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The Effectiveness of An Adaptive Serious Game for Digital Logic Design

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ABSTRACT

Most students benefit more deeply from guided learning than discovery learning. Even so, not all students are alike. Our research contention is that offering differentiated instructions that better fit students' educational needs in a narrative virtual reality (VR) environment will give them renewed hope for learning success. This paper presents such a development that augments an existing learning game, *Gridlock*, with an adaptive learning engine that assesses what really happens when a student's capacity is sabotaged in problem solving and to provide the help that is tailored to his/her needs. The game was deployed in *Computer Architecture* course at Rowan as a replacement to the traditional laboratory experiments. Its thorough assessment confirms the values of the game in promoting student learning.

INTRODUCTION

The fundamental problem with the traditional single-instructor class structure is that a singular teaching method is not always universally effective; not all students learn information the same way, nor do they each require the same amount of instruction. Some students are highly motivated and benefit most from the approach that gives them more freedom and opportunity to discover a realm of knowledge on their own. Others prefer coaching along with a more structured approach, with direct instruction from their educator. The so-called "just-in-time" instructional model has proven effective in understanding the individual or small group needs (Gremmels and Campbell 2013). However, even with this knowledge, instructors are often faced with limited resources and time limitations required to provide the level of support needed for small groups in large class sizes (Donnelly 2014).

For the past few years technological advances have sought to help in the students' instruction, so that educators can focus more on the material and the students who need more individual attention. Intelligent Tutoring Systems (ITS) are such systems that provide instructions to users of the learning system with little to no intervention from the instructor. The major goal of all ITS is to supplement or replace a human tutor's interaction with the student, sharing the responsibility with instructors for the type of modeling, coaching and scaffolding needed for guided learning. Typically, ITS systems seek to identify a student's strengths and weaknesses, offering help where needed either during questioning or after. Popular ITS systems such as Autotutor (S. D'mello and A. Graesser, 2012) have proven to be highly effective for individual students; however they rely on the user's ability to seek help on their own. In many cases, a student may be unaware of the help they need and may not even know where to start. Additionally, the reliance of many ITS systems on offering hints for questions often results in careless behavior from students, simply using all hints until the answer is simple to solve. This results in shallow learning, a criticism that has been mirrored by many studies (Pedro *et al*., 2014; Baker *et al*., 2012). Thus, rather than allow the student to guide their own learning path, it is advantageous to understand what help they need by studying the student's behavior.

The strengths of an Intelligent Tutor System as a teaching tool are obvious; however they do not serve to solve student engagement issues (Lucas, 2012). An additional structural layer is required if the strengths of intelligent tutor systems are to be leveraged, such as those offered by narrative based virtual environments. Narrative based virtual environments are environments inside of computer systems which create a story for the user to follow; ultimately inviting the player to become engaged in it. Due to the virtual environments unparalleled ability to interact with the player, using such a system to create a situation where the player will learn information has been done on many occasions (Pivec and Pivec, 2011). The topic has become increasingly discussed and popularized under the umbrella term “Serious Games,” or games that are meant to serve for educational purposes. There have been extensive successes related to the use of narrative based virtual environments as an engagement tool, such as the Crystal Island Learning Environment, developed at North Carolina State University (Sabourin and Lester, 2013). Research has shown that narrative games, attempting to combine realistic simulations of real-world phenomena with the motivational and goal-based features of commercial video games, provide better player engagement for all practical purposes and open-ended problems (Iacovides, 2009).

Given the obvious strengths of both ITS and “Serious Games,” there have been attempts at integrating popular ITS tools with game engines (Ray and Gilbert, 2013). However, there is still a conspicuous absence of both rigorous evaluations and metacognitive interventions for learning in those developments. Solving of domain problems is important, but the mere solving is unlikely to lead to improved skills or deeper understanding of subject matter (Anohina, 2007). Learning often takes place best when the learner is actively involved in the cognitive processes of problem solving and receives feedback from the system on how to be more metacognitively adept. Therefore, the merger of intelligent metacognitive tutoring with experiential and narrative-based learning games can augment the current attempts and open a new venue for personalized learning. This paper discusses such a development, where an existing game with three already in-place metacognitive strategies is leveraged to (1) automatically assess a learner’s domain knowledge levels through the use of probes, error and timing analysis; (2) systematically reason and infer the learner’s potential difficulties with problem-solving through the use of the a k-nearest neighbor (*k*NN) classifier; and (3) responsively provide explicit or in situ support that is precisely tailored to individual learners' needs. The evaluation of the game deployment in *Computer Architecture* course at Rowan University is presented to answer the research question as for how and to what extent interactions between learners and personalized instructional support within the narrative game modulate students’ cognitive and metacognitive processes of learning.

MOTIVATION

Gridlock is one of many serious games developed under the umbrella title of *Sustain City* (Tang. *et al.*, 2012a; Christopher *et al*., 2014a), a series of games that teach topics ranging from sustainable energies (Tang. *et al.*, 2012a) to thermodynamics (Christopher *et al*., 2014b). Aimed at entry-level engineering students, *Gridlock* offers an interactive, engaging educational experience that not only introduces digital logic topics but also leverages popular design tools such as *ModelSim* and *Multisim,* providing real-world relevance.

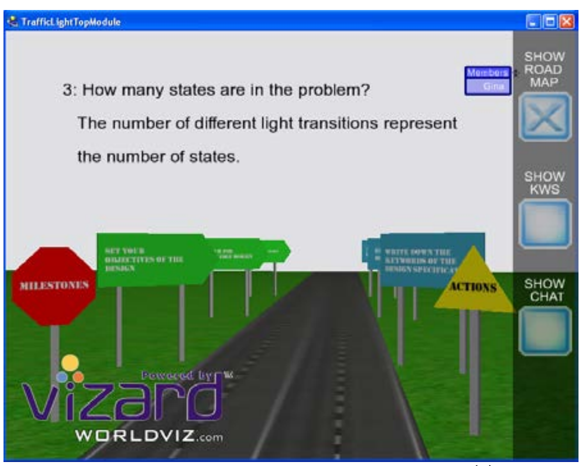
Designed from a first-person perspective, the game starts with a prologue narrative as shown in Fig. 1 (a) where an engineer character, Jack, witnesses a traffic accident at the major intersection of a town and then invites a player to help him fix the faulty traffic light system with the right logic specified in Fig. 1 (b). Rather than rely on dry instructional prompts, the game introduces the player to an artificial intelligence (AI) that guides him/her through the actions necessary to repair the logic circuit. Meantime, the AI presents learning roadmap to the player, one of the metacognitive interventions in the game to show the key milestones and actions that might be taken in the design process as seen in Fig. 2 (a). While the player walks through the map and advances from one stage to another, the AI asks the player a number of questions closely tied to the problem-solving stages, helping him/her synthesize the design ideas in a 3-column *What do I **K**now, What do I **W**ant to Know, and What have I **S**olved* (KWS) datasheet, another metacognitive intervention as seen in Fig. 2(b). Once the player finishes the design for testing, he can navigate to an in-game representation of a traffic intersection, and load the design files exported from his chosen design program. The file is parsed and the scene runs to properly reflect the student's logic circuit. If the design is a success, the lights change as expected and the cars do not crash, otherwise an accident may occur, forcing the student back to the design room to try again.

(a)

The sequence of lights switching per 5 clock cycles and starting at the Red-Red reset stage	
Side str. Light	**Main str. Light**
Red	Red
Green	Red
Yellow	Red
Red	Red
Red	Green
Red	Yellow

(b)

Fig. 1: (a) The street intersection and the narrative; (b) The light switch logic (inputs are highlighted in red and outputs in blue)



(a)

(b)

Fig. 2: (a) Sample learning roadmap in *Gridlock*; (b) Sample KWS in *Gridlock*

In the initial run of *Gridlock*, help was provided in a way that required students to actively seek answers to their problems. Although there were mechanics to allow students self-reflecting their level of proficiency, there was no connection between the learning roadmap and the identified student needs in *KWS*. When surveying students on the utility and usability of game interventions, they voiced their different views of system improvement. Some felt that the current support was just right to provide necessary assistance in identifying domain knowledge as "*(KWS)* concisely pointed you in the right direction", *and "(Roadmap) contained volumes of information that covered everything (it seems) that I would ever need to create a basic sequential circuit*". Others considered the expert guidance could be more detailed with additional coaching as "*directing me to the key ideas is good but not sufficient as I learn better by examples*". The students' responses clearly ratify that every pupil has their own needs and their own particular way of learning. If there were a way in which our game system can understand such differences and provide support accordingly, the resulting system could be more efficient and effective in promoting successful learning. The adaptive game that we discuss in the next section will be used to address solution feasibility to this critically important challenge: personalized learning.

OVERVIEW OF THE *k*NN-BASED *GRIDLOCK*

The challenge of understanding students' domain knowledge and mapping it to differentiated coaching is that the data to do so is not readily available and can only be obtained through observation of the learning process itself. Therefore, any attempt towards developing an accurate mapping solution, which is part of our work focus, must involve some algorithmic components that will allow the decision making process to (1) accumulate its past experience to a pertinently defined set of data structures, and at the same time, (2) exploit the "knowledge" captured in the data set towards improving the overall system performance. The idea is implemented using a kNN-based close-loop control as depicted in Fig. 3. The proposed system incorporates classification and feedback into the existing *Gridlock* game. In particular, the game partitions the entire design procedure into three major problem-solving steps, which are the problem statement comprehension, state machine design and state table design. At each milestone, the player is prompted with a series of questions that are closely tied to the goal, knowledge and facts of the specific problem-solving stage. Rather than score the student on overall performance, there are subset grades that indicate proficiency within each of the smaller topics. These values then provide specific insight into the strengths and weaknesses of the student. Instead of offering hints or self-guided discovery, the system then provides the student with the exact sections of help that best fit their needs. Here, we briefly explain each module of the adaptive system, but refer readers to (Johnson *et al.*, 2014] for the technical detail.

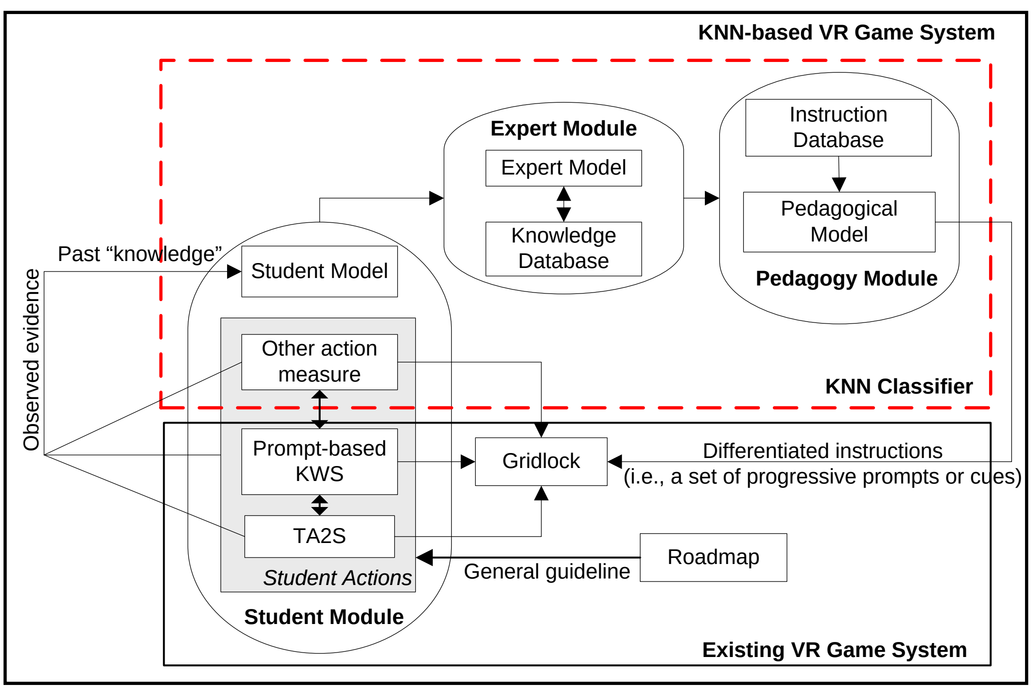


Fig. 3: The system architecture of the KNN-based VR game system

As shown in Fig. 3, the adaptive game system consists of three interactive modules: *Student Module*, *Expert Module*, and *Pedagogy Module*. The *Student Module* is responsible for the timeliness of system knowledge of the student reflected in the student model. In this module, the game system provides three different measures to capture student actions in game. Besides the prompt-based KWS to track student answers to prompted questions and Think-Aloud-Share-Solve (TA2S) (Tang *et al*., 2012b) training for student on-line communications, an additional measure is added in this version to gather information, such as the time spent on individual tasks, student frustration on task, and the frequency of reviewing a specific help documentation. Students' responses to those assessment queries then serve as observed evidence that is kept in the *student model* and will be accumulated as the prior knowledge for future decision-making. The constant updates on the *student model* whenever new observed evidence on student actions is obtained from the game system helps to bring the maintained value estimates closer to the ones corresponding to the observed student behavior.

The expert module is responsible for the classification, where the *expert model* serves as the actual classifier and the *knowledge database* contains all of the training data. The traditional expert module requires a student be on one of the known paths to the solution and for the computer to predict which path the student is on based on student actions in the system. This process requires all solution paths known *a prior* and mapped out, which can be very cumbersome with the increasing complexity of the problem to be solved. For this purpose, our expert model is not to determine the exact path the student is on, but to determine if the student has enough knowledge to complete a task in the future assignment. We model it as a classification problem. As stated earlier, the data used for the classification includes student answers to question prompts on the topic, the time spent to complete the questions, the frequency of student seeking a specific help document, student frustration, and the student's classification in the previous game stage. While classification is done at each game stage, the results from the final game stage will be used to update the *knowledge database*.

The pedagogy module consists of two components. The *instruction database* contains all of the instructional support that students may need to solve the problems presented in the environment, and the *pedagogy model* provides specific cues to a student according to his/her classification.

Implementation and Assessment

Gridlock, with the inclusion of the *k*NN system, was originally piloted in the fall of 2013 within the Computer Architecture course. Additionally, a follow-up trial was conducted in the spring of 2014 which was, again, for the Computer Architecture course. Each of the trials consisted of two separate groups, the treatment group that played *Gridlock* and the control one that did not. These groups were not chosen in any specific way; rather they were composed of students within two separate class sections taught by the same instructor, with the same textbook, and the same course material. A pre-test and a post-test were designed that ask each student to draw a sate diagram and Verilog description of a given sequential circuit, each part worthy of 10 points, for a total of 20 points. In the pre-test, the circuit is related to traffic light control logic, while the one in the post-test is for a vending machine design. Selecting a different context ensures that the students are engaging in deep learning and not simply reciting the knowledge gained by working with a traffic light control system.

In Fall 2013, twenty-two students in the treatment group took the pre-test one week prior to playing Adaptive Gridlock and the post-test two weeks after using the game. The average pre-test score was 14.10. The post-test showed an overall improvement, shifting the average score to

16.41. Out of the total 22 students in the treatment group, 15 of them (68%) showed improvement on the assessment. However, the distribution of gain scores was highly skewed (2.94) because two students made dramatic gains (400%) over very low pretest scores. Dropping those outliers from the data set, the sample size of 20 students yields an adjusted pre-test average of 15.25 and a post-test average of 16.80. Regardless of the change, the difference is still significant (paired t-test with 19 df=2.82, p=.011). The effect size was calculated to be 0.53, showing that the increase after use of Adaptive Gridlock amounted to approximately half of the pooled standard deviation.

Due to the logistic reason, the control group did not take the pre-test. Their post-test scores were significantly lower than the treatment group, with the average of 12.58 in comparison to 16.80 for the treatment group. The difference was found to be significant (independent groups t-test for 44 df = 2.97, p=.005) and amounted to an effect size (Cohen's d) for the treatment group of .9 of the pooled standard deviation. However, because no pre-test was supplied to the control group, no comment can be made regarding whether this improvement is due to adaptive *Gridlock* or some other factors (e.g., the control group might have had a substantial disadvantage going into the pilot).

The initial trial failed to provide any pre-test data for the control group, meaning that, although the average grades between the class sessions can be compared, little is known about the gains provided by *Gridlock*. The follow-up trial in the spring of 2014 included a pre-test for both control and treatment groups. The first trial indicated that 68% of students were able to increase their grades between pre and post-tests, although this is mirrored in the second trial (66.6%), the control group is also shown to have a similar number of students finding gains (64.3%) and is thus not a significant indicator. When viewing performance increases between the groups as shown in Table 1, however, results continue to indicate that *Gridlock* has a significant effect on the student's grades. The pre-test for the experimental group averaged a 76.73. When compared to the post-test score (93.11), the *Gridlock* section showed significant gains (repeated measures t=2.50, p<.05). The non-*Gridlock* section, however, showed an increase of only 10 points (from 48.81 to 58.79) which was not significant. Additionally, the *Gridlock* student's grades were significantly higher than the control class (two-sample t=3.72, p<.001). It should be noted that the control class had a far lower pre-test score, averaging 0.82 of the pooled standard deviation below the *Gridlock* group. It is possible that the comparison students lacked important pre-skills that would have allowed them to take advantage of the game and to earn higher grades. However, there is no evidence that the initial low performance influenced the instructors' grading. Low pretest scores were not in themselves a predictor of students' grades (F[1,31]=1.45, p=.24).

CONCLUSION

This paper discusses an approach that augments an existing serious game, *Gridlock*, with a metacognitive intelligent tutor to offer personalized learning experiences. The assessment of its deployment in two target courses provided promising results - *Gridlock* has had a significant effect on student's learning, resulting in higher grades for a majority of the student sample. The evaluation data also indicated that more investigation is needed to both verify the system's effectiveness as well as its performance. The insights gained through the study reinforce the concepts put forth by the team and may suggest that the system be brought to other serious games in the future.

Table 1: Survey results for Computer Architecture in spring 2014

Group	Grade%	Pre	Post	Change
Non-game Mean	70.43	48.81	58.79	13.73
SD	11.62	35.20	35.89	33.84
N	14	13	14	13
Gridlock mean	84.55	76.73	93.11	16.82
SD	10.37	28.94	6.33	29.35
N	20	20	19	19
Total mean	78.74	65.73	78.55	15.56
SD	12.84	33.96	29.03	30.76
N	34	33	33	32

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