Adaptation Improvement using Fuzzy Logic

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ABSTRACT
A module of a Student Model in a Virtual Learning Environment will be presented in order to promote the personalization of instructional material based on the dynamic knowledge levels and learning styles. The improvement is provided by the inclusion experts' experience in the teaching field whose opinions have been expressed in fuzzy rules using two input linguistic variables (*knowledge level* and *learning style*) and two linguistic output variables (*difficulty level* and *individual/group work*). These last two variables categorize instructional materials.

Keywords: adaptation, personalization, learning styles, fuzzy logic, engineering student.

1. INTRODUCTION

The progress in the development of information technologies produces a notable influence in education based on computers. In the search for improvement of educational computing systems, the most examined and used characteristics are *adaptability* and *personalization* of learning systems. The diversity as well as individual student needs are aimed to be supported. This objective sought-after by many researchers through the use of the Student Model, in which a combination of personal, behavioral characteristics as well as knowledge levels are described [1] [2]. The adaptive and/or personalized educational system consults the Student Model and delivers the learning material to each individual learner with respect to her/his personal characteristics.

Within the personal characteristics, the students have different learning styles. Regarding this, Felder and Silverman [3] claim that students who study with instructional material tailored to their learning styles learn more effectively and make better progress. In this paper, a model to personalize materials to learning styles and level of difficulty is presented.

Personalized learning, adaptive learning

In personalized learning, it is intended that the student got through their own road towards knowledge. This type of learning entails any action that a professor, as well as software, performs to teach a topic to a student understood as individuality. The personalization can be applied to the curriculum content, methods, learning pace, etc. It is an option that takes into account the students´ individual needs and respects their differences. Therefore, identifying the students´ characteristics, the professor can propose graphic material for a student, while he provides mainly text material for another student because that is the way they prefer it. The common idea of a personalized approach is to provide a learning experience to the student, valuing each individual in the classroom as well as through the use of educational software.

Adaptive learning can be understood as the adaptation to the student taking into account the data collected from the computer/student interactions, usually, online. Among other actions, the computational system modifies the presentation of instructional material as a response to the student's actions. The adaptive process changes itself to the demonstrated performance level and it tries to predict the type of material the student will need at a determined point in his/her learning progresses. The adaptive learning systems constantly attempt to hold the formative evaluation, in an effort to provide the following proper tutorial step in the students' learning process.

The educational computational systems, then, must consider different needs and the diversity in learning characteristics: uneven knowledge levels, cognitive abilities, preferences, learning styles, feelings, reactions, etc. A system that attempts to possess adaptive features must take into account such group of characteristics, in order to infer their needs and preferences, to deliver the appropriate learning material according to the students' needs, and, thus, be able to provide advice and effective feedback [4].

Adaptive techniques

A learning environment can be considered as adaptive if it is capable of monitoring the user's activities, interpret them following specific domain models, infer user's requirements and preferences beyond interpreting the activities, in order to finally act on all the users' acquired knowledge and dynamically facilitate the learning process. The adaptive behavior of environments presents diverse manifestations: adaptive interactions, the delivery of adaptive courses, articulation of instructional material and help in adaptive collaboration. The *adaptive interactions* are the modifications that take place in the system's interface in order to facilitate interactions without modifying the content. For instance, in adaptive interactions we use diagrams or graphics, different text font size, or reorganization of tasks using metaphors at a semantic level. The delivery methods of *adaptive courses* are the most common techniques used nowadays. Particularly, this concept refers to the courses tailored to an individual student. The goal is to optimize the adaptation between the content and the user/student characteristics. Examples of these techniques are the dynamic restructuring of the course, the help in adaptive navigation, and the adaptive selection of course materials [5].

The *discovery* and *articulation of instructional material* is done through different sources such as repositories or knowledge base. The adaptation, from this perspective, has models and knowledge derived from the student's monitoring as its adaptation base. Two views can be proposed as regards the search for relevant material: the student browses through the any material or the author/professor prepares the material oriented towards a specific group of students. In particular, a system that adapts the delivery of the learning material to each individual learner's need and pace according to professor decision is described.

2. ADAPTATION MODEL

The shown proposal uses the *adaptive courses* and mainly the *preparation of instructional material* planned by the author/professor aimed at specific groups of students as adaptive techniques. To apply these techniques, two sources of information for personalization have been used, *learning* *styles* and *knowledge level*. Knowledge level is translated into students' dynamic profiles that will be used to reflect their progress. In order to determine learning styles the results of Felder's and Silverman's questionnaire results have been used.

Learning styles

A learning style is the mode that characterizes an individual when he/she acquires holds and retrieves information. Students, in particular, show different strengths and preferences when they acquire, retain and recover information. That is to say, they have different learning styles. The present paper has adopted the model of learning styles formulated by Richard Felder and Linda Silverman [6] which was designed for engineering students, with the aim of identifying the differences in learning styles. From such identification, the authors point out that a teaching approach that responds to the students' learning needs can be formulated. The Felder and Silverman model classifies students according to their preferences for one or another category in each of the following four dimensions:

Sensing / Intuitive. The student with a preferentially sensitive style, tend to be concrete and oriented by facts or well established procedures; the student with an intuitive style is innovative and he/she is characterized by preferring abstract thought and guided by underlying theories and meaning, with general principles more than concrete data.

Visual / Verbal. The visual learning style indicates a preference for visual study materials such as images, diagrams, mind maps, graphics. At the other end of the dimension, the student with a verbal style, he/she will feel more at ease with written as well as oral explanations.

Active / Reflexive. The active student learns better when working with the material dynamically, tries things, and prefers working in groups. Conversely, the reflexive student prefers to think instead of trying things out, and is inclined to work alone or only with one partner.

Sequential / Global. The sequential style defines a student that learns better in small incremental steps, he/she is detailed; whereas a a student with a global learning style will learn in a holistic manner, establishing relationships with his/her experience and is more interested in general knowledge.

From the model, Soloman and Felder [7] have created the Index of Learning Styles (ILS), an instrument with 44 dichotomous answer items, in a row, and taking the four proposed dimensions into account. For the aims of the present paper, the questionnaire has been done with students from courses belonging to the Engineering course of study, the results being processed by the web page of the North Carolina University, provided by the aforementioned authors. Each dimension has a range that varies from 0 to 11. If the result to the questionnaire is from 0 to 3 (in either direction), the student is well *balanced* between the two dimensions that are at both ends of the scale; if the score is between 5 and 7, the student has a *balanced preference* for the extreme to which it is close and if the score is 9 or 11, the student has a *strong preference* for the extreme to which it is close. The active/reflexive dimension has been elaborated on 47 engineering students (Fig. 1).

For the knowledge level, *apprentice* stereotypes, *intermediate knowledge level* and *expert* developed in [8] have been used.

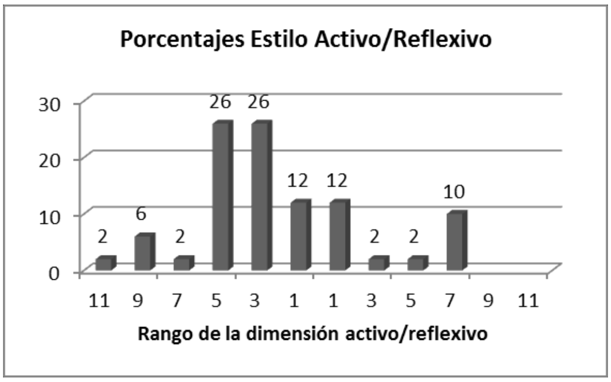


Fig. 1. Learners' answers (in percentage) about Felder Soloman questionnaire in active/reflexive dimension.

Fuzzy logic: introduction

Fuzzy Logic is a technique to handle the uncertainty which is based on imprecise data and human decisions, since it encounters the uncertainty problems that are caused by incomplete data and human subjectivity [9]. In the system's modeling variables with uncertain values tend to be used and this problem is solved with the use of fuzzy sets. Fuzzy sets describe the variables with values such as "bad", "regular", and "good" instead of Boolean values "true/false" or "yes/no" [10]. A fuzzy set is any set that allows its members to have different grades of membership (membership function) in the interval [0, 1]. Membership functions are mathematical tools for indicating flexible membership to a set, modeling and quantifying the meaning of symbols. They can represent a subjective notion of a vague class, such as person age, size of people, and student performance among others. A membership function is expressed by $\mu A(x)$ as shown in (1):

$$\mu A(x): X \rightarrow [0,1], \text{ in which} \tag{1}$$

$$\mu A(x) = \begin{cases} 1 & \text{if } x \text{ is fully included in } A \\ (0,1) & \text{if } x \text{ is partially included in } A \\ 0 & \text{if } x \text{ is not included in } A \end{cases}$$

The value of $\mu A(x)$ is referred to as degree of belonging and has a real value between 0 and 1. When x completely belongs to the fuzzy set A, $\mu A(x)$ is worth 1 and when x is not in A, $\mu A(x)$ is worth 0. All other values mean a gradual membership to the set A.

A fuzzy inference system (FIS) is a system that uses the theory of fuzzy groups in order to map input linguistic variables (characteristics in fuzzy classification) over output linguistic variables (classes in fuzzy classification). Fuzzy rules are a collection of linguistic sentences that describe how the FIS must make decisions on input or controlling output. **If-Then** fuzzy rules possess an antecedent and a consequent. For example, in (2), *the student is excellent* is the antecedent and *he or she will have great grades in exams* is the consequent.

If *the student is excellent* **then** (2)
he or she will have great grades in exams

Depending on the FIS, it may not be necessary to evaluate every possible input combination, since some may rarely or never occur.

Fuzzy inference

In order to adapt instructional material, two input linguistic variables have been defined. The first is *learning style* which takes into account 3 terms (fuzzy sets): active, balanced and reflexive. The second variable is *knowledge level* which takes into account 3 terms: apprentice, intermediate and near_expert. In figure 2 the definition of membership functions can be appreciated. In order to carry out this development, the FisPro® open code tool has been used (Fuzzy Inference System Professional)

The output linguistic variables characterize the instructional material that will be presented to students. The parameter, in the active/reflexive dimension, that has been taken into consideration is the preference to study in groups. For learning material, the following characteristics have been defined: *difficulty level* (with low, medium and high terms) and *individual/group work* (with individual, balanced and group terms) whose definition can be seen in figure 3.

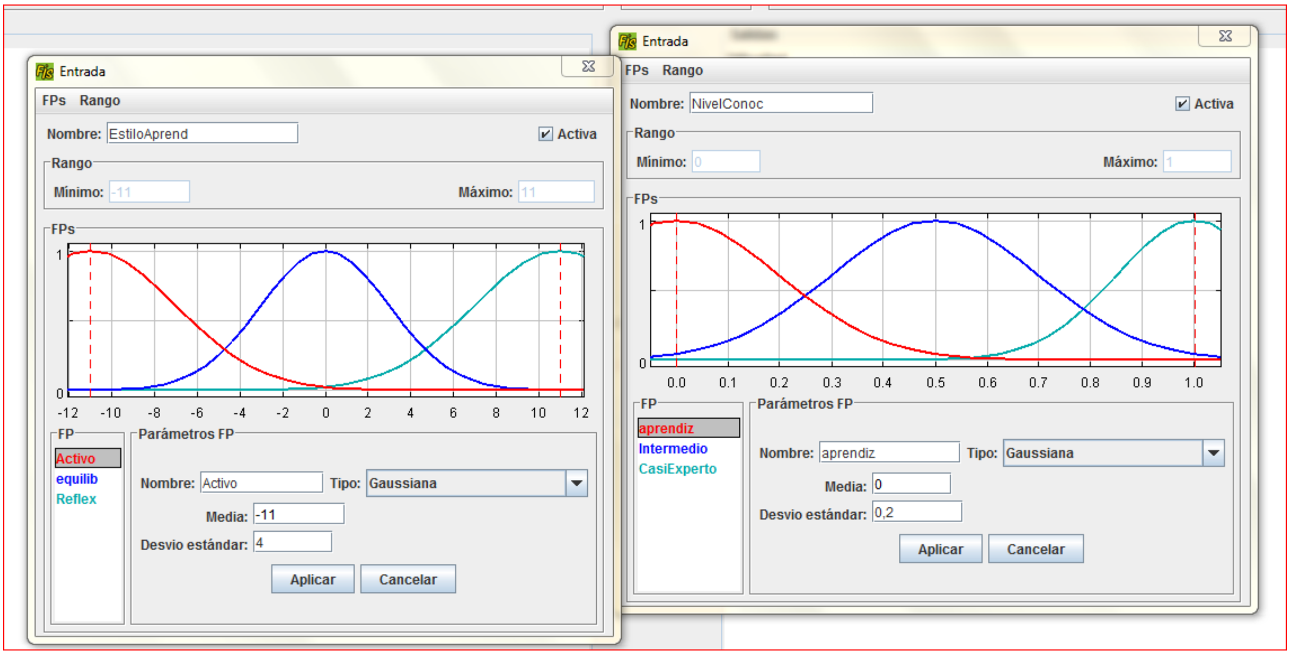


Fig. 2. A membership function is essentially a curve that defines how each point in the input space is mapped to a membership value (or degree of membership) between 0 and 1. Here, two input linguistic variables (*EstiloAprend* and *NivelConoc*) and their corresponding terms as fuzzy sets are illustrated in different colors.

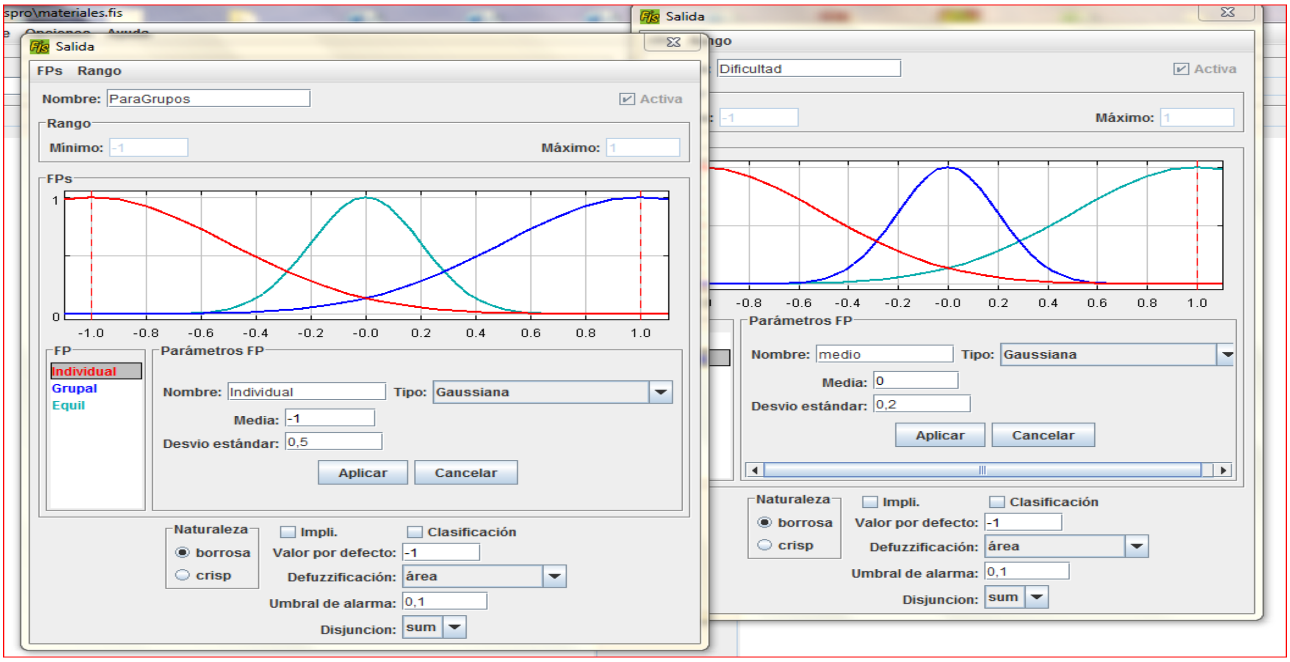
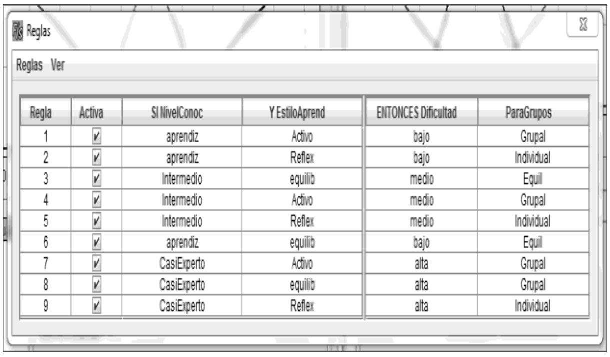


Fig. 3. In order to improve adaptability, the learning material should be delivered with respect to students' knowledge level and personal characteristics. Here, two output linguistic variables (*ParaGrupo* and *Nivel_Dificultad*) and their corresponding terms are defined to arrange instructional material is presented in distinct colors.

Our FIS have been defined according to the recommendation of experienced professors. It comprises nine fuzzy inference rules. In figure 4, the system is illustrated.



Regla	Activa	SI NivelConoc	Y EstiloAprend	ENTONCES Dificultad	ParaGrupos
1	✓	aprendiz	Activo	bajo	Grupal
2	✓	aprendiz	Reflex	bajo	Individual
3	✓	Intermedio	equilib	medio	Equil
4	✓	Intermedio	Activo	medio	Grupal
5	✓	Intermedio	Reflex	medio	Individual
6	✓	aprendiz	equilib	bajo	Equil
7	✓	CasiExperto	Activo	alta	Grupal
8	✓	CasiExperto	equilib	alta	Grupal
9	✓	CasiExperto	Reflex	alta	Individual

Fig. 4. Fuzzy inference rules in FisPro. It can be observed values for antecedents and consequents. For example, the first rule is: If **NivelConoc** is *aprendiz* and **EstiloAprend** is *active* then **Dificultad** is *bajo* and **ParaGrupos** is *grupal*.

In addition, the inference mechanism tracking can be observed dynamically with particular values for input linguistic variables. A case is presented in figure 5.

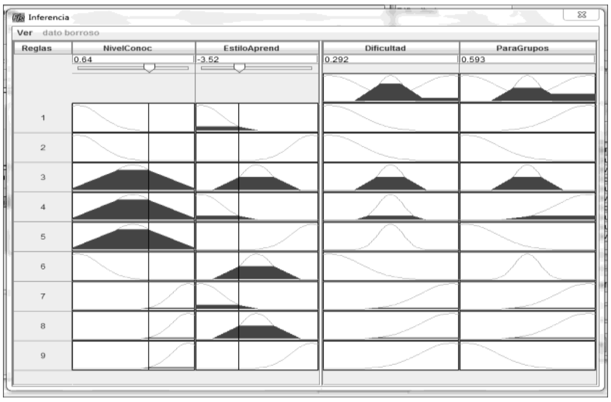


Fig. 5. Inference example where **NivelConoc** is *strongly intermediate* (0.64) and **EstiloAprend** is *active* and *balanced* in medium and equal manner (-3.52) implies that **Dificultad** is *medium* and *high* in medium and equal mode (0.292) and **ParaGrupos** is strongly *group* (0.593).

3. FUZZY INFERENCE CONSEQUENCES: INSTRUCTIONAL MATERIAL EXAMPLES

As a result of applying the fuzzy inference system previously mentioned, instructional material has been developed in the domain of basic programming corresponding to courses in the initial stage of the Computer Engineering course of study at Mar del Plata National University. Three types of exercises developed in Scratch and used in Moodle are shown. Scratch® is a very friendly tool in the teaching of programming at initial level because it provides a friendly graphic environment, develops algorithm reasoning and promote the use and exploration of resources (objects, graphics, audience, messages, control structures, variables, lists, etc.) intuitively, due to the way code is constructed (built-in blocks that represent their functionality visually) and also due to the fact that progress results can be easily validated. In each example, level of difficulty and whether it has developed for groups has been added between brackets, that is to say, the elements of the output linguistic variables.

Example 1 (Low difficulty, individual work): Study the next program that stores a list of person ages. The list numbers are entered by the user. In figure 6, the example is presented.

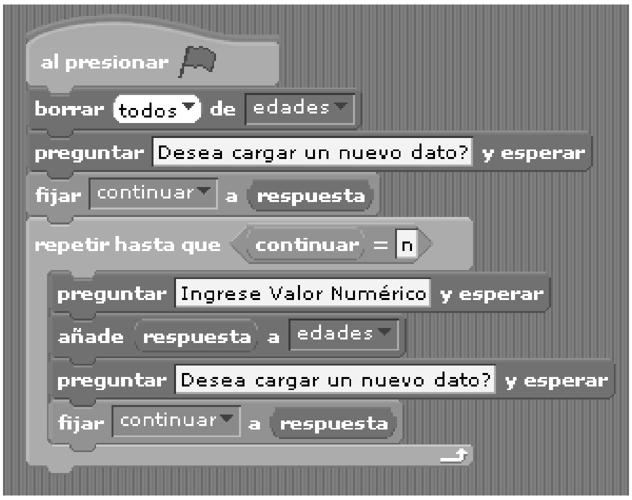


Fig. 6a. Screen shot of Scratch® running a program building for Low *difficulty* and *Individual work* learning material.

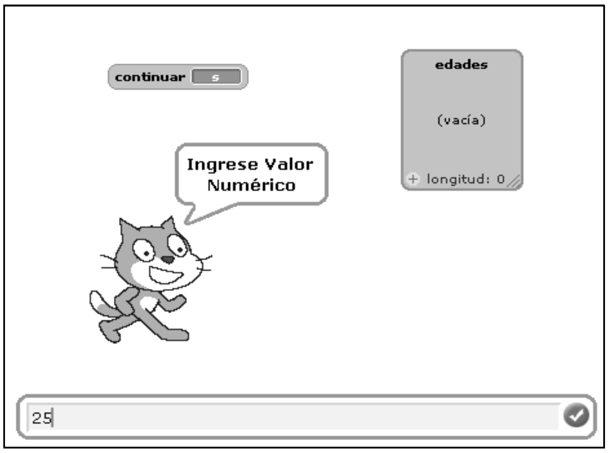


Fig. 6b. Screen shot of Scratch® with data entry.

Example 2 (Medium difficulty, balanced work). Explore the program that finds the minimum value in a list of person ages.

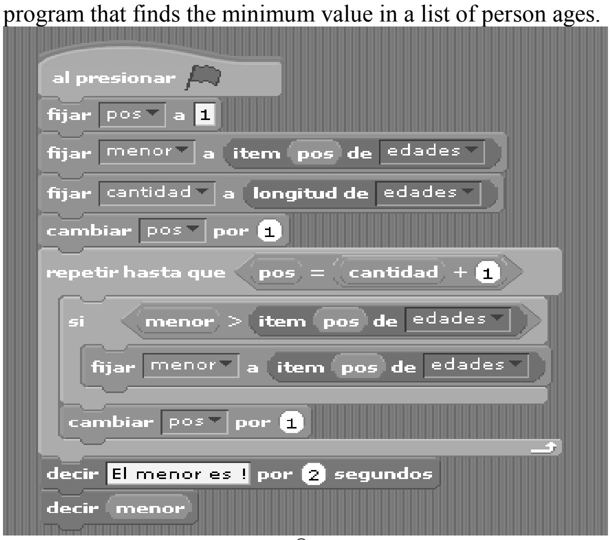


Fig. 7a. Screen shot of Scratch® running a program building for *Medium difficulty* and *Balanced work* learning material.

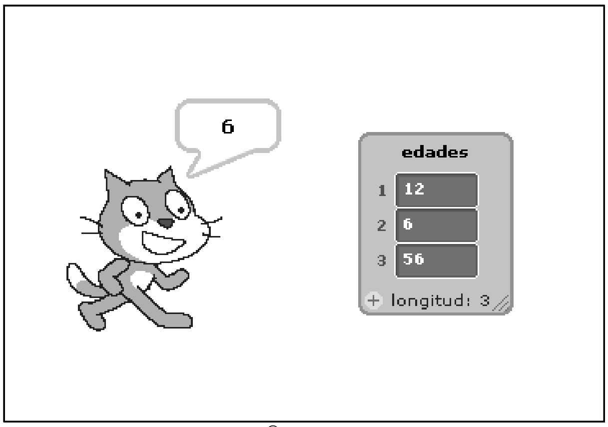


Fig. 7b. Screen shot of Scratch® with data entry.

Example 3 (High difficulty, Group work): Study the program of the game "The 5 steps". It is a question and answer game with the following characteristics: the player answers questions made by the game and as the contestant gets a right answer, he/she goes up a step. The contestant wins when he/she gets to the top of the steps (answering well 5 out of 8 questions). The people involved are: Trainer, Host, and Contestant. The Trainer of the game requires that 8 questions be entered with their corresponding answers and the game starts. The Host makes the questions to the contestant one by one until the contestant reaches 5 correct answers or until they reach the 8 questions. When the game is finished, the Host lets the Contestant know the result of the game with a message, if the message reads "winner" the Contestant celebrates; otherwise the Contestant leaves the game.
Three screen shots of learning material are presented in figures 8.

Fig. 8a. Presentation screen of "The 5 steps" game.

Fig 8b. Screen shot of data entry in "The 5 steps" game

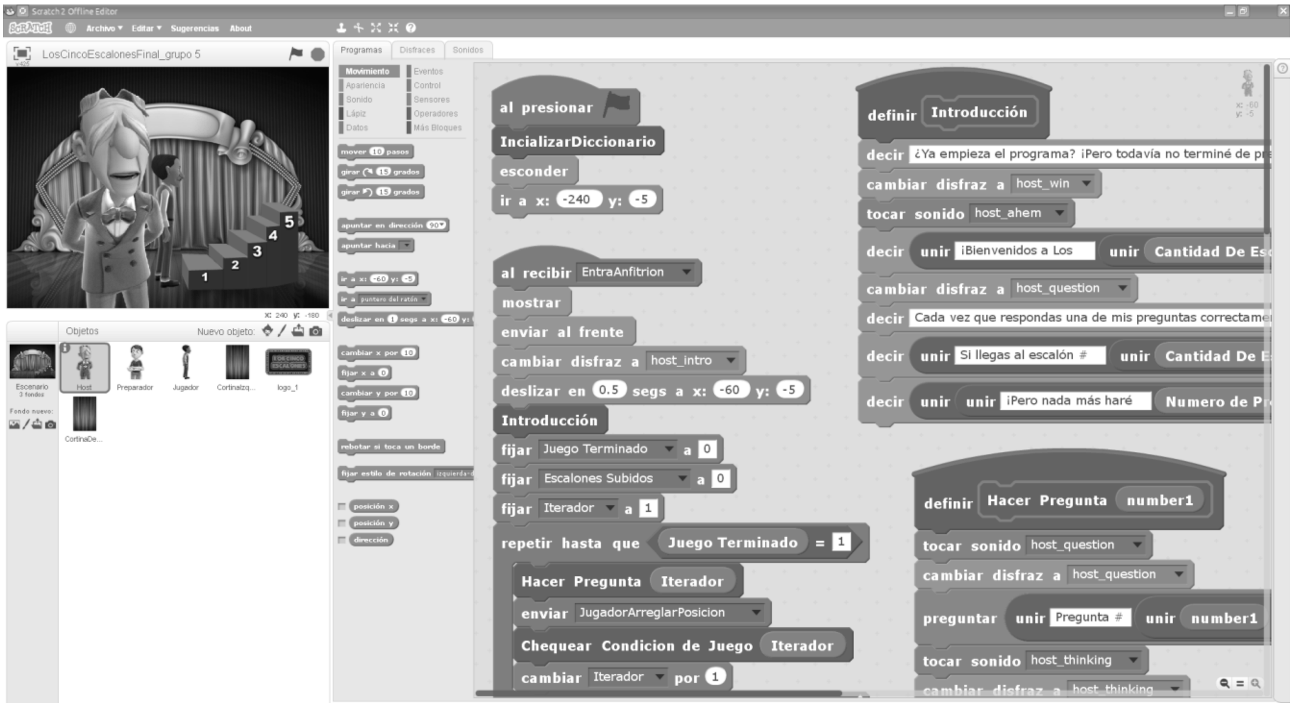


Fig. 9. Screen shot of the game creation that was extracted from an animated film and oral explanations about the development of the game in which the set , objects, variables, lists and part of the constructed code can be seen.

4. CONCLUSION

This paper aims at promoting the adaptation in Virtual Learning Environments. Learning is a complex processes that have to consider each individual student's characteristics and abilities in order to be effective. Therefore, if instructional materials are adapted to the students' personal characteristics, time and effort are optimized to achieve a proper acquisition of knowledge. In order to reach this goal, experienced professors have been consulted and their expertise has been applied to fuzzy rules in order to categorize instructional materials. Fuzzy Logic has been used because it realistically represents human expertise. Adaptive tests of the study material are planned in order to improve the adaptation to the student in a Virtual Learning Environment.

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