Proceedings of the Pakistan Academy of Sciences:
A. Physical and Computational Sciences 53 (3): 255–266 (2016)

ISSN: 2518-4245 (print), 2518-4253 (online)

Pakistan Academy of Sciences

Research Article

A Student-friendly Framework for Adaptive 3D-Virtual Learning Environments

Aftab Alam*, Sehat Ullah, and Numan Ali

Department of Computer Science and Information Technology,
University of Malakand, Dir (L), Pakistan

Abstract: Three dimensional virtual learning environments (3D-VLEs) with adaptive capability have made the learning process easy and closer to one-to-one tutoring. These systems have the ability to dynamically adapt to the learning capability of students and all the activities they perform, which results in improved learning. In this paper, we present a method for defining the adaptive aspect of 3D-VLEs where student learning is quantitatively measured. The contents of 3D-VLEs are changed according to the learning skill of students. A weak learner is provided more time to complete a given learning module while a good learner can finish his work in less time. As a result students become motivated towards learning. The proposed method is student friendly and it enhances the learning capability of the students by providing them learning materials which they can absorb. The experimental results show the effectiveness of our proposed approach for 3D-VLEs.

Keywords: Virtual reality and education, 3D-educational virtual environments, adaptive 3D-virtual learning environments, computer-aided learning, Fuzzy set theory, student learning evaluation

1. INTRODUCTION

Virtual reality (VR) has greatly changed human perception and working styles of organizations towards better performance [1]. The use of virtual technology is increasing day by day and many fields such as medical rehabilitation, architecture, business, training simulators, gaming, entertainment and education are utilizing virtual reality systems for achieving efficiency in their work processes [2, 3]. In desktop VR, three dimensional virtual learning environments are specially designed to assist students in learning[4]. 3D-VLE is a 3D computer representation of space in which students can easily change their view points and interact directly with the virtual world [5]. They can freely navigate inside the environment, select and manipulate different objects in real time which give them the sense of realism [6].

Virtual reality technology is very much suitable for education and all those systems where the physical alternative is not available, the cost of the actual work is very high or the procedure of the work is too dangerous to perform [7, 8]. In Medical field, it is not possible to provide human body to each student of the class for their experiments; therefore VR simulators are very much cost effective solutions for performing virtual operations and studying parts of human body. Another good example is flight simulators where the safety of pilot is very important, so he is trained in virtual environment about various situations which he may face during the fly.

It is obvious that 3D-VLEs have made learning process easy and cost effective but there are some drawbacks of this technology which need further attention for possible improvements. For example, 3D-VLEs are mostly saturated with different objects. Presenting large information on the screen negatively affect the performance of students in the virtual environment. The new user does not know what to do first or next. He is overwhelmed and easily get lost in the

Received, October 2015; Accepted, June 2016
* Corresponding author: Aftab Alam; Email: alam@uom.edu.pk

environment which results in low learnability [5, 8, 9]. The effectiveness of 3D-VLEs is also low for younger students especially those who have low motivation for learning. The reason is that they spend most of their time in activates which are not very much related to learning and hence results in low performance [10, 11]. One solution to the above problems is to make 3D-VLEs in such a way that dynamically adapt to the learning capability of an individual and all the activities which he performs while interacting with the environment [5]. It may prevent students from being overwhelmed by showing him objects according to has learning goals. Adaptivity could make the distinction between education and entertainment which motivate students for learning. Also it reduces the risk of astray navigation inside the virtual environment due to which students cannot focus on the actual learning materials. All these concerns have been discussed in [8, 12] with great detail.

From the above discussion it is clear that the purpose of 3D-VLEs is to enhance the learning capabilities of students. A very good literature is available regarding the adaptivity of 3D-VLEs but research on designing such environments is still immature [5]. Defining the adaptive aspect of 3D-VLEs is a difficult task because there is no clear strategy for how to generally modify the contents of 3D-VLEs to change a task level for a specific student [12, 13]. In this paper, we use "learning skill" is an adaptive criteria for 3D-VLEs. An attempt is made to quantitatively measure student learning in each level. The contents of 3D-VLEs are changed in the next level according to the learning capability of student measured in the previous level. By using this approach students get motivated towards learning, as a result the learning process is improved.

The remaining paper is organized as follows. Literature review is presented in section 2. In section 3, the proposed model is explained which is followed by experimentation in section 4. Experimental results are discussed in section 5 and discussion is given in section 6. Conclusion and future work are presented in section 7 and 8 respectively.

2. LITERATURE REVIEW

Adaptive learning is a 'promising alternative approach' for the improvement of students learning outcomes [14]. At the start of 20th century adaptive strategies were used in education for the enhancement of student learning and understanding [15]. Adaptive Hypermedia Architecture (AHA!) is a well known versatile adaptive hypermedia framework for adding adaptive features to different applications such as on-line courses, museum sites and encyclopedia etc. AHA! is used to build and maintain the student model for the purpose of providing specific and personalize learning content [16, 17]. Chittaro and Ranon published many papers regarding the adaptation of virtual environments. In 2000, they used an approach called ADVIRT for introducing adaptation inside VR store [18]. Based on some personalization rules the navigation and layout of the store is customized for different users. In 2002, they presented a software architecture solution called Adaptive Web 3D to customize the contents of 3D website according to the needs of the customers [19]. In 2007, same authors proposed adaptation for navigation and interaction which help user to efficiently utilize the information provided by the application [20]. They also worked on the extension of E-learning platform and introduced the concept of adaptive educational virtual environment (EVE) [12, 21].The environment was adaptive according to the learning style of students and they used AHA! engine to achieve adaptivity inside EVE [22]. Brusilovsky et al. [23] used adaptive hypermedia methods for 3D-E-Commerce applications. The environment support different navigation techniques and is adaptive according to the shopping needs of the customer. In [24], fuzzy set theory is used to update learning model. A pre-test is conducted to compute the learning level of learner which enables him to enter in the first module. There is no systematic way defined to assess the learning capability of the learner in depth. In 2004, Santos and Osorio [25] introduced an approach called AdapTIVE (Adaptive Three-dimensional Intelligent and Virtual Environment) for distance learning systems. The approach was based on some virtual agents which help users during interaction with the virtual environments. Similarly, Baziuke [26] designed and implemented a smart adaptive component for virtual learning environment. An agent oriented approach is used for the creation and upgradation of curriculum according to the needs of students. Giuffra and

Silveria [27] used similar approach to provide adaptability to distributed VLEs by considering and monitoring students performance and study material they accessed. D. Zakrzewska [28] applied clustering techniques to provide appropriate layouts to groups of students with similar preferences. Celentano and Pittarello [29] used software sensors to monitor user behavior for controlling navigation and interaction within virtual environment. The sensors record the data whenever a user interacts with the object. Based on interaction history, the environment is adapted. Dominique et al. [30] used mining techniques for the improvement of adaptive systems. According to them learners' interactions are observed through some parameters which are then used to trigger automatic application of rules that leads to the production of personal learning contents. A very good work is done regarding the adaptation of 3D virtual environments by Troyer and Ewais [5, 8]. They discuss different components of VE and then introduced a set of adaptation types and a set of adaptation strategies for 3D-VLEs. According to these authors adaptation can be applied to a single component as well as multiple components of VE.

As discussed above, different approaches have been used for the adaptation of VLEs. Some of these include personalization rules for customized navigation inside VR stores [18], observing customer behavior for shopping [23], using virtual agents that help users during interaction [25] and the use of software sensors that historically monitor user behavior for controlling navigation and interaction within virtual environment [29]. Similarly, in [24] a pre-test is conducted to compute learning level which is then used to update learner model. All these approaches are effective in their context but no one considered "learning skill" of student as adaptation criteria for changing the contents of 3D-VLEs. We tried to get an insight of student learning capability by quantitatively measuring learning skill of students. The contents of 3D-VLEs are changed according to the learning skill of the students which give them the sense of one-to- one tutor.

3. MODEL DESCRIPTION

In the proposed framework, knowledge is delivered to students in many levels where the number of objects or the amount of teaching material in a given level is dynamically decided and is based on the learning capability of student in the previous level (total number of levels are not fix i.e. less for an efficient student and more for a weak one).

Learning is a qualitative variable which cannot be measured directly but we can use some quantitative variables such as time, no of errors and test score etc to assess the learning skill of students in virtual environments. In general, if a student takes less time to complete an activity in a virtual environment as compared to another student who takes more time, the former is considered as an efficient learner. Similarly, a student who performs small number of errors while interacting with the virtual world and gets high marks in the test at the end of learning module is considered as a good learner. The system should be adaptive in such a way that it must give more time to a slow learner for a given module and at the same time it must be able to cope with the learning capability of good learner to make quick progress.

3.1 The Adaptive Frame Work

In the proposed framework, learning capability of a student is measured using a function called learning decision function (LDF) to update learner model. Based on the performance of the students, the system adapts itself in such way that it fulfills the learning goals of all type of students. More contents are displayed to good learners while weak learners are provided with teaching materials which they can absorb according to their learning skills. The basic diagram of the proposed framework is shown in Fig. 1.

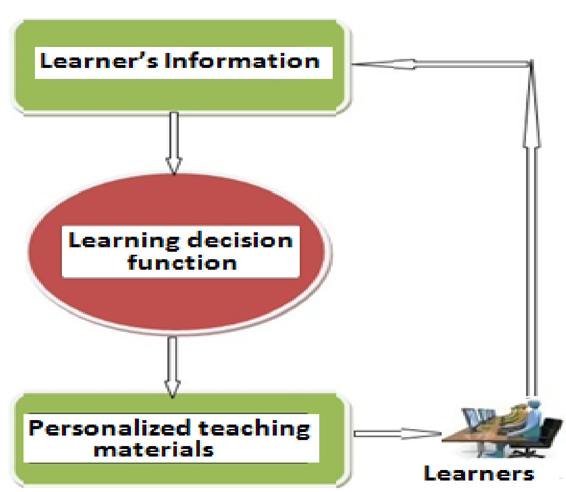

Fig. 1. A student friendly framework for adaptive 3DVLEs.

3.2 Learning Variables

3.2.1. Time

Time is the most important variable for measuring the learning capability of students in general and specially in virtual environments. Slow learner needs more time to understand the given concept while fast learner gets the desired knowledge quickly. In virtual environments, time taken by a student to complete a given module is also related to the way information is presented to the student. But this is a usability problem and is not in the scope of this research. A lot of work has been done in this regard to provide user friendly interface in order to enhance the learning capability of student [31, 32]. For this study, we assume that taking long time to complete a given module means that the student learning capability is low and vice versa.

To properly model time we must consider both total time taken by a student to complete a given module in a virtual environment and also the time to complete an activity within the module. The latter can also be used to identify how the student responds to a complex question. Let t_i presents the time to complete an activity A_i within learning module M in the virtual environment. Then the total time T_m to complete the learning module M is given by Eq.1.

$$T_m = \sum_{i=1}^{n} t_i \tag{1}$$

For more appropriate assessment we can take the arithmetic mean of the time of all previous modules to get an average learning time for the student.

3.2.2. Number of Errors

Counting the number of errors for a student also shows his efficiency. While interacting with the virtual environment; a good learner will perform less number of errors as compared to a weak learner. Errors may be divided into two types i.e. technical and non technical errors. Technical errors show that the student is not familiar with the virtual environment and needs more time to perform the given activity. A list of some most common technical errors is given below.

1. The student performs astray navigation and is lost in the virtual environment. The student becomes confused and deviates from the right path as a result he performs some undesirable actions.
2. The student may make a mistake during object selection and release. Precision and accuracy in object selection and releasing shows the performance of the student in the virtual environment.
3. The student may try to perform some incompatible manipulation on the selected object. e.g. try to move objects which are fixed in the given coordinates of the virtual environment.
4. Interaction devices also play an important role in the virtual environment. Some students are very good to use mouse and keyboard. Other will feel comfortable by using some advance devices such as wimote and leap motion etc. The student will perform more errors in term of precision and accuracy if he is new to the interactive device.

Non-technical errors occur because of poor knowledge of student in the given domain. Some of these types of errors are listed below.

1. Student selects two incompatible objects for manipulation.
2. Students try to perform an activity before doing its prerequisites.
3. Student is unable to map correctly the virtual objects with the real world objects. The reason is that the student does not know anything about the actual object in the real world so he is not able to identify it in the virtual environment.

If e_t represents technical errors and e_n represent non technical errors, then the total number of errors which a student performs in the given learning module M is given by Eq.2

$$E_m = e_t + e_n. \tag{2}$$

High value of Em shows that the student is weak while low value shows that the student is good and can learn quickly.

3.2.3. Test Score

The more appropriate way to assess the learning capability of a student is to give him a test after completing a given learning module. If a student gets high marks it means that he is a good learner otherwise the student has little ability to learn. In the latter case, student needs more time for learning the given module. If q_i represents the marks obtained by a student for solving i^{th} question. Then the total marks M_t obtained by the student in test after completing the learning module M is given by Eq. 3:

$$M_t = \sum_{i=1}^{n} q_i \tag{3}$$

High value of Mt is desirable and it shows the efficiency of a student.

3.3 Testing Hypothesis

The proposed framework is based on three hypotheses.

H1: A student who takes less time to complete a given module is good learner.

H2: A good learner performs fewer errors while learning a given module.

H3: A good learner takes high score in test as compared to weak learner.

These hypotheses are the backbone for our research. In order to test these hypotheses, we conducted a survey using questionnaire to collect data from teachers. Total of 44 questionnaires was distributed among senior teachers from different schools, colleges and universities. The results are summarized in Fig. 2.

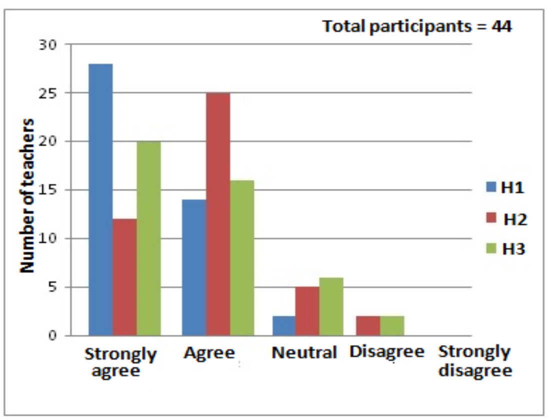

Fig. 2. Survey results for H1, H2 and H3.

The results show that H1 is strongly supported by the teachers i.e. 63% teachers were strongly agreed, 32% were agreed, 5% were neutral and we did not get any negative feedback for it. For H2, 27% were strongly agreed, 57% were agreed, 11% were neutral and 5% were disagreed. Similarly for H3, 45% were strongly agreed, 36% were agreed, 14 were neutral and 5% results were negative. The above results show that the three hypotheses H1,H2 and H3 are correct and can be used to quantitatively measure the learning skill of students.

To know the relative importance of these variables, teachers were also asked to rank these variables on the scale of 0 to 1. The results are summarized in Fig. 3.

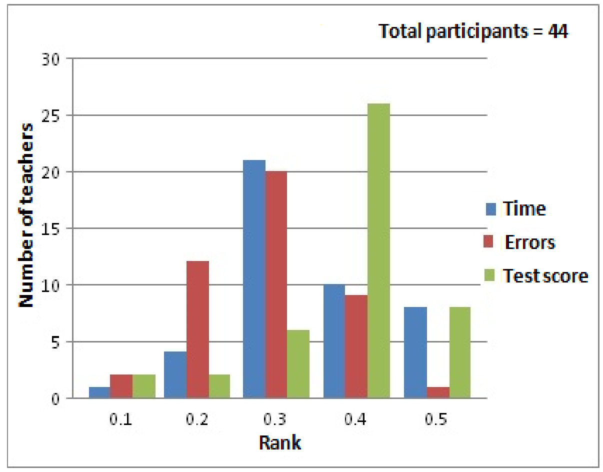

Fig. 3. Relative importance's of time, errors and test score.

The graph shows that total time to complete a given module and no of errors should be given 0.3 weightage each while the test score is given high weight of 0.4 on the scale of 0 to 1. These values show the relative importance of mentioned variables for measuring the learning skill of students.

3.4 Learning Decision Function

We defined a mathematical function called Leaning Decision Function (LDF) which quantitatively measures students learning. The function accepts time; errors and test score as an input, calculates the learning skill of the student in the range of 0 to 1 and displays it as an output.

The LDF can be calculated by using Eq. 4.

$$LDF = f1 + f2 + f3 \tag{4}$$

Where f1, f2 and f3 are functions which are used to calculate the time spent, no of errors and score of a student in the given module respectively.

Calculation of f1, f2 and f3

f1: f1 is a function which calculates total time spent by a student in completing a given module.

A fast learner requires less time to complete the work while slow learner needs more time for learning. Small value of f1 is desirable which shows that the student is fast learner. Therefore,

$$f1 \propto \frac{1}{Tm}$$

$$f1 = \frac{k1}{Tm} \quad (5)$$

Where Tm is the total time spend by a student to complete a given module and k1 is the constant of proportionality.

f2: f2 calculate the number of errors during the learning process. Again small value for f2 is desirable as it shows the efficiency of student.

$$f2 \propto \frac{1}{Em}$$

$$f2 = \frac{k2}{Em} \quad (6)$$

Where Em represents total number of errors and k2 represents constant of proportionality for f2.

f3: f3 is used to measure the score of a student in the test at the end of a learning module. High score means that the student is efficient and vice versa. Therefore, high value of f3 is desirable for good learner.

$$f3 \propto Ts$$

$$f3 = k3Ts \quad (7)$$

In Eq. 7, Ts represents test score of a student at the end of a learning module and K3 is the constant of proportionality.

Now the LDF function can be written as

$$LDF = \sum_{i}^{3} fi \quad (8)$$

This function can also be used in generalized form as shown in Eq. 9 to consider more variables for learning which will give more insight to measure the learning skill of a student.

$$LDF = \sum_{i}^{n} fi \quad (9)$$

3.5 Fuzzy Logic Decision Making

For the purpose of implementation and experiments, we used the results of survey and implement the learning decision function defined in Eq. 8 in such a way that it successfully obey the following two conditions for t ε [15,300], e ε [1,10] and m ε (0,5].

1. The function gives maximum value i.e. 1.00, when a student takes minimum time; perform minimum errors and gets maximum score. For example if a student takes minimum time of 15 seconds, makes a single error and gets maximum score of 5 marks. Then from Eq.8, LDF=1.00
2. The function gives minimum value i.e. 0+ε, when a student takes maximum time, performs maximum errors and gets minimum marks. Where ε is a Greek word, greater than zero, however small no matter. For example if a student takes maximum time of 300 seconds, makes 10 errors and gets minimum score of 0.01 marks. Then from Eq. 8, LDF=0+ ε. The LDF function returns a value in the range of [0, 1] that represent learning skill of a student. Learning is a qualitative variable and due to vagueness in knowledge acquisition, an efficient tool like fuzzy logic is needed to model the learning skill of students [24, 33, 34].

Let x be the be the linguist variable "Learning skill", then the terms weak learner, average learner, and good learner can be constructed as shown in Fig. 4.

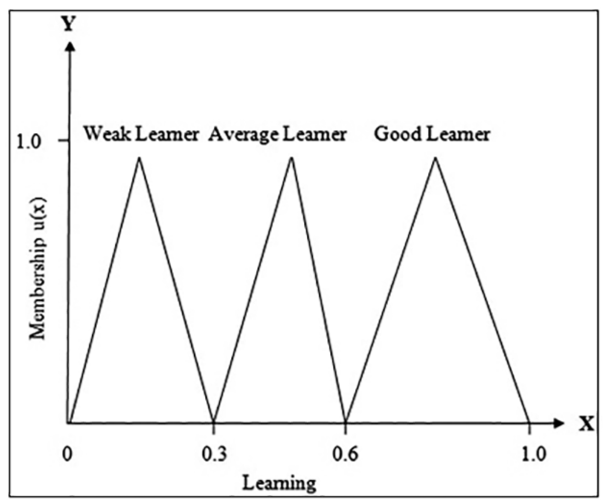

Fig. 4. Fuzzy based approach for measuring learning skill of a student.

Using fuzzy decision making, now we can easily model the learning skills of students on a scale of 0 to 1. All students for which the LDF returns a value in the range of [0, 0.3] are considered as weak learners and they will be provided same amount of teaching materials in the next teaching level. Similarly, students for which the LDF return values in the range of [0.3+ ε, 0.6] are considered as average learners by the system and they will be shown equal amount of teaching materials in the next learning module. The last range of student learning skill is [0.6+ ε, 0.1]. The students in this range are called good learners and they will be treated equally by the system.

The proposed frame work first calculates student learning skill and then use the fuzzy decision making process to provide appropriate teaching materials. Weak learners are provided small amount of information in the next level. Intermediate learners get the knowledge comparatively quickly as compared to weak students, so they are provided little more material in the next teaching level. Similarly, the system is also able to cope with the learning needs of good learners. They are provided more teaching material as compared to average learners in the next learning level. The beauty of our approach is that system treats weak, average and good learners differently and they are provided teaching material according to their actual learning skills. By nature weak learners are slow learners therefore; they will take more time to complete a given learning module. Similarly, good learners are fast learner. The system is providing them an opportunity to finish their work quickly. The detail description of the proposed system architecture is given in Fig. 5 as below.

4. EXPERIMENTATION

4.1 Experimental Setup

The proposed solution was implemented in MS Visual Studio 2010 using OpenGL Graphics Library installed on HP Corei5 Laptop having 2.4GHz processor, 4GB of RAM, ATI Mobility Graphics Card with 64- bit operating system. Mouse and keyboard both were used for interaction with objects within the environment.

For the purposes of comparison and evaluation of the proposed framework for 3D-VLEs, we also used the traditional system for learning in our experiments. Traditional system treats all students equally. Same amount of teaching material are shown to students when they enter the next learning level. The amount of teaching material in each level is predefined and constant. The proposed system evaluate learning capability of the student by considering total time to complete the learning module, total no of errors and test score at the end of each learning level. On the basis of these variables, LDF function quantitatively measure learning skill of a student and display teaching material in the next learning level according to his learning capability. The system dynamically decides how much information is to be displayed in the next teaching level which the student can easily absorb. Both systems were installed on two different laptops. The simulated environment of the proposed framework is shown in Fig. 6.

4.2 Experimental Protocol

We randomly selected 44 students of class 10 from different schools for the evaluation of the proposed system. Both systems i.e. traditional and proposed were introduced to the students and they

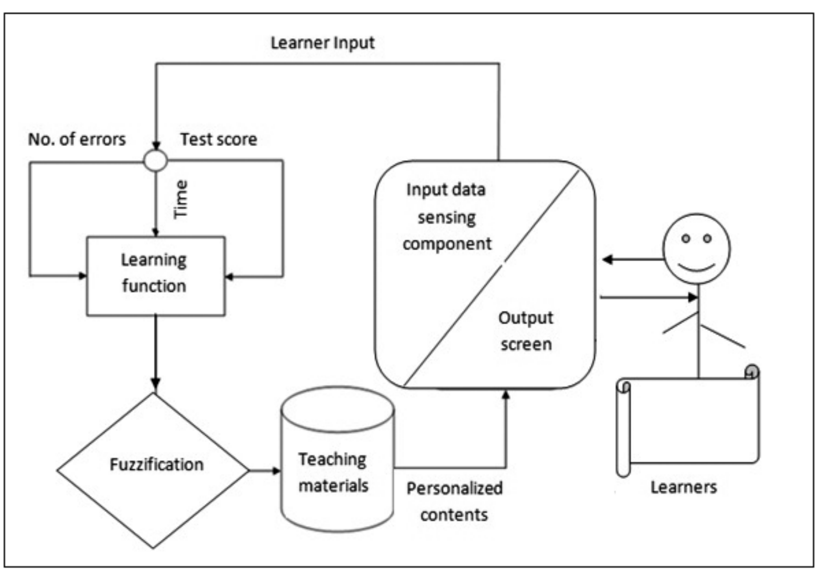

Fig. 5. The proposd system architecture.

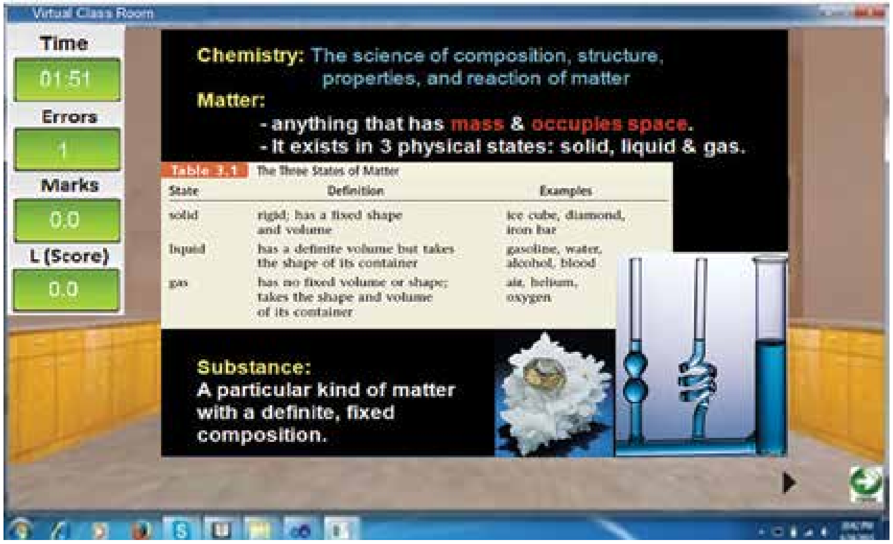

Fig. 6 Virtual class room.

were thought how to select, navigate and manipulate objects within the environment.

For the purpose of experimentation, we selected two different topics from the subject of chemistry of class 10. Participants were randomly divided into two groups i.e. G1 and G2 of 22 students each. G1 used traditional system for learning topic one and then used the proposed system to learn topic 2. Similarly, G2 used the traditional system for learning topic two and then used the proposed system to learn topic one. After the completion of a topic on either system, students were asked to appear in a test containing questions about the topic they covered. The purpose of the test was to check the overall learning of the students on either systems and then to compare the results for the evaluation of the proposed system. In Fig. 7 two students were shown, who are performing their experiments.

Fig. 7. Two students performing experiments.

4.3 Experimental Results

4.3.1. Student Learning

Overall performance of 44 students using the traditional and proposed systems is summarized in Fig. 8. At the end of each learning module, it was observed that most of the students got high marks when they were using the proposed system for learning. Statistically, 68% students showed positive results for the proposed system i.e. they got more marks when they were using the proposed system. 18% results were neutral and 14% results were negative i.e. they got less marks in the proposed system as compared to the traditional system.

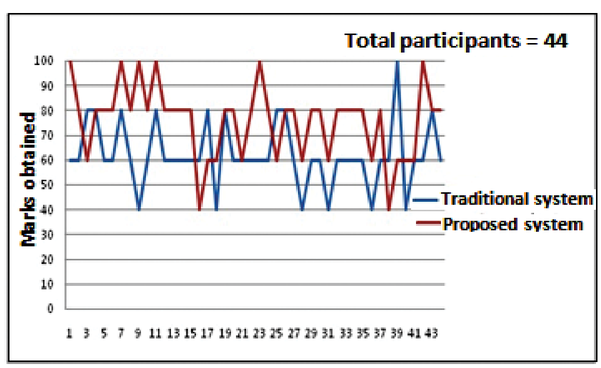

Fig. 8. Overall performances of students on both systems.

We performed ANOVA test on the overall performance of students on both systems based on their marks they obtained at the end of each learning module. The ANOVA (F (1, 43) = 23.72,

$p < 0.00001$) is significant. Comparing students' marks, we got, Mean of 61.89 and Standard Deviation of 14.19 for the traditional system while for the proposed system, Mean and Std. Deviation were 76.36 and 13.82 respectively. The statistical data show the effectiveness of our proposed framework for enhancing the learning capability of students in 3D-VLEs.

4.3.2. Subjective Evaluation

In this section we analyze the responses of students regarding the proposed adaptive framework. A questionnaire, consisting of six questions was distributed among the 44 tested students. The questions along with student's responses are given below. Table 1 contains list of five subjective questions about the traditional system and proposed system.

For Q1 to Q3, student's responses were recorded on scale of 5 points as shown in Table 2, while for Q4 and Q5 students were simply asked to give their opinion about the traditional and proposed system.

Table 1. List of subjective questions about the traditional and proposed systems.

Question No	Questions
(1)	The proposed system provided you learning materials in the next teaching level according to your learning skill.
(2)	Your concentration on the actual learning materials was high in the proposed system.
(3)	Did you feel that proposed system overwhelmed you with learning materails at any teaching level?
(4)	Which system was comparatively more saturated with learning materials?
(5)	Which framework do you prefer for 3D -VLEs?

Table 2 Student's responses for Q1, Q2 and Q3 about the proposed system (total participants = 44).

Question No	Strongly agree	Agree	Neutral	Disagree	Strongly disagree
(1)	(54%)	(23%)	(14%)	(9%)	(0.00)
(2)	(39%)	(36%)	(11%)	(14%)	(0.00)
(3)	(5%)	(11%)	(25%)	(32%)	(27%)

Table 3. Traditional system versus proposed system (comparison) (total participants = 44).

S. no.	System Attribute	Traditional System	Proposed System
1	Over all Simplicity of the system	43%	57%
2	Motivation towards learning	22%	78%
3	Memorability of teaching materials	14%	86%
4	Amount of irrelevant / unnecessary information	69%	31%
5	Ease of navigation inside the Virtual Environment	45%	55%
6	Student friendly	30%	70%

Table 4. No. of levels and completion time (total participants = 44).

S. no.	No. of students in percent	No. of levels	Average completion time	
			Minutes	Seconds
1	14%	4	10	22
2	50%	5	13	37
3	32%	6	16	34
4	4%	7	22	10

Most of the students showed positive response for question Q1 i.e. 54% students marked strongly agreed, 23% were agreed and 14% were neutral. The remaining 9% showed negative response and marked it disagree. For Q2, 39% students were strongly agreed, 36% were agreed, 11% remained neutral and 14% were disagreed. Similarly, for Q3, 5% students marked strongly agree, 11% were agreed, 25% remained neutral, 32% were disagreed and the remaining 27% strongly rejected the opinion.

From students' responses, it was observed that 77% marked the traditional system while 23% marked the proposed system for Q4. Similarly with response to Q5, 14% students marked the traditional system while the remaining 86% were in favor of using the proposed system.

In the questionnaire, students were also asked to compare different attributes of the traditional and proposed systems. The system attributes along with students' feedback are summarized in Table 3.

5. DISCUSSION

The purpose of the proposed framework is to enhance the learning capability of students in 3D-VLEs. In teaching practice, it has been observed that a teacher give more to weak students for understanding a given concept while the same topic is delivered in less time if students are sharp and intelligent. This attitude towards teaching fulfills the needs of all students and they get the desired time for understanding a given concept. Weak learners are not overwhelmed with teaching materials and at the same time good learners do not get bored because of listening the same thing again and again for a long time from teacher. In the proposed framework an attempt is made to implement this behavior in 3D-VLEs in order to make it student friendly. Knowledge is delivered to students in many levels where the number of objects/teaching material in a given level is dynamically decided and is based on the learning capability of the student in the previous level. Here the total number of levels is not fixed i.e. less for efficient and more for weak students. The competent students can complete all the work in less time and can utilize it in some other useful activities while weak learner is provided more time to get the desired knowledge. The experimental result shown in Table 4 confirms this opinion.

Using the proposed system, 14% students complete the given learning module in 4 levels by taking an average time of 10 minutes and 22 seconds. Similarly, 50% students finish the work in 5 levels with average time of 13 minutes and 37 seconds. 32% students spent 16 minutes and 34 seconds to complete the work in 6 levels. The remaining 4% students pass through 7 levels in 22 minutes and 10 seconds to get the desired knowledge. It is clear from Table 4, that behavior of proposed system is smart and clever. The same amount of knowledge is delivered intelligently. The first 14% students were treated as good learner and they were provided more teaching material in each level, therefore they finished quickly. The second and third serials students were considered as average learners, therefore intermediate amount of information were displayed to them in each levels. The last 4% students were slow learners and they completed the learning module in 7 levels. These students were provided more time for learning as compared to average and good learners.

6. CONCLUSIONS

In this paper, we presented a new approach regarding the adaptation of 3D-VLEs which is effective, efficient and student friendly. The proposed approach quantitatively measure student learning skill and use it as adaptation criteria for changing the contents of 3-DVLEs which has many advantages. It enhances the learning capability of the students by providing him learning materials which he can absorb at a given time. The student with little learning capability is provided more time to acquire the desired knowledge and at the same time it can cope with the learning capability of fast learners to make quick progress. Secondly, it prevents students from being overwhelmed with teaching material. The proposed solution also has the ability to handle the technical weakness of a student in 3D-VLEs. In initial stages, a student may perform many errors during interaction with the virtual environment. This increases total time for the student in the next learning level which gives him an opportunity to stay more in VE and becomes familiar with the technical aspects of the system. Finally, the proposed solution motivates students towards learning by showing their progress in each level. As a result the overall performance of students is increased in adaptive 3D-VLEs.

7. FUTURE WORK

Although, the proposed system is student friendly and enhances the learning capability of students in 3D-VLEs but there are still some limitations which need further attention for possible improvements. For measuring learning skill of a student, the LDF function considers only three variables i.e. time, errors and test score. More variable such as student initial profile, student GPA etc. shall be included in function definition to get more insight of student learning capability. Also, the teaching material displayed in the next level depends on student performance in the previous level. A good student may show low performance in next level because of some mental or physical stress. The proposed system does not handle this situation. The solution must be modified in such a way that if a good student shows low performance in some level, the system should be so smart to treat him as a good learner rather than weak one. Further, improvements can be made if the proposed solution provides different learning paths for three types of learners. Weak learners will go through more teaching materials and examples for understanding a given concept by following the appropriate path. This will enhance the efficiency of the proposed work.

8. REFERENCES

1. Idris, W.M.R.W., E.N. Madi, & M.Y.M. Saman. Developing dynamic virtual environments using hierarchical, tree-structured approach. *The International Journal of Multimedia & Its Applications* 3(2): 64-80 (2011).
2. Wright, W.G. Using virtual reality to augment perception, enhance sensorimotor adaptation, and change our minds. *Frontiers in Systems Neuroscience* 8(56): 1-6 (2014).
3. Garcés, A., R. Quiros, M. Chover, & E. Camahort. Implementing Virtual Agents: A HABA-Based Approach. *The International Journal of Multimedia & Its Applications* 2(4): 1-15 (2010).
4. Ali, N., S. Ullah, A. Alam, & J. Rafique. 3D Interactive Virtual Chemistry Laboratory for Simulation of High School Experiments. In: *Proceedings of EURASIA GRAPHICS 2014, Paper 12*. Hacettepe University Press, Ankara, Turkey (2014).
5. Ewais, A. & O.D. Troyer. Authoring adaptive 3D virtual learning environments. *International Journal of Virtual and Personal Learning Environments* 5(1): 1-19 (2014).
6. Ali, N., S. Ullah, I. Rabbi, & A. Alam. The effect of multimodal virtual chemistry laboratory on students' learning improvement. In: *First International Conference, Augmented and Virtual Reality (AVR).* Lecce, Italy, September 17-20, 2014, De Paolis, L.T. & A. Mongelli (Ed.), LNCS, Vol. 8853, Springer, Heidelberg, p. 65-76 (2014).
7. Mikropoulos, T.A. & A. Natsis. Educational virtual environmnets: A ten-year review of impirical reserach (1999-2009). *Computers & Education* 56: 769-780 (2011).
8. De Troyer, O., F. Kleinermann, & A. Ewais. Enhancing virtual reality learning environments with adaptivity: lessons learned, HCI in work and learning, life and leisure. In: *Proceedings of 6th Symposium of the Workgroup Human-Computer Interaction and Usability Engineering.* Klagenfurt, Austria, November 4-5, 2010, Leitner, G., M. Hitz & A. Hollinger (Ed.), LNCS, Vol. 6389, Springer, p. 244-265 (2010).
9. Bricken, M. & C.M. Byrne. Summer students in virtual reality: A pilot study on educational applications of virtual reality technology. In: *Virtual Reality Applications and Explorations.* A. Wexelblat (Ed.). Human Interface Technology Laboratory of the Washington Technology Center, University of Washington, Seatle, Washington, USA, p. 199-218 (1992).
10. Dede, C., D. Ketelhut & K. Ruess. Designing for motivation and usability in a museum-based multi-user virtual environment. In: *American Educational Research Association Conference*, Chicago, IL, USA, April 21-25, 2003 (2003).
11. Maria Virvou, A.G.K. On the usability and likeability of virtual reality games for education: The case of VR-ENGAGE. *Computers & Education* 56(1): 154-178 (2008).
12. Chittaro, L. & R. Ranon. Adaptive hypermedia techniques for 3D educational virtual environments. *IEEE Intelligent Systems* 22(4): 31-37 (2007).
13. Brusilovsky, P. Methods and techniques of adaptive hypermedia. In: *Adaptive Hypertext and Hypermedia.* Brusilovsky, P., A. Kobsa & J. Vassileva (Ed.). Kluwer Academic Publisher, Dordrecht, p. 1-43 (1998).
14. Jones, V. & J.H. Jo. Ubiquitous learning environment: An adaptive teaching system using ubiquitous technology. In: *Beyond The Comfort Zone: Proceedings of the 21st ASCILITE Conference*. Perth, Australia, December 5-8, 2004, Atkinson, R., C. McBeath, D. Jonas-Dwyer, & R. Phillips (Ed.), p. 468-474 (2004).
15. Talley, S. & D.H. Martinez. *Tools for Schools: School Reform Models Supported by the National*

Institute on the Education of At-Risk Students. Office of Educational Research and Improvement, US Department of Education, Washington, DC, p. 1-133(1998).
16. De Bra, P., A. Aerts, B. Berden, B. De Lange, B. Rousseau, T. Santic, D. Smits, & N. Stash. AHA! The Adaptive Hypermedia Architecture. In: *Proceedings of the ACM Hypertext Conference,* Nottingham, UK. ACM Press, p. 81-84 (2003).
17. Bra, P.D. & L. Calvi. AHA! An open adaptive hypermedia architecture. *The New Review of Hypermedia and Multimedia* 4(1): 115-139 (1998).
18. Chittaro, L. & R. Ranon. Adding adaptive features to virtual reality interfaces for e-commerce. In: *Proceedings of Adaptive Hypermedia and Adaptive Web-Based Systems,* Berlin, Aug 28, 2000. Springer-Verlag, p. 86-97 (2000).
19. Chittaro, L. & R. Ranon. Dynamic generation of personalized VRML content: a general approach and its application to 3D e-commerce. In*: Proceedings of 7th International Conference on 3D Web Technology*. February 24 – 28, 2002, ACM Press, USA, p.145-154 (2002).
20. Chittaro, L. & R. Ranon. Adaptive 3D websites. In: *The Adaptive Web - Methods and Strategies of Web Personalization.* Brusilovski, P., A. Kobsa & W. Nejdl (Ed.), LNCS, Vol. 4321, Springer Science & Business Media, p. 433-464 (2002).
21. Chittaro, L. & R. Ranon. Using the X3D language for adaptive manipulation of 3D web content. In: *Proceedings of the 3rd International Conference on Adaptive Hypermedia and Adaptive Web-based Systems.* Bra, P. D. & W. Nejdl (Ed.), LNCS, Vol. 3137. Springer, p. 287-290 (2004).
22. Chittaro, L. & R. Ranon. An adaptive 3D virtual environment for learning the X3D language. In: *Proceedings of the 2008 International Conference on Intelligent User Interfaces,* ACM Press, p. 419-420 (2008).
23. Brusilovsky, P., S. Hughes, & M. Lewis. Adaptive navigation support in 3-D e-commerce activities. In: *Proceedings of Workshop on Recommendation and Personalization in ECommerce at the 2nd International Conference on Adaptive Hypermedia and Adaptive Web-Based Systems,* Malaga, Spain, May 28, 2002, p.132-139 (2002).
24. Kasim & M. Al-Aubidy. Development of a web-based distance learning system using fuzzy decision making. In: *IEEE Second International Conference on Signals Systems Decision and Information Technology (SSD03),* Sousse, Tunisia, March 26-28, 2003, p. 1-9 (2003).
25. Santos, C.T.D. & F.S. Osario. Adaptive: An intelligent virtual environment and its application in e-commerce. In: *Computer Software and Applications Conference, 2004(COMPSAC 2004).* IEEE, p. 468-473 (2004).
26. Baziuke, D. Approach to an adaptive and intelligent learning environment. In: *Advances in Computer, Information, and Systems Sciences, and Engineering 2006.*Springer, p. 399-406 (2006).
27. Giuffra, P., E. Cecilia, & A.S. Ricardo. A multi-agent system model to integrate virtual learning environments and intelligent tutoring systems. *International Journal of Interactive Multimedia and Artificial Intelligence* 2(1): 51-58 (2013).
28. Zakrzewska, D. Cluster analysis in personalized E-learning systems. In: *Intelligent Systems for Knowledge Management*, Springer. p. 229-250 (2009).
29. Celentano, A. & F. Pittarello.Observing and adapting user behavior in navigational 3D interfaces. In: *Proceedings of the Working Conference on Advancedvisual Interfaces,* Gallipoli, Italy, 25-28 May, 2004, ACM, p. 275-282 (2004).
30. Verpoorten, D., C. Glahn, M. Kravcik, S. Ternier, & M. Specht. Personalisation of learning in virtual learning environments. *in Learning in the synergy of multiple disciplines*. Springer, Berlin, p. 52-66 (2009).
31. Bowman, D.A., J.L. Gabbard, & D. Hix. A survey of usability evaluation in virtual environments: classification and comparison of methods. *Presence* 11(4): 404-424 (2002).
32. Ewais, A., & O.D. Troyer. Usability evaluation of an adaptive 3D virtual learning environment. *International Journal of Virtual and Personal Learning Environments* 4(1): 16-31 (2013).
33. Saleh, I. & S.-i. Kim. A fuzzy system for evaluating students' learning achievement. *Expert Systems with Applications* 36(3): 6236-6243 (2009).
34. Saleh, I. & S.-i. Kim. Evaluating students' learning achievement based on fuzzy rules with fuzzy reasoning capability. *Expert Systems with Applications* 38(4): 4368-4381 (2011).