PERSONALIZATION OF LEARNING ACTIVITIES WITHIN A VIRTUAL ENVIRONMENT FOR TRAINING BASED ON FUZZY LOGIC THEORY

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ABSTRACT

Virtual Environments for Training (VET) are useful tools for visualization, discovery as well as for training. VETs are based on virtual reality technique to put learners in training situations that emulate genuine situations. VETs have proven to be advantageous in putting learners into varied training situations to acquire knowledge and competencies, especially when these situations are taking place in uncontrolled circumstances, or when they are dangerous, unrealizable, or expensive to establish in reality. However individual learners find it difficult to select suitable activities for their particular situations because there is no personalized service to respond to the user needs. The solution is to generate learning activities based on learner's profile. Yet, a learner's profile may contain uncertain data (such as the desired level of difficulty, etc). This paper presents an attempt to introduce the concepts of fuzzy set theory the design of an online educational module. Such a module can deal with uncertainties in the knowledge acquisition, representation and decision making. The fuzzy logic principles are used to create the learner profile and to provide the appropriate learning activities to each learner according to his/her profile.

KEYWORDS

Virtual Environments for Training, learning activities, fuzzy logic

1. INTRODUCTION

Some learning contexts have such a complexity that classical trainings cannot prepare trainees to handle every kind of situation they might face. VETs have proven to be a very useful alternative to deal with complex, dangerous and expensive or just sometimes unrealizable situations. VETs are also used to promote trial and error as an effective strategy for learning. A VET can be defined as a computer-supported environments for human learning (CSEHL) which; applies virtual reality technologies in order to immerse learners in a virtual environment enabling them to learn by doing (Nicolas, 2010). Virtual reality (VR) is a scientific and technical field that applies computer science and behavioral interfaces in order to simulate in a virtual world the behavior of 3D entities which interact in real time with each other and with a user (or users) in pseudo-natural immersion (Fuchs and Moreau, 2006).

Learning in open environments like a VET, demands even more personalization approaches to provide learners with individualized learning activities in order to assure the quality of learning. A learning activity contains several features of information necessary to achieve the objective of training, such as content description, lecture information, prerequisite information and so on. In a VET, the excellence of learners can be improved by recommending suitable learning activities (personalization), based on each learner's profile. Personalization of learning activities (PLA) relies on the fact that the learning ability of each individual can depend on several factors such as age, gender, duration of training, personal preferences, content of the material etc. However PLA is an issue with the uncertainty and imprecision of data that may contain a learner's profile. This paper is an attempt to integrate the fuzzy logic theory into the process of the personalization of learning activities is presented.

The general architecture of the approach in question consists of three fundamental elements namely, *Fuzzifier*, *Inference engine* and the *fuzzy rule base*. In the following, we first present the related works to the personalization of learning activities (adaptation). Then, we present our methodology. Finally, we conclude and reflect on the future of the present work.

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2. RELATED WORK

The learning ability of each individual can depend on several factors such as: age, gender, etc. The question of adapting to different learning activities is one of the main interests of current research about E-learning in general. The goal is to associate suitable learning activities, pedagogical resources, for instance, to each learner based on his/her profile. A profile may include information such as: learner 's knowledge level, as well as the desired difficulty level. To allow this personalization of learning, many solutions have been suggested. Current methods for personalization of learning can be divided into three groups: (i) oriented activities approaches (Naji and Ramdani, 2013) : where the learning process is represented by a graph in which the activities are identified and decomposed. (ii) oriented resources approaches (Karampiperis and Sampson, 2006; De-Marcos et al, 2008; Valigiani et al, 2007): in which case the learning process returns to select, assemble and present contents, (iii) oriented objectives approaches (Bouhdidi et al, 2013; Talhi et al, 2007): the learning process is seen as a process of satisfaction of pedagogical objectives already defined. These approaches use a set of algorithms and techniques from Artificial Intelligence and Web Semantics such as ant colony optimization (Kardan et al, 2014; Kumar et al, 2007; Pushpa, 2012; Valigian, 2007) Bayesian networks (Bouhdidi et al, 2013) the algorithm of Support Vector Machines (SVM) (Ouraiba, 2009), ontologies (Ghailani et al, 2014), to name a few. However, these methods are quite limited in term of handling uncertain and inacurate data.

3. FUZZY LOGIC THEORY

The human brain can deal with imprecise concepts. For instance, to answer a question about a hotel services, most answers could be likely ”Not Very Satisfied” or ”Quite Satisfied”, which are also fuzzy or ambiguous answers. To what extent exactly is one satisfied or dissatisfied with some hotel services? These vague answers can only be created and implemented by human beings, but not machines. so, how can computers and machines handle those vague data?. Based on this observation, Lotfi A. Zadeh (Zadeh, 1965; Zadeh, 1975) developed fuzzy set theory that generalizes classical set theory to allow the notion of partial membership. This invention was not well recognized until Dr. E. H. Mamdani, who is a professor at London University, applied the fuzzy logic in a practical application to control an automatic steam engine in 1974(Mamdani, and Assilion, 1974). The use of fuzzy logic allows working with quantitative and qualitative descriptions. In the fuzzy set theory, an element can belong entirely to a set (degree of belonging is 1), or ”almost” belong to it (with a degree of belonging equal to, say, 0.9). Fuzzy logic has been successfully employed in a variety of applications in recent years (Lin et al, 2006; Lin et al, 2006; Wallace et al, 2006).
Let consider, μ_A the membership function of the set A, U a reference, in the classical set theory:

$$\forall x \in U,\ \mu_A(x) = 0 \text{ if } x \notin A$$
$$\mu_A(x) = 1 \text{ if } x \in A$$

In the context of fuzzy set theory, a fuzzy set A of U is characterized by a membership function µA defined by:

$$\mu_A : U \rightarrow [0.1]$$
$$x \rightarrow \mu_A(x)$$

μ_A : Associates to each object x of U a value in the interval [0,1] which represents the degree of membership of x to A.

There is many application of fuzzy logic and fuzzy sets : Fuzzy Inference Systems(FIS), Fuzzy Decision Trees(FDT), etc. We have chosen FIS, because it seems to be the most suitable for our approach of personalization of learning activities.

4. PROPOSAL

The architecture of the system we are developing is shown in the figure 1. The first step in the task of our system is to collect user's data to build a learner profile. Information which form a learner profile are the following:

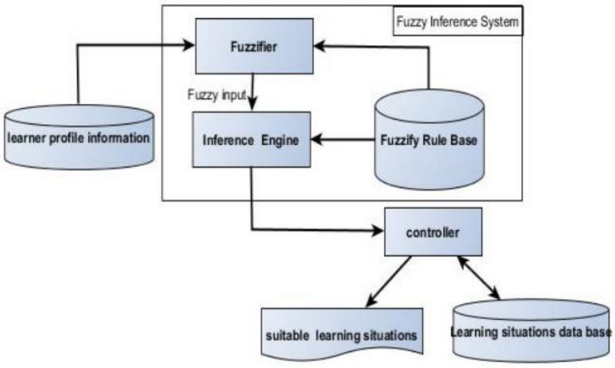

Figure 1. Overview of our approach

-Learning session duration
-Gender
-Level of difficulty
-Desired language
-Current knowledge level
-Age

The second step is fuzzification which involves a domain transformation where crisp inputs are transformed into fuzzy inputs. To do this, the fuzzy system designer must create membership functions. A membership function is a function that defines the degree of membership of a numerical data to a linguistic variable. Depending on their shapes, membership functions can take different form of representations, the most commonly used membership functions in fuzzification processes are Trapezoidal, Triangular, Bell curves, Gaussian and Sigmoid membership functions. The figure 2 comprises of half left trapezoidal, two triangular and half right trapezoidal functions.

To more understand the fuzzification step, let's take for example a mark obtained by a leaner after passing a test. That mark will reflect for instance his/her current knowledge level. We want to transform this numerical data into a linguistic variable. We can find several linguistic variables qualifying a mark: "weak", "average", "good", and "very good". In the figure 2, if we take a mark as equal to 17, after fuzzification, the grade will be good at 30%, very good at 70 %, weak at 0%, and average at 0%.

Now that we have linguistic variables, we will be able to pass them into the inference engine, which is the kernel of decision making process. Each rule of the inference engine is written by the fuzzy system designer according to the knowledge it possesses. The first thing to do for this second part is to list all the rules that we know and that apply to the system. The fuzzy rule base composed of expert **IF** antecedents **THEN** conclusions rules. These rules transform the input variables (The learner profile information) to an output that will tell us know the suitable learning activity. The following rule is an example of a fuzzy **If-Then** rule:

If (Age is young) And (gender is female) And (Level of difficulty is Medium) And (Current knowledge is Low) And (Learning session duration is Long) Then Learning activities are the "*LA set 3*".

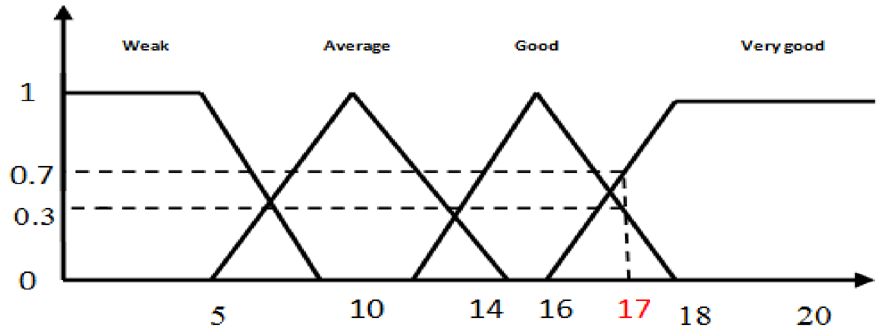

Figure 2. Graphical representation of the linguistic variable "Mark

Finally, the controller, based on the value given by the inference engine, picks up from the ” learning activities data base”, the suitable learning activities set appropriate for the learner profile of the input.

5. CONCLUSION

This paper has outlined the development of a fuzzy based approach for the generation of learning activities within a virtual environment for training. The main advantage of this proposed methodology is that it is efficient in handling the uncertainty in the learner’s profile. The fuzzy inference engine used the fuzzy rule base to generate suitable learning activities for each learner. However, a number of further data, in particular, learner’s feedback information is required to promote the functionality of the system. The ongoing work aims at including this proposed approach in our previous (Fahim et al, 2016), in order to generate adaptable and effective pedagogical scenarios for VET.

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