Adding Features of Educational Games for Teaching Physics

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Abstract - **Virtual Laboratories (VLs) have to overcome important challenges to improve student knowledge, understanding and motivation. This research aims to test the hypothesis that, through adding features of serious games to VLs and integrating artificial intelligence (AI) techniques, an enhancement of student motivation, knowledge and understanding can be attained. This work introduces the Olympia architecture, which is based on a previous architecture that combines VLs and intelligent tutoring systems (ITSs). In addition, Olympia enables the combination of serious games with ITSs, resulting in an educational game virtual laboratory (GVL). The GVL provides affective feedback through sound, a more engaging look-and-feel and defines student actions through the game mechanics module. Olympia was tested in a case study on teaching linear momentum in an undergraduate Physics course. For the first evaluation, a VL and a GVL were implemented. The results showed that students were motivated and learned in a similar way with both the GVL and VL environments. Later, several additions were integrated in both environments: the probabilistic student model was improved, tutorial videos were added, and the feedback was refined. For the second evaluation the results suggest that using the GVL resulted in higher learning gains than using VL.**

Index Terms - Active simulators, Educational Games, Teaching Physics, Virtual Laboratories, Olympia Architecture.

INTRODUCTION

Usually students tend to learn Physics as a group of disjoint concepts. Very often students do not understand and are not encouraged to understand the coherent structure underpinning Physics. The authors of this work believe that it is the lack of this understanding that makes Physics traditionally "difficult" and decreases the level of student confidence. Virtual laboratories (VLs) have the potential to provide significantly enhanced and more effective learning experiences. VLs can facilitate deep learning in model-based knowledge domains (e.g. Physics) and can enable learning, without most of the overhead inherent in traditional lab experiments. Virtual labs are simulations—mathematical models implemented on a computer [1].

VLs based on simulation enable students to link objects and events of a virtual learning environment (VLE) with concepts and phenomena of the real world. Students need to explore different parameters to observe their effects. However, in an open learning environment it is difficult to infer the acquisition of student knowledge. Specific objectives are needed to attain and enable an effective assessment of the learning goals. On the other hand, it is agreed that positive effects in student motivation for learning are obtained by enhancing human computer interaction (HCI), which result in an enhanced acquisition of student's knowledge and understanding. Virtual Laboratories (VLs) have challenges to overcome such as the objective of attaining student understanding and motivation while learning. Educational games easily obtain student attention. Research in the field suggests that this phenomenon is the result of an emotional link established between the game and the learner. The emotional link is due to the combination of multiple features and sources, such as graphics and sounds, which enable a high level of interactivity. However, educational games must still ensure that the student is gaining knowledge in a specific domain while learning to play the game successfully [2].

In Noguez et al. [3] a generic architecture that combined VLs with intelligent tutoring systems (ITSs) was introduced. Later, in Sucar & Noguez [4] the same architecture was refined. This architecture has proven to be effective for teaching robotics and other courses at undergraduate level. This research focused on enhancing the generic architecture in Noguez et al. [3] to include features and elements from the architectures of commercial and educational games [5]-[7]. The result of the addition of these features is the Olympia architecture. The student model is a probabilistic relational model that infers the student cognitive state through student interaction with the system. Probabilistic relational models (PRM's) provide a new approach to modeling and integrating the expressive power of Bayesian networks and the facilities of relational models. They allow the domain to be represented in terms of their entities, properties, and relationships [8]. Initially, the architecture in Noguez et al. [3] only combined VLs with ITSs, and was therefore adapted to also enable the combination of serious

games with ITSs. Therefore, Olympia enables a virtual learning environment to attain the level of interactivity offered by an educational game. It is inferred that an enhancement in the human computer interaction can increase student motivation for learning, which can improve student understanding. In the next section we comment about recent works related to ours. We then describe in detail the Olympia architecture. The following section describes the methodology employed, including the problem selection, the learning environment, and a subsection devoted to inferring knowledge from the user interaction. We then present a case study aimed to evaluate the Olympia and finally we summarize our main conclusions.

RELATED WORK

An innovative era of learning and delivering instruction arose at the beginning of 2000. The ultimate goals have been to make training, teaching and learning processes more effective, interesting, personalized, interactive and accessible [9]. As can be seen from the work of Conati [2], D'Mello et al. [10] and Sucar & Noguez [4], virtual learning environments (VLEs) and educational games have proven to be effective. However, there are still challenges to overcome in both areas. Research work in Williams [11] seeks the enhancement of educational games through the addition of subliminal messages that encourage the study of Science. Conati [2] and D'Mello et al. [10] are working towards the enhancement of intelligent tutoring systems through the recognition and generation of emotions during teaching and learning. The aim has been finding the most effective way of responding to student actions and enhancing student understanding accordingly.

Oblinger [12] described the impact that information technology (IT) has had on learners. Student attitudes and aptitudes have evolved to adapt to IT and applications with high media content changing their expectations. Also, it was observed that the generation of students between 18 and 22 years old had the tendency of being experiential learners and community-oriented [12]. VLEs and educational games arose to make the teaching, training and learning processes more engaging, interactive and effective.

Educational games easily engage the student. However, it is difficult to ensure that the student is focusing on the knowledge domain while learning to play successfully [2]. VLEs have had more difficulty attaining the student motivation, although VLEs have proven to be effective at enabling the student to understand the knowledge domain. Research has suggested that the success of educational games is due to an emotional link established between the game and the learner [5]. Sykes [13] notes that the emotional link is established through the high level of interactivity offered by educational games, since the high level of interactivity results in the delivery of immediate feedback on student actions. While comparing architectures of VLEs, commercial and educational games, it was noted that there are modules in the architectures of commercial and educational games that can enhance the human computer

interaction (HCI) level of a VLE. Analyzing the architectures of commercial games [6], [7], serious games [5] and VLEs [3], [14], it was noted that the graphics rendering and audio and playback modules are utilized principally to provide instantaneous feedback to the student actions. Hearing and sight senses play a key role in communication. In addition, the core mechanics module defines which actions the student can perform to overcome specific challenges [6]. In the following section, the Olympia architecture is described. Olympia enables the combination of serious games with ITSs, resulting in an educational game virtual laboratory.

OLYMPIA ARCHITECTURE

The Olympia architecture was originated from the premise, which suggests that the success of educational games is due to the emotional link established between the learner and the game [5]. This emotional link is explained as the result of a high level of interactivity, which enables immediate feedback to student actions through multiple media [13]. Olympia combines features of educational and commercial games with features of VLEs.

The Olympia architecture, shown in Figure 1, includes interaction modules at the *interface level*. The implementation of all the interaction modules is not compulsory. A combination of the modules can be selected to attain the level of interactivity desired. To improve realism during simulation, the *Physics and collisions module* contains the physics and maths driven objects and the *Interactive AI module* comprises artificial intelligence (AI) techniques applied to attain believability. To modulate the student's mood, the *Emotional feedback module* contains sounds. The management of the scenes and graphics in real-time, and the storage of graphics is handled by the *Graphics rendering module*. The tasks performed by the *Input model* are sensing and handling the input. The transmission of data across the network is controlled by the *Networking module*. To complete tasks efficiently, *the Utilities module* comprises tools such as resource managers. *The Scripting module* enables external control of the application. *The Game mechanics module* manages the challenges in relation to the available actions that can be performed by the student.

Olympia requires a *teaching and learning AI module* that comprises an ITS since Olympia uses a semi-open environment [15] where the learner interacts with the simulator exploring different parameters and their effects within the simulated lab. However, each experiment carries specific objectives that the student needs to achieve. As a result, it is necessary to infer student knowledge from the interaction. This feature is attained through the *student model*, which is implemented using probabilistic relational models. Once the student model sends its interpretation of the interaction to the Tutor model, the latter is able to decide which pedagogical action is required through deterministic rules. The pedagogical actions can have different forms such as messages, questionnaires and tutorials. With its respective features, Olympia can enable implementation of an ITS with

a traditional VL, a serious game or an educational game virtual laboratory (GVL), which has a higher level of interactivity than a traditional VL. A high level of interactivity is related to a high motivation for learning and a high degree of understanding of the domain knowledge. In addition, the educational games implemented with Olympia as a reference can enable the student to focus on domain knowledge while learning to play a game successfully. The GVL was developed in an Apache Tomcat application server under JSP, Servlet, JavaScript, HTML, Flash and MySQL technologies.
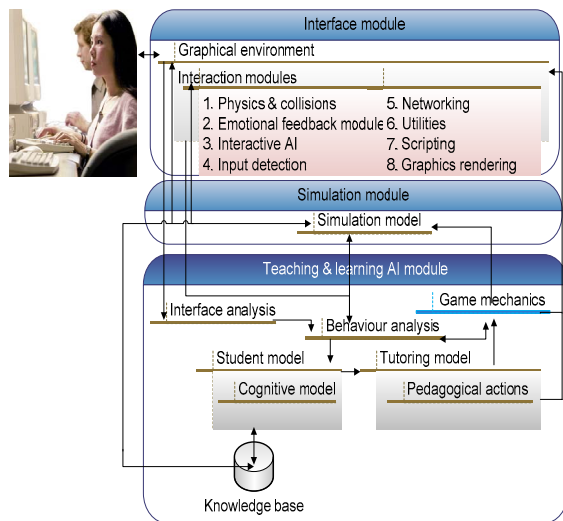

FIGURE 1
OLYMPIA ARCHITECTURE

METHODOLOGY

I. Problem Selection

In order to design a learning simulator that facilitates learning and attention, the instructor should consider an appropriate scenario with a challenging goal and with specific initial conditions. The goal should be motivating enough to enable student engagement through interaction with the simulator. The solution to the problem involves the selection and manipulation of several physical quantities by the student. The physical quantities are described through values in specific ranges defined by the instructor. In order to approach the learning goal, students have to explore the consequences of choosing different values for each physical quantity. In each trial the student will learn more about the role of the chosen physical quantity at a given time. Hence, in further attempts, the student will approach closer to the goal. In each attempt, the system will give feedback to the student. As a result, the student will make a better selection of parameters over time, until the student finally attains the goal. It is necessary to be careful when designing a problem. It must be essentially non trivial, i.e., it should not be solved from the beginning. Also, preventing simple memorization at each attempt, the initial conditions of the VL and GVL change randomly over specific ranges. The initial conditions influence the level of challenge involved in the problem.

Therefore, the value of the Physical quantity is not so important. The main goal is the overall understanding of the physical phenomenon modeled by the simulator.

II. Semi-open learning environment

In the design of both virtual learning environments (VL and the GVL), important aspects of Open Learning Environments were considered. This enables the free exploration of different parameters to observe their effects. However, a significant limitation of these systems is their learning effectiveness, which depends on the learner's exploration. The learner's ability to explore satisfactorily is influenced by specific features. Also, a clear definition of what constitutes exploratory behaviour does not exist [15]. Specific objectives were defined for each experiment. Students need to attain them while interacting with the corresponding learning environment (VL and GVL). As a result, the effective assessment of the results and the exploration behaviour are enabled [4].

Conservation of Linear Momentum is one of the key topics within course *Physics I* at *Tecnologico de Monterrey, Campus Ciudad de Mexico*. Therefore, a scenario where students can recognize the physical phenomenon and apply the principal concepts involved was chosen. With the concept of linear momentum, the main components of the system are Mass and Velocity, the latter being expressed as a vector [16]. Also, to conserve the Momentum of a given system, the student should realize that the resultant force on the system has to be zero. Hence, a problem was envisaged describing the story of an astronaut in trouble. The astronaut is located in interplanetary space far from his spaceship with a limited Oxygen supply in his tank. The astronaut attempts to save himself by returning to the spaceship. Initially, he is at rest relative to the spaceship and carries with him some hand tools. The hand tools should be thrown in such a way that the astronaut moves towards the spaceship. The problem statement is the following: "*The astronaut Patrick Mc Heaney is at mission in an asteroid near Europa, one of the four Galilean moons of Jupiter, he was outside of his spaceship repairing a sensor device set in the surface of the asteroid, when his primary source of oxygen supply, a cable connected to the spaceship, broke up; so now he just has his secondary source of supply, which is a tank of oxygen with an original capacity of 1.46 lt. at a pressure of 41368.5 Kpascals that only contains at that time a fraction of the oxygen. If the astronaut only possesses a screwdriver, pipe wrench and adjustable wrench, how could he use them to arrive to his spaceship before his secondary source of oxygen would be completely exhausted? Solve the problem through selecting the astronaut's mass, the tools that must be thrown, their mass and their velocity and direction*". After this description, the corresponding simulator is displayed, the VL or GVL, which are shown in Figure 2 and Figure 3 respectively. In this scenario, it is assumed that in interplanetary space, far away from massive bodies, the gravity force on the system composed by the astronaut and tools is small enough to be neglected in a first

approximation. Hence, the linear momentum of the system is zero (relative to the spaceship). In addition, it is implicitly suggested that the astronaut will be saved if he arrives to the spaceship before the oxygen in the tank is exhausted. The system assigns random values to the initial distance from the astronaut to the spaceship, D, and the time left indicating when the oxygen will be exhausted, T_{Oxygen}. The corresponding ranges are: $D \in [20, 25]$ m and $T_{Oxygen} \in [40, 60]s$. These values change each time that the student initializes or resets the simulation. Accordingly the VL and GVL are more "dynamic", therefore minimizing the risk of enabling the student to memorize values.
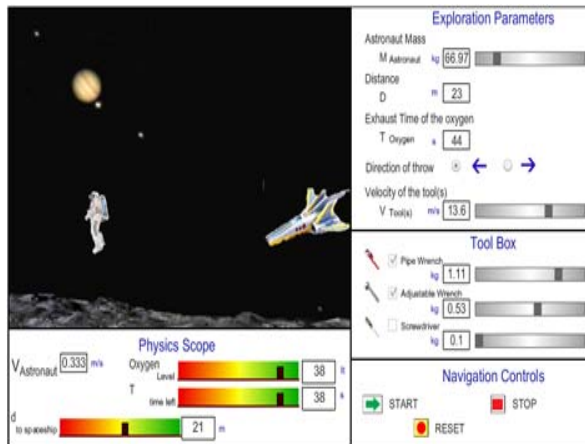

FIGURE 2
VL ENVIRONMENT

In order to save the astronaut, the student is asked to select: i) the tools to be thrown, ii) the direction to throw the tools, and iii) suitable values for the astronaut's mass, the mass of each tool and the throwing speed for the tools.
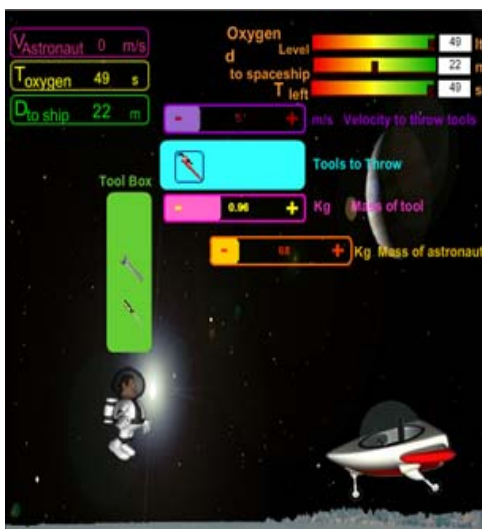

FIGURE 3
GVL ENVIRONMENT

The VL and GVL are available for students on http://elearning.ccm.itesm.mx:8080/EEXIP.

The tools to be selected are a pipe wrench, an adjustable wrench and a screwdriver. Their mass ranges are, respectively: $M_{pipe\ wrench} \in [0.8, 1.2]\ kg$, $M_{adjustable\ wrench} \in [0.3, 0.7]$ kg and $M_{screw\ driver} \in [0.1, 0.3]$ kg. The direction in which to throw the tools can be set to be towards the spaceship, "→", or away from the spaceship, "←". The astronaut´s mass range is $M_{Astronaut} \in [60, 100]$ kg, and the speed range to throw the tools is $V_{tools} \in [0, 20]$ m/s.

If the students truly understand the law of conservation of Momentum and the properties of linear momentum as a vector, they should recognize from the beginning that the tools must be thrown *away* from the spaceship, to enable the astronaut to move *towards* the spaceship. In this case, the values corresponding to the exploration parameters are not considered to provide relevant feedback. If the direction to throw the tools is *towards* the spaceship "→", the corresponding virtual laboratory, VL or GVL, will give the following feedback: "*YOU FAILED! The astronaut died…..You should repeat the experiment. To save the astronaut, which is the direction in which to throw the tools*?"

However, if the students choose the correct direction in which to throw the tools,"←" (i.e., away from the spaceship) and they do not select suitable values for the exploration parameters, the velocity acquired by the astronaut towards the spaceship will not be enough to arrive to the spaceship before the oxygen is exhausted. Indeed, the ranges of parameters have been selected to make the solution of the problem non trivial. Students should realize that, besides throwing the tools away from the spaceship, the best choice corresponds to the specific case of throwing the three tools with their maximum masses, selecting the minimum astronaut's mass and setting the maximum value of the speed at which to throw the tools. If they select unsuitable values for these variables and therefore the astronaut dies, the system gives the following feedback: "*YOU FAILED: the astronaut died….You should repeat the experiment. Please review the impact that the mass of the tools and the astronaut has over the Conservation of Momentum. Are lighter tools or heavier tools better? Is a slim astronaut better than a fat one? Please review the impact that the velocity of throwing the tools has over the Conservation of Momentum. Is high velocity or low velocity better?"*

It is important to note that the probability of success depends on the random initialization of the distance to the spaceship, D, and the time left to finish the oxygen in the tank, T_{Oxygen} and both are set by the VL and GVL. For the most restrictive case, D maximum and T_{Oxygen} minimum, only the best selection of parameters will save the astronaut. In contrast, for the least restrictive case, D minimum and T_{Oxygen} maximum, there is a wider range of parameter combinations that will enable the astronaut to be saved. However, even in the latter case, the parameter ranges were selected in such a way that the astronaut will be saved by only 30% of the student's selections of parameter values, leaving the problem non trivial. In addition, in the GVL, the

feedback messages are synchronized with sounds and graphics to express happiness and sadness when the student attains or fails to attain the learning goals, while in the VL only plain text messages are displayed. Also, learners interact through keyboard events in the GVL, which increases the immersion of the student in a game atmosphere. In contrast, students interact with the VL through buttons and sliders.

III. Inferring Knowledge

Some important characteristics of intelligent tutoring systems (ITS) were integrated into the VL and GVL. The ITS works in the following way: when a student performs an experiment in the VL or GVL, the student model uses the inference mechanism to propagate evidence from evaluation within the experiment to knowledge objects in the knowledge base. Based on this evidence the results are used by the tutor module to decide the best pedagogical action (feedback). In both environments, it was necessary to handle uncertainty during the process. A relational student model was used to adapt the learning experience to suit the learner's needs [4]. A general skeleton, in the form of a Bayesian net, was defined and is shown in Figure 4.
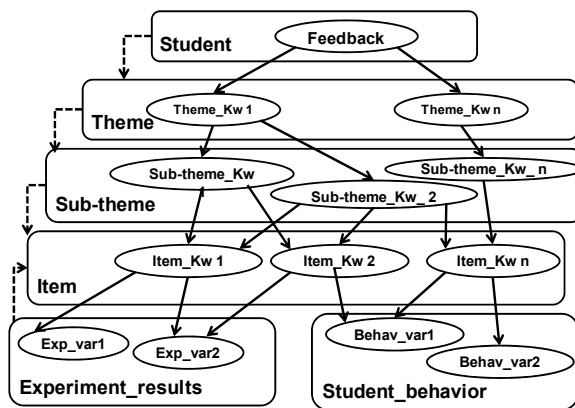

FIGURE 4
A GENERAL SKELETON FOR AN EXPERIMENT DERIVED FROM
THE RELATIONAL STUDENT MODEL

A specific Bayesian network, related to the topic of Conservation of Linear Momentum, was generated for the experiment. The Bayesian network, shown in Figure 5, was used to update the student model via standard propagation techniques.
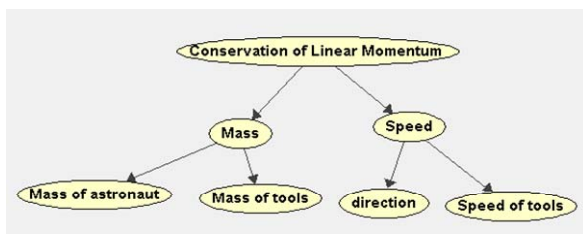

FIGURE 5
A BAYESIAN NET DERIVED FROM THE RELATIONAL STUDENT
MODEL

EVALUATION OF OLYMPIA

The first evaluation of Olympia was conducted with two learning environments, a VL and a GVL. The results showed that students were motivated and learned in a similar way in both environments [17]. In a second study, the probabilistic student model was improved, tutorial videos were added, and the feedback was refined in both environments. The second evaluation of Olympia also used both learning environments. By analyzing the learners' parameter explorations while interacting with the corresponding virtual learning environment, insight has been obtained into the general effectiveness of the experiment performance. The study was applied during Semester I of 2009. The process of application is described as follows:

- **The pre-phase**. A written *Pre-test* that included 4 questions involving Physics situations related to the Conservation of Momentum theme, was conducted to students from several undergraduate Physics groups. To avoid the lecturer influence over the results, they did not give the corresponding lectures on this theme during the period when students worked with both systems.

- **Participants.** A total of 57 students, registered for Semester I & II of multidisciplinary majors from the Faculty of Engineering, participated in the study. They were divided randomly in three groups: a control group that did not interact with any learning environment, a second group using the VL and an experimental group using the GVL.

- **Experiment design.** 34 students did not use any system. 12 students used the VL and 11 students used the GVL. Both systems were available to interact with online for one week. In addition, they stored log files to register the students' sessions and results.

- **The post-phase.** This consisted of a written test of 4 questions, or *Post-Test*, very similar to those applied in the *Pre-Test*.

- **Calculation and analysis of the results.** Learning gains were calculated from the results of this study, which were obtained from the application of the *Pre-test* and *Post-test*. The total number of students, N_{total}, was 57.

In order to compare the results a relative gain for each student, shown in Equation (1), was calculated as defined by [18]:

$$G_{rel} = \frac{(PostTest - PreTest)}{(100 - PreTest)} \qquad (1)$$

Also, a gain, shown in Equation (2), was analyzed and defined by:

$$G = (PostTest - PreTest) \qquad (2)$$

As is shown in the results shown in Tables 1, 2, and 3 the students using the GVL had a higher learning gain than the students using the VL. Furthermore, the students using both environments improved their learning when compared to the students that did not use any learning environment.

However, increased student sample size will ensure confidence in the derived differences between the learning gains.

TABLE 1
SUMMARY OF GAINS AND EFFICIENCY RESULTS FOR THE GROUP USING THE VL (GROUP, N = 11)

Pre-Test	Post-Test	G_{rel}	G	Efficiency
59 ±23	73 ±26	0.27±0.33	14 ±13	0.28±0.15

TABLE 2
SUMMARY OF GAINS AND EFFICIENCY RESULTS FOR THE GROUP USING THE GVL (GROUP, N = 12)

Pre-Test	Post-Test	G_{rel}	G	Efficiency
65 ±27	79 ±18	0.57±0.20	15 ±14	0.49±0.38

TABLE 3
SUMMARY OF GAINS AND EFFICIENCY RESULTS FOR THE GROUP NOT USING THE VL OR THE GVL (CONTROL GROUP, N = 34)

Pre-Test	Post-Test	G_{rel}	G	Efficiency
71 ±23	74 ±16	0.19±0.15	3 ±10	-

CONCLUSION AND FUTURE WORK

From the research conducted, it was noticeable that features of commercial and educational games can enhance the HCI level of a VLE. Olympia is an architecture that combines VLs, educational games and GVLs with ITSs. An educational game virtual laboratory (GVL) has a level of interactivity comparable to an educational or commercial game. Olympia was applied to the specific case study of teaching introductory Physics at undergraduate level. For the case study, a VL and a GVL were implemented. The GVL has sounds that are synchronized with the pedagogical actions to provide emotional feedback. In addition, the GVL has high quality graphics and the student can interact with the experiment through keyboard events. When Olympia was evaluated initially the results showed that students were motivated and learned in a similar way in both environments [17]. Here we focus on the second evaluation of Olympia and the results show that the students who used the GVL had a better performance when compared to the students using the VL. The students using both environments improved their level of understanding when compared to the results of the control group. Furthermore, we note that the efficiency for GVL students is higher than that for VL students, which shows that GVL students were more engaged with the system. However, increased student sample size will ensure confidence in these results.

The evaluation of both systems is being extended through the implementation of more experiments and validation of the best pedagogical actions in the tutor model. The student's affective behaviour will be modelled and combined with features of educational games for teaching Physics. The goal is to provide a suitable pedagogical and affective response for students interacting in a serious game virtual laboratory.

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