A General Framework and Control Theoretic Approach for Adaptive Interactive Learning Environments

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Abstract. From a systems theoretical point of view, adaptive learning systems (ALS) for education and training contain in their core - in a simplified form - closed feedback control loops in which the control is determined by the measured users' performance. Improving this performance can increase the learning outcome, especially for critical disciplines such as education or training for disaster risk management. However, for this special form of intelligent (e-learning) assistance systems learning theories and behavioral models have to be considered, e.g., game flow theory, cognition models or learning models. The research question is how adaptive interactive learning environments (ILE) such as serious games and computer simulations can be characterized and analyzed to determine optimal adaptation strategies. Adaptive learning environments should adapt to the context-related needs of the user in order to ensure and optimize learning success, especially for disaster management training. This contribution presents a concept for an interoperable, adaptive ILE framework which follows control theory and its models, contributing to the state of the art for adaptive games or simulations in disaster risk management.

Keywords: Adaptivity · Assistance systems · Interactive learning environments · Modelling of human performance · Closed loop feedback

1 Introduction

Effective assistance systems for education and training try to improve the users' learning experience. One key factor in effective training and tutoring is to motivate the users. In contrast to external motivational factors (e.g., social or economic pressure to succeed), intrinsic motivation can sustainably optimise learning outcomes [28]. One way to increase user motivation is to utilize the principles from digital game based learning. Further optimisation can be achieved through personalised learning in which adaptive learning systems (ALS) adapt to the individual needs of the user [34]. This is typically referred to as intelligent tutoring systems (ITS), *cf.* Woolf 2009 [36]. They can be regarded as a special form of intelligent assistance systems for learning. A special form of adaptive learning systems is found in interactive learning environments (ILE) such as computer simulations and serious games. The latter are digital learning games with a characterizing or “serious” goal - in the case of digital learning games, education and training, *cf.* Dörner et al. 2016 [12]. Particular challenges lie in modelling and analysis. In the 4-phase adaptivity process by Shute et al. 2012 [30], our focus is on the analysis phase and the learner model or, more generally, user model. This contribution deals with the modeling and analysis of adaptive ILE (aILE). The research question is how aILE such as serious games and computer simulations can be characterized and analyzed to determine optimal adaptation strategies.

Fig. 1. (left) Application of a quadrocopter for aerial image intelligence in a disaster scenario. (right) Smartphone with mobile assistant to support the action force in the field.

The problem statement originates in our application area, which is adaptive e-learning for professional aerial and satellite image interpretation. It is a discipline which is also of help for disaster response tasks such as search and rescue operations (S&R). Fig. 1 shows an example S&R application with a quadrocopter looking for buried victims and a mobile learning app for operators training. Image based intelligence systems have become increasingly important for emergency and security services [8,18], e.g., for dynamic disaster response training. To provide rapid and targeted assistance in case of disaster the emergency services and security forces depend on up-to-date and location relevant information of the current situation in the field. Combined sensor systems with all kinds of sensor platforms, e.g., robots and balloons, can support emergency services. An example of a relevant application of such combined information systems is the remote sensing of damaged reactors at the Fukushima nuclear power plant disaster. Another example is the training of disaster scenarios for emergency services. Scientists and rescue teams test new technologies to assist emergency services and to help protect the people in real-world settings. The interpretation of aerial and satellite images poses a wide range of challenges because of different imagery sensor types, difficult image material, unknown objects or situations that are hard to interpret. Professional image interpretation is done in various fields, ranging from the microscopic level in medicine, e.g., diagnostics in histopathology, to the macroscopic level of aerial or satellite images, e.g., civilian applications like search-and-rescue, agriculture, oceanography, or military intelligence [26]. Special face-to-face training courses blended with technology-enhanced learning tools, such as e-Learning courses, simulations and serious games, ensure that image analysts are qualified to a high standard. Adaptive assistance systems support the users in this.

2 Related Work

2.1 Disaster Management and Educational Serious Gaming

As can be seen in the comprehensive literature review by Solinska-Nowak et al. 2018 [31], serious games, i.e., games with a characterizing goal [12], are widely applied to disaster management. The benefits arise from their hands-on or experiential learning experience which strengthens knowledge acquisition and activates learning, as depicted by Kolb 1984 [17].

The characterizing goal of serious games for disaster management typically concerns the character of disaster itself - real disasters are not for game entertainment. Often this aspect already fulfils the “serious” aspect. However, there are combinations of other serious aspects as well, such as education and training, or learning. For the latter the term educational serious games is typically used [12]. In our work we focus on this very combination of serious gaming, education and disaster management, and adaptivity to further increase the intrinsic motivation and learning outcome [34].

The literature review from Solinska-Nowak et al. 2018 [31] lists various examples for serious gaming for disaster management. Such examples comprise serious games on disaster risk reduction to raise awareness about geohazards [21] or [15]; or games on natural resource management [4]; on climate or climate change [27].

Regarding the topic of adaptive educational serious games for disaster management only a very limited number of matching publications can be found. The search terms “disaster management” and “serious game” and (adaptive or adaptivity or personalization) shows only a handful of matching results, “adaptive“ or “adaptivity” being the limiting factor.

Arnold et al. 2013 [2] focus on an adaptivity for a serious game for disaster management. They describe a storyboarding approach combined with a user model to implement an adaptive behavior.

Oulhaci et al. 2014 [24] present an adaptive approach with a multi-agent system which addresses human-like behavior of non-player characters (NPC) in a game for crisis management.

Capuano et al. 2013 [6] show an adaptive game approach to teach school students how to behave in case of natural disasters.

From a system theoretic perspective, control theory has long been an active, well established and vastly applied field of research [19,3]. One of its main problems studied is adaptive control [3,5]. A comprehensive literature review can be found in the book by Chalam 2017 [7], which highlights its importance for various fields of application, including electrical and electronic engineering, chemistry, mechanics, aerospace, biomedicine, shipping, transport and power plant engineering. While there is adaptivity in e-learning (e.g., [36,35]), little is to be found on the transfer from systems theory to e-learning. Our work contributes to this aspect, to benefit from the combination of both worlds. We apply adaptive control theory to our models of adaptivity in e-learning.

2.2 System Theory and E-Learning

Advantages can arise when two disciplines are combined - in the combination lies the strength. In this case, the established methods of systems theory [19,7] are transferred to e-learning and there especially to adaptive learning systems. In both disciplines there are approaches to adaptive systems. In systems theory, it is the adaptive control systems that adapt to dynamic changes in environmental parameters at runtime [3,16]. Similarly, in e-learning it is the adaptive learning systems that adapt to the dynamic behaviour of the user. While there are established and proven adaptive systems in system theory and control engineering for decades (e.g., [19]), this is not yet the case with e-learning. In control engineering, adaptive control systems that are standardized, tested and certified in engineering terms can be used interoperably in similar applications thanks to generic modeling. For example, adaptive altitude control systems for aircraft are so similar that they can easily be exchanged at the same interfaces if the underlying flight characteristics are modelled identically. In adaptive learning systems there are no uniform interfaces or models with regard to inputs and outputs. More recent approaches use the usage tracking standard protocol *Experience API* (xAPI) for the acquisition of input data [34]. There is no standard yet for adaptive responses. Here, a transfer of the approaches from control engineering can show the directions. The added values can be found in the definition of the interfaces as well as in the modeling. It is also possible to learn from the development history and identify dead ends and wrong directions at an early stage. Another point is that one should try to transfer the robustness aspects like dealing with unmodeled dynamics or uncertainties. The theory of adaptive control is quite vast and incorporates robustness in many settings [3,29]. Adaptive learning systems must also be robust to dynamic inputs in terms of reliability and correctness. In control engineering critical situations that necessitate robust reaction can arise immediately, for example the automatic control of airplanes to prevent dangerous situations such as stalling. However, the consequences of adaptive assistance systems in e-learning can be rather long-term, for example the wrong training of action patterns, which are difficult to relearn.

2.3 Adaptive Assistance in E-Learning

Adaptivity for education and training has long been an active research topic, generally seen as intelligent tutoring systems [23,36], and also in specialized forms for serious gaming [14,34]. To achieve an adaptive behavior, A.I. methods such as data mining and machine learning are used in all adaptivity phases, *cf.* Frutos-Pascual and Zapirain 2019 [14], and, as stated by Yannakakis 2012 [37], A.I. for decision making and player experience modeling (PEM) are key research areas. Cruz et al. 2017 [10] show how the well-established theory of flow is used for player-centered game adaptivity. In respect to our generic modeling approaches, Mäses et al. 2017 [20] present a similar approach to define user performance metrics and scores. On completeness, the more technical aspects of interoperable adaptivity frameworks and its related work have already been described in other contributions from the authors, e.g., Streicher et al. 2017 [33].

Regarding the transfer of systems theory to ALS, in particular control theory and adaptive control, no related literature has been found, to the best of our knowledge.

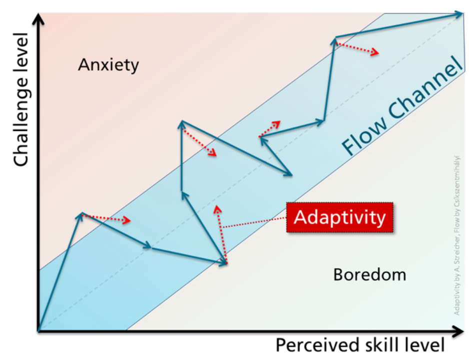

Fig. 2. A.I. to control the flow channel alignment (based on the original three-dimensional model by Csikszentmihalyi et al. 2014 [11])

3 Adaptive Control for Adaptive Learning Environments

As learning efficacy is directly linked to high intrinsic motivation, one possibility to keep the users motivated is to engage them to continuously participate in the (e-learning) programs. For educational serious games one can try to keep up high immersion levels by keeping the users in the so called flow channel [9]; Fig. 2 depicts this and how adaptivity comes into play. An adaptive learning system should control the ILE to keep the users in the flow channel, i.e., by automatically adapting the game to fit the users' skills and competencies. This balance between skill and competence is typically called the flow channel [11,9].

3.1 Control Systems

Taking this to the broadest sense, the ALS measures how the users interact with the system and modifies it in a way that the next inputs produce certain expected outputs [19]. This perfectly fits the description for general (linear) closed-loop feedback control systems where the output y is fed back as feedback to the input r (see the block diagram for a negative feedback closed-loop control system Fig. 3). The controller issues actuating signals u to the process or plant which gives the output y. A comparator function produces an error signal $e = r - y$ as difference between input and the feedback signal.

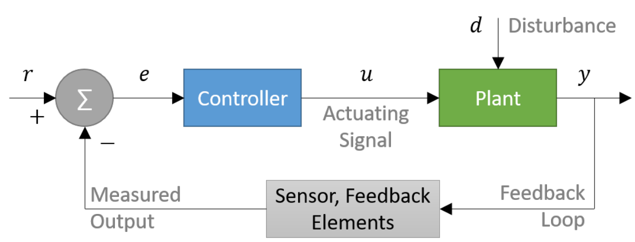

Fig. 3. Closed loop feedback control system

3.2 Control Systems from Learner-Perspective

This control system model can also be seen differently from the learner or e-learning perspective where the learning outcome of the users should be "controlled". Fig. 4 depicts this transfer to the learner perspective: the "system under control" could be seen as the learner, the controller is the ILE which should influence the learning outcome. In the feedback loop we measure the learner's performance (e.g., assessments) and issue feedback elements to the ILE.

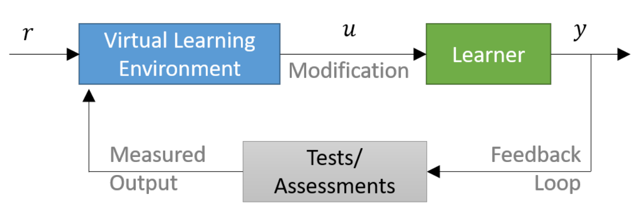

Fig. 4. Learner perspective for a closed loop feedback control system for e-learning

3.3 Control Systems from System-Perspective

Since we are interested in the systems theoretic perspective we can use the control system model and apply it to ILE systems, so the ILE itself becomes the system under control, see Fig. 5. From a software design view an ILE has a controlling back-end to adjust the game state, as well as a user interface for presentation and user interaction. The actuating signal u can be seen as the dynamic elements in a game, e.g., virtual consoles, NPCs, resources, etc.

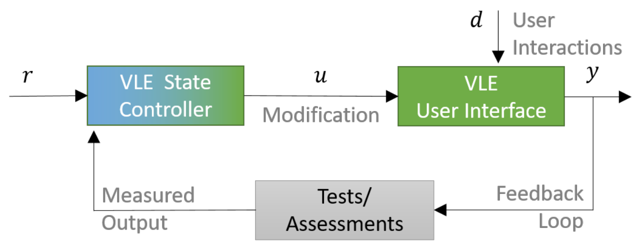

Fig. 5. System perspective for a closed-loop feedback control system for e-learning

3.4 Ideal Path Control Framework

But, normally human learning cannot be measured and controlled in deterministic ways. Hence nonlinear and learning-based adaptive control must be considered [25]. With human learning in the loop we typically deal with complex, nonlinear processes which motivates the use of adaptive control theory [3]. In adaptive control the controller must adapt to initially uncertain or varying parameters. This perfectly fits the idea of ALS - at the beginning we deal with the so called cold-start problem because no information on the user is available. Typically ALS start with assessing the users' knowledge level by initial questionnaires or tests to classify the user, e.g., stereo-typing the user as beginner, intermediate or expert. Over time ALS must adapt to parameter changes, e.g., change of playing pace, performance, or motivation (*cf.* section 1).

To define the closed loop performance we need a reference model as basis for deviation estimation, i.e., a model to characterize the users' playing behavior. One approach in adaptive control is model reference adaptive controller (MRAC) systems [3,22]. We propose to see the reference model as an "ideal path" through an ILE, as suggested with the ideal path model (IPM) [33]. The IPM is basically a "ground-truth" how an ideal interaction through a game would look like, "ideal" meaning an optimal sequence of interactions to play through a game without unnecessary detours. Based on the game mechanics there can be just one or multiple ideal paths. Of course, a beginner would not play a game as straightforward as an expert, thus the deviations from IPM would be very different for the beginner and for the expert.

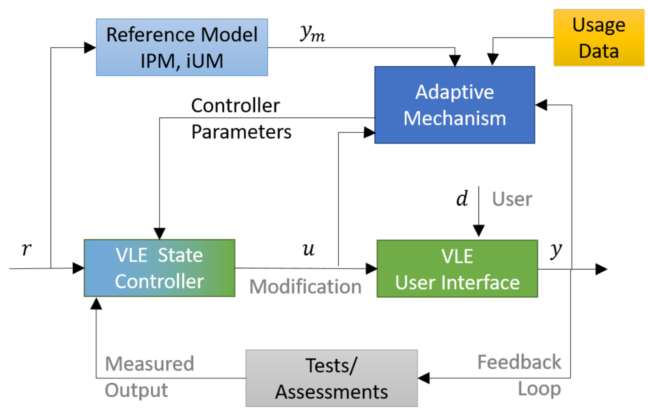

Fig. 6. Model reference Adaptive Control (MRAC) for adaptive Interactive Learning Environments

The IPM [33] is intended to improve the adaptive control of ILE by more accurately assessing performance and the need for help based on player interaction. The IPM is particularly useful in combination with additional sensor data observing the users' behavior while interacting with an assistance system, for example gaze or eye tracking. Eye tracking can provide insights into the cognitive states of users by tracking their visual attention. A typical example would be that attention is directed to the first area of interest by moving the fovea to that point. Once the movement is complete, the feature is inspected with higher attention before moving on to the next area of interest [13]. This gaze data can make an adaptive system more robust: a high correlation between gaze direction and pointing coordinates (mouse clicks or touch events) could indicate a high level of attention by the user. To evaluate the attention level with respect to goal orientation, the IPM has been developed as a reference model. This fits perfectly to the MRAC approach and its reference model. The reference model serves as a reference for comparisons, e.g., to evaluate the deviation of users during a game. Combined with a metric, this allows the calculation of a distance value, the ideal path score (IPS), which reflects the user's goal-orientedness. In a forthcoming contribution this theoretical framework will be validated by assessing a suitable performance parameter.

3.5 Ideal Path Model (IPM)

The ideal path model (IPM) describes all necessary steps to achieve the goals of the game without unnecessary detours. Essentially, it is a sequence of episodes

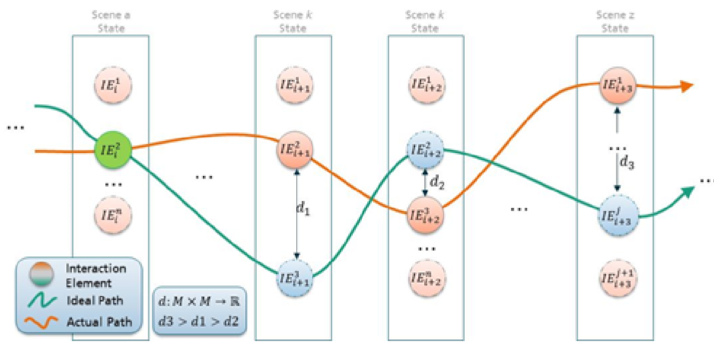

Fig. 7. Ideal Path Model with scene states, interaction elements and distances.

and interactions in an ILE that leads most directly to the next goal [33]. In an adventure game, for example, the ideal path would be the optimal passage, i.e., the optimal sequence of interactions from the start of the game to the end of the game. The building blocks of IPM comprise (Figure 7):

1. Scene manifestations, which capture the current state of a scene. New scene states develop when the user interacts with the scene.
2. Interaction elements (IE), which are all game elements with which a player can interact.
3. Ideal path through the sequence of all scene manifestations and interaction elements, can be seen as a reference model.
4. Actual path which reflects the actual sequence of steps a player has taken to interact with the game.
5. A metric which defines a distance $d_i : M \times M \rightarrow \mathbb{R}$ or deviation from an ideal path to an actual path.

3.6 Ideal Path Score (IPS)

The ideal path score (IPS) supports the calculation of the users' progress, i.e., to calculate a performance score how well the used plays a game. It is a metric defined on the IPM and described the distance between an ideal path and an actual path. The score is normalized to $[-1; 1]$ to be invariant for different game genres or different users.

- $IPS = 1$ means a perfect move, congruent with an ideal path.
- $IPS = 0$ is a move without significant progress.
- $IPS = -1$ is a degrading move (negative progress), e.g., a move in the complete opposite direction.

For ILE with continuous moves, the IPS could be in $\{x | x \in \mathbb{R}, -1 <= x <= 1\}$. While the ideal path model is generic and can be modeled independently of the game, the IPS and its metrics are typically game-specific. In step-by-step games, for example, this could be a string similarity distance; or in a 3D shooter-type game, the metric could be a distance between way-points.

3.7 Ideal Path Model Creation

A scene can have multiple manifestations for each possible interaction that a user can perform. The IPM can be built manually or automatically by recording the steps that an "optimal player" would take [32]. The recording of both the ideal path and all actual paths can be created using the data format *Experience API* (xAPI) [32]. The xAPI protocol records the experiences of the user while using an (e-learning) system. In it's very core xAPI is based on the W3C standard *activity streams*, so basically it is a (typically chronological) sequence of actions a user undertakes while using a software - such as an ILE - which includes an xAPI or activity stream tracker. Collections of such activity statements are used to form the ideal or actual paths through a ILE. It is worth mentioning that there is no fixated definition on the granularity of the events being tracked, it could range from micro-level mouse click tracking (lot's of events) to macro-level tracking of whole usage episodes (very few events). Typically, for the e-learning or serious gaming context, one records meaningful learning experiences as xAPI statements, such as the start or end of a session or the completion of an assessment task, e.g., "John completed the assessment of image interpretation task 5.3". Using xAPI all data can be stored in an xAPI compliant database, a so called learning record store (LRS).

3.8 Technical Concept

Following the generic input-processing-output model from systems theory the input is the captured user interaction with the ILE, e.g., with a computer simulation or a (serious) game. To achieve easy applicability and interoperability we propose to use the e-learning usage tracking standard *Experience API* (xAPI) which is based on the W3C standard *activity streams* [1]. The captured xAPI statements with the triple structure actor-verb-object act as measurement input to our adaptive learning system (ALS). We store these triples in a graph database. This offers several advantages, e.g., efficient analysis of relations (path finding, cluster detection, social network analysis, etc.), flexibility due to the absence of fixed data models (it is a NoSQL database), or it brings with an easy and naturally understandable visualization as graphs for visual analysis.

3.9 Application

To apply control theory we first need to define the involved processes and signals. We use the authors' proposed ALS architecture, as depicted in Fig. 8 [33]. It consists of three main parts: (1) the ILE; (2) a controlling interface which collects user interaction data and also modifies the ILE; (3) the adaptivity controlling system including an interpretation engine for analysis and an influence engine for selecting the best adaptation strategy. The signals include the user interaction tracking data and the adaptation control messages. In general, as depicted in Fig. 9 an ALS follows the scheme of (1) using an ILE like a serious game; (2) acquiring data from the ILE and on the user (a human tutor would observe the

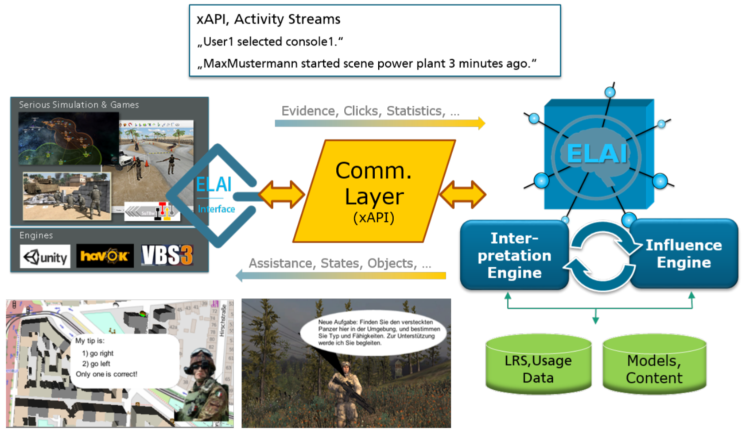

Fig. 8. Software architecture *E-Learning A.I.* (ELAI) for adaptive interactive learning environments

student); (3) interpreting that data with reference to models on the student, domain or teaching (like a human tutor); (4) selecting appropriate adaptation strategies like recommending relevant learning material or modifying the ILE by dynamic difficulty adjustments. In the following and for process structuring of our adaptivity system we follow an extended 4-phased adaptivity cycle. It basically extends the model from Shute et al. 2012 [30] by combining the analysis phase and the learner models (from the current user and also from other users).

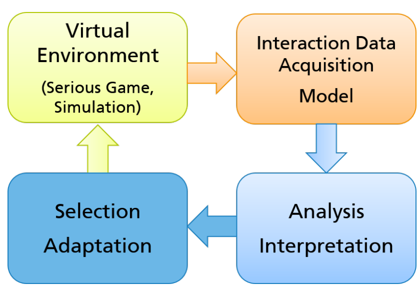

Fig. 9. General scheme for adaptivity

When applying control system theory to our ALS architecture we can see the ILE as the signal model which is to be controlled. Over time this model changes because it is being adapted to the user or, more precisely, towards the user model. Similar to the previous control system from the system perspective (section 3.3, Fig. 5) we have the basic structure of an ILE back-end controller and a controlled ILE user interface. This is depicted in Fig. 6. The input r is the ILE in its current state, the output y is the next (adapted) state. In

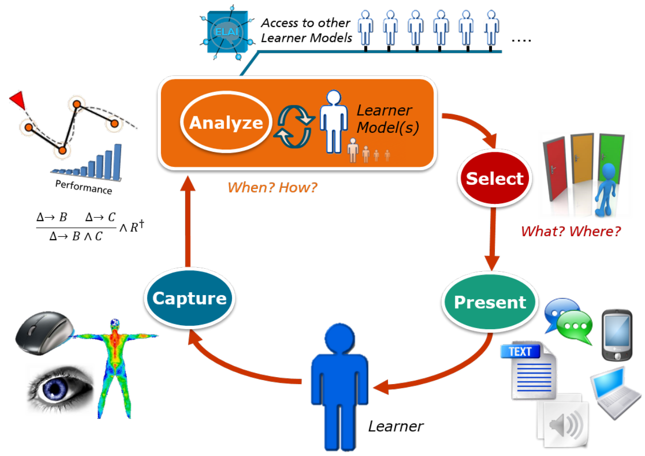

Fig. 10. Extended 4-phased adaptivity cycle

relation to MRAC the reference model is the previously mentioned IPM plus a user or student model which takes as input the current state r and outputs a model of the desired output y_m. For the IPM this could be the next interaction element to take, for the user model it could be information on suggested concepts (e.g., from player experience model or individualized knowledge tracing model). Input to the adaptive mechanism are the next state y, the reference models y_m, and also usage tracking data. Additionally the usage information should also contain assessment results. The controller parameters are when and how to adapt, e.g., given a virtual agent as one possible feedback mechanism, the adaptive mechanism controls the parameters the point in time this virtual agent should show up. This aspect will be elaborated in a forthcoming contribution.

4 Conclusion & Outlook

Disaster risk management (DRM) can benefit from applying serious games as motivational and engaging tools to foster disaster response competencies [31]. Whereas serious games for DRM are an active research topic [31], the number of *personalized or adaptive* interactive learning environments (aILE) are limited. The objective here is to benefit from adaptive serious gaming also for disaster risk management. This contribution presents the transfer of adaptive control to adaptive learning systems (ALS) with special focus on interactive learning environments like educational serious games (also known as digital game based learning) or computer simulations. The general idea is to adapt systems theory and control theory to the control processes of ALS. An adaptive system must react to the user - it measures how the users interact with the system and modifies it in a way that the next inputs produce certain expected outputs. Since we deal with complex systems with nonlinear and stochastic processes, we propose to adopt adaptive control theory with reference models (MRAC). For aILE we use an ideal path model as a reference model for adaptive control.

The next steps are to detail the needed user modeling and the systems control parameters. For the former we propose to use flexible models consisting of semantic triple data structures and graph models; for the latter (control parameters) we follow the idea of using an ideal path model as reference model to detect deviations and to modify parameter ensembles derived from the theory of flow. Of further research interest is the applicability of multiple models as well as fuzzy adaptive control systems.

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