Supporting the Development of Mobile Adaptive Learning Environments: A Case Study

Estefanía Martín and Rosa M. Carro

Abstract—In this paper, we describe a system to support the generation of adaptive mobile learning environments. In these environments, students and teachers can accomplish different types of individual and collaborative activities in different contexts. Activities are dynamically recommended to users depending on different criteria (user features, context, etc.), and workspaces to support the corresponding activity accomplishment are dynamically generated. In this paper, we present the main characteristics of the mechanism that suggests the most suitable activities at each situation, the system in which this mechanism has been implemented, the authoring tool to facilitate the specification of context-based adaptive m-learning environments, and two environments generated following this approach will be presented. The outcomes of two case studies carried out with students of the first and second courses of "Computer Engineering" at the "Universidad Autónoma de Madrid" are also presented.

Index Terms—Personalization systems, adaptive hypermedia, Web-based interaction, computer uses in education.

1 Introduction

The rapid evolution of wireless technologies, the development of handheld devices, and the increasing easiness of accessing to wireless networks from different devices have encouraged researchers and companies to make advances in mobile technologies. Mobile devices join connectivity and portability issues to allow more opportunities in the real life. It is a fact that many people usually carry one or more mobile computing devices with them, including smart phones, personal digital assistants (PDAs), or laptops. These personal devices are normally used with different purposes, some of which are related to entertainment, working, or learning, among others.

Nowadays, people usually spend a lot of time working and also traveling from one place to another (from home to work/study and vice versa, for meetings, business, and so on). Time has become a really valuable good in our society, and in many cases, organizing one's time in an optimal way is rather complicated. In such a scenario, the use of mobile devices either to get on with pending tasks or even to ask for advice about how to spend well time is pretty useful. Moreover, sometimes tasks not only depend on the user himself, but also on other persons (partners). In these cases, the use of mobile portable devices connected to the Internet constitutes an added value, making it possible to support communication and cooperation between users.

In the context of learning, mobile devices and wireless technologies can be used to motivate students to learn in different contexts and active ways, for example, by proposing and allowing them to interact with online educational resources through handheld devices, suggesting them different activities according to their particular context so that they can benefit from idle time to study. These devices can be used from anywhere to take notes, communicate with other students and teachers, as well as to perform learning tasks (either individually or collaboratively) in real time. Mobile learning can be combined with traditional education. This combination has given rise to the concept of blended learning [1], where students can learn in classes or laboratories, as well as by doing different activities outside (i.e., through the Web).

Within the last decades, the use of the Web supports not just information access, but also learning activity realization has proliferated. When interacting with the Web, not all users have the same goals, interests, or needs. It is well known that aspects such as background, goal, preferences, learning styles, or personality can influence the way in which they interact with information. Moreover, this can determine their specific needs. In the context of mobile systems that support individual and collaborative task realization, activities can be (un)suitable to be broached by users depending not only on user features, preferences, or behaviors, but also on their context (i.e., device, location, or available time) [2]. When considering mobile collaboration environments, the context of group members, as well as group features and needs, are important too. In this framework, it is also useful to support the recommendation of activities and resources to users and groups according to not only their individual and collaborative features and needs, but also to their context to help them to organize their tasks and time too.

This paper is structured as follows: Section 2 presents some related work. Next, Section 3 describes the mechanism that supports the specification and generation of context-based adaptive mobile environments. These environments support the realization of different types of individual and

- *E. Martin is with the Escuela Politécnica Superior, B-207, Universidad Autónoma de Madrid, c/ Francisco Tomás y Valiente 11, 28049 Madrid, Spain. E-mail: estefania.martin@uam.es.*
- *R.M. Carro is with the Escuela Politécnica Superior, B-318, Universidad Autónoma de Madrid, c/ Francisco Tomás y Valiente 11, 28049 Madrid, Spain. E-mail: rosa.carro@uam.es.*

Manuscript received 18 Sept. 2008; revised 20 Nov. 2008; accepted 20 Dec. 2008; published online 31 Dec. 2008.
For information on obtaining reprints of this article, please send e-mail to: lt@computer.org, and reference IEEECS Log Number TLTSI-2008-09-0090.
Digital Object Identifier no. 10.1109/TLT.2008.24.

collaborative activities in different contexts. It selects the most suitable activities taking into account different adaptation features (users' context, individual and group features and needs, etc.). In Section 4, the recommender Web-based system where this mechanism has been implemented will be explained. This system supports the generation of different environments for diverse application areas. For example, it allows the generation of environments to manage and support company work, including functionality for both on-the-fly task recommendation and task realization for employees in different contexts. The system has been successfully used to generate different real context-based adaptive mobile educational environments. In this type of environment, educational activities are recommended to students according to their personal features and context, also considering those of their partners. For example, it is possible not to propose complex activities to users when they want to take advantage of a short period available. Moreover, the same activity can be recommended to some users while not being recommended to others, even if they are in the same context, because of their different personal features or needs. For example, it is possible to propose an exercise to an active student that has 10 minutes available while proposing a reflective student to read a summary of certain contents in the same situation. In addition, multimedia contents and tools to support the interactions can be adapted according to both the features of the device used and user features (including learning style). Section 5 shows the results obtained in two case studies carried out with real students of first and second course of "Computer Engineering" degree in "Operating Systems" and "Data Structures" subjects will be commented on. Issues such as the appropriateness of learning activity recommendation, multimedia contents, tools, and navigational guidance offered for each user, depending on his personal features, dynamic information, and context will be presented including also information about users actions and their opinions regarding the recommendation process. Finally, conclusions are presented.

2 Related Work

The earliest applications of Adaptive Hypermedia (AH) date from the beginnings of the 1990s. Brusilovsky presented the first classification of AH methods and techniques in 1996. It considers mainly adaptive presentation (content-level adaptation) and adaptive navigation support (link-level adaptation). More details about the different methods and techniques can be found in [3]. With the aim to supporting adaptive e-learning, managing information about students is necessary. User data, such as personal features, preferences, needs, or context, can be considered with adaptation purposes. These data are stored in the User Model (UM) and must be updated [4]. The values of each attribute of the user model can be directly asked to the user, extracted from specific tests, such as learning style [5], personality [6], or intelligence [7], or got on the fly [8]. Some well-known e-learning adaptive systems based on these AH techniques are ELM-ART [9], AHA [10], TANGOW [11], and WHURLE [12].

In the context of learning, collaborative activities are essential for facilitating not only knowledge acquisition [12], but also the development of different personal and social skills [13], [14]. Moreover, it increases student motivation and participation [15], [16]. A detailed description of well-known Computer Supported Collaborative Learning (CSCL) systems is presented in [17]. In our opinion, in collaborative systems, it is very important to make sure that the activities to be carried out, as well as the tools provided to users, fit user needs, so that they feel comfortable interacting with the environment. Therefore, we think that it is useful to adapt different collaborative issues to facilitate collaborative learning. In order to perform adaptation in CSCL, it is necessary to store information about individuals and groups in the corresponding user and group models including roles (if defined), opinions about previous collaborations, and dynamic data related to group and individual performance. Some research dealing with adaptation in CSCL has been done and implemented in systems such as WebDL [18] or COL-TANGOW [19].

Another line of research dealing with adaptation of information according to user needs is that of recommender systems. These are a specific type of adaptive systems based on modeling user interests and preferences [20]. Recommender systems give personalized suggestions for each user and guide them through interesting and useful objects in a huge space (i.e., films, music, books, news, images, Webpages, etc.) [21]. A recommender system usually compares user features with information about each element, also considering the opinions of experts or other users. Markov models are statistical models that can be used by recommender systems in order to predict event sequences [22].

Many recommender systems use Markov models to do predictions in different areas, such as biology, speech recognition, or natural language processing [23]. In [21], a review of different recommendation techniques is presented, including their advantages and problems. Several adaptive systems use some of the techniques proposed with a temporal adjustment to make old votes have less influence than new ones [24]. Recommender systems are used in different areas such as tourism (i.e., GUIDE [25] or [26]) or shopping [27], among others. In general, mobile recommender systems assist users in unknown environments in finding what best suits their preferences [21].

The use of mobile devices for learning increases learner motivation and promotes interactive learning [28]. Learners are motivated to be more engaged in learning activities when new technology is used in a meaningful way. Thus, it is desirable to develop some instructional implications on how these fascinating technologies can be proportioned to the conventional learning activities [29]. A review related to the use of new technologies for learning is presented in [30], including information about

1. how mobile devices used for improving access to learning resources and evaluation system (i.e., enabling students to look at information any time and anywhere);
2. new changes in teaching and learning processes (i.e., revision material tailored to the needs of the

individual, providing a flexible context-awareness system that can react to their needs); and

3. the establishment of relationships between academic goals and business (i.e., allowing users to use their personal devices with educational purposes, blending mobile technologies into e-learning infrastructures to improve interactivity and connectivity to the learner).

Some mobile learning approaches can be found in [31], [32], [33]. In [31], a pedagogical and technical approach to support learning activities both outside the school and in the classroom is presented. Students use PDAs with GPS cards to record bird observations about natural environment that are analyzed afterward. JAPE-LAS [32] is a context-aware language learning support system for learning Japanese polite expressions. Finally, in [33], an evaluation of a mobile learning organizer developed for graduate students is described. This study was designed to discover the patterns of use of a mobile learning organizer when used by students in a wirelessly networked study environment and other locations of their choice. Although there is no indication that the mobile learning organizers used in this study greatly altered students' styles or patterns of learning, they did have some impact on the way the students worked and demands placed on their lecturers.

Regarding contents and their appropriate presentation in different devices, designers must consider the specific device characteristics such as size of screen and possible memory limitations. Different versions of contents can be developed for personal computer applications and mobile devices. In [34], the architecture of a system capable of adapting contents to devices and user profiles without duplicating efforts for PDAs and computers is proposed.

3 Basis

The basis of the platform developed consists of an underlying mechanism that supports recommendations of individual and collaborative activities to users in mobile environments facilitating time management and organization. This mechanism recommends the most suitable activities for each user, taking into account not only his personal features and behavior, but also his current context and information about other users. In order to perform the adaptation, the mechanism is fed on the specification of the information about users and groups (user and group models), the description of the activities that can be performed (activity model), the rules describing adaptation capabilities and recommendation criteria (adaptation model), and information about previous interactions with the system (logs stored as part of the user model to be further used with adaptation purposes).

User and group models store stable information, which does not significantly change over time, and dynamic information. Some features that can be considered as stable information are: background, learning style, or preferred language. Examples of dynamic information are: data about the learning process (activities performed, results obtained), opinions (i.e., about collaborative experiences), or context at a certain time (physical location, available time, and devices). The possible values for each parameter stored in the user and group models can be defined as stereotypes or numeric values. These characteristics will be used to recommend the most suitable activities at each time and also to adapt the workspaces dynamically generated.

Regarding learning activities, it is necessary to specify

1. the common characteristics of the whole set of activities, such as available languages, general set description, adaptation features to be considered, and general aspects related to collaboration workgroups,
2. information for each activity (type, descriptions, deadline, and so on),
3. different versions of contents associated to each activity, and
4. collaborative tools to be offered to support collaborative task accomplishment. This information is stored in the activity model.

Finally, recommendation and adaptation criteria to select the most suitable activities, contents, and tools at each time are described and stored in the recommendation model as adaptation rules. The recommendation mechanism supports five different types of adaptation, each of which can be different for distinct types of students. They are based on the following:

- Relationships between activities, which can be established in different ways according to the type of user(s) for which they are intended.
- Navigational guidance offered within each set of activities, which can also be different according to user needs or preferences (direct guidance versus free).
- (Un)suitability of certain types of activities according to the type of activity and the user(s) context. This can also be established in different ways for different types of users, even in the same context.
- Specific activity accomplishment requirements: If they are not satisfied, the activity is not proposed to the corresponding users. Different requirements can be specified even for the same activity, each of them for a certain type of users.
- Collaborative workspace configuration: Problem statements and collaborative tools can be differently combined to generate different collaborative workspaces, even for tackling the same task, each of them adapted to each group of users' features and needs, stored in the group model [19].

The description of adaptation and recommendation criteria is supported by means of rules. Each set of rules represents an adaptation filter through which activities pass. The first one recommends activities considering the relationship between them, which can be established in different ways for different types of students. The second one takes into account the types of activities to be recommended at each context. The third one deals with individual activity requirements. In each filter, recommendation degrees for the different activities are set, taking into account the criteria expressed in the corresponding rules. Rule conditions can be related to any parameter stored in the user or group model. Only the rules whose conditions are satisfied are triggered. Recommendation criteria can be specified in different ways according to different types of students by means of rules with different activation conditions. This leads to a personalized annotation of activities at each time. Synchronous activities are not proposed to students if not all of the members of the group are online. More details about the rule-based recommendation mechanism can be found in [36].

However, there is no need to provide rules for every single activity. In case there is no information available about the suitability of recommending an activity to a certain user in a particular context, previous recommendations and actions of users with similar features in similar contexts are analyzed in order to provide a recommendation. This part of the recommender mechanism is based on the use of Markov models [22]. Logins of user actions are analyzed offline to obtain navigational path graphs. These path graphs are combined to get new graphs representing paths followed by similar users. These graphs represent a Markov model in which states represent activities, and the transition probability matrix indicates the probability that a user moves from one activity to another. Therefore, at runtime, if no criteria for recommending (or not) a certain activity are available, transition probability matrices are analyzed along with user features and context in order to provide the most suitable recommendation. If there is not enough information about the suitability of the recommendation of a certain activity, for a specific type of user, the activity will be available but not specially recommended.

The mechanism, therefore, consists of two main phases. The first one deals with rule processing, while the second one is based on Markov model usage. The final aim is to provide useful recommendations to users at runtime, as well as to generate the corresponding workspaces to support activity realization. During the whole process, each activity is annotated as follows:

- *Recommended*. Prerequisites, if any, are satisfied, and the activity is suitable for the user context.
- *Not recommended*. Prerequisites, if any, are satisfied, but the context of the user is not appropriate to perform the activity.
- *Available*. There is no pending prerequisite for the activity to be performed, although there is no information about the suitability of the activity for the user context.
- *Not available*. Any condition related to user personal features or previous actions is not satisfied.
- *Already done*. The user can access to it again.

The output of the mechanism, once activities have passed all filters and Markov models are checked (if needed), consists of a list of activities, each of them annotated with the recommendation degree for a given user in a specific context. Once the user selects an activity, a workspace to support the activity realization is dynamically generated and adapted to user features and device. In the case of individual activities, content fragments are selected according to the user features and context, and combined within one or more Webpages depending on the device used. In the case of collaborative activities, collaborative workspaces

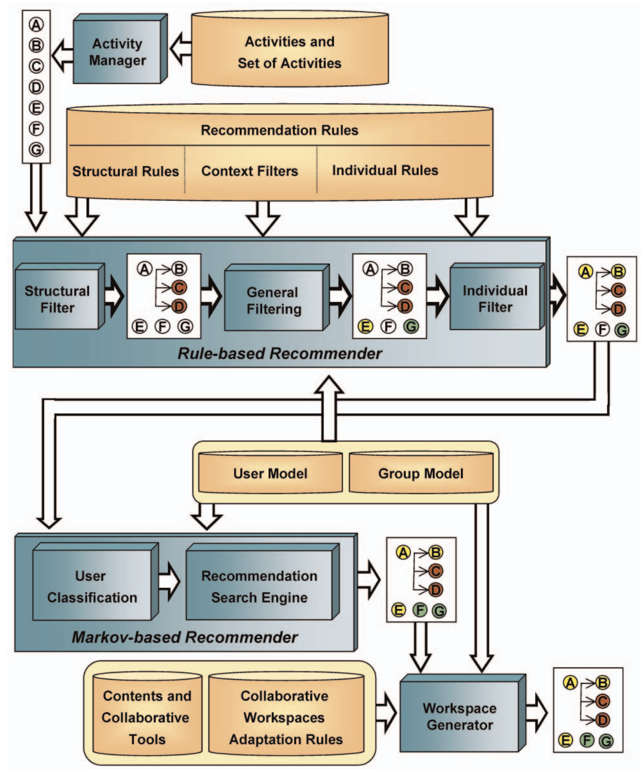

Fig. 1. Schema of the recommendation process.

are generated by selecting the most suitable problem statement and the most appropriate collaborative tools for each specific group of students, considering their personal features and context. This is supported by means of collaborative workspace rules [35]. The implementation of this mechanism within a system is depicted in Fig. 1 and described in detail in next section.

4 The Platform: CoMoLE

The mechanism described in the previous section has been implemented into a platform called *Context-based adaptive Mobile Learning Environments* (CoMoLE) [37]. Users can access to the environments supported by CoMoLE from different devices through a Web browser.

CoMoLE supports the recommendation and the accomplishment of different types of learning activities such as reading explanations, observing examples, making tests, doing short free-answer exercises, solving problems collaboratively, downloading electronic material for their study, sending/receiving messages to/from partners of the same workgroup, and so on. Activities can have associated multimedia contents as well as collaborative tools to support the interaction between members of the same group in the case of collaborative activities. Each activity can be devoted to everybody, to certain types of users, or only to users in particular contexts. These adaptation capabilities are defined by means of rules.

Information about activities, contents, collaborative tools, relationships between them, and adaptation decisions must be specified in the design phase and is stored in XML files. Information of users and groups, generated at runtime, is

Fig. 2. Example of a Webpage dynamically generated by CoMoLE.

stored in XML files too. These data are processed by CoMoLE when users are interacting within the environment.

CoMoLE is implemented in two main modules, each of them corresponding to a different phase of the mechanism (rule-based recommendation and Markov-model-based recommendation). These modules are responsible to annotate each activity, indicating the recommendation degree (recommended, not recommended, available, unavailable, or already performed) and to select the most suitable resources for a user, taking into account his current situation. Besides, an activity manager generates the initial list of activities to be processed by these modules.

Three different adaptation filters compose the rule-based recommender: *structural filter*, *context-based general filter*, and *individual filter* [38]. Each of them processes a different type of rule: structural rules, context-based general filters, and individual accomplishment restrictions, respectively. This fact facilitates the use of each module in an independent way. Therefore, the person in charge of each environment can choose the recommendation modules to be used. This can be done in the authoring phase. The input of each adaptation module is the output of the previous one, except for the first one, which receives the initial list of available activities from the activity manager. The final output of recommendation modules is an annotated activity list with a recommendation degree for each of them.

It is possible that no information is available for some activities in the rules and, therefore, the rule-based recommender does not know how to annotate them. In this case, the Markov-model-based recommender checks the path graphs obtained previously, and completes the annotations according to probabilities in the graphs.

Once the list of activities has been annotated, the workspace generator creates a Webpage with the recommendations, and builds the most appropriated workspace for accomplishing the activity selected by the user, including the most suitable contents and tools. This workspace is sent to the user through the Web.

Fig. 2 shows a snapshot of a Webpage dynamically generated. It has been built for a student with sensing learning style who has 30 minutes available and is using a personal computer at home to study "Operating Systems." This Webpage is structured in three areas: recommended activities (① in Fig. 1), activity index (②), and content and tools area (③). In this example, the activities recommended to that student at that context are *"Test1," "Test2,"* and *"Test3."* The current activity name is presented at each time in the right side of the recommendation area (*"Concepto"* in the example). In the middle of this area, two buttons are placed. The one in the upper part is for closing the session and the one below allows showing/hiding the activity index in order to extend/reduce the size of the workspace area ③.

In the left side (area ②), the activity index for a certain user is presented. This index is generated on the fly starting from the activity list annotated by the recommendation module. Each activity is colored according to the semaphore metaphor to represent different types of recommendation degrees:

- Green: recommended at that time.
- Yellow: available but not recommended in this context.
- Red: not available.
- Orange: available.
- Black: already accomplished.

Finally, on the right side of the page (area ③), contents and tools are combined to support the realization of the corresponding activity. In the case of individual activities, contents are selected by the workspace generator from the available fragment versions for the activity, considering user personal features (i.e., visual/verbal learning style), dynamic behavior (i.e., activities done, scores obtained in each activity) and context (i.e., adapted to PCs or PDAs), and comparing this information with the features for which each fragment is intended.

For collaborative activities, the workspace generator is the responsible to select problem statements and collaborative tools to support interaction between users and task accomplishment. It processes collaborative-workspace rules and generates the corresponding workspaces accordingly [29].

When interacting within the environment, students can select the next activity to be performed by clicking on the following:

- A link of recommended activities from the recommendation area.
- Any link to recommended, not recommended, or already performed activities in the activity index (area ②). Not recommended activities are annotated as not suitable in the index (yellow color), but the learning environment does not block the access to them. Unavailable activities are annotated in red color and students cannot access to them until the recommendation state changes.
- The button "next recommended activity" included at the bottom of area ③. In this case, the workspace that will be presented will correspond to the first activity in the list of recommended activities.

In the example of Fig. 2, the learning environment suggests three activities to the student in the recommendation area of the Webpage generated. When the set of recommended activities consists of more than three activities, students can access to them through the annotated index on the left since all recommended activities would appear there, annotated in green color. The decision of selecting only three activities as maximum to be proposed in the recommendation area has been taken with the aim to avoid burdening students with too many recommendations. In such a way, on the one hand, the environment guides disoriented students through the recommended activities. On the other hand, the access to the whole set of recommended activities is possible through the activity index for those most familiar with these environments.

4.1 Authoring Support

Developing mobile learning environments, where individual and collaborative activities can be recommended to users (and workspaces can be generated on the fly) according to users' features and contexts, can become an impossible task for some teachers, and frustrating for others. With the goal to help them to create and configure this type of environments, as well as to manage all the information, an authoring tool has been developed. This tool is accessible through the Web. The information required for each element of the environment, which is maganed by CoMoLE, can be provided through Web forms in an easy way. In order to create a new educational environment, authors must follow four steps:

- Creating a set of activities (whose realization and recommendation will be supported), and defining types of activities and common characteristics of the whole set.
- Providing general context filters related to the (un)suitability of certain types of activities in different contexts.
- Specifying the sets of tools to be used to accomplish collaborative activities.
- Describing the learning activities themselves, along with structural rules and accomplishment requirements (if any), and specifying the different versions of contents associated to each activity.

The authoring tool offers some additional help to describe environment features, such as adaptation rules, general context filters, or collaborative tools to be used by default. Starting from the descriptions provided by authors (either created by themselves or selected from default options), the authoring tool generates *XML* files to store the corresponding models.

Regarding means to facilitate user model acquisition once features to be considered for adaptation purposes are specified, the corresponding forms to get information from users are generated accordingly. Some features, such as learning styles, are offered in the authoring tool to be incorporated by default in the environments created. If learning styles are selected, then a specific questionnaire will be posed to students the first time they connect to the system. This questionnaire includes a selection of questions from an ILS questionnaire that includes the most relevant questions to get this information without asking the 44 questions of ILS [41].

A snapshot of the authoring tool is presented in Fig. 3. This page corresponds to the first step of the design process (creation of a new set of activities and definition of common characteristics). As can be seen in the upper half of the page, it is possible to indicate the adaptation type(s) to be supported (corresponding to different types of filters for the rule-based recommendation phase), as well as the desire of using dynamic grouping for collaborative activities. In the lower half of the page, features to be considered with adaptation purposes can be either selected from those available or specified (including potential values for each of them).

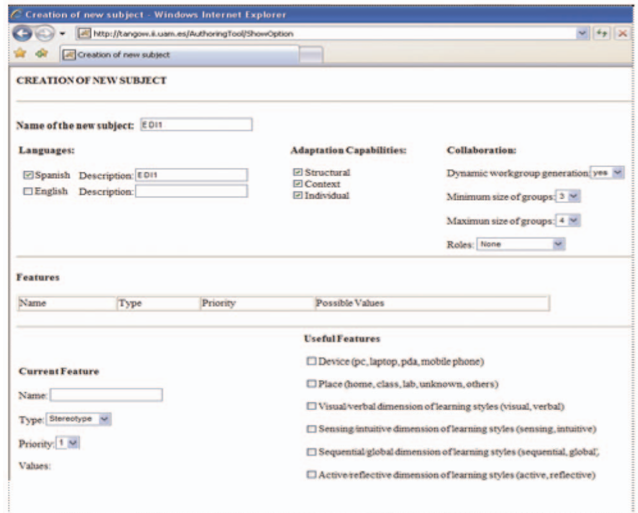

Fig. 3. Snapshot of the authoring tool.

Both the authoring tool and the mobile learning environment have been implemented in Java language, and share a library with common functionalities. They also use an external library (jdom) to manage the information stored in *XML* files from Java code [39].

5 Two Case Studies

With the aim to check the impact and usefulness of these mobile learning environments in education (focusing on helping students with time management by recommending them specific learning activities according to their features and context), two case studies have been carried out with students of the first and second grade of "Computer Engineering" studies at the "Universidad Autónoma de Madrid." Two learning environments were developed with the authoring tool described above to be used as additional educational resources for "Data Structures" (first course) and "Operating Systems" (second course) subjects. In each environment, different types of learning activities related to the corresponding subject were included. Students were able to perform these activities through different devices such as PCs, laptops, or PDAs.

The case studies offered feedback about: the usefulness of context-based recommendations for these students to learn these subjects; the quality of the recommendations offered; the (in)convenience of using different devices for accomplishing specific activities; whether the system helped students to organize their time for studying; whether students would use it again; what students think and how they feel about these new ways of learning; and some details about the experience.

In order to motivate students to connect to the Web-based environments developed and to allow them to benefit from the context-based recommendation process, some handheld devices were lent to those that had none of their own. Some technical characteristics of PDAs lent were: Windows Mobile 5.0 software, 240 × 320 pixels, 12-65 MB of available memory, WLAN IEEE 802.11g Wifi, and USB. The number of students enrolled in "Data Structures" and "Operating Systems" subjects were 285 and 230, respectively.

The m-learning environments were made available one week before the end of the semester (23 May) because of logistics. They were used by 135 students in "Data Structures" and 160 students in "Operating Systems" (47 percent and 69 percent of participation in each case). The date of the final exam for "Data Structures" was the 6 June and it was 23 June for "Operating Systems." Therefore, "Data Structures" students had less time to interact with the learning environment. They were the first students using it, and detected some small problems with the environment, which were fixed due to their feedback.

The "Data Structures" environment deals with learning activities related to data structures and programming using C language. Teachers explained these topics during the first months of the semester in the class. The "Operating System" subject has main nine topics and, in this case, the learning environment recommends activities related to one topic ("Memory Management"). Both learning environments contain activities to support learning of theoretical concepts and procedures, revising examples, practising with self-assessment tests, answering open-ended questions, reviewing already done activities and, in the case of "Operating Systems," solving a problem collaboratively.

Learning activity organization is expressed by structural rules, in which tasks are grouped; the guidance to be offered to different types of students when accessing to each group of tasks is specified in the corresponding rules. "Data Structures" environment has 133 activities, 95 of which are atomic. "Operating Systems" has 79 atomic activities out of 91 that composed the whole set.

In both environments, learning activities and contents were recommended to students considering the information stored in the user model. In these particular environments, the parameters constituting the user model are as follows:

- *Personal features*: Learning styles (visual-verbal, active-reflective, and sensing-intuitive dimensions), as defined in Felder's model [5].
- *Actions previously done*: Activities already accomplished and results in practical tasks.
- *Context*: Device used (PC, laptop, or PDA), available time (numerical value), and physical location (classroom, laboratory, home, or others).

These parameters (including their potential values) are specified in an XML file associated to the environment and can vary from one environment to others. Regarding the way of obtaining information from each student, specific questionnaires were presented, included that for learning styles mentioned in Section 4.1.

TABLE 1
Example of General Context Rules

ID	USER FEATURES	USER CONTEXT	REC.	TYPE
①	Actvref=active	(time<10)	Not	Collaborative Short_Text
②	Actvref=reflective	(time<20)	Not	Collaborative Short_Text

The general context filter was used in both subjects, and authors included two rules, which specify the minimum time needed to perform short text exercises and collaborative activities for active/reflective students (10 minutes for the former, 20 minutes for the latter). Table 1 shows these rules.

Finally, specific constraints were also included, related to student physical location, device used, starting and ending dates, activities already performed, and results obtained in practical tasks. These requirements are checked while students interact with the system to provide the most suitable recommendations at each step.

Once a student selects an activity to perform, the most suitable contents associated to this activity are selected for this student. Each activity has different versions of content fragments associated. In these environments, multimedia contents were adapted to student learning styles and devices. On the one hand, contents presented for visual learners contained more images and graphical explanations, and less text. On the other hand, contents offered to verbal students had more detailed textual explanations. Content versions of "Operating Systems" use a different cascade style sheet to adapt multimedia contents to devices. When users were using a PC or a laptop, a content page was built from joining the most suitable content fragments (one or more). However, when a PDA was used, only one content fragment was presented at each step in order to facilitate visualization. Content fragments are selected taking into account the user personal features and his context, including device used.

User actions at each time, including activity done and result obtained, are stored in the user model, along with the student context and the recommendation provided at that time, to be used for further recommendations.

5.1 Results and Discussion

Students gave us specific feedback about the recommendations received, as well as their opinion, while interacting with the mobile learning environments and at the end of the course. They were asked to indicate, for each recommendation offered by the environment at each step, whether they found it appropriate. With the aim to support this type of feedback, the workspace generator included the question "*Do you consider that the current recommendation was appropriate?*" at the bottom of the content area. Learners could select among "Yes," "No," or "I do not know" (this was the default option, see "-" in Fig. 1). The user selection was stored and analyzed along with user features and the context in which the activity was proposed. However, just in case students found providing feedback at each step tedious, and with the aim of getting more information, an

TABLE 2
Information about the Use of CoMoLE

INFORMATION ABOUT THE USE OF COMOLE	DS	OS
Students enrolled	285	230
Students that used CoMoLE	135	160
Percentage of use of CoMoLE	47%	69%
Number of atomic activities in each subject	95	79
Average number of atomic activities performed by each user	33	39
Percentage of atomic activities performed	35%	49%
Total number of atomic activities performed or reviewed by students	4387	6101
Number of accesses to CoMoLE	190	381
Total minutes performing activities	3867	4015

"Data Structures" – DS, "Operating Systems" - OS

TABLE 4
Student Answers about the Suitability of Recommendations for "Operating Systems" Subject

DATE	YES	NO	I DON'T KNOW
Until 28/05/2008	42	2	63
Until 29/05/2008	53	4	70
Until 30/05/2008	91	5	84
Until 02/06/2008	108	8	113
Until 03/06/2008	112	8	113
Until 06/06/2008	163	15	177
Until 13/06/2008	253	32	374
Until 17/06/2008	280	36	546
Until 18/06/2008	330	50	751
Until 19/06/2008	359	54	815
Until 22/06/2008	617	89	2393
Until 23/06/2008	657	98	2613

online survey was made accessible from the environment so that they could express their opinions freely.

Before analyzing the feedback obtained, general data about the use of CoMoLE are presented in Table 2. The global participation percentages (students that used CoMoLE from those enrolled in a course) were 47 percent and 69 percent. Students in "Data Structures" performed 4,387 activities and those in "Operating Systems" did 6,101. The average of atomic activities accomplished were 33 in "Data Structures" and 39 in "Operating Systems" from 95 and 79 atomic activities, respectively. "Operating Systems" students performed more activities on average (49 percent) than "Data Structures" students (35 percent).

Next, information about the suitability of the recommendations at each step, according to student answers, is presented. Table 3 shows the number of good and bad recommendations, as indicated by the students, until a certain date for "Data Structure," as well as the number of times that students did not give us any feedback. Table 4 represents the same information for "Operating Systems."

When analyzing the feedback of students presented in these two tables, it is important to remember that both case studies started at the end of May and the final exam was the 6 June for "Data Structures" and the 23 June for "Operating Systems." When considering only the information stored before the exam, the data are those are presented in Table 5.

TABLE 3
Student Answers about the Suitability of Recommendations for "Data Structure" Subject

DATE	YES	NO	I DON'T KNOW
Until 29/05/2008	61	3	190
Until 30/05/2008	122	8	441
Until 02/06/2008	269	15	869
Until 03/06/2008	352	20	1183
Until 06/06/2008	614	39	2891

As can be observed in Tables 3 and 4, there is a large increase in the number of times students selected the "I do not know" option in the previous days of the final exam in both studies. Before we received more detailed feedback from surveys, we thought that this was because students were quickly training for the final exam, with not enough time to provide feedback. The survey done after the final exam confirms our thoughts.

Both case studies show a lack of use of the selection box, but when comparing only "Yes" and "No" options, there are much more students who considered the recommendations suitable (94.3 percent versus 5.7 percent for "Data Structures," 87 percent versus 13 percent for "Operating Systems").

In order to know what happened with recommendations annotated as unsuitable, data about the activities proposed, along with student features and contexts, were analyzed. The main goal was to get explanations about which type of students considered the task unsuitable and their context at that time, in order to see whether it would be necessary to modify recommendation criteria. The first approximation to this analysis consisted of finding out which activities were proposed in "unsuitable recommendations," and how many students considered them unsuitable. A list of activities related to "unsuitable recommendations" was obtained for each subject.

In the case of "Data Structures," the list contained 22 activities. However, there were only eight activities annotated as "unsuitable" by more than one student. These activities were those whose contents are essential. For example, examples of atomic types in C (considered

TABLE 5
Final Results about (Un)Suitability for "Data Structures" (DS) and "Operating Systems" (OS)

	YES	NO	I DON'T KNOW
Data Structures	23%	1%	76%
Operating Systems	29%	4%	67%

TABLE 6
Information about Personal Features and Context Who Consider Unsuitable "AtomicEjem"

	LEARNING STYLES	CONTEXT
U1	Visual, global, active, sensing	Pc, 30 min, home
U2	Visual, global, reflective, sensing	Pc, 20 min, home
U3	Verbal, sequential, reflective, sensing	Pc, 10 min, home
U4	Visual, sequential, active, sensing	Pc, 4 h, others
U5	Visual, global, reflective, sensing	Pc, 10 min, home
U6	Visual, sequential, reflective, sensing	Pc, 30 min, home
U7	Visual, sequential, reflective, sensing	Pc, 2 h, others

TABLE 7
Information about Personal Features and Context Who Consider Unsuitable "Mem_Test2"

	LEARNING STYLES	CONTEXT
U1	Visual, global, reflective, sensing	Pc, 20 min, home
U2	Visual, global, active, sensing	Pc, 1 h, home
U3	Verbal, sequential, reflective, sensing	Pc, 1 h, home
U4	Visual, global, reflective, sensing	Pc, 30 min, home
U5	Visual, global, active, sensing	Pc, 20 min, home
U6	Visual, global, reflective, sensing	Pda, 10 min, class

unsuitable seven times, representing the 18 percent of the "not suitable" recommendations in this subject), theory about atomic types, "if" and "switch" conditionals, examples of operators and loops in C, and review activities proposed only to students who obtained low scores in tests and short exercises related with conditionals and loops. Regarding "Operating Systems," the activities involved in recommendations annotated as unsuitable with highest frequency are also related to the most basic concepts. Apart from theoretical activities and examples related to "Pagination" and "Simple Segmentation," there are some tests related to basic memory management. From the whole set of atomic activities in this subject (79), 23 recommendations were selected as not suitable by more than one student.

In order to know whether there is any relationship between the recommendations annotated as unsuitable, the context in which they were done, and the features of users who did these annotations, we analyzed all the information stored in the system about the two activities annotated as unsuitable in most occasions. There are "AtomicEjem" for "Data Structures" and "Mem_Test2" for "Operating Systems."

Table 6 presents information about students who annotated "AtomicEjem" as unsuitable. This activity is the first activity recommended to sensing students and the second activity that intuitive learners must accomplish, independent of their context. In all, seven students annotated this activity as unsuitable, but 45 other students marked it as suitable, as shown in Table 6. The contexts of these users when the task was proposed to them were different. However, all of them are sensing. When looking for information about students who annotated this activity as suitable, 39 were sensing students and only six were intuitive learners. Therefore, we think that neither learning styles nor context features influenced the student selection of (un)suitability for this activity.

Table 7 shows personal features and context of students that considered unsuitable the recommendation of "Mem_Test2." This activity was annotated as suitable by six students and as not suitable by six learners. Furthermore, this is the activity with more "unsuitable" votes in this subject. This one was proposed to all students, independent of their learning style. It is a subactivity from "Memory Management" and, in this case, navigational guidance between subactivities was not different according to student learning style. Furthermore, context features were different for each student. Therefore, we cannot get conclusions about which students in which situations considered the task unsuitable, to update recommendation criteria.

The next analysis done consisted of looking at the type of activities annotated as unsuitable, in order to find out whether there exists any relationship between the types of activities annotated as unsuitable and user features and context. The aim here was to find out whether criteria for general filters should be modified.

Fig. 4 shows the frequency of recommendation unsuitability according to the types of activities. In Fig. 4a, the results of "Data Structures" are presented. The answers for "Operating Systems" are in Fig. 4b. In both cases, theoretical explanation is the type of task involved in recommendations marked as unsuitable with the highest frequencies.

For each activity selected at least once as inappropriate, we analyzed the number of students who considered it unsuitable versus those who considered it suitable. Fig. 5 presents the number of votes for "Yes" and "No" options. All of the activities had more positive than negative answers, but an open-ended question, which received only a few votes, had mostly negative answers. When we checked the question, it turned out that its feedback was wrong. We think that this may be the reason why students did not consider the recommendation of the activity suitable (maybe they thought they were not ready to answer the question correctly, or they simply got disturbed).

Taking into account these results, it seems that the activity recommendation process works well, selecting suitable activities at each step, according to criteria specified by teachers. It is a fact that a significant amount of times students do not give us their feedback about specific

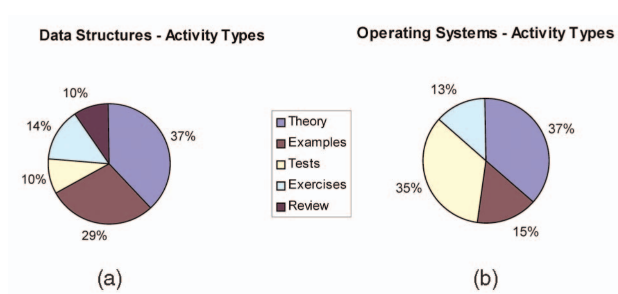

Fig. 4. Frequency of unsuitability according to the activity types.

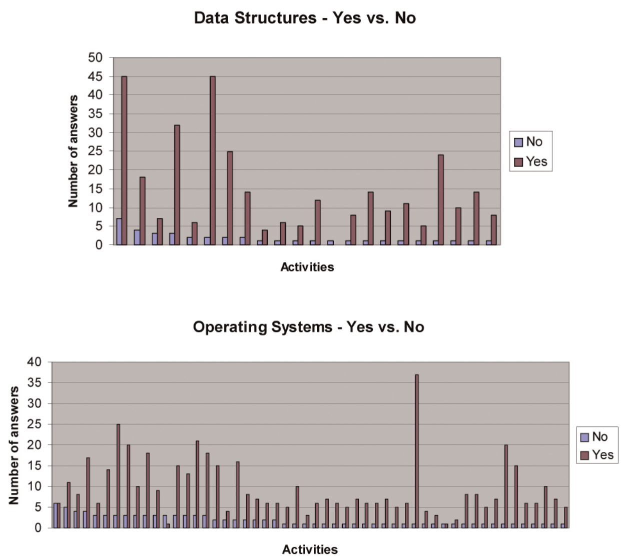

Fig. 5. Suitability versus unsuitability of activities.

recommendations, which we thought could be a possibility from the beginning. For this reason, an online survey was made available through the environment interface with free-text questions. Many students gave us more detailed feedback through these surveys, as it is explained in detail next.

Sixty eight students answered this survey: 21 from "Data Structures" and 47 from "Operating Systems." It consisted of 18 questions. Some of them were oriented only to students that used a PDA as one of the devices to connect to the environment. Some students had their own laptops/PDAs, and we lent some extra PDAs to facilitate mobile learning. Most of the students answered the online survey after the final exam. The questions and the corresponding student answers are presented next.

The first question was "*Do you prefer that the environment recommends you activities in each step according to your characteristics and current context or would you have preferred that it had not done any suggestion?*" Students were able to choose between three options:

- It is better with recommendations.
- It does not matter.
- It is better without recommendations.

Most students prefer recommendation (71 percent from "Data Structures" and 85 percent from "Operating Systems," see Fig. 6).

Students were allowed to explain their selection in a text box. Those who preferred suggestions of the learning environment emphasized several positive aspects of the environment:

- These systems guide one over the whole set of activities and help to decide the starting point (what are the best activities to be done according to one's personal needs and learning process).
- It helps to know which topics have been wrongly learned, and it proposes review activities for consolidating these concepts.

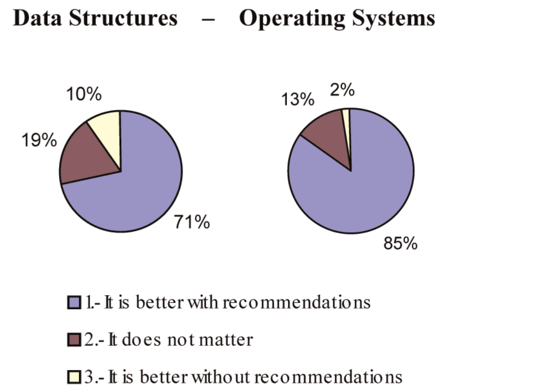

Fig. 6. Feedback about recommendation preference.

- It includes many exercises and I can train for the final exam since teachers do only a few exercises in class.
- It is useful that the system annotates the most important topics of the whole set of topics.
- These environments are more attractive because they allow me to do many types of activities, not only study theory from a book or my personal notes.
- This type of learning environments helps to organize one's free time, so they are very useful when one has only a few minutes available.

In a few cases, students said that they better understood the concepts when they were explained by the environment rather than by the teacher in the classroom.

Students that chose "It does not matter" or "It is better without recommendations" stated that contents were the relevant elements of the environment, and said that they prefer to choose the activities to be performed at each time. Some of these students have a global learning style and the environment did not consider adapting the learning activities to this type of students. Other learners said that sometimes they could not concentrate on studying some contents because they are tired.

The second question was *whether students think it is useful to be guided through the whole set of activities according to personal features such as learning style.* Students can score between 1 and 5, where 1 means very useful and 5 means useless. In both case studies, no student selected the useless option and only one student per case scored 4. As it can be seen in Fig. 7, 71 percent of "Data Structures" students and 79 percent of "Operating Systems" consider very useful or useful the adaptation based on personal

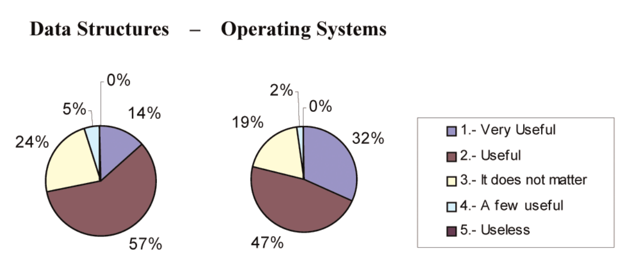

Fig. 7. Usefulness of adaptation to student personal features.

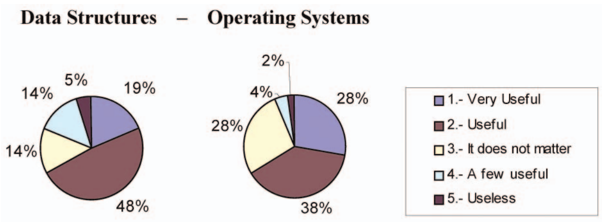

Fig. 8. Usefulness of adaptation to student context.

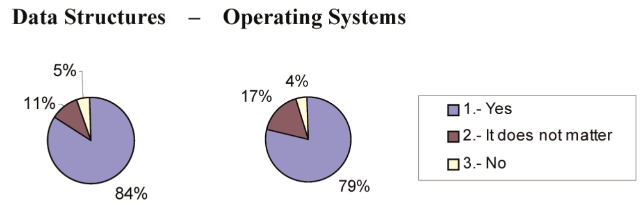

Fig. 9. Usefulness of recommender environments.

features. Only 5 percent and 2 percent of students considered it a little useful.

The third question was about *the suitability of adapting the learning activities according to student current context*. Students consider the context slightly less important than personal features. In this case, the percentage of "very useful" and "useful" answers are 67 percent for "Data Structures" and 66 percent for "Operating Systems" (see Fig. 8). Furthermore, "few useful" and "useless" options are selected by seven students in total, considering the two environments.

We asked students *if they followed the recommendations suggested in the upper area of the Webpages, if they selected other recommended activities from the activity index, or if they accessed to activities annotated as not recommended*. The percentage of students that followed the environment recommendations always or most times was 62 percent in both cases. The percentage of students who did not follow the recommendations sometimes is low (three students per subject). Finally, those students who followed the suggestions of the learning environment sometimes was 24 percent for "Data Structures" and 32 percent for "Operating Systems."

Another question was "*Do you find recommender environments that adapt learning activities to personal features and context useful?*" Fig. 9 shows that 84 percent of the students in "Data Structures" and "79 percent" in "Operating Systems" consider these environments useful. Only 5 percent and 4 percent, respectively, did not find them useful for learning.

Students stated that these environments are useful because they are able to support content adaptation according to the user context (available time and device used) at each time. They said that it contributes to the learning process, guiding them through topics of a given subject. They experienced that this mobile learning environment helped them to approach the subject in a new way, and see it as an incentive to study more in less time.

Some students said that they find e-learning more attractive if activities can be performed without staying in front of a PC for hours (i.e., using PDAs). Others considered contents themselves more important than content adaptation to different devices. They prefer different versions of contents, with different levels of difficulty, i.e., rather than contents adapted to devices, with not that many differences between them. Finally, many of them pointed out that they do not own PDAs yet.

Regarding *the easiness of use of the mobile learning environment*, 90 percent of "Data Structures" students and 94 percent of "Operating Systems" students selected the "really easy" and "easy" options. Four students selected the "neither easy nor difficult" option. Only one student of the first grade said that using the learning environment was a little bit difficult.

The next question was "*Has the learning environment helped you to study the subject?*" In general, students are satisfied with the environment. They used it as an additional resource, not instead of traditional lectures and lab work. For this reason, if we sum up the number of students that think the system helped them, we obtain a 92 percent: 13 percent said that it helps a lot, 35 percent that it helps enough, and 44 percent that it helps a bit. Only 8 percent of the students answered "it does not matter" or "not enough."

The survey included a question about motivation. Students were asked *whether the mobile learning environment motivated them to study this subject*. In "Data Structures," 45 percent of them felt especially motivated to study more because of the use of the environment, and 50 percent of them said that they studied with the same motivation. Only 5 percent said that this environment did not motivate them at all. For "Operating Systems," better results have been obtained: 83 percent, 11 percent, and 6 percent, respectively.

Regarding external Web resources, two questions were asked. The first one was *if they looked for additional learning resources through the Web (i.e., notes, messages in forums, blogs, and so on)*. There are significant differences between both subjects. "Data Structures" students had looked for resources in Internet either regularly (45 percent) or from time to time (45 percent). However, only 19 percent of "Operating Systems" students usually looked for additional resources and 53 percent only did it from time to time. The next question related to this issue was "*If you had not had this mobile learning system available, would you have looked for more, less or equal quantity of resources in the Web?*" Similarly, there were different opinions between students from first and second grade. The majority of "Data Structures" students would have looked for the same quantity of learning resources; 24 percent said that they would have looked for more resources and only 10 percent would have looked for less material. However, 45 percent of "Operating Systems" students would have looked less if they had not had the learning environment; 30 percent had looked for the same quantity of resources, and 25 percent would have looked for more information. It is worth mentioning that in the second case, this may be because when interacting with the environment, they are more motivated to learn through the computer instead of reading books and notes, and end up looking for additional information.

With respect to students using PDAs, most of them said to have no *previous experience with PDAs*. The number of those using PDAs before these experiences is higher for

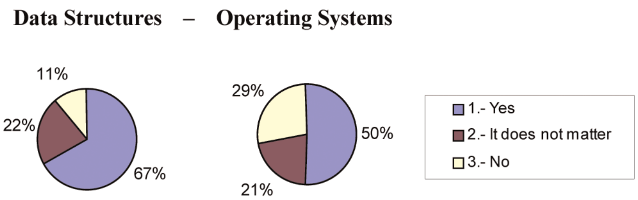

Fig. 10. Satisfaction of using PDAs for learning activity tackling.

students in the second year. Students with previous experience using PDAs do not consider themselves experts, but users who use PDAs in sporadic situations do. Only two "Operating Systems" students consider themselves experts with PDAs, and they use them quite a lot.

The *possibility of accessing this mobile learning environment through a PDA* was something students liked (see feedback in Fig. 10). Of the "Data Structures" students, 67 percent liked using PDAs, while 50 percent from "Operating Systems" did. A significant number of students did not care about using any specific device.

Students argued that PDAs can be used anywhere at anytime due to wireless connection. They can carry it with them easily because of its small dimensions, and it allows having most one needs in a small device. They emphasized that they were very useful to access to the learning environment when they had some minutes available. However, students who did not like using PDAs in both studies commented that Internet wireless connexion was interrupted in some occasions and, for this reason, the use of them was uncomfortable. "Eduroam" supports wireless connection available in the campus. Yet, sometimes there are problems with the coverage in some buildings.

With respect to *the visualization of multimedia contents presented for each activity*, students had a few problems in certain activities in spite of using CSS templates for the contents of "Operating Systems." Instructions to extend the images presented in some activities for correct visualization (full screen) were given to students. Content length was suitable in general. However, the small scroll in the lower part of the Web browser for some contents with images and tables was a problem for certain students, who said that they prefer using a mouse in PCs or laptops rather than using the stick in PDAs.

The next question was *whether they found the possibility of automatically hiding the menu on the left (index of activities) when they are using PDAs appropriated*. Most students said that hiding the index by default and letting the user press a button to see it is a good option (56 percent in "Data Structures" and 40 percent in "Operating Systems"). However, 22 percent of "Data Structures" students and 53 percent of "Operating Systems" students answered that "It does not matter."

Regarding the most suitable types of activities to be recommended while students are using a PDA, they chose tests and review activities as the most appropriate. Examples and short free-answer exercises are considered only in a few cases. Theoretical and collaborative activities were not considered as suitable for PDA devices.

Finally, the last two questions posed to everybody were related to future improvements for these mobile learning environments and comments or additional suggestions about this new learning experience.

Summarizing, most students liked this new way of learning through adaptive mobile environments. They described the experience as positive and suggested the use of this type of environments in other courses of "Computer Engineering." The learning environment developed helped students to extract the most important topics to organize their time for learning, access to educational resources from anywhere, and train though additional learning material for the final exam.

Furthermore, student motivation increased, as they stated, when they used CoMoLE (50 percent in Data Structures and 83 percent in Operating Systems). Students wrote many comments related to this, stating that: learning became more attractive and enjoyable; when they were bored or tired of studying a book or their own notes, they were able to study through their PC, laptop, or PDA in an interactive and dynamic way; and it has promoted discussions between classmates regarding the topics involved.

The environment encouraged discussions with other colleges about the learning activities proposed (theoretical activities, examples, exercises, and feedback in the exercises). It also favored the exchange of ideas between learners and constructivism learning.

There were two main complaints: 1) they did not have enough time for interacting with these environments (because of the date in which they were completely available) and 2) the learning activities were related only to some parts of the whole set of topics of the subjects. They proposed to make the environment available from the semester starting date for next academic year. Finally, they proposed a new type of learning activities ("exam") to be recommended once students finish performing the whole set of activities. They suggested this with the aim of not only learning, but also training for the final exam.

Regarding the whole environment, students suggested the possibility to switch on/off the recommendations in order to give more freedom to students. They also proposed to include, at the beginning of a session, review activities related to the exercises failed in the previous session. Other proposal was to allow students to access to content versions intended for other user profiles, once they have finished the whole set of activities, to be able to see different variations of the contents related to the same topic (i.e., visual-oriented and verbal-oriented versions).

With respect to potential navigational improvements, some students would like to be able to access to advanced activities as soon as they have acquired the required previous knowledge instead of receiving recommendations of other simpler tasks. We think that they followed the recommendations given in the upper side of the interface (which included only the first three recommended activities at each step), and maybe they did not see the activation of all recommended activities in the index on the left.

Finally, students suggested two content-related improvements. The first consisted of providing detailed feedback in exercises, even when the student gets the right solution, since sometimes they are not really sure why this is the correct answer (complete feedback was given in some exercised, but in others, only wrong questions received this detailed information). The second improvement consists of using low-quality multimedia materials for contents to be accessed through PDAs, since downloading some of the images from 3G mobile phones or PDAs took quite an amount of time.

6 Conclusions and Future Work

The work presented in this manuscript demonstrates, on the one hand, that it is possible to bring advanced adaptive mobile learning environments (including context-based recommendations and dynamic workspace generation) nearer to real users. Providing authoring tools to facilitate teachers their creation, as well as including features and criteria to be used by default with recommendation and adaptation purposes, is essential. In our case, some aids have been provided in this direction: an authoring tool including features to be incorporated to user models, adaptation rules, recommendation criteria, and indications for workspace generation, to be used by default, and a recommendation module based on the use of Markov models, so that providing or selecting rules is not necessary. Functionality in CoMoLE is very well separated in modules and authors can select these to be used within their environments.

On the other hand, the results and feedback obtained from students in two case studies support the confidence in the usefulness and acceptance of this type of educational environments for mobile learning. In the two case studies carried out, feedback about different aspects was obtained, including: the usefulness/uselessness of context-based recommendations to learn two subjects of "Computer Engineering"; the quality of the recommendations offered by these environments; the (in)convenience of using different devices for supporting activity accomplishing; whether the recommendations offered by the system helped them to organize their time for studying; whether they will use it again; and how they feel about these new ways of learning, among others.

The feedback and opinions obtained regarding these and other aspects are explained in detail in the previous section, also including discussions about the results obtained. Students found the environments useful to support other ways of learning. Recommendations of activities to be accomplished mostly helped them to organise their time for learning, especially in situations where they had not much time available. Their motivation increased not just for learning, but also for discussing with their partners about theoretical explanations, examples, or exercises proposed by the environment.

They found recommendations based on their personal features, previous actions, and context useful. However, when dealing with contents, adaptation to personal features (including learning styles) and knowledge was considered more important than context-based adaptation (mainly content adaptation to devices).

In both studies, sensing-intuitive and visual-verbal dimensions of student learning styles were considered, either as criteria for recommending activities in different contexts or for content adaptation. However, some students realized that it would have been useful to consider the sequential-global dimension too, especially for activity recommendation. More conclusions of the results obtained have already been explained in the previous section, when analyzing the results.

Finally, the fact that students proposed to extend the environments to cover the whole course programs and suggested to make it accessible since the beginning of the semester gives clues about the acceptance of this type of environments among students.

Currently, we are extending the set of adaptation rules and recommendation criteria to be used by default in each filter of the recommendation mechanism in order to facilitate authoring as much as possible. For future work, we are planning to modify the two environments created including some of the suggestions given by the students, and create new ones related to different subjects.

We are also planning to do different experiments using a combination of rules and Markov models, only Markov models, and no recommendations at all to analyze the relevance of each part of the recommendation mechanism and also to obtain information about the most relevant parameters to be considered in recommendation criteria. These parameters could be the ones used to classify users and obtain the path graphs for the Markov-based recommendation phase, so that the number of user types will be lower, more graphs would be available for each of them, and therefore, more information for the recommendation process would be available earlier.

Another interesting issue would be analyzing all user actions to extract conclusions about what is going on within the environment. Some works have already been done in this direction [40]. We are also doing research on user model acquisition, trying to obtain information about student features (i.e., learning styles) without asking them to fill in the corresponding questionnaires [8], or trying to shorten the number of questions posed to students [41]. Finally, it is worth mentioning that the mechanism developed is a general purpose. Learning is one of the application areas, but this can be used wherever different users must accomplish tasks either individually or collaboratively in different contexts, have different personal features and needs, and need help to organize themselves and benefit from spare time.

Acknowledgments

This work has been supported by the Spanish Ministry of Science and Education, project number TIN2007-64718.

References

[1] C.R. Graham, "Blended Learning Systems: Definition, Current Trends, and Future Directions," *The Handbook of Blended Learning*, San Francisco Pfeiffer, 2006.
[2] M. Müehlenbrock, "Formation of Learning Groups by Using Learner Profiles and Context Information," *Proc. 12th Int'l Conf. Artificial Intelligence in Education*, pp. 507-514, 2005.
[3] P. Brusilovsky, "Methods and Techniques of Adaptive Hypermedia," *User Modeling and User-Adapted Interaction*, vol. 6, nos. 2/3, pp. 87-129, 1996.
[4] A. Kobsa, *Generic User Modeling Systems*, vol. 4321, pp. 136-154. Springer, 2007.

[5] R.M. Felder, "Matters of Style," *ASEE Prism*, vol. 6, no. 4, pp. 18-23, 1996.

[6] P.T. Costa and R.R. McCrae, "The NEO-PI/NEO-FFI Manual Supplement," Odessa, FL Psychological Assessment Resources, 1989.

[7] L.L. Thurstone, *Primary Mental Abilities.* Chicago Univ. Press, 1938.

[8] D. Spada, M. Sanchez-Montanes, P. Paredes, and R.M. Carro, *Towards Inferring Sequential-Global Dimension of Learning Styles from Mouse Movement Patterns*, vol. 5149, pp. 337-340. Springer, 2008.

[9] P. Brusilovsky, E.W. Schwarz, and G. Weber, "ELM-ART: An Intelligent Tutoring System on World Wide Web," *Intelligent Tutoring Systems,* pp. 261-269, Springer, 1996.

[10] P. De Bra, A. Aerts, B. Berden, B. de Lange, B. Rousseau, T. Santic, D. Smits, and N. Stash, "AHA! The Adaptive Hypermedia Architecture," *Proc. 14th ACM Conf. Hypertext and Hypermedia,* pp. 81-84, 2003.

[11] R.M. Carro, E. Pulido, and P. Rodríguez, "Dynamic Generation of Adaptive Internet Based Courses," *J. Network and Computer Applications,* vol. 22, pp. 249-257, 1999.

[12] A. Moore, T.J. Brailsford, and C.D. Stewart, "Personally Tailored Teaching in WHURLE Using Conditional Transclusion," *Proc. 12th ACM Conf. Hypertext and Hypermedia,* pp. 163-164, 2001.

[13] B. Barros and M.F. Verdejo, "Designing Workspaces to Support Collaborative Learning," *Tasks and Methods in Applied Artificial Intelligence,* pp. 668-677, Springer-Verlag, 1998.

[14] P. Dillenbourg, *Collaborative Learning: Cognitive and Computational Approaches.* Elveiser Science Ltd., 1999.

[15] T. Koschmann, "Paradigms Shift and Instructional Technology," *CSCL: Theory and Practice of an Emerging Paradigm,* pp. 1-23, Lawrence Erlbaum Assoc., 1996.

[16] D. Johnson, R. Johnson, P. Roy, and B. Zaidman, "Oral Interaction in Cooperative Learning Groups: Speaking, Listening, and the Nature of Statements Made by High, Medium, and Low Achieving Students," *J. Psychology,* vol. 119, no. 4, pp. 303-321, 1985.

[17] A. Soller, A. Martínez-Monés, P. Jermanna, and M. Muehlenbrock, "From Mirroring to Guiding: A Review of State of the Art Technology for Supporting Collaborative Learning," *Int'l J. Artificial Intelligence in Education,* vol. 15, no. 4, pp. 261-290, 2005.

[18] E. Gaudioso and J.G. Boticario, "Supporting Personalization in Virtual Communities in Distance Education," *Series on Innovative Intelligence,* vol. 1, pp. 327-362, World Scientific, 2002.

[19] R.M. Carro, A. Ortigosa, E. Martín, and J. Schlichter, "Dynamic Generation of Adaptive Web-Based Collaborative Courses," *Groupware: Design, Implementation, and Use,* pp. 191-198, Springer, 2003.

[20] P. Brusilovsky and E. Millán, *User Models for Adaptive Hypermedia and Adaptive Educational Systems*, vol. 4321, pp. 3-53. Springer-Verlag, 2007.

[21] R. Burke, "Hybrid Recommender Systems: Survey and Experiments," *User Model and User-Adapted Interaction,* vol. 12, no. 4, pp. 331-370, 2002.

[22] A.T. Bharucha-Reid, *Elements of the Theory of Markov Processes and Their Applications.* McGraw-Hill, 1960.

[23] L. Rabiner, "A Tutorial on Hidden Markov Models and Selected Applications in Speech Recognition," *Proc. IEEE,* vol. 77, no. 2, pp. 257-269, 1989.

[24] D. Billsus and M.J. Pazzani, *User Modeling for Adaptive News Access*, vol. 10, pp. 147-180. Kluwer Academic Publishers, 2000.

[25] K. Cheverst, N. Davies, K. Mitchell, and A. Friday, "Experiences of Developing and Deploying a Context-Aware Tourist Guide: The Guide Project," *Proc. Sixth Int'l Conf. Mobile Computing and Networking,* pp. 20-31, 2000.

[26] A. Zimmermann, M. Specht, and A. Lorenz, "Personalization and Context Management," *User Modeling and User-Adapted Interaction,* vol. 15, nos. 3-4, pp. 275-302, 2005.

[27] I. Chun and I. Hong, "The Implementation of Knowledge-Based Recommender System for Electronic Commerce Using Java Expert System Library," *Proc. IEEE Int'l Symp. Industrial Electronics,* pp. 1766-1770, 2001.

[28] G. Zurita and M. Nussbaum, "A Constructivist Mobile Learning Environment Supported by a Wireless Handheld Network," *J. Computer Assisted Learning,* vol. 20, pp. 235-243, 2004.

[29] M. Chen and J. Yen, "An Evaluation of Learners' Satisfaction toward Mobile Learning," *Proc. Sixth WSEAS Int'l Conf. Applied Computer Science,* vol. 6, pp. 382-388, 2007.

[30] J. Traxler and A. Kukulska-Hulme, "Evaluating Mobile Learning: Reflections on Current Practice," *Proc. World Conf. Mobile and Contextual Learning (mLearn '05),* 2005.

[31] M.F. Verdejo, C. Celorrio, E. Lorenzo, and T. Sastre-Toral, "An Educational Networking Infrastructure Supporting Ubiquitous Learning for School Students," *Proc. Sixth IEEE Int'l Conf. Advanced Learning Technologies,* pp. 174-178, 2006.

[32] H. Ogata and Y. Yano, "Context-Aware Support for Computer-Supported Ubiquitous Learning," *Proc. IEEE Int'l Workshop Wireless and Mobile Technologies in Education,* pp. 27-34, 2004.

[33] D. Corlett, M. Sharples, S. Bull, and T. Chan, "Evaluation of a Mobile Learning Organiser for University Students," *J. Computer Assisted Learning,* vol. 21, no. 3, pp. 162-170, 2005.

[34] T. Goh and Kinshuk, "Getting Ready for Mobile Learning-Adaptation Perspective," *J. Educational Multimedia and Hypermedia,* vol. 15, no. 2, pp. 175-198, 2006.

[35] R.M. Carro, A. Ortigosa, and J. Schlichter, "A Rule-Based Formalism for Describing Collaborative Adaptive Courses," *Knowledge-Based Intelligent Information and Engineering Systems,* pp. 252-259, Springer-Verlag, 2003.

[36] E. Martín, R.M. Carro, and P. Rodríguez, "A Mechanism to Support Context-Based Adaptation in M-Learning," *Innovative Approaches for Learning and Knowledge Sharing,* pp. 302-315, Springer, 2006.

[37] E. Martín, R.M. Carro, and P. Rodríguez, "CoMoLE: A Context-Based Adaptive Hypermedia System for M-Learning," *Proc. Eighth Simposio Nacional de Tecnologías de la Información y las Comunicaciones en la Educación at CEDI 2007,* pp. 79-86, 2007.

[38] E. Martín, N. Andueza, and R.M. Carro, "Architecture of a System for Context-Based Adaptation in M-Learning," *Proc. Sixth IEEE Int'l Conf. Advanced Learning Technologies,* pp. 252-254, 2006.

[39] http://www.jdom.org, 2009.

[40] A. Ortigosa and R.M. Carro, *The Continuous Empirical Evaluation Approach: Evaluating Adaptive Web-Based Courses*, vol. 2702, pp. 163-167. Springer, 2003.

[41] A. Ortigosa, P. Paredes, and P. Rodriguez, "An Adaptive Hierarchical Questionnaire Based on the Index of Learning Styles," *Proc. Sixth Int'l Workshop Authoring of Adaptive and Adaptable Hypermedia at the Fifth Int'l Conf. Adaptive Hypermedia and Adaptive Web-Based Systems,* pp. 45-53, 2008.

Estefanía Martín received the PhD degree in 2008 from the Universidad Autónoma de Madrid and is a teaching assistant at the Universidad Rey Juan Carlos. She has been working in adaptive hypermedia and collaborative learning since 2002. Her PhD thesis dealt with the recommendation of activities in mobile environments and dynamic workspace generation, taking into account user personal features, actions, and context. Her research focuses on adaptive hypermedia, collaborative systems, and mobile learning. More information can be found at http://www.eps.uam.es/~emartin.

Rosa M. Carro received the PhD degree in 2001 from the Universidad Autonoma de Madrid and is an associate professor at the same university. Her research focuses on adaptive hypermedia, user modeling, mobile learning, and collaborative systems. She did research on adaptive educational games at the University of Aveiro in 2001-2002. She joined the Cooperative Systems group of the Technical University of Munich in 2002. She is a member of several associations and committees, such as the IASTED Committee on Education, AIPO, and ADIE. She has coorganized international workshops such as Adaptive Hypermedia and Collaborative Systems at ICWE 2004 and the series of workshops on Authoring of Adaptive and Adaptable Hypermedia at AIED 2005, AH 2006, UM 2007, and AH 2008. She is a reviewer for international journals such as *IEEE Internet Computing* and the *IEEE Transactions on Knowledge and Data Engineering*. She is a coauthor of more than 70 publications related to her research areas.