Fuzzy-Based Knowledge Design and Delivery Model for Personalised Learning

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Abstract. Adaptation to the level of knowledge of each student remains one of the key challenges of e-learning and education in general. E-learning systems provide opportunity for systematic data collection about learning activities offering valuable insights into the students' knowledge. In order to achieve the personalised learning, this study introduces a Knowledge Design and Delivery Model (KDDM) for intelligent tutoring systems. This model uses a hybrid approach that combines traditional overlay student models with fuzzy logic and multi-criteria decision-making methods. Unlike popular machine learning approaches, these methods do not require existing datasets and they allow direct teacher involvement in knowledge delivery. The KDDM associates student stereotypes with Bloom's revised taxonomy levels, providing a reference point for the cybernetic model. KDDM has been successfully implemented and examined in a two-year experiment which confirmed its effectiveness on 370 participants from two universities in two countries.

Keywords: Personalised learning· Student modeling· Cybernetic model· Multi-critera decision· Intelligent tutoring system

1 Introduction

Traditional e-learning systems simplify delivery and display of static content, but in general do not provide the opportunity for adaptive learning. A special type of systems used not only for the delivery of teaching content, but also for the delivery of knowledge are called the intelligent tutoring systems (ITS). Intelligent tutoring systems are a generation of computer systems aimed to support and improve learning and teaching process in certain domain knowledge, taking into account the individuality of a student as it is done in a traditional one-to-one instruction. The goal of ITS is to provide a learning experience for each student that is similar to the standard of learning that learner would receive in one-to-one instruction from a human teacher.

Considering students learning capabilities, intelligent tutoring systems take into account the knowledge about what to teach, the way to teach, as well as the relevant information about what student has been taught. In this manner, there are three main components of the ITS conceptual model, namely the (i) domain knowledge, (ii) the teacher, and (iii) the student(s). The most complete discussion is the one initiated and proposed by Shute and Psotka [9] in order to determine the meaning of the sign I in the intelligent tutoring system slogan. Conclusion of the debate highlights two determinants of intelligence: (i) diagnostics of the students' knowledge and (ii) real time help in getting rid of misconceptions and ignorance of concepts of the domain knowledge.

In this paper, the Knowledge Design and Delivery model (KDDM), a novel approach for the Intelligent Tutoring Systems (ITS), has been introduced. The model, utilized for transferring propositions tailored to the student's level of knowledge. Additionally, the cybernetic-based system that effectively implemented this model is showcased. The major contributions of our research are the following (i) cybernetic knowledge design and delivery model for adaptive learning and (ii) a novel hybrid student model based on multi-criteria decision methods. The paper is substantially divided into 7 sections including Introduction. Section 2 includes and analyzes similar and related research; section 3 describes the structure of the cybernetic model of KDDM. In the fourth section, we describe how KDDM is modeling students. Furthermore, section 5 introduces KDDM prototype implementation inside the CMTutor system while section 6 includes experiments and results. Finally, the last section combines conclusion and future work.

2 Related work

In this section, we analyzed papers that are connected to this research area. We listed 22 systems developed in more than last two decades that share common ground with the approaches which CM Tutor use. The level of research was, in descriptive view, based on structural attributes of the KDDM according to: (i) domain knowledge of the system; (ii) student modeling in the system; (iii) adaptive knowledge acquisition. We conducted a systematic overview of literature based on recommendations appropriate to research within program engineering [22]. As basis of research, we used scientific databases[1] to locate relevant publications as well as an array of keywords as following: (i) Intelligent Tutoring System, (ii) Student modeling, (iii) Adaptive learning, (iv) Adaptive learning with learning analytics. Besides that, we set the research questions as following: (i) How we model a student? and (ii) On what basis the system adapts?.

After detailed analysis and processing of the field, the scientific publications which are focused on more narrow fields which pertain to our research and mostly the ones that are connected to student modeling and student adaptive learning were taken into consideration. The result of our analysis and processing is shown in Table 1. Although not shown in the table, it is important to emphasize that some of these systems use other approaches in system modeling, mostly machine learning and constraint-based approach.

[1] Digital libraries ACM and IEEE, Scopus, SpringerLink, Elsevier i Google Scholar.

In the last ten years, many researchers have combined different methods of student modeling and ways of adaptive knowledge acquisition to construct a hybrid student model that represents student attributes. In this manner, the student model can show different individual characteristics and preferences of every student [29]. The authors [40] have encompassed the publications related to the application of artificial intelligence on student modeling during the five year period and concluded that there are eight different student modeling approaches, which are: (i) Bayesian Knowledge Tracing, (ii) Fuzzy logic (FL), (iii) Overlay (OL), (iv) Differential Model, (v) Perturbation Model (PT), (vi) Constraint-Based Model, (vii) Machine Learning, (viii) Stereotype Model (ST)

Table 1. Review of comparable systems/approaches of student modeling and adaptive tutoring with CMTutor

	System/approach name	Year	Student modeling				Adaptive
			OL	ST	PT	FL	
1	INSPIRE [10]	2001	X			X	X
2	Intelligent Learning System [13]	2002				X	
3	Why2-Atlas [12]	2002	X		X		
4	F-CBR-DHTC [16]	2003				X	X
5	TADV [14]	2003	X			X	
6	Multitutor [15]	2003					
7	InterMediActor [17]	2004	X			X	X
8	Vectors in Physics and Mathematics [19]	2005				X	
9	MBTI [20]	2006				X	
10	ADAPTAPlan [21]	2007				X	
11	ADOPTA [23]	2009		X			
12	CoLaB Tutor [25]	2010	X		X		
13	AcWare Tutor [27]	2012	X	X			X
14	ELaC [28]	2013	X	X		X	X
15	BioWorld [31]	2014	X				
16	Java Sensei [34]	2015	X			X	X
17	OSCAR-CITS [41]	2017				X	X
18	CaFAE [43]	2018				X	
19	SLA [44]	2019				X	X
20	POLYGLOT [45]	2020	X	X			X
21	Quiz Time! [46]	2020		X		X	X
22	PARSAT [47]	2022		X		X	X

The system presented in this paper uses a hybrid model of students which combines overlay and stereotype with fuzzy logic, and also falls into the category of adaptive learning system. The authors [30] [32] [39] [42] consider that it is evident that ITS represents a powerful educational tool with a strong foundation and a bright future. On the one hand, it means that the field is well explored. Conversely, a great number of questions still remain unanswered [37]. We want to emphasize that, a decade ago, intelligent systems, despite certain limitations, have shown results comparable to those of a human (one-on-one) tutor in terms of teaching STEM topics [26].

3 Cybernetic model

Design and delivery of teaching is prerequisite for acquiring the knowledge and testing the students' knowledge. Theoretical framework of KDDM is determined by the basic functionalities of the same model and it is based on instructional design, student modeling and adaption to the current level of student's knowledge. Instructional design is a very complex process which includes set of methods, techniques and tools for designing learning content. We will pay special attention to development of a reliable component for instructional design. To achieve this, we will use conceptual maps [7] as one of the main tools for delivering knowledge. Evaluation of students' knowledge is the foundation for the realization of the idea of student modeling and adapting the knowledge delivery in accordance with the current level of student's knowledge. This achieves the basic premise of intelligent behavior of our system. The adaptation is achieved in the environment of the cybernetic model [8] in which a student is guided, according to a defined reference model, through the process of learning, teaching and testing the knowledge. The current level of the student's knowledge is presented by a manageable input size and observed by the output size of the this process [6]. Elements of the cybernetic model are described in the following subsections.

3.1 The process of KDDM

The process of KDDM is related to the learning, teaching and testing of the students' knowledge which is conducted as part of the intelligent tutoring system based on the designed and delivered educational content over the defined domain knowledge ontology. To execute the process of determining the level of the students' knowledge the most important question is how to assess it. To achieve that, it is necessary to link the question templates (according to the objective type questions model) with the expected outcomes that questions must achieve. With regard to the definition of student knowledge level, trace attributes are used. This allows the system to determine and adapt to the level of students' knowledge based on the propositions or even concepts from domain knowledge. The adaptation in this system is done with respect to the reference value.

3.2 The reference value in KDDM

The reference value of the KDDM has two structural determinants, the first one is related to the syntactic and semantic structure of the concepts and the relation of the domain knowledge over the ontology and the second is associated with attributes for describing the student's stereotype. The idea of the KDDM is basically oriented towards fulfilling the fundamental objective of the educational process - to determine the current level of knowledge with defined reference model over the domain knowledge. We want to discern which concepts of the domain knowledge the student has learned (knows the propositions) and which concepts the student has not learned (does not know the propositions). However, the measure of the learned domain knowledge does not follow a plain binary logic, which justifies the introduction of a fuzzy logic. In order to determine the level of student knowledge, we grouped users with similar knowledge level. In this manner, we are able to define a set of all stereotypes that are directly associated with different levels of Bloom's revised taxonomy of cognitive goals. For this, we define the stereotype and a list of all trace attributes as the reference value on which the process and the control implement the process of teaching and testing.

3.3 The control in KDDM

The control in the original cybernetic model includes the measurement, control and operation of the executive device [6]. Measurement from KDDM is now transformed into student modeling, while the control is an adaption to the current level of the student's knowledge with the help of the question generation for the given domain knowledge. Trace attributes that are considered by this model are the following: (i) the time spent on the test, (ii) learned propositions, (iii) propositions that student has not learned, (iv) hints used during the test and (v) test results. Evaluation is conducted according to the adapted protocol with a mathematical model based on the principles of multi-criteria approach Analytic Hierarchy Process (AHP) [11] as well as its fuzzy variant Fuzzy AHP (FAHP) [18]. Implementation and definition of student model includes: (i) collecting and editing data from the track records of learning and testing students, (ii) evaluation of the attributes from the point of view of their relative connection, which is written in the matrix form with triangular numbers, (iii) applying a FAHP method to determine the attribute weights and (iv) the result of the FAHP method calculation which is a single column weighting attribute matrix.

The student's knowledge diagnostics was achieved through the multi-criteria TOPSIS method [4] and the modified Bloom's taxonomy of cognitive domain knowledge. In a mathematical view, mapping current trace attributes to the relevant student stereotype is realized by the TOPSIS method. The element of the stereotype vector with maximum value indicates the achieved level of student's knowledge.

4 Student model

Student modeling is a fundamental part of this model because it encompasses the most important processes expressed with learning, teaching, testing and evaluating of the student's knowledge. Student modeling is, by its nature, a process composed of two phases: (i) student model shaping and (ii) diagnostics of the student knowledge. Student model is described by an array of data - we call them trace attributes trace, while diagnostics of the student knowledge is a process led by these attributes. In the idea of this model we implement hybrid modeling overlay model with the mathematical formalisms FAHP and TOPSIS method of multi-criteria decision making during student stereotype determination. With regard to what was already written, we base this part of the theoretical frame on two approaches of student modeling. One is connected to VanLehn classification [5], and the other with literature overview and Chrysafiadi and Virvou classification [29]. The former approach is traditionally accepted in referent literature, and the second is based on other modeling method - fuzzy modeling of the students as well as the ontological model.

In literature, we have noticed numerous approaches to student modeling, and the reason why we opted for the combination of FAHP and TOPSIS methods is because the knowledge of students cannot be expressed by traditional logic. Hence, the reason we needed fuzzy logic. We consider that the combination of these methods is the best choice for student modeling because we included multiple domain knowledge experts (three in our case) in the process of attribute evaluation. Based on mathematical calculations by FAHP method set the difficulty of every attribute was set. Furthermore, TOPSIS method helps to set student stereotype based on weight value of the trace attributes. The approach we use for development and setting of the process of monitoring student stereotype is not based on the assumption that all members of a certain group of students behave in the same way. Indeed, it is important to emphasize that in this regard we do not neglect the individual differences of the students. Within our approach, two students with the same stereotype can have different paths during learning, teaching and testing of their knowledge. This is done to display an integral image of the application of the modified Bloom taxonomy of student knowledge for a cognitive area in KDDM. The taxonomy was derived according to the categories of student's knowledge as shown in Table 2.

5 Prototype system and model implementation

Conceptual maps are used as the knowledge representation for testing and learning. Conceptual maps are introduced from the point of view of the e-learning paradigm and implementation in the environment and the space of the e-learning system. From the aspect of information and communication technology (ICT), it is obvious that concept mapping is a suitable technique for representing knowledge in intelligent tutoring systems. However, the Moodle, in its original distribution, cannot provide knowledge representation of the domain knowledge

Table 2. Relationship of stereotypes with question templates and knowledge levels

Question template (T)	Expected outcomes (i)	Stereotype (S)
Template 1 (t_1)	Knowledge (i_1)	Stereotype_Z (s_1)
Template 2 (t_2)	Understanding (i_2)	Stereotype_R (s_2)
Template 3 (t_3)	Understanding (i_2)	Stereotype_R (s_2)
Template 4 (t_4)	Understanding (i_2)	Stereotype_R (s_2)
Template 5 (t_5)	Analyzing (i_3)	Stereotype_A (s_3)
Template 6 (t_6)	Evaluating (i_4)	Stereotype_V (s_4)
Template 7 (t_7)	Creating (i_5)	Stereotype_S (s_5)

based on the concepts and relationships. A prototype of the Content Modeling Tutor (CM Tutor) software [33] was developed, implemented and installed as an integral part of the KDDM architecture. CM Tutor is set up as an activity in Moodle and can be used in the same manner as all other Moodle activities (e.g. lessons, quizzes, forum and chat). It can also be run as a standalone application, but for testing purposes it is integrated as an activity in Moodle system. The CM Tutor consists of four components described in figure 1 which implements following functionalities (i) Interaction module - textual and graphical interface for the delivery of teaching content; (ii) Testing module - knowledge testing is done after the generation of a series of questions (by the model of objective type questions); (iii) Teaching module - learning and teaching using interaction modules according to the concepts that the student did not learn at the test phase and (iv) Stereotype module - determining student's stereotypes in accordance with the current level of student's knowledge and the reference model.

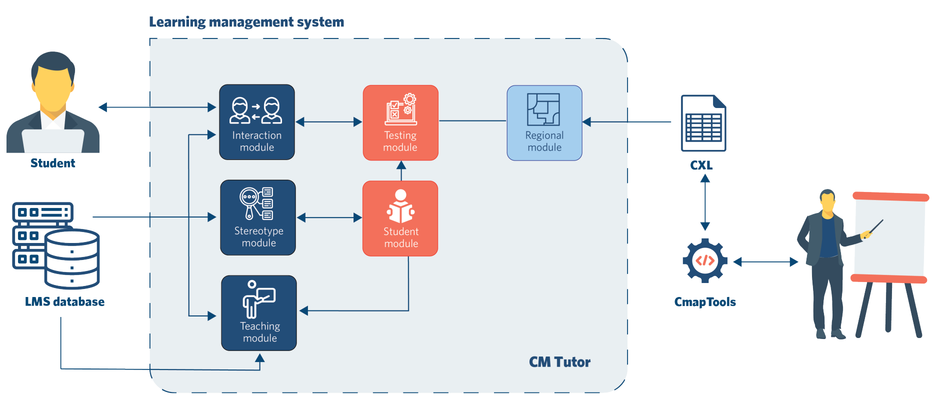

Fig. 1. Structural components of the CM Tutor system.

Determining the level of knowledge of the domain knowledge concepts is carried out by the objective type questions [2][3]. Objective type questions are non-calibrated knowledge tests and an instrument that determines the student's knowledge which is the reference value of the cybernetic model. Diversity of objective question types allows the measurement of knowledge at all levels of the Bloom's knowledge taxonomy for cognitive domain [1]. The revised Bloom's taxonomy for the cognitive domain has been opted for this research [24].

6 Experiments and results

The ultimate goal of the experiments was to resolve the performance and quality of the presented system as well as the participants satisfaction during learning, teaching and testing of knowledge, but also to provide comparative analysis of CM Tutor and other applied e-learning platforms. The experiments were carried out in two periods with a gap of one year.

6.1 First experiment period

The purpose of the first experiment period was to obtain qualitative indicators of CMTutor compared to CoLaB Tutor [25], AcWare Tutor [27] and Moodle. Common for all four platforms was that the domain knowledge was defined over the ontology of concepts and relations between them. In addition to the CM Tutor platform, the remaining three platforms were available and well known as the examples of good practice in previous research in this area. This experiment period was carried out in three time periods lasting two weeks each (six weeks in total for online learning). In each period, students used one e-learning system and one area of knowledge in the learning and teaching area, while in the remaining 9 weeks, traditional classes were conducted in the classroom. In general, at the level of the entire educational period, we organized and conducted the teaching process according to the sub-model of the mirrored classroom of the rotating model of hybrid learning.

A total of 370 students from two countries (Bosnia and Herzegovina and Croatia) participated in these three cycles on the 4 mentioned platforms. The sample in the research is students from the University of Mostar and the University of Split. The students from Mostar are students from the Faculty of Science and Education, from undergraduate and graduate studies at the teacher's course. The students from Split are students of the Faculty of Science and the Faculty of Philosophy (specifically students of the fourth and fifth year of teacher studies). They studied from three topics, (i) "Computer as a system", (ii) "Environment and space of e-learning and e-learning systems" and (iii) "Introductory teaching of programming". The results of the experiment were analyzed in two categories, performance on test and user experience. In terms of performance, the best of the four mentioned platforms was CMTutor with 22 students with a rating of 5 (highest grade), and in terms of satisfaction (user experience), the best was Moodle (which was expected considering that students have been using that platform for years), followed by CMTutor.

6.2 Second experiment period

The purpose of the second experiment period was to determine the effect of learning, teaching and testing of the knowledge on CM Tutor with initial and final testing. We conducted the experiment with one group of students over a period of two weeks. The instruments for carrying out the research are objective-type tasks (remembering tasks, completion tasks, alternative tasks, multiple choice tasks, correction tasks, arrangement tasks, connection tasks and essay-type tasks). We introduced the students to the content of the teaching unit "Environment and space of e-learning and e-learning systems". The research was conducted on a sample of 38 students, 28 of whom took both the initial and final test. All students were from the University of Mostar (Faculty of Science and Education), specifically the graduate study of Computer science and Computer science with combinations (Mathematics, Geography, Chemistry).

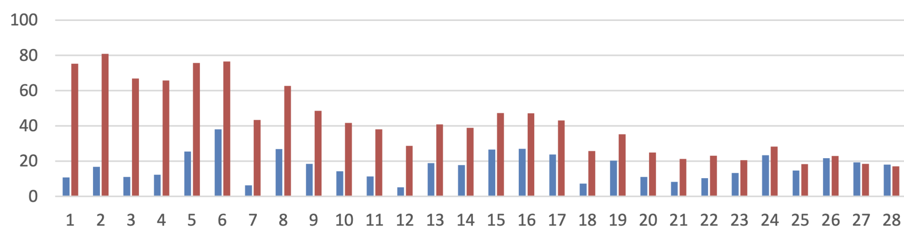

Fig. 2. Comparison of students' performance on initial and final test

The initial test was carried out because the experiment involved students with different skills and backgrounds. It was necessary to identify the initial state of their understanding of the domain knowledge in order to quantify the student knowledge change. A comparison of the results from the initial test and the final test, after learning through CMTutor, is shown in Figure 3 (blue bar is initial test). ANOVA has confirmed that there is no statistically significant difference between the control and experimental group, mean values concerning pre-test results ($F = 0.842, p - value = 0.474$). The large effect size for CMTutor was $d = 1.791$ so we can say that the resulting effect sizes are statistically significant.

7 Conclusions and future work

This paper presented the fuzzy-based cybernetic model for designing and delivering the knowledge in an intelligent tutoring system. CMTutor demonstrated superiority in student performance and user satisfaction compared to compared learning systems. The results of empirical evaluation presented in this paper have shown that the observed intelligent tutoring systems based on ontological domain knowledge representation are effective when compared with traditional learning and teaching process and could be used in addition to traditional methods. Finally, it is shown that this modeling approach adapts to the student's level of knowledge. However, there are certain limitations and opportunities for improvement. Based on the insights from the satisfaction survey, we concluded that it is necessary to improve the user experience for the production version of CMTutor. The ultimate goal is to enable automatic conceptual maps creation from text which has been shown to be possible [35][36]. Also, we plan to create a deep learning model that will detect at-risk students in the early stages of learning and implement data augmentation techniques, since it has been shown that it is possible to improve such models [38]. These features would greatly facilitate the use of this system for teachers and students.

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