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The Artificial Mentor: An assessment based approach to adaptively enhance learning processes in virtual learning environments

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Abstract: Emerging e-learning systems cover a wide range of application fields satisfying user expectations such as rapid information access or flexibility in time and location. Still a challenge is to automatically respond to individual learner's perceptions. This paper presents a glimpse on concepts, evolution and practical implementation of the Artificial Mentor, a highly flexible, adaptive software component. The Artificial Mentor selects and triggers micro adaptations within a learning environment, intended to enhance the learning process. It was initially developed in the setting of a 3D virtual learning environment to address modern learner's individual learning needs.

Keywords: Adaptive Learning Environments, Monitoring, Noninvasive Assessment

Introduction

E-learning systems are broadly used as tools for distance and blended education. Despite the substantial benefits of online learning, users often complain about problems like missing motivation or a lack of instructional guidance [16]. This paper describes the theoretical background and technical attempts of a framework intended to improve a learner's psycho-pedagogical state. A first prototype of the so called *Artificial Mentor* (AM) was implemented for a Digital Educational Game (DEG) in the course of a learning platform called TARGET. This platform is based on a 3D virtual environment, in which a user is represented by an avatar, interacting with so called non-playable characters (NPCs), with their own beliefs, desires and interests [5]. The virtual environment consists of story dependent indoor and outdoor locations where the learner has to communicate or negotiate with NPCs and to gather pieces of information in order to master the scenario.

A virtual learning environment (VLE) that adapts to the learner`s current state is expected to increase the probability of learners being motivated to engage with it. The prerequisite for providing appropriate adaptations is a valid assessment of the learner`s current state. An explicit assessment by means of a short questionnaire appearing in regular time intervals would most likely destroy the learner`s flow experience [7]. Thus, it is necessary to assess these constructs by applying implicit and noninvasive techniques.

The implicit assessment technique described in this paper is based on the interpretation of the learner`s actions and behavior while he or she is engaged with the virtual environment. This technique aims to extend the *microadaptivity approach* established in the European research project ELEKTRA (http://www.elektra-project.org/). In ELEKTRA, the assessment of the learner`s competence state has been continuously updated based on the interpretation of the learner`s actions and behavioral patterns within game scenarios. When necessary, the scenario is adapted through the application of microadaptive interventions [10]. For example, an NPC provides a hint to the learner on how to solve a particular problem within the scenario.

In this attempt, the microadaptivity approach is extended by taking also motivational and emotional constructs into account in addition to problem-solving related processes. These motivational, emotional and problem-solving related processes and constructs are considered as important parts of a holistic view on the individual`s learning process. A conceptual overview of the extended microadaptivity approach is shown in Figure 1. It consists of the noninvasive assessment of considered constructs, the interpretation of raw values in terms of sufficient and insufficient values and interventions selected based on didactical rules.

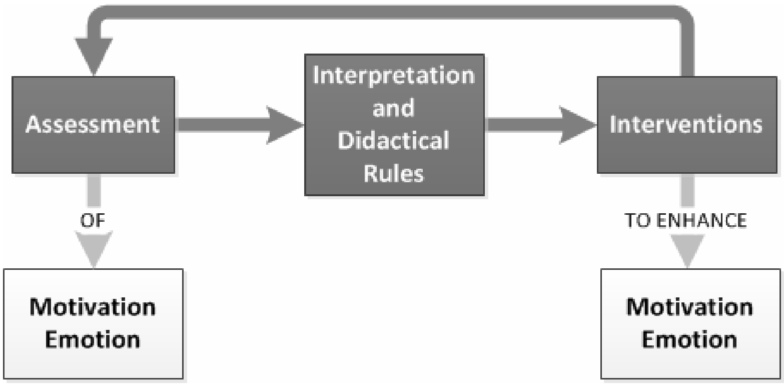

Figure 1: Conceptual Overview of the extended Microadaptivity Approach

The component diagram in Figure 2 outlines the position of the AM in a system context. It represents the technical interpretation of the conceptual ideas illustrated in Figure 1. To ensure platform independence, the AM prototype has been developed in JAVA. Although the AM was designed as a highly adaptable and portable component, access to certain information and necessary services need to be provided by the Learning Environment (LE). Collected raw data is forwarded to a Performance Analyzer (PA) component for further processing, necessary to draw conclusions about the learner's psycho-pedagogical state. As a decision basis, the AM requests this information periodically from the PA. After applying a set of rules, context information is fetched by the AM that triggers a fitting service in the LE.

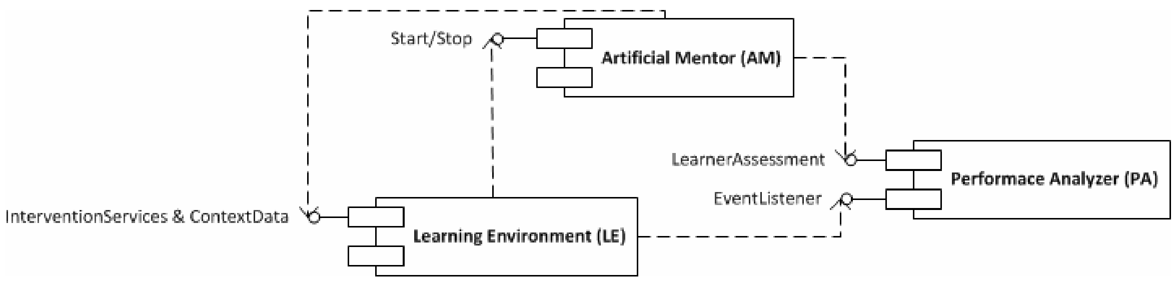

Figure 2: The Artificial Mentor illustrated as a System Component

The learner assessment embodies a substantial part of the system. Thus, all components contribute to it to some extent. Logic regarding the interventions is split between the Learning Environment (LE) that actually implements the process and the AM that decides based on various factors (e.g. context information, learner assessment, didactical rules, etc.) about the most fitting intervention to be introduced. Within the next chapters the identified concepts are explained in greater detail with regard to theoretical background and technical implementation.

1. Assessment

Two selected constructs which are (complemented by competence and clearness) part of the extended microadaptivity approach are further presented in this chapter.

Motivation: Achievement motivation [1][13] can be defined as the motivation to develop competences (approach motivation) and the motivation to avoid incompetence (avoidance motivation) [8]. Our model is based on the quadripolar achievement motivation model [6] which considers approach and avoidance motivation as independent factors.

Emotion: Our emotional model is based on the circumplex model of emotion suggested by [11]. The circumplex model consists of the two continuous dimensions pleasantness (valence) and activation. The effect of emotion on learning and memory processes is complex and further described in [3]. However, with respect to activation, a medium level of activation leads to a superior learning process [15].

The constructs *motivation* and *emotion* are assessed by continuously retrieved behavioral indicators, which represent a learner's interactions with the virtual learning environment. Up to now, an extensive set of behavioral indicators has been conceived, whereof some can be found in [12]. In this paper the focus is on a new approach towards the identification of behavioral indicators that is inspired by the theory of Information Foraging [14].

Information Foraging: The theory of Information Foraging [14] describes strategies to gather and consume information, for instance during a game-play. Human search behavior is supposed to be adaptive to gain information from external sources that are termed patches, for example on-line documents or NPCs in a virtual environment. An ideal information forager maximizes the rate of gaining valuable information through a balanced ratio of explorative and exploitative search behavior: To acquire knowledge efficiently, available time has to be divided into the search for new sources (e.g. NPCs) as well as into the elaborate processing of them (e.g. by conducting an informative conversation with an NPC). While the time spent on exploration is called *Between-Patch* processing and is represented by the variable T_B, the time spent on exploitation is termed *Within-Patch processing,* represented by T_W. We assume that indicators reflecting this allocation of time among T_B and T_W allow for inferences about motivational and cognitive states of a learner during game-play. Learners who balance well between exploration and exploitation are assumed to be aware of a current problem state and motivated to solve the problem.

Besides T_B and T_W, additional variables that are taken from [14] have to be computed to obtain two behavioral indicators, namely Information Gain (G) and Rate of Information Gain (R). G stands for the total amount of information gained and is given by equation (1),

$$G = \lambda \cdot T_B \cdot g \qquad (1),$$

where λ is the prevalence, the average rate of communications with NPCs, and g is the average gain of information during a conversation with an NPC. λ is simply given by equation (2),

$$\lambda = 1/t_b \qquad (2),$$

where t_b represents the average time in seconds spent on searching for NPCs in the course of a predefined time-slice. The higher the value of t_b, the lower is λ, reflecting low motivation. Finally, g is – in our case – the number of relevant propositions extracted during the conversation. To simplify the assessment process, the number of propositions may be equated with the number of relevant content words used by an NPC. Relevant content words are terms referring to topics of an informative conversation.

Finally, R, the rate of valuable information gained per time-slice can be obtained. It is given by

$$R = G \,/\, (T_B + T_W) \qquad (3).$$

The more information is extracted during conversations and the less time is needed for this information gain, the higher the value of *R*.

All indicators are continuously measured during the game-play. After each time slice, the raw values for all behavioral indicators *i* are standardized by means of *z*-transformation for the sake of comparability. Afterwards the standardized values z_i are inserted into the following logistic function

$$p(z_i) = \frac{1}{1+e^{-z_i}} \qquad (4),$$

where $p(z_i)$ represents the value of the indicator *i*. The logistic function is positively accelerated and differentiates primarily in a range between -3 and +3. Finally, the values $p(z_i)$ are combined with a linear regression equation which results in an aggregated value $p(c_i)$ for each construct.

2. Interventions

Interventions, in this context are sensitive attempts to positively influence a learner's psycho-pedagogical state and therefore enhance the learner's learning experience. This chapter provides a glimpse on firstly the theoretical ideas and secondly this approach's highly adaptable integration and development architecture.

To explain the theoretical background, we elaborate on one example, which is the introduction of field records. Field records are sounds naturally occurring in our environment, for instance the chirping of birds outdoor or the clicking of a keyboard indoor, of which we do not become aware most of the time. However, psychological research suggests that external stimuli do not have to be processed consciously in order to influence behaviour. To the contrary, unconscious, i.e. automatic processes can activate our implicit motive system [2], which is in turn related to affective reactions. Thus, we make use of field-records to create a nonintrusive, acoustic atmosphere affecting the learner's motivational and emotional state. To this end, we decided to apply the psychological database IADS [4], consisting of sound-tracks that are classified by the two dimensions of activation and valence. This classification enables the selection and provision of sounds that both affectively stimulate the learner and are congruent with the current emotional state. The provision of sounds that are in accordance with the learner's emotional state should avoid unpleasant feelings of dissonance [9]. In case of low values on the activation and valence dimensions, the learner should not be confronted with sounds characterized by high activation and very positive valence. In order to improve the state in a gently way, sounds should be selected that are moderate with respect to both dimensions. However, a learner with intermediate or even high valence- and activation-values may be stimulated by activating and happy sounds.

Interventions in their structure and logical implementation have a natural dependency on the virtual learning environment as different kinds of environments are expected to offer different possibilities of interaction (e.g. compare 3D virtual worlds with 2D learning platforms). Therefore, interventions in their implementation and integration in the AM need to be easily exchangeable. In order to address this major requirement in the prototype, concrete interventions derive from a superclass Intervention, that possesses an abstract method *trigger*. This method is called to execute the intervention and therefore needs to introduce the respective logic. After a new intervention class was created correctly it only has to be registered in the class "InterventionManager", dedicated to a type of intervention classification (e.g. EmotionalIntervention). Whenever an Intervention of such a specific kind is required, the InterventionManager can be called to return objects of the registered classes. In this sense, a pluggable structure to integrate Interventions is provided.

3. Discussion

This paper describes background and genesis of a digital learning support tool. The Artificial Mentor monitors and interprets a learner's psycho-pedagogical state in a noninvasive way. This assessment is grounded on the continuous observation and interpretation of behavioral indicators, providing evidence for a learner's cognitive, emotional and motivational state. In order to ensure an efficient and sustainable learning process, interventions are introduced based on predefined didactical rules. Future work will be carried out in respect of validation of behavioral indicators and evaluation of intervention efficiency. Taken the results of this research as a basis, the goal is to provide an extensive set of atomic indicators as building blocks for more complex behavioral indicators to offer an easily adjustable approach applicable in variable VLEs.

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