Teacher Strategies Simulation by Using Fuzzy Systems

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ABSTRACT: Fuzzy system technologies are of emerging interest in the specification and implementation of complex systems. This article introduces fuzzy instructional planner, which models the tutor module in a intelligent tutorial system (ITS). The behaviour of this system is defined by strategies which adapt the learning process for individual students by applying appropriate pedagogical methodologies. For this reason, the purpose of a instructional planner is to mimic the behaviour of the teacher able to control learning process satisfactorily. The knowledge acquisition is based on the reasoning carried out by the teacher in a learning process. Usually, this information is obtained from human expert who supplied linguistic information. The capacity to use linguistic information is specific to fuzzy inference systems. Comput Appl Eng Educ 18: 183–192, 2010; Published online in Wiley InterScience (www.interscience.wiley.com); DOI 10.1002/cae.20128

Keywords: fuzzy system; intelligent tutorial system; instructional planner

INTRODUCTION

Computer-assisted instruction (CAI) is an interactive instructional technique whereby a computer is used to present the instructional material and monitor the learning that takes place [1]. It is also known as computer-assisted learning (CAL), computer-based education (CBE) and computer-based training (CBT). CAI learning uses a combination of text, graphics, sound and video in the learning process. It is especially useful in distance learning situations. The explosion of the Internet as well as the demand for distance learning has generated great interest and expansion of CAI. However, these programs suffer from the problems all traditional systems face, namely:

- *An inflexible algorithm*: The knowledge about how to teach is bound to the particular algorithm of the program.
- *Data dependency*: The algorithm manipulates the data supplied by the student rather than the knowledge of the student.

An attempt to overcome these deficiencies was generative CAI. These systems had the capability to generate new problems from the combination of different elements in a database. Unfortunately, this adaptivity was limited and often unrelated to the individual student needs. An alternative line of research is to consider whether the techniques and tools used in artificial intelligence (AI) can be used to enhance CAI programs.

AI technology provides techniques for developing computer programs for carrying out a variety of tasks, simulating the intelligent way of problem solving by humans. The problems that humans solve in their day-to-day life are of a wide variety in different domains. Though the domains and the methods are different, AI technology provides a set of formalisms to represent the problems and also the techniques for solving them. What AI technology provides us is what is described in the above sentences. Based on this, it is very difficult to precisely define the term AI. Different people working in this topic for many years have proposed different definitions. According to Rich and Knight [2], AI is the study of how to make computers do things at which, at the moment, people are better. It is observed that it is equally difficult to define human intelligence. Some of the essential activities associated with intelligence are listed in reference and they are given below.

- To respond to situations flexibly.
- To make sense out of ambiguous or contradictory messages.
- To recognise the relative importance of different elements of a situation.
- To find similarities between situations despite differences which may separate them.

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- To draw distinctions between situations despite similarities which may link them.

Topics in areas AI have included:

(1) *Problem solving and planning*: This deals with systematic refinement of goal hierarchy, plan revision mechanisms and a focused search of important goals.
(2) *Expert systems*: This deals with knowledge processing and complex decision-making problems.
(3) *Natural language processing*: Areas such as automatic text generation, text processing, machine translation, speech synthesis and analysis, grammar and style analysis of text, etc. come under this category.
(4) *Robotics*: This deals with the controlling of robots to manipulate or grasp objects and using information from sensors to guide actions, etc.
(5) *Computer vision*: This topic deals with intelligent visualisation, scene analysis, image understanding and processing and motion derivation.
(6) *Learning*: This topic deals with research and development in different forms of machine learning.
(7) *Genetic algorithms*: These are adaptive algorithms, which have inherent learning capability. They are used in search, machine learning and optimisation.
(8) *Neural networks*: This topic deals with simulation of learning in the human brain by combining pattern recognition tasks, deductive reasoning and numerical computations.

Intelligent computer-assisted instruction (ICAI) is the application of AI to CAI, namely intelligent tutorial systems (ITS). Expert system technology is the branch of AI that is most relevant to ICAI, because expert systems provided the much-needed capability to automate decision-making in learning process [3]. The key components of an ITS (Fig. 1) are: (a) the knowledge base, that is, what the student is to learn, that is, the model expert that represents the relevant knowledge in the domain and that can solve problems as an expert, based on this knowledge; (b) student model, in which a model is constructed by comparing the student's performance to the computer-based expert's behaviour on the same task; and finally (c) a tutor, that is, instructional techniques for teaching the declarative or procedural knowledge. This final component represents the teacher and must be able to apply the appropriate instructional tactics at the appropriate times. It should model the desirable properties of a human tutor. In general, the tutor must know what to say and when to say it. In addition, it must know how to take learners from one stage of skill to another and how to help learners, given their

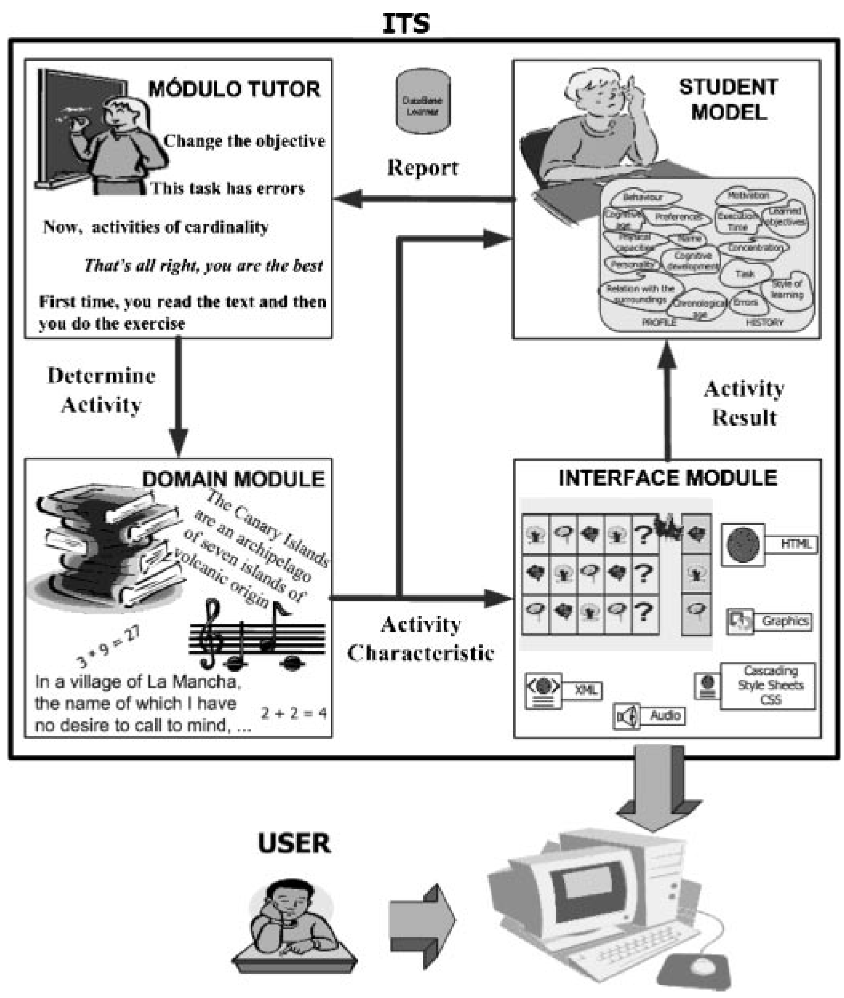

Figure 1 The generic architecture of ITS.

current state of knowledge [4]. This article presents the design of this final component, namely instructional planner.

For this purpose, we design the ITS architecture (based on criteria of reusability) as shown in Figure 2. The ITS follows this sequence:

(1) The manager requests information from the student model about the personality as well as information about his/her learning progress.
(2) The manager sends these parameters to the instructional planner and requests the difficulty level of the next activity from the instructional planner.
(3) The manager searches for activities in the database that correspond to this difficulty level.
(4) The chosen activities are sent to the multimedia interface, which generates a Web page. When the task is finished the multimedia interface sends the results to the manager, which are then stored in the database.

INSTRUCTIONAL PLANNER

The type of problems addressed by ITS is as follows: diagnosing, debugging and repairing student behaviour. For most of the existing ITS, expert system or CBR approach is widely used as instructional planner which decides the teaching tasks [5]. However, we propose using fuzzy logic because the method of handling imprecision must be excellent for ITS to succeed in becoming a useful tool. It also needs to be natural so that the knowledge flows freely from the expert. There are currently quite a few different ways that imprecision may be handled in an expert system. The ones that are complete tend to allow imprecision and uncertainty to be managed in only a small degree or in an awkward fashion. Most methods of handling imprecision are probability based. It is interesting that experts often do not think in probability values, but in terms such as much, usually, always, sometimes, etc. By fuzzy expert system we mean an expert system which incorporates fuzzy sets and/or fuzzy logic into its

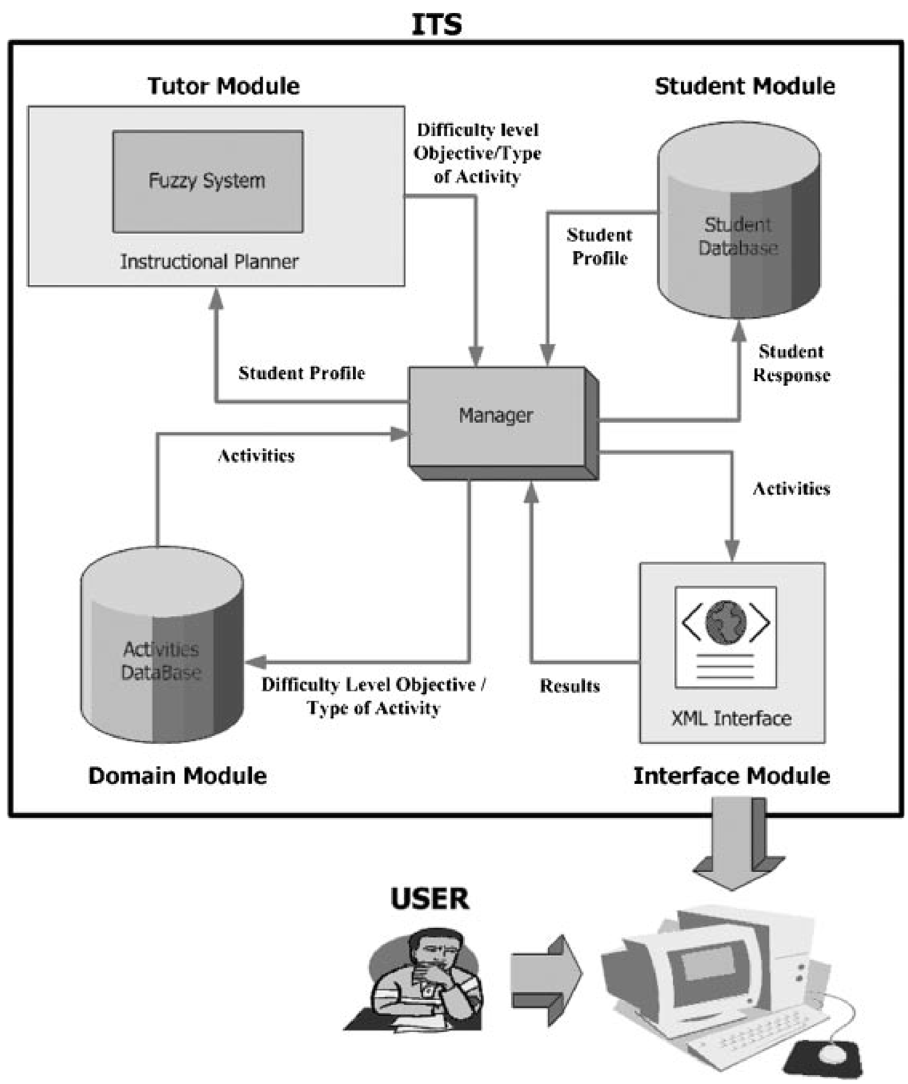

Figure 2 ITS for the reinforcement of the addition operation.

reasoning process and/or knowledge representation scheme. The theory of fuzzy sets and fuzzy logic is well founded and strong. The theories have been in existence for over 25 years and have been shown useful in several control applications among others. Several expert systems have been developed which incorporate fuzzy techniques [6].

In our ITS, the process of individualised education consists of determining the learning objectives from the characteristics of each student. Different activities are then generated to carry out by the student. These activities allow the student to learn the concepts, which are determined by the objectives. The set of activities to be carried out by the student for each objective changes from one student to another since their personalities and characteristics differ. For this reason, the instructional planner must be a dynamic module that is able to generate plans, to monitor their execution and to plan again when necessary. Fuzzy logic methodology was used to model the uncertainty in the student's knowledge and the teaching strategy.

We propose an instructional planner for each specific objective, considering the activity success rate for a determined objective in a given phase and the historical student profile. The planner then determines the difficulty level of the activities in the near future based on this information.

The fuzzy logic methodology in systems such as the instructional planner is appropriate because its behaviour is based on defined rules of imprecise form. This vagueness is due to the complexity of the system. The way to solve problems of this type is to reduce their complexity by means of increasing the uncertainty on the variables. The behaviour of the planner is defined by a set of rules that are often imprecise, or that use linguistic terms with uncertainty. Rules of the type: 'If the student advances well then increase the difficulty level of the activity' are formulated. The resultant set of rules that tries to model the actions which obtain the desired results is then obtained and is known as the knowledge base of the system. These rules are provided by the expert (the teacher), whose classroom experience guides him/her in selecting the techniques to use when instructing students with particular characteristics.

The fuzzy instructional planner is characterised by the following elements [7] (Fig. 3):

- *Rule base*: A set of fuzzy rules which describes how to teach an objective. Such rules quantify with fuzzy logic the linguistic descriptions of the teacher.
- *Inference*: Simulates the decision-making process of the expert. It interprets and applies existing knowledge to determine the best action to take in a specific situation.
- *Fuzzification interface*: Converts planner inputs into fuzzy information that the inference process can easily use to activate and trigger the corresponding rules.
- *Defuzzification interface*: Converts the conclusions from the inference process into the exact inputs that the multimedia interface needs to create the activities.

FUZZY MODELLING

In order to modelling a system, we design a fuzzy inference system based on the past known behaviour of a target system. The fuzzy system is then expected to be able to reproduce the

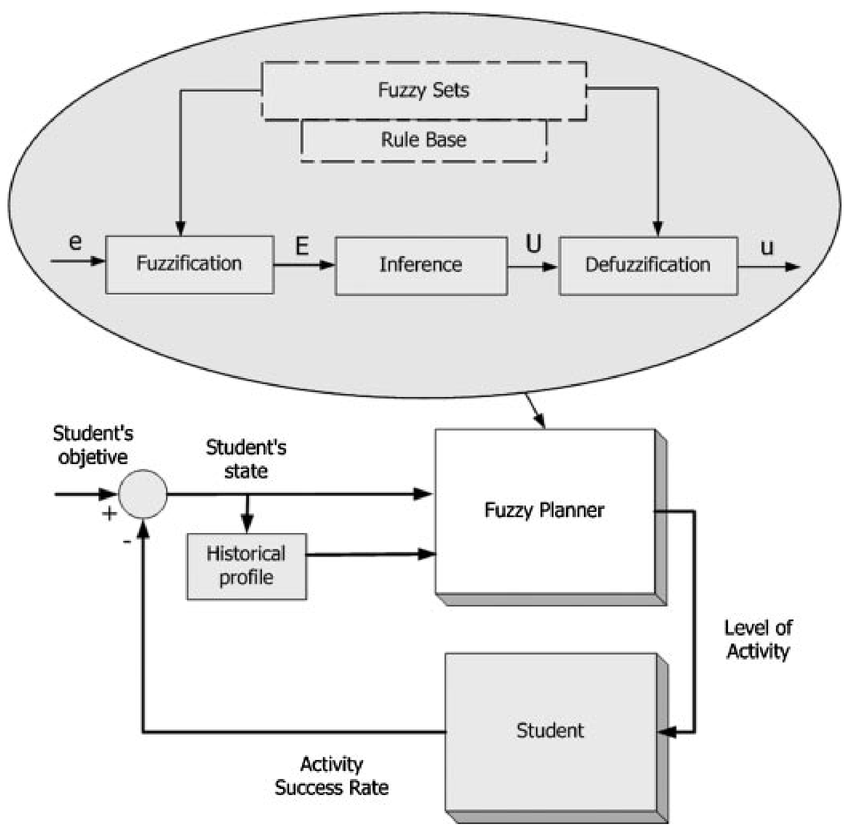

Figure 3 Components of the fuzzy instructional planner.

behaviour of the target system. For example, if the target system is a human operator in a control process, then the fuzzy inference system becomes a fuzzy logic controller that can regulate and control the process. Similarly, if the target system is a teacher, then the fuzzy inference becomes a fuzzy expert system for learning process.

The standard method for constructing a fuzzy inference system, a process usually called fuzzy modelling, has the following features: the rule structure of a fuzzy inference system makes it easy to incorporate human expertise about the target system directly into the modelling process [8]. Namely, fuzzy modelling takes advantage of domain knowledge that might not be easily or directly employed in other modelling approaches.

Let us now consider how we might construct a fuzzy inference system for modelling instructional planner. Conceptually, fuzzy modelling can be pursued in two stages, which are not totally disjoint. The first stage is the identification of the surface structure, which includes the following tasks:

(1) Select relevant input and output variables.
(2) Choose a specific type of fuzzy inference system.
(3) Determine the number of linguistic terms associated with each input and output variables.
(4) Design a collection of fuzzy if−then rules.

Note that to accomplish the preceding tasks, we rely on our own knowledge (common sense, simple physical laws and so on) of the target system, information provided by human experts who are familiar with the target system, or simply trial and error.

After the first stage of fuzzy modelling, we obtain a rule base that can more or less describe the behaviour of the target system by means of linguistic terms. The meaning of these linguistic terms is determined in the second stage, the identification of deep structure, which determines the membership functions (MFs) of each linguistic term. Specifically, the second stage includes the following tasks:

(1) Choose an appropriate family of parameterised MFs.
(2) Interview human experts familiar with the target systems to determine the parameters of the MFs used in the rule base.

The remainder of this article is organised as follows: In the following sections we describe each step in the design of fuzzy instructional planner. We analysed inputs and outputs, linguistic variables and fuzzy rules of the instructional planner that we have modelled by means of fuzzy methodology in the Choosing Fuzzy Planner Inputs and Outputs, Linguistic Descriptions and Fuzzy Rules Sections, respectively. Fuzzy inference system is presented in the Choose a Specific Type of Fuzzy Inference System Section. In the Rule Base Section we examine some results of the fuzzy planner. The work finishes with conclusions.

CHOOSING FUZZY PLANNER INPUTS AND OUTPUTS

The instructional planner is to be designed to automate how a teacher who is successful at this task would control the learning process. First, the expert tells us (the designer of the fuzzy planner) what information she/he will use as inputs to the decision-making process. In this case, the expert says that she/he will use the success percentage in the total number of actions

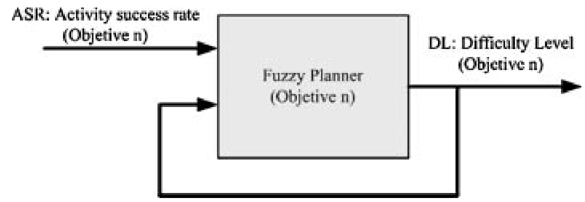

Figure 4 Fuzzy instructional planner for learning of objective n.

(precision). This input variable is known as the activity success rate (ASR). In addition, the historical profile of the student is an another input variable and indicates how the student evolves. Next, we must identify the controlled variable. For the learning process, the expert determines the difficulty level (DL) of the following activities, as shown in Figure 4. These variables are fuzzy sets.

Fuzzy sets incorporate an infinite number of gradations in categories through its MFs defined in [0, 1]. For example, five broad categories (or fuzzy sets) for ASR can be defined, namely very low (VL), low (L), medium (M), high (H) or very high (VH) (see Fig. 5).

Memberships are defined as triangular function ($\mu[0, 1]$) over possible ASR values (horizontal axis). This function μ quantifies the certainty that ASR can be classified linguistically as 'very low', 'low', etc. The overlap in sets indicates the possibility for a value to have simultaneous membership in more than one set. This eliminates potential anomalies resulting from abrupt transitions. A student can have a ASR that is low to some extent while at the same time being medium to a degree as well. As an illustration (see Fig. 5), an ASR that is 30% of total would have a membership of 0.25 in the medium set, and at the same time have a membership of 0.7 in the low set. This implies that applicable evaluation rules are those related to a low ASR as well as those related to a medium ASR. Creating categories of fuzzy sets and specifying the transition between sets are part of the system parameterisation that is discussed in a later section.

CHOOSE A SPECIFIC TYPE OF FUZZY INFERENCE SYSTEM

After all the inputs and outputs are defined for the fuzzy planner, we can specify the fuzzy inference system.

The fuzzy inference system is a popular computing framework based on the concepts of fuzzy set theory, fuzzy if−then

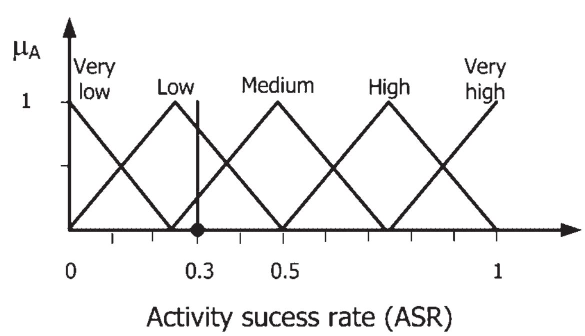

Figure 5 Fuzzy set categories for activity success rate.

rules and fuzzy reasoning. It has found successful applications in a wide variety of field, such as automatic control, expert system, decision analysis, etc.

The basic structure of a fuzzy inference system consists of three conceptual components: a rule base, which contains a selection of fuzzy rules; a database or dictionary, which defines the MFs used in the fuzzy rules and a reasoning mechanism, which performs the inference procedure upon the rules and given facts to derive a reasonable output or conclusion.

The basic structure of a fuzzy inference system can take either fuzzy inputs or crisp inputs (which are viewed as fuzzy singletons), but the outputs it produces are almost always fuzzy sets. Sometimes it is necessary to have a crisp output, especially in a situation where a fuzzy inference system is used as a controller. Therefore, we need a method of defuzzification to extract a crisp value that best represents a fuzzy set. A fuzzy inference system [8] with a crisp output is shown in Figure 6.

The differences between the fuzzy inference systems lie in the consequences of their fuzzy rules, and thus their aggregation and defuzzification procedures differ accordingly. In what follows, we first introduce fuzzy rules and fuzzy reasoning. Then we will introduce Mamdani fuzzy inference system, which is used in instructional planner.

Fuzzy Rules

A fuzzy if−then rule assumes the form 'if x is A then y is B' ($A \to B$), where A and B are linguistic values defined by fuzzy sets on universes of discourse X and Y, respectively. In a fuzzy rule there are two fuzzy sets, the fuzzy antecedent and the fuzzy consequence. If we interpret $A \to B$ as A coupled with B, then

$$A \to B = T(\mu_A(x), \mu_B(y))$$

where $T(,)$ is a T-norm operator (fuzzy intersection). Then different fuzzy relations $A \to B$ result from employing a different T-norm operator. If we use the minimum as T-norm operator which was proposed by Mamdani [8]:

$$(A \to B) = \frac{\min\{(\mu_A(x), \mu_B(y))\}}{(x, y)}$$

Fuzzy Reasoning

Fuzzy reasoning is an inference procedure that derives conclusions from a set of fuzzy if−then rules and known facts. The basic rule of inference in traditional two-valued logic is modus ponens, according to which we can infer the truth of a proposition B from the truth A and the implication $A \to B$. However, in much of human reasoning, modus ponens is employed in an approximate manner. For example, if we have the same implication rule 'if the activity-success-rate is correct, then difficulty-level is high' and we know that 'the activity-success-rate is more or less correct', then we may infer that 'the difficulty-level is more or less high'. This is written as

Premise 1 (rule)	If x is A	THEN	y is B
Premise 2 (fact)	x is A'		
Consequence (conclusion)			y is B'

where A' is close to A and B' is close to B. When A, B, A' and B' are fuzzy sets of appropriate universes, this inference procedure is called generalised modus ponens, since it has modus ponens as a special case.

The fuzzy set B induced by 'x is A'' and the fuzzy rule 'if x is A then y is B' is defined by

$$B' = A' \circ (A \to B) = A' \circ R$$

where $^\circ$ denotes the compositional operator. If we use Mamdani's fuzzy implication functions (minimum as fuzzy intersection) and the classical max−min composition (Fig. 7):

$$\mu_{B'}(y) = \max_x \min[\mu_{A'}(x), \mu_R(x, y)] \quad \max - \text{mincomposition}$$

The interpretation of multiple rules is usually taken as the union of fuzzy relations corresponding to the fuzzy rules. Figure 8 shows graphically the operation of fuzzy reasoning for multiple rules with multiple antecedents.

Mamdani Fuzzy Models

The process of fuzzy inference system can be divided into four steps:

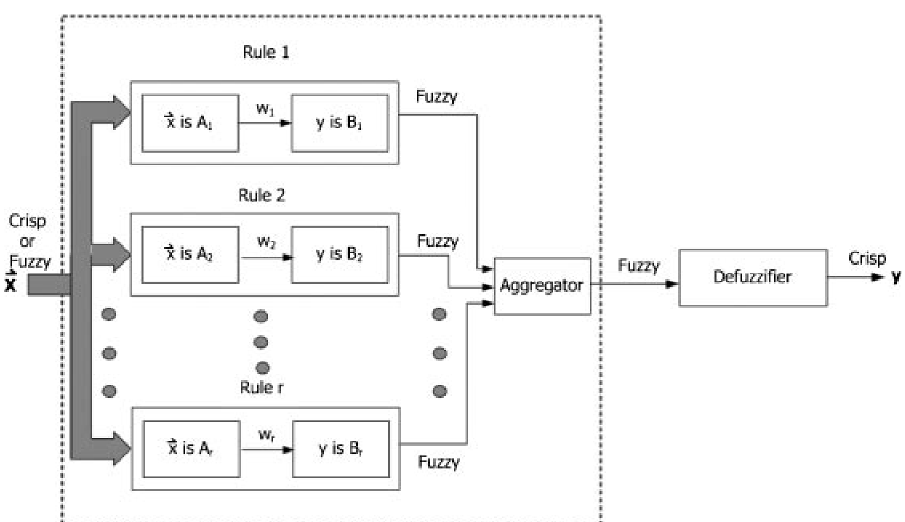

Figure 6 Block diagram for a fuzzy inference system.

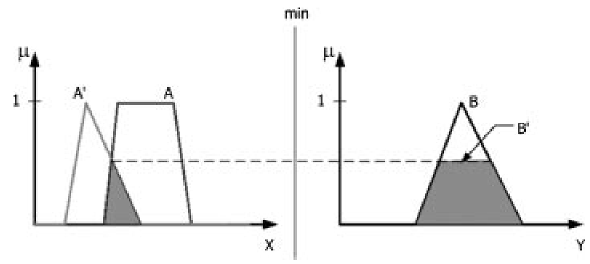

Figure 7 Graphic interpretation of generalised modus ponens using Mamdani's fuzzy implication and the max−min composition.

(1) *Degrees of compatibility*: Compare the known facts with the antecedents of fuzzy rules to find the degrees of compatibility with respect to each antecedent MF.
(2) *Firing strength*: Combine degrees of compatibility with respect to antecedent MFs in a rule using fuzzy AND (*T*-norm) or OR (*T*-conorm) operators to form a firing strength that indicates the degree to which the antecedent part of the rule is satisfied.
(3) *Qualified consequent MFs*: Apply the firing strength to the consequent MF of a rule to generate a qualified consequent MF.
(4) *Overall output MF*: Aggregate all the qualified consequent MFs to obtain an overall output MF.

Mamdani fuzzy inference system adopts max and min as *T*-norm and *T*-conorm (fuzzy union) operators, respectively. Figure 8 shows two-rule Mamdani fuzzy model which derives the overall output *z*.

Defuzzification refers to the way a crisp value is extracted from a fuzzy set as a representative value. In general, there are five methods for defuzzifying a fuzzy set C' of a universe of discourse *Z*, as shown in Figure 9. The fuzzy planner uses centroid of area as defuzzification method.

LINGUISTIC DESCRIPTIONS

The teacher provides a description of how best to control the student in some natural language. We seek to take this 'linguistic' description and load it into the fuzzy planner. The linguistic description provided by the expert can generally be broken into several parts. There will be 'linguistic variables' that describe each of the time-varying fuzzy planner inputs (ASR) and outputs (DL). Linguistic variables have 'linguistic values' and are defined as the values of the linguistic variables as time changes. In our instructional planner we have the following values:

ASR: VL: Very low	DL: RG: Regression
L: Low	PM: Permanency
M: Medium	PG: Progression
H: High	
VH: Very high	

The linguistic variables and values provide a language for the expert to express her/his ideas about the decision-making process in the context of the framework established by the choice of fuzzy

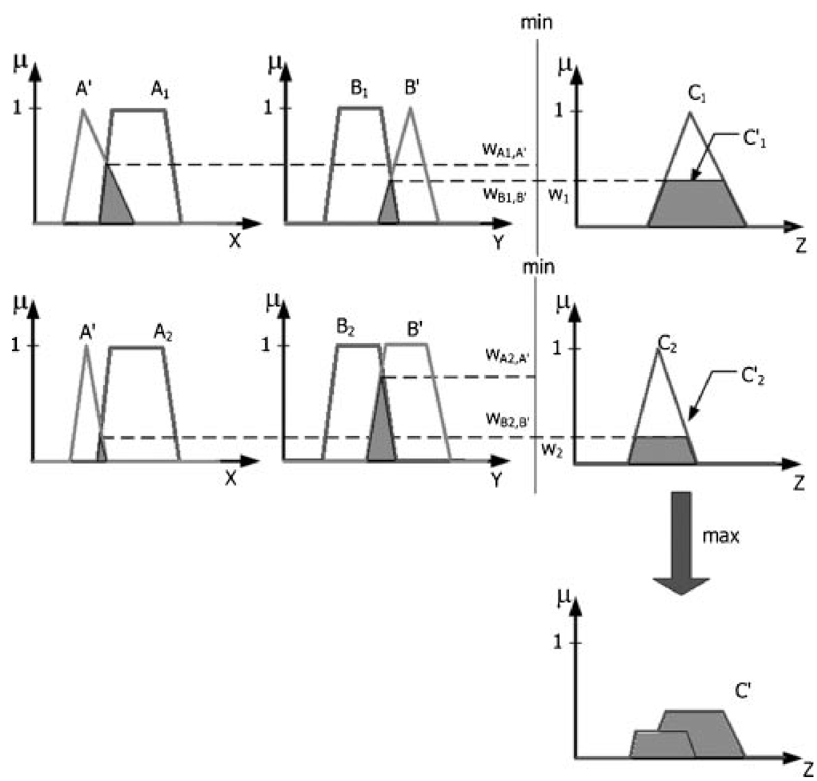

Figure 8 The Mamdani fuzzy inference system using min and max for T-norm (fuzzy intersection) and T-conorm (fuzzy union) operators, respectively.

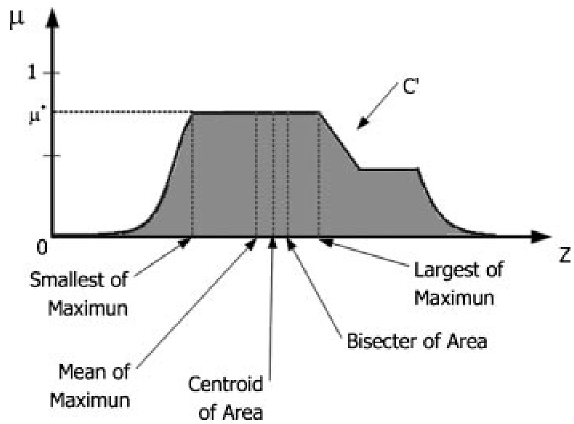

Figure 9 Various defuzzification scheme for obtaining a crisp output.

planner inputs and outputs. For the learning process each of the following statements quantifies different actions:

- The statement 'ASR is low' can represent the situation where the student has not correctly answered the proposed activities.
- The statement 'DL is regression' can represent the situation where the previous student's interactions were wrong.

RULE BASE

Next, we will use the above linguistic quantification to specify a set of rules that captures the expert's knowledge about learning process. A convenient way to list all possible rules for the case where there are not too many inputs to the fuzzy controller (less than or equal to two or three) is to use a tabular representation. A tabular representation of one possible set of rules for the learning process is shown in Table 1a–c, depending on the student's characteristics.

MEMBERSHIP FUNCTIONS

Up to this point we have only quantified, in an abstract way, the knowledge that the expert has about the decision-making process. Next, we will show how to use fuzzy logic to fully quantify the meaning of linguistic descriptions so that we may automate, in the fuzzy planner, the control rules specified by the expert.

First, we quantify the meaning of the linguistic values using 'membership functions'. Consider Figure 4, this is a plot of a function μ versus ASR that takes on special meaning. The function μ quantifies the certainty that ASR can be classified linguistically as 'very low', 'low', 'medium', 'high' and 'very high'.

The MF quantifies, in a continuous manner, whether values of ASR belong to (are members of) the set of values that are 'very low', for example, and hence it quantifies the meaning of the linguistic statement 'ASR is very low'. It is important to recognise that the MF in Figure 5 is the only one possible definition of the meaning of 'ASR is very low'; we could use a bell-shaped function, a trapezoid or many others.

Tuning the Parameters of the Membership Functions (MFs)

We see that depending on the application and the designer (expert), many different choices of MFs are possible. MFs are subjectively specified in heuristic manner from experience. For the fuzzy planner setting, it is necessary to perform different simulation experiments until the acceptable values are found.

Initially, the fuzzy partition in the planner was assumed using triangular MFs, Figure 5. This approach brings the system to the significant oscillations, Figure 10a. When the gaussian MFs are used instead of triangular ones the described phenomena of oscillations disappear, Figure 10b. Finally, Figure 11 shows the choice MFs in the fuzzy planner.

CONCLUSION

This work presents a fuzzy instructional planner. We design a ITS where the tutor module has been implemented using fuzzy methodology which has been shown useful in several applications. The ITS must be a flexible system that can adapt its teaching rules to the individual's performance. For this reason, we have modelled the uncertainty in the student's knowledge and the teaching strategy by means of a fuzzy system. To construct a fuzzy planner, we need to perform knowledge acquisition, which takes a expert's knowledge about how to learn and generate a set of fuzzy if–then rules as the backbone for a fuzzy planner that behaves like the original teacher. In this process, we obtain linguistic information. The capacity to use linguistic information is specific to fuzzy systems. The teacher summarise his/her reasoning process in arriving at final decisions as a set of fuzzy if–then rules with imprecise but roughly correct MFs. This

Table 1 Rule Base for (a) Student With Fear of Failure, (b) Hyperactive Student and (c) Motivated Student Who Is Unaffected by Mistakes

DL\ASR	VL	L	M	H	VH
(a)					
Regression	Regression	Regression	Regression	Permanency	Permanency
Permanency	Regression	Regression	Permanency	Permanency	Progression
Progression	Regression	Permanency	Permanency	Progression	Progression
(b)					
Regression	Regression	Regression	Permanency	Permanency	Permanency
Permanency	Regression	Permanency	Permanency	Permanency	Progression
Progression	Permanency	Permanency	Permanency	Progression	Progression
(c)					
Regression	Regression	Permanency	Permanency	Permanency	Progression
Permanency	Regression	Permanency	Permanency	Progression	Progression
Progression	Permanency	Permanency	Progression	Progression	Progression

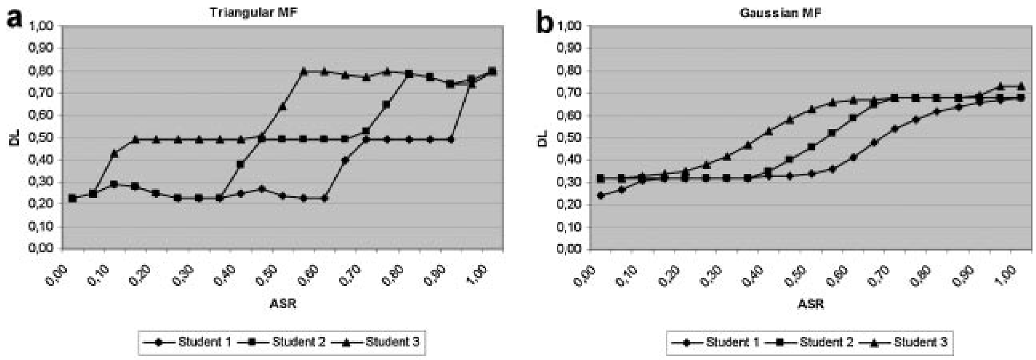

Figure 10 Fuzzy instructional planner output (a) with triangular MFs and (b) with gaussian MFs.

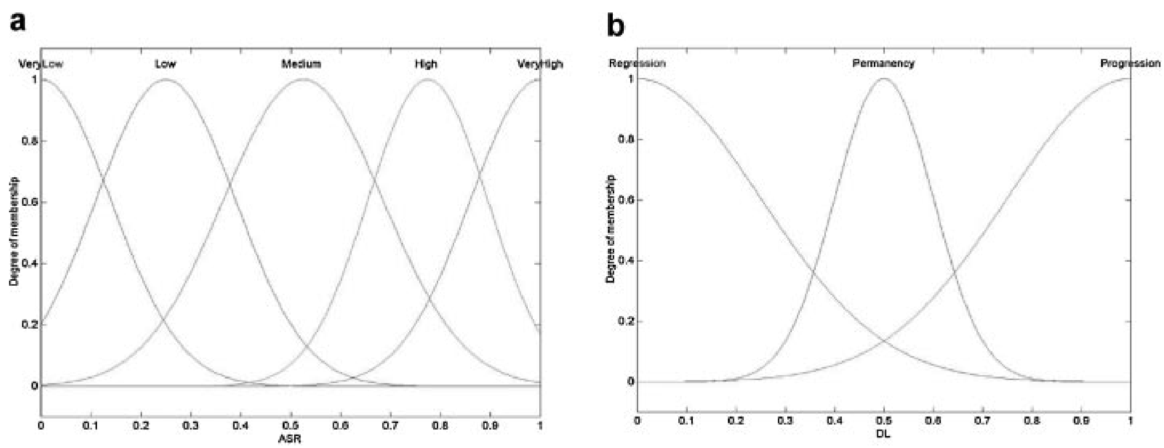

Figure 11 Fuzzy set categories for (a) activity success rate and (b) difficulty level.

corresponds to the linguistic information supplied by human experts, which is obtained via a lengthy interview process plus a certain amount of trial and error. The next step involves manual trial-and-error tweaking processes to fine-tune the MFs.

Successful fuzzy instructional planner has been used in a ITS for the reinforcement of the addition operation. Currently, it is being used by Asociación Tinerfeña de Trisómicos 21 (ATT21).

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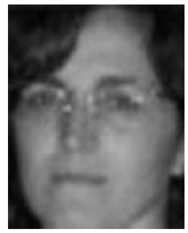

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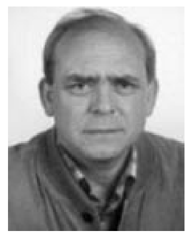

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