Mobile learning adaption through a device based reasoning

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Abstract

In the e-learning systems developed along the last two decades, developers focused on the user characteristics in order to adapt the proposed content to the user needs and preferences. This adaption is especially based on a user model where the user preferences are stored. When coming with the mobile learning, the wide variety of technical characteristic and standards of devices (notebook computers, cellular phones, Personal Communication System (PCS), Personal Digital Assistants (PDAs)…) faces us to take into account new features in the adaption process: the device “preferences”. So, delivering tailored contents tend to adapt to not only learner’s needs and preferences, but also to mobile device used. In this paper, we propose architecture for mobile learning where we integrate two principal models: the user model and the device model. The Case Based Reasoning (CBR) approach is used to manage both the user model and the device model.

1. Introduction

In the e-learning systems developed along the last two decades, developers focused on the user characteristics in order to adapt the proposed content to the user needs and preferences. All the information about learner preferences, knowledge and behavior is accumulated and treated in a user model which is a kind of repository about the user and forms the heart of a learner centric and adaptive system. User model is used to drive instructional decisions in order to make an adaptive e-learning system for individual students (Chorfi & Jemni, 2006).

When coming with the mobile learning, the wide variety of technical characteristic and standards of devices (notebook computers, cellular phones, Personal Communication System (PCS), Personal Digital Assistants (PDAs)…) leads us to take into account new features in the adaption process: the device “preferences”. So, delivering tailored contents tend to adapt to not only learner’s needs and preferences, but also to mobile device used. Mobile learning is sometimes considered as an extension of e-Learning (Brown, 2005), but quality m-Learning is dependant of the special limitations and benefits of mobile devices. This assumption leads us to call for an explicit model of the device as an integral part of the overall knowledge model. In the other hand, personalization is a key component of m-Learning since the difficulty of navigation and small screen size of mobile devices makes it decisive to adapt learning material as much as possible.

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To achieve adaptive and smart systems, our hypothesis is that Case-Based Reasoning (CBR) is a promising way. Many works have clearly shown the potential of CBR. Ma et al. (2005) use CBR for adapting the behaviour of smart homes to users’ preferences. In Chorfi & Jemni (2004), using CBR techniques is twofold: on one hand, it allows to minimize the number of questions to ask to the student. On the other hand, it minimizes the time for finding a new solution (personalized course) by adapting previous ones.

In this work, we study how CBR can be a suitable method for achieving a device adaptive system. We propose architecture for mobile learning where we integrate two principal models: the user model and the device model. The CBR approach is used to manage system adaption.

The paper is structured as follows. In the second section, we present the system architecture. We give a brief description of each component. In third section, details of CBR process in our system are given. Finally some conclusions and future work are remarked.

2. System architecture

We propose a new Mobile Learning Adaption System (MLAS) which applies CBR approach to determine the appropriate content for the learner. The advantage of using CBR techniques is principally to minimize the time for finding a new solution (personalized content) by adapting or re-using previous ones. Figure 1 shows the general architecture of MLAS.

![Figure 1. MLAS. Architecture](image-url)

In this system, we manage three types of data: data about the user (Learner Profile), data about the device (Device Profile) and the content that will be delivered to the learner (Learning Objects Repository).

The MLAS is based on two systems: the CBR system and the adaption system. In the following sections, we give a brief description of each MLAS component.
2.1. Learner Profile

Students achieve higher learning performance if the learning content can be customized and offered according to their diverse learning needs (Beekhoven et al., 2003). In MLAS the learning content is generated according to the learner profile (LP) and his feedback taking into consideration the device capabilities.

In the learner profile, we store data about the learner’s personelle information (name, gender, level etc.), cognitive information (score, time taken, date of last access etc.) and the learner’s preferences in term of multimedia (the desired maximum delivery time, image format, presentation style, the ratio of audio to picture, animation, etc.) (Hassan & Al-Sadi, 2009).

2.2. Device Profile

In the market there are many different types of wireless devices and each type has different features and capabilities. When the learner requests content via wireless device, the MLAS should detect learner device and send appropriate content according to device features and capabilities. Our system achieves device detection problem by using some information such as user-agent, profile headers, etc. in the header of HTTP request send by learner.

The HTTP headers of two wireless devices received at the server-side (learnto.mobi) are shown in Figure 2. Although the headers provide basis information about device such as device model, manufacturer, client device's OS version, browser version, Java capabilities, etc. MLAS may need different features than basis ones such as screen size, storage, streaming, sound format, and image format, etc.

![Figure 2. Samples of the HTTP headers (a) send by HTC Desire smart phone (b) send by iPod 1.0](image)

As a result, the device profile in MLAS should support all information about device capabilities and features for a variety of wireless devices. There are some projects which collect all device features in one file. Wireless Universal Resource File (WURFL) is one of these projects. It presents a set of proprietary APIs and XML configuration file. The detail information about WURFL is given in (Passani & Kamerman, 2011).

In our proposed MLAS, the component of device profile first analyzes HTTP request to detect device model then uses WURFL to access and retrieve more features of user device.

2.3. Learning Objects Repository

A Learning Object (LO) is the elementary learning material (text, picture, video...). It is described by a set of metadata defined by the IEEE LOM standard (IEEE, 2002). LOM metadata schema is divided into 9 categories. Particularly, the relation category defines the relationship between the current LO and other LOs. The kind of relation is described by the sub-element kind. This later holds 12 predefined values: is version of, has version, is required by, requires, is part of, has part, is referenced by, references, is format of, has format, is based on, is basis for.
2.4. CBR System

The CBR system is responsible for detecting the capability of mobile device and the learner preferences in order to create a new case to be solved.

The CBR system gets device and learner information from the learner requests. Further details on the CBR system are given in the section 3.

2.5. Adaptation System

The adaptation system takes the responsibility of adapting the content to be delivered to the learner. It creates the adaptive contents based on rules. The rules are constructed by the CBR system in the solution depending on both learner and device profile. Each rule is associated to a conversion function or a filtering process. For example, to provide each mobile device with the markup language that supports (WML, CHTML, XHTML), we use the WALL library (Passani & Kamerman, 2011). Also, if the device supports GIF format and the LOR contains only JPG format, the system should create a new GIF image based on original JPG image dynamically (the LOR will be consequently updated). The different conversion rules will be described in future work.

3. MLAS.s CBR process

The content generation is based on the CBR approach (Kolodner, 1993). The main hypothesis behind CBR is simply that similar problems have similar solutions or that you can reuse the solution of a similar problem in order to solve your actual problem (Wilke & Bergmann, 1998). A case is the most basic element representing an experienced situation. The techniques that make up CBR are: case representation, indexing, retrieval techniques, and adaptation.

A case is the most basic element representing an experienced situation. It is, generally a couple of (problem, solution). In our MLAS, the problem corresponds to the learner profile and the device profile. The solution is the rules to be applied to adapt the delivered content.

Kitano & Shimazu (1996) have proposed that CBR applications have been too narrowly focused on domain specific problems. They suggested that a CBR system should be viewed as a medium to be used in conjunction with the mainstream corporate information system. In this context, we think that a standard way of marking up cases will facilitate this. We suggest XML as the likely candidate to provide such standard.

The extract below shows the XML schema of the case.

```
<xs:complexType>
  <xs:sequence>
    <xs:element name="problem">
      <xs:complexType>
        <xs:sequence>
          <xs:element name="user_profile"/>
          <xs:element name="device_profile"/>
        </xs:sequence>
      </xs:complexType>
    </xs:element>
    <xs:element name="solution"/>
  </xs:sequence>
</xs:complexType>
```

When a new learner logs in and in order to construct a new problem, the system gets the device and learner information from the learner request, the device profile and the learner profile. When a new case is constructed, the CBR system retrieves the most similar problem among the existing problems in the case base. For that, the system
calculates its similarity with the cases of the case base. The algorithm to compute similarity generally uses the Nearest Neighbour Algorithm (Aha, 1991). The Nearest Neighbour Algorithm is a formula as shown here.

\[ \text{Similarity}(N,S) = \sum f(N_i,S_i) \times w_i \]

Where: 
- \( N \) is the new case (new student and new device)
- \( S \) is the source case (past cases)
- \( n \) is the number of features in each case
- \( i \) is an individual feature from 1 to \( n \)
- \( f \) is a similar function for feature \( i \) in cases \( N \) and \( S \)
- \( w \) is the importance weighting of feature \( i \)

We consider that two cases are similar if their similarity is lower than a certain threshold. This similarity is calculated to permit the system to minimize time of constructing a new solution for the current problem by using or adapting the solution of an old and similar case stored in the case base. The result of the similarity measure allows the system to decide on the adaptation to perform. Different forms of adaptation exist, such as null adaptation, transformational adaptation (including substitutional and structural adaptation), and generative adaptation (Wilke & Bergmann, 1998). *Null adaptation* simply applies the solution from the retrieved case to the target case. Since users are not categorized in MLAS, null adaptation is used.

When the case is constructed, it is sent to the adaptation system in order to construct the adaptive content based on the rules of the case solution.

4. Conclusion

In this paper, we propose a new architecture for mobile learning system based on CBR approach. CBR strenghts the m-learning system by storing previous cases to be reused when solving the actual one. Our system shortens the retrieval time of content by reusing similar cases in an intelligent way. Another strong aspect of this system is that CBR works with learner profile as well as with device profile. So the system can send most appropriate content to learner by taking into consideration both learner and his device preferences.

The system is under implementation and we would like to test it on real problem. As a future work, we would like to improve this architecture by using real time information such as GPS location or network connection signals received by learner’s wireless device.

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References


