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Evaluating Students Performance in Adaptive 3D-Virtual Learning Environments Using Fuzzy Logic

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Abstract: Fuzzy logic better evaluates student performance and can be applied for aptitude testing, recruitment procedure, skill based certification and experimental learning. In this paper we use fuzzy logic to measure the learning capability of students in 3D-Virtual Learning Environment. The system enables student to enter in the next learning level through different transition paths. Fuzzy logic makes the approach more realistic and efficient. It enables weak student to make gradual improvement in the learning process while at the same time it provides an opportunity for a good learner to make quick progress. The students get motivated towards learning; hence the learning process in 3D-VLEs improves.

Keywords: Virtual reality, Adaptive Three dimensional virtual learning environments, Fuzzy logic, Linguistic variables, Student evolution methods.

1. INTRODUCTION

Three dimensional virtual learning environments (3D-VLEs) are computer representation of 3D-space in which students can easily change their view points and perform interaction directly with the virtual world (Al-Aubidy 2003, Ali *et al.* 2015). It enables students to freely navigate inside the virtual environment, select and manipulate objects in real time which give them the sense of realism (Ali*et al.* 2014). Adaptive 3D-VLEs 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 display customized teaching material for them which results in improved learning. A very good work has been done regarding the adaptivity of 3D-VLEs but this area is still immature and need further attention for possible improvements(Ewais and Troyer 2014). In literature, there is no clear strategy for defining the adaptive aspect and modifying the contents of 3D-VLEs for a specific learner (Brusilovsky *et al.* 1998, Chittaro and Ranon 2007). Some people used personalization rules for customized navigation inside Virtual Reality (VR) stores (Chittaro and Ranon 2000). Observing customer behavior for shopping is another effective approach for the adaptation of virtual shops (Brusilovsky *et al.* 2002). For customized navigation and interaction within virtual environments, some people used software sensors that historically monitor user behavior (Celentano and Pittarello 2004). Virtual agents can also be used that help users during interaction (Santos and Osario 2004). Similarly, learner model is updated by conducting a pre-test to compute the learning level of a student and showing him customized teaching material (Al-Aubidy 2003). Web 3.0 approach based XML and ontologies was introduced by (Kurilovas *et al.* 2014), which is suitable for personalization of learning objects (LOs) in VLEs. Similarly, (Moghim *et al.* 2015) designed an adaptive dynamic virtual environment which is capable of responding to human emotions. Cloud computing based APIs were introduced by(Hegazy *et al.* 2015) that helps to improve users experience with VLEs and better meet users' needs. Yan*et al.* worked on an immersive theatre that monitors and improves audience engagement level by triggering the adaptive performing cues (Yan *et al.* 2016).

All these methods are effective and efficient for changing the contents of virtual environments but nobody considered "learning skill" of students as adaptation criteria for 3D-VLEs.

In this study, we have made an attempt to quantitatively measure "learning skill" of a student in 3D-VLEs and use it an adaptation criterion for displaying customized teaching material to different students. A learning decision function (LDF) is mathematically defined which takes time, errors and test score as an input. The function calculates the "learning skill" of a student in the range of 0 to 1 and displays it as an output. Based on the performance of a student in last six levels, a fuzzy logic module puts the student in a proper group i.e. Good, Average or Weak learner. The contents of 3D-VLEs are changed for a student in the next level according to LDF value calculated for him/her. The approach makes the adaptive system student friendly and they get motivated towards learning in the virtual environment.

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2. LEARNING VARIABLES

In the proposed model we used time, errors and test score to calculate the learning skill of a student in the virtual learning environment. For this study, we assume that a weak student takes long time to complete a given learning module as compared to a good student and vice versa. Similarly, a weak learner performs more errors as compared to a good learner. Also a weak learner gets fewer marks in a test as compared to a good learner. These three hypotheses are the backbone of our proposed approach and have been tested through a questionnaire from fifty five teachers of different schools and colleges.

2.1 Time Variable:

To measure the learning capability of students in virtual environments, time play important role. In general, a good learner understands the given concept quickly while slow learner needs more time to get the desired knowledge. In 3D-VLEs, a learning module M consists of many activities. Let t_i be the time taken by a student in the virtual environment to complete an activity A_i within learning module M. The total time T_m to complete the module M can be calculated with Equ.1 as given below.

$$T_m = \sum_{i=1}^{n} t_i \quad (1)$$

Small value of T_m shows that the student is good learner and vice versa.

2.2 No. of Errors:

During interaction with the virtual environment a weak learner performs more errors as compared to a good learner. We divided errors into two type's i.e. technical errors and non-technical errors. The student performs technical errors because he is not fully familiar with the virtual environment or interaction mechanism used. Some most common technical errors in virtual environment are listed below:

- **Astray Navigation:** Student deviates from the right path and is lost in the environment.
- **Incompatible manipulation of objects:** Student tries to move fixed objects in the virtual environment.
- **Precision and accuracy:** Student is unable to precisely select and release an object.
- **Interaction devices:** Some students are good to use mouse and keyboard for interaction while others feel happy to use leap motion and wimote etc.

Similarly, if the student knowledge is poor in the given domain he performs more non-technical errors. Some non-technical errors are: selection of two incompatible objects for manipulation, performing an activity before doing its prerequisites and incorrect mapping of virtual object with real world object.

If technical errors are represented by e_t and non-technical errors are represented by e_n, then the total number of errors E_m, performed by a student in the given learning module M is calculated using Equ.2

$$E_m = e_t + e_n. \quad (2)$$

Again small value of E_m is desirable.

2.2 Test Score:

In general, a good learner takes high marks in the test as compared to a weak learner. If a student gets q_i marks by solving i^{th} question, then the total marks M_t of a student in the test for the learning module M is calculated using Equ.3 as below.

$$Mt = \sum_{i=1}^{n} qi \quad (3)$$

High value of $M_t$shows that the student is good learner and vice versa.

Now we define the learning function LDF as below.

1. A good learner needs less time for understanding the given concept while slow learner needs more time to acquire the same knowledge, therefore

$$LDF \propto \frac{1}{Tm} \quad (4)$$

2. A good learner performs less number of errors as compared to a weak learner, therefore

$$LDF \propto \frac{1}{Em} \quad (5)$$

3. Similarly, a good learner takes high marks in test as compared to a weak learner, therefore

$$LDF \propto Ts \quad (6)$$

Now combining equations 4, 5 and 6, we have

$$LDF = K \frac{TS}{Tm.Em} \quad (7)$$

Where Ts represents test score of a student, Tm represents total time to complete the learning module M and Em represents number of errors.

The learning decision function defined in Equ.7 successfully obeys the following two conditions.

1. When a student takes minimum time; perform minimum errors and gets maximum score, the function gives maximum value i.e. 1.00.
2. When a student takes maximum time, performs maximum errors and gets minimum marks, the function gives minimum value i.e. 0+ε. Where ε is a Greek word, greater than zero, however small no matter.

The three variables i.e. time; no of errors and test score are taken as input by the LDF. The function calculates the learning skill of a student in the range of 0 to 1 and returns result. Based on the performance of a

student in last six levels, a fuzzy logic module put the student in a proper group (i.e. Good, Average and Weak learners). The system adapts itself in such a way that it display customized teaching materials to each type of student. The approach makes the adaptive system student friendly and they get motivated towards learning in the virtual environment.

The operation of the proposed adaptive system is summarized as follows.

1 In each learning module, student is awarded a letter grade based on the performance measured in terms of time spent, no. of errors and tests score.

2. Letter grading is done using a three point scale as given below.

$$\left.\begin{matrix} G = Good \\ A = Averge \\ W = Weak \end{matrix}\right\} Three\ Point\ Grading$$

I. A student can make a transition from the current learning module to the next learning module through learning path X, path Y or path Z.

- Path (X):This path includes the summary of the learning unit which is quite enough for good quality learners.
- Path (Y): Path (Y) includes standard information as that given by the teacher for average learner.
- Path (Z): This path includes in depth details of the learning unit that facilitates the learning process of weak learners.

II. According to the learning capability of student, the system enable good learner to follow path X for the next learning module. Similarly, average learners will follow path Y and weak will follow path Z to enter the next learning level**. (Fig. 1 and 2)** graphically represent the proposed model.

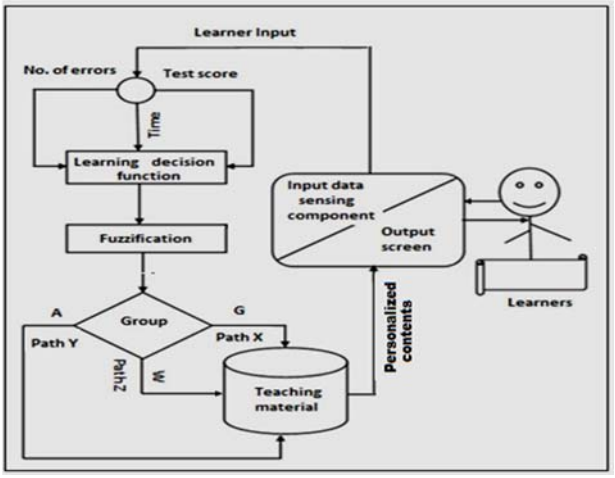


Fig. 1 System Architecture

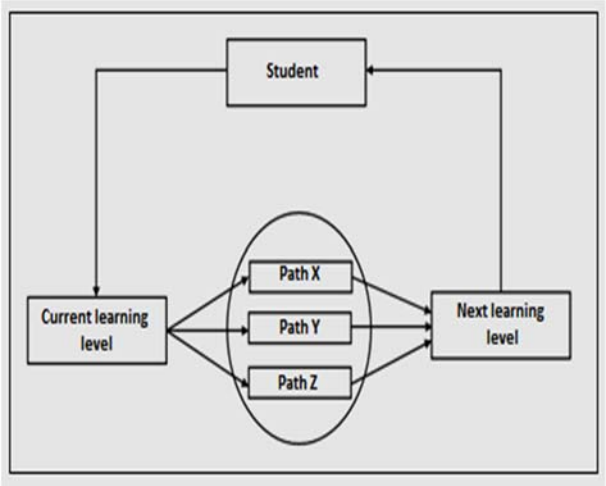


Fig. 2 Transition Paths

3. FUZZY EVALUATION OF STUDENT PERFORMANCE IN 3D-VLEs

The linguistic variables good, average and weak have a lot of vagueness and thus show a substantial amount of fussiness. The fuzzy sets and membership values are the most powerful tool to model these inexact concepts and subjective judgments (Biswas 1995, Saleh and Kim 2009, Saleh and Kim 2011). Here we present our fuzzy approach for the evaluation of student performance in 3D-VLEs. In each learning module, student performance is measured using the LDF function. A six-dimensional vector approach is used to provide a correct letter grade to a specific student. Based on the grade of a student, system displays appropriate teaching materials on the screen.

Before presenting our proposed system, we need to know some useful definition of fuzzy set theory (Zadeh 1965, Biswas 1995, Zimmermann 2010) .

- **Fuzzy set:**

Let X is the universe of discourse. A fuzzy set F is defined as the following set of pairs:

F = {($\mu_F(x)$,x):x □ X}, where, μ_F: X→[0, 1] is a mapping called the membership function of the fuzzy set F and $\mu_F(x)$, is called the degree of belongingness or membership of x □ X in the fuzzy set F.

- **Degree of similarity between two fuzzy sets:**

The degree of similarity between two fuzzy sets A and E is denoted by S(A, E), and is defined by Equ.8 as given below.

$$S(A, E) = \frac{\hat{A}.\hat{E}}{\max(\hat{A}.\hat{A},\hat{E}.\hat{E})} \qquad (8)$$

Where Â=<μA(x1), μA (x2), μA (x3),….>, Ê=<μE(x1), μE (x2), μE (x3),….>, are vectors and X={x1, x2, x3,…} are dot products.

- **Universal set:**

For this paper we have assumed the set U = {0, 20, 40, 60, 80, 100} as the universal set.

- **Standard Fuzzy Sets:**

There exist n Standard Fuzzy Sets (SFS) of the universal set U. For this paper we have only considered three as below.

G (Good) = {0, 0, 0.8, 0.9, 0.9, 0.8}
A (Average) = {0, 0.1, 0.8, 0.9, 0.4, 0.2}
W (Weak) = {0.4, 0.4, 0.9, 0.6, 0.2, 0}

The above values for SFS are proposed by Biwas (Biswas 1995) and are not standards. For the purpose of simplicity we just used it, which generate the following standard values.

$\hat{G}.\hat{G}$= 2.90
$\hat{A}.\hat{A}$= 1.66
$\hat{W}.\hat{W}$= 1.53

3.1 Procedure

1. The first six levels are used as trials in which student learning capability is measured using the LDF function. The values returned by the function are represented by Fi and are stored in a data structure which will be explained later.
2. Before the student enter in the 7th level, his learning capability is evaluated as below.

- The degree of similarities are calculated for S (G, Fi), S (A, Fi), S (W, Fi), where G, A and W are SFS as explained earlier.
- Find the maximum of the above values. For the sake of simplicity let it is S (A, Fi). The system considers the student as an average learner and put him in group A. This student is now able to enter in the next learning level through path Y.
- If the maximum value is S (G, Fi), the student group is G (i.e. good learner) and will follow path X for entering into the next level. Similarly, for S (W, Fi) the student group is W (i.e. weak learner), therefore this student will follow path X.

1. For next learning levels, the last six values of LDF are used to calculate the group of the student.
2. To evaluate multiple students, a two dimensional array of eight columns and rows are used as shown in **(Table 1),** where n represents total number of students.

Table 1: Shows learning skill of students in the last six modules using LDF

Student No	Learning Skill (Fi)						Group
	i	ii	iii	iv	v	vi	
S.1	0.3	0.4	0.9	0.8	0.7	0.9	G
S2	0.3	0.9	0.2	0.9	0.3	0.9	A
S.3	0.3	0.8	0.7	0.5	0.3	0.2	W
S.4	0.2	0.4	0.8	0.7	0.3	0.2	G
S.n	.	.	.	.	.	.	.

The proposed approach is mainly inspired from the work of Biwas (Biswas 1995) and Al-Aubidy (Al-Aubidy 2003). We combined their efforts into a single effective procedure and used it for adaptive 3D-VLEs.

3.2 Examples

Consider four students whom performance is given in Table 2: The group of each student is calculated as below.

Student 1:
Fi= {0.3, 0.4, 0.9, 0.8, 0.7, 0.9}

1. Calculate degree of similarities S (G, Fi), S (A, Fi) and S (W, Fi) using Equ.8, as given below.

$$S(G, F_i) = \frac{(0x0.3) + (0x0.4) + (0.8x0.9) + (0.9x0.8) + (0.9x0.7) + (08x0.9)}{\max((0x0.0) + (0x0.0) + (0.8x0.8) + (0.9x0.9) + (0.9x0.9) + (0.8x0.8),(0.3x0.3) + (0.4x0.4) + (0.9x0.9) + (0.8x0.8) + (0.7x0.7) + (0.9x0.9))}$$

$$= \frac{2.97}{\max(2.9,3)}$$

$$= \frac{2.97}{(3)}$$

$$= 0.99$$

$$S(A, F_i) = \frac{(0x0.3) + (0.1x0.4) + (0.8x0.9) + (0.9x0.8) + (0.4x0.7) + (02x0.9)}{\max((0x0.0) + (0.1x0.1) + (0.8x0.8) + (0.9x0.9) + (0.4x0.4) + (0.2x0.2),(0.3x0.3) + (0.4x0.4) + (0.9x0.9) + (0.8x0.8) + (0.7x0.7) + (0.9x0.9))}$$

$$= \frac{1.94}{\max(1.66,3)}$$

$$= \frac{1.94}{(3)}$$

$$= 0.64$$

$$S(W, F_i) = \frac{(0.4x0.3) + (0.4x0.4) + (0.9x0.9) + (0.6x0.8) + (0.2x0.7) + (0.0x0.9)}{\max((0.4x0.0.4) + (0.4x0.4) + (0.9x0.9) + (0.6x0.6) + (0.2x0.2) + (0x0),(0.3x0.3) + (0.4x0.4) + (0.9x0.9) + (0.8x0.8) + (0.7x0.7) + (0.9x0.9))}$$

$$= \frac{1.71}{\max(1.53,3)}$$

$$= \frac{1.71}{(3)}$$

$$= 0.57$$

2. The maximum of the above value is S (G, Fi) =.94, therefore the student is put into Group G.

3. The same process is repeated for student 2, 3 and 4, and the results are summarized in **(Table 2)** as shown below.

Table 2: Shows the grades and transition paths for students using the proposed approach

S.No	F_i	S (G, Fi)	S (A, Fi)	S (W, Fi)	Max.	Transition Path
Student 1	{0.3, 0.4, 0.9, 0.8, 0.7, 0.9}	**0.99**	0.64	0.57	S (G, Fi)	X
Student 2	{0.3, 0.9, 0.2, 0.9, 0.3, 0.9}	0.61	**0.63**	0.47	S (A, Fi)	Y
Student 3	{0.3, 0.8, 0.7, 0.5, 0.3, 0.2}	0.49	0.75	**0.86**	S (W, Fi)	W
Student 4	{0.2, 0.4, 0.8, 0.7, 0.3, 0.2}	**1.70**	1.47	1.44	S (G, Fi)	X

4. CONCLUSION

In this paper we used fuzzy logic to measure the learning capability of students in 3D-VLEs. Based on performance, the system enables students to proceed for the next learning level through different transition paths. Weak students are provided more teaching materials as compared to a good learner. In this way the systems provide an opportunity for a good learner to make quick progress while weak learner is provided more time to stay and learn. For the evaluation of student performance, we used fuzzy logic which makes the approach more realistic and efficient. It enables weak student to make gradual improvement in the learning process. Also if a of good learner show low performance in some level, the system put the student in group G and give him an opportunity to maintain his performance.

Although the proposed approach is effective and can be used to enhance the learning capability of students in 3D-VLEs, there are some drawbacks which need attention for possible improvements. We used time, no of errors and test score to measure learning skill of a student. These three variables are not enough for the said purpose. The LDF function needs to be extended in order to get more insight of student learning capability. In this paper we also assumed the membership values of SFS used for Good, Average and Weak. Defining SFS is difficult task. It needs expert's opinions, and must be according to the standards of Institution. In the next phase we have planned to implement the proposed solution. The results will be evaluated to check its efficiency against other benchmarks.

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