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Application of context-aware and personalized recommendation to implement an adaptive ubiquitous learning system

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ABSTRACT

Advances in wireless networking, mobile broadband Internet access technology as well as the rapid development of ubiquitous computing means e-learning is no longer limited to certain settings. A ubiquitous learning (u-learning) system must however not only provide the learner with learning resources at any time and any place. However, it must also actively provide the learner with the appropriate learning assistance for their context to help him or her complete their e-learning activity. In the traditional e-learning environment, the lack of immediate learning assistance, the limitations of the screen interface or inconvenient operation means the learner is unable to receive learning resources in a timely manner and incorporate them based on the actual context into the learner's learning activities. The result is impaired learning efficiency. Though developments in technology have overcome the constraints on learning space, an inability to appropriately exploit the technology may make it an obstacle to learning instead. When integrating the relevant information technology to develop a u-learning environment, it is therefore necessary to consider the personalization requirements of the learner to ensure that the technology achieves its intended result. This study therefore sought to apply context aware technology and recommendation algorithms to develop a u-learning system to help lifelong learning learners realize personalized learning goals in a context aware manner and improve the learner's learning effectiveness.

1. Introduction

Advances in wireless networking and mobile broadband Internet access technologies, the maturing of portable mobile devices as well as the rapid development of ubiquitous computing and pervasive computing mean people today are no longer limited to certain environments in their lives or education. They can now enjoy an e-learning experience at any time and any place (Hall & Bannon, 2006; Hong, Suh, & Kim, 2009; Hwang, Yang, Tsai, & Yang, 2009; Kwon, Choi, & Park, 2005; Patten, Sanchez, & Tangney, 2006; Pownell & Bailey, 2001; Rogers et al., 2005; Tatar, Roschelle, Vahey, & Penuel, 2003).

In the traditional classroom teaching environment, the learner's learning model is often limited by the formal teaching activity. This tends to produce a passive attitude to learning that weakened the motivation to learn. In recent years, online e-learning has become a relatively widespread learning method. The ubiquitous learning model has with the support of network communications and context aware technologies leveraged its highly mobile and accessible mobile carriers to improve the learner's level of independence and mobility. The "ubiquitous" concept emphasizes the provision of suitable courseware at an appropriate time and place. It also gives particular emphasis to provide each learner with a personalized learning review feature. IT assistance is also used to enable the ubiquitous learning system to track learners' learning status then actively push courseware that match their individual ability and interests. The ubiquitous learning system therefore plays a very important role when it comes to improve future learning effectiveness.

In the information explosion age however, the development of the learning system must not only consider the capability of delivering courseware to the learner in any time and space but also how to actively push the learning resources needed by the learner for their actual learning context at the right time. In the traditional e-learning environment, the lack of timely learning assistance, the limitations of the screen interface or inconvenient operation means the learner is unable to receive learning resources in a timely manner and incorporate them based on the actual context into the learner's learning activities. However, this means the learner may miss out on an opportunity to learn.

This study takes into account the learning requirements of learners in an actual context as well as differences in personal lifelong learning preferences. First, the Sharable Content Object Reference Model (SCORM) platform was used as the basis and integrated with Radio Frequency Identification (RFID) technology to develop

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an adaptive ubiquitous learning system. Collaborative Filtering (CF) and an association rules mining model (Balabanovic & Shoham, 1997; Cho & Kim, 2004; Sarwar, Karypis, Konstan, & Riedl, 2000; Sarwar, Karypis, Konstan, & Riedl, 2001; Schafer, Konstan, & Riedl, 2001) was used to develop an adaptive smart ubiquitous learning system. Adaptive learning materials are recommended to lifelong learning learners using this association rules mining model in order to improve the learning motivation and effectiveness of lifelong learning learners. Generally speaking, the adaptive ubiquitous learning system developed in this study possesses the following features:

1. Context awareness: RFID technology is applied to implement a context awareness function. The system automatically senses learning objects in the actual environment in order to assist the learner carry out learning activities that match their actual context.
2. Standardized courseware: Courseware that conform to the SCORM standard were developed that offer reusability and multiplatform support.
3. Personal learning management: The system can automatically record each learner's personalized learning profile and progress in order to assist the learner with learning self-management.
4. Adaptive course recommendation: The system can analyze the learners learning requirements and preferences based on their personal learning profile. It then recommends to him or her suitable course resources. To simplify the associated human–machine interactions, the interface design takes into account the context aware and adaptive recommendation functions. This enables the learner to more easily acquire learning resources that match their requirements through a simple interface.

2. Related work

2.1. Ubiquitous learning

Developments in information and communications technology have led to many changes in people's way of life today. E-learning models have been adjusted in response as well. E-learning forms the revolutionary and new way to empower a workforce with the necessary skills and knowledge (Karpouzis, Caridakis, Fotinea, & Efthimiou, 2005). To realize the above goal, the trend is for developers of e-learning systems to make use of different technologies. Nevertheless, the way to improve personalized capabilities as well as track the learner's learning profile or learning feedback is now becoming increasingly important. With today's open e-learning environment and the widespread use of the Internet, it becomes particularly important to provide personalized support for learners. The ubiquitous learning system is based on using highly mobile, thin, compact and easy to carry PDAs or smart phones as the learning platform. The learner is able to access courseware related to their particular context over the wireless network and have it displayed immediately on their learning platform. This setup satisfies the requirements of personalized learning. Furthermore, Curtis et al. also defined the following features for ubiquitous learning: permanency, accessibility, immediacy, interactivity, situating of instructional activities (Curtis, Luchini, Bobrowsky, Quintana, & Soloway, 2002). These features represent a break through in how e-learning systems make use of space and time. In recent years, however, many researchers have turned to adaptive web-based educational systems in the hope of helping learners successfully acquire e-learning resources for specialized fields that match their personal learning needs (Henze & Neidl, 2001). Most related research, however, is focused on applying recommendation algorithms to provide the learner with adaptive learning resources. Learning spaces are now increasingly being expanded into open areas so the learner's learning activities often take place in the actual environment. The way how e-learning systems can detect the learner's current situation and then automatically recommend the learning resources required by the user in a timely manner is an important direction in the development of ubiquitous e-learning systems. To realize the above goal, this study made use of Collaborative Filtering (CF) and the association rules mining model in the development of an adaptive ubiquitous learning system. RFID technology was also incorporated to provide a context awareness function, strengthening the immediacy and situational learning capability of ubiquitous learning.

2.2. Context aware system

Since Mark Weiser first proposed ubiquitous computing as a form of "calm technology", its information and service applications have gained increasing attention (Dey, 2001; Weiser, 1991). One of the key technologies involved in ubiquitous computing is context aware technology (Kang, Suh, & Yoo, 2008). Through context aware technology, the system can sense the user's context and automatically adapt it to the known context in order to provide immediate services and applications (Bolchini, Schreiber, & Tanca, 2007; Kwon, Choi, & Kim, 2007; Yang, Cheng, & Dia, 2008; Zhu, Mutka, & Ni, 2005). Dey and Abowd (1999) also defined the context aware application as the use of the entity context to adjust the system behavior and satisfy the user's situational requirements in an optimal manner. The context aware application must be able to sense and acquire the current context status. When a system is able to make use of this sensed context information in an effective manner as well as interpret, adapt and apply it to the current context, it is referred to as a context-aware system (Byun & Cheverst, 2004). Context-aware systems acquire and utilize information on the context of a device in order to provide services that are appropriate to particular people, place, time, event, etc. These systems aim to provide context-aware access to information communication and computation (Kwon, 2003). Context-aware u-learning can actively support the learner's learning effectiveness in an actual setting. In recent years, several studies have reported on the benefits of applying the context-aware u-learning approach including the promotion of learning motivation (Chu, Hwang, Huang, & Wu, 2008) and the improvement of learning effectiveness (El-Bishouty, Ogata, & Yano, 2007; Rogers et al., 2005).

2.3. Collaborative filtering and association rules mining

Recommendation methods generally refer to ways of finding out what the customer or user is interested in then providing the user with a list of recommendations. The recommendation method forms the core of the recommendation system and its results have a direct effect on the quality of the recommendation results. A compilation of methods commonly used in related research (Kelly & Teevan, 2003; Oard & Kim, 2001) produced the following: 1. Raw retrieval; 2. Manually selected; 3. Statistical summaries; 4. Attribute-based; 5. Item-to-item correlation and 6. User-to-user correlation.

Among these, collaborative filtering (CF) can be considered the predecessor to the recommendation system. It was first proposed in 1992 by Goldberg, Nichols, Oki, and Terry (1992) for use in the e-mail sorting system TAPESTRY. The basic concept of CF is that users can use information they already know to help each other filter out useful information. This is similar to us asking someone with experience for advice before we do something. A common practical application of CF in e-commerce is the construction of the customer-product matrix, also known as the rating matrix (Delgado & Ishii, 2001). The values in the matrix are the customer's rating for the product. The similarities between customer interests can be derived from this matrix. Customer similarities and other customers' ratings for the product can be used to predict a customer's level of preference of a product they had not yet rated. CF-based recommendation often use the association rules mining method to find useful association rules that can be used as a basis for recommendations (Agrawal, Imielinski, & Swami, 1993). Using association rules mining, item associations and user associations can be identified and used in conjunction with each other to make recommendations. With a customer group that has similar buying habits, when a recommendation is made to one particular customer in the group, the system can also recommend to him (or her) products that other people in the same group often purchased as well. Associating rules mining is a data mining technique that is frequently used in product transaction record databases. Users' transaction behaviors are analyzed in order to identify association rules between product or information items (Mobasher, Cooley, & Srivastava, 2000). However, after Agrawal proposed the algorithm for mining association rules in transaction databases, other researchers have gone on to apply the concept of association rules to other fields and come up with algorithms for those fields as well.

This study draws upon inquiry-based learning theory as well as the learner's individual requirements such as learning themes, personal preferences and learning experience to enable the user to combine learning units into a complete course on their own. With the reciprocal instruction method as the foundation, the e-learning system's courseware recommendation system sorts through the courseware and analyzes user behavior. Suitable course resources are then recommended based on courseware associations and learner preferences in order to support the learner's inquiry-based learning. Courseware recommendation is mainly based on a combination of CF and the association rules mining model. Each learner is offered courseware tailored to his (or her) personal requirements and connected to the back-end learning management system over wireless Internet through a PDA or smart phone in order to realize the goal of adaptive u-learning in any place and at any time.

3. The adaptive ubiquitous learning system

3.1. System architecture and development environment

For the lifelong learning learner, the first challenge is quickly finding courseware that matches his or her requirements or interests from among the extensive and complicated learning resources available. These must then be presented in a complete and organized manner so the learner can construct a self-managed and personalized learning environment. Such a setup is crucial to strengthening u-learning effectiveness. In this study, inquiry-based learning, social learning and context learning theories were used to develop a u-learning system based on PDAs or smart phones as the main learner carrier. Using wireless network transmissions and as well as real-time sensing of learning targets in actual situations, the courseware recommended for that context is then recommended to the user's learning platform. As Fig. 3.1 shows the system workflow of the adaptive ubiquitous learning system. However, the study hoped to implement an adaptive u-learning system to enhance the learner's lifelong learning effectiveness.

3.2. System functions

In the u-learning system developed by this study, the learner simply connects to the Internet over a wireless or 3G broadband to access open indoor or outdoor learning in a wireless environment. Through the Radio Frequency Identification (RFID) system, the learner can apply the RFID reader to sense the location of learning objects in the real world at any time. The system then transmits the associated learning resources to the user. The learning activity becomes more lively and a part of actual daily life to realize the goal of real context learning for the user. The courseware recommendation module can also provide adaptive courseware in real-time based on the learner's learning behavior and personal preferences. This encourages learners to continue their lifelong learning efforts in order to systematically construct their personal knowledge. Associated system function modules are described below.

1. Courseware presentation and learning profile management module:
   This module is based mainly on the SCORM-compliant Run-Time Environment (RTE). The course content is presented through the web browser while learning records use the SCORM data model to record learner–courseware interactions. Any problems are also reported immediately.
2. Courseware management module:
   This module is responsible for courseware management. Taking into account the completeness and correctness of courseware, the main functions of this system are courseware addition, submission, review and modification.
3. Courseware recommendation module:
   To construct the courseware database, a botanical knowledge database is converted into a SCORM-compliant courseware database to facilitate system access. This was then integrated with RFID to set up a context sensing function. Once the system detects learning targets in the actual environment, the learning recommendation module automatically generates a recommendation list that matches the learner requirements. Courseware recommendation in this study was based on the CF method that

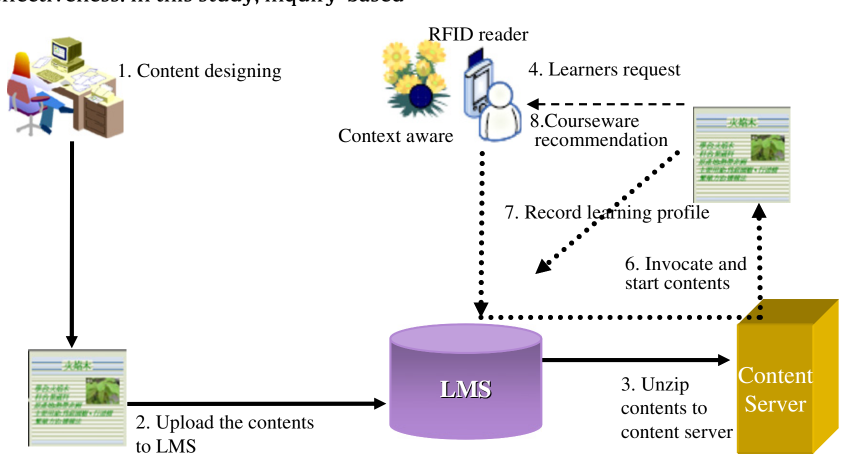

Fig. 3.1. The system flow of adaptive ubiquitous learning system.

has gained wider acceptance among experts and academics. To solve the problem of spare information often encountered with CF as well as performance issues that arise when the amount of courseware increases significantly, the study referred to the MONERS online news recommendation system (Lee & Park, 2007), the Web CF-PT recommendation method (Cho & Kim, 2004), and the study into integrated recommendation systems (Weng & Liu, 2004) carried out by Weng and Liu in 2004. Refinements were made based on the scope and requirements of this study in order to analyze the learner's learning behavior and develop a learner-oriented adaptive learning system that delivers better courseware recommendation quality and system performance. The courseware recommendation module contains six operational processes: "grain specification", "learner profile creation", "segment formation", "preference detection and segment reformation", "recommendation generation" and "learner feedback". The courseware recommendation system architecture is shown in Fig. 3.2.

3.3. Courseware recommendation steps

Step 1: Grain specification.

The courseware database used in this study was a botanical database. It is based on the botanical classification hierarchy used by the natural science and humanities e-library at the National Museum of Natural Science. For this study, the flowering plants courseware database was used as an example. The knowledge units were divided into groups and the knowledge organized into a tree hierarchy structure. At the top of the flowering plants class is the root node. Below are leaf nodes for dicot and monocot plants. Under these two classes are 46 families, with the bottom layer being individual plants and course units. There are a total of 80 knowledge packs and each leaf node has its own parent node. The reading rate of courseware was also used as the basis for sorting. Based on the effective and flexible algorithm proposed by Han and Fu (1994), the top-down big nodes promotion and bottom-up small nodes merging method was used to group the courseware in the flowering plants database into Grain G. Inside Grain G there was a total of $|G|$ course classes so a stable distribution of grain ratings. This served to enhance the accuracy and performance of the recommendation system.

Step 2: Learner profile creation.

The main purpose of the learner profile is to provide an appropriate description of learner preferences. In the CF method recommendations are based mainly on learner preferences. In this phase, the Web Usage Mining method was used to continue exploring learner interests in grains different from phase 1. This study defined the user's learning behavior as the three following steps:

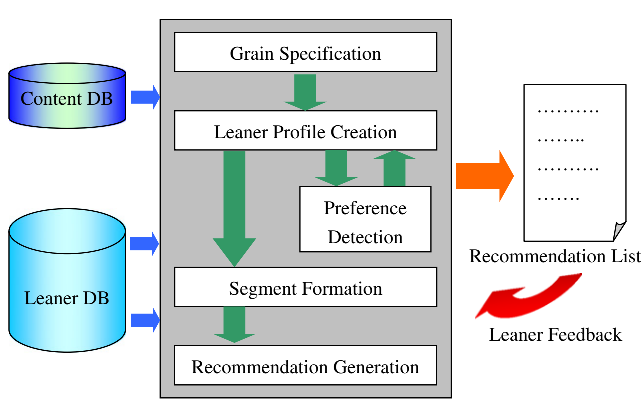

Fig. 3.2. The process of courseware recommendation module.

1. Click-through: This action is defined as the selection of courseware.
2. Bag placement: This action is defined as courseware selected and placed in the school bag.
3. Learning: This action is the reading of courseware. In other words, the entire courseware has been read and completed.

Through these three user behaviors, it is possible to calculate each learner's relative preference P_{ij} for each individual grain and construct a learner profile. The formula is as follows:

$$P_{ij} = \frac{P^c_{ij} - \min_{1\leqslant j\leqslant |G|}(p^c_{ij})}{\max_{1\leqslant j\leqslant |G|}(p^c_{ij}) - \min_{1\leqslant j\leqslant |G|}(p^c_{ij})} + \frac{P^b_{ij} - \min_{1\leqslant j\leqslant |G|}(p^b_{ij})}{\max_{1\leqslant j\leqslant |G|}(p^b_{ij}) - \min_{1\leqslant j\leqslant |G|}(p^b_{ij})} + \frac{P^l_{ij} - \min_{1\leqslant j\leqslant |G|}(p^l_{ij})}{\max_{1\leqslant j\leqslant |G|}(p^l_{ij}) - \min_{1\leqslant j\leqslant |G|}(p^l_{ij})} \quad (1)$$

P^c_{ij}, P^b_{ij} and P^l_{ij} represent the number of click-throughs, bag placements and learning actions made by user i in Grain j respectively. $\max_{1\leqslant j\leqslant |G|}(p^c_{ij})$, $\max_{1\leqslant j\leqslant |G|}(p^b_{ij})$, $\max_{1\leqslant j\leqslant |G|}(p^l_{ij})$ represents the maximum number of click-throughs, bag placements and learning actions made by learner i in G grain. $\min_{1\leqslant j\leqslant |G|}(p^c_{ij})$, $\min_{1\leqslant j\leqslant |G|}(p^b_{ij})$ and $\min_{1\leqslant j\leqslant |G|}(p^l_{ij})$ represents the minimum numbers of clik-throughs, bag placements and learning actions made by learner i in G grain. The value of P_{ij} will fall between 0 and 3. And between these three types of user behaviors, the learner must complete the bag placement before reading and also click-through before bag placement.

Step 3: Segment formation.

In this phase, the learner profile is used as the basis for forming each learner's neighborhood. Using similarity analysis and giving precedence to those with the higher levels of similarity, the "similar objects attract each other" characteristic was used to separate learners in the learning management system into N segments. The main purpose of this phase is to reduce the data dimensional space of the courseware recommendation system to improve system performance and recommendation quality. More commonly used methods for similarity analysis include using the Pearson correlation analysis or Cosine method to compare the level of similarity between learner preference sin the system (Sawar et al., 2001) then use best-n-neighbors (Herlocker, Konstan, Borchers, & Riedl, 1999) to decide the number of neighborhoods. In this study, the Pearson correlation analysis was used as the method for computing the level of similarity between learner preferences. The level of similarity between learner a and learner b's preferences in the learning system can be calculated using the following equation:

$$sim(a,b) = corr_{ab} = \frac{\sum_{j=1}^{G}(p_{aj} - \overline{p_a})(p_{bj} - \overline{p_b})}{\sqrt{\sum_{j=1}^{G}(p_{aj} - \overline{p_a})^2 \sum_{j=1}^{G}(p_{bj} - \overline{p_b})^2}} \quad (2)$$

p_{aj} and p_{bj} represent learner a's and learner b's level of preference for courseware Grain J respectively. $\overline{p_a}$ and $\overline{p_b}$ on the other hand represent learner a's and learner b's mean preference for all courseware grain. After carrying out Pearson correlation analysis, M learners with the most similar preferences were formed into segments.

Step 4: Preference detection and segment reformation.

In the real world, learners' learning preferences will change over time. A good recommendation system must therefore effectively detect changes in user preferences and adjust recommendations to suit the user's current preferences. As CF traditionally assumed user preferences to be unchanging, to overcome this problem this study used the number of times that the learner logs into the learning management system as a baseline to detect any shifts in user preferences from their most recent logins and courseware access. A different factor (DF = 0.5) was also added so when there is no change or no significant shift in learner preferences, the detection results do not affect the parameter's weighting.

Step 5: Recommendation generation.

The final phase in the courseware recommendation system is to generate a top-*N* recommendation list for learners from the *N* segments formed in step 3. The recommendation method adopted by this study used the three learning steps experienced by neighborhoods of users with similar learning targets as the basis to calculate the learner's level of preference for each courseware (Lee & Park, 2007). The complete learner courseware preference prediction equation is as follows:

$$P_{ic} = popularity_c \times [1 + seg_{sj}] \times \left[1 + \frac{l_c}{\sum_{n=1}^{m} l_n}\right] \times \left[\log\left(\left(\frac{P_{js\_time}}{P_{jl\_time}}\right)(10^{1-DF} - 1) + 1\right) + DF\right] \quad (3)$$

Here, P_{ic} represented learner *i*'s level of preference for botanical courseware *c* as predicted by the recommendation module. $popularity_c$ gives a weighting for courseware *c* based on its level of popularity. To avoid skewing the recommendation system results with an excessive weighting, the log of c_{tl}, the number of times courseware *c* was read, was used as the equation for calculating the weighting parameter:

$$popularity_c = P_{ij} \times (1 + \log c_{tl}) \quad (4)$$

seg_{sj} represented the level of preference for grain *j* that courseware *c* belongs to exhibited by the segment *s* that learner *i* belongs to. This is calculated in the following way:

$$seg_{sj} = \frac{l_{sj}}{\sum_{j=1}^{N} l_{sj}} \quad (5)$$

l_{sj} represents the number of articles read from grain *j* that courseware *c* belongs to by learner *i*'s segment *s*. When compared to the total number of courseware read by learner *i*'s segment *s* in the learning management system, this gives its relative level of preference.

This study also weighted the courseware *c* to be recommended to learner *i*'s neighborhood. $\frac{l_c}{\sum_{n=1}^{m} l_n}$ represented how l_c, the number of times that learner *i*'s neighborhood had read courseware *c*, relates to $\sum_{n=1}^{m} l_n$, the total number of courseware read by learner *i*'s neighborhood in the learning management system.

From the above, a complete recommendation list *RL* generated by the courseware recommendation system for the target learner *i* can be expressed as:

$$RL_i = (P_{i1}, P_{i2}, P_{i3}, \ldots, P_{iN}) \quad (6)$$

Step 6: Learner feedback. Finally, after the recommendation list is presented to the learner, whether the recommended items are accepted provide an important measurement of the recommendation system's effectiveness. It is also an important parameter used by the recommendation system for making self-adjustments. The design of the recommendation algorithm for this study uses the predicted learner's preference P_{ic} as the basis. Courseware with a higher level of preference has a better chance of being recommended. In the learner's recommendation list, the learner my click-through or not click-through the list. To reduce the possibility of courseware a learner is not interested in (i.e. courseware never clicked on) may reappear in the recommendation list, some suitable adjustments must be made. The equation is as follows:

$$\tilde{p}_{ic} = P_{ic} \times \beta, \quad \beta < 1 \quad (7)$$

Here β is a parameter less than 1. Its purpose is to reduce the ranking of courseware that the learner is not interested or even exclude it from the recommendation list altogether. The actual value will have to be adjusted depending on factors such as courseware content and teaching strategy. An optimal value must be established through repeated testing and research by experts in the field.

4. Experiments

To evaluate the effectiveness of the learning assistance provided by the adaptive u-learning management system developed for this study, the accuracy and time taken by subjects to complete learning tasks was used to verify the effect on learning effectiveness from "context awareness" and "courseware recommendation" provided by the u-learning system.

4.2. Experiment design

1. Subjects: The u-learning system developed in this study is mainly targeted at lifelong learners. To assess the system's level of acceptance in a real-world environment, university students and members of the community (aged 18–32) were randomly grouped into an experimental group and a control group for this study. There were a total of 30 people, with 15 in the experimental group and 15 in the control group. Subjects who wore glasses had corrected eye sights of over 0.8 and none were color blind.
2. Experimental task: The experiment for this phase was held at the Botanical Garden of the National Museum of Natural Science. A botanical knowledge learning tour was held on-site in an area equipped with wireless network sensory coverage. During the experiment, each subject was given three types of random learning tasks involving horticultural plants, sidewalk plants and medicinal plants. Once the experiment commenced the subject was required to learn about the plant in their assigned learning task and browse the learning support system through a handheld PDA. The data collected during this phase included the learning profile, courseware reading time, courseware reading progress, task completion time and use of the courseware discussion forum.
3. Experimental equipment: Each subject in the experimental group was provided with a RFID reader-equipped PDA and wireless connectivity. RFID tags were placed on the plants in the learning tasks. The control group was provided with one PDA and wireless connectivity. The Learning Management System Server (LMS Server) and wireless access point was set up at the experiment site.
4. Independent variables: The independent variable was the u-learning assistance method as described below:
   Experimental group: "Context awareness" and "courseware recommendation" functions were provided by the u-learning system as Fig. 5.1.
   Control group: "Course awareness" and "courseware recommendation" functions were not provided by the u-learning system. Only text search of courseware was provided.
5. Dependent variables:
   Learning task completion time: The subject was timed from the point they started reading the problem descriptions of the learning task. The total time taken to search for the real-world learning objects assigned by the learning task, query the e-learning system resources and finally answer the question was recorded.
   Learning task accuracy: The percentage of learning task questions accurately answered by the subject.

5. Results and discussion

In this phase, the objective of statistical analysis is to verify the effect of the "context awareness" and "courseware

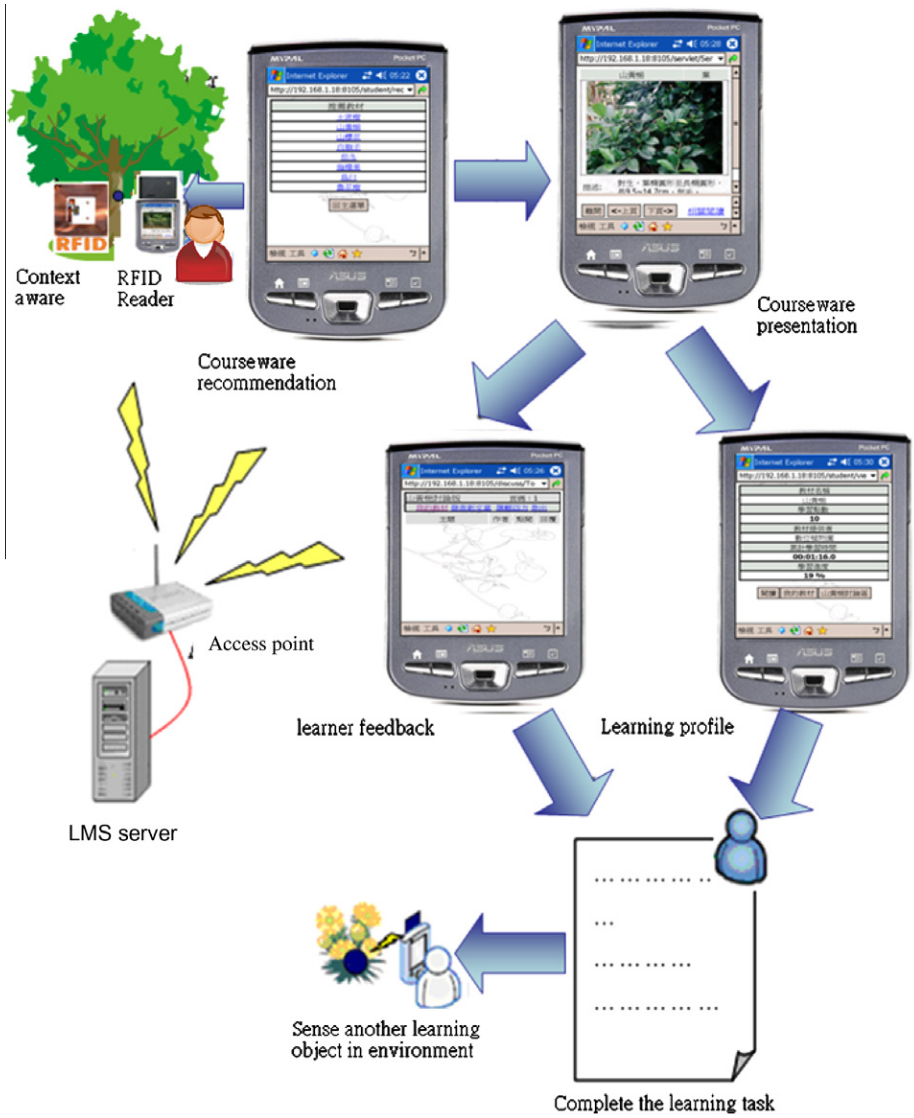

Fig. 5.1. Example image showing of the "context awareness" and "courseware recommendation".

recommendation" functions provided by this system on learning effectiveness. In other words, the goal is to measure whether the provided learning support helped the learner to complete their learning task more quickly and more accurately. To determine whether there were any significant differences in the two study groups' learning effectiveness, the *t*-test was used.

5.1. *t*-Test analysis for learning task accuracy

According to the co-variant Levene test did not pass the test for significance ($F = 2.250$, $P = 0.144 > 0.05$) so there was no significant difference between the distribution of the two samples. The null hypothesis for the covariance in the two samples should therefore be accepted.

The accuracy rates of the experimental and control group were subjected to the *t*-test are shown in Table 6.1. In the *t*-test of covariance, the results passed the test for significance ($t = 10.062$, $P = 0.000 < 0.05$). This showed that when "context awareness" and "courseware recommendation" was provided by the learning management system it made a significant difference to the accuracy of subjects when answering learning task questions.

5.2. *t*-Test analysis for learning task time

According to the co-variant Levene test did not pass the test for significance ($F = 3.924$, $P = 057 > 0.05$) so there was no significant difference between the distribution of the two samples. The null

Table 6.1
The *t*-test results of the accuracy rates of the experimental and control group.

	Levene's test for equality of variances		*t*-Test for equality of means				
	F	Sig.	*t*	df	Sig. (2-tailed)	95% confidence interval of the difference	
						Lower	Upper
The accuracy rates	2.250	0.144	10.062	28	0.000	1.793	2.706

Table 6.2
The *t*-test results of the time taken of the experimental and control group.

	Levene's test for equality of variances		*t*-Test for equality of means				
	F	Sig.	*t*	df	Sig.(2-tailed)	95% confidence interval of the difference	
						Lower	Upper
The time taken	3.924	0.057	−16.330	28	0.000	−512.990	−398.942

hypothesis for the co-variants in the two samples should therefore be accepted.

The time taken by the experimental and control groups to complete the learning tasks and answer the questions on the u-learning system was subjected to the *t*-test are shown in Table 6.2. In the *t*-test of covariance, the results passed the test for significance ($t = -16.330$, $P = 0.000 < 0.05$). This showed that when "context awareness" and "courseware recommendation" was provided by the learning management system it made a significant difference to the time taken by subjects to answer the learning task questions.

6. Conclusion

In this study, an adaptive u-learning system was developed in the lifelong learning context in combination with associated learning theories as well as context aware technology. When compared to mobile learning models based on conventional offline reading materials, the system offers a more flexible, user-friendly and independent learning environment. The design of the study's courseware recommendation model uses the lifelong learner's characteristics, learner behavior and learning preferences to make appropriate courseware recommendations. After an experimental trial incorporating the context-aware function enabled through RFID technology, the results showed that providing the "context aware" and "courseware recommendation" had a positive effect on learning effectiveness. Subjects with learning support provided were able to complete their learning tasks in less time and with answer more questions correctly. The contributions made by this study can be summarized as follow:

1. This system used CF and association mining to enable system learners to share learning experiences and engage in adaptive learning through the courseware recommendation model. The effectiveness of lifelong learning is enhanced.
2. This system provides a record of personal learning history. This feature can be used by future researchers for studying learner behavior and to realize adaptive learning.
3. The u-learning platform proposed in this study integrates RFID technology and data mining to enhance real-world u-learning effectiveness so lifelong learning can be conducted more efficiently.

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