks and Fossils" was designed for the students to conduct ubiquitous learning in the museum. The learning time for the students was limited to 40 minutes.

In order to trace the influence of the learning guidance, we observed the learning profiles at several points in time, namely 10, 15, 20 and 40 minutes. The score of the post-test was also calculated with the learning path of the learners' profiles. For example, if a learner visited learning targets A and B in 15 minutes, the score invoked in A and B was accumulated. Note that if this learner failed the question invoked in A and B, the score was not accumulated. The t-test analysis of the post test at the four points in time is listed in Table 2.

First, we observe the result at the 10 minute point. From Table 2, we can find that the p-value between groups A and B at the 10 minute point is 0.018 (<0.05), implying that significant difference exists between the two groups. As the mean value of group B is larger than that of group A, it is concluded that the navigation guidance is helpful to the students in terms of enhancing their learning achievement. When the observation period extends to 15 and 20 minutes, the difference between groups A and B is even more significant than at 10 minutes.

TABLE 2
t-Test Analysis of the Post-Test Scores of the Two Groups

Time (minute)	Group	N	Mean	S.D.	t-vale
10	A	23	27.13	14.01	-2.47^{*}
	B	23	37.22	13.72	
15	A	23	42.78	10.68	-2.84^{**}
	B	23	54.09	15.86	
20	A	23	47.65	10.51	-2.81^{**}
	B	23	58.61	15.47	
40	A	23	59.13	12.06	−0.76
	B	23	62.26	15.62	

$^{*}p < 0.05$, $^{**}p < 0.01$

TABLE 3
Summary of Survey Results from 46 Students (5-Point Likert Scale)

	Items	Mean
1	The ALESS functions are easy to use.	4.46
2	The ALESS user interface is friendly.	4.30
3	Using ALESS keeps me from wandering.	4.00
4	Using ALESS to tour the museum makes my touring smoother and saves time.	4.17
5	I like the navigation style provided by ALESS during the museum touring.	4.52
6	The ALESS learning material increases the interaction with the exhibits.	4.29
7	The ALESS learning material improves the efficacy of learning about the exhibits.	4.43
8	Overall, I enjoy the touring and feel satisfied.	4.36
9	Overall, I think ALESS helps me learn better.	4.29
10	I would like to use ALESS to tour the museum in the future.	4.52

4.5 Learning Efficiency Analysis

Besides the achievement analysis, we also examined the influence of the learning guidance on learning efficiency. Learning efficiency is defined here as the time spent to complete the whole learning activity. From Table 3, we can find that the p-value between groups A and B is less than 0.001, meaning that there exists a significant difference between the two groups. Therefore, the average learning time of group B is shorter than that of group A. Hence, we can say that the learning guidance is helpful in terms of enhancing the students' learning efficiency.

4.6 Results of the User Satisfaction Questionnaire

After conducting the experiment, a survey was administered to the 46 students. The survey was a questionnaire with a five-point Likert-scale, where 1 represents "strongly disagree" and 5 represents "strongly agree". There are 10 items in the survey, designed to collect data regarding the satisfaction of the students who used our learning system. Table 4 lists the 10 items and the survey results. Items 1 to 4 are focused on the students' satisfaction with the developed system, while items 5 to 10 are focused on their learning experience. The average ranking is greater than 4 (agree), meaning that most of the students felt satisfied with the system.

The responses to items 1 and 2 indicate that most of the students think that ALESS is easy to use ($m = 4.46$) and user friendly ($m = 4.30$). The responses to items 3 and 4 indicate that the system can keep students from wandering ($m = 4$) and makes the navigation process more efficient ($m = 4.17$). The responses to item 5 indicate that most students like the navigation style of ALESS ($m = 4.52$), with the average ranking the highest among all items. The responses to items 6 and 7 indicate that the ALESS learning material can increase the interaction ($m = 4.29$) and the understanding of the exhibits ($m = 4.43$). The responses to items 8 and 9 indicate that most of the students were satisfied with the new touring experience ($m = 4.36$) and they also think that ALESS can improve their learning ($m = 4.29$). The responses to item 10 indicate that most students would like to use ALESS for future museum touring ($m = 4.52$).

5 Discussion and Conclusions

In this study, an adaptive navigation supported learning system, ALESS, was developed to guide students to learn in real-world environments by taking the environmental constraints into account. Differing from other ubiquitous learning systems, active RFID technology was applied. Learners can interact with the learning targets without finding the identifier tags first. Meanwhile, more contextual information is provided such as the capacity and importance of the learning target, the distance between each learning target, the time on task, the content learned, etc. An experiment was conducted in an museum, and the results show that most participants felt satisfied with the system and gave positive responses regarding ALESS.

Moreover, we also found that the group with navigation support outperformed the group without support in the first 20 minutes, but the difference was eliminating in the later 10 minutes. In order to identify the reason, we re-examined the students' learning profiles and found that most of the students finished their learning in 30 minutes. This means that the learning performance would be the same, as long as there was enough time for learning. Most students, no matter whether in Group A or B, could learn all the teaching materials and answer all the questions in the post test, meaning that there was no significant difference after 30 minutes. This result conforms to the simulation result in our previous work. Because the learning time is enough for the participants to learn about the learning targets, their knowledge levels are similar after learning. However, in most application cases the learning or visiting time of the activity or traveling schedule is limited, so the time is not enough to visit all the targets. ALESS can enhance the learning efficacy and also improve the performance significantly when there is insufficient time to complete the learning tasks.

Many studies have shown the ability of here and now learning to be effective based on the fact that students have shown significantly improved post-test scores, improved learning outcomes and significant positive results in terms of their learning. In the meantime, we would like to state that the innovation of this study is not mainly with the technology, but with the learning approach that guides individual students to learn in the museum by taking several real-world contexts into consideration based on the information provided by the sensing technology.

In this paper, we have addressed the educational learning purpose and obtained a positive experiment result, but we all agree that there is a need for more research on the learning effects on student achievement, engagement and attitude toward learning [40]. We will consider using these perspectives to evaluate the learning results of other activities in the future. Moreover, more experiments about the different perspectives of the effectiveness and efficiency of learning will be conducted by considering the rationale of museum learning in our future work.

Although the importance and the capacity of the learning targets are considered in ALESS, the curriculum sequencing is ignored. If the navigation ordering can be assigned to follow the relationship between the learning targets, the learning performance will be improved. Hence, we will attempt to take the relationship between the learning targets into consideration to provide a better learning path for the students. Due of the available mobile devices in the selected school are a set of PDAs, we used PDAs as our development platform. However, PDAs are now outdated and have been replaced by smartphones and tablet computers, which we intend to use in further research. We also plan to re-modify ALESS to use QR-codes, NFC solutions or advanced sensing technologies such as AR (augmented reality) technology, and to extend the system by providing more personalized navigation strategies and taking more real-world parameters into consideration. It is expected that navigation in ubiquitous learning environments can become more sophisticated and can better satisfy individuals' requirements in the future.

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