PlayPhysics: An Emotional Games Learning Environment for Teaching Physics

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Abstract. To ensure learning, game-based learning environments must incorporate assessment mechanisms, e.g. Intelligent Tutoring Systems (ITSs). ITSs are focused on recognising and influencing the learner's emotional or motivational states. This research focuses on designing and implementing an affective student model for intelligent gaming, which reasons about the learner's emotional state from cognitive and motivational variables using observable behaviour. A Probabilistic Relational Models (PRMs) approach is employed to derive Dynamic Bayesian Networks (DBNs). The model uses the Control-Value theory of 'achievement emotions' as a basis. A preliminary test was conducted to recognise the students' prospective-outcome emotions with results presented and discussed. *PlayPhysics* is an emotional games learning environment for teaching Physics. Once the affective student model proves effective it will be incorporated into *PlayPhysics*' architecture. The design, evaluation and post-evaluation of *PlayPhysics* are also discussed. Future work will focus on evaluating the affective student model with a larger population of students, and on providing affective feedback.

Keywords: Affective Student Modelling, Control-Value Theory, Dynamic Bayesian Networks (DBNs), Game-based Learning Environments, Intelligent Tutoring Systems, PlayPhysics, Probabilistic Relational Models (PRMs).

1 Introduction

Information Technology (IT) has influenced the world that surrounds young learners. They expect to feel motivated and engaged when learning [1]. Traditional education is evolving into a student centered-approach, which will support the development of learner's skills, e.g. creativity, self-organization and decision making [2]. Game–based learning environments are being used to actively involve students in their own learning [3]. Intelligent tutoring systems (ITSs) are assessment mechanisms that are included in the architectures of game-based learning environments to ensure students' understanding [4-5]. ITSs follow the learner's performance, identify the learner's needs and provide suitable feedback. The learners' emotional state has proven to be deeply interrelated with their motivation and cognition [6]. Affective Computing and Affective Gaming seek to identify and influence the user's emotion [7-8]. Incorporating an affective dimension into ITSs involves the challenges of how to reason about and respond to the learner's emotion. Here we focus mainly on the former. The latter may involve multimodal output modulation.

An ITS is comprised of several modules. The student model enables an ITS to understand the learner's behaviour [9], whilst a tutor model selects the most suitable pedagogical action and the most effective way of conveying the teaching message [10]. Affective student modelling is a task that involves uncertainty, since diverse social, personal and cognitive factors influence the learners' emotional state [6]. Identifying whether students' emotions facilitate or impede learning will provide ITSs with the capability of ignoring or changing the learner's disposition to enhance understanding [7]. To date, there is no system that can identify all the relevant emotions that take place in a teaching and learning context. In addition, an affective student model that effectively reasons about the learner's emotional state using motivational and cognitive variables does not yet exist. Therefore, here we propose and discuss the design of such an affective student model, which uses the Control-Value theory of 'achievement emotions' as a basis, and uses observable behaviour and answers to posed questions as part of the game dialogue as evidence to update its knowledge. A Probabilistic Relational Models (PRMs) approach and Dynamic Bayesian Networks (DBNs) are employed for the design and implementation of the affective student model.

To evaluate the affective student model and the approach, a prototyping exercise will be carried out with undergraduate students enrolled in an Introductory Physics course. The prototyping exercise uses a "Wizard-of-Oz" experiment [11] as a basis. A preliminary test was carried out with students at postgraduate level to identify possible weaknesses in the prototyping material, and to evaluate the accuracy of the affective student model when reasoning about the students' outcome prospective emotions and results are discussed and presented. Once the effectiveness of the affective student model is ensured, it will be incorporated into *PlayPhysics*' architecture, *Olympia* [12]. The *Olympia* architecture will be modified to select the pedagogical actions, e.g. motivational, affective or cognitive, that maximize learning. It is important to signal that motivational, affective and cognitive strategies can be independent, complementary or in contraposition [13]. Therefore, selecting the most suitable pedagogical action or actions and finding the most suitable way of communicating errors to the students are also considered challenges. *Olympia* will provide pedagogical feedback through modulating game elements, e.g. game-characters, sounds and colours.

Students frequently experience problems when trying to understand the underlying principles of Physics [12]. *PlayPhysics* is an emotional game-based learning environment for teaching Physics at undergraduate level. Section 2 reviews state of the art research related to the challenges of reasoning about the learner's emotion and influencing the learner's emotional state. Section 3 describes the design and implementation of the affective student model. Section 4 describes *PlayPhysics'* design, implementation and future evaluation. Section 5 presents and discusses the results of the preliminary evaluation of the affective student model. Section 6 concludes by outlining the benefits of this research and describing its future work.

2 Background

To enhance learning and engagement, computer tutoring must be able to identify and influence the learner's emotional state. This section discusses the state of the art related to both challenges.

2.1 Identifying Emotion

ITSs are being updated to enable them to recognize the learner's motivation or emotion. Approaches identified in the field of ITSs are: (1) recognizing the physical effects of emotions [14], (2) predicting emotion from its origin [15] and (3) a hybrid approach derived from the previous two approaches [4]. Recognizing the physical effects involves using additional hardware to recognize gestures, body position, prosodic features and psycho-physiological data that is mapped to emotional meanings. Limitations of this approach are the acquiring of large quantities of data and also that hardware is intrusive and prone to failure. Predicting emotion from its origin is an approach that involves using a cognitive theory to reason about the possible causes of an emotion. Research is usually based on the Ortony, Clore and Collins (OCC) model, which classifies emotions according to their sources [16]. This theory must adapt to the learning context and account for the learner's attitudes, standards and beliefs. A hybrid approach predicts the existence of an emotion and matches data patterns to ensure that the emotion actually happened.

To recognize the motivational state of the learner using observable behaviour, an approach using quantitative and qualitative characteristics has proven effective [17]. The approach focuses on analyzing the learner's actions and mapping them to values associated with effort, independence and confidence. This work showed that self-efficacy could effectively infer the learner's disposition whilst learning. A self-efficacy model was derived from observable behaviour and physiological data [18]. Results showed that the model achieved 70% accuracy and this accuracy was increased by 10% by adding physiological data. To date, there is no ITS capable of identifying all students' emotions in a learning context. Therefore our research focuses on creating an affective student model using as a basis the 'Control-Value theory of Achievement Emotions'.

The Control-value theory of 'achievement emotions' is an integrative theory of emotion that considers control and value appraisals as the most relevant factors when determining an emotion [6]. 'Achievement emotions' are emotions that take place when academic or achievement activities are performed and a desired outcome is expected as a result of performing these activities. These emotions are domain dependent. *Control* can be defined as the perceived *control* over a specific activity and its outcomes, e.g. self-efficacy, before starting to solve a specific Physics or Mathematics problem. *Value* is the perceived importance of the outcome and the desirability of the activity, e.g. the learner's intention or interest. The Control-Value theory, instead of opposing the OCC model, incorporates some assumptions of that theory. The Control-Value theory classifies emotions according to their focus and time-frame: *outcome-prospective*, *activity* and *outcome-retrospective* emotions. For example, anticipatory joy, hope, anxiety, anticipatory relief and hopelessness are considered *outcome-prospective* emotions. The Control-Value Theory uses the Achievement Emotions Questionnaire (AEQ), a self-report tool designed and evaluated through Structural Equation Modelling (SEM) [19]. The AEQ has been used to assess accurately the learners' achievement emotions in the English, German, Mathematics and Physics domains.

2.2 Influencing and Modulating Emotion

Systems are embodying experts, synthetic characters or embodied pedagogical agents (EPAs), in diverse fields with the objective of enhancing the effectiveness of the message [20]. The challenge is creating in the user a feeling of believability. To achieve this aim, research has focused on domain knowledge representation, emotional intelligence, personality, social relations and common sense.

Some ITSs use an EPA to communicate their pedagogical, motivational and affective responses [4-5, 14]. In these cases the response is accompanied by the inferred data of the student model. Herman, the EPA of the virtual learning environment (VLE) 'Design a Plant' [21], synchronises multiple modalities addressing context and time. Herman's behaviours are assembled in real time with segments of animations and audio using a sequencing-engine. To facilitate access to the behaviour space, the authors employed ontological, intentional and rhetorical indexes for handling explanatory, advisory and emotional behaviours. A hierarchy of pre-requisites and dependencies between behaviours was defined, as in The Oz Project [22]. To enable the EPA to move in the virtual environment, compositional and full-body animations may be employed, e.g. Cosmo's behaviours [23]. Some EPA architectures, e.g. Cosmo's architecture [23], are very similar to the architecture of an ITS. Research into Embodied Characters has created several visual languages, with their own syntax and semantics, to attain animation coherence. Examples of applications using a visual language are BEAT [24], Smartkom [25] and the Oz Project [22].

The control of the system over the character can be modelled as a central management entity that controls which actions are performed when and where, as is common with video games, or indicating the general direction of the interaction or narrative, but not the actions, as is common with interactive dramas [26]. Cognitive theories of emotion and personality theories have been used as a basis to create the reactive behaviour of embodied characters and EPAs. Theories employed commonly are the OCC model and the Big Five, as in The Oz Project [22], Fear Not! [27] and PrimeClimb [4].

Video games are multi-sensorial environments, where acoustic and visual sources serve diverse purposes [28-29], e.g. setting a mood, indicating changes in narrative, creating a feeling of immersion, focusing attention, conveying meaning, identifying objects and actors and decreasing the player's learning curve, therefore impacting on the reception of a video game. Colours have a diverse range of meanings, from the cultural to the personal as well as possessing innate meaning [30]. Colours have been employed for self-reporting of emotion in the classroom [31] and in virtual learning environments [32], and to communicate and emphasize the existence of an emotion [33].

3 Affective Student Model Design and Implementation

Student modelling is an undertaking that involves domains with inherent uncertainty [9], since it is not clear how the learner achieves knowledge and how personal differences, social standards and the knowledge domain influence the learner's emotion and motivation. Selecting the data to be considered when updating the model also constitutes a challenge. Bayesian Networks (BNs) are employed to handle uncertainty and represent causal relations between random variables. They have been applied to implement cognitive, affective and motivational student models [12, 4-5].

Table 1. Summary of the Control-Value Theory by Pekrun et al. [6]

Time frame/focus on	Value appraisal	Control appraisal	Emotion
Prospective/outcome	Positive	High	Anticipatory Joy
	Success	Medium	Hope
		Low	Hopelessness
	Negative	Low	Hopelessness
	Failure	Medium	Anxiety
		High	Anticipatory relief
Retrospective/outcome	Positive	Irrelevant	Joy
	Success	Self	Pride
		Other	Gratitude
	Negative	Other	Anger
	Failure	Self	Shame
		Irrelevant	Sadness
Present/activity	Positive	High	Enjoyment
	Positive/Negative	Low	Frustration
	None	High/Low	Boredom
	Negative	High	Anger

To facilitate BN design, Probabilistic Relational Models (PRMs), object-oriented representations of the knowledge domain, can be employed to overcome the limitations of selecting significant domain data, applying the model to diverse domains and handling the complexity of the resultant BNs [9]. We derived the PRM based on the Control-Value theory of 'achievement emotions' [6], summarised in Table 1, along with considerations related to the goals of the *PlayPhysics* application. From this PRM were derived three Dynamic Bayesian Networks (DBNs), each corresponding to one of the types of emotion defined in [6]. It is important to note that whilst an appraisal of control or value is absent there is no emotion. The DBN corresponding to the '*outcome-prospective*' emotions is shown in Figure 1.

Each DBN was derived from analyzing the AEQ [19], e.g. one of the statements in the AEQ related to the emotion enjoyment is, "I am looking forward to learning a lot in this class", from this statement it was inferred that the student's level of performance, a cognitive factor, may be an indicator of positive, neutral or negative value and low, medium or high control. In addition, from analyzing the work in [18], we decided to focus only on motivational and cognitive variables in this stage of the research, since it was inferred that physiological variables can slightly increase the accuracy of the model. The work in [18] and [17] were used as a reference to identify observable variables and to define some dependencies with the motivational variables' effort, confidence and independence. The Conditional Probability Tables (CPTs) were set using common sense related to the learning context. To know the student's beliefs, attitudes and standards and to assess qualitatively and quantitatively the learner's intentions, questions posed in game-dialogues are employed. These questions were derived using the 'Theory of Planned Behaviour' [34].

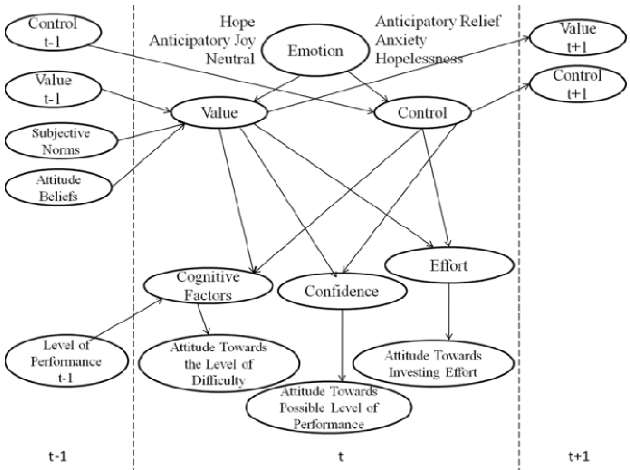

Fig. 1. *Outcome-prospective* emotions DBN

An evaluation of this affective model will be carried out with students of Physics at undergraduate level. The prototyping exercise, using a "Wizard-of-Oz" experiment [11] as a basis, will be performed with written material, which defines the dynamic of the game and the first game challenge. The student will be located in a Gesell dome. One lecturer will be in the same room providing assistance to solve the problem in the case the student needs it. Two lecturers will be behind the mirror, both making annotations of the observations related to the random variables. One of them will introduce the evidence acquired through these observations into 'Elvira' [35], a tool for implementing BNs, and will compare the results of the corresponding DBN with the emotion reported by the student. When the accuracy of the affective student model is significant, the model will be incorporated into *PlayPhysics*' architecture, *Olympia*. A preliminary evaluation of the prototyping material and the affective student employed for identifying the *outcome-prospective* emotions, discussed in section 5, was conducted with seven students at postgraduate level in the University of Ulster.

4 PlayPhysics Design and Implementation

An online survey was conducted with undergraduate students enrolled in an introductory course of Physics at Trinity College Dublin and Tecnológico de Monterrey, Mexico City, from March to December, 2009. According to identified requirements, the design of *PlayPhysics* was derived. Therefore, the topics that *PlayPhysics* is focused on teaching are circular movement, movement of rigid bodies, vectors and linear momentum, which are generally considered to be the most difficult topics on an introductory Physics course and involve Newton's laws of motion. *PlayPhysics*' storytelling scenario is a space adventure, where the student takes the role of an astronaut and is tasked with solving challenges using principles and knowledge of Physics. This section describes *PlayPhysics*' architecture, *Olympia*, the design and implementation of *PlayPhysics*' first challenge and the definition of PlayPhysics' knowledge-base, i.e. cognitive model, related to this challenge.

4.1 PlayPhysics architecture

The architecture of *PlayPhysics*, namely *Olympia* [12], has proven effective for teaching Physics at undergraduate level. *Olympia* is being modified in this research to incorporate the affective dimension and is shown in Figure 2. *Olympia* handles *dynamic* and *static interactive modules*.

Dynamic modules change over time while static modules remain the same. Olympia is a semi-open game learning environment [36], where learning goals guide the learner's interaction. Olympia includes an ITS. Events are selected by the interface analysis module, which sends them to the behaviour analysis module to be evaluated. The resultant evidence is communicated to the student model. The result of the inference is transferred to the tutor model and will be implemented using DDNs. The tutor model selects the action that will maximize learning or engagement. After receiving the action, the cognitive and affective modulators select the media according to the decisions taken by the planner. The presentation content manager modifies the world model and game mechanics module. Finally, the world model and the game mechanics influence the dynamic modules. To test the effectiveness of PlayPhysics, students at undergraduate level will be divided in control and experimental groups. Both groups will conduct a pre-test before learning the topics practiced with PlayPhysics. Then the experimental group students will interact with PlayPhysics and also attend their lectures, the control group will only attend the lectures. Both groups will conduct a post-test where the learning gains and learning efficiencies will be measured.

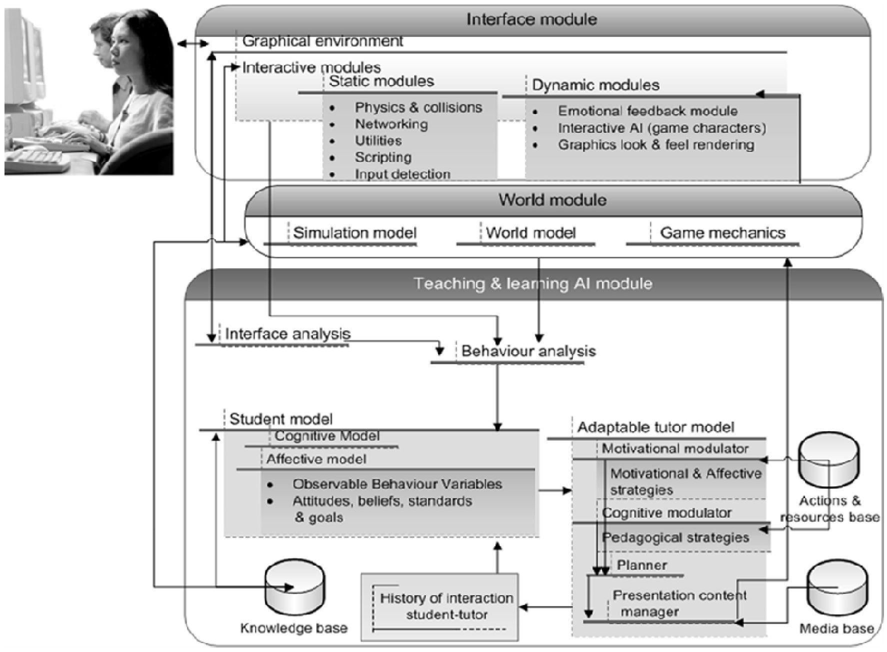

Fig. 2. Olympia Architecture

4.2 PlayPhysics' First Challenge Scenario Design and Implementation

The main goal of the game is to save Captain Richard Foster and re-establish control over the space station Athena. VNUS-2781, a super-computer, which controls Athena has been infected with a harmful virus and has attacked Athena's crew. Foster was the only person that could not escape. He was injured during the attack. To achieve the main goals, the student has to overcome challenges applying principles and concepts of Physics. The first challenge begins when NASA asks for the student's help. During this dialogue, *PlayPhysics* acquires information related to the student's attitudes, beliefs and standards through posed questions. This information and the result of a pre-test are used as evidence to reason about the learner's *outcome-prospective* emotions. In the first challenge, the astronaut has to dock his spaceship with Athena. Athena orbits around the sun and is located between Mars and Jupiter orbits and rotates with a constant angular velocity. The spaceship's initial velocity and location are randomly initialised to avoid triviality on the problem solving process. To preserve fuel, a minimal number of translational and rotational movements must be performed to dock with Athena. To achieve this goal the student must apply knowledge on linear and circular kinematics, Newton's laws for motion of particles and rigid bodies and vectors.

The spaceship is initially launched from Earth. First, the student has to slow and stop the spaceship. The spaceship stops somewhere in front of Athena's rotational axis using its front engines, i.e. the spaceship linearly decelerates. Second, the student must align the spaceship's longitudinal axis with Athena's longitudinal axis through turning on the upper and lower engines. Third, the spaceship's lateral engines are employed to achieve Athena's rotational velocity. Finally, the student enters slowly into Athena station though performing slow movements along its rotational axis. The student can explore the effects of modifying the spaceship's mass and rotational inertia relative to its three axes, e.g. longitudinal, zenithal and azimuthal. In addition, the forces and torques corresponding to spaceship's motors can be changed to modify the spaceship's angular acceleration and deceleration. The game-based learning environment is being implemented with the Unity Game Engine, Java Web, Elvira and Poser.

PlayPhysics' pedagogical actions will be defined through the suggestions of expert lecturers and implemented through Dynamic Decision Networks (DDNs). Game characters, colours and sounds will be mapped and displayed according to the emotions defined by Control-Value theory. *PlayPhysics*' learning effectiveness will be tested through dividing undergraduate students into control and experimental groups. Both groups will solve a pre-test before receiving the lecturers corresponding to the topics. The control and experimental groups will proceed to receive the lecturers. The experimental group will also interact with *PlayPhysics*. Finally, both groups will answer a post-test. The calculated learning gains and learning efficiencies between groups will be compared.

5 Preliminary Evaluation of the Affective Student Model

A pre-test, comprised of five questions related to the topics taught by *PlayPhysics*, and a questionnaire, comprising PlayPhysics' game dialogue, were applied to twenty eight students at undergraduate level from the Tecnológico de Monterrey (ITESM-CCM), Faculty of Engineering. The game dialogue questions correspond to the students' attitudes, beliefs and standards with regard to Physics. The previous experience of solving the pre-test was also considered whilst answering these questions. The evidence obtained through both questionnaires was propagated into the *outcome-prospective* emotions DBN. The main aim of this evaluation was to identify possible deficiencies in the prototyping material and to evaluate the *outcome-prospective* DBN accuracy at reasoning about the students' emotions. Results, obtained through comparing the inferred emotion by PlayPhysics' affective student model with the students' reported emotion, showed an accuracy of 60.71% (Figure 3).

The results were promising, but the model still needs to be evaluated through a larger population of participants. As an example, the authors in [19] validated the AEQ with the participation of 389 students. Students signalled that to enhance the understanding of the questions comprising the pre-test, an explanation of some terms comprising formulae and diagrams supporting the questions can be included. In addition, it was noted that some students did not know how to classify the emotion that they were feeling. Therefore, in a future version, examples corresponding to the emotions will be included. The probabilities in the Conditional Probability Tables (CPTs) set using common-sense related to the learning context may also be influencing the results. In addition, each student will be evaluated separately in the Gesell dome, since it was noted that when the students are sharing the same task in the same location, some of them have a tendency of behaving in a competitive way. For example, two students reported anxiety, even when they achieved a performance of over 70% in their pre-tests. They thought that their performances will be published and made available to everyone who took the pre-test.

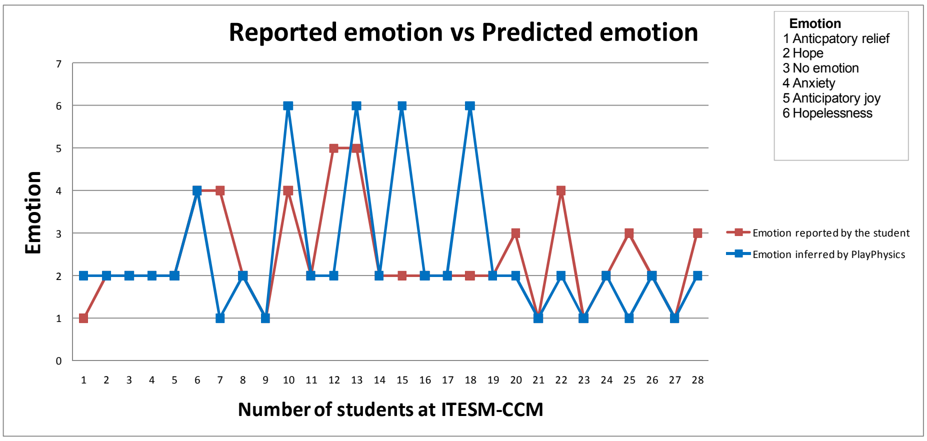

Fig. 3. Students' reported emotion and PlayPhysics' inferred emotion.

6 Conclusion and Future Work

The state of the art related to research challenges in identifying and influencing the learner's emotion was reviewed. As of today, there is no system that reasons effectively about the learner's emotion using a combination of cognitive and motivational variables. Therefore we focus on creating such affective student model. The model was designed using the Control-Value theory as a basis and was implemented using a PRMs approach and DBNs. The advantages of modulating the output to influence the learner's affective state were noted. Game elements, e.g. sounds, visuals and colours, serve meaningful purposes and will be employed to reduce the learning curve and set a mood. A preliminary evaluation showed that the affective student model has an effectiveness of 60.71% when reasoning about the students' *outcome-prospective* emotions. However, the complete affective student model will be tested on a larger population of students at undergraduate level, enrolled on an introductory Physics course. Deficiencies, which were detected in the prototyping material, will be modified. In addition, the effectiveness of *PlayPhysics* for teaching will be evaluated though the comparison of learning gains and efficiencies.

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