Computers in Human Behavior 47 (2015) 98–107

Contents lists available at ScienceDirect

Computers in Human Behavior

journal homepage: www.elsevier.com/locate/comphumbeh

Visualisation of student learning model in serious games

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ARTICLE INFO

Article history:
Available online 3 October 2014

Keywords:
Learning analytics
Data visualisation
Serious games

ABSTRACT

Application of serious games in distance learning can raise quality of education and student satisfaction on a higher level. However, when student learns through game, his focus is moved from learning domain to different context of the game. This actually enables to achieve fun and learn at the same time. But this approach also makes harder for educators to track and analyse students learning progress during game session, which is crucial in order to provide immediate feedback and to help students reach established learning goals. Such a specific learning environment requires concrete real-time analytical tool that will adequately match the dynamic game environment. This paper proposes a new tool for visualisation of student learning model during gameplay session. Tool can be used by educators and by students to track the game progress. Using this tool educators are provided with real-time tracking of students learning and it enables them to react and influence the overall learning process. Evaluation of the proposed approach was done through an empirical study, conducted on educators group monitoring an educational game session, using the combination of traditional analytic tool and the newly proposed visualisation approach. Initial quantitative results and recorded opinions of the participants speak in favour of the proposed approach and justify further investment in development of this specific learning analytics method.

1. Introduction

Application of serious games in distance learning can raise quality of education and student satisfaction on the higher level. However, when student learns through game, his focus is moved from learning domain to different context of the game. This actually enables fun and learning in the same time. But this approach also makes harder for educators to track and analyse students learning progress during game session, which is crucial in order to provide immediate feedback and to help students to reach established learning goals. Such a specific learning environment requires a specific real-time analytical tool that will adequately match the dynamic game environment.

Existing distance learning environments, such as LMS (Learning Management System) usually apply log analysis, produced by student's activities, and apply some data mining methods on them in order to discover useful patterns (Colomo-Palacios, Casado-Lumbreras, Soto-Acosta, & Misra, 2014; Jovanović, Vukićević, Milovanović, & Minović, 2012). Such approach enables post-festum learning analytics. Unfortunately, similar approach applied in the domain of educational games would not be so effective, since things are more complicated, mostly due to the complex nature of the games. While student plays the game, his focus is on the player goals and solving game puzzles, while the educator is concerned with learning goals and learning progress. Hiding learning context behind playing is what makes learning through games more fun and consequently more motivating for students.

Our research problem is how to enable teacher to track and analyse students learning progress in real-time, during the educational game session. Approach that will be presented is part of our efforts to expand learning platform produced and maintained by our team, based on the educational games development framework (Minović, Milovanović, Lazović, & Starčević, 2008). The platform provides educators with the ability to define a 2D adventure game and gives students the ability to play such a game via browser or mobile phone (Minović, Milovanović, Štavljanin, & Starčević, 2010). Students' knowledge is represented by student overlapping model (Brusilovskiy, 1994), while learning path is modelled using primitives defined in our framework. In order to provide educator with real-time feedback on students' progress, we will propose visualisation of students' knowledge by new kind of graphical representation. Using that tool, the educator will be able to track how well the student grasps the provided knowledge. Additionally,

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http://dx.doi.org/10.1016/j.chb.2014.09.005
0747-5632/

based on that information he can assess student or influence his game plan in order to support him.

In the next section we provide a brief literature review on the area of learning analytics and educational games. After that, we define problem statement, followed by models relevant to knowledge modelling in Section 4. Section 5 describes our educational game development environment from the educator's perspective. Next section presents a new approach to visualisation of students' knowledge. Section 7 is devoted to an experimental study conducted to evaluate the proposed approach. Final section is dedicated to discussion and conclusion.

2. State of the art

It is a common fact that new generation of students finds traditional methods of teaching less suitable. Our students are no longer the people that our educational system was designed to teach (Minovic, Štavljanin, & Milovanovic, 2012; Sancho, Gómez-Martín, & Fernández-Manjón, 2008) and also the formality of traditional learning materials is increasingly transforming to more popular informal approach (García-Peñalvo, Conde, Johnson, & Alier, 2013; García-Peñalvo, Johnson, Alves, Minović, & Conde-González, 2014). That is why many researchers are attempting to find a way of including student's daily activities, such as video games, into educational process (Hatton, Birchfield, & Megowan-Romanowicz, 2008; Kurniawan, 2008). It is claimed that electronic games can inspire players to explore new ideas and concepts (Hoffmann, 2009).

Games are distinguishing as a great channel for knowledge transfer. They have the ability of holding participants attention by creating an impression of fun in learning. In regard to technology advances, computer games are taking a dominant role in learning through games. For that reason we proposed and developed a software system that provided the ability of developing educational games with no need of programming skills and that provided educators a good way to integrate knowledge (Minović et al., 2008). Its upside is reusability of knowledge as well as multimedia game content (graphic, music...).

Important issue that opens in regard to educational games is finding a way of performing analytics and retrieving quality information from the learning process intertwined in a vivid, real time game environment. Learning analytics is a fast-growing area of Technology-Enhanced Learning (TEL) research. It is the use of intelligent data, learner-produced data, and analysis models to discover information and social connections, and to predict and advise on learning (Siemens & Baker, 2012). It has strong roots in a variety of fields, particularly business intelligence, web analytics, educational data mining and recommender systems (Ferguson, 2012). As Duval asserts, learning analytics focuses on collecting traces that learners leave behind and upon that, using those traces to improve learning (Duval & Verbert, 2012). There are different approaches and strategies to achieve this. Some consider how to process traces algorithmically and discover patterns (Romero & Ventura, 2007) while others attempt to visualise and exploit such information (Duval, 2011). Both strategies can be joined in order to facilitate decision-making.

Our paper considers using learning analytics in educational games for the purpose of visualizing learning information. Since this is a relatively new field, not much was done in research on this topic. Some authors propose an approach that relies on gathered data graphically presented to teacher with an extra layer that enables automatic inferring of conclusions from game-specific data (Serrano-Laguna, Torrente, Moreno-Ger, & Fernández-Manjón, 2012). Other authors try to define a general model for application of learning analytics to games, taking into account common game characteristics and therefore a basic but fundamental set of interaction traces for analysis (Serrano, Marchiori, del Blanco, Torrente, & Fernandez-Manjon, 2012). Some research directions led to application of these techniques to assessment of students' performance in educational games (Ketamo, 2012). There are also experiences that applied educational data mining techniques, such as cluster analysis of logs in order to identify learning patterns from students' play (Kerr, Chung, & Iseli, 2011).

When it comes to information visualisation, one approach focused on how visual cues could be used to support learning by, for example, increasing student motivation to work with non-mandatory content (Ahn & Brusilovsky, 2009). Building up a holistic picture of student progress and taking sentiment into account in order to enable 'computer-based systems to interact with students in emotionally supportive ways' is now seen as a real possibility (Blikstein, 2011). New tools such as the GRAPPLE Visualisation Infrastructure Service (GVIS) do not deal with just one LMS, but can extract data from different parts of a learner's Personal Learning Environment (PLE) and employ these data to support meta-cognitive skills such as self-reflection (Mazzola & Mazza, 2011). Some researchers dealt with the use of visualisation in different perspective. Instead on providing information analysis they used it as a part of the learning process or as a supportive resource for coursework (Lauer, 2006; Dicheva, Dichev, & Wang, 2005; Robling et al., 2006).

Visual analytics is a research area that draws roots from the fields of information visualisation. While purely automatic or purely visual analysis methods were developed in the last decades, the complex nature of many problems makes it indispensable to include humans at an early stage in the data analysis process. Visual analytics methods allow decision makers to combine their flexibility, creativity, and background knowledge with the enormous storage and processing capacities of today's computers to gain insight into complex problems (Keim, Mansmann, Schneidewind, & Thomas, 2010). The goal of visual analytics research is to turn the information overload into an opportunity. The specific advantage of visual analytics is that decision makers may focus their full cognitive and perceptual capabilities on the analytical process, while allowing them to apply advanced computational capabilities to augment the discovery process (Keim, Mansmann, Schneidewind, Thomas, & Ziegler, 2008).

We believe that providing educators and students with real-time visualisation tools is essential for success of educational games. With the help of analytic tools, students and instructors can better understand the learning process and take action to improve learning outcomes.

3. Problem statement

Distance learning makes education accessible to a broad audience. There is no constraint of physical presence and teacher can work with a larger group of students. Although working at a distance is convenient, such a form of knowledge exchange is usually the cause of disconnection between educator and student. Communication in person helps educators grasp the specific progress of students learning. In this case, teachers lack the visual cues that can signal when students are not sufficiently challenged, when they are bored, confused, overwhelmed or simply absent (Ferguson, 2012).

One of the most important things in running a successful educational game session is feedback on student's progress. Educator needs a tool to help him monitor learning progress for entire students group as well as for each student individually. This way, he can assess students, and based on that, moderate game session and perform corrections to the game world in real-time. This process can improve students learning experience and help them perform better and complete the game with success.

Research objective of this paper is to enable teacher to easily analyse progress of players/learners in real time in 2D adventure educational game session.

4. Relevant meta-models

Our approach to the development of educational games is inspired by the model-driven development. It uses a platform-independent base model (PIM) and one or more platform-specific models (PSM), each describing how the base model is implemented on a different platform (Obrenović & Starčević, 2004). In this way, the PIM is unaffected by the specifics of different implementation technologies (e.g., web-based LMS, game-based learning environment), and the necessity of remodelling the application or content, each time a new technology or presentation format appears, is circumvented (a virtual-reality LMS in the future, for example).

In this section we will present models related to knowledge and learning path representation, because they represent a basis for real-time learning analytics that we will propose in the upcoming section.

4.1. Knowledge model

Knowledge model provides a good basis for modelling domain knowledge and integration of knowledge within the game. Model enables manageable learning path, through the game, as well as knowledge reusability. In addition, model provides the ability of knowledge assessment and integrating that assessment in the game (Fig. 1).

Domain model represents a specific knowledge area and consists of domain concepts, which are self-related. Domain concept is a specific unit of knowledge that constitutes a building block of the knowledge area. Relation between domain concepts has two important aspects. If concept relates to other concept, then correlation attribute will have value between zero and one (one for exactly the same concept and zero for non-related concepts). Second important relation is prerequisite, which signifies concepts that must be adopted before related concept.

4.2. Game objects model

EduGameLO (Educational Game Learning Object) and EduGameAO (Educational Game Assessment Object) introduce a relation between game and knowledge (Fig. 2). One EduGameLO/EduGameAO is related with one or more domain concepts. Finally, EduGame scene consists of zero or more EduGameLO and zero or more EduGameAO. Inspiration for using the name scene came from the field of movies. As in movies, scene represents an integral set of constituting parts that are presented to the viewers as a whole. In educational games domain, scene represents a composition of learning materials and assessments, that have a specific educational purpose, but its presentation depends on many different factors. Adequate interaction with learner required from us to develop another part of our framework, targeting Game Interaction (Jovanović, Starčević, Štavljanin, & Minović, 2008).

Although learning and assessment is often overlapping, in our model we distinguish between Learning Object (LO) and Assessment Object (AO). In this way, we can achieve separated management of learning and assessment paths, as well as easier manipulation by computers. Specific nature of educational games leads us to separation of LO and AO. Another reason why we separated two groups of knowledge objects is because of the different interaction and presentation aspects that games require. This does not mean that same units of knowledge cannot be used in both these forms; they only require slightly different adaptations using transformations. In order to keep learners motivation high, game should provide a sense of achievement. Learner should be provided with a challenge adequate to current knowledge state, which is established by use of AOs. Game platforms enable implementation of Assessment Objects that are different than in classical eLearning

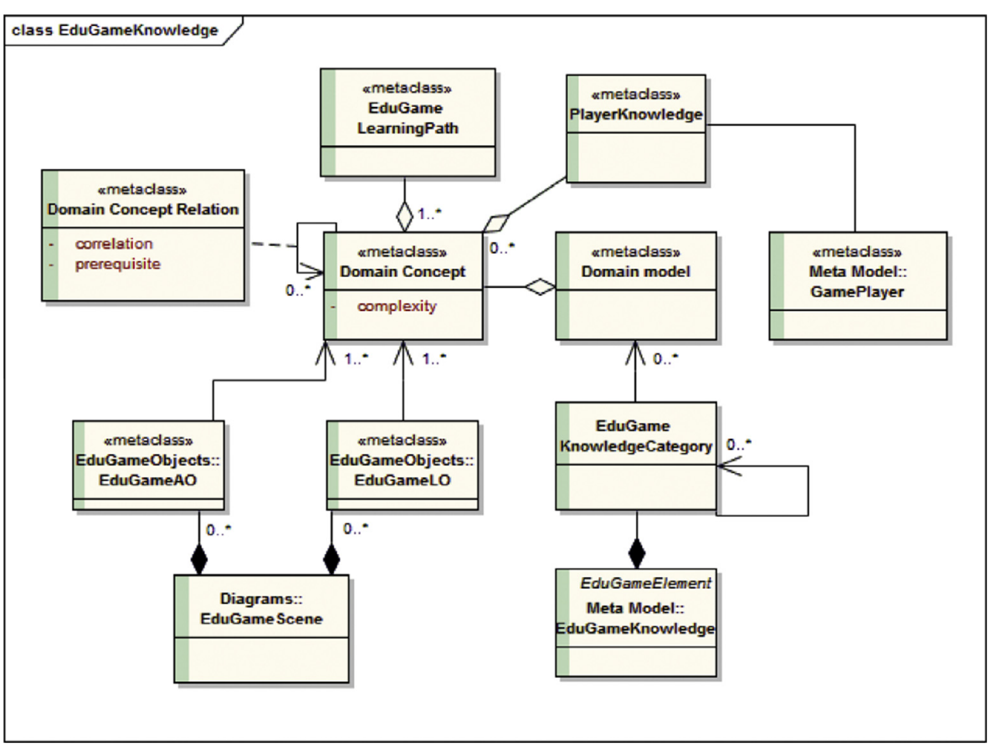

Fig. 1. Knowledge model.

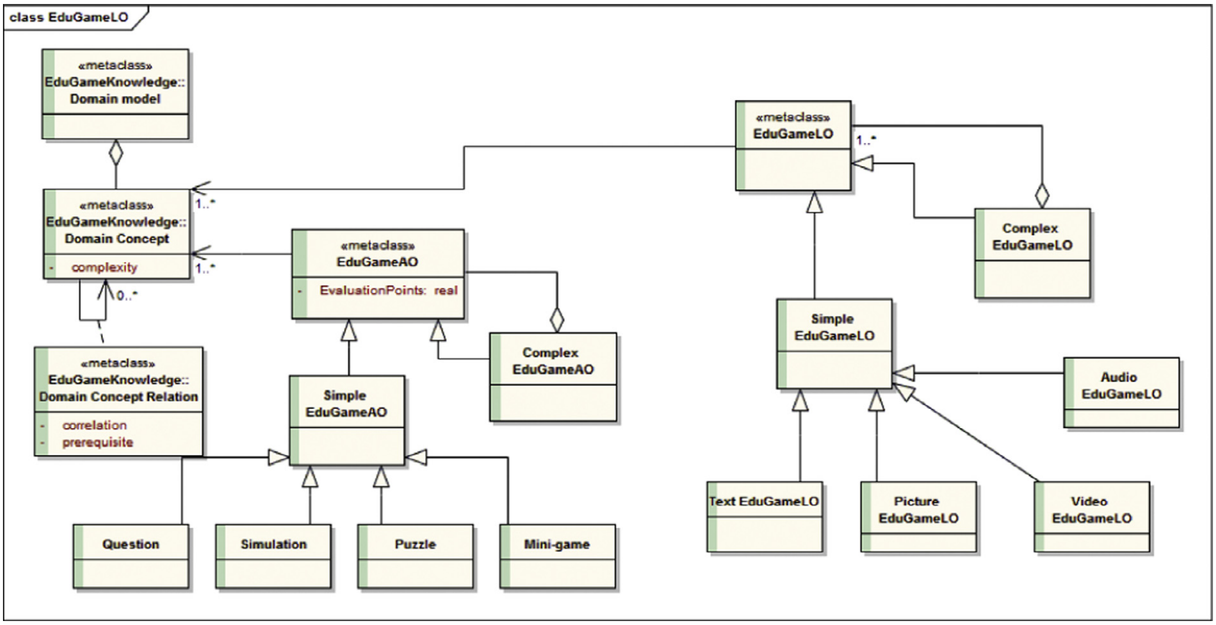

Fig. 2. Educational game objects.

(for example mini-game inside the game which will verify acquired knowledge or skills). Finally, for learner, this separation does not have to be so clear, since advanced educational games should mix these two concepts and blur the separation line between them.

4.3. Andersons taxonomy models

Bloom's taxonomy from 1956 is a classification of learning objectives within education (Bloom, Engelhart, Furst, Hill, & Krathwohl, 1956). It refers to a classification of the different objectives that educators set for students (learning objectives). It is considered to be a foundational and essential element within the education community.

In the 1990s, a former student of Bloom, Lorin Anderson with David Krathwohl, revised Bloom's taxonomy and published Bloom's revised taxonomy in 2001 (Anderson, Krathwohl, & Bloom, 2001). Anderson and Krathwohl considered creativity to be higher within the cognitive domain than evaluation.

One of the key revisions in the revised Bloom's taxonomy was the change to verbs for the actions describing each taxonomic level:

- *Remembering* – recognising, listing, describing, identifying, retrieving, naming, locating, finding.
- *Understanding* – interpreting, summarising, inferring, paraphrasing, classifying, comparing, explaining, exemplifying.
- *Applying* – implementing, carrying out, using, executing.
- *Analysing* – comparing, organising, deconstructing, attributing, outlining, finding, structuring, integrating.
- *Evaluating* – checking, hypothesising, critiquing, experimenting, judging, testing, detecting, monitoring.
- *Creating* – designing, constructing, planning, producing, inventing, devising, making.

These verbs describe many of the activities, actions, processes and objectives we undertake in our daily classroom practice. They do not address the newer objectives, processes and actions presented by the emergence and integration of Information and Communication Technologies (ICT) into the live of ourselves and our students; into our classrooms and increasingly into almost every activity we undertake.

We included Anderson's taxonomy into our development framework by creating a meta-model (Fig. 3). Classes defined by this model will be used in order to setup required assessment level for each of domain concepts. Such approach will enable learning and assessment of the same concepts on the different cognitive levels.

4.4. Learning path model

Building a UML Profile for Educational Games (Minović, Milovanović, & Starčević, 2011), based on developed meta-models, we define a new kind of activity diagram, named Learning path model. Activity element can be learning or assessment, each related to one domain concept, with cognition level defined. Using this kind of UML tool, educator can precisely define a learning path for different knowledge areas. For the purpose of explaining how such diagram can be used, we provide toy example (Fig. 4).

In the given example, student starts and advances to the first activity that includes learning of the *Protocol* concept at a cognitive level of remembering. Second activity is assessing his knowledge on the given concept. Using some of the following methods does assessment process: recognising, listing, describing, identifying, retrieving, naming, locating, and finding. If it proves he reached a cognitive level of remembering he advances. Alternatively, he is taken back to the starting point. Next activity involves learning of the TCP Protocol concept at a cognitive level of understanding. Afterwards, using some of the following methods assesses his knowledge: interpreting, summarising, inferring, paraphrasing, classifying, comparing, explaining, exemplifying. Finish is reached if the assessment proves he reached a cognitive level of understanding. Otherwise, he is returned to a starting point. By defining a learning path educator can determine an educational game flow.

Major benefit of proposed approach is that construction of educational games can be driven by "learning scenario", which actually defines domain concepts and learning path that learner should adopt. Less experienced educator can construct an

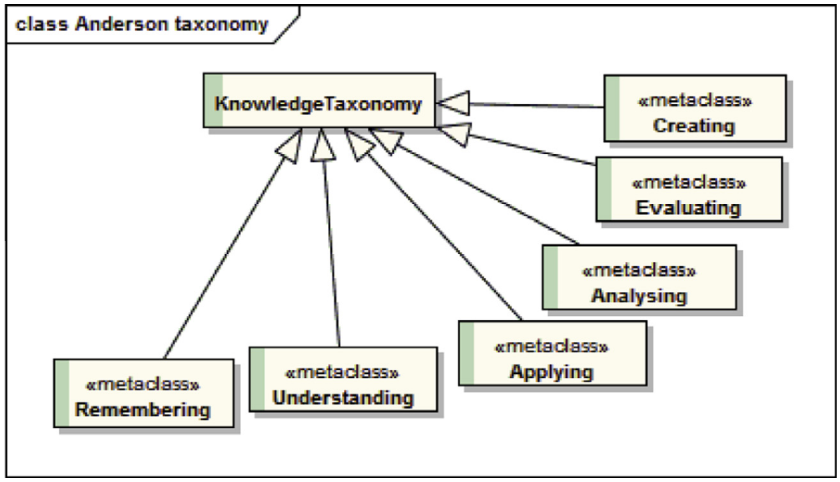

Fig. 3. Andersons taxonomy model.

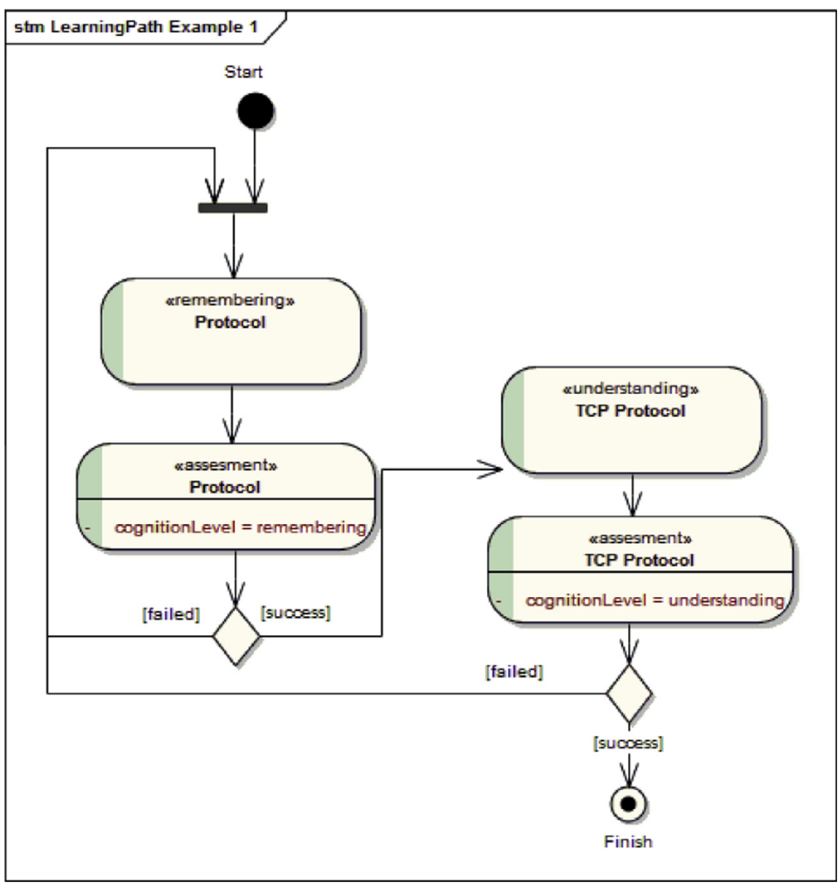

Fig. 4. Learning path example.

educational game, simply relying on the domain model developed by experts in specific knowledge area, utilizing already established relations between concepts for the given domain model.

Student knowledge was modelled according to Overlay Student Model (Brusilovskiy, 1994). Student's knowledge is presented as a set of domain concepts, that overlays expert model (domain model). Since *EduGameLearningPath* also consists from the set of domain concepts, by overlaying students knowledge (*PlayerKnowledge*) with learning path we can effectively track student's progress during learning of new concepts. Major idea of this paper is to propose how to visualise this progress in order to enable teacher to perform real-time analytics of student's progress.

5. Integrating knowledge within game

Educational game is constructed by combining knowledge with games scenario and environment. Using developed software package, game is built by educator (Minović et al., 2008). Adventures are consisted of quests that are further divided into quest steps. Player has to go through all quest steps in order to complete the quest. Game is over when all given quests are solved.

For the knowledge integration, educator defines new or reuses existing domain models. In our example its computer networks model. After that, educator uses game editor, from our development environment, in order to create new adventure game. When new quest is created, educator has to choose domain model and central (major) domain concept for the created quest. Next, for each quest step, he has to choose one or more game objects, which could be LO (Learning Object), AO (Assessment Object) or MMO (multimedia object) from the repository. He can choose only from game objects for chosen domain model and all available game objects are already related with concrete domain concepts from that domain model.

After the game is defined, educator makes it available to the students and game session can start. Second tool that educator use during the game session, described in the next section, gives educator an overview of learning progress for all active students in the game session. This way, we can expand our environment in a way to allow educators to influence the game session in order to further assess student's knowledge and help them reach learning goals.

6. Visualisation of student learning model

During the educational game session, students and educator have different goals. Students are mainly focused on the game itself, working to complete all given quests. They need the ability to track their game progress and how far are they in completing the quests. On the other side, educator is mostly concerned with the learning progress of the student group and of each student individually. Having feedback on how students are accepting knowledge is essential for a successful educational session.

Games are very dynamic, and there is a constant change in player's progress. In such conditions educators require real-time analytics on students progress. Relying on some textual or tabular reports for this purpose is inappropriate. Based on this, we can conclude that tool for learning analytics during the game session must utilize some kind of data visualisation. Such a tool must be simple, but informative.

For this purpose, we proposed a specific form of circular graph that is simple but offers key information on student's progress. There are certain similar visualisation principles as seen in *Circular View* approach (Keim, Schneidewind, & Sips, 2004). Authors also used circular diagram for visualising time-related multi-dimensional data sets. The basic idea of *Circular View* displays is to divide a circle in a number of segments, depending on the number of dimensions of the data set. Each segment is then divided in sub segments in order to visualise the distribution and changes of the time dependent data. The colour of each subarea shows the aggregated value of an attribute at a certain point in time. Colours include a green spectrum that switches to bright red after threshold value. According to the problem we are tackling our proposed diagram will retain only certain aspects of the proposed *Circular View* approach.

Our intention is to visualise only actual data values while segmentation will be used to divide the circle in to neighbouring domain concepts. The result should provide all the information educator needs. Representation of the state of the learning progress for one student, or for the whole group, will be based on specific visualisation of student overlapping model (Fig. 5). Same visualisation principle can be used for presenting players progress through the adventure and discovered quests.

6.1. Centre of the circle

In the centre of the circle is one domain concept. There is an overall percentage of learning progress and adequate colour representation. Overall progress percentage is affected by learning progress for the current concept and by the progress of all neighbouring concepts. Since neighbouring concepts are also affected by their neighbouring concepts, by simply looking at one circle graph we can gather the info on overall progress over the entire knowledge domain model. Colours are going from red to green, in gradient (0–100% respectfully). Switch from red to green occurs when a defined minimal level for passing is reached (for example, over 50%). Centre of the circle always represents an average number and gives an overall presentation of students progress.

6.2. First-level ring

There is a learning progress scale at the inner ring of the circle, based on Anderson's taxonomy model. In order to make it easier to find out students progress, only levels included in concrete learning path are shown, but rings with more levels use richer colour palette. At the beginning, this ring is without any colour. As student progresses through the learning path, this ring is filled in the clockwise direction. On the way, student interacts with Learning Objects and Assessment Objects that are set at different cognitive levels. All interactions with LOs and results of AOs are taken into consideration for calculating progress regarding the given domain concept.

6.3. Second-level ring

At the outer ring of the circle stands a first-line relation domain concept or major quest concepts for the student. Percentage number represents a value of learning progress, calculated on the basis of students advantage through his learning path (for one student or an average for the group of students), using the same formula described for the centre of the circle. This way their progress is influenced by progress over all their neighbouring concepts.

6.4. Third-level ring

Final ring shows again progress on the Andersons scale, but now for each one of the neighbour domain concepts, given on the previous ring level. This scale is progressive, which visually implies that higher cognition levels are more significant.

This way, just one glance on the diagram gives to educator information about overall learning progress of the students for the current game session (Fig. 5). In this example, total progress on *Network protocols* is 69% (influenced also by progress of all other concepts in domain model) and its still red which implicate that student did not pass all required assessments, even if three related concepts are green.

This progress can be calculated using a simple mathematical model (Eq. (1)). In this case, *DomainConceptProgress* is a progress determined for a main domain concept, *ConnectingDommainConcept Progress* is a progress of each connected domain concept. In this case n is the number of connected domain concepts while x and y are weighting coefficients for each equation segments. These coefficients can be reached analytically or can be set by experienced educator.

$$x \cdot DomainConceptProgress + y \cdot \frac{\sum_{i=1}^{n} ConnectingDommainConcept_i}{n} \qquad (1)$$

Equation 1. Mathematical model for determining progress on a specific domain concept.

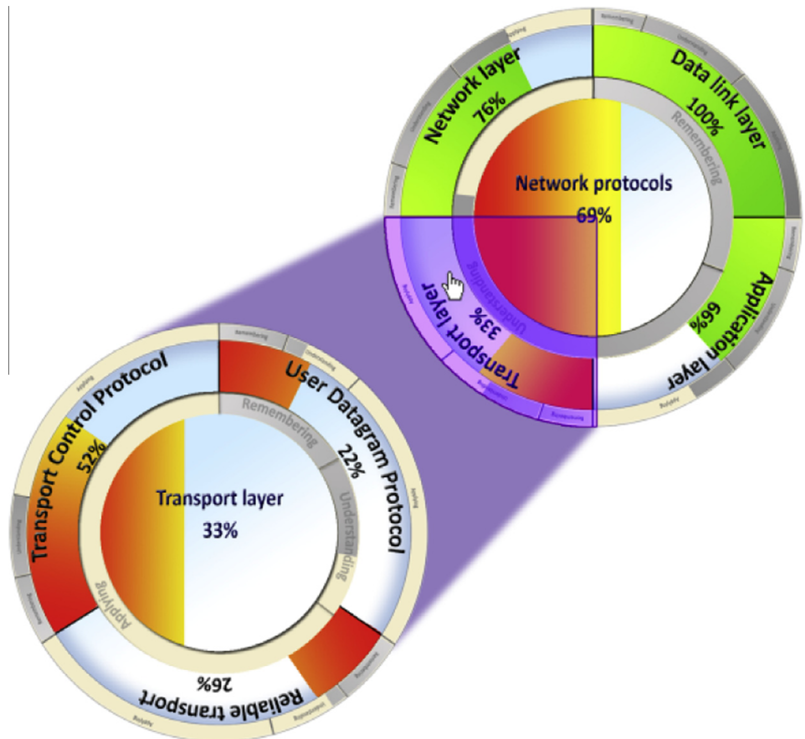

Fig. 5. Visualisation of student knowledge.

On the first ring we can see progress on the Anderson's scale. This student remembered the concept and also understanding is on the high level.

In order to find out what are problematic concepts for the student, educator can gather more detail information by expanding each circle section. In the example given on Fig. 5, educator retrieves information on concepts related with transport layer (coloured red[2]). By doing this, one can expand the entire student model. For the purpose of easier navigation, mouse click on the circle centre will zoom-in and expand all concepts around, while click on the concrete concept will expand to one more node, with selected concept in the centre.

Same visualisation technique can be used on the player side (Fig. 6), in order to give a player fast feedback about the game progress. Circle is positioned in the lower-left corner of the screen, with player profile picture in the middle. Progress through the quests is provided in the surrounding ring sections. This could be a step toward utilizing open student model approach (Alkhalifa, 2009).

7. Experimental study

Visualisation can contribute to many aspects of the analytical process. Nevertheless, it is difficult to determine in what extent this contribution can be of positive nature, especially in regard to a concrete mode of application. Visualisation approach can affect many roles in learning process. In our setting highest effect is expected with the educators using the proposed tools.

In order to measure the effects of the proposed visualisation approach one can rely on two measures. One being the impact on student progress while the other can be seen in educator's increase of ability to better grasp the students' comprehension of the given material. Our goal is to determine whether the proposed approach provides good improvement of the analytical process as well as to discover it had positive effects on educators. We decided to approach this problem using a simulation method that should provide objective evaluation of educators' abilities to target upcoming learning issues with the help of the proposed tool. Additionally, educators' impressions on the proposed tool will be interrogated through interview. The complete evaluation approach can be regarded as a combination of two established approaches, HCI (Human Compute Interaction) based (expert evaluation) and measuring insight (Van Wijk, 2013).

7.1. Experimental settings

Visual analytics has a broad scope and aims at knowledge discovery, evaluating the methods used in this field is challenging (Van Wijk, 2013). In order to interrogate the effectiveness of the proposed visualisation approach we conducted an experimental study that involved a group of 6 educators monitoring one learning game session for 20 students. The experiment was performed in two stages.

Initially, the group of students played 15 min of educational role playing adventure game whose purpose was to teach them basic concepts of computer network Protocol stack. The specific learning path was designed that covered the introduction to several connected domain concepts such as transport layer, application layer, and data-link layer. During the execution of the game, students were interacting with non-playing characters and were given small quizzes in order to advance through the game. Student's actions and quiz choices were logged. Based on the gathered data from this session, analysis was done, learning problems were identified (such as specific student is trailing behind, domain concept is too difficult, or group is imbalanced) and an effort was made in order to develop a simulator that will replicate the entire learning game session.

[2] For interpretation of colour in Fig. 5, the reader is referred to the web version of this article.

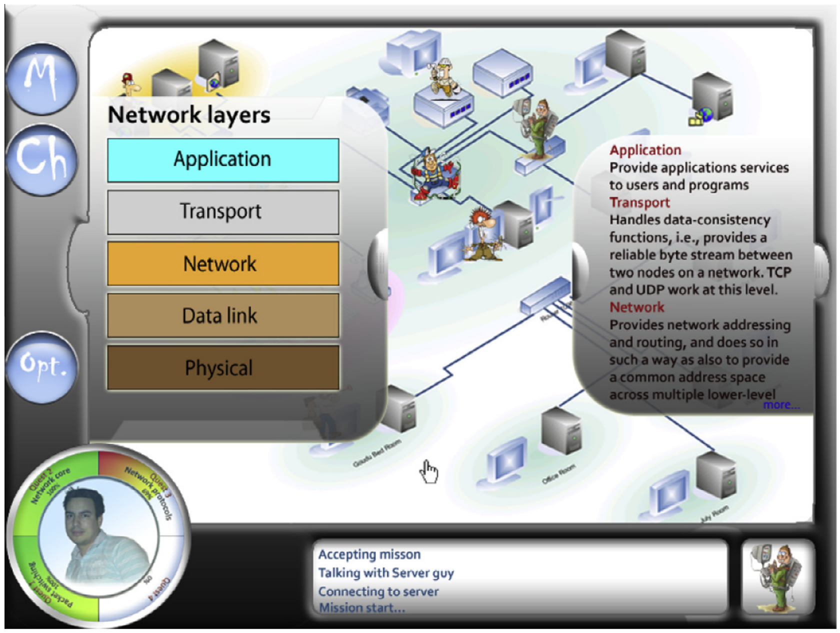

Fig. 6. Computer networks adventure game (player perspective).

This was done in order to create a controlled scenario that will be used for evaluation of the learning analytics tool. In the next stage, 6 educators were asked to monitor students 15 min learning game session that was reinterpreted using a developed simulator. Educators were unaware of the fact they were monitoring the outputs of a simulator. Since the research team identified problems that occurred, we set out to determine whether educators will also be able to identify the same problems. Additionally, we were able to draw a conclusion whether new visualisation approach helped in the decision making process.

After the study, a guided interview was performed with the participating educators in order to gather the qualitative information about user experience.

Educators had the ability of using a combined set of tools for monitoring the students learning game session.

First tool was a report in a table form that provided information on the individual and average success of students in evaluation segments of the game. This tool was created using the same structure and data usually provided in popular LMS tools, such as Moodle, for analysing student's activities.

Second tool provided was the proposed visual learning analytics tool that provided insight in to individual progress of each student, including the level of comprehension of each domain concept. Additionally, tracking groups' progress on the learning path was enabled through visual graph showing average progress for each domain concept.

Educators were asked to record the time they identify the problem, indicate which tool helped them in the process. Also, they were asked to determine the cause of the identified problem and indicate which tool was used in this case. Additionally, they were asked to identify whether the problem is due to a problem concerning individual student, group of students, specific domain concept or other.

7.2. Experiment results and discussion

The simulated learning session had 4 simulated problems that were identified through analysis. As seen in Table 1 average rate of the entire group of educator in identifying these problems was at 79%, while some educators were able to identify all problems. In this case the dominant tool used was tabular reporting with the share of 72%. This fact can be attributed to one major downside of the proposed visualisation tool that was pointed out by most of the educators during the interview. They claimed that the tool lacks in combine group/individual view that was more common for tabular reporting. This is one important aspect for further development.

When it comes to determining the cause of the arisen problems educators reached an average success rate of 71%. Slightly lower rate than in problem identification can be expected due to a higher complexity of the issue at hand. In this case, educators relied on a newly proposed visual analytic tool, at an average of 88%. The specific approach, that gives in depth view of the student's progress by visually appealing and comprehensive manner stood out in this scenario.

When it comes to qualitative information that was drawn from the interview portion of the experiment, the general impressions of educators are highly positive. Educators pointed out that they feel that the tool provides good basis for tracking of individual student's progress. The graphical model was marked as satisfying and easy to interpret. The participants stated that it is easy to detect when there is a certain misbalance in hardness of domain concepts.

The majority of the participants also found the graphic model of the visualisation tool appealing. They stated that interpretation is easy and that comprehension is possible without detailed user instructions. All participants claimed that it is much easier to track student's progress visually than by relying on tabular reports. Overall opinion stated by participants is that they would venture out on using this tool in their future lectures.

Participants have also provided some valuable information on possible improvements of the tool and evident shortcomings. Three participants indicated that it would be very helpful to include some comparative view on progress between domain concepts regarding the entire group. Also they stated that current representation of the fulfilment levels set by Anderson's taxonomy (Anderson et al., 2001) requires some effort to notice and track. Finally, an occurring change in state should be more emphasized in the visual analytic tool.

Table 1
Tabular results from the experimental study.

Educators	Number of identified problems	Number of correctly identified problems	Success percentage (%)	Percentage tool is used for successful problem identification (%)		Number of determined problem causes	Number of correctly determined problem causes	Success percentage (%)	Percentage tool is used for a successful determination of problem cause identification (%)	
				Table report	Visual LA				Table report	Visual LA
Educator 1	4	2	50	50	50	1	1	25	0	100
Educator 2	7	3	75	33	67	3	3	75	0	100
Educator 3	3	3	75	100	0	2	2	50	50	50
Educator 4	7	4	100	100	0	4	4	100	25	75
Educator 5	10	4	100	100	0	4	4	100	0	100
Educator 6	6	3	75	50	50	3	3	75	0	100
Number of simulated problems: 4		Group average	79	72	28			71	13	88

8. Conclusion

Focus of this paper was on the problem of real-time learning analytics during active educational game session. Our approach is based on combination of specific educational game development platform with specially designed data visualisation for tracking of students learning progress. This new form of diagram is introduced in order to visualise student-overlapping model. Same model can be used on student groups as well as for analysing individual students. Diagram construction provides additional ability to inform player on his game progress.

Introducing such analytic tool enables educators much better involvement into game session. Based on the information retrieved with this tool, educator can actively influence game activities in order to improve students learning outcomes. For example, educator can use the information to give hints to students or interact with them in certain manner. One of the choices can be manipulating with students learning path in order to improve knowledge adoption. Also, educator might decide to increase the hardness level to challenge high performing students or to make manual assessment of their progress to higher levels of cognition by Anderson's taxonomy.

In order to test our visualisation approach we conducted an experimental study. The study involved 6 educators monitoring a learning game session involving 20 students. The quantitative results indicated that new visualisation tool helped in identifying and solving learning problems in most of the cases. Interview responses from our participants indicated high level of appeal of our tool. Participants stated that the tool gives good insight in to each student learning process as well as good foundation for tracking groups' progress. Additionally, interview responses provided substantial feedback in helping future development.

In future work significant effort must be invested in simulation of game progress through a specific domain model. Simulation would provide educators with a specific view on dynamics of student's model development. Additionally, inclusion of open student model would be a major benefit. It would provide student with the option of visualising its learning progress in greater detail in order to foster better self-regulation and self-motivation.

Acknowledgements

This research is partially funded by grants from the Serbian Ministry of Education and Science, contract nos. TR 32013 and EU funded, Lifelong Learning Programme, PROJECT NUMBER-519141-LLP-1-2011-1-ES-KA3-KA3MP.

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