RIGA TECHNICAL UNIVERSITY

Alla ANOHINA

DEVELOPMENT OF AN INTELLIGENT SUPPORTING SYSTEM FOR ADAPTIVE TUTORING AND KNOWLEDGE ASSESSMENT

Summary of Doctoral Thesis

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DEVELOPMENT OF AN INTELLIGENT SUPPORTING SYSTEM FOR ADAPTIVE TUTORING AND KNOWLEDGE ASSESSMENT

Summary of Doctoral Thesis

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Date:...........................................

The doctoral thesis is written in Latvian and includes introduction, 4 sections, conclusions, bibliography, 12 appendixes, 39 figures and 10 tables in the main text, 240 pages. The bibliography contains 177 references.
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INTRODUCTION

Historical transition from industrial age to information age in 70-ties of 20th century built foundation for development of knowledge-based economy nowadays. Today new requirements, technologies and demands for the highly skilled and educated labor force define the needs for changes in teaching and learning processes in order to comply with new reality and requirements of labor market.

Motivation of the research

Motivation of the research is related with substantial decisions and documents of European Union [BRN 2003, CEC 2000, CEU 2005, KPP 2004] where the main attention is concentrated on improvement of education quality, using information and communication technologies as well.

Nowadays various information and communication technologies provide new opportunities for people to learn by choosing individual learning time, place, amount and pace. However, technology integrated in learning process partially or completely takes over a role of the human-teacher. To carry out this role effectively it is necessary to improve intelligent and adaptive abilities of technology. In this context it is necessary to note that research in the field of intelligent tutoring systems has more than three decades history. Based on stored information on learner, problem domain, tutoring plan and strategies such systems provide adaptation of learning process to characteristics of a particular learner. In spite of the fact that intelligent tutoring systems are capable to create curriculum, to offer units of theoretical material and to generate practical tasks adaptively their adaptive abilities still are not high enough. There is a number of unanswered questions, for example, what psychological and emotional characteristics of a learner should be taken into consideration, how to provide such "learning experience" which is optimal and unique for a particular learner, as well as how to provide individualized adaptive problem solving support. Knowledge assessment systems, in their turn, generally are based on objective tests which have predefined answers. Even if such systems are capable to choose the next question in adaptive fashion on the basis of learner's previous answers, they do not allow the learner to offer original judgments and can assess only factual knowledge instead of attaining learner’s insight on interrelation and significance of knowledge units within the learning course. On the other hand, systems which try to eliminate these drawbacks are based on natural language processing, i.e. on essays and free-text responses that make them dependent on the learning course and natural language. Therefore they have complex structure and functional
mechanisms. Thus, there are no intermediate solutions between systems of objective tests and essay-based systems which additionally would be adaptive.

**The goal of the thesis**

The goal of the thesis is to develop methods for adaptive tutoring and knowledge assessment and to implement them in a software system, as well as to evaluate the developed system in learning courses.

**The tasks of the thesis**

In order to achieve the goal of the thesis the following tasks are specified:

- analysis of differences between traditional and technology-based learning process;
- analysis of intelligent tutoring and knowledge assessment systems in order to identify unresolved tasks in their development;
- development of methods for adaptive tutoring and knowledge assessment in order to resolve previously found unresolved tasks;
- development and implementation of an intelligent supporting system for adaptive tutoring and knowledge assessment;
- evaluation of the developed system in learning courses.

**Research object**

Research object of the thesis is intelligent tutoring and knowledge assessment systems.

**Research subject**

Research subject of the thesis is adaptive characteristics and their implementation opportunities in intelligent tutoring and knowledge assessment systems.

**Research methods**

Theoretical research is based on incompleteness and drawbacks of known systems acquired as a result of the analysis of available information sources. Theoretical results are obtained by using methods of sets theory, classification and modelling. Methods of software engineering and artificial intelligence were used for implementation of prototypes of the developed systems. The developed prototypes were approbated in learning courses and evaluated by questionnaires offered to students involved in evaluation process.

**Scientific novelty of the thesis:**

- the concept and architecture of the concept map based knowledge assessment system with possibility to change the degree of task difficulty, and the intelligent tutoring system providing adaptive hinting has been developed;
• an algorithm which compares teacher's and learner's concept maps and is sensitive to the arrangement and coherence of concepts has been developed;
• two approaches for changing of the degree of task difficulty in concept map based knowledge assessment system have been developed;
• the scheme of problem-solving modes and kinds of feedback for intelligent tutoring systems has been developed;
• the two-layer model of hints for adaptive hinting and the algorithms for its usage in intelligent tutoring systems have been developed;
• a set of agents in architecture of an intelligent tutoring system and their functions have been defined;
• five categories of content stored in the student model of intelligent tutoring systems have been defined;
• eight groups of terms describing technology-based learning process and subset relationships between them have been defined;
• a definition of intelligent tutoring systems on the basis of their characteristics have been given.

Practical value of the thesis

Practical value of the thesis is related to the developed concept map based knowledge assessment system and the intelligent tutoring system which can be used in learning process of Riga Technical University or other educational institutions.

Approbation of the obtained results

Ten presentations on the main results of research were made in 8 international scientific conferences (4 of them in foreign countries, i.e. in Romania, Estonia, Hungary and Lithuania, and 6 in Latvia), as well as one local conference:

• 1st International Conference on Virtual Learning, Bucharest, Romania, October 27-29, 2006.
• 47th Scientific Conference of Riga Technical University, Riga, Latvia, October 12-14, 2006.

• 7th International Baltic Conference on Databases and Information Systems (Baltic DB&IS 2006), Vilnius, Lithuania, July 3-6, 2006.


• 46th Scientific Conference of Riga Technical University, Riga, Latvia, October 13-14, 2005.

• 45th Scientific Conference of Riga Technical University, Riga, Latvia, Riga, Latvija, October 13-14, 2004 (2 presentations).

• 44th Scientific Conference of Riga Technical University, Riga, Latvia, October 9-11, 2003.

Approbation of the thesis was also performed using the developed systems for tutoring of students and assessment of their knowledge in 7 learning courses since 2005 till 2007.

The results are included in the reports of two projects financed by Latvian Ministry of Education and Science and Riga Technical University, i.e. F6962 "Intelligent system for the effectiveness analysis support of process-oriented learning" (project leader J.Grundspenkis, year 2005) and U7117 "Concept maps and ontology based intelligent system for student knowledge self-assessment and process oriented knowledge control" (project leader J.Grundspenkis, year 2006).

About the results of the thesis the author has given a lecture for students of Doctoral studies in Riga Technical University on the topic "Information technologies for improvement of higher education" within the learning course "Didactics of Higher Schools" (Humanitarian Institute of Riga Technical University, Latvia) on May 11 in the year 2006.

The main results of the thesis are reflected in 16 papers (twelve of them have been already published, 1 is in print, 1 has been accepted and 2 submitted for publication):


The author's paper „Analysis of the Terminology Used in the Field of Virtual Learning” (Journal of Educational Technology & Society, 2005) has been located in the section „Fundamentals of Virtual Learning and Technological Knowledge” on website for 1st International Conference on Virtual Learning (Bucharest, Romania, October 27-29, 2006) and 2nd International Conference on Virtual Learning (Constanta, Romania, October 26-28, 2007).

**Structure of the thesis**

The thesis includes introduction, 4 chapters, conclusions, bibliography and 12 appendixes.
In the introduction the motivation of the thesis, research goals and tasks are defined. Applied scientific methods, novelty, practical value of the thesis and approbation of the main results are described as well.

Analysis of traditional learning process by defining its main processes, components and their interaction, characteristics and problems is performed in Chapter 1 in order to determine general requirements for the tutoring and knowledge assessment system. Terminology describing technology-based learning process and differences between traditional and technology-based learning processes are also analyzed.

Chapter 2 is devoted to the analysis of intelligent tutoring and knowledge assessment systems in order to identify unresolved tasks in the development of such systems and to concretize requirements for the tutoring and knowledge assessment system. The architecture of intelligent tutoring systems, functional principles and adaptive abilities, as well as possibilities to use agent paradigm for development of a system are described.

The developed concept map based knowledge assessment system, its conception, implementation details and evaluation results are specified in Chapter 3.

The main attention in Chapter 4 is concentrated on the developed approach which includes two modes of practical problem solving and a two-layer model of hints for adaptive hinting. The approach is implemented in the prototype of the intelligent tutoring system "MINIMA". Implementation details and evaluation results of the prototype are specified in this chapter.

Main results of research and conclusions are presented in the last part of the thesis.

1. TRADITIONAL LEARNING PROCESS VERSUS TECHNOLOGY-BASED LEARNING PROCESS

It is important to achieve not only the same learning efficiency which is provided by habitual educational environment, but to increase learning efficiency when integrating technology in learning process. This can be possible by retaining important characteristics of traditional learning process and by solving its problems. The analysis of traditional learning process is carried out in this chapter in order to determine general requirements for technology-based tutoring and knowledge assessment.
1.1. Traditional learning process: characteristics and problems

Three main processes (perceiving and realizing of new information, improvement of new knowledge and development of skills, as well as control and assessment of acquired knowledge and skills) and three participants (a teacher, a learner and learning content) are identified as a results of the analysis of traditional learning process. Moreover, it is found out, that activities in which the teacher and the learner are involved simultaneously underlie learning process. However, there are also activities which each of participants carries out in solitude, but they are not mandatory. The teacher is capable to recognize a situation and the learner, to judge about them and use results of judgments in order to adapt both to the situation and to the learner. Thus certain intelligent and adaptive abilities are characteristic of the teacher.

In spite of the fact that traditional learning process exists already for a long time, many problems are still not solved. This chapter formulates the following problems that are crucial within the thesis: insufficient adaptation to a particular learner, lack of systematic knowledge assessment and ignoring of knowledge self-assessment. All mentioned problems can be partly solved by integration of information and communication technologies in learning process.

1.2. Technology-based learning process: technologies and characteristics

The spectrum of technologies which can be used in traditional learning process is wide and varied. Therefore, the broad terminology describing possible technology-based learning ways and approaches has appeared. The thesis contains analysis of terms performed on the basis of investigation of 90 information sources. Results of the analysis include two schemes for formation of terms, as well as meaning of connectives and concepts from pedagogics which are parts of terms. The presented analysis is described in details in [ANO 2005].

Terms describing technology-based learning process are formed by using one of the following schemes:

A WORD CHARACTERIZING LEARNING + AN EDUCATIONAL CONCEPT

or

A TECHNOLOGY DESCRIBING WORD + A CONNECTIVE + AN EDUCATIONAL CONCEPT

The mentioned schemes determine the main differences among terms. This allowed to define eight basic groups of the most widespread terms: ‘C’ (computer), ‘D’ (distance), ‘I’ (Internet), ‘O’ (online), ‘T’ (technology), ‘W’ (Web), ‘E’ (electronic) and ‘R’ (resource) [ANO 2005].
Terms of group ‘C’ (computer-based learning) includes the word “computer”. Even if it can be applied to any use of a computer in learning process, however, when a computer is used as a learning media or a media for managing of learning process, it defines that a computer is offline and not connected to any network during the use of the learning course, as well as learning content is local and delivered primarily via CD-ROM or floppy disk.

The word “distance” within terms of group ‘D’ (distance learning) points out that a learner and a source of learning are physically separated one from another and they do not have continuous and direct contact. Any information and communication technology can be used which allows to provide learning at remote locations: correspondence, TV, phone, audioconference, videoconference, course material on Web, radio, satellite broadcasts, audiotape, videotape, facsimile, and etc.

Terms of group ‘E’ (e-learning) imply that learning is organized through any electronic media or environment. These media could be computer offline or connected to a network (Internet, intranet, extranet), audio and video devices, satellite broadcasts, CD-ROM or DVD discs, interactive TV, phones, and etc.

Terms of group ‘I’ (Internet-based learning) point out that learning content is delivered via Internet. In contradistinction to learning that is characterized by terms of group ‘C’ Internet-based learning allows to access not only local content, but also materials outside the course.

Definitions of terms from group ‘O’ (online learning) in the broad sense refer to presence of a network connection. The more narrow meaning of the word “online” stresses that a computer is connected to Internet. In this case terms of this group often are used as synonyms of terms from groups ‘I’ and ‘W’.

In resource-based learning (terms of group ‘R’) learners have a central role in learning process and they become active participants which use different resources to study a subject. Resources include printed and electronic books, dictionaries, documents, drawings, maps, newspapers, slides, audiorecords, videorecords, computer software, games, humans, TV, models, and etc.

Terms of group ‘T’ (technology-based learning) emphasize that some technology used for delivering of learning content and development of skills and knowledge has the primary role in learning process. It can be any technology: computer (also connected to Internet, intranet or extranet), TV, audiotape, videotape, DVD discs, CD, satellite broadcast, phones, facsimile, and etc.
Terms of group ‘W’ clearly describe technology that is used in learning process, namely, Web technology. Thus, learning content is delivered over the public or private computer network using a Web browser. Learning content usually contains links to resources outside the course.

Subset relationships are defined among the groups of terms as a result of the analysis (Figure 1.2.1):

\[ W \subset I \subset O \subset E, \ C \subset E, \ E \subset D \subset T \subset R, \]

where used letters correspond to terms of a corresponding group.

![Diagram showing subset relationships among the groups of terms](image)

**Fig.1.2.1.** Subset relationships among the groups of terms

Regardless of which technology is used, all three main processes of traditional learning should be incorporated in technology-based learning process. Technology can support any of them separately or any of their combinations. Integration of technology causes changes both in the number of participants of traditional learning process and in their interaction that is described in detail in the thesis. Here it is necessary to note that the most important changes are related to the fact that technology partially or completely takes over the role of the human-teacher.

In order to achieve the same learning efficiency provided by traditional learning process technology-based learning process should retain important characteristics of traditional learning. The greater learning efficiency can be provided if technology will solve problems existing in traditional learning process.

### 1.3. Conclusions

The following general requirements are defined for technology-based tutoring and knowledge assessment on the basis of the determined characteristics of traditional learning process and identified problems:

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• all main processes of traditional learning or their particular activities should be supported;
• teacher's activities should be carried out on the level not worse than the level of the human-teacher, and reactions to actions of a learner should be provided;
• adaptation both to situation and to a learner should be provided;
• it is necessary to support such activity of the human-teacher which is performed in solitude as improvement of learning content by offering means for systematic knowledge assessment and analysis of its results;
• it is necessary to support such activity of the learner which is carried out in solitude as knowledge self-assessment.

The novel theoretical result in this chapter is related to the groups of terms describing technology-based learning process and subset relationships among them.

2. INTELLIGENT TUTORING AND KNOWLEDGE ASSESSMENT SYSTEMS

Analysis of intelligent tutoring and knowledge assessment systems is presented in this chapter. Its main goal is to identify unresolved tasks in development of such systems and to concretize requirements for the tutoring and knowledge assessment system.

2.1. Intelligent tutoring systems: concept and architecture

Definition of intelligent tutoring systems, architecture and widespread kinds of adaptation is considered within the thesis. As a result of study an explanation of the term "intelligent tutoring system" is offered based on characteristic frequently used by various researchers. Thus, it is an adaptive and intelligent computer-based system which emulates a human teacher, tries to provide benefits of one-on-one tutoring and is based on the theory of learning and cognition [ANO 2006e]. Furthermore, intelligent tutoring systems store three basic kinds of knowledge [CAP 2000, FRA 1997]: domain knowledge, pedagogical knowledge, and knowledge about the learner.

One of the most important parts of the architecture of intelligent tutoring systems is the student model. It provides basis for tailoring learning process in accordance with needs of a particular learner. As a result of analysis of available information sources 5 categories of content stored in the student model are defined: learner’s identifying information, information about progress of learning process and learner's current knowledge and skills level,
information about important learner’s cognitive, emotional and psychological features, information about his/her past experience, interests and general knowledge, as well as information about system’s options usage by the learner.

Analysis of available information sources and developed systems allows to identify several common basic kinds of adaptation in these systems: adaptive curriculum sequencing [BRU 1999, DEV 2000, JER 2004], adaptive presentation [BRU 2001, KEL 2002, LIE 2000] and adaptive problem solving support [VIR 2001, WAR 1997]. Despite the prevalence of the described kinds of adaptation adaptive abilities of intelligent tutoring systems still are not high enough. The thesis reveals two unresolved tasks. Firstly, the system typically gives the learner an immediate feedback after each action performed during problem-solving. However, such policy ignores peculiarities of particular students when they would like to perform a series of steps, receive feedback about their correctness and find out what step has led to the incorrect solution. Secondly, system's hints are organized in a range from the most general to the most specific and are given sequentially. This is not flexible enough because it demands from the learner to pass through a chain of informativeless hints before he/she receives a hint that is appropriate to his/her knowledge level.

2.2. Agents in intelligent tutoring systems

Intelligent tutoring systems in their architecture and functioning apply a wide range of artificial intelligence methods. However, one of the leading research directions in the development of intelligent tutoring systems is the agent paradigm for more than three decades. The notion of agent and its characteristics, as well as multi-agent systems and agent programs are described in this subchapter within the thesis. However the main attention is devoted to the following questions: what components of intelligent tutoring systems can be implemented as agents and what functions agents can perform in each component.

The performed analysis allows to conclude that all components of the general architecture of intelligent tutoring systems can be implemented in the form of multi-agent architecture. The possible set of agents is shown in Figure 2.2.1 [GRU 2005]. The summary on functions of agents within the main components of an intelligent tutoring system is given in Table 2.2.1.
Fig. 2.2.1. A set of agents comprising the architecture of an intelligent tutoring system (grey boxes are managing agents in each of components)

Table 2.2.1.

Agent functions within the main components of an intelligent tutoring system

<table>
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<th>The component of an intelligent tutoring system</th>
<th>Agent functions</th>
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| The student diagnosis module                  | • building a model of learner’s current level of knowledge and skills based on assessments (knowledge evaluation agent)  
• building a profile of learner’s psychological characteristics, i.e. learning preferences, learning style, attentiveness, personality traits etc. (psychological agents)  
• registering history of learner’s interactions with the system (interaction registering agent)  
• determining and registering learner’s mistakes and their causes (cognitive diagnosis agent) |
| The pedagogical module                        | • evaluation, updating and generation of the curriculum (curriculum agent)  
• implementation of different teaching strategies (teaching strategy agents)  
• generation and presentation of feedback, explanations and help (feedback and explanation agent)  
• generation of tasks/problems/questions tailored to a learner (tasks/problems/questions generation agent) |
| The communication module                     | • monitoring the interaction between the learner and the system  
• management of various interaction devices |
| The expert module                             | • solving problems and tasks related to the subject matter (expert agents) |
2.3. Intelligent and adaptive support in knowledge assessment systems

Intelligent tutoring systems are capable to provide systematic knowledge assessment and knowledge self-assessment. In Subchapter 1.3 these requirements for technology-based tutoring and knowledge assessment are stated. However, such kinds of knowledge assessment are applicable only to the learning course for which the system is developed. Knowledge assessment in traditional learning process demands high workload, is time consuming and requires support of technology regardless if technology is used in other learning processes or not. Main attention of this subchapter is devoted to the analysis of computer-assisted assessment systems, especially to the intelligent and adaptive support in such systems.

Computer-assisted assessment systems are divided in two classes: systems of objective testing and systems of subjective testing [SEA 2002]. Systems based on objective tests offer the learner a set of questions, which answers are pre-defined [CAA 2002]. Systems of subjective testing can assess learner submitted papers for content, style, originality, etc. Typically, they are based on essays and free-text responses [SEA 2002]. In spite of the fact that both kinds of systems have some definite advantages, the following drawbacks are identified as a result of performed analysis:

- objective testing does not allow the learner to offer original judgments, so there are some restrictions on knowledge and skills which it can assess;
- objective testing assess only factual knowledge instead of learner's insights on interrelation and significance of knowledge units within the learning course;
- systems of subjective testing use methods of artificial intelligence especially natural language processing, so they depend on the learning course and natural language, as well as have complex structure and functional mechanisms;
- the use of tasks based on essays and free-text responses for systematic knowledge assessment is doubtful due to a high cognitive load for learners.

The identified drawbacks allow to conclude that it is necessary to develop such knowledge assessment system which would eliminate listed drawbacks and would provide intermediate solutions between systems of objective tests and subjective testing. The thesis offers to use concept maps as a basis for such system.

Concept maps are a kind of mental models which uses a graph with labeled nodes corresponding to concepts in a problem domain and with arcs indicating relationships between pairs of concepts. Arcs can be directed or undirected and with or without linking phrases on them. Linking phrases specifies the kind of relationship between concepts. The
performed analysis revealed that concept maps allow to assess higher order skills, to offer tasks of different degree of difficulty and to assess learners' understanding of knowledge structure in the learning course, instead of a degree of memorization of separate facts. They are universal enough and independent from the learning course. Concept maps allow to develop computer-assisted knowledge assessment systems based on manipulation of graphic objects instead of natural language processing. They can be used in any stage of the learning course and for any knowledge assessment form.

**2.4. Conclusions**

The following requirements are defined, considering general requirements for technology-based tutoring and knowledge assessment formulated in subchapter 1.3, as well unresolved tasks and their solutions described in this chapter:

- an intelligent tutoring system which provides two modes of problem solving and adaptive hinting should be developed;
- an adaptive concept map based knowledge assessment system which provides systematic knowledge assessment and self-assessment, as well as supports the teacher in improvement of the learning courses should be developed;
- both systems should be developed using the agent approach.

The achieved theoretical results in this chapter are, firstly, the definition of intelligent tutoring systems on the basis of their characteristics, secondly, five categories of content stored in the student model, thirdly, a set of agents in the architecture of intelligent tutoring systems.

**3. CONCEPT MAP BASED KNOWLEDGE ASSESSMENT SYSTEM**

This chapter describes the concept map based knowledge assessment system which has been developed within the thesis. The conception of the system and evaluation results are specified.

**3.1. Conception of the system**

Figure 3.1.1 displays the developed scheme for concept maps usage in systematic knowledge assessment [ANO 2007a]. The main idea is that the teacher divides the learning course into several stages and build concept maps for each of them in such a way, that a concept map of each stage is nothing else than an extension of the previous one. In this case
the concept map of the last stage includes all concepts and all relationships among them. Created concept maps are offered to learners for knowledge assessment at the end of each stage of the learning course.

![Concept Map Diagram](image)

**Fig. 3.1.1.** Concept map usage for systematic knowledge assessment

The general scenario of interaction between the system and its two users, as well as the agent-based architecture of the developed system [ANO 2006a] is presented in Figure 3.1.2 [ANO 2006b]. In general the system is a multi-agent system which consists of the software agent (the concept map based knowledge assessment system itself) and two human-agents (the teacher and the learner) which communicate with the software agent. The intelligent agent who makes assessment of the learner’s current knowledge level is defined within the system and is a core of the system’s intelligence. This agent at the moment consists of four other agents, which are used in intelligent tutoring systems and were defined in Subchapter 2.2., i.e. communication, knowledge evaluation, interaction registering and expert agents. The learner solves the tasks during knowledge assessment. In the context of the system a task is a filling or construction of a concept map of a particular stage by using offered set of concepts and/or linking phrases depending on the degree of task difficulty. The communication agent perceives the learner's actions on the working surface, i.e. changing of arrangements of elements of the concept map and clicking on the buttons within a window. It is also responsible for visualization of a structure of a concept map and its elements after receiving them from the agent-expert, and for the output of feedback coming from the knowledge evaluation agent. After the learner has submitted his/her solution, the communication agent delivers the learner's concept map to the knowledge evaluation agent. This agent compares the concept maps of the learner and the teacher, calculates the score of the learner, gathers statistics information and generates feedback which is delivered back to the communication agent. The interaction registering agent receives the learner's concept map from the
communication agent and results of its comparison with the teacher-created concept map from the agent of knowledge evaluation, and stores them in a database. The agent-expert forms a task of the current learning stage on the basis of the teacher-created concept map and the learner's results of the previous stage. The formed structure and/or its elements are delivered to the communication agent for its visualization on the working surface. The agent-expert also delivers the teacher-created concept map to the agent of knowledge evaluation for its comparison with the learner-completed concept map.

![Diagram of the concept map based knowledge assessment system]

**Fig. 3.1.2.** The agent-based architecture of the concept map based knowledge assessment system

The knowledge evaluation agent uses the developed algorithm that compares the teacher’s and learner’s concept maps and is sensitive to the arrangement and coherence of concepts. The algorithm can recognize five patterns of learner solutions. It is applicable for tasks of filling of a concept map structure in which linking phrases are not used, arcs are undirected and two types of relationships are used, i.e. important conceptual relationships which show that relationships between the corresponding concepts are considered as important knowledge in a given learning course, and less important conceptual relationships which specify desirable knowledge. Taking into account that a value of the completely correct relationship is 100%, the following contributions of particular parts are defined:
• presence of the relationship in the learner's concept map - 50% (a fact that the learner understands the presence of the relationship between concepts has the primary value);
• correct type of the relationship - 30% (the learner should be able to distinguish, what is important and what is less important in the learning course);
• both concepts related with the relationship are placed in the correct places - 20% (this factor has the greatest subjectivity).

Thus, the learner’s solutions (Figure 3.1.3) which the algorithm is capable to distinguish and which make the knowledge base of the knowledge evaluation agent are the following [ANO 2006c, ANO 2006d]:

Pattern 1. The learner has related concepts as they are related within the teacher's concept map. In this case the learner receives 5 points regarding every important relationship and 2 points for less important relationship.

Pattern 2. The learner has defined a relationship, which does not exist in the concept map of the teacher. In this case he/she does not receive any points.

Pattern 3. The learner’s defined relationship exists in the teacher's map, the type of relationship is correct, but at least one of concepts is placed in an incorrect place. The learner receives 80% of the maximum score for that relationship.

Pattern 4. The learner’s defined relationship exists in the teacher's map, the type of relationship is wrong, and at least one of concepts is placed in an incorrect place. The learner receives 50% of the maximum score for the correct relationship.

Fig. 3.1.3. The patterns of the learner’s solutions which the system can recognize: a) the teacher’s concept map; b) – f) the patterns within the learner-created concept map
Pattern 5. A concept is placed in a wrong place, but its place is not important. The learner receives the maximum score for a corresponding relationship.

Statistical information which is collected by the knowledge evaluation agent regarding differences between the teacher's concept map and the learners' concept maps is the following:

• a list of relationships that learners typically define in their concept maps, but which does not exist in the teacher’s concept map (Pattern 2 in Figure 3.1.3);
• a list of relationships that are in the teacher’s map but rarely appear in learners’ concept maps;
• a list of relationships which are important in the teacher’s concept map, but learners define them as less important relationships (Pattern 4 in Figure 3.1.3 taking into account only less important relationships in learners' concept maps).

The knowledge evaluation agent is the knowledge-based agent [RUS 2003] which knowledge base stores knowledge about points which have to be given to patterns of learner's solutions (Figure 3.1.3). Knowledge has the form of production rules (IF...THEN rules):

IF (pattern=X) AND (type_of_relationship=Y) THEN points=Z,

for example,

IF (pattern=1) AND (type_of_relationship=less_important_relationship)
THEN points=2,

IF (pattern=3) AND (type_of_relationship=important_relationship)
THEN points=5*0.8.

Other agents are implemented as simple reactive agents, i.e. the agents which immediately give a response to changes in their environment. Their programs unambiguously specify all possible percepts to actions so they do not have knowledge base.

Two approaches are offered within the thesis, which allow to assess a learner's knowledge level more accurate on the basis of changing the degree of task difficulty. These approaches are described in [ANO 2006d, ANO 2007a, ANO 2007c, ANO 2007d].

3.1.1. Concept map based knowledge assessment with changing the degree of task difficulty by inserting additional concepts

In the approach of changing the degree of task difficulty by inserting additional concepts only one type of tasks is used: filling of a teacher-prepared concept map structure by a given list of concepts. During the task performance the learner can ask to reduce the degree
of task difficulty. In this case the system inserts additional concepts into the structure of the concept map reducing the number of concepts which the learner should insert. Concept insertion is no more possible in three cases: a) the learner has completed the task; b) the remaining list of concepts to be inserted contains only the minimal number of concepts (pre-defined by the teacher) that the learner should insert by him/herself; and c) by inserting the next concept the learner would lose the possibility to complete the task successfully (to receive 50% of the maximal possible score).

Difficulty reduction consists of two steps. Firstly, the analysis of the learner’s concept map is done and incorrectly inserted concepts are removed from the concept map structure and added to a general list of concepts. Concepts are considered as incorrectly inserted if they have no correct relationships or they are in the incorrect place and the place is important. Secondly, after removing the incorrectly inserted concepts the learner chooses the number of concepts which he/she wishes the system would insert into the concept map structure. The system inserts additional concepts being based on the algorithm shown in Figure 3.1.1.1 [ANO 2007e]. This algorithm makes the basis of the agent-expert in Figure 3.1.2. Additional concepts are inserted according to the degrees of free nodes of the concept map structure.

In this approach appearance of a concept map structure depends on the knowledge assessment stage. At the first stage only initial concepts pre-defined by the teacher are already inserted in the concept map structure. At all other stages the concept map structure is extended by new concepts and relationships and contains teacher pre-defined concepts, as well as concepts which the learner has correctly or partly correctly (patterns in Figure 3.1.3) inserted in the previous stages or the system has inserted performing reduction of the degree of task difficulty.

The learner’s concept map is evaluated using the following equation [ANO 2007e]:

\[
P = \left( \sum_{i=1}^{n} p_i \times c_i \right) \times (1 - c_s) \times s - \sum_{i=1}^{j} (a + \Delta \times (i - 1) / m) / m
\]

(3.1.1.1)

where

- \( P \) - the learner’s score after the completion of the task;
- \( p_i \) - the maximal score according to the type of i-th relationship (5 points for each important relationship and 2 for less important relationship);
- \( c_i \) - the coefficient which corresponds to the degree of i-th relationship’s correctness (based on the patterns in Figure 3.1.3);
- \( n \) - the number of relationships in the concept map structure;
- \( c_s \) – the penalty for each difficulty reduction time;
Fig. 3.1.1.1. Algorithm for additional concept insertion into the structure of a concept map in order to reduce the degree of task difficulty
The number of difficulty reduction times; a - the penalty for insertion of the first concept by the system; j - the total number of concepts inserted by the system; m - the total number of concepts in the concept map; \( \Delta \) - the penalty increase for each concept insertion.

The following values of the coefficients have been chosen for system implementation purposes by analyzing 13 different concept maps: \( c_s = 0.01 \), \( a = 0.07 \) and \( \Delta = 1.5 \). This choice is based on the assumption that the learner is allowed to ask the system to insert approximately 35% of all concepts and still be able to complete the task successfully in case he/she inserts all other concepts in correct places.

### 3.1.2. Concept map based knowledge assessment with changing the degree of task difficulty by offering different tasks

In this approach several tasks of different degrees of difficulty are implemented. As a research result five tasks have been selected [ANO 2007a, ANO 2007c] which are logical and realizable from the point of view of transitions among them. There are both “fill-in” and “construct-a-map” tasks. The tasks are ranged from the easiest to the most difficult (Table 3.1.2.1) based on information given to the learner and workload needed to complete the task.

<table>
<thead>
<tr>
<th>The type of task</th>
<th>Ordinal number of the task</th>
<th>The structure of a concept map</th>
<th>Linking phrases</th>
<th>Concepts</th>
<th>Degree of task difficulty</th>
<th>Comments</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fill-in</td>
<td>1</td>
<td>1 Is given</td>
<td>Inserted in the structure</td>
<td>Need to be inserted</td>
<td>The easiest</td>
<td>Linking phrases that are inserted in the structure can help to find where a particular concept should be inserted</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>Is given</td>
<td>Are not used</td>
<td>Need to be inserted</td>
<td>No information available that would allow to understand, where a particular concept should be inserted</td>
<td></td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>Is given</td>
<td>Need to be inserted</td>
<td>Need to be inserted</td>
<td>No information available that would allow to understand, where a particular concept should be inserted, as well as the amount of work is increased</td>
<td></td>
</tr>
<tr>
<td>Construct-a-map</td>
<td>4</td>
<td>Is not given</td>
<td>Are not used</td>
<td>Need to be related</td>
<td>The most difficult</td>
<td>The amount of work is increased in comparison with Task 4</td>
</tr>
<tr>
<td></td>
<td>5</td>
<td>Is not given</td>
<td>Need to be inserted</td>
<td>Need to be related</td>
<td>The most difficult</td>
<td>The amount of work is increased in comparison with Task 4</td>
</tr>
</tbody>
</table>
The appearance of a particular concept map depends on the knowledge assessment stage. At the first stage the learner receives the task which has the teacher's pre-defined degree of difficulty (by ordinal number from Table 3.1.2.1). During the task performance the learner can ask to reduce the degree of difficulty. In this case the transition is performed reducing the ordinal number of the task by 1 (Table 3.1.2.1). Of course, it is not valid for the first task. The learner can ask to reduce the degree of difficulty several times during the same stage. At the subsequent stages the degree of task difficulty depends on the learner's result at the previous stage. If the learner has reached the teacher's specified number of points without reducing the degree of difficulty of the original task, the degree of task difficulty at the subsequent stage is increased by 1 (by ordinal number in Table 3.1.2.1). Otherwise, the degree of difficulty remains the same. The process continues until the learner reaches the highest degree of difficulty or completes the tasks of all stages.

Thus eight transitions between tasks are implemented in the system (Figure 3.1.2.1) [ANO 2007c]. Transitions A, B, C and D are transitions that increase the degree of task difficulty. They are carried out after receiving and analysis of the learner's solution. This is a system’s adaptive reaction to the learner's behavior. Transitions E, F, G and H are transitions which reduce the degree of task difficulty. They are carried out by voluntary request from the learner during the task performance.

In this approach the patterns of learner's solution (Fig.3.1.3) are extended, as well as the points for relationships are modified. Taking into account that a value of the fully correct relationship is 100 %, the following contributions of particular parts are defined:

- presence of the relationship in the learner's concept map - 40% (a fact that the learner understands the presence of relationship between concepts has the primary value);
- correct linking phrase - 30 % (semantics of relationships are important knowledge units);
• correct type of the relationship - 20% (the learner should be able to distinguish, what is important and what is less important in the learning course);

• both concepts related with the relationship are placed in the correct places - 10% (this factor has the greatest subjectivity).

Therefore, extended set of patterns of the learner's solutions (Fig.3.1.2.2) and knowledge base of the knowledge evaluation agent (Figure 3.1.2) is the following:

Pattern 1. The learner has defined a completely correct relationship. In this case the learner receives 5 points regarding every important relationship and 2 points for less important relationship.

Pattern 2. The learner has defined a relationship, which does not exist in the concept map of the teacher. In this case he/she does not receive any points.

Pattern 3. The learner’s defined relationship exists in the teacher’s map, both the type of the relationship and the linking phrase are correct, but at least one of concepts is placed in an incorrect place. The learner receives 90% of the maximum score for that relationship.

Pattern 4. The learner’s defined relationship exists in the teacher’s map, but the type of the relationship is incorrect. The learner receives 80% of the maximum score for the correct relationship. This pattern is characteristic only for "construct-a-map" tasks (tasks 4 and 5 in Table 3.1.2.1) where places of concepts are not important.

Pattern 5. The learner’s defined relationship exists in the teacher’s map, but the linking phrase is incorrect. The learner receives 70% of the maximum score for the correct relationship.

Pattern 6. The learner’s defined relationship exists in the teacher’s map, the type of the relationship is incorrect, and at least one of concepts is placed in the incorrect place. The learner receives 70% of the maximum score for the correct relationship.

Pattern 7. The learner’s defined relationship exists in the teacher’s map, the linking phrase is incorrect, and at least one of concepts is placed in the incorrect place. The learner receives 60% of the maximum score for the correct relationship.

Pattern 8. The learner’s defined relationship exists in the teacher’s map, but both the type of the relationship and the linking phrase are incorrect. The learner receives 50% of the maximum score for the correct relationship. This pattern is
characteristic only for "construct-a-map" tasks (tasks 4 and 5 in Table 3.1.2.1) where places of concepts are not important.

Pattern 9. The learner’s defined relationship exists in the teacher’s map, both the type of the relationship and the linking phrase are incorrect, as well as at least one of concepts is placed in the incorrect place. The learner receives 40% of the maximum score for that relationship.

Fig. 3.1.2.2. The patterns of the learner’s solutions which the system can recognize: a) the teacher’s concept map; b) – j) the patterns within the learner-created concept map (numbers on links display different relationships and represent linking phrases)
The learner's score assessing the learner's solution of the task is calculated using the following equation:

\[ P = \sum_{i=1}^{n} l_k_i \cdot p_i \cdot c_i, \]  
(3.1.2.1)

where:
- \( P \) - the learner's score for the given task;
- \( l_k_i \) - the coefficient of the degree of difficulty for the given task;
- \( p_i \) - the maximal score according to the type of the \( i \)-th relationship (5 points for each important relationship and 2 for less important relationship);
- \( c_i \) - the coefficient which corresponds to the degree of the \( i \)-th relationship’s correctness (based on the patterns in Figure 3.1.2.2);
- \( n \) - the number of relationships in the teacher's concept map.

The concept map of the current stage can contain relationships which were defined at the previous stages on different degrees of difficulty. Therefore, the coefficient \( l_k_i \) is assigned to each relationship, but not to the whole task. The following values of the coefficient \( l_k_i \) have been found empirically by analyzing 10 different concept maps: Task 5 – 1; Task 4 – 0.71; Task 3 – 0.89; Task 2 – 0.65; Task 1 – 0.67.

### 3.2. Evaluation results

In the year 2006 two prototypes of the concept map based knowledge assessment system were implemented. Each prototype supported one of the approaches of changing the degree of task difficulty. Both prototypes have been evaluated in learning courses and a questionnaire was offered to students who participated in evaluation. The purpose of the questionnaire was to get students’ opinion on the method of knowledge assessment and an opportunity to change the degree of task difficulty, as well as advantages and disadvantages of the developed prototype.

The prototype of the system with changing the degree of task difficulty by inserting additional concepts was evaluated in four learning courses. 44 students were involved in evaluation and 35 of them filled the questionnaire after using the system. In general it was difficult for students to fill-in the concept map structure (21 (60%) student answered that it was difficult and 4 (≈11%) students that it was very difficult). However, only one third of students used the difficulty reduction. Other students mentioned in their answers that they did not want to reduce their results. However, 80% (8 students) of the learners who used difficulty reduction rated it as useful because it facilitated the further performance of the task.
The prototype of the system with changing the degree of task difficulty by offering different tasks was evaluated in one learning course. For its evaluation the author of the thesis has developed a concept map of three stages. Thirty students participated in system's evaluation and 28 of them filled out the questionnaire after finishing knowledge assessment. In general, it was difficult for students to complete the concept map based task (16 students or ≈57%). They explained that such method of knowledge assessment is not used in other learning courses and thus is unusual, as well as that it is necessary to activate thinking processes. Twelve (≈43%) students from those, who had difficulties to complete the task, used the opportunity to change the degree of task difficulty. Others did not want to reduce a score. Nine (75%) respondents from those, who reduced the degree of task difficulty, have pointed out that it has facilitated the further performance of the task, and 3 (25%) students have disagreed with this assertion. In general, 11 (≈92%) students have found that after reduction of the degree of task difficulty the easier task was offered to them. The degree of task difficulty was increased for almost one third of the students (9 students or ≈32%) after successful completion of the task at the previous stage. Eight (≈89%) from these students have found that the more difficult task was offered to them, especially, if it was necessary to complete a task of concept map construction. Thus, it allows to conclude that the transitions between the tasks implemented in the system are logical.

3.3. Conclusions

The main conclusions are the following:

- The intelligent concept map based knowledge assessment system has been developed. It uses the agent paradigm in its architecture and functioning and includes the knowledge-based and reactive agents. The system performs knowledge assessment on the level that is not worse than the human-teacher level because it uses the algorithm of concept maps comparison which is sensitive for concepts arrangement and coherence instead of examination of exact equivalence of two relationships.
- The system with changing the degree of task difficulty by offering different tasks implements adaptive increasing of the degree of task difficulty if the learner has performed the previous task successfully.
• Results of experimental evaluation of the developed prototypes allow to conclude that the opportunity to change the degree of task difficulty is a useful system's function.

• The developed system supports systematic knowledge assessment.

• The system can be used also for knowledge self-assessment because it automatically assesses learners' concept maps and displays feedback which shows mistakes and incompleteness in the learners' concept map.

• The developed system supports the teacher in improvement of the learning course because it collects statistical information about differences between the teacher's and the learner's concept maps.

The developed concept map based knowledge assessment system has been elaborated within the framework of two projects financed by Latvian Ministry of Education and Science and Riga Technical University, i.e. F6962 "Intelligent system for the effectiveness analysis support of process-oriented learning" (project leader J.Grundspenkis, year 2005) and U7117 "Concept maps and ontology based intelligent system for student knowledge self-assessment and process oriented knowledge control" (project leader J.Grundspenkis, year 2006). Within the framework of the projects the author of the thesis has developed the scenario of interaction between the system and their users, the algorithm for concept map comparison, the agent-based system's architecture and two approaches for changing the degree of task difficulty. Together with other participants of the projects the scheme for concept map usage in systematic knowledge assessment, the system's feedback and the scoring mechanisms, as well as the questionnaires have been defined and developed. The system has been implemented by two students of Master's studies program of The Department of Systems Theory and Design of Riga Technical University, i.e. by Dmitrijs Pozdnakovs and Egons Lavendelis. The author has developed the concept map of three stages for the topic "Minimax algorithm for two-person games" within the learning course "Fundamentals of artificial intelligence". The concept map was offered to students during evaluation of the system.

The developed system has three discriminative features in comparison with other systems based on concept maps. Firstly, the system uses the author's developed new algorithm that compares the teacher’s and the learner’s concept maps and is sensitive to the arrangement and coherence of concepts. Secondly, possibility to change the degree of task difficulty is included and allows more accurate assessment of a knowledge level of a particular learner.
Thirdly, the system supports systematic knowledge assessment and allows the teacher to extend the initially created concept map for the new stage of assessment.

The most important and novel theoretical results are, firstly, the author's developed algorithm for concept maps comparison, and, secondly, two defined and implemented approaches for changing the degree of task difficulty which till now are not described in other papers and are not implemented in other known systems. The theoretical results are practically implemented as two prototypes of the concept map based knowledge assessment system.

4. INTELLIGENT TUTORING SYSTEM FOR MINIMAX ALGORITHM

Considering the unresolved tasks in the development of intelligent tutoring systems which are described in Chapter 2 the approach has been developed which provides two modes of problem-solving and adaptive hinting by using a two-layer model of hints. The approach, its implementation details in the prototype of the intelligent tutoring system "MINIMA" and evaluation results of the prototype are described in this chapter.

4.1. Conception of the system

Generally an intelligent tutoring system can provide two modes of problem-solving [ANO 2007b, ANO 2007d]: step-by-step mode, where the system monitors each learner's problem-solving step and gives feedback about its correctness, and completeness mode, where the learner chooses the moments of feedback presentation to check correctness of a series of steps. It should be emphasized that the described problem-solving modes can be implemented only if the process of problem solving consists of several steps. Granularity and meaning of a step depends on specificity of a task in a problem domain.

Both modes are further subdivided on the basis of information kind given to a learner (Figure 4.1.1) [ANO 2007b, ANO 2007e]. The learner is rewarded (receives a positive feedback) if he/she has performed the correct action. If the step was incorrect, criticism (negative feedback) is given. The learner is not rewarded or criticized for each performed step in the completeness mode. He/she receives a total estimation of all performed actions, instead. The estimation specifies how far the learner is from the correct solution of a problem.

It is obvious, that it is necessary to provide an opportunity to a learner to change the problem-solving mode and a kind of feedback by him/herself, as well as to ask a hint in case when he/she receives only a text of negative feedback or a total estimation of the performed
steps. Moreover, before the learner starts to solve practical problems it is necessary to determine a problem-solving mode and a kind of feedback suitable for him/her. In the simplest case the learner can be suggested to make a choice by himself/herself based on the received explanations of the problem-solving modes and the kinds of feedback. In a more sophisticated case it is necessary to develop a series of tasks or questions, which analysis will allow to determine the most suitable mode and feedback.

Fig. 4.1.1. The problem-solving modes and kinds of feedback for an intelligent tutoring system

In order to support adaptive delivery of hints in both mentioned problem-solving modes a two-layer model of hints has been developed within the thesis [ANO 2006e]. It consists of a layer of the general hint categories and a layer of hints within these categories (Figure 4.1.2). There are three general categories of hints [ANO 2007e]:

- specific hints directly say or show, what should be done, or refer to the step earlier performed by a learner from which it is possible to conclude where a mistake is made and how it can be corrected;
- hints of average informativeness indirectly specify an incorrect action and opportunities to correct it, for example, offering a definition of a concept underlying a mistake;
- general hints are based on information which specifies an incorrect action in an abstract form and high level knowledge is necessary in order to allocate a mistake and to determine ways of correction.
Each category contains one or more hints which also are ranged from less informative to more informative.

Before a learner starts to solve practical problems testing should be taken with the purpose to determine a general hint category which is suitable for the learner. It is important to note, that the model of hints is based on the assumption, that one or several concepts typically underlie any practical task. A mistake made by a learner is related with lack or low level of knowledge of one of these concepts. It demands to determine a learner's knowledge level of each concept. For this purpose any knowledge assessment method can be used which allow to define a knowledge level using three values: low, average and high.

An algorithm for hints delivery has been developed for the usage of the two-layer model of hints within an intelligent tutoring system (Figure 4.1.3) [ANO 2007e]. It is based on a knowledge level of a concept underlying a mistake.

According to the algorithm a knowledge level of a concept underlying a mistake determines an appropriate category of hints. Further on the learner receives an average hint by number from the hint category suitable for him/her. If the learner is not capable to perform a correct action after receiving a hint and the same mistake is made repeatedly, he/she is presented with a subsequent hint by number. The process proceeds while he/she reaches the last hint for the mistake of a certain kind.

There is a difference between the usage of the model of hints in the completeness and in the step-by-step problem-solving modes. In the completeness mode a hint can be given after performance of several steps. The performed steps can be both correct, and incorrect. Moreover incorrectly performed steps can correspond to several mistakes of different types. Therefore, it is necessary to identify a type of a mistake which the hint will be given on to the learner before usage of the model of hints. For this purpose the algorithm (Figure 4.1.4)
[ANO 2007e] has been developed within the thesis. It is based on the critical degrees of mistakes.

Fig. 4.1.3. The algorithm for hint delivery

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Figure 4.1.4. The algorithm for determination of a mistake type in the completeness problem-solving mode

Taking in account the fact that several mistakes can characterize the same task, it is necessary to implement the two-layer model of hints for each of them. In case the learner has reached the last (most specific) hint for a mistake of any type, the system should perform remedial pedagogical actions, for example, to offer the same task with other initial data or to display teaching material which corresponds to the task.
4.2. Implementation details

The prototype of an intelligent tutoring system "MINIMA" has been implemented. It helps to learn the topic "Using heuristics in two-person games" of the learning course “Fundamentals of artificial intelligence” for third year students of bachelor programs at the Faculty of Computer Science and Information Technology of Riga Technical University. The topic is related to the algorithm for implementation of two-person games with full information, i.e., the Minimax algorithm [LUG 2002].

Figure 4.2.1 displays an operating scheme of the developed prototype.

![Operating scheme of the developed prototype](image)

Fig. 4.2.1. The operating scheme of the developed prototype

The practical problem solving mode consists from five tasks in three blocks: refining of a game tree, propagation of heuristic values and determining of winning paths. The tasks allow to master the basic skills concerning application of the Minimax algorithm. All tasks consist of a sequence of steps. In the task of refining of the game tree a step is the removing of one arc (correct or incorrect) from a graph representing a state space of a game. Obtaining a heuristic value (correct or incorrect) for one node of the game tree is a step in the task of propagation of heuristic values. In the task of determining of winning paths adding of one sector (correct or incorrect) to a current path is a step.

It allows to provide two modes of practical problems solving in the system. The learner makes his/her choices of the problem-solving modes and the kinds of feedback (according to Figure 4.1.1) without any assistance after receiving system's explanations.

There are three opportunities when the learner can change the mode of practical problems solving and the kind of received feedback:

- If the learner has finished the previous tutoring episode by solving practical problems then a report window about tasks performed earlier is shown before
beginning a new tutoring session. The learner can change both the practical problems solving mode and the kind of feedback in this window.

- While solving any practical problem the learner can change the kind of feedback within the framework of the mode in which he/she is currently working.

- After completion of the current task a result window is shown, where the learner can change both the practical problems solving mode and the feedback.

In the step-by-step mode the system keeps track of each learner's performed step and delivers him/her reward if the learner has performed a correct action and criticism in case of an incorrect step. A special button is provided in order to check correctness of a series of performed steps in the completeness mode. After performance of the analysis of the learner's solution the learner receives feedback in the form of a total estimation which includes the following: the number of correctly and incorrectly performed steps after the previous check of the solution and the number of correct and incorrect steps after the current check. In case the learner receives feedback which does not provide an automatic delivery of hints there is a button for hint requesting in both modes.

In order to provide the usage of the two-layer model of hints, the possible types of mistakes and their critical degrees were defined for each task. The types of mistakes were determined on the basis of the analysis of course and examination works of third year students of bachelor programs. The two-layer model of hints is maintained for each type of mistakes. Delivery of hints during practical problems solving is carried out on the basis of algorithms shown in Figures 4.1.3 and 4.1.4.

In order to identify a learner’s knowledge level of each concept underlying the tasks after the theoretical knowledge acquisition multiple answer questions are offered to the learner. For each concept there are three questions with different degree of difficulty: simple, average and difficult. The questions have their weights corresponding to the level of difficulty. Each constituent part of an answer has a definite number of points. Thus, the learner receives the following score for each concept:

\[ C = \sum_{i=1}^{3} s_i \cdot p_i, \]  \hspace{1cm} (4.2.1)

where \( C \) - the total score for a particular concept,
\( s_i \) - the weight of \( i \)-th question,
\( p_i \) - the learner’s received points.
The following weights are assigned to the questions: simple question- 1.5, question of average difficulty - 3.5, difficult question -5. The knowledge level of a particular concept is determined as follows:

- if C is in the range of \([0…4]\) then the knowledge level is low;
- if C is in the range of \([4…8]\) then the knowledge level is average;
- if C is in the range of \([8…10]\) then the knowledge level is high.

The ranges of values are chosen on the basis of Latvian grading system, where 10 and 9 correspond to very high knowledge level, 8 and 7 to high level, 6,5, and 4 to average level and 3,2 and 1 to low level.

Any practical task can be completed in two cases: the learner has solved it or the last hint for any type of mistakes has been given. In any case the system checks, how many times the learner carried out the given task, whether he/she has made mistakes and has used hints. Each task can be performed only two times in the developed system. It is based on the following assumption. If the learner was offered to repeat the task, it means, that he/she has received the last hint for a certain type of mistakes. The last hint includes demonstration of task performance and reading explanatory material. Thus, after that it will be easy to solve the same task even with other initial data. In the worst case repeated task execution also can be finished with demonstration.

If the learner has completed the task at the first time then the analysis of the solution is the following:

- The learner should perform the task repeatedly in the following cases:
  - if for any type of mistakes the learner's category of hints was specific hints and the learner has made mistakes of the given type, or
  - if for any type of mistakes the learner's category of hints was hints of average informativeness or general hints and the learner has reached the specific category of hints.

- The system gives the learner an opportunity to choose between repetition of the same task and execution of a subsequent task in the following cases:
  - if for any type of mistakes the learner's category of hints was the hints of average informativeness and the learner has received more than one hint from this category, or
  - if for any type of mistakes the learner's category of hints was general hints and the learner has reached the category of hints of average informativeness.

- The learner passes to the subsequent task in the following cases:
- if for any type of mistakes the learner's category of hints was general hints and the category has not been changed, or
- if for any type of mistakes the learner's category of hints was hints of average informativeness and the learner has received only one hint from this category, or
- if for any type of mistakes the learner's category of hints was specific hints and the learner has not received hints from this category.

The category of hints is changed for each type of mistakes after the performance of analysis, reducing a degree of informativeness. Thus, the category of specific hints is replaced by the category of hints of average informativeness and the hints of average informativeness are replaced by the category of general hints. If the learner has performed the task for the second time than he/she receives the next task in any case.

The developed prototype "MINIMA" is implemented as a multi-agent system (Figure 4.2.2) on the basis of a set of agents shown in Figure 2.2.1. Agents functions and their interaction are described within the thesis in detail.

It is necessary to note that agents in the student diagnosis module are simple reactive agents. Curriculum agent, feedback and hints delivery agent, agent of domain knowledge retrieving and agent of task generation and solving are knowledge-based agents [RUS 2003] which knowledge bases are implemented in the form of production rules (IF..THEN rules). The knowledge base of agent of task generation and solving includes rules which condition part (IF pattern) contains ordinal numbers of learning activity and task, but action part (THEN pattern) defines, what should be done, in order to generate task conditions:

IF    (learning_activity=X) AND (ordinal_number_of_task=Y)
THEN  (action_1) AND (action_i) AND (action_n),

for example,

IF    (learning_activity=problem_solving_mode)
AND   (ordinal_number_of_task=2.1)
THEN  (generate_number_of_levels) AND (generate_nodes) AND
      (generate_arcs) AND (divide_the_tree) AND
      (assign_values_to_terminal_nodes).

Moreover, this agent stores the conditions of the generated task in order to solve it when the learner will complete the task.

In the similar way the knowledge bases of other agents are developed:

• rules of agent of domain knowledge retrieving describe which problem domain knowledge units should be given (THEN pattern) to the learner accordingly to the current learning activity (IF pattern);
rules of curriculum agent describe which next learning activity should be performed (THEN pattern) in dependence of the current state of environment (IF pattern);

rules of feedback and hint delivery agent define which hint (THEN pattern) should be given to the learner in the current task on the basis of the type of made mistake and the last number of given hint for this type (IF pattern).

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**Fig. 4.2.2. Agent-based architecture of the intelligent tutoring system „MINIMA”**

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mutual exchange of information and control flow between the modules of the system, as well as between the system and the learner

writing/reading of information from the model

reading of information from the model/knowledge base
4.3. Evaluation results

In the year 2007 the developed prototype was evaluated in the learning course "Fundamentals of artificial intelligence" for the third year students of bachelor programs at the Faculty of Computer Science and Information Technology of Riga Technical University. Thirty four students were involved in evaluation and 32 of them filled a questionnaire after using the system. The purpose of the questionnaire was to get students’ opinion on the offered problem-solving modes and the kinds of feedback, adaptive hinting and advantages and disadvantages of the developed prototype.

In general 30 (≈94%) students worked in the mode of practical problems solving. Other 2 (≈6%) successfully completed pre-requisite knowledge assessment test. Seventeen (≈57%) students chose the step-by-step problem-solving mode, 9 (30%) learners- the completeness mode, and 4 (≈13%) tried both modes. Three (75%) students from those who tried both modes evaluated the step-by-step as more convenient and only 1 (25%) learner preferred the completeness mode. Results of questionnaires demonstrated that there was definite number of students for all kinds of feedback in both modes and none of them changed the kind of feedback during problem solving.

Seventeen (≈57%) students asked/received hints. Twelve (≈71%) of them asked/received only one hint. They explained that hints were very informative.

4.4. Conclusions

The main conclusions are the following:

- Practical tasks which solution consists from several steps allow to provide two problem-solving modes in an intelligent tutoring system: step-by-step mode, where the system monitors each learner's problem-solving step and gives feedback about its correctness, and completeness mode, where the learner chooses the moments of feedback presentation to check correctness of a series of steps.
- It is possible to provide different kinds of feedback in both mentioned modes. Four kinds of feedback have been defined for the step-by-step mode and two kinds for the completeness mode.
- Hints which correspond to a definite type of mistakes can be divided in 3 categories: general hints, hints of average informativeness and specific hints. It is possible to provide such hinting policy which spares the learner from
informativeless hints by determining a knowledge level of each mistake type in the terms of three values, i.e. high, average and low, which correspond to mentioned hints categories.

- The developed prototype is an intelligent system because it is based on agent architecture and includes reactive and knowledge-based agents.
- The developed prototype is an adaptive system too, because it provides adaptive curriculum sequencing in terms of theoretical knowledge units and adaptive hinting.
- Results of experimental evaluation allow to make the following conclusions:
  - support of two problem-solving modes and several kinds of feedback makes the system more flexible and suitable for different learners;
  - the offered two-layer model of hints provides such hinting policy that mostly it is enough to receive only one hint in order to avoid the same mistake repeatedly and to solve the task.

The most important and novel theoretical results in this chapter are the scheme of problem-solving modes and kinds of feedback, as well as the two-layer model of hints and algorithms for its usage. The theoretical results are practically implemented in the prototype of an intelligent tutoring system "MINIMA".

**MAIN RESULTS AND CONCLUSIONS**

The main goal of the thesis is to develop methods for adaptive tutoring and knowledge assessment on the basis of the analysis of known systems and identification of unresolved tasks and to implement the developed methods in the software system, as well as to evaluate the system in learning courses. In order to achieve the goal the following tasks have been performed:

- Analysis of traditional and technology-based learning processes which allow to define the general requirements for technology-based tutoring and knowledge assessment by identifying differences between two processes, as well as problems of traditional learning process.
- Analysis of intelligent tutoring and knowledge assessment systems in terms of main concepts, architecture, kinds of adaptations and usage of agents for their development. It was done with the purpose to identify unresolved tasks in the
development of such systems and to concretize requirements for the tutoring and knowledge assessment system.

- Development of methods for adaptive tutoring and knowledge assessment in order to resolve previously found unresolved tasks.
- Development and implementation of the intelligent supporting system for adaptive tutoring and knowledge assessment on the basis of the developed methods.
- Evaluation of the developed system in learning courses.

The following most important and novel theoretical results are achieved:

- The concept and architecture of the concept map based knowledge assessment system with possibility to change the degree of task difficulty and the intelligent tutoring system providing adaptive hinting has been developed;
- The algorithm which compares the teacher's and learner's concept maps and is sensitive to the arrangement and coherence of concepts has been developed;
- Two approaches for changing the degree of task difficulty in the concept map based knowledge assessment system have been developed: one of them reduces the task difficulty on the basis of a voluntary request from the learner, other additionally provides adaptive system's reaction by increasing the degree of task difficulty if the learner has performed the previous task successfully;
- The scheme of problem-solving modes and kinds of feedback for the intelligent tutoring systems has been developed;
- The two-layer model of hints for adaptive hinting and the algorithms for its usage in intelligent tutoring systems have been developed.

The acquired theoretical results are practically implemented in 3 prototypes:

1. The concept map based knowledge assessment system with changing the degree of task difficulty by inserting additional concepts;
2. The concept map based knowledge assessment system with changing the degree of task difficulty by offering different tasks;
3. The intelligent tutoring system "MINIMA".

The development of the prototypes and their evaluation results allow to make the following conclusions:

- The usage of concept maps provides the development of such knowledge assessment system that assess the learner's understanding of interrelation of
knowledge units in the learning course, is not dependent of learning subject and natural language, has more simple structure and functional mechanisms, is based on manipulation of graphic objects instead of natural language processing, and can be used in any stage of assessment.

- An opportunity to change the degree of task difficulty is a useful function in the concept map based knowledge assessment system because it facilitates the further solution of the task and helps the learner to find a task which is suitable for his/her knowledge level.
- Support of two problem-solving modes and several kinds of feedback makes the intelligent tutoring system more flexible and suitable for different learners.
- The offered two-layer model of hints prevents the learner from receiving of informativeless hints and provides such hinting policy that mostly it is enough to receive only one hint in order to avoid the same mistake repeatedly and to solve the task.

Additional theoretical results acquired within the thesis are the following:

- the set of agents in the architecture of an intelligent tutoring system and their functions have been defined;
- five categories of content stored in the student model of intelligent tutoring systems have been defined;
- eight groups of terms which describe technology-based learning process and subset relationships between them have been defined;
- the definition of intelligent tutoring systems on the basis of their characteristics has been given.

The possible directions of future research are the following:

1. Implementation of the different kinds of hints relevant to the learner's actions.
2. Development of hinting methods which are based not only on a knowledge level of concept underlying a mistake but also on a knowledge level of concepts within hints.

BIBLIOGRAPHY


World Conference of the AIED Society, Kobe, Japan, 18-22 August, 1997, pp.54-60.