A Reactive Architecture for Ambient E-Learning

C. Beckstein, J. Denzler, M. Fothe, B. König-Ries, H. Sack, and J. Vogel

Fakultät für Mathematik und Informatik, Friedrich-Schiller-Universität Jena
beckstein|denzler|fothe|koenig|sack|vogel@informatik.uni-jena.de,
WWW home page: http://www.informatik.uni-jena.de

Abstract We present an architecture for a new ambient E-Learning system. In contrast to existing solutions, the envisioned E-Learning system shall offer a constant, on-the-fly adaptation of the course units and their presentation to the current needs and preferences of the individual user. This will guarantee a significant, individual success of such a learner. This goal makes it necessary to acquire information about the user during learning and to model his learning abilities and strategies. Additionally, the content must be represented in such a way that course generation can select and present the material depending on the individual user, his progress, his current mental state and the learner's environment.

1 Motivation

Lifelong learning is one of the main demands to people nowadays. Learning will no longer be restricted to the first few years of our life nor will it be restricted to class room settings. Thus, new methods for teaching and learning must be developed that allow learning anytime and anywhere. As a consequence E-Learning, i.e., learning with support of or even solely with a computer will become more and more important. In the future, E-Learning systems cannot be restricted to the presentation of material only, but must be able to dynamically and individually structure the presented topics and to evaluate success of the learner.

Today's E-Learning systems have their focus on the representation of the content such that the presentation using multimedia on the computer is possible. The individual learner is not taken into consideration, in general. Learning success is verified on statically integrated tests only. The learner is neither observed nor modeled during learning with respect to his individual learning disposition. As a consequence, problems arise w.r.t. the adaptation of the amount of new material per lecture, the abstraction level of the presentation as well as the media and way of the presentation Also, up to now most if not all systems do not take into consideration the important aspect of attention or how and when to adjust the presented topic based on the current attention level of the learner.

Individualization of learning scenarios will become more important. We claim that next generation E-Learning systems will only be successful, if they are able to use all information that can be acquired from the user during learning and to feedback such information to individually adapt the structure of a single lesson as well as the whole course. The latter makes it necessary to represent the material in a way that a course generator can easily construct and adjust lessons. For this purpose the generator must take into account the user's global, general learning behavior and short term behavior variations, like, e.g., those based on attention.

In order to get a better understanding of the goal we pursue, envision the following situation: We are looking into the class room of a high school computer science class in 20XX. After a brief introduction of today's subject by the teacher, each student works at his own pace on his computer. Bob goes very quickly through the introductory text and plunges into an example at once. Since he skipped all the background information, he quickly becomes confused and doesn't really know how to approach the problem. The system notices both his frustration and his unwillingness to read long explanations and suggests to start the course with a more basic hands-on exercise. Once Bob has completed this activity, the system then offers additional information and more challenging tasks. Alice on the other hand, first reads the introductory material and then starts working on an example. She solves this problem quite quickly which results in the system offering a more challenging one immediately. Alice is somewhat puzzled by this new problem and starts to randomly try out possible solutions. Again, the system deduces that Alice needs some additional support. The system suggests to switch to a different representation of the same problem. Indeed, this helps Alice to overcome the problems she had initially and to successfully work through the entire course. Meanwhile, the bell rings, and school ends for the day. By now, Bob has started working on a problem set that really intrigues him. So, once he is settled in the street car on his way home, he plugs in his earplugs and uses his cell phone to continue working. The course material is adapted to this new device. The system will also take into account the fact that Bob gets diverted from time to time in this situation.

In the text above, we claimed that "the system notices" and then adapts its presentation based on these observations. This is a behavior that we all know from (good) human teachers. In order for a computer system to be able to emulate such behavior, ambient intelligence is needed. For this purpose the system needs to be equipped with sensing devices to unobtrusively observe the behavior of the human user. In addition, a certain intelligence for the interpretation of this behavior is needed that allows to infer how to adapt the system's presentation accordingly. Consider, e.g., the situation where Alice starts to randomly try out solution candidates. Assume that the system is able to track among other things Alice's eye movement, her usage of the mouse, her posture and her facial expression. All four will be quite different when she is determinedly pursuing a solution than in the current situation. Based on Alice's user model (including the knowledge she acquired so far, indications about her learner type, her preferences etc.), a model of didactic approaches and the available content, a planner can now decide that it might be helpful to present Alice with a graphical instead of textual representation of the problem she is trying to solve.

We will now first discuss ambient E-Learning systems and will then present the architecture and the key components of our envisioned system. Afterwards, we will give an overview of related work and then conclude the paper.

2 Ambient E-Learning Systems

Ambient Intelligence is one of the key concepts to the success of E-Learning systems. According to the 2002 final report of the IST Advisory Group of European Commission the term Ambient Intelligence deals with systems that offer intelligent services to a user in a transparent way. The corresponding user interfaces are embedded in all kinds of objects providing an intelligent environment that is capable of recognizing and responding to the presence of different individuals in a seamless unobtrusive and almost invisible way [1]. Besides applications in the context of the intelligent house, assisted living, health and work, teaching and learning is one area, that could benefit from ambient intelligence. In aggrement with [2, 3] the main challenges of ambient intelligence in E-Learning systems are:

- transparent integration into the environment: Adaptation of the presented material, repetition of certain aspects of a lesson and integration of exercises should be possible in different contexts. The system shall work with the user (as human teachers do) in the best possible way the current environment allows.
- adaptive software platform: Ideally, such a system shall not be bound to a specific computing environment. Rather, the learner should be able to take the course with him wherever he happens to move. This requires the underlying software to be highly adaptive.
- perception of the environment: already available techniques should be integrated into such a system to observe the user and to get information about his current state. Examples range from eye-tracker, CCD cameras up to sensors that measure movements of the user on a seat. Methods from affective computing [4] that estimate the (emotional) state of a user, for example mimic and gesture recognition, shall be used in such a system to continuously feedback information about the user and his reaction to the system.
- multimodal interaction: Depending on the learning style of the user, the system needs to use different modalities alone or in combination to achieve the most success.
- learning and adaptation: The system should be able to adapt to a user's learning style. If it didn't manage to teach a certain concept with the approach it planned on at first, it needs to be able to find alternative routes to achieving it's teaching goal.

An E-Learning system that is able to cope with these challenges must maintain an internal model of the learning environment. Such a model consists of a representation of the physical environment (the *environment model*), where the learning takes place as well as a representation of those aspects of the learner's mental states that are relevant to the learning process (the *user model*). The environment model provides a description of the interaction facilities (the *interaction repertoire*) being available to the learner. The environment determines the repertoire of sensors being deployed and the way how the raw sensor data are aggregated. Ambient E-Learning requires a continuous adaption of this repertoire, because learning must be possible anywhere, at any place with any subset of possible interaction facilities. An important result and precondition of the aggregation process is the classification of the environment w.r.t. its interaction possibilities (the *environment type*). The user model provides the information that is necessary to adjust the learning process to the current state of the learner. This information ranges from the interaction history to more psychological parameters such as attention, motivation, frustration, or preferred ways of interactions as it is inferred from sensor data aggregation and interpretation.

3 Architecture of the System

Any E-Learning system that meets the above mentioned requirements for ambient E-Learning must address at least the following key tasks:

Sensor data processing: Continuous aggregation of the sensory data into a dynamic environment and user model.

Didactic guidance: Determination of learning objectives and context – and goal-specific selection of primitive learning units.

Dynamic course composition: Generation of structured and adaptive learning workflows from elementary learning units.

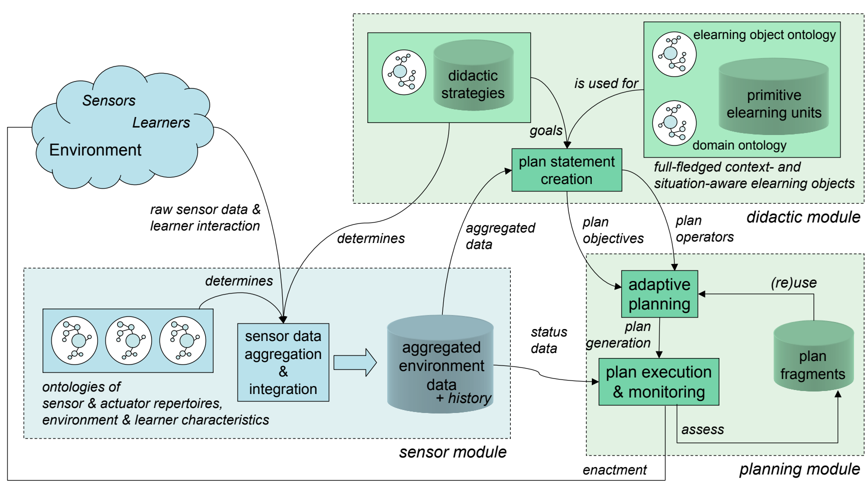

Figure 1. Architecture of an ambient E-Learning system.

We therefore propose an E-Learning architecture, where each of these tasks is handled by a specific module (see Fig. 1).

Sensor Module. Continuous classification of the state of the user and the context, in which he is learning, is the task of the sensor data processing module. The state of the user comprises all quantities that might influence learning, for example, attention, motivation and understanding of the presented materials. The state of the user is something that should be analyzed continuously. On the other hand, the context, which includes the environment in which the user is learning, will only change slowly over time. Thus, classification of the context will be done on a larger time scale.

Analyzing the state of the users means that algorithms must be provided that can work with different modalities, for example, audio, video or signals from the input devices, like keyboard or mouse. Gesture and facial expressions must be analyzed by means of well known techniques from computer vision. Eye movements and reaction time to stimuli by the system (for example, new figures on the screen, or exercises) are further cues to identify the state of the users. Thus, besides algorithms to analyze individual sensor modalities aggregation (fusion) and integration of different modalities play an important role as well. Also, fusion should be adaptive, over time as well as for each individual user. Finally, the algorithms must work for data from natural environments and for non cooperative, naive users that have no understanding from the underlying sensor data processing techniques. Tracking must be robust with respect to unpredictable movements, inhomogeneous background and changing illumination.

Didactic Module. It is the task of this module to provide the E-Learning system with suitable course material and didactic strategies that guide the presentation of this material for the best achievement of the overall learning goal.

The course material needs to be hierarchically structured from primitive units. This will ensure that its parts can be flexibly combined into new and more complex learning units by an automated course generation system as the situation requires. Keeping primitive learning units at a fine-granular level allows to maintain a dynamic and personalized learning workflow.

The individual learning units need to be annotated with a rich set of meta data that describes what the learning units can contribute to the overall learning goal assuming the current learning situation. The current learning situation itself must be reconstructed from the information in the environment model and the information in the user model. This process is strongly influenced by the type of the environment where the learning currently takes place. The meta data associated with the learning units is rich enough to formally model these units as activities with pre- and postconditions. The preconditions characterize the learning situations that must be satisfied before the learning unit can be reasonably presented to the learner (e.g., necessary previous knowledge, data about the applicability in the current didactical context, requirements with respect to the user's state and information about the compatibility of the activity with the current environment type). The postconditions characterize the effects that a successful execution of the learning unit has on the user model and the future choice of a didactic strategy (e.g., assertions about the knowledge and skills a user will obtain by working through the learning unit). In our dynamic context, neither pre- nor postconditions can be described fully in advance. With the exception of pre- and postconditions given by semantic dependencies between the primitive learning units, all pre- and postconditions must be regarded as varying over user state, environment type, and didactic strategy. The activities connected with learning units therefore must be constantly adapted at run time. Meta data will be described using ontological models of both the domain of the contents and the didactical model underlying the system. The first consists of a taxonomy of domain concepts to be taught together with their dependencies. The latter includes a classification of didactical methods, the steps they are comprised of, the techniques that can be used to implement the individual steps and the goals that can be achieved by using them.

Planning Module. If we want to adapt teaching to the individual learner and to changing environments, we can no longer use a static learning schedule describing subsequent steps of teaching. Rather, we need a course generation regime that can produce course schedules in the form of flexible workflows of primitive learning units. These workflows must allow for the formulation of temporal and causal relationships between the primitive learning units at a level which is adequate for the types of environment they are executed in.

Since primitive learning units are modeled as activities with pre- and postconditions a reactive planning system will be used to create learning workflows that fit the learning goals determined by the didactic module. Note that the pre- and postconditions controlling the use of the learning units are not fixable in advance but vary depending on the type of the learner's current evironment: for complex learning workflows different parts of the workflow may be executed in different environments not yet known at planning time. As a consequence the planning domain belonging to the course composition is incomplete and must be incrementally refined with the help of the sensory module as knowledge about the environment, especially its interaction repertoire, enters the system. This hinders the reuse of course fragments in the form of workflow cases. It also affects the formulation of the goal structure and the planning statement that govern the overall planning process and must be provided by the didactic module to the planning module. The planning process has to make use of a domain ontology describing the learning area of interest as well as of a general model that describes the process of splitting learning goals into sub-ordinate learning targets featuring a lower level of abstraction. This data must be provided by the didactic module.

To be useful for ambient learning, workflows must be adaptable to the current situation during execution. If a pending learning goal cannot be achieved directly, a new planning process must be activated in the related sub workflow, resolving the assigned objective to appropriate lower level goals. A close interaction of this module with the didactic module is therefore needed. Also, throughout planning and execution of learning units, the learner's state must be constantly evaluated and taken into account. This will frequently result in adaptations of the learning workflows to better fit the user's needs.

Composing learning workflows for ambient E-Learning requires planning systems that interleave planning with acting, execution monitoring, failure recovery, plan supervision, plan revision, and replanning mechanisms.

4 Steps towards Implementing the Architecture

In this section we will discuss our own prior works that can serve as building blocks for the system described above as well as work by others that could be either helpful to realize such a system or that has similar goals to the one envisioned here.

Computing the state of a user has been done before for different purposes. First, facial expression analysis is a whole research area in computer vision. One area of applications are intelligent human-machine interfaces (for example, the SMARTKOM project [5]), another one the automatic classification of human emotions according to FACS [6]. More recently, *affective computing* has drawn the attention of the community of computer scientists, psychologists and includes also ideas from cognitive science, neuroscience, sociology and psychophysiology. According to [4], 'affective computing is computing that relates to, arises from, or deliberately influences emotion or other affective phenomena'. A prominent example of affective computing closely related to our E-learning system can be found in [4], where a system has been presented that estimates attention in a classroom based on different sensor information from the audience.

Intelligent Tutoring Systems (ITS) allow the emulation of a human teacher in the sense that an ITS can know what to teach (domain context), how to teach (didactic strategies), and learn certain teaching relevant information about the student being taught [7]. Current ITS [8] preassume a more or less static tutoring environment, whereas ambient E-Learning requires constant adaption to a changing environment.

In our previous work we have investigated real time object tracking in natural environments [9] and adaptive sensor data fusion [10]. Object recognition has been investigated during the past year [11], too, also with special focus on generic recognition [12], which will be a challenging problem in the recognition of individual characteristics of one single emotion.

[13] describes a courseware system with a strong didactical model we developed previously. The system consists of three main components: A contents' repository that contains learning units. Each learning atom is annotated with relevant terms from a domain ontology and with its didactical function. The second main component is a repository of didactical strategies and methods. It contains, e.g., information about the classical three-step approach to teaching where one step is the introduction to the topic. This introduction can be done by giving a presentation, setting up a brainstorming session, or triggering group work. The third component is a tool, that supports a teacher in putting together courses. The teacher selects the relevant subject areas from the domain ontology and decides on a didactical strategy to use. The system then proposes a possible course outline which reflects the requirements with respect to contents and

didactics as well as constraints like available time, number and prior knowledge of learners, or available technical support. The repository of teaching material together with the didactics repopsitory are a valuable basis for the proposed ambient E-learning system. However, a number of significant extensions are needed: First, up to now, the system is not geared towards automatic, dynamic adaptation. The meta data associated with the learning units is not yet rich enough to automate these adaption processes with the help of an automated planner. Also, human intervention will still be needed for the production of good initial versions of complex courses. To ensure that these initial versions can be further processed by an automatic planning system, techniques from the Hierarchical Interactive Case-Based Architecture for Planning (HICAP, [14]) should be useful. Second, no knowledge about the appropriateness and usability of didactical strategies in a given situation has been encoded. In the current system, the decision which methods to use is mostly being left to the human teacher. In order for the system to automatically make this decision, considerable input from didactics experts is needed. This is a non-trivial task, since didactic expertise is rarely formalized. Third, no attention has been paid this far to adaptation to different devices, e.g., desktop computers, PDAs, and cell phones. Here, we can build on a large body of work that deals with the adaptation of content to mobile devices. This work ranges from theoretical work analyzing information equivalence in different modalities over purely syntactical or manual adaptations to attempts to semantically adapt contents (for an overview c.f. chap. 7 in [15]). None of this work, however, is specific to E-Learning scenarios. It remains to be investigated how useful it is in our specific context.

There are several projects related to ambient E-Learning, e.g., "ambient Learning"[1] or "MOBIlearn"[2]. While "MOBIlearn" focusses on mobile learning paradigms such as making use of handheld mobile devices and a seamingless integration of ambient computing and communication facilities into the learning process, "ambient Learning" also considers ambient, multimodal and context-sensitive lifelong learning. Both projects are based on a static user model that only takes into account the user's direct interaction. Our approach relies on a more diligent monitoring of the user and the reactions not necessarily related to direct interaction. For this reason, additional sensor data have to be acquired, aggregated, and related to the user's current state to achieve a much more accurate adaption of the learner's personal learning preferences.

In [16] we describe a meta level architecture for workflow management called Act!. Systems based on this architecture presuppose a plan representation for workflow models supporting concurrent execution, nondeterministic activities, just in time completion of partially specified plans, and time map management. The architecture allows to implement intelligent failure handling for workflows on the basis of plan repair techniques and to directly support workflow modeling and execution very much like [17]. The Act! architecture can not yet handle planning domains where the repertoire of the pre- and postconditions of the

[1] http://www.ambient-learning.com/
[2] http://www.mobilearn.org/

activities varies over time. But we believe that techniques known from the EXPO system[18], a system that uses PRODIGY as a baseline planner and improves its domain knowledge in several domains when initial domain knowledge is up to 50% incomplete, will be useful to solve this problem. ACT! can generate and reuse plan macro operators but it is still an open problem how to do case-based planning with these operators in the style of [14] when the planning domain is incompletely specified as in the case of ambient learning.

5 Conclusion

We have presented a vision for a novel E-Learning system. The architecture of this system is specially tailored towards leasrning in changing environments by constantly adapting weakly prestructured learning material to the individual learner's state and environment. This adaption process is governed by an automatic planning system that uses knowledge about the learning domain and the current learning environment together with explicitly represented didactic strategies. Since we believe that such a kind of adaptability is necessary for ambient E-Learning we are currently undertaking first steps towards the realization of a prototype of a corresponding reactive E-Learning system.

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