DEVELOPMENT OF THE ADAPTATION MECHANISM FOR THE INTELLIGENT KNOWLEDGE ASSESSMENT SYSTEM BASED ON THE STUDENT MODEL

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Abstract

The paper provides the detailed description of the adaptation mechanism for the intelligent knowledge assessment system developed by the researchers from the Riga Technical University. Adaptation areas that are under consideration include selection of the difficulty degree of a task and presentation of the most suitable type of concept explanations for each student. Therefore, the main attention of the paper is devoted to the four algorithms developed to solve the mentioned issues. The overview of the mentioned assessment system and use of the student model in general is given as well.

Keywords: Adaptation, student model, intelligent knowledge assessment system, concept map.

1 INTRODUCTION

The Department of Systems Theory and Design of the Faculty of Computer Science and Information Technology of Riga Technical University has been developing the concept map based intelligent knowledge assessment system (IKAS) since the year 2005 [1]. It is a Web-based application which uses concept maps as a tool for knowledge assessment. The system has twofold goals in the context of the integration of technology into the traditional educational process: 1) to promote learners' knowledge self-assessment, and 2) to support the teacher in the improvement of learning courses through systematic assessment of learners' knowledge and analysis of its results. Concept maps (CMs) as a pedagogical tool for knowledge assessment represent knowledge in form of a graph which nodes correspond to concepts in a domain and arcs denote relationships between concepts. Arcs can be directed or undirected and with or without linking phrases on them. A linking phrase specifies the kind of a relationship between concepts. The main semantic unit of a CM is a proposition displaying a relationship between two concepts. Various CM tasks based on task demands and constraints [2] can be offered to students. However, two main groups of them are: a) "fill-in-the-map" tasks, where the structure of a CM is given and a student must fill it using the provided set of concepts and/or linking phrases, and b) "construct-the-map" tasks, where a student must decide on the structure of a CM and its content by him/herself. The current direction of the development of the IKAS is devoted to the elaboration of a student model and adaptation mechanism needed for the provision of adaptation of assessment content and presentation. The paper presents initial results of the mentioned development process.

The paper is structured as follows. The second section gives a brief overview on student modelling and the use of a student model. The architecture and functionality of the IKAS is described in the third section. The fourth section presents the student model implemented in the IKAS focusing on the content of the model and methods used for the collection of student's data. Adaptation algorithms based on the student model are presented in details in the fifth section. At the end of the paper conclusions are given and future work is discussed.

2 THE STUDENT MODEL

Today developers that care for the creation of competitive and usable e-learning systems typically integrate a student model into the system. The model provides system's flexibility in terms of individualized learning that is the most suitable for the abilities and needs of a particular learner. Thus the system, during its functioning, collects information about the learner, his/her cognitive state and psychological characteristics and stores it in the student model created for each particular student. The information in the student model serves as an input for the system's pedagogical decisions and adaptation of a learning environment.

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On the basis of the analysis of different works the content stored in the student model is classified in five categories [3]:

- Learner's identifying information. It allows the system to identify the learner who starts the tutoring session. It is achieved by the creation and further management of a user account. This information, as a rule, includes a login name and a password. Student identification numbers or personal data (name, identifier, e-mail address, etc.) can be used, as well;
- Information about the progress of the learning process and the state of the learner's knowledge and skills: learning level, evaluations obtained in control tasks, tests, questions and problems; right and wrong answers on tasks/questions and their number, or the exact sequence of performed steps during the solving of a task/problem; information about tasks/problems solved by the learner in the past and tasks/problems he/she is solving now; information about units of theoretical material mastered by the learner in the past and units he/she is mastering now; information about how many times the learner tried to solve a task/problem or to answer a question; time spent by the learner during the solving of a task/problem; time spent by the learner during the reading of units of theoretical material; learner's mistakes and misconceptions; frequency, types and number of demanded hints, explanations and help;
- Information about the learner's significant cognitive, affective and psychological features, such as characteristics of cognitive processes, concentration level, emotional states, etc.;
- Information about the learner's preferences in learning such as types of examples, perceptive capabilities, etc.;
- Information related to the experience of the learner, his/her interests and background knowledge;
- Information about the use of system's options.

Considering the mode of obtaining the values of student's characteristics, the content of the student model is classified in the following way [4, 5]:

- directly obtainable information which is received from the learner's answers to questions on system's offered questionnaires;
- inferable information which can be obtained through test diagnosis related to the determination of the learner's state from results of tests, or functional diagnosis that monitors and fixes different influences of the environment on the learner and his/her corresponding reactions, or a combination of both mentioned types.

As a rule, the collection and processing of information about the learner have the following scenario. The student model is created when the learner registers for the first time on the system. During the learning session the system stores in the student model information about all events significant for the system's pedagogical decisions. Starting a new session, information about the last learning episode is read from the student model in order to determine where the learner has stopped last time.

3 THE OVERVIEW OF THE IKAS

The developed system is used in the following way [6]. A teacher defines stages of knowledge assessment and creates CMs for all of them by specifying relevant concepts and relationships among them in such a way that a CM of each stage is nothing else then an extension of the previous one. Thus, the CM of the last stage includes all concepts and relationships among them. During knowledge assessment a student solves a CM based task corresponding to the assessment stage. After the learner has submitted his/her solution, the system compares the CMs of the learner and the teacher, calculates the score of the learner and generates feedback. Two modes of system's operation are provided: a) a mode of knowledge self-assessment which purpose is to allow a student to assess his/her knowledge level and to learn more about a specific topic in case of incomplete knowledge, and b) a mode of knowledge control intended for the determination of students' knowledge level by a teacher.

At the moment the system offers 6 CM based tasks with different degree of difficulty (Table 1). As a result ten transitions between tasks are implemented allowing a student to find a task most suitable for his/her knowledge level. Five transitions increase the degree of task difficulty. They are carried out after the analysis of the student's solution if a student has reached the teacher's specified number of points in the current assessment stage without reducing the degree of difficulty of the original task. So, this is a system's adaptive reaction to the student's behavior. Other five transitions reduce the degree of task difficulty and they are carried out by the voluntary request from a student during the solving of a task.

Table 1. Tasks implemented in the IKAS

Degree of difficulty	Task type	Structure	Concepts	Linking phrases
1st – the simplest	fill-in-the-map	Provided	One part is inserted into the structure, other part is provided as a list and must be inserted by a student	Inserted into the structure
2nd		Provided	Provided as a list, must be inserted by a student	Inserted into the structure
3rd		Provided	Provided as a list, must be inserted by a student	Not used
4th		Provided	Provided as a list, must be inserted by a student	Provided as a list, must be inserted by a student
5th	construct-the-map	Must be created by a student	Provided as a list, must be related by a student	Not used
6th – the most difficult		Must be created by a student	Provided as a list, must be related by a student	Provided as a list, must be inserted by a student

A teacher's created CM serves as a standard against which students' CMs are compared in the system. Moreover, a comparison algorithm [7] has been developed which is sensitive to the arrangement and coherence of concepts taking into account such aspects as existence of a relationship, locations of both concepts, type and direction of a relationship, correctness of a linking phrase, etc. Two types of relationships are used: a) important relationships (weighted by 5 points) showing that relationships between concepts are considered as important knowledge in a course, and b) less important (weighted by 2 points) relationships specifying desirable knowledge. At the moment the system can recognize more than 36 different patterns of correct and partly correct propositions in students' CMs. Moreover, recently processing of the so called "hidden" relationships [8] in students' CMs was introduced. "Hidden" relationships are nothing else than the derivation of relationships presented in a teacher's CM, so they are recognized as correct too and could appear in students' CMs. "Hidden" relationships are scored by 0 if a student creates all obligatory relationships and also their derivation, and 1 – if not all of obligatory relationships are presented in a student's CM.

At the moment the system provides rich student's support in comparison with other systems. After the completion of a task a labeled student's CM and a window with quantitative and qualitative data is provided to a student. In the student's CM relationships are colored in different tones according to their correctness. The student can acquire detailed information about each relationship by clicking on it. In this case he/she sees contribution to the correctness of a relationship of all parts of a relationship: linking phrase, type, direction and placement of concepts. Quantitative data are a set of numerical indicators aimed to inform a student about his/her performance and degree of achievement in a given task. They are interpreted by the student him/herself and no explanation or pedagogical remarks are provided. Quantitative data include assessment stage, degree of difficulty of the current assessment stage, mode of the system's operation, student's score and the maximum possible score, time spent by a student, details concerning calculation of student's score and peers' results at other degree of difficulty. A qualitative description is a text summary which explains a student how well he/she has mastered concepts in a given task and points out concepts which require revision.

During the solving of a task a student has possibility to receive explanations of concepts, to insert concepts into the right nodes and to check propositions. In all previously mentioned tasks a student can choose a concept from the given set of concepts and ask the system to explain it using one of the following types of explanations: definition, description or example. In "fill-in-the-map" tasks a student can choose a concept from the given set of concepts and ask the system to insert it into the right place (node) within the structure of a CM. Checking of a proposition is supported at all previously described degrees of task difficulty. The idea is that a student points out his/her created proposition (a pair of concepts) and the system checks its correctness. In case of incorrectness the system presents explanations (definition, description or example) of both concepts involved in the proposition.

The system's goals stated in Introduction are reached in the following way. The system supports knowledge self-assessment as it makes the analysis and evaluation of learners' CMs, as well as provides feedback which shows the student's errors. It promotes systematic knowledge assessment by providing opportunities to extend an initially created CM for other assessment stages. Moreover, statistical information about differences between learners' CMs and teacher's CM is collected providing opportunities for the teacher to improve the learning course.

4 THE STUDENT MODEL IN THE IKAS

As it was mentioned in Section 2 a student model plays the major role in adapting a learning environment to student's needs. The student model is used in the IKAS as well in order to individualize assessment content and presentation. Content of the student model currently implemented is displayed in Table 2.

Table 2. Content of the student model in the IKAS

Section in the student model	Parameters within the section	Initially set by	Updated by	Usage of parameters
General data	Name Surname ISEC number Email Group Login name Login password Login role	Administrator	Administrator Student	Adaptation of assessment content: selection of assessment tasks to be completed by a student
Knowledge & Mistakes	Initial knowledge level Student's completed CMs Scores for completed CMs Wrong relationships in CMs Assimilation degree of concepts Individual text feedback	Student	System	Adaptation of assessment content: selection of the difficulty degree of the next assessment tasks
Psychological characteristics	Learning styles	System (default setting)	Student	Adaptation of assessment content: selection of the difficulty degree of the next assessment tasks Adaptation of presentation: selection of initial type of explanations for concepts
Preferences	Type of concept explanations GUI language Themes & Colours	System (default setting)	Student System	Adaptation of presentation: selection of best suitable type of concept explanations, selection of graphical and language preferences
Other characteristics	Statistical data related to the usage of different types of concept explanations	-	System	Adaptation of presentation: selection of best suitable type of concept explanations

The section "General data" contains the general information about a student. This section includes the following data: Name (name of a student), Surname (surname of a student), ISEC number (identification number of a student), Email (email address of a student), Group (title of groups to which a student belongs), Login name (login name to enter the system), Login password (login password to enter the system), Login role (role in the system "Student" by default). The general data are entered by an administrator of the system, because an administrator is responsible for registering students and adding them to groups. The general data could be updated by an administrator or a student afterwards. A student can modify all his/her personal data excluding groups. The general data are used to filter assessment content for every student, i.e. a student will receive only those assessment tasks that are associated with courses assigned to the groups to which the student belongs.

The section "Knowledge & Mistakes" contains the following information: Initial knowledge level (initial knowledge level set by a student for each course), Student's completed CMs (CMs completed by a student), Scores for completed CMs (number of points that a student has got for his/her CMs), Wrong relationships in CMs (set of incorrectrelationships created by a student), Assimilation degree of all concepts (percentage of assimilation degree of each concept in a course), Individual text feedback (textual feedback that indicates student's knowledge weak and strong areas). The only parameter set by a student is the initial knowledge level that indicates how well the student masters the given course. The student just selects his/her level of knowledge – Low (a student knows up to ≈25% of a course), Average (a student knows up to ≈50% of a course) or High (a student knows almost all study material from a course) – for each assessment course. After that all the data from section "Knowledge & Mistakes" are updated automatically by the system. The system calculates scores for each completed CM, composes a list with wrong relationships from CMs, calculates assimilation degree of each concept in CMs and generates individual feedback for the learner. Information about student's knowledge and mistakes is used to select the difficulty degree for the next assessment tasks (see Section 5 for details).

The section "Psychological characteristics" stores learning styles of a student according to Felder-Silverman learning styles model [9]. Student's dominance in 4 learning styles dimensions is considered: Visual/Verbal – indicates through which interface sensory information is perceived most effectively (visual – pictures, diagrams, graphs, demonstrations, or verbal – sounds, written and spoken words and formulas), Sensory/Intuitive – shows what type of information the student preferentially perceives (sensory – sights, sounds, physical sensations, or intuitive – memories, ideas, insights), Sequential/Global – defines how the student progresses towards understanding (sequentially – in a logical progression of small incremental steps, or globally – in large jumps, holistically) and Active/Reflective – indicates how the student prefers to process information (actively – through engagement in physical activity or discussion, or reflectively – through introspection) [10]. Learning styles are set by default by the system for every student after student's registration in the system. Default settings for learning styles are as follows: Visual – Sensory – Global – Active [11]. Learning styles could be modified by a student afterwards through filling in the "Index of Learning Styles Questionnaire" [12]. The original questionnaire was refined in order to leave only 5 more important questions for each dimension [13]. Thus, the questionnaire that is currently used in the system contains only 20 questions. Learning styles of a student are used in two ways: 1) to choose the degree of difficulty for the next assessment tasks (see Section 5 for details), and 2) to select initial type of concept explanations, thus incorporating adaptation of presentation (see Section 5 for details).

The section "Preferences" stores student's preferences regarding customization of presentation. It includes the following data: type of concept explanations (priorities of three possible type of explanations – Definition, Description and Example), GUI language (language of graphical user interface), and Themes & Colours (design and colour of GUI elements). Preferences are initially set by the system. A student can update his/her preferences afterwards using a personal profile configuration form. The system could update priorities of concept explanations as well if after observing student's behaviour the system concludes that the priorities should be changed (see Section 5 for details). Student's preferences are used for adaptation of presentation only.

The section "Other characteristics" currently includes only statistical data concerning usage of different types of concept explanations. The data are updated by the system each time when a student asks for concept explanation and are analyzed afterwards in order to determine if there is a dominant type of explanations (Definition, Description and Example) for the student. Dominant type is treated as a type of explanations that best suits needs of a particular student.

Table 1 shows that information on some parameters in the student model can be acquired from more than one source. For example, priorities of type of concept explanations can be set by the student directly or by the system after analyzing statistical data related to the usage of different types of explanations. Therefore, the question is – what source to trust more in order to avoid conflicts? To deal with this problem we range all sources of information in accordance to their reliability (see Table 3). Ranging is made on our own assumptions about usefulness of different sources of information.

Table 3. Possible sources of information and its reliability

Reliability of information	Source of information	Examples of information
1 (highest)	Direct input from a student	- Initial degree of difficulty of an assessment stage - Priorities of types of concept explanations
2	Results of questionnaires filled by the student	- Learning style
3	Conclusions/statistical data from the system	- Priorities of types of concept explanations
4	Direct input from a teacher	- Initial degree of difficulty of an assessment stage
5 (lowest)	Default settings made by an administrator	- Learning style - Priorities of types of concept explanations

According to Table 3 the highest reliability has information that comes from a student (ranks 1 and 2). We suppose that a student knows better what is best for him/her. After that information that is collected or concluded by the system is considered (rank 3). The system performs all necessary observation of student's behaviour in order to make reliable conclusions. At the end parameters that are set by teachers or administrators are taken into account (ranks 4 and 5). These two sources are not very reliable because information that comes from them is the same for all students, i.e. no personalization is done.

Ranks of reliability of different sources of information are used in the system to resolve conflicts when assigning values for parameters in the student model. For example, if the system concludes that the best suitable type of explanations for a student is "Description", but the student selects "Definition", then the type of explanations "Definition" will be stored in the student model as the most suitable type, because information input from a student is considered as a more reliable source than conclusions made by the system.

5 ADAPTATION RULES IN THE IKAS

This section describes in details how data stored in the student model (see Section 4) are used for adaptation purposes in the IKAS. In general, student's data are used to perform 4 adaptation operations: 1) to select the degree of difficulty for the first assessment stage of each course, 2) to set initial priorities for types of concept explanations, 3) to change the difficulty degree of the next assessment stages in a course, 4) to change priorities for types of concept explanations. Four adaptation algorithms underlying mentioned operations are described in following subsections.

5.1 Selecting the degree of difficulty for the first assessment stage

The task is related to the selection of the most appropriate degree of difficulty of the first assessment stage of each course available to the student. In general, the degree of difficulty depends on: initial knowledge level set by the student, student's learning style and settings made by a teacher for a course. Thus, selection of the initial degree of difficulty is made according to the following algorithm (see Fig. 1):

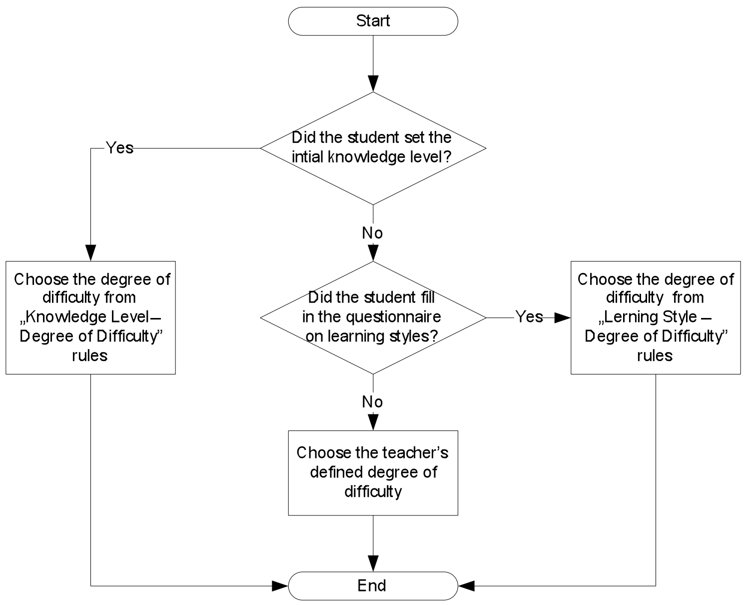

Figure 1. The algorithm for the selection of the degree of difficulty of the first assessment stage of each course

According to the algorithm the system checks first if a student set the initial knowledge level (Low, Medium or High) for a course. If the initial knowledge level was set for the course then the system selects the degree of difficulty for the first stage of a course on the basis of "Knowledge Level (KL) – Degree of Difficulty (DD)" set of rules. These rules are as follows:

Rule KL-DD 1: *IF KL = Low THEN DD= 2*

Rule KL-DD 2: *IF KL = Medium THEN DD= 4*

Rule KL-DD 3: *IF KL = High THEN DD= 6*

These rules are based on the simple logic: the higher is the knowledge level of the student the more difficult task is given to him/her.

If the initial knowledge level was not set by the student then the system checks whether or not the student filled in the questionnaire on learning styles. If the questionnaire was filled in then the system selects the degree of difficulty for the first stage of a course on the basis of "Learning Style (LS) – Degree of Difficulty (DD)" set of rules. These rules are as follows:

Rule LS-DD 1: *IF LS = Sequential THEN DD= 3*

Rule LS-DD 2: *IF LS = Global THEN DD= 5*

Our analysis on learning styles shows that the only dimension that could be used to choose the degree of difficulty for an assessment task is Sequential/Global dimension. A sequential student likes learning logically, in small steps, with increasing complexity. Therefore, a task of the third degree of difficulty is given to the student. This task allows the student to use the provided structure of the CM, thus logically progressing toward creation of his/her CM in small steps. A global student prefers system thinking; he/she likes learning holistically. Therefore, a task of the fifth degree of difficulty is given to this student. This task allows the student to construct his/her CM from scratch (structure of the CM is not given), thus providing opportunity for the student to think globally and see a big picture.

If the student did not set the initial degree of difficulty for a course and did not fill in the questionnaire on learning styles then the system chooses the degree of difficulty that was set by a teacher for this course.

5.2 Selecting initial priorities for types of concept explanations

This task is related to the selection of initial priorities for three types of explanations – Definition, Description and Example – available for concepts. Priorities define order in which each type of explanations will be shown. Thus, they also display significance and value of each type of explanations for a student.

In general, the selection of initial priorities of types of concept explanations depends on: initial knowledge level set by the student, student's learning style and settings made by a teacher for a course. Thus, the selection of initial priorities is made according to the following algorithm (see Fig. 2):

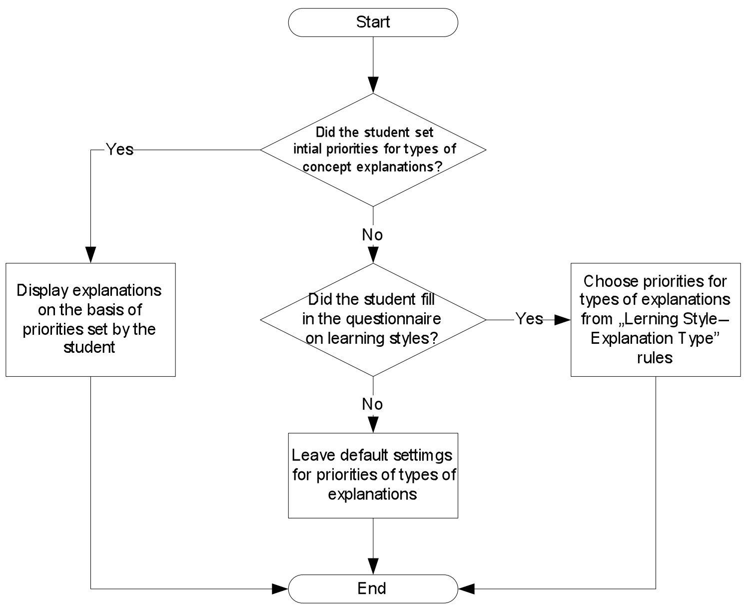

Figure 2. The algorithm for the selection of initial priorities for types of concept explanations

According to the algorithm the system checks first if a student set initial priorities for available types of explanations (Definition, Description, Example). If initial priorities were set then the system displays explanations of concepts on the basis of choices made by the student, i.e. type of explanations with the priority “Highest” (the most suitable type of explanations) will be displayed first, type with the priority “Average” (explanation type that fairly suits a student) will be displayed for a concept when the type with the priority „Highest” is not defined for a concept, and finally, type of explanations with the priority “Lowest” (explanation type that least suits a student) will be displayed for a concept only when no types with priorities „Highest” or „Average” are defined for a concept. Otherwise, if the student did not set initial priorities for types of explanations then the system checks whether or not the student filled in the questionnaire on learning styles. If the questionnaire was filled then the system selects initial priorities for types of explanations based on “Learning Style (LS) – Explanation Type (ET)” set of rules. These rules are as follows:

Rule LS-ET 1: *IF (LS = Visual) THEN (ET: Example = Highest)*

Rule LS-ET 2: *IF (LS = Verbal and Sensory) THEN (ET: Description = Highest)*

Rule LS-ET 3: *IF (LS = Verbal and Intuitive) THEN (ET: Definition = Highest)*

Selection of most suitable types of explanations depends on two dimensions of the learning style model – Visual/Verbal and Sensitive/Intuitive. A visual student prefers pictures, diagrams and graphs. Therefore, the most suitable type of explanations for a visual student is Example that typically contains picture with an example of concept usage. A verbal student prefers written words and formulas. In addition, if a student is sensory then he/she would rather use Description, because it gives practical description on concept usage. In turn, if a student is intuitive then he/she would prefer Definition, because definition gives more theoretical and abstract description of a concept.

If the student did not set priorities of types of concept explanations and did not fill in the questionnaire on learning styles then the system leaves default settings for explanation priorities: “Highest” – Definition, “Average” – Description, “Lowest” – Example.

5.3 Changing the degree of difficulty of the next assessment stages

This task is related to the changing the degree of difficulty of the second and all other forthcoming stages within a course. The degree of difficulty could be either increased or decreased (see Fig. 3).

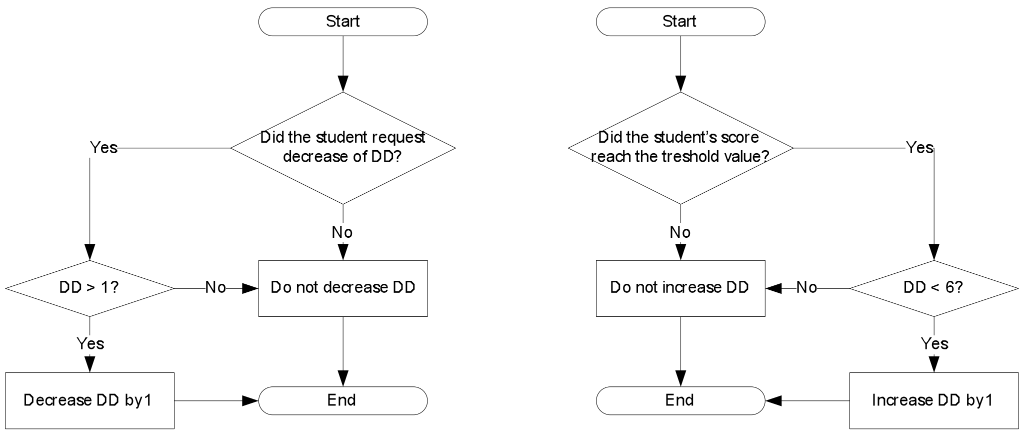

Figure 3. The algorithm for changing the degree of difficulty of the next assessment stages

Increase of the degree of difficulty of the next stage (see the right side of Fig. 3) depends only on student’s results in the previous stage. If the number of points received by a student for the current assessment stage exceeds a threshold set by the teacher then the degree of difficulty of the next assessment stage is automatically increased by 1. The teacher can define freely the threshold value for his/her courses. But, typically the threshold value is equal to 0,8 (so, when a student receives 80% of maximum possible score for the stage the degree of difficulty of the next stage is increased by 1).

Decrease of the degree of difficulty (see the left side of Fig. 3) is initiated by a student only and depends on student’s confidence about his/her ability to complete the current assessment stage on the current degree of difficulty. After student’s request the degree of difficulty of the current assessment stage is decreased by 1. The student can make several decreases of the degree of difficulty during the same assessment stage. Each time the degree of difficulty is decreased by one until the first degree is reached.

5.4 Changing priorities for types of explanations

This task is related to the changing priorities of types of explanations in case if during student's interaction with the system it could be concluded that initial priorities set for types of explanations (see Section 2.2) do not really meet student's needs. Consider the following situation. The type of explanations "Example" was set initially as the most suitable type of explanations for a student, but the student used "Definition" in most cases in order to get explanation of concepts. Therefore, such inconsistencies require changing of priorities for types of explanations in order to satisfy student's needs better.

In general, selection of initial priorities of types of explanations depends only on statistical data related to the usage of different types of concept explanations. During the solving of assessment tasks the system collects the mentioned data and makes necessary corrections in priorities of explanation types on the basis of that data. The algorithm is as follows (see Fig. 4):

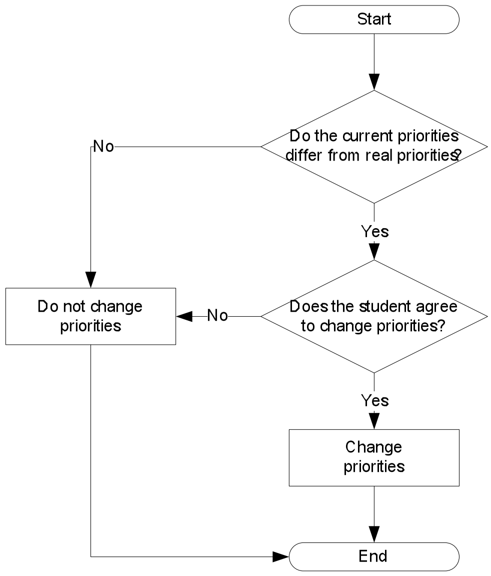

Figure 4. The algorithm for changing priorities for types of concept explanations

So, after an assessment task is completed the system starts to analyze the statistical data. If the system detects that there are differences between real priorities of explanation types (see the left side of Fig. 5) and priorities that were set before the assessment task (see the right side of Fig. 5), then the system asks the student whether he/she wants to align current priorities with real priorities. If the student approves changing priorities for explanation types then the system changes the priorities accordingly to the latest statistical data.

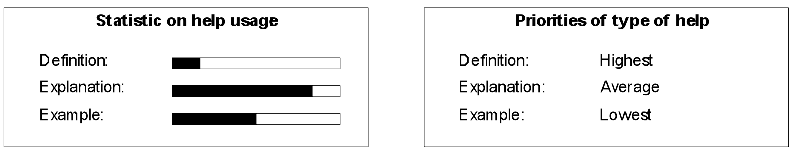

Figure 5. Real priorities versus initial priorities of explanation types

6 CONCLUSIONS

The student model implemented in the IKAS so far contains 5 sections – general data, knowledge & mistakes, psychological characteristics, preferences and other characteristics. Different types of information stored in the mentioned sections allow adaptation of both assessment content and presentation. As a result adaptation is based not only on student's knowledge, but on other characteristics as well (learning styles, for example).

There are four main algorithms that are currently designed for the IKAS that take into account data stored in the student model. These algorithms are: 1) selection of the degree of difficulty for the first assessment stage of each course, 2) selection of initial priorities for types of concept explanations, 3) changing the degree of difficulty of the next assessment stage in a course, 4) changing priorities for types of concept explanations. These algorithms are under development currently and are not tested yet. It is possible that after testing some adaptation rules will be changed slightly, some new adaptation rules will be added, but other inconsistent rules will be removed.

REFERENCES

[1] Grundspenkis,J., A.Anohina. Evolution of the Concept Map Based Adaptive Knowledge Assessment System: Implementation and Evaluation Results. Proceedings of the 49th Scientific Conference at Riga Technical University, October 15, 2009, Riga, Latvia, pp.13-24.

[2] Ruiz-Primo,M., R.Shavelson. Problems and Issues in the Use of Concept Maps in Science Assessment. Journal of Research in Science Teaching, 33, 1996, pp. 569-600.

[3] Anohina, A. The Problem-Solving Modes and a Two-Layer Model of Hints in the Intelligent Tutoring System for Minimax Algorithm. Proceedings of the 1st International Conference on Virtual Learning, October 27-29, 2006, Bucharest, Romania, pp. 105-112.

[4] Conlan, O. Novel components for supporting adaptivity in education systems -model-based integration approach. Proceedings of the 8th ACM International Conference on Multimedia, Marina del Rey, California, United States, 2000, pp.519-520.

[5] Prentzas, J., Hatzilygeroudis, I., Garofalakis, J. A Web-based intelligent tutoring system using hybrid rules as its representational basis. Proceedings of the 6th International Conference ITS-2002, Biarritz, France and San Sebastian, Spain, June 2-7, 2002, pp.119-128.

[6] Vilkelis, M., Anohina, A., Lukashenko, R. Architecture and Working Principles of the Concept Map Based Knowledge Assessment System. Proceedings of the 3rd International Conference on Virtual Learning, Constanta, Romania, 2008, pp. 81-90.

[7] Anohina, A., Vilkelis, M., Lukasenko, R. Incremental Improvement of the Evaluation Algorithm in the Concept Map Based Knowledge Assessment System. International Journal of Computers, Communication and Control, Vol. 4, No. 1, 2009, pp.6-16.

[8] Grundspenkis, J., Strautmane, M. Usage of Graph Patterns for Knowledge Assessment Based on Concept Maps. Proceedings of the 49th Scientific Conference at Riga Technical University, October 15, 2009, Riga, Latvia, pp.60-71.

[9] Lukasenko, R., J. Grundspenkis. Adaptation of Intelligent Knowledge Assessment System Based on Learner’s Model. Proceeding on the 16th International Conference on Information and Software Technologies, Kaunas, Lithuania, 2010 (in publishing).

[10] Learning Styles. Embedding Learning Technologies. Available online at: http://www2.plymouth.ac.uk/ed/ELT%20documents/umistlearningstyles.pdf (last visited on 14.05.2010)

[11] Montgomery, S. Addressing Diverse Student Learning Styles through the Use of Multimedia. Proceedings, 1995 Frontiers in Education Conference, Vol. 1, pp.3a2.13-3a2.21

[12] Soloman, B., R. Felder. Index of Learning Styles Questionnaire. NC State University. Available online at: http://www.engr.ncsu.edu/learningstyles/ilsweb.html (last visited on 14.05.2010)

[13] Graf, S., S. Viola, Kinshuk, T. Leo. Representative Characteristics of Felder-Silverman Learning Styles: an Empirical Model. Proceedings of the IADIS International Conference on Cognition and Exploratory Learning in Digital Age (CELDA 2006), Barcelona, Spain, pp. 235-242