Adaptive Object Re-Ranking Mechanism for Ubiquitous Learning Environment

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Abstract—Ubiquitous Learning (U-Learning), as an emerging learning paradigm, makes it possible for learners to carry out the learning activities at any places and at anytime. With the advantages of the devices, learners can obtain a variety of supplementary materials from the Internet. In the scope of distance learning, LOR (Learning Object Repository) stands for managing and sharing of learning related materials (known as learning objects). However, some challenges may raise while performing these activities. For instance, a huge amount of learning objects may appear while learners utilize the search service provided by LOR. Learners have to spend time on collecting relevant resources for specific purposes. This situation may discourage the reusability of learning objects especially in a ubiquitous environment. In this paper, based on systematic re-examination of reuse scenarios, an adaptive mechanism, as a resource discovery and search middleware, was proposed to assist learners in obtaining possible objects under ubiquitous environment. Achievement of the proposed mechanism can produce search results adaptive to specific situations in order of similarity degree based on the mixed information. We try to filter out some irrelevant results by using the past usage history, current geographical information and input query, so as to enhance the efficiency of learning objects retrieval in a ubiquitous environment. As a pilot test, Apple iPhone was utilized to be the major client testbed.

Index Terms—object retrieval, re-ranking algorithm, ubiquitous learning, information filtering

I. INTRODUCTION

With the development of Internet technologies, there are lots of research organizations that make efforts in developing relevant systems (i.e., RELOAD, MOODLE) to meet the needs of distance learning (or e-Learning). Furthermore, with the advanced mobile hardware and communication technologies, the GIS (Geographical Information System), and GPS (Global Position System) also make it possible for learners to obtain context awareness and ambient awareness information. Accordingly, an emerging learning paradigm, known as the u-learning (Ubiquitous Learning), has grown up and makes learning activities available without any limitations from the environment. In the scope of u-learning, the learning activities can be considered as a seamless process.

Thanks to the concept of WEB 2.0, users can access a huge amount of resources and information from the Internet. For the same reason, instructors can benefit from various kinds of multimedia resources, such as web pages, interactive videos, 3-D virtual objects, to create plentiful learning materials, and, on the other hand,
learners can also find additional information related to the learning activities. In order to manage the increasing resources (or learning objects) in distance learning repository efficiently, a de facto standard named SCORM (Sharable Content Object Reference Model) has been proposed to achieve the reusability, sharability, and interoperability of the resources (or learning objects) made specifically for learning purposes. And CAM (Content Aggregation Model) of SCORM also provide sufficient metadata to assist users in searching relevant learning objects. Although the issues of common repository were addressed [12][13], the storage infrastructure to allow public searchable learning objects had brought an important open issue for u-learning research.

Unlike the e-learning, it is difficult to represent all the possible information to users in the limited display screen of ubiquitous device. For example, learners may strengthen their domain abilities by finding out some relevant information, or may collect resources for different learning purposes. It is almost the same with the instructors in creating the learning materials. In this situation, a well-designed search mechanism that can meet the users’ needs will make learning process more efficient and flexible. Recently, lots of recommendation mechanisms have been adapted in e-learning systems to provide adaptive search results based on users’ personal profiles [5][21].

In our earlier works [26], we developed a series of integrated services to assist users in doing e-learning process. We also made use of the research achievements to develop an outdoor adventure game to support learning procedures based on the use of geographical information and RFID (Radio Frequency Identification) technologies. In this research, we go further to propose an adaptive retrieval mechanism, or a search middleware, that can assist users in filtering out irrelevant search results and reorganizing results based on different usage scenarios in ubiquitous environment. This mechanism includes two major parts: Profile Management (PM) module and Search Wrapper (SW) module. The PM is responsible for collecting information corresponding to ongoing learning activity and synchronizing back to SW for further usage. And the SW is responsible for the resource retrieval algorithm and the representation of search results. As a contribution, the proposed mechanism can reduce the cost of time while searching for supplemental resources related to their current activities. In addition, this service can serve any external learning systems not only limited in this study.

A. Motivation and Contributions

Although SCORM provides preliminary solutions for searching and reusing learning objects, a few important points were still missing. After the learning objects have been created, the external information, such as the attributes of metadata, may also be changed. A huge amount of learning objects may increase the difficulty to discover and thus to retrieve more appropriate and relevant learning objects. In general, users can search for learning objects through parameters and their corresponding categories described in CAM (Content Aggregation Model) of SCORM. However, in this situation, two major problems will come into existence: (1) Users may not realize the definition or meaning of metadata elements and cannot utilize them well, and (2) It may take time for users to filter out irrelevant search results.

In order to give well solutions to the problems above, we emphasize on the search process in this research by proposing an adaptive retrieval mechanism. Our contribution has two major parts. First, we provide personalized services for the u-learning environment by capitalizing upon the revised IMS LIP (Learner Information Packaging) and OpenID mechanism. Furthermore, through the proposed service, we can represent the significance of learning objects by ranking them in specific order based on the mixed information and users’ individual needs.

The organization of this paper is as follows: We will give a brief introduction to some related works in Section II. The proposed service framework and its corresponding mechanisms will be addressed in Section III. In the IV section, we will present the evaluation process and the system implementation, and will make a conclusion in Section V.

II. LITERATURE REVIEWS

Nowadays, with the progressive improvement of relevant technology in the semiconductor, the development trend of computers becomes smaller, cheaper and more quickly, even more intelligent [18]. It is helpful for people to improve their quality of life, especially in education and entertainment domain. More and more research issues have been pointed out that ubiquitous devices have advantages to attract and help instructors and learners conduct the learning activities. In this section, we will give a brief summarization of previous works related this research issue.

A. Applied Technologies in U-Learning Environment

Recently, lots of technologies, such as RFID (Radio-Frequency Identification) and GPS (Global Position System), have been adapted to assist instructors in creating highly-interactive learning activities. For instance, Chen [4] proposed a framework to assist learners in retrieving learning content by using portable devices and passive RFID tags. Learners can access the corresponding learning information or functionalities as long as the tags on have been triggered. Hsu et al. [9] also utilize the same strategy to construct an asynchronous self-regulated learning environment. Learners can get involved into the learning scenario created by instructors through this strategy. Moreover, instructors can also realize the learning status or learning history of each learner, and, if necessary, can give feedbacks to learners instantly based on individual needs.

However, it still has some limitations while using the RFID tags. For example, the tags must be triggered in a short distance so that the devices can receive the messages correctly. If instructors would like to have this
technologies applied into a large field like a town or a city, it may need a great cost. For this reason, the GPS (Global Position System) has been proposed to give solutions to the disadvantages of RFID tags. For example, Ogata and Yano [15] propose a context-awareness language supporting system. It makes use of the GPS/GIS to assist learners in studying vocabularies and display the information on ubiquitous devices. Wu et al. [32] utilize the GPS and wireless network to construct a life information platform. This platform not only lets users annotate their photos and share them but also help them find relevant experience from others. Besides, Hinze et al. [2] also propose a tour guidance system for the users who are first time to get the tourist attractions based on the same technologies.

As to the learning aspect, Ogata et al. [16] also propose a language learning system to help foreign learners study Japanese. Learners have to collect necessary data in an outdoor environment to complete the mission assigned by instructors. Brown et al. [19] pay emphasis on the learning content design and the learning history design on m-learning (Mobile Learning) environment. Chen et al. [6] construct an outdoor mobile-learning activity, and observe the learning process of each learner by utilizing the mobile devices. Learners will be divided into several groups and instructor will ask learners to discover different kinds of birds and find out relevant information. This research will like to prove the use of portable devices can raise the learning motivation and the learning efficiency. Summarizing up the research issues above, they all take the benefits from the portable devices and ubiquitous technologies, and it is obvious that they also show the importance of the retrieval of learning resources to us.

B. Information Filtering Methodologies

For the sake of obtaining useful learning resources in efficient way, the use of IR (Information Retrieval) technologies is necessary. The original purpose of IR is to identify the relation between two or more documents, and to assist users in getting the information [20]. The common examples are the search engine provided on the internet like Google, Yahoo, or the ones in specific systems. Sometimes, the IR technologies are also regarded as a kind of information filtering technology. The information filtering technology known as a middleware works between users and data emphasizes on providing long-term customized services actively based on users’ profiles. It utilizes the filtering algorithm to exclude the unnecessary information, and to control the problems caused by information overload efficiently. Summing up the researches recently, the information filtering technology can mainly be categorized into three to meet the needs in various domains as followed:

- **User-based Collaborative Filtering**
  This filtering strategy will classify users based on the similarity discriminate method including users’ interests or hobbies, to generate users’ model for specific groups [8]. After that, system can provide items, such as search results or goods, which users may be interested in based on KNN (K-Nearest Neighbor) algorithm [7].

- **Item-based Collaborative Filtering**
  With the increasing number of users, the user-based filtering methodology exposes the problem of excessive computation time. Sarwar et al. [23] propose a novel concept that the items that cause users’ interests must have certain similarity with the ones that users are interested in before. It can provide more stable recommendations based on the similarity between items. In addition, it can be taken offline in order to reduce the load on the server, and raise the system efficiency. However, the recommendation accuracy may be low because it does not take consideration of the difference of users’ information [3].

- **Model-based Collaborative Filtering**
  The methodologies above are the property of memory-like collaborative filtering technology. This methodology always comes with the problems of information scarcity and information scalability, and reduces the accuracy of recommendation results [14]. Consequently, the model-based filtering methodology was proposed. The model can be obtained by analysis of samples trained from the users’ history information [27][29]. The most common used training methodologies are the Bayesian Networks, SVM (Support Vector Machine), and etc.

Recently, the information filtering technologies have also been widely used in LOR (Learning Object Repository) for assisting users in obtaining relevant information or for providing recommendations. In this research, we go further to optimize the search process in a ubiquitous environment. Moreover, the resource types, both in text and/or multimedia format, are also taken into consideration.

III. PROPOSED MECHANISMS

This issue is an extension of our previous works. The design concept will be discussed in this section. We will start from the system framework and then introduce how the proposed PM module and SW module work respectively.

A. System Framework

The overall system framework is shown in Figure 1. The solid line (orange one) and the dotted line (blue one) are utilized to represent the data access flow of profile information and search information respectively, and the communication between client (portable device) and server (back-end server) are based on a series of web services.

The system can be separated into five parts. The first part is working as the Entry Portal (or External Service Access Portal) which is for the internal user registration.

1. All of the mentioned learning objects in this paper were stored in MINE Registry [22] and may be modified by the authoring system addressed in [26]. The learning platform is also based on [31], and the retrieval mechanism is now available on iPod Touch simulator.
and authentication, and provides the portal for users to interact with external services provided by others. The second part is MINE Registry which serves as the backend database for the proposed system. In order to provide the ambient-related information, the change of storage schema is necessary. Except the Learning Object database addressed in [24][25], we created the other two databases for storing and managing the geographical-related information and profile-related information. The fourth, to improve the efficiency of learning process, the two cloud service sets, Learning Management Cloud and Authoring Service Cloud, are proposed to provide basic functionalities and tools that may be needed. Specifically, Learning Management Cloud is designed to meet learners’ needs, and the other one is for instructors’ ones. Concerning the Learning Service Middleware, it includes the two main modules, PM and SW, which is responsible for the search-related services, and it is also the focus of this research. The details of PM and SW will be described in the following sections.

Figure 1. Overall Learning System Architecture

B. Profile Management Module

As stated above, a series of functionalities and tools are developed to assist the learning process through web services. To reduce the complexity of duplicate authentication procedure and to manage learning history efficiently, it is necessary for the system to provide a well-organized profile management service especially in a ubiquitous environment. The personal profile can also be considered as one of key factors to filter out the appropriate search results. As to distance learning aspect, there are two standards to serve this goal. One is the LIP (Learner Information Packaging) [11] proposed by IMS and the other one is the PAPI (Personal and Private Information) [10] proposed by IEEE. Lots of systems adopt the LIP specification to record the learning history and the training history for users and to assist users in achieving lifelong learning scenario. As mentioned, there become more and more web-based systems that have been developed their functionalities or tools as separate services. This approach can help reduce the limitation of environment for both stand-alone and ubiquitous devices. However, with the development of services on the Internet, it has become difficult for users to manage their identification in commonly used services. It will obviously become a challenge for researchers/developers to record and manage users’ profiles. Fortunately, the OpenID project [17] provides a good solution to solve this issue. It utilizes a united authentication mechanism by providing each registered services on the Internet a unique identification (UID). Specifically, the mentioned UID is a combination of URL (Uniform Resource Locator) and corresponding user information that will be used to access such service.

In this research, we will make use of the LIP as the strategy to record related information. The concept of OpenID will also be considered to be the solution of authentication challenge. We propose a descriptor named LIP-ID to transfer the format difference between LIP and OpenID. The detail process flow and transformation algorithm will be discussed in the following section.

1) Workflow of PM Module

Figure 2. The workflow of profile management module

Figure 2 shows the detail workflow of the PM module. Users can utilize their portable devices with certain Internet capability like 3G or WiFi to access our system. Before accessing the system, Entry Portal will check the personal profile stored in users’ device and request for corresponding authentication information. As long as they get authorized, the connection between backend system and portable devices will be established, meanwhile, the PM module will be activated. PM module is composed by three major components, Data Cache Scheduler (DCS), Data Synchronization Processor (DSP), and LIP-ID Descriptor, which will be discussed in the following paragraphs.

As it is difficult to keep the connection status online in a ubiquitous environment, we must take advantage of the storage capability on user’s device to record the learning related information temporarily, and synchronize it to backend database. In this situation, lots of the
synchronization requests have to be taken into considerations. The DCS was proposed to schedule such requests through the following algorithm:

DataCacheScheduler( )
1: check if the request was sent from end-user
   if (listener.wait > 0) goto step 2
   else listener.wait
2: check request information from client device
   requestInfo = (deviceId, waitTime)
3: initialize request queue requestQueue[i][j], where |i|, |j| = {0, 1, 2, …, N}, i ∈ {waitTime}
4: sort requestQueue by waitTime, and generate a new
   candidate queue candidateQueue[m][n], where [m][n] = {0, 1, 2, …, N}, m ∈ {sorted deviceId}, n ∈ {sorted
   waitTime}
5: return candidateQueue

Figure 3. Algorithm for Scheduling Synchronization Requests

First, DCS will create a listener (listener.wait) to receive the requests from users. Once users request for synchronization, system will sum up the requests and retrieve the information from the device. The deviceId is assigned by the system, and the waitTime represents the timescale since last synchronization. The synchronization will be proceeded from candidateQueue according to the waitTime (from high to low).

As long as the candidateQueue has been confirmed, the synchronization event (sync.event) in DSP will be triggered. In PM module, DSP is responsible for the actual process of synchronization. The detail process is shown in Figure 4.

DataSyncProcessor( )
1: check if the synchronization event was triggered
   if (sync.event) goto step 2
   else DataCacheScheduler( )
2: initialize the synchronization candidate set synccdt = (deviceId, A, L), where deviceId ∈ {candidateQueue}
3: retrieve profile information from device by deviceId
   A deviceId = (uid, upwd)
   L deviceId = {selected LIP elements}
4: initialize consistence checker cstCkr = (deviceId, A’, L’), where csCkt.deviceId = synccdt.deviceId, where A’ and L’ are the existing records in User Profile Database
5: for (m=0; m<candidateQueue.getNum(m); m++)
   check consistence of data in Synccdt and in database
6: return candidateQueue

Figure 4. Algorithm for Synchronization Process

As long as the value of (sync.event) was set to 1 (0 for nothing), the synchronization set (synccdt.set) will be initialized. The factor A includes the basic authentication information, identification and password, which can be marked as A = (uid, upwd). The factor L represents for recording the specific learning process done on learners’ device. To maintain user profile efficiently, we select only four sub-elements in LIP [X] as shown in Table I. The L can be described as L = (goal.status, act.date, cmp.exref, aff.role). While synchronizing, DSM will initialize a candidate set (synccdt.set) to store the data in synccdt.set, and a checker (sync.cheeker) to coordinate the data in synccdt.set are continued from the ones existing in User Profile database. The information will be parsed to SW for further process.

<table>
<thead>
<tr>
<th>Category</th>
<th>Sub-Element</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Goal status</td>
<td>status</td>
<td>to record current learning status and achievement</td>
</tr>
<tr>
<td>Activity date</td>
<td></td>
<td>to record the date information the learning activity was proceeded</td>
</tr>
<tr>
<td>Competency exrefrecord</td>
<td></td>
<td>to record external information user may collect by using provided search service</td>
</tr>
<tr>
<td>Affiliation role</td>
<td></td>
<td>to examine user status while performing learning activities</td>
</tr>
</tbody>
</table>

2) Purpose of PM Module

In our previous achievement [23], we allow learners to download learning resources, especially mention to those courses created by instructors, to their portable devices. In this study, we make use of Apple iPhone and/or iPad as major terminal device. The scenario is that when learners are reading these downloaded materials, the device can help record the related information such as learning history and/or personal habits. These data will be updated to back-end profile database so that the SW can utilize the information to provide adaptive search results. However, it is difficult to ensure that devices can always be connected to the Internet. Thus, we provide the PM, also known as a non-synchronization data caching mechanism, to meet this purpose. Learners can conduct the learning activities through offline devices and update the data as soon as the devices have Internet connection.

After that, the LIP parser in the personal profile management will transfer the necessary information to the OpenID format. The personal OpenID information will always synchronize and keep the information both in the learners’ devices and in back-end database. This information can also be exchanged with others under the mutual agreement.

C. Search Wrapper Module

In the ubiquitous environment, the resource format has become more and more plentiful. The resources can represent as web pages, videos, 3-D virtual objects, and so on. In the current web-based search mechanism, they provide lots of search rules for assisting learners in finding out what they need. To take Google for example, after users input specific queries, such as keywords and/or file types, Google will list the results based on their ranking algorithm. No matter what kinds of situations learners are in, the same queries will always lead to the same results. The results seem not very useful in this situation. Users have to spend a lot of time in filtering search results to meet their different needs.

In the scope of distance learning, instructors may make use of lots of Internet resources, such as web pages, slides, and multimedia files, to create courses for specific purposes. In this situation, these resources used to compose the courses will lead to more external resources.
It is why learners may have to spend time in finding out some useful supplemental resources to make themselves understand what the topic is taught in a specific course. However, if we develop a search mechanism same as search engine mentioned above does, it will definitely lead to the same disadvantages. Thus, an adaptive mechanism to enhance the search process will be necessary.

1) Workflow of SW Module

In order to provide efficient solutions to above disadvantages, we proposed an adaptive mechanism, an object re-ranking algorithm, to reorganize the initial search results by integrating the mixed information. The mentioned mixed information that may cause the change of results’ order includes the:

- **Query Information**
  The first factor that is learners’ input queries. Learners can obtain corresponding results based on their queries. Learners can utilize different keyword to search the LOR. Since the learning objects stored in our LOR are followed the SCORM specification. We also define several search criteria to assist learners in making queries when performing search process based on LOM specification [1].

- **Ongoing Learning Activity**
  We also take the ongoing activities into consideration. It is because learners may need external information to make themselves understand. Since the search process is related to specific learning activities, it is necessary to rank those results that have less similarity with the ongoing activity.

- **Resource Types**
  The resources may be represented in different types such as text-based file and multimedia-based file. The needs to different type of resources shall be according to the ongoing activity and user’s preference.

- **Geographical Information**
  The last factor that makes affect the ranking results is the current location learners are in. We can detect learners’ location through their portable devices. Once when we receive the information from PM module, the proposed SW can use this information to give more weight to those results that have higher similarity to learners’ current places.

Our proposed SW module makes use of mentioned information to produce adaptive search results to learners. We not only assist learners in finding out related objects in LOR but provide a better way for each learner to get learning objects they expect to obtain. As shown in Fig. 5, in the search process, learners enter the specific query into our system. The search service in SW module will cope with the terms first. After that, our system will check if request to backend database for learners’ previous profile. Meanwhile, learners’ information from their devices will also be detected for confirming what the current situation is. In the Knowledge Set, system will proceed this information by integrating them into one measurement unit. The unit here is a number between zero to one. It can also be regarded as a kind of weight of learning objects, but the weight is not fixed. It is assigned dynamically. Through the process, the system will return the final search results to learners. Our aim is not in the scope of recommendation provision but to reorganize the original search results to meet learners’ needs in different situations. That is, the results with higher rank identify the ones that have highest weight, or highest similarity, at the moment. It may change dynamically in accordance with the alteration of mentioned factors.

2) Algorithms in SW Module

We define two coefficients to calculate the weight learning objects have: Author Expect Coefficient (AEC), and Ranking Coefficient (RC). In AEC, we utilize the keywords requested by learners as the first step to conduct adaptive search process. And then we utilize the following algorithm to calculate the assign weight to each learning object based on similarity between them.

**SimilarityCal()**

1: initialize elements array \( E_a[r_a][s_a], E_a[r_a][s_a]\) for \( LO_a \) and \( LO_a \), where \( r_a, r_{\text{y}} \in \{\text{LOM elements}\} \), and \( s_a, s_{\text{y}} \in \{\text{elements in corresponding category}\} \)

2: initialize selected elements array \( SE, SE \in \{\text{title, language, …, typical learning time}\} \)

3: for each match elements in \( E_a, E_{\text{y}} / \)

   - check if \((r_a \text{ equals to } r_{\text{y}})\)

     - if \((s_a \text{ not exist in } SE)\)

       \[
       Sim_{\text{exp}} = \sum \frac{s_a^T s_y}{||s_a|| ||s_y||}
       \]

     - else

       \[
       Sim_{\text{exp}} = \frac{SE^T S_{\text{exp}}}{SE^T S_{\text{y}}}
       \]

   - else continue

4: return \( Sim_{\text{exp}} \)

**Figure 6. Algorithm for Similarity between Learning Objects**

After obtaining the first results, we go further to integrate the factors mentioned in the previous section to change the default weight of each object. Before starting to do this, we have to define three corresponding data sets to meet this as follows:
• **Match List (ML)**
  This set calculates the weight for extra information. The items in this set affect the default search results. This set includes the learners’ location, learners’ profile, current time, ongoing task/assignment, metadata of learning material based on LOM, and etc.

• **Response List (RL)**
  This set represents the query results requested by learners’ query terms. They are executed in the back-end database. The returned process list can be considered the set of response list.

• **Match Item (MI)**
  This set is responsible to compare the ML and RL. It calculates the corresponding items between them. For example, if there is a result in RL relevant to the one in ML, the statistics value is taken as MIi.

With the previous definition, when learners send the request to the database, search wrapper will utilize RI to find out corresponding information. We make use of ML to get the value for each member in MI. The proposed formula of AEC is shown as follow.

\[
AEC = \beta \cdot SIM(R_i, R_j) + (1 - \beta) \cdot \frac{1}{|ML|} \sum_{RI} MI
\]

\[
\beta \in [0,1]
\]

In AEC, we do cross matching based on different information. The different parameters lead to different weights. The beta threshold is to get the optimal balance between original query and extra weight for specific information.

Besides, it is not appropriate to utilize the AEC to be the final scores to sort the search results. Thus, we have to make use of the original sort scores given when learners send query terms to repository. It is like that we integrate the original ranking weight into AEC. We name the original sort scores the Rcoe (Repository Coefficient). In the RC, we integrate the Rcoe and AEC. We also set three thresholds to balance the two coefficients. The value of alpha threshold can be adjusted by learners to meet their current needs. The proposed calculation formula of RC is as follow.

\[
RC = \alpha \cdot R_{coe} + (1 - \alpha) \cdot AEC
\]

\[
\alpha \in [0,1]
\]

**D. The Comparisons**

In the literature, lots of researchers focus on the development of u-learning environment and the usage of such ubiquitous devices to enhance the learning process. Some fundamental issues are raised while there are few articles addressed the restrictions, such as connection capability and transmission rate, under the ubiquitous environment. Since learning material can be regarded as central component of learning process, it will be a challenge for researchers to figure out how to make learners to retrieve useful resources related to specific learning activities. In traditional e-learning, related issues have been discussed \[22\][28][30] and provide efficient solutions to assist instructors/learners in obtaining resources. In some cases, the concept of retrieval mechanisms can be applied to u-learning related environment and give preliminary solutions. In this paper, we propose a novel mechanism to enhance the efficiency of learning objects retrieval under ubiquitous environment. Through cross-calculation, we can re-rank the search results and return necessary ones may be corresponded to users’ current needs back to their devices instead of sending all of the results to them. For the same reason, we can also pre-download the files of these returned results to reduce the waiting time.

**IV. SYSTEM IMPLEMENTATION & EVALUATION**

In this section, we will first demonstrate our implementation through a concrete example, and then we will make use of the IR evaluation methodology to evaluate the system performance.

**A. System Implementation**

We create a scenario for learners to find out specific learning objects. In our proposed system, the ranking algorithm will be affected by learners’ personal profile and geographical information. It is difficult to evaluate performance with two variables. Thus, we assign one student to go to different location in Taipei, Taiwan. Figure 9 and Figure 10 represent the different search results while student is in Tamkang University, National Taiwan University, Taipei 101, and Chiang Kai-Shek Memorial Hall through the same query term.

To take Figure 9 for example, the interface can be separated into four parts. No. 1 is the search bar where learners can input the keywords. No. 2 represents the learners’ personal information and their current geographical information. No. 3 will automatically generate the pagers for the results. The search result will be shown in No. 4. It represents the content of search results including the file format and the functionalities.
B. System Evaluation

In this section, we will start from the optimization process of our proposed formula, both in AEC and RC. And then the precision-recall test will be discussed after we find out the optimal value of assigned thresholds.

In our proposed formula, we define three thresholds to AEC and RC. As stated, these thresholds are used to balance the factors that we concern for re-ranking the search results. We make use of specific keyword, such as “photoshop” and/or “introduction”, to be the basic input. The system calculates the similarity between both keywords and selected metadata elements to get the AEC. According to the experiment results, we could get the match chart for beta shown as Figure 11. It is not difficult to find out that we could get the optimal AEC when beta is “0.4” based on this graph.

After getting the optimal beta value (0.4), we would like to continue the same experiment on proposed RC. When giving the RC a fixed beta value (0.4), and we could get the match chart for beta shown as Figure 12. The baseline is the default Rcoe value. We could see that the RC would be shown as a curves line, and we could get the optimal alpha value for our RC is on “0.6”.

After obtaining the optimal value of our proposed thresholds, we go further to conduct a system evaluation to assess the overall performance of our repository system by obtaining the accuracy of the search results. We choose three topics and corresponding queries (using only keywords for example) to perform this experiment. The first topic (K1) is “Photoshop Introduction”, and the input query is “ps + intro”. The second one (K2) is about “Data Structure” and the query is “ds”. The third one (K3) is about “Multimedia Computing” and its query is “mm + computing”. Before the evaluation, we have to define the accuracy function [8] that will be used in this experiment.

Precision’= # of relevant LOs retrieved / # of retrieved LOs
Recall’ = # of relevant LOs retrieved / # of relevant LOs

The detail evaluation result is shown in Table II. It is worth mentioning that overall recall value is higher than 0.9. It represents that the search service provided by our repository can respond relevant results in the first step.

<table>
<thead>
<tr>
<th></th>
<th>K1</th>
<th>K2</th>
<th>K3</th>
</tr>
</thead>
<tbody>
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<td>Relevant LOs in Repository</td>
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<td>1247</td>
<td>2084</td>
</tr>
<tr>
<td>Retrieved LOs</td>
<td>1671</td>
<td>1336</td>
<td>2099</td>
</tr>
<tr>
<td>Relevant LOs Retrieved</td>
<td>1371</td>
<td>1183</td>
<td>1879</td>
</tr>
<tr>
<td>Precision</td>
<td>82.1%</td>
<td>88.6%</td>
<td>89.5%</td>
</tr>
<tr>
<td>Recall</td>
<td>90.7%</td>
<td>94.9%</td>
<td>90.2%</td>
</tr>
</tbody>
</table>

V. CONCLUSIONS AND FUTURE WORKS

In ubiquitous learning environment, the resources have become plentiful. The search services provided by system developers can only list the results in the order by a specific ranking algorithm. It also makes learners spend a lot of time in filtering out the resources that really meet their needs. In this work, we provide a re-ranking algorithm for assisting learners in finding out the relevant learning resources based on mixed information such as personal profile, current geographical information, and ongoing learning activities. It can provide the adaptive search process and makes it more flexible. Learners can utilize the thresholds we set to adjust the weight for different parameters. Moreover, we have also developed our proposed system functionalities as separate services...
that we called it Search Wrapper. This can reduce the load of back-end server and make our system extendable. We adopted the OpenID and IMS LIP to manage the personal profile. In the future, we plan to integrate the current profile management sub-system with other learning management systems developed by international education organizations, especially the universities or companies, to provide external services. The training and learning histories can be recorded in their personal profiles and can also be exchanged between universities and organizations. We aim at providing a well-organized lifelong education environment through ubiquitous devices. Furthermore, if the technologies supported, we can also utilize this concept to provide seamless services to learners.

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