An Event Detection Approach for Identifying Learning Evidence in Collaborative Virtual Environments

Samah Felemban *, † , Michael Gardner * , Victor Callaghan *

* Department of Computer Science, University of Essex, UK. E-mail: ssyfel@essex.ac.uk
† Umm Alqura University, Makkah, Saudi Arabia

Abstract — **3D virtual environments support collaborative learning through connecting users in real-time allowing them to accomplish learning tasks together, in addition they enhance the students' exploration, engagement, and interactivity. However, collecting learning evidence to evaluate students in these environments has many difficulties. Therefore, the intention of this paper is to describe our approach for assessing student's learning within collaborative groups in 3D virtual worlds (VWs). It combines a computational mechanism that integrates software agents and natural agents (users) with an ontology approach that supports the identification of learning evidence from collaborative activities that mimics classroom observation. The software agents track the users and collects different actions, clicks, and events to evaluate the quantity of interactions, while the natural agents perform peer evaluations of the students to assess the quality of their performance. The aim is that such a computational model can support more in-depth assessment of learning activities in 3D spaces.**

Keywords: E-learning; 3D Virtual Worlds; Assessment; Collaborative Learning; Learning Evidence; Software Agents; Natural Agents; Ontology.

I. INTRODUCTION

A. Collaborative Learning Environments

Collaborative learning supports the enhancement of skills and the achievement of knowledge through working with other students. Collaborative learning has been widely applied in 3D virtual worlds (3D-VWs) [1, 2]. 3D-VWs have been developed based on various platforms such as Open Wonderland[1], Second Life[2], Active Worlds[3], Open Simulator[4], and Unity 3D[5]. These worlds can enhance decision-making and teamwork between groups [3] through connecting users in real-time, allowing them to work together, and they also can potentially improve the students exploration, engagement, and interactivity. Furthermore, they can assist in the understanding of complex phenomena and in the visualization of objects and the relationship between them [4]. However, these environments need more exploration in order to increase their potential for learning and to properly exploit their affordances for teaching and learning [5].

Teachers may have several concerns when designing collaborative activities and trying to evaluate the learning outcomes in these environments. 'Learning within technology creates a pedagogical shift that requires teachers to think about measuring outcomes in non-traditional ways'[6]. The assessment of the students' interaction, knowledge and skills requires identifying learning evidence from student performance. On the other hand, tracking users' behaviour and collecting events that prove learning has taken place is potentially very difficult to do in VWs. Many skills, including the interpersonal skills, could be achieved from the learning activities, but it is problematic to detect evidence of them automatically. Additionally, recognising and labelling the events of different learners in real-time is complex because many users can be contributing simultaneously, which makes tracing each users contribution more difficult.

Consequently, discovering an event-recognition technique that dynamically identifies the users' actions, gathers learning evidence, and analyses actions is essential. Such a mechanism can help to collect evidence during collaborative activities and link the evidence to learning objectives to measure the individual learning outcomes.

B. Multi-agent and Ontology based Approaches

- *The Use of Ontologies and the Semantic Web:*

An ontology is defined as 'a formal representation of a knowledge domain. It is often the key component to using the semantic web approach for searching repositories' [7]. It contains object classes, object properties, and the relationship between the objects [8]. The relationships represented in ontologies can provide a better understanding and definition of the meanings of the concepts, causing enhanced communication between different objects. Ontologies provide a standardised vocabulary by creating sets of vocabularies and connected semantics that can be reasoned with. Ontologies can be expressed using a range of different approaches such as

[1] http://www.openwonderland.org/
[2] http://secondlife.com/
[3] https://www.activeworlds.com/
[4] http://opensimulator.org/
[5] Unity3D: https://unity3d.com/

using the OWL, RDF, and XML languages. However, the OWL language is typically more expressive than the other approaches [9].

To use an ontology, additional software is usually required, such as a 'reasoning engine' or 'inference engine'. The 'inference engine' is essentially software that can conclude and infer logical results from a set of stated rules and facts. Examples of this engine is Pellet [10], Jena [11], and RACER [12]. By using an appropriate ontology and reasoning engine to define a domain and set logical facts, software applications can generally infer more detailed knowledge, using a richer domain model, and deliver more complex services to users.

- *Multi-Agent Systems:*

The multi-agents system (MAS) approach is comprised of several agents that have diverse roles and objectives and are connected to each other to produce a variety of outputs. The structure of MAS consists of protocols for interaction and communication between agents. Agents often need to communicate via a common communication method [13]. The multi-agent system is also defined as a set of problem-solvers (agents) that perform together to solve issues that are beyond a single agent's knowledge or abilities [14]. Sánchez [15] classified agents based on their capabilities into several types: 1) *programmer agents* can deal with hardware and software entities; 2) *network agents* act in distributed systems; 3) *user agents* are explicitly available for end users which either collect users' data, provide visualised characters and objects for user interfaces, or run synchronously with user applications to watch the users' actions. The significant advantages of agents and using them in MAS systems have increased their scope for interesting research and novel applications.

Many researchers have found that combining both technologies, MAS and ontologies yields more advantages. Hadzic et al. [16] have integrated multi-agent-system and ontology technologies by creating a framework that utilises software agents with an ontology repository. The agents can read and reason from published information with ontology guidance, and the ontology enables more meaningful communications between the different components of the system. Software agents can make decisions, solve problems, and communicate, and they have beliefs and capabilities. The combination of MAS and ontologies facilitates communication by aggregating shared knowledge into a shared information resource, allowing it to be shared among users. Moreover, ontologies enable the software agents to provide better information to users when a problem is recognised [16].

This is a work-in-progress paper; essentially, it is a concept paper that describes a novel approach to assessing learning from collaborative groups in 3D-VWs. It illustrates a computational mechanism that extends the integration of MAS and ontologies via combining software agents and users evaluation with ontology technology to support the identification of learning evidence from collaborative activities. Such a computational model can help to solve issues that may occur when collecting learning evidence and assessing learning outcomes in 3D collaborative virtual spaces.

II. Related Work

Recognising individual learning evidence by using assessment activities, such as written assignments or multiple-choice tests, is relatively straightforward. On the other hand, it becomes more challenging in educational games or 3D spaces because of the unclear relationship between the objects and students' actions and decisions. Researchers face obvious problems when assessing learning in simulation environments. Firstly, there are limited evaluation techniques for student assessment in 3D spaces and a lack of a theoretical basis for doing this in the learning and educational literature. Secondly, the literature lacks the guidance to analyse and aggregate the data streams produced from students' using these environments in order to assess their performance [17].

In 3D-VWs, primarily the learners' performance can only be extracted from the players' auto-generated log files. Some studies assessed students by investigating the data log files to trace the learners' pathway and to study what actions they made to complete their tasks. For instance, Annetta et al. [18] applied a customised tracking system or intelligent agent to track users by collecting the user login time, chat logs, users' decisions, and patterns of interaction. Then the data collected was analysed via different data mining approaches. In addition, Kerr and Chung [19] have identified learning evidence from analysing log data via cluster analysis algorithms to recognise the key features of the students' performance in educational game environments. Nevertheless, the log files record all users' responses and actions to the specific educational tasks, including the correct actions and their mistakes, which increases the challenge when we try to analyse their performance. Log files create large amounts of data which can create serious problems for researchers trying to gather learning evidence from VWs [20].

Saving data in immersive environments without thinking about how the data will be scored or assessed is usually not a good technique for evaluating the learning outcomes. Some studies have used data mining methods to understand this data, but these methods are often limited to inferring the correlation between the data and their intended learning objective. Tesfazgi [21] stated that it is more preferable to design and create the learning space from the start to enable the capturing of the learning evidence and the assessment of the student's performance.

Evaluating the quality of the learners' performance is another issue in 3D-VWs. Quite a few skills can be acquired from collaborative activities, nevertheless it is difficult to automatically collect evidence of them [22]. For instance, using regular assessment techniques, it is usually more difficult to measure the quality of the students' interpersonal skills, (including collaboration, negotiation, teamwork, and communication), than it is to measure the quantity of them. Although Ibáñez et al. [23] proposed techniques that permit the assessment of learning outcomes (skills, knowledge, and competencies) by using elements such as smart objects in 3D spaces, these methods lack the ability to assess the quality of individual performance in collaborative spaces.

The general conclusion that we can make from the literature is that technologies can assist in collecting data for different type of scenarios, however analysing this data to assess both the quality and quantity of learning is a more difficult procedure. Thus, in order to evaluate the quality and quantity of students' performance and assess their learning in 3D virtual environment, we have proposed a model, a Mixed Agents model. Such a model can be used to track the users' behaviour and capture evidence in real-time from collaborative activities. More details about this model is provided in the following section.

III. Mixed Agents Conceptual Model (MixAgent)

In our previous work [24], we introduced the mixed intelligent virtual observation (MIVO) framework, which included the virtual observation model that maps between observing students in classrooms and observing learners in 3D worlds to assess the students' performances. This can be achieved by applying a mechanism that combines agents to simulate teachers' observation(s). This paper demonstrates this mechanism whereby we can collect different kinds of evidence in VWs in order to determine the learning outcomes of individuals and of groups. To record these learning events, we extend the integration of MAS and ontology approaches from being a group of software agents connected with an ontology to also comprise another kind of agent, the natural agents, which are made up of the students participating in the event. In the MixAgent model (Figure 1), two types of software agents are applied: ontology agents and user agents. Moreover, the natural agents are combined with them. The agents' roles and abilities including their specific assessment capabilities are as follows:

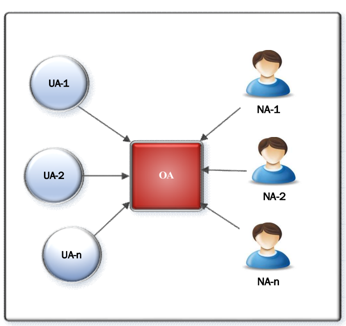

Figure 1. Mixed Agents Model (MixAgent)

- *User Agents (UA):* These agents are created once a learner is authorised in the virtual world, an agent for each student. UA monitor users' behaviours, logs, and decisions in real-time; translates any actions into data; and then directs the data to the other software agents, and the ontology agent.
- *Natural Agents (NA):* Peer evaluation is considered an effective method for group assessment [25]. Likewise, it can help to capture implicit evidence that is difficult to detect with regular technology [22]. Accordingly, learners are considered the natural agents who are able to produce information that reflects the quality of each others' skills by regularly assessing the communication, negotiation, teamwork, and active learning skills of the individuals taking part. While the natural agents are working together in their tasks, they can use a sliding scale (scored from 1 to 5) which allows them to rate each other performance frequently. These scores are stored then as events that trigger the system and are sent to the ontology agent which saves them in the ontology repository. Employing natural agents will enable the quality of the learning outcomes to be captured, which is often too complicated to be identified by more automated approaches.
- *Ontology Agent (OA):* All the agents have a shared goal and they communicate and work together in real-time to collect events and send them to the OA. The OA is based on an ontology approach that models the objects in the learning environment. It performs as a bridge and a communication agent between the other agents. This agent has the capability to receive data from the other agents and store them in the appropriate repositories. The obtained data from the agents can then be analysed based on logical rules that can assist in evaluating the students performance. The OA can help to resolve the relationships between the gathered data and its underlying meaning in terms of infering the intended learning evidence. Using the reasoning engine permits further reasoning using the repositories and more meaning to be infered from the data collected from the different agents.

IV. Proposed Learning Scenario

Linda is an eager computer science instructor who teaches on-line classes using a 3D-VW that supports collaborative programming activities. The interface allows students to work as agents and evaluate each other using a sliding tool with a rating from 1 to 5. Linda has formulated activities to teach her students how to programme embedded systems. She grouped them together, each group contains three students. She then gave them several tasks and problems to be solved.

The students practiced the activities and tried to collaborate to accomplish the tasks the instructor had assigned to them. Some students were highly involved and made numerous contributions, while others contributed less. During the collaboration, they rated the quality of each other's performances frequently by using the evaluation tool.

Moreover, the software agent tracked the students' actions and events. Finally, when they completed the last task, the students received dashboard reports that assessed the learners' performances individually and showed them the learning outcomes they had achieved. The teacher and the learners were also able to review the work through video recordings that captured when their performance was high and when it was low. Furthermore, this evidence was recorded in the learners' portfolios to enrich their life-long learning. Linda reported high satisfaction with the platform, which helped her greatly when reviewing the students' work and enabled her to gain more insight into ways of improving the learning activities in the virtual classes. She also stated that peer evaluation gave her greater awareness regarding the quality of the learners' performances. Correspondingly, the feedback provided by the system helped the learners to understand their weaknesses and how they could enhance their performances. Evaluating students is a critical aspect of learning because it can help to determine whether the students have achieved the learning objectives.

V. The Learning Environment

The environment that is applied in this research is called the InterReality Portal [26]. It was created on the Unity platform, which is a platform for creating collaborative 2D/3D environments. The InterReality Portal was developed using the programming language C# at the University of Essex as part of a PhD project. It can assist teachers to organise learning tasks that help learners to understand the functionality of sensors in intelligent environments. It does this by allowing the students to formulate rules for the sensors to observe the effects of these sensors in the virtual environment by using the programming buttons shown in Figure 2.

Figure 2. Graphical user interface (GUI) – InterReality Portal

VI. High-Level System Architecture

To implement the MixAgent model, we have proposed a system architecture for the research prototype (Figure 3), which contains the following:

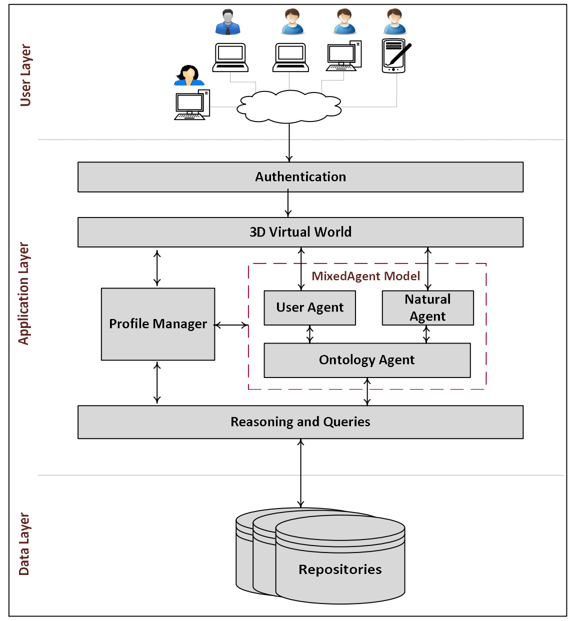

Figure 3. High-Level System Architecture

1) *Authentication:* This identifies users (learners or instructors) in order to recognise their roles and tasks in the environment.
2) *Virtual 3D Environment:* This displays the environment interface that users can employ to participate in their roles. From the learners' point of view, students will work together on the learning activities and evaluate each other. From the teacher's perspective, the interface will enable the organisation of the activities and the assignment of roles for each learner. Once the activities have been completed, the interface will describe the learners' work and evaluate it.
3) *MixAgent Model:* This is the model described earlier. A user agent for each learner will be created to trace users' actions in real time; this agent will be developed using C#. Learners also will work as agents who evaluate others; therefore, the natural agents are responsible for collecting the evaluation data. All the agents will trigger the system and produce data that will be sent to the ontology agent. The ontology agent is responsible for maintaining and managing all information going in/out of the data layer (repositories and ontologies). In addition, it is responsible for obtaining and sending data from/to the reasoning engine.

4) *Profile Manager:* This manages and maintains the students' repository. It also manages the roles and tasks available for learners in the virtual environment. It maintains learners' portfolios and the evaluation results thereof.
5) *Reasoning and Queries:* This is responsible for formulating and executing all the rules governing searching for retrieving data in the ontological repository. Using an appropriate inference engine to rationalise the information will provide the system with richer mechanisms when working with the information and will produce satisfactory search results for the users. A Java-based OWL 2 reasoning engine, the Pellet reasoner [10], is employed to reason and infer about the data in the ontologies. In addition, the SPARQL[6] query language is utilised for reasoning and creating different queries to retrieve, update, extract and construct information/data about learners' activities and to formulate rules for different entities in the environment.
6) *Data Layer:* This layer offers a standardised vocabulary to describe the knowledge domain of the environment by including ontologically based repositories to set up all the relationships among elements and to provide better communication among them. The ontology repository is created using OWL 2 description logic (OWL 2 DL) language via Protégé[7].

VII. Conclusion and Future Work

This paper has presented the MixAgent conceptual model that plays a significant role in identifying real-time events, collecting learning evidence and evaluating students' learning during learning activities in a collaborative 3D space. MixAgent pairs natural agents with software agents to enhance the overall evaluation and to provide better feedback results.

This is a work-in-progress paper and much more work is required to complete the research. In the future, we are planning to continue implementing the research prototype as a proof of concept. The InterReality Portal virtual world allows us to apply the new MixAgent that should provide better results for collecting evidence of learning. The experiments will show how software agents can be combined with natural agents to improve the collection of learning evidence and prove the MixAgent concept. The evaluation of our work is also a vital phase in the continuing progress of this research. The research models will be evaluated through user-based evaluations. Finally, we are planning to present the investigation and evaluation results at future conferences.

[6] SPARQL: https://www.w3.org/TR/rdf-sparql-query/
[7] PROTÉGÉ: http://protege.stanford.edu/

Acknowledgment

We are pleased to acknowledge Dr Anasol Pena-Rios for providing us with the InterReality Portal and her technical support with this environment.

References

[1] K. Andreas, T. Tsiatsos, T. Terzidou, and A. Pomportsis, "Fostering collaborative learning in Second Life: Metaphors and affordances," Computers & Education, vol. 55, pp. 603-615, 2010.
[2] A. Belazoui, O. Kazar, and S. Bourekkache, "A Cooperative Multi-Agent System for modeling of authoring system in e-learning," Journal of e-Learning and Knowledge Society, vol. 12, 2016.
[3] A. P. Schouten, B. van den Hooff, and F. Feldberg, "Real Decisions in Virtual Worlds: Team Collaboration and Decision Making in 3D Virtual Worlds," in ICIS, 2010, p. 18.
[4] B. Dalgarno and M. J. Lee, "What are the learning affordances of 3-D virtual environments?," British Journal of Educational Technology, vol. 41, pp. 10-32, 2010.
[5] I. Duncan, A. Miller, and S. Jiang, "A taxonomy of virtual worlds usage in education," British Journal of Educational Technology, vol. 43, pp. 949-964, 2012.
[6] M. Gardner and J. Elliott, "The Immersive Education Laboratory: understanding affordances, structuring experiences, and creating constructivist, collaborative processes, in mixed-reality smart environments," EAI Endorsed Transactions on Future Intelligent Educational Environments, vol. 14, p. e6, 2014.
[7] M. Gardner, "Using Ontologies to Support the Sharing of Learning Resources," Available on-line at: http://istr. wordpress. com/2007/01/18/jisc-paper-delta, 2007.
[8] W3C, "Semantic Web," in Ontologies, ed: W3C, 2015.
[9] P. Szeredi, Gergely Lukácsy, and T. Benkő., The Semantic Web Explained: Cambridge University Press, 2014.
[10] B. Parsia and E. Sirin, "Pellet: An owl dl reasoner," in Third International Semantic Web Conference-Poster, 2004.
[11] B. McBride, "Jena: A semantic web toolkit," IEEE Internet computing, pp. 55-59, 2002.
[12] V. Haarslev and R. Möller, "Description of the RACER System and its Applications," Description Logics, vol. 49, 2001.
[13] H. S. Nwana, "Software agents: An overview," The knowledge engineering review, vol. 11, pp. 205-244, 1996.
[14] E. H. Durfee and V. R. Lesser, "Negotiating task decomposition and allocation using partial global planning," Distributed artificial intelligence, vol. 2, pp. 229-244, 1989.
[15] J. A. Sánchez, "A taxonomy of agents," Rapport technique, ICT-Universidad de las Américas-Puebla, México, 1997.
[16] M. Hadzic, E. Chang, T. Dillon, J. Kacprzyk, and P. Wongthongtham, Ontology-based multi-agent systems vol. 219: Springer, 2009.
[17] J. D. Gobert, M. A. Sao Pedro, R. S. Baker, E. Toto, and O. Montalvo, "Leveraging educational data mining for real-time performance assessment of scientific inquiry skills within microworlds," JEDM-Journal of Educational Data Mining, vol. 4, pp. 111-143, 2012.
[18] L. A. Annetta, E. Folta, and M. Klesath, "Assessing and Evaluating Virtual World Effectiveness," in V-Learning, ed: Springer, 2010, pp. 125-151.
[19] D. Kerr and G. K. Chung, "Identifying key features of student performance in educational video games and simulations through cluster analysis," JEDM-Journal of Educational Data Mining, vol. 4, pp. 144-182, 2012.
[20] R. J. Mislevy, R. G. Almond, and J. F. Lukas, "A brief introduction to evidence-centered design," ETS Research Report Series, vol. 2003, pp. i-29, 2003.
[21] S. H. Tesfazgi, "Survey on behavioral observation methods in virtual environments," research assignment, Delft Univ. of Tech, 2003.
[22] B. Csapó, J. Ainley, R. Bennett, T. Latour, and N. Law, "Technological Issues for Computer-Based Assessment," in Assessment and Teaching of 21st Century Skills, P. Griffin, B. McGaw, and E. Care, Eds., ed: Springer Netherlands, 2012, pp. 143-230.

[23] M. B. Ibáñez, R. M. Crespo, and C. D. Kloos, "Assessment of knowledge and competencies in 3D virtual worlds: A proposal," in Key Competencies in the Knowledge Society, ed: Springer, 2010, pp. 165-176.

[24] S. Felemban, M. Gardner, and V. Challagan, "Virtual Observation Lenses for Assessing Online Collaborative Learning Environments," presented at the Immersive Learning Research Network (iLRN 2016), Santa Barbra, USA, 2016.

[25] E. C. f. T. Excellence. (29/1/2016). How can I assess group work? Available: https://www.cmu.edu/teaching/designteach/design/instructionalstrategies/groupprojects/assess.html

[26] A. Pena-Rios, "Exploring Mixed Reality in Distributed Collaborative Learning Environments," Doctor of Philosophy in Computer Science, School of Computer Science and Electronic Engineering, University of Essex, 2016.