

A Context-Based Adaptation In Mobile Learning

F. Soualah Alila, F. Mendes, and C. Nicolle

Abstract—Recent developments on mobile devices and wireless technologies enable new technical capabilities for the learning domain. Nowadays, learners are able to learn anywhere and at any time. The dynamic and continually changing learning setting in learner's mobile environment gives rise to many different learning contexts. The challenge in context-aware mobile learning is to develop an approach building the best learning content according to dynamic learning situations. This paper aims to develop an adaptive system based on the semantic modeling of the learning content and the learning context. The behavioral part of this approach is made up of rules and metaheuristics to optimize the combination of pieces of learning content according to learner's context.

Index Terms—Adaptation, context, mobile learning, semantic web.

I. INTRODUCTION

MOBILE learning (m-learning) is a natural extension of e-learning. It has the potential to make learning even more widely available, thanks to the rapid development on wireless technologies and the widespread use of mobile devices.

In the professional environment, training employees is at the heart of the concerns of human resources. Indeed, developing employees' skills has become a critical issue because of the continuing evolution of companies, to make sure that employees gain new knowledge. At the same time, there is an increasing number of employees working outside the office. Given the speed of business today and the problems due to information overload, employees require information and knowledge just when they need it, in their desired format and on the device of their choice, particularly as the use of mobile devices has become second nature. This is why the traditional training paradigm is shifting to just-in-time transmission of knowledge and information to boost employee performance. With personalized m-learning, an organization can deliver targeted pieces of content that help an employee on the spot, rather than heavyweight classroom or just computer-based training.

The dynamic and continual changing of learner settings in a mobile environment and the diversity of learner's characteristics as well as mobile devices and networks, give rise to different learning situations and therefore requires

personalization for different cases. The search of educational content in a m-learning system can be defined as an activity whose purpose is to locate and deliver educational content to a learner according to his needs and the environment in which he is. So far, the learning environment was either defined by an educational setting (work, trainer, etc.), or imposed by the educational content (the learner must arrange his environment to receive training). In our approach we change the paradigm where the system adapts learning flow to the *context* of the learner.

The term *context* appeared the first time in 1994[1]. Here, location, identity, time, environment, and mobile technology have been suggested as primary types of context [2] [3] [4] [5]. Many previous studies in mobile computing provided various definitions of context. A commonly used one is: "any information that can be used to characterize the situation of an entity participating in the interaction between a user and a system" [6]. In the case of m-learning, location, time, identity and the mobile technology used to learn are the primary context types for characterizing the situation of a particular learner. These context types not only answer the questions of who, what, when, and where, but also act as indications for other sources of contextual information. For example, given a learner's identity, we can acquire many pieces of related information such as user tasks, roles, beliefs, desires, objectives, relationships with other users in the environment, etc. Furthermore, context can be information about devices (smartphone, tablet, connectivity, etc.), time (time of day, day of week, holidays, etc.), localization (in train, at home, at work, public place, etc.) and physical environment (lighting, noise level, etc.) since this may change the way users interact with any device they may be using. This set of information is useful to adapt the interaction and generally adapt the application behavior to the learner situation.

This paper presents ongoing research on an adaptive context-aware m-learning system that aims to offer a new approach for designing and adapting learning content as part of industrial training. This approach take into account the context of mobility related to the industrial training environment. To achieve this goal, it is necessary to improve the current e-learning systems with adaptation techniques to support the generation and management of m-learning environments so that, given a specific learner context, the system is able to suggest the most suitable learning activities to be accomplished in that specific situation.

II. ADAPTIVE EDUCATIONAL SYSTEMS

The objective of adaptive educational systems is to adapt the presentation of knowledge to learner. These systems have become very popular since 1990s, to allow users to access to

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personalized information [7]. In e-learning, learning content has witnessed high dropout rates as learners become increasingly dissatisfied with contents that do not engage them [8]. Such high dropout rates and lack of learner satisfaction are due to the "one size fits all" approach that most current learning content developments follow, delivering the same static learning experience to all learners, irrespective of their prior knowledge, experience, goals and context. Adaptive educational solutions have been used as possible approaches to address this dissatisfaction by attempting to personalize the learning experience for the learner. This learner empowerment can help to improve learner satisfaction with the learning experience.

In the recent years, many initiatives aimed at building educational resources to share and reuse them, have emerged. Learning Management Systems (LMS) are based on techniques of collaborative work, where communication processes come to support learning. These platforms should dispose of well-structured and organized pedagogical warehouses. Explaining a training course around items of knowledge offers advantages and opportunities to individualize training. In this case, the contribution of semantic web technologies is significant. We suggest the use of ontologies to allow the modeling of complex networks knowledge.

III. CONTEXT-BASED ADAPTATION MECHANISM

The aim of our adaptation mechanism described below is to satisfy learners' needs when connecting and interacting with the system.

Traditionally, adaptation systems in learning domain deal with applications that have two types of entities, which are users and items. To provide adaptation in a mobile environment incorporating contextual information, we propose a multidimensional adaptive model (MD model) based on the multiple dimensions of context (spatial, temporal, environment and device dimensions) and, therefore, extends the classical two-dimensional User \times Items paradigm to a multi-dimensional paradigm.

To develop such a m-learning system, we have to bridge the gap of two different levels of heterogeneity: semantic heterogeneity and heterogeneity of use between the current design of the learning content and the willingness to adapt these resources to different learner profiles and context.

On one hand, in e-learning, resources are designed and developed by different organizations and trainers, usually constituting semantically autonomous and heterogeneous data sources. Therefore, interoperability between these resources is complex: systems should be adapted to determine the required syntax and resource specific terminology to be able to combine relevant content and construct the final training result.

On the other hand, learners have different prior knowledge and objectives and are located in different learning environments (heterogeneity of time, learning time, visual support, ambient noise, etc.). By having a better knowledge of these learners

and of their learning environment, that we can efficiently query on pedagogical strategies, and set them up to respond to everyone needs.

To bridge this gap, our system is made up of a semantic level and a behavioral level (see Fig. 1.): the *semantic level* aims to express semantic characteristics of learning contents and learner context (what, how, when, where, via which device, etc.). Semantic modeling consists in describing the meaning of data by experts. This transfer of knowledge from experts to the computer enables our system to perform more intelligent reasoning according to changing constraints. The *behavioral level* is an adaptive system designed to overcome the problem of information overload by providing users with only the most relevant information. Here adaptation must be made considering the learner context while maximizing its benefit. The behavioral level contains the best learner practices (transformed in a set of logical rules) and algorithms of combinatorial optimization.

Combining the semantic and behavioral levels allows us not only to generate learning content, but also to generate learning methods adapted to the context of each learner. In what follows, we present these two levels.

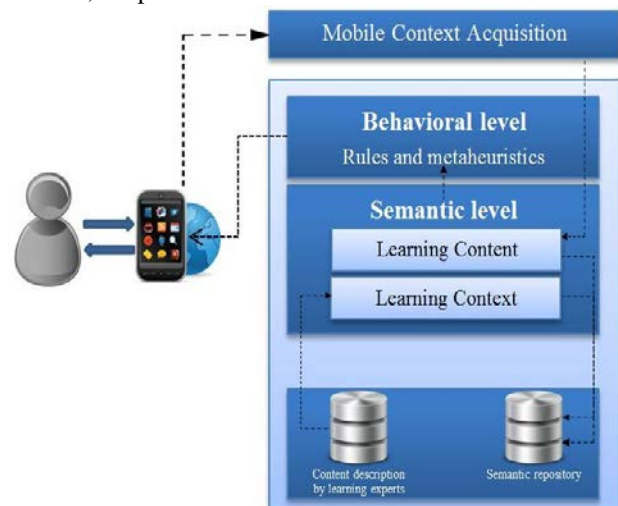


Fig. 1. M-learning context-based adaptive system architecture.

In the following, we focus respectively on the semantic level and behavioral level of our proposed architecture.

A. Semantic Level

The semantic web, envisioned as an extension of the current web [9], was proposed to provide enhanced access to information based on the use of machine-processable metadata annotating the web resources. To facilitate this process, RDF¹ (Resource Description Framework) and OWL² (Web Ontology Language) have been developed as standard formats for the sharing and integration of data and knowledge, the latter in the form of rich conceptual schemas called ontologies. Ontologies offer a way to cope with heterogeneous representations of resources on web and their interoperability. An ontology

¹ <http://www.w3.org/RDF/>

² <http://www.w3.org/2004/OWL/>

representing a model of a specific domain can be used as a unifying structure for giving information a common representation and semantics. Ontologies are becoming very popular due to their promise to allow a shared and common understanding of a domain that can be communicated between people and applications.

Realizing the potentials of semantic web technologies in education, initiatives using semantic web technologies in e-learning started in late 90's [10] [11]. The major argument for this is that the availability of massive information is of no use, unless the right information in the right context with the right level of details to the right person at the right time [12] is delivered.

In the recent years, to build an approach of quality and to make learning platforms and their contents interoperable, international standards are developing in educational technologies³. Standardization initiatives do not seek to standardize teaching methods or multimedia technologies used. They just aim to set up rules that will help in sharing and reusing educational modules. These standards are still in constant evolution. The IEEE proposes the LOM (Learning Object Metadata) standard⁴. This standard specifies a conceptual data schema that defines the structure of a metadata instance for a Learning Object (LO). For this standard, a LO is defined as any entity, digital or non-digital, that may be used for learning, education or training. ADL (Advanced Distributed Learning)⁵ has recognized the need for a model that aims to make learning platforms and their content interoperable. This model is the standard SCORM⁶ (Sharable Content Object Reference Model) which has become a major asset for distance learning platforms. It integrates a set of related technical standards, specifications, and guidelines designed to combine LOs around a package accessible, interoperable and reusable on other SCORM platforms.

To benefit from both the adaptive qualities of ontologies and the high scale interoperability brought by SCORM, we opt for an approach where the adaptive system output will be packaged as SCORM content. However, the learning content is modelled, indexed and manipulated by the system thanks to ontological models. This ontology is called *domain ontology of m-learning*. It presents the main concepts related to m-learning domain. It is largely based on concepts of LOM schema organization to describe LOs. Using a LOM model for indexing LOs enables a better understanding of learning contents, and therefore facilitates their descriptions. We followed some rules described in [13] to transform this schema into a set of ontological concepts and relations.

The second step to define the semantic level is modeling mobile learning context. We believe that ontologies are key requirements for building context for two reasons: first, a context can be considered as a specific kind of knowledge; and

as such, ontologies are the state of the art for an efficient modification of context. Ontology-based models of context allow representing complex context knowledge and provide a formal semantic to context knowledge, which supports the sharing and integration of context information [14]. Second, a common ontology enables knowledge sharing in an open and dynamic distributed system [15]. To describe context, we model concepts related to different context dimensions:

- 1) Temporal dimension. In this dimension we try to answer two questions: "when?" to define the exact temporal localization of an event, and "how long?" to define the duration of an event. With the concept *Laps* we can measure the duration of an event (15 min, 2 days, etc.). With the concept *Time* we can determine when an event should take place. We distinguish two sets of temporal localization type: *Abstract_Time* (in the morning, at the week-end, monday, etc.) and *Concrete_Time* (at 10 am, the 12/10/2012, etc.).
- 2) Spatial dimension. This dimension refers to a position or a place. A position is a *Concrete_Location* and refers to *Geographic_Coordinates*. A place is an *Abstract_Location* (at home, in a restaurant, in a train, etc.). We have also collected some characteristics of environment such as *Location_Type* (dynamic, public, etc.) in this dimension, and *Location_Properties* (comfort, noise level, etc.).
- 3) Device dimension. Information related to devices is generally divided into three sets depending on the type of information they provide [16]: *General_Description*, *Hardware_Description* and *Software_Description*. *General_Description* contains basic information related to a device such as *Device_Name*, *Device_Type* (smartphone, tablet, etc.), etc. *Hardware_Description* regroups hardware properties of the device such as *Connectivity*, etc. and *Software_Description* regroups software properties of the device such as *OS*.
- 4) User dimension. This dimension regroups all data concerning LMS's user. To support the interactions of the various users intervening during the training and to propose LOs corresponding to their role, we suggest quoting them with the concept *User_Type* (learner, teacher, author, etc.). These users are described by a collection of information. A set of *General_Information* such as *First_Name*, *Last_Name*, *Birth_Date*, etc. is assigned to any type of user. Further, a set of *Specific_Information* is assigned to a specific user in the system. For example, an *Author* is assigned a *Biography* and a *Reputation*, whereas a *Learner* is assigned *Goals* and *Centers_Of_Interest*.

Once the content of the ontology is determined, we must consider the representation formalism we have to use to model it. RDF and RDFS are not powerful enough to define the complex relationships that exist between LOs and context elements. The proposed OWL recommendation actually consists of three languages of increasing expressive power: OWL-Lite, OWL-DL and OWL-Full. They are basically very expressive description logics (DLs) with RDF syntax. DLs are a family of knowledge representation languages that are widely

³ http://www2.tisip.no/quis/public_files/wp5-standards-for-elearning.pdf

⁴ http://ltsc.ieee.org/wg12/files/LOM_1484_12_1_v1_Final_Draft.pdf

⁵ <http://www.adlnet.org/>

⁶ <http://scorm.com/scorm-explained/>

used in ontological modeling. An important practical reason for this is that they provide one of the main underpinnings for the OWL. To model our ontology we need a set of constructors of DL. In particular, the DL *SHOIQ*, corresponding to OWL-DL, is used to define all complex relations and concepts of our model.

Once the ontological schema is achieved, we integrate data from CrossKnowledge database using Talend Data Integration tools⁷. Then, we use the OWLIM Sesame middleware⁸ as a triple store, to store the corresponding ontology. The mobile context-aware ontology is stored in the triple store and is connected to the learning repository containing the physical data of learning modules.

B. Behavioral Level

To implement contextualized learning, each learner's context is saved into the m-learning ontology. Given the learner's activity at a given time, location, learning style, and the course of study; the learner can be offered corresponding LOs. Using the Semantic Web Rules Language (SWRL)⁹, specific rules are written. Then a reasoned tool can infer the list of LOs that will be offered to a given learner. These rules are defined by experts in the learning domain. As these experts do not necessarily have the technical competences to write SWRL rules, we developed a rule generator to easily manipulate m-learning ontology concepts and generate automatically SWRL rules. This rule generator is provided as a web application to experts.

When connected to the mobile learning system, the platform should propose an optimized panel of LOs corresponding to the current context of the learner. Optimization algorithms may improve various objectives such as minimizing learning time, minimizing the number of non-required LOs for training, maximizing learner satisfaction, etc. If each LO was accessible on every learning device, it would be easy to choose at any time the best support for training according to the learner's context. Actual cases that we studied showed us, on the contrary, a great heterogeneity of LOs available according to different devices. Training has different structure and different duration, depending on the device used. This forbids changing learning devices while training without risking redundancy of some LOs. In our case, the problem can be reduced to a variant of the well-known shortest path problem called the *multimodal shortest path problem*.

This challenging problem extensively studied in recent years [17], consists of rallying a point B from a point A by taking various means of transport, with different traveling time, routes and transportation costs. We can make approximation considering that an optimized training is equivalent to the shortest path to join learning objectives by different means of transport (here different learning devices). Just like two paths may follow different routes depending on means of transport,

two training courses may include different LOs. Similarly, just as traveling time between two points depends on the means of transport, the time needed to learn a set of LOs may vary depending on the broadcasting device. Finally, the availability of each learning device varies over time, like the availability of means of transport.

This problem cannot be resolved by an exact method, because of the exponential growth in complexity depending on the size of the problem; we propose to use metaheuristics in order to ensure the achievement of a solution in a reasonable time. The metaheuristics used must be adapted to take advantage of rules described by learning experts. We therefore link the semantic modeling techniques in the training offer and user profile with powerful algorithms derived from combinatorial optimization. The objective is to provide an adaptive system that maximizes the availability of m-learning. Various heuristics have been proposed for solving the problem of multimodal shortest path search [18] [19].

IV. CONCLUSION

In this paper, propose an approach for context-based adaptation for m-learning, making use of learning practices already deployed in e-learning systems and adopting them in m-learning. Our system is built around an ontology that both defines the learning domain and supports context-awareness. The use of this ontology facilitates context acquisition and enables a standard-based learning object metadata annotation. We also use a set of ontological rules to achieve personalized context-aware LOs by exploiting knowledge embedded in the ontology. The future adaptive system will offer an optimized panel of LOs matching with the current context of the learner.

In future work, we are going to compare the effectiveness of some heuristics for solving the problem of multimodal shortest path search with a metaheuristic inspired from simulated annealing that has been already successfully used in the TourismKM project [20].

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⁷ <http://www.talend.com/>

⁸ <http://www.ontotext.com/owlim>

⁹ <http://www.w3.org/Submission/SWRL/>

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