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Adaptive Mobile Learning

Anastasios A. Economides
Information Systems Department
University of Macedonia, Thessaloniki, Greece
economid@uom.gr

Abstract

This paper presents a general framework for adaptive mobile learning. The mobile learner performs an educational activity using the infrastructure (e.g. handheld devices, networks) in an environment (e.g. outdoors). An adaptation engine personalizes the educational activity and the infrastructure to the learner according to the context. The adaptation engine may be deterministic or probabilistic. Learning automata are employed as probabilistic adaptation engines. The context is described by the learner's state, the educational activity's state, the infrastructure's state, and the environment's state.

Keywords: *adaptation, adaptive learning, context, handheld devices, learner profile, learner model, learning automata, mobile learning, personalized learning, pervasive learning, ubiquitous learning.*

1. Introduction

The mobile learner will carry multiple heterogeneous wearable and handheld devices [1]. She will move and interact unrestricted with other learners, hardware and software resources in her neighborhood or on remote locations. She will be able to continually learn wherever she is moving without any mobility, time and other restrictions.

The objective of this paper is to present a general framework for adaptive mobile learning in order to stimulate and support potential research and development efforts. According to this framework, at the core of the adaptive mobile learning system there is an adaptation engine that acquires input data and produces the adaptation results. The input to the adaptation engine is the learner's state, the educational activity's state, the infrastructure's state, and the environment's state. The adaptation engine may use either deterministic or probabilistic decisions in order to produce adapted educational activity and infrastructure. Learning automata are used to implement the probabilistic adaptation decisions.

Part of the input data into the adaptation engine is related to the context of ubiquitous computing. Location, identity, time and activity have been suggested as primary types of context [2]. Computing context, user context, and physical context have been also proposed as main context categories [3]. Others [4] regard context to be location, identities of nearby people and objects, and changes to those objects. Dimensions of context are also considered to be Environment (physical and social), Self (device state, physiological and cognitive), and Activity (behavior and task) [5].

2. Adaptation engine

Let describe the proposed adaptation engine. The Input to the Adaptation engine includes the learner's state, the educational activity's state, the infrastructure's state, and the environment's state (Table 1). The variables that describe the Input may be either declared by the user or measured. Based on the input variables and the adaptation decision algorithm, the adaptation engine produces an Output. The Output consists of the adapted educational activity's state, and the adapted infrastructure's state. Let define the following states:

- L(t): the learner's state at time t, that it can take K different states $\{L_1, \ldots, L_K\}$.
- A(t): the educational activity's state at time t, that it can take M different states $\{A_1, \ldots, A_M\}$.
- I(t): the infrastructure's state at time t, that it can take N different states $\{I_1, \ldots, I_N\}$.
- E(t): the environment's state at time t, that it can take V different states $\{E_1, \ldots, E_V\}$.

Let also $U(t)=[L(t), A(t), I(t), E(t)]$ be the input to the adaptation engine at time t.
Let also $O(t+1)=[A(t+1), I(t+1)]$ be the output from the adaptation engine at time t+1.

Let at time t, the learner's state be $L(t)=L_k$, the educational activity's state be $A(t)=A_m$, the infrastructure's state be $I(t)=I_n$, and the environment's state be $E(t)=E_v$.

Considering deterministic adaptation decisions, we have the following:

If $U(t)=[L_k, A_m, I_n, E_v]$, then $O(t+1)=[A_{m'}, I_{n'}]$ and of course $U(t+1)= [L_k, A_{m'}, I_{n'}, E_v]$

In case the information about the context is not very accurate, probabilistic adaptation decisions would be employed. Instead of deciding definitively about the adaptations, a more soft decision would be done.

3. Learning automata adaptation

In this section, we propose probabilistic algorithms to adaptively select the most appropriate state of the educational activity or/and the infrastructure. We employ learning automata that reinforce a good decision and penalize a bad one [6].

Assume that at time t, the adaptation engine selects the state for the educational activity to be $A(t)=A_m$ with probability $PA_m(t)$, and the state for the infrastructure to be $I(t)=I_n$ with probability $PI_n(t)$. Define $PA(t)=[PA_1(t),\ldots, PA_M(t)]$, and $PI(t)=[PI_1(t),\ldots, PI_N(t)]$.

Considering *Learning Automata Adaptation decisions*, we have the following:

Assume that at time t, the $A(t)=A_m$ is selected probabilistically according to PA(t).
If this results in "good" outcome (e.g. the learner is satisfied),
then increase the probability of selecting again the A_m and decrease the probabilities of selecting all other As.
Otherwise, do the opposite.

Assume that at time t, the $I(t)=I_n$ is selected probabilistically according to PI(t).
If this results in "good" outcome (e.g. the learner is satisfied),
then increase the probability of selecting again the I_n, and decrease the probabilities of selecting all other Is.
Otherwise, do the opposite.

For example, let assume that there are two networks in the vicinity of the mobile learner. The problem is to select the network that will provide her the best communication performance and reliability in order to achieve her educational activity.

Therefore, let I_1 be the Infrastructure including the first network, and I_2 be the Infrastructure including the second network.

Let also, PI_1 be the probability of selecting the I_1, and PI_2 be the probability of selecting the I_2.

Let at time t, I_n (n=1 or 2) is selected with probability $PI_n(t)$.
If the communication performance and reliability delivered to the learner is "good",
then increase $PI_n(t+1)$, the probability of selecting again infrastructure I_n:
$PI_n(t+1)=PI_n(t)+a*(1-PI_n(t))$, $0<a<1$,
otherwise, decrease $PI_n(t+1)$: $PI_n(t+1)=PI_n(t)-b*PI_n(t)$, $O<b<1$,
of course, $PI_1(t+1)+PI_2(t+1)=1$.

In the example above, the Linear Reward-Penalty learning automaton has been used. However, other learning automata algorithms [6] may also be used depending on the situation. Also, the meaning of "good" communication performance and reliability may have various interpretations. For example, one can consider "good" to be the very small delay or the very small transmission error or the very small cost per bit.

4. Context model

In this section, we describe the context with respect to the learner's state, L(t), the educational activity's state, A(t), the infrastructure's state, I(t), and the environment's state, E(t). Due to space limitation, we only state their main dimensions.

4. 1. Learner's state, L(t)

We define the Learner's state, L(t), to consist of the following dimensions: *Demographics, Education & Profession, Preferences & Interests, Objectives, Aims & Plans, Health, Physical Abilities, Cognitive Abilities, Social Abilities, Emotions & Feelings, Intentions, Wills & Values, Time Availability & Schedule, Location, Mobility, Current Needs & Desires, Wearable & Handheld Resources, Tasks, Results & Achievements, and Restrictions.*

4,2. Educational Activity's state, A(t)

We define the educational Activity's state, A(t), to consist of the following dimensions: *Subject, Requirements, Purpose, Objectives, Expected Outcomes, Pedagogical Theory, Management, Content, Presentation, Structure & Sequencing, Resources, Participants & Teams, and Achievements & Results*.

4.3. Infrastructure's state, I(t)

We define the Infrastructure's state, I(t), to consist of the following dimensions: *Devices, Networks, Hardware & Software Resources, and other Adaptable Activities* in the vicinity of the learner.

4.4. Environment's state, E(t)

Finally, we define the Environment's state, E(t), to consist of the following dimensions: *Terrain, Weather, Environmental Characteristics, Neighbors (not participating in the educational activity), and Non-Adaptable Activities or Activities that should not be interfered with.*

5. Conclusions

The paper presents a general framework for adaptive mobile learning. To our knowledge, there is no such framework in the literature. The mobile learner learns and performs an educational activity as she moves in an environment. She is supported by an adaptation engine that adapts the educational activity and/or the infrastructure.

This paper formulates the adaptive mobile learning system as a system of an adaptation engine with input and output. The adaptation engine may employ deterministic or probabilistic adaptation decisions based on learning automata. The input to the adaptation engine is the learner's state, the educational activity's state, the infrastructure's state, and the environment's state. The output is the adapted educational activity and/or infrastructure. For example, the adaptation engine may present to the mobile learner adapted content and media according to her current position and available networks.

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Input U(t)	*Output O(t+1)*
L(t): Learner's state, A(t): educational Activity's state, I(t): Infrastructure's state, and E(t): Environment's state.	A(t+1): adapted educational Activity, and I(t+1): adapted Infrastructure.

Table 1. Input and Output of the Adaptation Engine.