Design of an Instructional Planner for an Intelligent Tutorial System using Fuzzy Methodology and MAS

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Abstract: - The goal of this paper is to present a Fuzzy Instructional Planner belonging to an Intelligent Tutorial System (ITS) which has been designed as a tool for the reinforcement of the addition operation. We have modeled the uncertainty in the student’s knowledge and the teaching strategy by using principles from a rigorous fuzzy logic methodology.


1 Introduction

The goal of this paper is to present a Fuzzy Instructional Planner belonging to an ITS which has been designed as a tool for the reinforcement of the addition operation. Ones of the Artificial Intelligence contributions to education have been Intelligent Tutorial Systems [1]. These emulate the interaction between a teacher, who is an expert in a given domain and a student who wants to learn some concepts of the domain. ITS are instructional systems having as a core an expert system that helps the student to solve a problem. The expert system detects those concepts and contents that are not known, or not use properly, making the necessary changes to the instructional plan [2]. We have modeled the uncertainty in the student’s knowledge and the teaching strategy by using principles from a rigorous fuzzy logic methodology. Many problems require some vágueness in the problem formulation and subsequent analysis. The conventional formulation does not capture such linguistic and heuristic knowledge in an effective manner. Fuzzy logic implements human experiences by means of membership functions and fuzzy rules. Due to the use of linguistic variables the system can be made understandable to an operator who is not expert in the subject. In summary, we can use fuzzy logic as a methodology to incorporate knowledge, heuristic, intuition and experience into our ITS.

The remainder of this paper is organized as follows. In the following section (Section 2) we describe the design of the ITS architecture based on criteria of reusability. In Section 3, the teaching strategy is described. In addition we have analyzed inputs and outputs, linguistic variables and fuzzy rules of the Instructional Planner that we have modeled by means of fuzzy methodology. Rule Base and Fuzzy Inference also is presented. In Section 4 we examine some considerations regarding the Intelligent Agents techniques used in the ITS. The work ends with the conclusions.

2 Design of the ITS architecture

The system architecture was planned based on criteria of reusability as well as generalization. The modular structure in the architecture can therefore be applied to other application domains. Figure 1 shows the main components of the ITS.

![Fig. 1. The architecture of the ITS.](image-url)

Two characteristics are essential for the generalization of the ITS to other domains: a) the static and dynamic information is stored in a
The database, and b) the design of a fuzzy system for implementing the Instructional Planner.

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. This process is very important in children with learning difficulties because the presentation of contents depends on the difference between cognitive and chronological ages.

2. The manager sends these parameters to the Instructional Planner and requests the difficulty level of the 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. In this Web page, a pedagogical agent presents the activity to be carried out by the student. When the task is finished the multimedia interface sends the results to the manager, which are then stored in the database.

3 Fuzzy Instructional Planner

The process of individualized education consists of determining the learning objectives from the characteristics of each student. Different activities are then generated to be carried 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.

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 were used to model the uncertainty in the student’s knowledge and the teaching strategy.

We propose a design for each concrete 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 (Figure 2) based on this information.

The fuzzy logic methodology in systems such as the instructional planner is appropriate because its behavior 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 behavior of the planner is defined by a set of rules that often are 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 in selecting the techniques to use when instructing students with particular characteristics.

The fuzzy instructional planner is characterized by these elements [3] (Fig. 2):

- Rule Base: a set of fuzzy rules that quantify with fuzzy logic the linguistic descriptions of the teacher concerning how to teach an objective. The rules have a common syntactical presentation such as if-then. The general form of the rule is: if (conditional part) then (action part).

- Inference: simulates the decision making process of the expert. It interprets and applies existing knowledge to determine which is the best action to take in a given 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.

Fig. 2. Components of the Fuzzy Instructional Planner.
3.1 Inputs and Outputs

A fuzzy planner must be designed that automates the form in which the human expert carries out his decision making. The expert must indicate to the designer of the fuzzy instructional planner what information to receive as input in the decision making process.

The professor who advises a student observes the success percentage in the total number of actions (precision). This input variable is known as the activity success rate. The historical profile of the student is another input variable and indicates how the student evolves.

This fuzzy system is characterized by one input and its state, all of which are fuzzy variables, defined as:

- Activity success rate for an objective in a given phase.
- State of the fuzzy system. Each state defines a difficulty level in the activities to be carried out by the students.

The fuzzy system outputs determine the difficulty level of the activities in the near future.

As the subject learning consists of several objectives, we must construct as many fuzzy systems as the number of learning objectives.

The objectives are grouped by phases. The transition between phases: forward (progression), backward (regression) and no change in the same phase, has been modelled using a fuzzy aggregation. This system uses the states of each phase objective as inputs. The aggregation operator produces a fuzzy number as output. This number will also establish three fuzzy sets: progression, regression and permanency (Figure 3).

There are three linguistic variables in the fuzzy system for each objective:

- ASR: “Activity success rate for a determined objective in a given phase”
- ST: “Difficulty level”.
- STR: “Difficulty level result in the activities to be carried out by the student”.

The fuzzy system that determines the phase of work will also use the following linguistic variable:
- WP: “Work Phase”

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 for the ASR:

- VL: Very Low
- L: Low
- M: Medium
- H: High
- VH: Very High

Linguistic variables ST, STR and WP have the following values:

- RG: Regression
- PM: Permanency
- PG: Progression

3.2 Linguistic Description

The expert uses linguistic variables to describe the inputs and outputs of the fuzzy instructional planner.

Fig. 3. Fuzzy System
value of the consequent one of a rule, and the column
of the left and the superior row contain the linguistic
values of the variables of the antecedent. Examples
for the instructional planner depending on the type of
student are shown in tables 1, 2 and 3.

<table>
<thead>
<tr>
<th>ST</th>
<th>ASR</th>
<th>VL</th>
<th>L</th>
<th>M</th>
<th>H</th>
<th>VH</th>
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</thead>
<tbody>
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<td>Regression</td>
<td>Regression</td>
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<td>Permanency</td>
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<td>Permanency</td>
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<td>Progression</td>
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Table 1. Rule base for the student with fear of failure.

<table>
<thead>
<tr>
<th>ST</th>
<th>ASR</th>
<th>VL</th>
<th>L</th>
<th>M</th>
<th>H</th>
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<tbody>
<tr>
<td>Regression</td>
<td>Regression</td>
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<td>Permanency</td>
<td>Regression</td>
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<td>Progression</td>
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<td>Permanency</td>
<td>Progression</td>
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</tbody>
</table>

Table 2. Rule base for the hyperactive student.

<table>
<thead>
<tr>
<th>ST</th>
<th>ASR</th>
<th>VL</th>
<th>L</th>
<th>M</th>
<th>H</th>
<th>VH</th>
</tr>
</thead>
<tbody>
<tr>
<td>Regression</td>
<td>Regression</td>
<td>Regression</td>
<td>Permanency</td>
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<td>Permanency</td>
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<td>Progression</td>
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</table>

Table 3. Rule base for the motivated student who is
unaffected by mistakes.

3.4 Membership Functions
We assumed different difficulty levels in the
activities of all the objectives. In addition, we
assumed five fuzzy sets for the ASR (very low, low,
medium, high, and very high) and three fuzzy sets for
the State, State Result (regression, permanency and
progression). We also established three fuzzy sets in
WP: progression, regression and permanency. Figures
4 and 5 show a representation of all the inputs and
outputs.

3.5 Fuzzification, Fuzzy Inference and
Defuzzification
The ASR variable has to be fuzzified with a singleton
membership function before entering the
 corresponding fuzzy system. The ST variable has not
to be fuzzified because it is the feedback of the fuzzy
system.

The fuzzy system model inference mechanism
definition can be expressed with T-norm and S-norm
operators defined as a minimum and maximum,
respectively [4].

The states of each fuzzy system have to be
defuzzified in order to be used by the manager (Fig.
1). The tutorial uses the centroid method to calculate
the centroid of the resultant fuzzy set based on the
calculation of aggregate consequents.

4 Intelligent Agents
The fuzzy system defines a difficulty level in the
activities to be carried out by the students. In order to
determine the objective (and what activity within that
objective) is used a MultiAgent System (MAS) [5].

The approach of use a MAS is from vital
importance for the creation of an intelligent platform
of education, because it provides great capacity of
reaction. This is reached thanks to the distribution of
tasks to agents working in concurrent form. In
addition the realization of agent-based computing
provides the decomposition, organization and
abstraction of multifaceted applications. The Agents
can run continuously and autonomously in the
background by intelligent interacting with different
parts of the application, thereby hiding system
complexity from their users. This means, for
example, that while the student makes the final
exercises, the agents can be deciding the education
strategy to follow in the next objective which allows
to diminish the time of delay in the interaction of the user with the ITS.

To facilitate successful interoperation between agents, there is a need for standardised means and methods of the exchanged messages. Hence, a communication protocol is required. There is a need for a language for agents to share a framework of knowledge to interpret the exchanged message. We have decided to use the FIPA Protocol. These specifications have become a strong standard in MAS development and it involves not only agent language specifications but also agent management, conversations, etc. The use of this standard involves more robustness.

Negotiation is seen as a method for coordination and conflict resolution and in our ITS we used it for resolving goal disparities in planning (next objective and activity to be carried out by the student). We used first-price auctions (each bidder submits a bid in a sealed envelope; the highest bidder gets the good and pays the amount of his bid) using intelligent agents who modify the bid value adaptively. Advantages of the auctions are promoting efficient allocation and investment and quick assignment resources.

MAS framework is composed of 4 different types of agents apart from FIPA ones (Fig. 5.):

- **Objective Supervisor Agent.** This agent must construct as many Objective Agents as the number of learning objectives for each phase. Auctioneer decides who gets the resource (next objective to be carried out by the student) based on the offers from the agents trading in the auction.

- **Objective Agent.** There is an agent for each phase objective. It calculates an objective function using the data of the student for the objective which the agent represents. Submits this value in a sealed envelope to the Objective Supervisor Agent.

- **Activity Supervisor Agent.** Its behaviour is equivalent to Objective Supervisor Agent but Objective Agents have been replaced with Activity Agents.

- **Activity Agent.** There is an agent for each objective activity. It calculates a bid value using the data of the student for the activity which the activity represents. This value is weighted depending on the importance of the activity. The bid value is sent in a sealed envelope to the Activity Supervisor Agent.

Figure 6 shows the sequence transmission.
4 Conclusion
This work has presented the Fuzzy Instructional Planner from an Intelligent Tutorial. A Fuzzy System has been modelled to define a difficulty level in the activities to be carried out by the students. In addition we have design a MAS in order to determine objectives and activities. Our experience is that the teaching of the addition operation is satisfactorily modelled by using the existing methodology for fuzzy systems. Motivation must also be considered when working with children. The creation of attractive interfaces, the use of multimedia resources, the fact that the activities are shown as a game, and the use of pedagogical animated agent for social interaction within the system are crucial [6].

References: