Journal of Universal Computer Science, vol. 24, no. 2 (2018), 171-191
submitted: 27/11/17, accepted: 19/12/17, appeared: 28/2/18 © J.UCS

Mixed Agents Virtual Observation Lenses for Immersive Learning Environments

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Abstract: 3-D virtual worlds and other immersive environments offer features that other learning systems cannot easily replicate. As such, they have the potential to revolutionise the way in which people learn. They are well suited to visualise 3-D objects and their relations to explain complex phenomena. In addition, they enable practical experiments to be performed that are difficult to conduct in the real world. They can also help to facilitate collaborative learning in real-time and enable students to become fully engaged in what they are doing. However, these environments require further exploration to improve their learning affordances. For instance, assessing students' performance and collecting learning evidence is still in its early stages. This paper is primarily devoted to furthering our understanding of observation and assessment. In so doing, a virtual observation model has been developed to effectively map classroom-based observations with how people can be evaluated in virtual 3-D environments. The observation model has been applied to a multi-user virtual environment (MUVE) and examples that illustrate its potential effectiveness are provided. In essence, our research aims to support and enhance the learning experience by demonstrating the advantages of 3-D virtual worlds as a means for advancing learning processes.

Keywords: Virtual Observation; E-learning; Collaborative Learning; 3D Virtual Worlds; Learning Evidence; Assessment; Fuzzy Logic.
Categories: H.1.2, L.0.0, L.3.0, L.3.1, L.3.5, L.5, L.6.2

1 Introduction

Numerous technologies have been developed since the turn of the millennium and they have been used to enhance education and promote collaborative learning such as 3-D virtual worlds (3-D VWs), also known as Multi-User Virtual Environments

(MUVEs). Examples of these innovations include Open Wonderland[1] , Second Life[2], Active Worlds[3], and Open Simulator[4]. It has been suggested that these technologies can be advantageous to educational learning [Dalgarno, 2010] [Duncan, 2012] because they offer features that are not available when using conventional Internet-based learning applications. The ability to illustrate 3D objects and their relative position to each other can help to explain complicated phenomena. For example, Alrashidi [Alrashidi, 2017] suggested an approach for gathering hidden pedagogical gains from embedded computing activities and providing learners with real-time feedback using 3-D objects in immersive environments .

3-D VWs can also enable students to conduct practical experiments that may be difficult to perform in the real world [Dalgarno, 2010]. It has been shown that they can make it considerably easier for participants to collaborate in real-time and share their ideas in a group setting [Gardner, 2017] [Felemban, 2015] [Pena-Rios, 2012]. Such collaboration is particularly beneficial in terms of supporting a shared experience and student's knowledge development.

If a teaching exercise is to be effective, it is necessary to be able to assess how the students are performing. Importantly, this assessment must not be an afterthought but should instead be given careful consideration from the outset of the learning process. Indeed, Wells [Wells, 2001] stresses that teachers should evaluate the entire learning process, not merely the end result. This can prove problematic because it involves appraising how individuals behave. It can be especially difficult to determine the extent to which individuals are acquiring certain skills. Therefore, it exists a clear need to evaluate learning outcomes gained as a result of collaborative activities. 3-D virtual environments offer great potential as teaching tools but their value needs to be confirmed before time and effort is invested in their roll-out [Duncan, 2012]. A serendipitous but significant advantage associated with virtual worlds is that all of the actions of the participants can be automatically recorded, offering an important feature which should be fully exploited.

The process of measuring, gathering, analysing and reporting students' data for the purposes of recognising when the learning occurs is called Learning Analytics (LA) [Siemens, 2011]. An important feature of LA is the visualisation of data. Users should be able to review the analysed results and relate it to learning objectives directly or indirectly [Greller, 2012]. Our work is a contribution to the LA research stream by presenting models for gathering and analysing learners' data, and it supports students with visualised feedback to report learning outcomes from collaborative activities in virtual worlds. We have previously advocated various conceptual models including the mixed agents model (MixAgent) [Felemban, 2016] and the virtual observation model (OLens) [Felemban, 2016] to facilitate the collection and analysis of learning data in order to monitor how individual students are performing. The research presented in [Felemban, 2017] was concerned with the ways by which conventional classroom-based observations could be transferred to collaborative learning in virtual environments. This paper builds on this earlier work by continuing to develop the

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1 http://www.openwonderland.org/
2 http://secondlife.com/
3 https://www.activeworlds.com/
4 http://opensimulator.org/

OLens model and its application in virtual learning environments. Furthermore, careful consideration has been given on how this model could be deployed in order to assess the skills of students in collaborative learning environments. The paper is structured as follows: the next section introduces the various methods that have previously been used to evaluate the progress being made by students in virtual worlds. Section three provides an introduction to the fuzzy logic approach. The OLens model and its observation layers are then explained in the fourth section, while the fifth section gives details of how the lenses are utilised, providing supporting examples. This is followed by a description of the system architecture as well as the fuzzy logic system that has been developed. Section seven presents assessment feedback within the virtual environment, followed by conclusions and our future plans in section eight.

2 Assessment in Immersive Environments

Angelo [Angelo, 1995] describes the evaluation of student progression as "*an ongoing process aimed at understanding and improving student learning. It involves making expectations explicit and public; setting appropriate criteria and high standards for learning quality; systematically gathering, analysing and interpreting evidence to determine how well performance matches those expectations and standards; and using the resulting information to document, explain and improve performance*". It is suggested that these monitoring exercises should attempt to gauge the progress being made by students across a number of different criteria, including their gained knowledge, overall success, performance levels and acquired skills. However, it is important to note that there is not a single method that is capable of assessing each of these qualities; instead various different approaches will be required. For example, formal examinations are well-suited for gauging a person's knowledge but different approaches are required in order to rate a person's skill levels. This is where virtual environments can make a valuable contribution because they can test complex scenarios that would be difficult to replicate in the real world [Dalgarno, 2010]; whilst actively promoting the acquisition of new skills. Providing assessments and feedback can be beneficial to the learning process and it can improve the students' overall learning and performance.

There are various different methods that have previously been employed to monitor how students are progressing in virtual environments. Conventional written tests have been used, often involving multiple-choice questions that can be answered either during the learning exercise or immediately afterwards. For example, teachers have used Second Life to evaluate learners using classroom summative tests [Reiners, 2011]. The quizHUD project [Bloomfield, 2009] in SLOODLE [Livingstone, 2008] is an example of assessing students learning by means of using multiple choice questions. This method of assessment is ideal when virtual environments are used to replicate conventional classroom settings and there is a need to measure an individual's knowledge. Such tests might not be suitable, however, when the virtual environment is being used to teach practical or experimental activities. Summative tests are generally ill-suited to this task because they are unable to interpret the full spectrum of learning and there is often a delay in providing the students with feedback in the learning setting. It has been shown that virtual environments are a valuable tool for distance learning because they enable collaborative work, but this type of learning can be difficult to assess, often requiring assessment methods that have been specifically designed for the purpose. Indeed, according to Thompson and Markauskaite [Thompson, 2014]: "*educators need to move beyond traditional forms of assessment and search for evidence of learning in the learner interactions with each other and the virtual environment, and artefacts created*."

Another method of assessment is to monitor and appraise the ways in which students act. This is typically derived from techniques related to cognitive task analysis and involves applying logical rules that can monitor an individual's behaviour, thereby determining how each student is performing on their learning activities [Schunn, 1999]. Alternatively, generated log files can be used to monitor the actions of students by means of data mining or machine learning. An example of this is provided by Kerr and Chung [Kerr, 2012] who employed cluster analysis algorithms to study individual's log data in education game environments. This enabled them to identify the specific features of student performance. In a separate example, Bernardini and Conati [Bernardini, 2010] modelled successful and unsuccessful learning strategies by means of cluster methods and applying class rules on the students log data. These methods are intended to examine how students behave but their effectiveness is often limited to interpreting the relationships between the data and the quality of learning outcomes based on the log files. It is also important to note that evidence of learning in collaborative activities is significantly more difficult to obtain when there is a large number of people contributing. Log files can record the actions of users related to specific problems, but this can result in an unwieldy volume of data which can hinder the researcher's efforts to accumulate evidence of learning and identify specific learning outcomes [Mislevy, 2003]. Ideally, to have effective assessments, users' data should be captured using a method that identifies how they can be scored. This indicates that the learning environment should be designed with careful consideration for how students will be assessed and how learning will be measured [Tesfazgi, 2003].

Teachers face numerous problems when attempting to measure learning progress in immersive environments [Gobert, 2012]. Not only is there little theoretical advice for interpreting the vast amount of data produced relating to how students are performing, but there is also a lack of any theoretical foundations in the empirical literature regarding the measurement of learning progress. Mislevy and Riconscente [Mislevy, 2006] [Mislevy, 2003] developed the Evidence-Centred Assessment Design (ECD) framework that has been applied in numerous studies. ECD offers means for evaluating the progress being made by students based on computer tests. ECD contains various models, including the task model (where can we measure performance?), student model (what should we measure?), and the evidence model (how should we measure performance?). ECD has also been applied to monitor the progress being made by students in simulated environments [Shute, 2011]. Stealth assessment is based on ECD and was developed by Shute [Shute, 2011] as a method for modelling student actions according to a Bayesian network in game environments. This approach has been shown to be useful in assessing how capable each student is at problem solving. Shute confirmed that inferred learning events accurately mirrored how students learn but such assessments rely on in-game settings to interpret how competent or skilful an individual is.

In summary, there is a lack of standardised assessment models to monitor learning and interpret the various elements of learning including student's knowledge, interaction, skill and success levels. It is also striking that the empirical literature has focused on measuring the performance of individuals yet it is the collaborative features of virtual environments that are arguably their most valuable quality. Therefore, we would argue that it would be advantageous to monitor the performance of the wider group and not only the individual. This is something that has been largely overlooked in the empirical literature. As such, in this paper we hope to demonstrate an innovative approach that can make a valuable contribution to the assessment of students participating in collaborative learning in immersive environments (based on our OLens model which is described in Section 4).

3 Fuzzy Logic Approach

The merits of monitoring each student's performance and skill level for identifying areas requiring further attention is apparent, but doing so in immersive environments is highly complex. Therefore, this paper utilises an approach based on fuzzy logic in order to interpret data for each individual student and infer their learning outcomes as well as their skill levels. Fuzzy logic (FL) is essentially the transfer of expert reasoning into a format that can be comprehended by computers. FL underpins fuzzy expert systems and has been utilised in a variety of expert systems and also some of the latest artificial intelligence programs [Yadav, 2011] [Peña-Rios, 2017] [Albertos, 2002]. More importantly, unlike conventional computer systems, FL can handle uncertainty in a dataset, and is able to model human reasoning mechanisms. Classic set logic is based on 'true' and 'false' values; fuzzy logic extends this to calculate intermediate values between 'true' and 'false', based on linguistic labels such as 'poor,' 'moderate' and 'excellent'. As such, FL enables more complex, real-world inputs to be interpreted without being limited merely to binary information. This is why fuzzy logic has been referred to as 'multiple value logic' with a reasoning logic purpose. Crucially, fuzzy reasoning allows inferences to be drawn from data that may be sprawling and incomplete. Figure 1 [Mendel, 1995] presents a diagram of the general fuzzy logic system that is used in the current research to appraise how students perform.

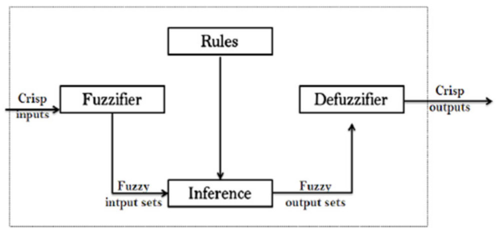

Figure 1: Fuzzy Logic System[Mendel, 1995]

The components of the fuzzy logic system are described below:

a. Crisp input is the data that generates the fuzzy inputs;

b. Fuzzifier is to use membership functions to convert the data (crisps value) into fuzzy variables;
c. Fuzzy inference contains the rule base inference engine;
d. Defuzzifier is to convert the output of the inference into a numeric value; and
e. Crisp output is to produce the final data output.

Fuzzy logic is well-suited to the purpose of our current research which seeks to assimilate agents to produce a system that reasons in the same manner as a human would. More details about applying FL in a virtual world are available in Section 6.2.

4 Virtual Observation Lenses Model (OLens Model)

The Virtual Observation Lenses model (OLens) has been demonstrated in other papers [Felemban, 2016] [Felemban, 2017], so this paper briefly defines it and then describes our new work to apply the model. The OLens model was designed to evaluate collaborative learning in immersive environments by effectively acquiring and interpreting related data. The inspiration for the model came from conventional classroom settings in which teachers interpret different aspects of learning, in order to understand how each student behaves. To this effect, the observation lenses [Borich, 2016] for student learning were adapted for virtual worlds. The OLens model gives details of the granularity levels when monitoring students and stipulates what it is possible to observe. It also defines the learning evidence of collaborative learning, beginning with high level to low level observations (see Figure 2 below).

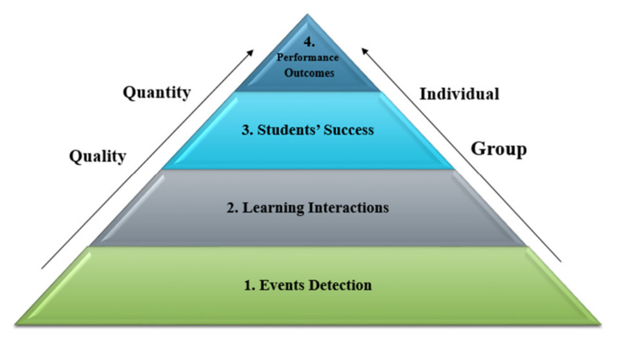

Figure 2: Observation Lenses Model (OLens Model)

The OLens model consists of four layers, as described below:

The Events Detection Lens. This refers to 'arms-length' observation, such as when a teacher observes collaboration between students without paying great attention to what is occurring in relation to a specific task. In the virtual world this equates to recording a sequence of events without making any attempt to interpret these processes. The aim is to acquire details for all implicit and explicit learning events relating to the students. This includes storing the actions and logs of users for use in the other lenses where greater attention is paid to analysing and interpreting these actions.

Learning Interactions Lens. More thorough observations are made in this lens. This includes observations of social interactions between students and environmental interactions between the students and the virtual world. Not only do these observations relate to the quantity of interactions but also the quality of the interactions; thereby making it possible to infer which students are making the most valuable contribution to the group. The number of interactions is recorded, in terms of the number of interactions by each individual and also the number of interactions by the group as a whole.

Students' Success Lens. Teachers are capable of observing students in real world classrooms, thus, this lens extends this behaviour to the virtual world. Success can be interpreted as the ratio of correct to incorrect responses that students provide to a series of exercises, questions, or assignments [Borich, 2016].

Performance Outcomes Lens. In this lens, students are observed in greater detail in order to recognise the results from learning activities. There are various types of learning outcomes that can be assessed. For instance, learning outcomes can be interpreted as what a student knows, understands, or can do to fulfil the learning exercise [Ibáñez, 2010]. As such, these outcomes relate to the student's overall knowledge, skill and competence levels. It is possible to interpret student data in order to evaluate certain skills and competences.

In effect, using the OLens facilitates the measurement of student performance for a variety of learning outcomes. Section 5 provides further details about the virtual environment used to test the different lenses. It also offers a number of examples to illustrate how pedagogical lenses can be mapped to gauge the performance of students in virtual worlds. In addition, Section 5.2 provides information regarding how the lenses can be applied in practice.

5 Virtual Environment

To illustrate how the OLens model can be applied in practice, we have used the Interreality Portal [Pena-Rios, 2016]. This is a 3-D virtual environment created using Unity5. Unity is a cross-platform game engine that can be used to build 2D and 3D virtual environments, including multi-user games. The Interreality Portal was originally developed to allow students to engage in collaborative learning activities based on concepts related to the use of embedded systems and the associated functionality of smart homes. Thus, the Interreality Portal is an ideal platform for collaborative learning pursuits that require the participants to become involved in 'hands-on' learning activities. Students are typically required to engage with their fellow participants in programing actuators and sensors in a virtual smart home by establishing IF-THEN-ELSE rules in real time. To do so, they have access to a collaborative programming board and a number of icons representing either a part of the IF-THEN-ELSE rule, or a sensor or actuator (Figure 3).

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[5] https://unity3d.com/

Figure 3: Graphical User Interface (GUI) – InterReality Portal [Pena-Rios, 2016]

5.1 Learning Scenario

As part of our OLens model implementation and testing, our remote collaborative learning scenario is designed as follows: first, each student is assigned to a group and then asked to log in to our virtual environment via the Internet. Each group comprises two to four members, where each student has their own avatar. Within these groups they must collaborate in order to explore solutions to a variety of problems. Such scenarios help the students to learn the functionality of embedded systems, and also reveal ways in which they can use the programming board and icons to develop new programming rules. Figure 4 illustrates how syntactically correct rules impact on the virtual smart home.

Figure 4: Student interaction via virtual scenarios

The GUI contains a chat box that the students can use to communicate with each other during the task. It also offers a feature that enables each student to rate the performance of the other participants by means of a rating tool (see Figure 4). The technology also monitors the actions of each participant and accumulates details of the triggered events in the repository. As the students complete various tasks, the virtual platform automatically stores evidence of learning and evaluates each individual's actions. As soon as a task is completed, the participants are presented with a dashboard giving details of how they and their group performed, thereby summarising their performance and what has been learnt. Recorded videos of each student are also available to compare their performance to the provided assessments.

5.2 Application of the OLens Model

In this section, we present examples to illustrate the various methods for applying and pedagogically mapping the lenses to amass data, establishing rules for its use in virtual worlds.

Event Detection. As previously pointed out in section 4, at this stage the system merely collects details of how the various students act, saving the data to mimic how a teacher may observe students from a high level perspective without providing any detailed assessment of how the students are performing. In our previous work [Felemban, 2016, Felemban, 2017], we illustrate MixAgent model (Figure 5) which monitors the learning activity in real time, accumulating evidence of learning in order to grade how students perform in terms of quality and quantity when participating in virtual worlds.

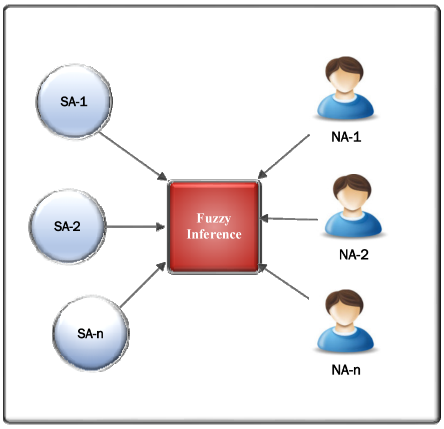


Figure 5: MixAgent Model. Abbreviations: SA = software agent; NA = natural agent

A combination of software agents and natural agents (users) are employed in the MixAgent model. Software agents automatically observe how students behave, capturing their behaviour events in system logs, converting actions into data that can be stored in an underlying repository. Students perform the role of the natural agents.

They appraise other students and accumulate implicit evidence that could not otherwise be easily discerned by the technological approach [Csapó, 2012]. Each student is able to observe the quality of their peers' performances and provide their opinion on each other's collaborative skills. Figure 4 illustrates the rating tool that each student can use to rate their peers, based on a scale from zero to two, where zero is negative, one is neutral and two is positive. This data is stored in the repository, and the data gathered by both, the natural and the software agent, which is subsequently interpreted by the OLens model.

All the agents work towards the same goals, interacting in real time to accumulate data that can subsequently be used in a fuzzy inference mechanism. These inferences are generated by a fuzzy logic system (FLS) which uses the data provided by the agents. Fuzzy rules interpret the data stored in the repository, inferring how each individual user is performing. Crucial learning evidence can be identified based on these inferences, which can lead to a better clarification of the relationship between the data and its underlying meaning (in this context this is the associated learning performance for each user). The value of Fuzzy Logic lies in its ability to accommodate numerous values and reason about this data much in the same way as a human would do. This helps to arrive at a unified vision of agency in the model. Section 6.2 below offers further insight into the FLS that has been developed.

Learning Interactions Lens. Since this lens focuses on more thorough observations, it requires common interfaces to query the data amassed (e.g. APIs), in order to evaluate each participants' contribution when engaging in the virtual environment. Table 1 below offers examples of the quantity and quality indicators that are used to assess the contributions of participants and their interactions with other students in the virtual world.

	Quantity Indicators	**Quality Indicator**
Individual	-The amount of actions in the chat log during a period. -The amount of actions in using the virtual objects during a period. -The amount of actions involved in creating programs during a defined period.	-The average rating scores for a student from other members in a period. Rating scores: Negative= 0, Neutral = 1, Positive= 2
Group	-The sum of all the actions of all the members in a group. Also the actions derived from the chat log, objects log, and program log during a defined period.	-The average rating scores for all members in one group in a defined period. Rating scores: Negative= 0, Neutral = 1, Positive= 2

Table 1: Interactions Indicators

Student Success Lens. This lens aims to mimic the ability of teachers in real world classrooms to evaluate the overall performance of students. In this context, student performance can be inferred from the ratio of correct to incorrect answers given in response to various questions and tasks [Borich, 2016]. Table 2 below provides a summary of the indicators that can be used to determine the success of a group or an individual when attempting a task.

	Quantity Indicator	**Quality Indicator**
Individual	-The amount of correct/wrong answers during a defined period. -The amount of completed/ uncompleted tasks for a set time.	-The rating scores from other members about the quality of a student's work when completing a task.
Group	-The amount of the groups correct/wrong answers during a defined period. -The number of completed/ uncompleted group tasks for a set time.	-The sum of the rating scores from all members about the quality of the group's work when completing a task.

Table 2: Task Success Indicators

Performance Outcomes Lens. This lens goes beyond merely counting the number of correct answers and instead provides a summative evaluation of the quality and quantity of learning outcomes. Multi-user virtual environments (MUVE) are usually used for collaborative learning exercises and, therefore, due consideration should be given to the participants' collaborative skills. There are a number of distinct collaborative skills which can be examined, such as leadership, communication, creative conflict and the maintenance of trust [Johnson, 1991]. Hesse [Hesse, 2015] proposed an alternative skills taxonomy which suggested a number of different skills that should be measured when students are engaging in collaborative pursuits. The framework proposed by Hesse is particularly well suited for assessing the cognitive and social skills of students. What is more, the framework is able to distinguish between various collaborative skill levels. For this reason, Hesse's framework has been utilised to assess the collaborative problem solving levels in the current version of the OLens model. Figure 6 presents an example of social skill classifications based on [Hesse, 2015].

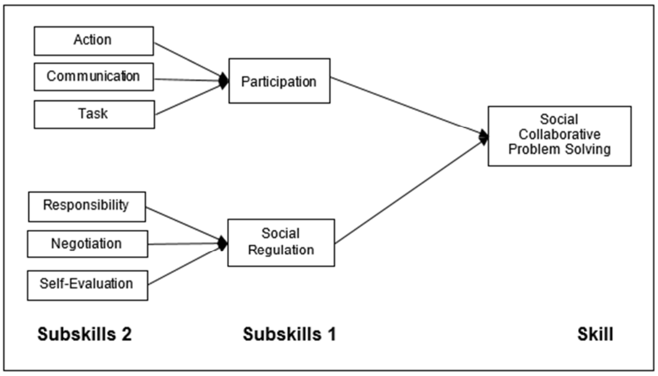


Figure 6: Collaborative social problem solving skills

The data that the system amasses does not naturally lend itself to being used for measuring the skills of individual participants. This can only be meaningfully achieved with additional feedback from the students (natural agents). It has been shown that peer evaluation techniques can be used to measure the skills of students [Kyllonen, 2012]. Indeed, such an approach can provide more thorough insights into the quality of the collaborative skills demonstrated by students when engaging in collaborative tasks. Therefore, all of the students were required to offer their opinions on how their peers performed during the exercises. At the end of each session, a rating panel appears on the screen, allowing each student to rate each other's performance. Table 3 offers instances of learning outcome indicators used for evaluating the skills of individuals by this lens.

	Quantity Indicator	**Quality Indicator**
Individual	Evaluate the participation subskills: actions, communications and task completions as follow: 1-The amount of student's actions. 2-The amount of student's communications. 3-The amount of student's task completed	The student rating scores of the following collaborative skills: -negotiation -self-evaluation -responsibility initiative
Group	Evaluate the participation subskills: actions, communications and task completions for the group	The group rating scores of the following collaborative skills: negotiation, self-evaluation, and responsibility initiative.

Table 3: Learning Outcomes Indicators

In summary, the OLens model provides granularity levels and details of what it is possible to observe and assess in VWs. It also specifies the learning evidence of collaborative learning and identifies the indicators for assessing students in each level. First, the Event Detection lens identifies the method for gathering events by automated and natural agents to mimic teacher observations from high altitude. Secondly, the Learning Interactions lens concerns the environmental and social interactions between learners and the virtual world. Thirdly, the Students' Success lens focuses on the success of doing collaborative tasks. Finally, the Performance Outcomes lens mimics teachers' observations in more detail to recognise the results from learning activities. Many types of learning outcomes can be assessed but this paper evaluates certain collaborative skills and competences.

6 System Architecture and Fuzzy Logic Approach Used

6.1 System Architecture

The system architecture developed for the research prototype in order to facilitate the research model described above is illustrated in Figure 7 below:

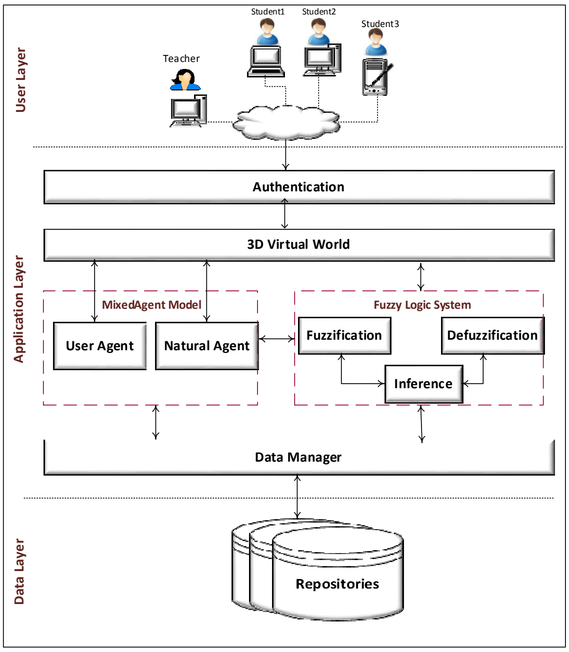


Figure 7: System architecture

The components of the system architecture are described below:

a. **Authentication**: The system identifies learners and teachers, specifying what roles they can fulfil. These roles can be played out in the virtual 3-D environment. For instance, students are free to engage with their peers to achieve educational goals and also appraise each other's progress. Teachers use the same interface to devise educational activities and inform the students about what they need to do to complete a task. When a student completes an activity, the graphical user interface displays the learner's evaluation (see Section 5 for an explanation of the learning environment).

b. **MixAgent Model**: Students' actions are automatically observed by software agents in real time. Students perform the role of natural agents by rating how well their fellow students perform. This insight contributes to subsequent evaluation processes.

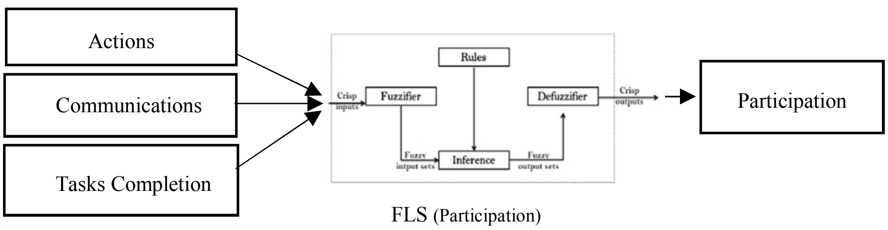
c. **Data Manager**: The data manager has access to all of the data yielded, retrieving it from the repositories when required. Client agents submit data via the data manager, which is subsequently stored in the repositories. Similarly, the data manager is responsible for transferring data to and from the fuzzy logic system when necessary.

d. **Fuzzy Logic System**: This model processes the raw data in order to derive usable outputs for evaluation purposes. This involves fuzzification, inferencing and defuzzification activities.

e. **Repositories**: The repositories store data in real time, accumulating details about events and the actions of participants.

6.2 Applying the Fuzzy Logic Approach

We applied the fuzzy logic method to amalgamate the data produced by natural agents and automated agents in order to make decisions about students' performance and assess their interactions, success and skill level. The value of fuzzy logic lies in its ability to accommodate many values and reason about this data much in the same way as a human would. Different fuzzy logic subsystems (FLS) have been created for each level in the Olens model to analyse and interpret agents' data. This section provides an example of a FLS in the Learning Outcomes lens. For instance, in the previous figure (Figure 6), in order to evaluate students' participation skill in the learning activity, we should evaluate three subskills: actions, communications and task completion [Hesse, 2015]. Thus, we developed the following FLS in Figure 8.



FLS (Participation)

Figure 8: FLS for Participation Subskills

Within this diagram (Figure 8), the FLS contains the following:

a. **Crisp inputs**: They represent specific individual students' data to be evaluated, which was acquired via natural / software agents during the learning activities. In this example, the crisp inputs are student actions, communications and tasks completion.

b. **Fuzzifier**: The fuzzification process involves converting crisp values into fuzzy inputs by applying a suitable membership function (MF). In the current study, to evaluate the level of participation skill in the previous example (Figure 8), student data are evaluated against particular fuzzy sets using a triangular membership function. Three parameters are used to specify each membership function (x, y, z) and this function represents each piece of student data. In order to develop the MF of each subskill (input), students are observed while collaborating and get input from experts (teachers) about when they consider each subskill to be high, middle or low. For example, for the task completion subskill, experts mark high task completion for students who developed three or more rules for the smart home, middle task completion for creating between 1 and 4 rules, and low task completion for developing less the two rules. Upon this the MF of task completion is developed (Figure 9) to be used as an input for the FLS. Each subskill has its MF based on observing teachers evaluations.

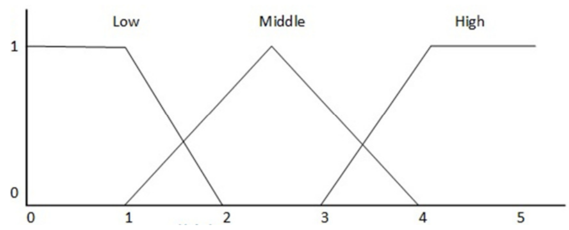


Figure 9: Membership function for task completion

c. **Fuzzy Rules**: Fuzzy rules are established using various linguistic labels to facilitate student evaluation. These rules take the form of IF-THEN rules. Examples of the linguistic rules that have been developed for the system are:

- *IF (Actions IS High) AND (Communications IS High) AND (TaskComp IS High) THEN Participation IS High*
- *IF (Actions IS Middle) AND (Communications IS High) AND (TaskComp IS Middle) THEN Participation IS Middle*

d. **Inference**: The inference mechanism calculates the firing strengths of each rule to decide whether a rule will be fired in response to a specific input, generating fuzzy output sets.

e. **Defuzzification**: Finally, the defuzzification process is applied to convert fuzzy output sets into crisp output values using a particular defuzzification method. Our implementation uses centroid defuzzification as it has been widely applied in the empirical literature [Padhy, 2005]. The following section (7) gives examples of the system evaluation output.

7 Assessment Feedback within the Virtual Environment

By applying the OLens model in the system previously described, we aim to better assess students' overall performance of collaborative learning activities in the virtual world, providing users with more useful feedback. Once an individual learning session has been completed in the virtual world, the progress that has been made by each student can be viewed on a dashboard. The dashboard is customised for each learner so that they can only see their own review and the accumulated results of their group.

Figure 10 presents an image of the assessment screen that appears once a student has completed a session. It provides details of the student interactions that are derived from the underlying agents and inferred by the fuzzy logic system. Figure 11 shows that the student is also able to review their performance by watching a recorded video with reference to the assessment dashboard. If the student has been criticised in some way at a certain stage of proceedings, they can watch that particular episode in the task and then better appreciate why they have received these results.

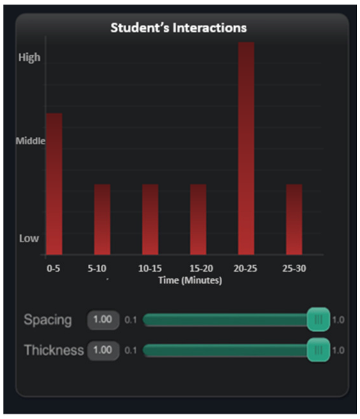


Figure 10: Student's interactions by time in the learning activity

Figure 11: Video recording to review the student performance

For instance, Figure 10 shows that student X was criticised during minutes 20 and 25 with a high level of interactions, while during minutes 5 and 10 was assessed as low-level interactions. Thus, the student or teacher can go back through the video to understand the marks.

Figure 12 presents a dashboard that can be used to review the student's success. This illustrates the progress that has been made in the tasks. As demonstrated in the success lens, both the number of tasks completed over the learning activity and the rating scores from other members about the quality of a student's work when completing a task are used as the yardstick for quantifying progress. The quantity and quality of student performance has been used as crisp values in the FLS to infer the degree of task success. For example, the image below shows that student X completed Task 5 to a highly successful level.

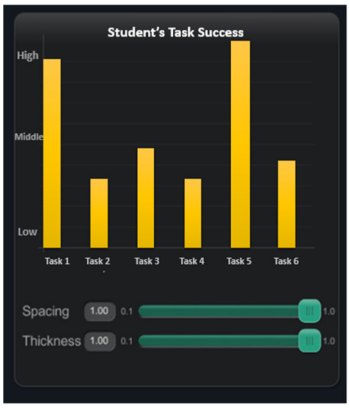


Figure 12: Student's task success dashboard

Figure 13 illustrates the dashboard that shows the students how their social collaborative skills have been rated in the learning activities. These results are based on observations gathered by the natural agents (fellow students) and also the automated agents. These details are also interpreted by the FLS in order to provide a thorough assessment of each student's skills and they are marked as high, middle or low.

We believe that it is necessary to continually monitor each student's progress because otherwise it would not be possible to establish whether they are achieving what would be expected of them. It is hoped that this feature will prove valuable to teachers because it enables them to evaluate the student's output and amend the learning activities in the virtual world accordingly. This monitoring process is substantially enhanced by the feedback received from peers about how the other students are performing. We anticipate that all of the progress reports will help individuals and groups to identify their areas of weakness that should be focused upon in order to facilitate further improvements in performance.

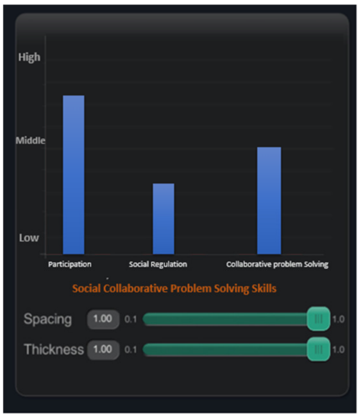


Figure 13: Dashboard summarising the student's level of skill

7 Conclusion and Future Work

There is extensive coverage in the empirical literature of the merit of observing and appraising students in real world classrooms, however, there is a paucity of research concerning observing and appraising students in virtual worlds. An advantage is that virtual worlds are able to automatically capture details about students' actions in a way that would not be possible in the real world. The presented research aims to exploit the affordances of 3-D virtual worlds by investigating how students can be appraised in order to enhance their learning effectiveness. It is also a contribution to the Learning Analytics research by proposing models for accumulating and analysing student data in virtual worlds and providing them with visualised dashboards to assess learners' performance in collaborative activities. In this paper, we have explained the OLens and the MixAgent models with a fuzzy logic approach to achieve this.

The OLens model comprises four lenses: events detection, learning interactions, the success of students, and performance outcomes. These lenses appraise student performance from a variety of perspectives. For assessment purposes, it is important to monitor the progress being made by individual students in order to confirm whether or not their learning objectives have been achieved. Moreover, this monitoring process could inform the teacher about any improvements that could be made in terms of the collaborative learning task.

The paper has also presented the MixAgent model which helps to recognise events in real time, gathering learning evidence and assessing student performance in collaborative learning environments. The MixAgent model utilises a fuzzy reasoning approach as a mechanism to combine the generated data from the agents inferring the learning outcomes that learners obtain from collaborative activities. The Olens and MixAgent models have been applied in the InterReality Portal as an example to provide superior insight into the performance of students.

However, one potential weakness with this work is the susceptibility of the proposed assessment methods to the possibility of students deploying gaming tactics to artificially inflate their marks and increase their scores. Automated assessments are particularly vulnerable to such tactics. For example, if the assessment rules are published, students may focus their efforts on satisfying those rules in ways that don't necessarily reflect the objectives of developing the system. This requires further investigation to prevent cheating the system by users.

Another shortcoming with the current work is the lack of experimental data. We have already developed the explained prototype by applying the models with the fuzzy logic system to generate the assessment dashboards in the virtual environment. Evaluating this work is of great importance because it will help the research to advance. Therefore, we will run user (students) and expert (teachers) evaluations to validate the models. The evaluation will comprise many educational sessions in the virtual world. Each session will include a group of two students to imitate collaboration between learners and one teacher to imitate classroom observations. The teacher participants will be computer science experts who have been teaching programming courses and observing students in computer labs. The teachers will be invited to observe the collaborative activity and evaluate the students in the virtual world. The students are undergraduates who haven't used the system before and they will be asked to collaborate and program the smart house appliances. While learners are working, the system will assess their performance virtually and the teachers also will evaluate them manually. Then, the results from the system will be compared with the results from the experts' observations. In addition, participants feedback and acceptance of the system data will be gathered. Completing the evaluation sessions will help to validate the approaches and models used in our research. Finally, the results of these evaluations will be reported in forthcoming publications.

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