A Smarter Collaborative Mobile Learning Solution

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***Abstract*— Mobile learning has been receiving increased attention from diverse publications and events. The assimilation of mobile computing by education allows students to access education calmly, flexibly and seamlessly. This area of mobile services is getting wide attention by developers, strongly supported by the notion of context-aware. It permits that systems can take the location and position of a user, her interactions and even 'smart' objects into account to present more personalized services. This work presents the addition of a personalization module to PortableLab, a mobile learning solution that allows students to analyze several poor quality power supply occurrences. The developed system is a step forward in the development of mobile learning courses, presenting content adapted to each student. The paper presents the PortableLab system and how its integration of personalization is being done in order to have the right mobile interfaces tailored to the students.**

Keywords-personalization; smart interfaces; adaptation; android; m-learning

I. Introduction

Nowadays, mobile devices are essential tools for peoples' daily living. The assimilation of Ubiquitous Computing (Ubicomp) [1], strongly based on Mobile Computing, by education, marks an important step forward allowing students to access education calmly, flexibly, and seamlessly. The term Mobile Learning (M-Learning) is frequently used to refer to the use of handheld mobile devices that enable the learner to be 'on the move', providing anytime anywhere access for learning [2]. Moreover, lifelong learning is also a requirement of our era and mobile technologies can help meeting this challenge through the offer of access to "just-in-time knowledge".

M-learning is considered more innovative and student-centered than typical e-learning or classic distance education methods, representing an effective pedagogical method as any other conventional learning method [3, 4]. Furthermore, it is desired that a mobile learning system proactively reacts to individuals who use it, in a pervasive and persistent way. This human-centered vision demands for adaptive and personalized services also according to the context. Personalization must be a major component in m-learning systems, and generally in Ubicomp scenarios. M-learning combined, as much as possible, with other Ubicomp's features can offer great innovation to the learning process, allowing an adaptive learning through personalization according to students' preferences and learning capabilities.

However, this personalization requirement needs more than wirelessly networked computers, sensors and mobile devices working together, as it relies implicitly on some kind of recommendation mechanism to directly serve the individual or the group. The offer of the right personalized content, interfaces and services is a challenge due to various issues such as diverse user interests and particular needs, heterogeneous environments and devices, dynamic user behavior and user privacy. The process of obtaining and choosing relevant content and interfaces for user interaction in m-learning systems is still a critical challenge, being a hard task in many applications from diverse domains [5].

This paper presents PortableLab [6], a mobile laboratory with several interfaces for power quality assessment, giving special attention to the addition of a personalization module, which is still in progress. The main goal of PortableLab is to improve students' interest and motivation, making resources available as much as possible at any place and any time. This mobile remote laboratory is being used as a complement to the usual classroom laboratory type lessons. The developed system integrates a server with a data acquisition board and a central database to be accessed by the mobile application, programmed for the Google Android platform. The mobile application includes a collaborative learning module that it is essential for the growth of students. With this module, they can annotate content to be seen by teachers and colleagues, giving additional information about their understandings or helping others in the learning process. Furthermore, we are in the process of integrating a module responsible for adapting contents and functionalities to the level demonstrated by students and also according to the interactions stream, which is defined by screens and components clicks and functionalities executed by users.

The paper is organized as follows. In Section II, we present a summary of related work. The third Section introduces the system's architecture and the mobile application interfaces. Section IV adds the ideas about the personalization process and smart adaptation of PortableLab interfaces. Finally, in Section V, conclusions and future work are presented.

II. Related Work

Nowadays, m-learning is a very active research field, with the development of many important and interesting projects. M-learning is rapidly growing from a set of research projects into worldwide deployment of services for classrooms, field trips, workplace training and informal education, among other areas.

Frohberg et al. presented a deep and critical analysis of m-learning projects published before the end of 2007 [7], yet without important focus on personalization to tailor content and interfaces to the right student and even teacher. Major m-learning projects have been concentrating on the generic platforms development for m-learning and explored new supports for a kind of technology-mediated learning across locations and life transitions [8, 9].

Smaller projects are more directed to develop new pedagogical solutions for specific cases and to explore how learning on handheld mobile devices interweaves with personal interests and individual learning needs [10], which is much more of our interest. The SHAPE project [11] is one that can benefit from this approach in a next phase. It aims to enhancing the conceptual understanding of how to undertake design of computing in public spaces and to create exemplars for how new computing can be used to augment educational and social interaction in public environments. A part of the project is used to simulate an archaeology dig, where the aim is to enhance children's collaborative learning in museums, through supporting sensorial experience and capturing embodied knowledge. It can be tailored to each user. UNIWAP [12] is another interesting m-learning project created to assist in teacher training. The project used relatively simple technologies, short message service (SMS) and digital pictures, to enable students to create digital portfolios built from materials created in the field. Messaging was used to enable the trainees, who were widely distributed when training in different schools, to collaborate with each other and share their experiences. These projects are interesting because of the collaborative approach they include, presenting some personalization possibilities.

Finally, Kay presents a "vision for the lifelong user model as a first class citizen, existing independently of any single application and controlled by the learner" [13]. She argues that it has a key role for a vision of personalized lifelong learning, enabling students/learners to supplement their own knowledge with readily accessible digital information based on information they have accessed or used. The paper also presents a good overview of Intelligent Tutoring Systems, which are important in terms of features related to adaptation.

Although being possible to find m-learning projects using personalization or adaptation concepts, it is clear that none uses a general model based on web-services platform that integrates machine learning modules like the approach applied to PortableLab.

III. PORTABLELAB

This Section is used to present PortableLab, its architecture and technologies, also introducing the main screens in order to understand where personalization can be applied.

A. *Implementation of PortableLab*

The architecture of PortableLab can be seen as a typical client-server approach. The data acquisition is done by current and voltage sensors that send signals to a data acquisition board, which is connected to a server that runs signals processing and data management modules. These modules store the received data in the server's main database. This database is updated every time new values are read, independently of the requests of the mobile clients. Apart from the existence of the server database (remote to the mobile user), the user can also choose to use a (local) database, located in the mobile learning application. To access the remote database, mobile devices need to use a PHP (PHP: Hypertext Preprocessor) API (Application Programming Interface) through HTTP (Hypertext Transfer Protocol) connections to obtain the necessary information for the reproduction of various types of charts, including harmonic content, voltage, and current charts. This API is also used to synchronize the information between the two databases, with the communication being made in a bidirectional way. The master database is always the remote database, since it will store the real-time measured data. Its content is copied to the mobile database every time the user chooses to synchronize both databases. The main programming language of the mobile application interfaces is Java, mostly using libraries provided by the Android SDK and the AChartEngine library that provides graphical functionalities to reproduce the various types of charts. A detailed description of the system and its technologies can be found in [6].

B. *PortableLab's Interfaces*

The Login screen where the user, a student or teacher, has to authenticate is the entrance of the application (Fig. 1, left image). After a successful login, the user finds the main screen where s/he can choose the visualization of charts with the most recent reads related with power quality (Fig. 1, right image at bottom). Another functionality included in this screen is the search of reads by date, time, or by both.

Figure 1. Mobile application's initial screens (in Portuguese).

The left image in Fig. 2 presents how the PortableLab application appears in a real device in terms of representation of charts, and the right image shows below the charts the comments/annotations made by students and teachers, illustrating the collaborative role of the tool. A student can use this functionality to annotate some results, put questions to teachers, or help other students. A teacher can use it to respond to students or to better explain an idea about the results.

Figure 2. Mobile application's screens on a HTC device: charts visualization and list of recent annotations by users (in Portuguese).

The application presents other functionalities, such as, the application's operation mode configurations, the user personal data and the user authentication definitions. Depending on the user profile, other options are available, such as the possibility of seeing a detailed list of users that have used the system. Only teachers have access to this screen.

IV. INTEGRATION OF PERSONALIZATION

This Section discusses how to apply personalization, smart adaptation, to Ubicomp and Mobile Computing systems, presenting a general solution. Moreover, it presents initial decisions regarding PortableLab's personalization integration.

A. A Web-based Personalization Model Solution

An essential input for every intelligent adaptation or personalization technique is the user model [13]. However, it is important to define the information integration level since the focus should be on the integration of personal (from the user model) and contextual information (from the context) about the user in the current domain of application. Additionally, the adoption of ontology for smoothly modeling the domain, the context and the personalization process can contribute to tailor the right information, services or interfaces to users, thus, facilitating and enriching the HCI (Human-Computer Interaction) process. Ontologies can also be very important for the reuse of parts of the user model in a ubiquitous environment. This requires protocols for ontology understood by applications and/or a mechanism for mapping different ontologies within them [13]. At the moment, we are working on the ontology definition as we consider it very important to obtain the best personalization model. We are also developing the user and context models that are part of the latter.

A partial taxonomy of what we consider the starting point for user modeling integrates: demographics, preferences, roles, and knowledge. In terms of intelligent adaptation of the interfaces and content, it will work much better if besides the usual user profile we consider the location, both physical and semantic (e.g., at home), the situation (e.g., alone, in family or lunching) and the emotions felt by the user (initially, s/he can choose from a list), connecting to the context model. Context awareness plays a major role in Ubicomp, being tightly coupled with user modeling [14]. Moreover, an interactions stream (set of interactions between the user and the application) is used to know the "degree of empathy" between the user and the system/application.

So, the personalization model is based on a generic configuration data model that is mainly composed of Personalization Options, Parameters and Resources (see Fig. 3). Data concerning direct user interaction with the application, such as clicks, time spent on menus, and numbers of log-in operations are considered as Resource data. Parameters are usually defined by mathematical expressions based on the Resources (seen as variables) and used to characterize the different options for each desired personalization (see Table 1 for an example). This configuration model is also a part of the general personalization model, being closely connected to the user and context sub-models.

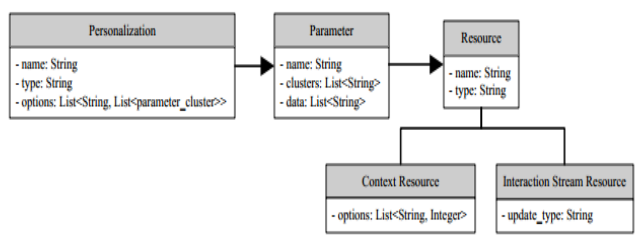

Figure 3. The personalization configuration model.

When interacting with an application, users do not behave in a uniform way. Different users may present different interests, different knowledge and different capabilities to interact with the system. Therefore, it is important to assign users to categories that represent them to facilitate the personalization process. It is possible to use the interaction stream data, in conjunction with user and context (if considered) data, in a clustering operation with a defined number of clusters, each one basically representing a user category. The result of this operation is a set of categories (clusters) where each one contains a collection of users (points). After the clustering operation, a recommendation service checks which personalization options are associated to the user categories in order to link the options to the users. Moreover, we are still working on the use of Recommender systems (RS) to improve personalization, adding levels of detail to the machine learning (ML) algorithm.

RS can be seen as mediators of the user experience in the digital world and are increasingly helpful in doing the same in the physical world [15]. The goal of a common RS is to proactively suggest and prioritize items the user may be interested in, taking into account the context at the moment of the interaction, and predicting the user behavior [16]. The application of context to RS can be tightly integrated into the recommendation algorithm, or used independently to improve its recommendations. Based on the general personalization model, integrating user, context, application and domain, and configurations sub-models, candidate items such as interface customization and learning information are selected to feed up the ML algorithm, which we propose with a composition of four main sub-modules (Fig. 4).

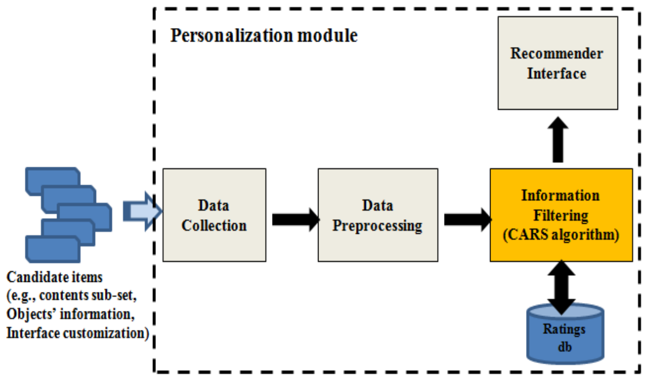

Figure 4. Architecture of modules involving the recommendation process.

Being based on RS, the personalization module needs a ratings database, also based on feedback provided by users and on their interactions stream. In an m-learning system, based on Ubicomp characteristics, the goal is to have a system that is as unobtrusive as possible. So, how can the system gather the ratings from users, requiring as little interaction as possible? The rating can be explicit when in specific moments the system asks for a simple rating of an interface or some piece of information. More interesting are the implicit ratings, which can be inferred from the interactions of the user with the system. It can be based on the time spent in front of the display, analyzing face expressions, or more simply on number of screens and components clicks and functionalities executed by users.

Furthermore, we intend to have this general personalization model being applied to different applications, systems, even if from different domains. The model is deployed as a framework, a web-services platform – personaX - designed to provide orientation and tools to help developers in the implementation of a standard personalization. On the other side, users will be less bothered when starting to use a new system/app. This one already might know something about s/he. User interactions within one system might be useful to help personalizing another one.

The core of personaX (Fig. 5) is working, being used in the form of personalization APIs and configuration modules, which give the developer a high-level of implementation. The personalization algorithms are already implemented and the developer only needs to apply the model according to specific project's needs.

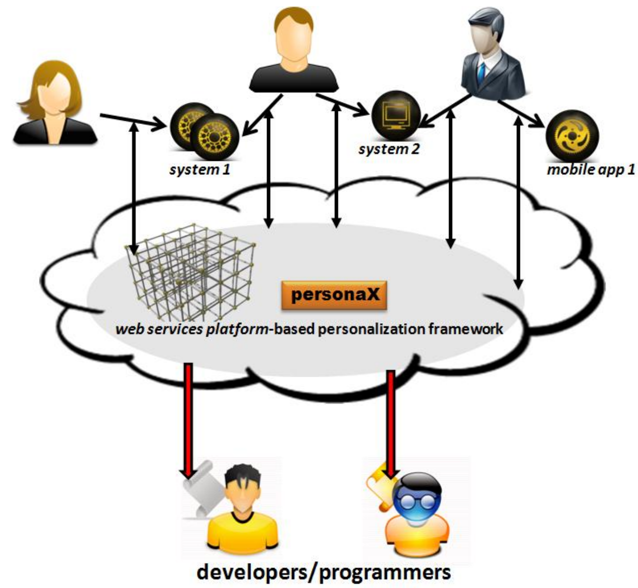

Figure 5. personaX: a web-services platform for personalizatin.

B. *PortableLab's Initial Personalization Decisions*

Furthermore, we have to decide about the user data that can and should be captured and included as a basis for the personalization. To accomplish that capture, which are the potential sources for user modeling information?

The data can be collected from, for instance: life logging sensors, personal devices and in the cloud, besides the specific Information System of the University using PortableLab. With more sensors, such as GPS, camera, and gyroscope, embedded in mobile devices, it is possible to record the activities and behavior of a user. Additionally, the usage of wearable sensors enables the capture of users' physical and physiological data and, this way, the emotional model [15] can be predicted and not only stated by the user. The captured sensor data can be used to represent a situation event and extract patterns from the activities data logs. In relation to context, the environment conditions can be easily inferred with the usage of sensors, while the location information can be known using GPS and Wi-Fi technologies.

TABLE I. EXAMPLE OF PERSONALIZATION OPTIONS FOR PORTABLELAB

Personalization	***Personalization Options***	**Parameters**	**Resources**
Initial screen	- Communicator - Solitary	Communication profile: - numberPosts /numberVisual	-numberPosts -numberVisual

V. CONCLUSIONS AND FUTURE WORK

The use of m-learning tools, if correctly contextualized and built, can benefit the traditional learning methodologies and methods. However, these m-learning applications should integrate a personalization approach to have better chances of being really efficient working as complementary learning tools. This work focuses on a proposal for facilitating the implementation of personalized m-learning systems.

PortableLab is being tested as a first m-learning prototype with an explicit personalization module. The research is studying how the personalization model can be defined, distributed and executed among different devices. These personalization features are currently being defined in order to choose the best ML algorithms, along with the definition of the final user and context models. The applicability and maturity of the proposal should be shown through its usage in the development of the prototype.

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