Enhancing the Adaptive E-learning Environment by using the Markov Decision Process (MDP)

Norah Alqahtani, Mahmod Kamel, Mostafa Saleh
Information systems Department
Faculty of Computing and Information Technology
King Abdulaziz University
Jeddah-Saudi Arabia

Abstract

Adaptive learning assists by increasing the number of learners, as it overcome barriers to learning such as distance and time factors. Recently, there has been much research into adaptive e-learning, which has helped to improve the learning process. This paper discusses some models that have been used to improve adaptive e-learning systems and suggests that the Markov Decision Process (MDP) should be used to improve adaptivity in the learning process. The results indicate that the MDP can help in the development of adaptive e-learning.

Keywords: e-learning, adaptive, adaptive learning, learning style, Markov Decision Process, dynamic programming.

I. INTRODUCTION

In the past, the learning process was complicated by students’ needing to attend a place of learning and then having to use the learning materials that were prepared for all students regardless of their individual abilities, goals, and preferences. With the development of the internet and rapid technological advances in communication, many new opportunities have opened for the delivery of high quality education [1]. The traditional learning approach was based on a "one size fits all" model, because in the typical class, the teacher normally had to deal with many students at the same time. This situation forced students to study the same subject matter, regardless of their personal needs, characteristics, or preferences. As teachers learned to provide the structured instruction that is needed by their students, the productivity of the classroom increased. However, it is still very difficult for a teacher to define the ideal learning strategy required by each student in a class. Even if a teacher is able to identify all the strategies needed, it is still extremely hard to apply all those teaching strategies in a single classroom [2]. Implementing a range of learning approaches in the traditional learning context is further complicated by the varying levels of prior knowledge, preferences and intellectual abilities of the different learners [2].

The e-learning approach aims to solve this problem by enabling each learner to receive teaching materials that are better suited to him or her [2]. E-learning has helped to overcome many of the problems previously faced by learners, for example, by reducing the costs and time, as learning materials can now be delivered to students regardless of place and time [3]. The e-learning environment has thus met many requirements of students and has played a major role in making education more accessible and therefore more popular [4]. A system of adaptive e-learning can be used to substitute for a conventional learning approach, providing improved educational courseware [5]. Adaptive e-learning provides an appropriate way for different learners to learn, which can be adapted to meet the individual learner's requirements.

This paper discusses the adaptive approach to learning and suggests the use of the Markov Decision Process to enhance and improve the adaptive e-learning environment. The paper is structured as follows: the next section presents a review of related work in adaptive e-learning, the following section introduces the proposed model for supporting the adaptive e-learning environment, and the last section presents a discussion and conclusion.

II. RELATED WORK

A. Adaptive learning

Adaptive e-learning refers to an approach in teaching that utilizes computer technology to facilitate comprehension and retention and is based on the individual needs of the students. Stoyanov and Kirschner [6] define adaptive e-learning as "an interactive system that personalizes and adapts e-learning content, pedagogical models, and interactions between participants in the environment to meet the individual needs and preferences of users if and when they arise." Burgos et al. [7] define e-learning as "a method to create a learning experience for the student, but also for the tutor, based on the configuration of a set of elements in a specific period aiming to increase the performance of pre-defined criteria." The standards for e-learning may be economic, time-based, educational, or user acceptance-based [7]. Systems of adaptive learning have three basic elements: an instructional model, a learner model, and a content model [8]. The instructional model defines how the system chooses certain content for a particular student at a certain
time, in other words, it collects information from the two other models (the content and the learner) to generate teaching materials and to provide feedback on the learning of the individual student. This assists in improving the learning of the students. The learner model holds the learners' information, meaning that it stores information about the various learners in the system [9]. The content model refers to how the specific subject, or content field, is organized around carefully defined educational outcomes and includes identification of the tasks to be completed [8]. The sequencing of the content may be pre-determined, but it will be modified depending on the individual learner's performance. The system must be able to determine the appropriate content, which will depend on what learners know at any given point in time. The adaptive e-learning system should be able to analyze the individual learners' characteristics, interests, and prior knowledge [10]. Each learner has a learning style, which is defined as a group of factors, attitudes, and behaviors that facilitate the process of learning for that particular learner. A number of different learning styles can be used in an adaptive e-learning system. The Felder-Silverman learning style model (FSLSM) is often utilized to introduce adaptability into the e-learning environment [10]. The FSLSM describes four dimensions to the individual's learning approach. These dimensions are the sensing/intuitive, active/reflective, sequential/global, and visual/verbal [9]. Kuljis and Liu differentiates between theories on learning style and discuss their appropriateness for e-learning [11]. These authors propose that FSLSM is the most suitable model for utilization in adaptive e-learning systems. Some technologies are particularly suited for establishing environments for adaptive learning; these include the web services, the semantic web, multi-agent systems, and AI techniques such as the Bayesian networks and neural networks.

B. Adaptive E-Learning Systems Design

Many recent studies have discussed the matter of adaptivity in the e-learning environment and have suggested various approaches for enhancing adaptivity in e-learning. In this section, we present some studies that have utilized different techniques and have suggested new ways to enhance the adaptive e-learning environment. Idris et al. [12] focused on a method for sequencing adaptive courseware that utilizes the techniques of soft computing, which have the ability to deal with incompleteness and the problem of uncertainty. Their system involves first classifying the learning objects, and then connecting suitable learning objects with suitable learners according to their needs. They used artificial neural network (ANN) techniques for their classification purposes, and then employed back propagation (BP) and the self-organizing map (SOM) to detect the connections among the individual learners' learning requirements and the domain concepts of the learning objects. Their results show that they can identify appropriate learning objects for individual learners in an adaptive learning environment. In 2010, Essalim et al. [13] suggested a new approach to learning where the personalization depends on two levels: The first level depends on personalization strategies that are already defined and permits the personalization of the learning environment. The second level allows the instructor to select the personalization parameters and to combine them to define the various personalization strategies according to the details of the course. This study used web service technology to execute its approach and to investigate its interoperability with other systems of e-learning personalization. The outcomes were promising for future combinations of personalization parameters around which the personalization strategies are formed. Most e-learning systems ignore the importance of providing learners with an adaptive test and focus only on the learning content and the sequencing of learning objects. Baylari and Montazer [15] propose a personalized multi-agent e-learning system that depends on the artificial neural network and on item response theory (IRT). Their system provides tests for adaptive learning that are dependent on IRT and are based on ANN to present personalized recommendations. The architecture of this system involves three layers: the learner layer, which is the interface for users; the repository layer that contains the database of learner profiles; the learning objects including a test. The middle layer is also the agent layer and holds four different agent types: The activity agent registers the learning activities of learners and saves them under the particular learner's profile. The learning process is planned by the planning agent who provides three types of test (pre-tests, review-tests and post-tests) to the learners, in cooperation with the test agent, who submits the session contents based on the profile of the learner. The test agent presents a test type that is suitable for the learners and is based on their abilities. These tests are requested from the planning agent. The last agent is the remediation agent who analyzes the outcomes of the review tests and works with the teacher to diagnose the learning problems of learners and to suggest suitable learning materials for them. These agents add interactivity and adaptivity to the learning environment [15]. Yasir and Sami propose an approach that enhances the learning process by adapting the presentation of course content to the learning styles of the learners [16]. A combination of MySQL, Apache, and PHP are utilized in executing the system, depending on the learning style, in order to identify suitable content, including the format of the content, and the media type. This system is separated into three models: the domain, learner and adaptation models. These models interact with each other to increase adaptively [16]. An experiment was conducted with two students groups to estimate the effect of the approach on learning achievement. Deductive statistics were used to draw conclusions from the sample data and to relate them to conditions that are more general. Metadata were applied to describe what is going on in the sample data. The outcomes indicated that the academic achievement of learners who had been taught utilizing the adaptive system of learning were far better than those of others who had been taught the same learning content without personalization of learning style. The results support the utilization of personalized learning styles in the hypermedia systems [16].
III. THE PROPOSED MODEL

The e-learning industry is trying to facilitate the work of teachers and provide them with features that will speed up the learning process as learning environments become increasingly complex [17]. The task of designing e-learning is difficult and takes a great deal of time. However, it can be facilitated with intelligent components that assist teachers in building activities for e-learning. The Intelligent Learning Design Recommendation System (ILD-RS) is a software application that suggests a suitable path for learning through phases of learning design in a learner management system (LMS).

The environment for adaptive learning is random. Therefore, the Markov Decision Process (MDP) model is suitable for creating an appropriate learning path. The MDP is frequently used for optimization in problem areas in different fields, especially in operational research, since it helps in decision making in an uncertain environment [18]. Furthermore, it detects the best action in a sample space [19]. The MDP is therefore recommended as a way to provide a uniform format for describing a multi-stage decision-making process in a probabilistic environment [19]. The Markov model is used in various areas, such as marketing, banking, business processes, and e-learning. The MDP has four significant operators, namely, state (S); action (A); the transition probabilities (P t), a matrix that contains the probability of moving from one state to another under the action (A); and a reward function (R), which is the immediate reward following a specific action [20]. The goal of the MDP model is to determine a policy, that is, to identify a base for a decision or action executed. This records every decision time point and each historical record of a process that optimizes a system’s performance [21] and returns a high reward. In the learning process, students with different learning styles select from a series of learning materials or learning objects (LOs). The learning style refers to the way or method that the student prefers to obtain and retain information. Students have different learning styles, some prefer to use images and sketches during their learning, and others prefer texts instead of pictures. Some students prefer to learn in a sequential way while others prefer a global approach, and so on. Students may have more than one learning style. There are various models for learning styles (LS), such as the Grasha-Riechmann LS, the Kolb LS, the Honey Mumford LS, the Gregorc LS, the VARK LS, the Dunn and Dunn LS, and the Felder-Silverman (FS) LS. The Grasha-Riechmann LS (GRLS) model concentrates on the interactions of students with their peers and with their teachers. It consists of six major learning styles, a number of which will be evident in every learner, but to different degrees. These styles are the avoidant, competitive, participative, collaborative, dependent, and independent. The Honey and Mumford LS identifies four different preferences or learning styles: the pragmatist, activist, reflector, and theorist. Learners naturally prefer one of these styles. Honey and Mumford recommend that one maximize one's own personal learning style. They use a questionnaire that enables them to determine the individual’s style of learning. Hawk and Shah explain various other models in detail [22]. This paper aims to find the best learning path for different students during the learning process and chooses the Felder-Silverman LS (FSLS) model as a learning style for these students. The FSLS style has four dimensions: the active/reflective, visual/verbal, sensing/intuitive, and sequential/global. Learners with active LS learn by experimenting and working in groups, while reflective learners learn through abstract thinking and individual action. Sensing learners learn through their senses or through visual thinking with an orientation toward facts and concepts, while the intuitive learners learn through abstract thinking and an orientation toward theories and further meaning. Learners with a visual style tend toward visual representations of the material through images and graphs versus oral and written explanations as in the verbal style. In the last dimension, sequential learning is through accurate steps versus the total thinking about the situation as in the global dimension. Figure 1 illustrates these dimensions.

![Figure 1: Four bi-polar dimensions of the FSLSM](image)

The optimal learning path is a path that contains LOs of a suitable learning style that match the learning style of the learner or the nearest style to theirs, as from this they will receive the greatest reward. The reward function is defined as:

\[
R(s,a) = \frac{P(s,a)}{||TS(Teacher,TS(s))|| + ||LS(Learner,LS(s))||}
\]

Where \(S\) is the learning subject who will execute the action to move the learning object \(S':([TS(Teacher,TS(s')))\) is a distance operator among the teaching styles of the teachers and the teaching styles of the learning object \(s'. [([LS(Learner,LS(s'))])\) is the performance of a distance operator among the learner learning styles or a group of learners and the learning styles related to the learning object \(s'\) [17]. To generate a transition probability, we use the Monte Carlo simulation, which is a mathematical technique for producing random variables for modeling the risk or uncertainty of a specific system. The policy will be identified through this equation:

\[
\pi = \max_{n} \frac{\sum_{s=1}^{S} R(s,a)}{n}
\]

Where \(n\) is the number of learning objects. This is called an exhaustive search. It is a problem-solving mechanism consisting of a list of all possible solutions, which examines whether each possibility supports the problem's statement. This search can take a long time so, to achieve
this, we turn to the MDP. Using the MDP, we consider the LOs as state (S), the learning style as action (A), the transition from one LO to the next LO as transition probability P(S, A), and the reward is generated from a policy that is followed to achieve high reward. To solve the MDP, we use a dynamic programming (DP) technique. DP is an optimization mechanism that converts a complicated problem into a series of simpler problems. Because our problem, finding the best learning path with the highest reward, has an ideal substructure it can be divided into subproblems. This means that DP is the most suitable way of solving it [23]. This problem is almost similar to that of a traveling salesman who must find the shortest route if he is to increase his profits. If we have N number of LOs and students with different learning styles learning these LOs, we can use DP to find most efficient route. According to the MDP process, this path will offer the highest cumulative reward [17]. We used Matlab to construct the DP code. Matlab computes the shortest distance path between the learning style of objects and the learning style of learners from the first learning object to the final learning object. Figure 2 illustrates an example from the Database Management course, the SQL query chapter, a chapter with nine LOs. After applying the DP code, the ideal learning path was determined.

![Optimal Learning Path](image)

Figure 2: Optimal Learning Path for Learner with Style \{1, 1, -1, 1\}

IV. CONCLUSION

Adaptive learning is learning that is presented according to the patterns, methods, and characteristics of the different learners, according to the learning characteristics of each learner, whether traditional or electronic, and taking into account individual differences. This adaptation to the educational environment considers content, presentation, students and teacher and can be expressed quantitatively and qualitatively. Because the adaptive learning environment is stochastic (not deterministic), we used the Markov model to enhance its adaptivity. The MDP is used in this paper to support adaptivity through generating the best path of learning for different students with their various learning styles. DP is utilized to solve the Markov process since it contributes to minimizing the time spent searching for the optimal learning path.

REFERENCES