A AIED Game to help children with learning disabilities in literacy in the Portuguese language

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Figure 1: Execution of the game's prototype.

Abstract

This work has the objective to create a Game-Based Learning, which aims to assist teachers and psychologists in the literacy process for students with learning difficulties. For such, two systems of Artificial Intelligence in Education were separately developed in association with behavior analysts. A Machine Learning was created to evaluate the student's learning. After this analysis, the results output are sent to a fuzzy system that would generate a task of adapted teaching. The game consists of stages that contain those teaching tasks that are generated during game play. The game ends when the player is considered, by AI techniques, literate and with knowledge of all the words of the system.

Keywords: AIED, Machine Learning, Fuzzy System, teaching tasks, literacy.

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1. Introduction

Digital games have conquered an important place in the lives of children, adolescents and adults, and are now one of the fastest growing sectors in the media and entertainment industry. Besides this market, digital games have also been combined with various fields of simulations and learning, generally known as Game-Based Learning (GBL) [Xiangfeng et al., 2010], and also in Artificial Intelligence in Education (AIED) [Du Benedict, 1997].

Good learning requires collaboration between student and teacher. The student's interest in studies is of fundamental importance [Timothy, 2010] so that they maintain the fullness of their potential. For teachers, it is concluded that any attempt to improve the students' achievements should be based on the development of effective teaching behaviors [Brophy, 1986]. In other words, they should give proper guidance to students.

The behavioral analysis, an area linked to cognitive experimental psychology [Claudio, 1982], historically studies the human learning processes. The field has developed techniques and methods to facilitate and fasten the process of human cognition, examining issues such as memory, attention, perception, reasoning and creativity.

In recent decades, some games have incorporated the features of literacy teaching and that studied behavior analysis, aiming to help in the learning process. As an example, the ALE-RPG [Sarmanho, 2011] which promoted a more entertaining way to interact with the tasks of teaching reading and writing supported by an educational program commonly used in UFSCar (Federal University of São Carlos). This game is based on GEIC (*Gerenciador de Ensino Individualizado por Computador*) [Marques et al. 2011] that allows the remote connection of various tasks of teaching, learning repertoire, tutors and students.

This research has the objectives: i) identify, analyze and evaluate student learning through the computational processing as an expert would; and ii) generate teaching tasks adapted to the degree of knowledgment of the student who is learning, making it possible to build an automated process of teaching tasks. The game-based system aims to acquire the motivation that games have by being playful, increasing interest in completing the game and making the learning process more enjoyable.

2. Related Work

Studies in the field of AIED, according to Du Boulay [1998], state that the individualization of teaching can be effective and is regarded by the author as the "Holy Grail of AIED". This paper compares the educational differences in AI systems (AIED) with conventional educational systems used in the classroom or traditional methods of Computer-Assisted Instruction (CAI).

Self [1998] presented a "bottom-up" approach to show the relevance of artificial intelligence systems in support of teaching should be primarily motivational and pedagogical. He comments that there are important rules for Computer Based Learning (CBL) such as: provide individualized education through a cognitive model and identify the inherent difficulties of learning.

Azevedo et al. [2001], discusses methods of teaching which, although of satisfactory standard, still present different efficiency levels for each student. This is discussed in examining the computational and educational resources and their degree of adaptability to the individual needs of each student.

The research developed by Mahlmann et al. [2010] features the exploration of the potential to predict aspects of player behavior and his interest in the game with the supervised learning for the title TombRaider: Underworld.

Also the work of Puzenat et al. [2010] has shown that human cognitive processes can be evaluated using a neural network through an appropriate interface. His idea was, through digital games, to measure user actions with machine learning. In two of his prototypes, the author discovered the mental age and whether the child is left handed or right hand.

The "*Gerenciador de Ensino Individualizado por Computador*" (GEIC - An Individualized Education Manager for Computers) [Marques et al. 2011] approaches the problem of ensuring the dynamic generation of content for educational use, by providing software for programming procedures based on teaching choice tasks. It allows the creation of Teaching Units that combine various teaching tasks, and represent discrete attempts to provide choice tasks. The objective of this work is to aid teachers in teaching reading and writing to children with learning difficulties. Further details of this program will be given in Section 3.

The GEIC learning program [Marques et al., 2011] was transformed into a game called ALE-RPG (Aprendendo a Ler e Escrever – RPG in portuguese, or Learning to Read and Write - RPG) [Sarmanho, 2011]. However, it should be stressed that the structured progress that the game kept in the GEIC proved to be a little static. The progression of the player through the teaching tasks does not allow a fully customized advance to be made, since it is conditioned by the need to learn all the words of each teaching unit. The non-acquisition of any word component of the teaching units delays the teaching progress of the next units.

There are games like Diablo [Schaefer et al., 1996], Torchlight [Baldree, 2009], Spore [Wright, 2008] and MineCraft [Person et al., 2009] that use automatic levels of generation when the player starts a new game, but keeps the missions and game objectives distributed randomly on the map that was generated. However, all this randomness follows 'brute force' algorithms, without any predetermined scale of difficulty.

The approach of Dormans et al. [2011] investigates strategies to generate levels of action-adventure games that are divided into two individual structures, so that they generate missions first and then locations. The different types of generative grammar are analyzed in a search for the one that best fits.

Xiangfeng et al. [2010] uses Fuzzy Cognitive Maps to design Game-Based Learning (GBL). The goal is to use the Hebbian learning rule to increase learning capacity by employing the game data and Unbalance Degree to establish the lack of prior knowledge.

3. Teaching Methodology

The proposal of the game is grounded in the teaching program called "ALEPP" ("Learning to Read and Write in Small Steps" or "Aprendendo a Ler e Escrever em Pequenos Passos" in portuguese) [Rose et al., 1989], which presents some features designed to help people with difficulties in the process of reading and/or writing.

This educational program is individualized, which allows each person to fulfill the teaching activities according to their own pace. It is organized into **Teaching Unit**, where each unit is divided into **Teaching Sections** which contain a set of **Teaching Tasks**. The student can repeat learning units if not reached the learning criterion previously established. This ensures that progress during the program will only occur after the acquisition of previously taught repertoires. Thus, the program is a product of contingencies arranged in order to promote learning [Skinner, 1965].

The program teaches the relationship between printed words, pictures and dictated word by a Matching-to-Sample [Rose et al., 1989] procedure. In this procedure, the student must choose between two or more alternatives, for example, pointing at a figure between two others or pointing between two printed words, indicating the equivalent alternative with model word. The organization of the educational structure is based on the research conducted by Reis et al. [2009] about different presentation formats and the relationship of stimuli in chains.

The teaching tasks or teaching trials are divided according to their type, as shown in the Table 1. For example, in the attempts of the AC type, the model stimuli is spoken and the choice is a stimuli in text format. In attempts BC type, the model stimuli is a picture at the top of the screen and the choice stimuli are presented in text. A task of the AB type, the model stimuli is a sound stimuli and the choices are presented by figures. But in attempts like the CB type, the model stimuli is a text and the choice stimuli are pictures of choices [Marques et al., 2011].

There are also tasks that are characteristic of word construction where the correct model is presented and the child needs to build the word syllable by syllable, or letter by letter, that is equivalent to the correct model, whether it is a figure type stimuli, sound stimuli or text type stimuli. For example, in attempts like the BE type. The model stimuli is a picture and the choices are scrambled syllables where there is at least one sequence of syllables of the correct word. The student must select the syllables that correspond to the model in the correct order. Table 2 displays tasks for writing acquisition.

Therefore the objective of this work is to use this educational program combined with artificial intelligence to classify and generate computational tasks in a game and make the activity more entertaining and interesting for students.

Table 1: Illustrations of teaching tasks related to reading acquisition.

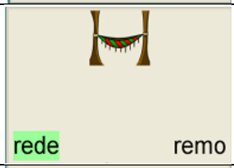
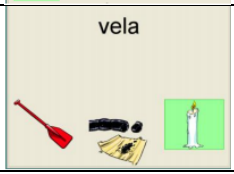
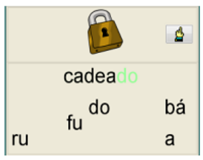
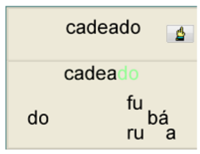
Task Type	Task illustration	Role of the Child
AB		Given the spoken statement "Point at Student" the student must select the student figure.
AC		Given the spoken statement "Point at Cat", the student must select the word 'cat'.
BC		Given the figure of a hammock, the student must select the word “hammock”.
CB		Faced with the word "candle", the student must select the candle figure.

Table 2: Illustrations of teaching tasks relating to the acquisition of writing.

Task Type	Task illustration	Role of the Child
AE		Given the spoken statement "Type Hammock", the student should write the word "hammock" by choosing the letters in the correct order.
BE		Given the spoken statement "What figure is this?", the student should write the word "lock" by choosing the letters in the correct order.
CE		Given the spoken statement "What word is this?" , The student should write the word "lock" by choosing the letters in the correct order.

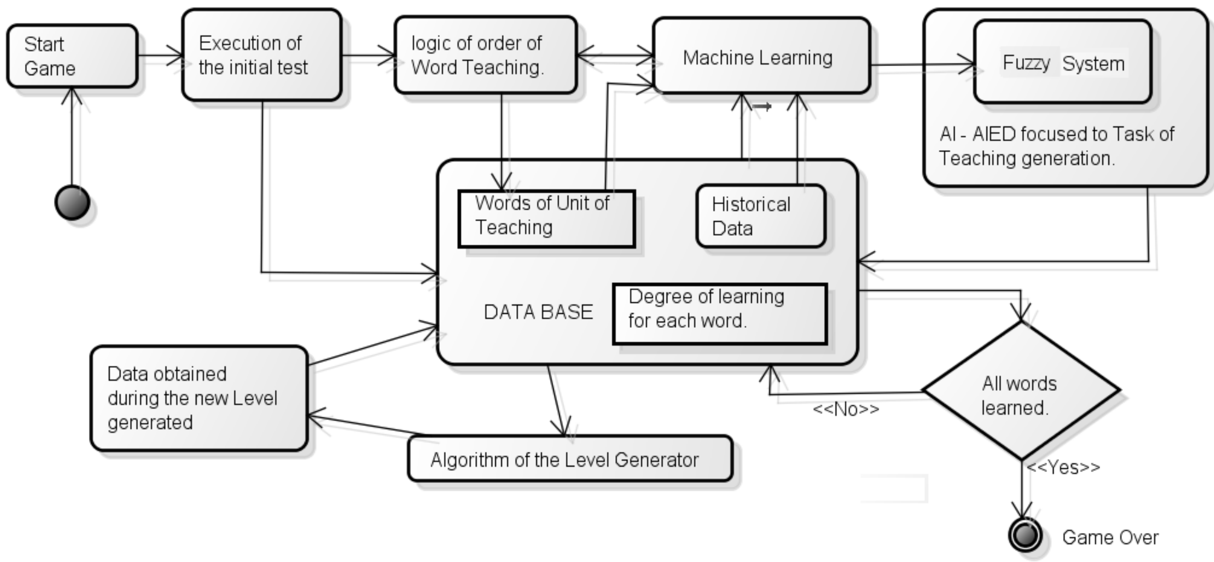


Figure 2: Proposal of the Integrated Prototype Game with AI.

4. Proposal e Prototype of the game

The AIED was developed based on considerations of the curriculum mentioned above (ALEPP), and interviews with psychologists that are members of the project. Also, a game, which demand to integrate those two systems and make the teaching tasks adapted, individual and more fun, is in development.

In this approach, to assist the instructors, the general purpose of the project is initially focused in creating the AIED for teaching reading and writing and embedded it in a digital game. The AIED will be composed of two intelligent systems, ML (Machine Learning) and Fuzzy System, whom will act together as shown in the diagram in Figure 2.

4.1 Story and Mechanic of Game

The story of the game consists of the problems that an alien acquires when he accidentally falls on our planet. Coming from a distant planet in his spaceship, the main character is a traveler who seeks to explore new planets and learn about them.

In order to continue his journey, he needs to get some parts to be able to repair the ship. In order to move on, our character, named Amaru (Figure 3), needs to learn to communicate by reading and writing in the language of the earth. During his journey he learns to communicate and gets to know humans that will help him get the parts of his ship. He will also have help from his robot Urama (Figure 4), an NPC (Non Player Characters), which will help to solve the teaching tasks of the game.

Figure 3: Amaru.

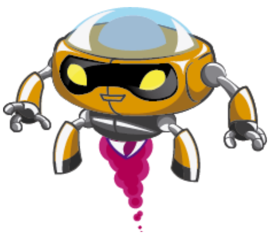


Figure 4: Urama.

The platform-style game is made up of a series of different challenges, in which the teaching tasks are docked and occurs in several different environments on the planet. Each type of challenge will be worked on separately and will be called a mini-game. Each will have its own logic and mechanical solution.

The player will be able to move the character in a two-dimensional plane, but the game's graphics are also composed of objects in three dimensions. To control the game will be necessary only the use of mouse.

4.2 Prototype

The prototype of the game is being developed with: Unity3D [2012] engine, MonoDeveloper [2012], Microsoft Visual Studio [2012], C# [Visual C# 2012] programming language and Blender [2011] for 3D modeling and animation.

The sequence of tasks follows a logic of teaching. For specialists there is a preferred order for each word being taught, and new words will enter in the teaching tasks gradually, depending on the degree of literacy of the word.

For each Teaching Unit there are fifteen words that have to be taught. The ML will decide the level of knowledge and evaluate if the student has learned every single word. As in the case of the execution of new ML generated tasks, they will always be calculated on the basis of this new information regarding the degree of knowledge of a particular word. The words are determined as literacy appears less frequently, and when every word has been learned, the game is over. Figure 2 shows a diagram of the operation of this proposal.

The system is a digital game that begins with an initial pre-test of static tasks to generate the minimum data required to enable the Machine Learning system to correctly analyze the student. After processing the information obtained during game play, for each word, a new task is generated by the Fuzzy System and is stored in the database. The level of the game is created by using the features of the generated task.

5. Artificial Intelligence Systems.

This session aims to describe the artificial intelligence used in the game.

5.1 Machine Learning

In this work the Machine Learning's goal is to evaluate the degree of learning of reading and writing of individual words, using it to analyze the behavior of the student during the teaching session. This aim proposes the word's learning and guarantee that the student didn't the task randomly or for exclusion in their responses, rather than actually mastering the word.

Basically, for the ML, a teaching task is a set of information as shown in Figure 5. One of the extracted information of this scheme is equivalent to the difficulty of the task described in the next topic.

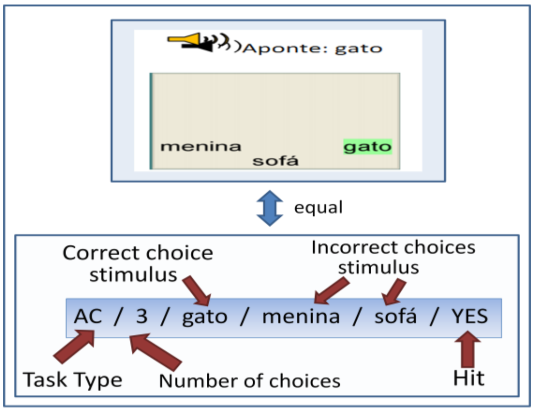


Figure 5: Schematic of various data of a learning task to reading as example.

5.1.1 Difficulty of a task of teaching

In order to determine the learning characteristics of the student in the game, was defined two equations to figure out how much a learning task is complex for the educational program in focus, scoring the factors of task difficulty [Nerino et al., 2012]. All equations were based on certain attributes discussed in conjunction with psychologists, i.e., each element of the equations were considered one factor of difficulties which can increase or decrease the complexity of tasks according to psychologists. Below are the equations 1 and 2 that describe the difficulty of the reading task and the difficulty of the writing task, respectively.

$$Dr = \begin{cases} \frac{\sum_{i=1}^{n-1} Pin}{n-1} * \alpha + T * \beta + \frac{n}{n_{max}} * \gamma & ,n > 1 \\ T * \beta + \frac{n}{n_{max}} * \gamma & ,n = 1 \end{cases} \quad (1)$$

where,

Dr: Difficult of the reading task,

Pin: proximity factor to incorrect choices in relation to the model word,

T: score of the task type,

n: number of choices available in this task,

$\boldsymbol{n_{max}}$: maximum of possible choice stimulus,

α, β and ***γ:*** score of the difficulty factors, obtained empirically.

$$Dw = \frac{S_i}{S_t} * \alpha + T * \beta + \frac{S_t}{S_{max}} * \gamma + \frac{S_m}{T_{sm}} * \sigma \quad (2)$$

where,

Dw: Difficulty of the writing task,

Si: Number of incorrect choice of syllables over the word model,

St: total number of choices in the task,

T: score of the type of writing task,

S_{max}: total number of syllables possible for a task,

Sm: total number of choices or syllables of the word model of the task,

T_{sm}: total number of choices or syllables of the word with the greatest amount of syllables system,

α, β, γ and σ: score for the factors of difficulty regarding the writing tasks obtained empirically.

5.1.2 Classification of Learning

With the difficulty of each task set we can now apply Machine Learning together with the rightness or wrongness of each task presented to a student. Thus, the method used to perform the prediction of student learning was **logistic regression**, which is used to solve problems in classification of supervised learning where there is an output variable of the binary type based on previously recorded data [Medeiros et al., 2007]. The purpose of using logistic regression is to provide a level of knowledge to a specific word and must be performed for each word model in order to define a standard of student learning's for each word [Nerino et al. 2012]. The Figure 6 represents the model of Machine Learning.

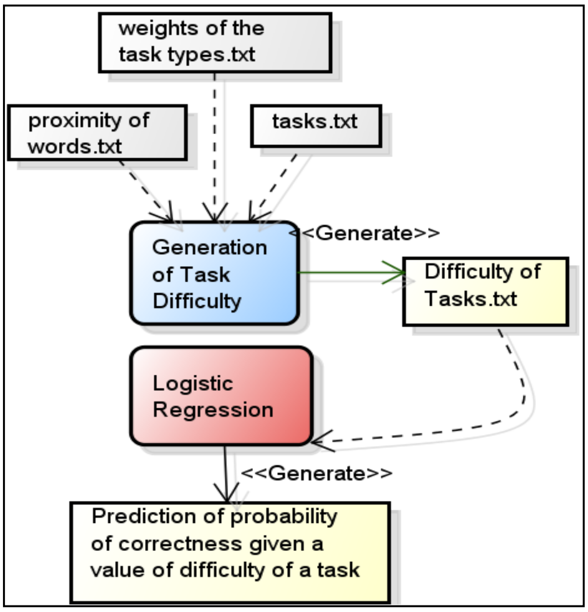


Figure 6: Diagram of the program generator of task difficulty of teaching integrated with logistic regression.

The model proposed above tells us a lot about student learning, but there are some conditions and statistics suggested by the psychologists that must be taken into account in deciding the learning of a particular word in the system. These data are processed and placed in first-order logic to obtain data closer to the real student learning. These parameters are illustrated in the Figure 7.

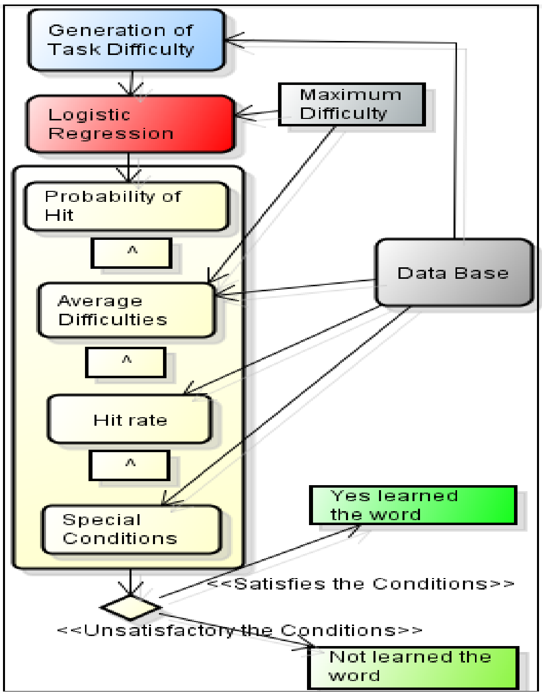


Figure 7: Machine Learning with First-Order Logic.

5.2 Fuzzy Generation Task

For task generation, the ML will be used to assist the fuzzy system with the input parameters used in this system to generate a new task.

The main objective of the fuzzy system is to make use of data generated by the ML correctly in order to generate an adjusted task. Fuzzy Logic was chosen to carry this out for the following reasons: it has a distinct capacity to express the vagueness and uncertainty of the knowledge it represents [Pedro et al., 2003]; it is able to model a system close to logical grammatical rules; it ensures a better approximation to the knowledge of a specialist through semantic representations and linguistic terms; and it operates by choosing few rules and working with imprecise terms [Moratori et al., 2005].

5.2.1 Fuzzyfication

All the data processed and generated by ML, are abstracted and normalized in three fuzzy sets corresponding to a numerical range, from 0 to 100% and a degree of pertinence ranging from 0 to 100% [Moratori et al., 2005], as shown in Figure 8. The fuzzy values represented in this approach correspond to the descriptors for the trapezoidal and triangular functions illustrated in Figure 8. In the present work all the fuzzy sets have these same values of classification.

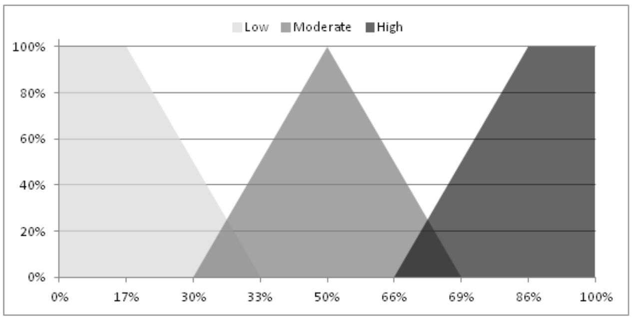


Figure 8: Graphical representation of fuzzy set.

The fuzzification is done individually for each input variable described in Table 3.

Table 3: Input variables, provided by ML, of the fuzzy system.

Input Variable
PTT: Probability of hit with determined Task Type.
TTT: Hit Rate of Task Type.
PNC: Probability of hit with determined number of Comparisons.
TNC: Hit Rate of number of Comparisons.
PPI: Probability of hit with determined incorrect word.
TPI: Hit Rate with determined Incorrect Word.

The above inputs used in fuzzy system are the outputs of the machine learning.

5.2.2 Fuzzy Inference

The fuzzy inference system utilized in this work uses the Mamdani [1976] model. It corresponds to the algorithm of fuzzified information processing in accordance with linguistic rules [Pereira et al., 2012] which are defined by specialists and research studies referred to. Table 4 correlates the input variables with the output in logical terms and the "**if-then**" form in causal terms, this table shows some examples of rules from the rule set inference.

Table 4: Output variables of the fuzzy system.

PTT	TTT	DTT
Low	Low	Low
Moderate	Low	Moderate
High	Moderate	High

For each task feature there is a correspondent output variable and also fuzzy inference. At the end of the system, the output is the completion of the task, as shown in Figure 9. The Table 5 shows the output variables of the fuzzy system.

Table 5: Output variables of the fuzzy system.

Output Variable
DTT: Need for Task Type.
DNC: Need for number of comparisons.
DPI: Need for incorrect word.

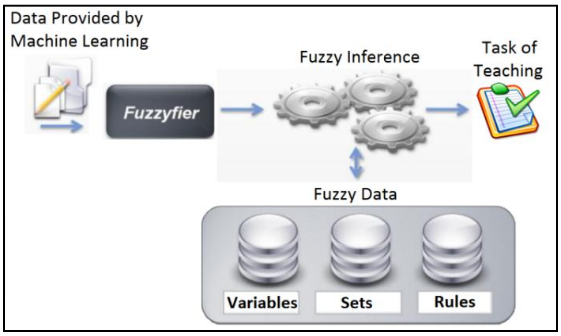


Figure 9: Macro view of the Fuzzy System.

As an example that points to a rule set for the task type BC: "**If** the Probability of the Task Type BC **is** Low (pertinence 85%) **and** the Hit Rate of Task Type **is** High (63% pertinence) **then** the Need for Task Type BC is Medium (pertinence 74).

5.2.3 Defuzzyfication

Each activation of the rules is analyzed separately, and then the linguistic value of fuzzy set assigned as Highest is chosen as the best option for each feature of the new task that is being generated.

The logic presented above is applied to establish Type of Task, the number of incorrect comparisons and choice of words. For the words choices, instead of only one value, the algorithm that chooses the words returns a list with ***n*** words, where ***n*** is previously defined by the fuzzy logic responsible for deciding the number of comparisons.

There is no need, in this work, to defuzzify the output variables because the choice is given by the highest degree of pertinence as stated previously. This leads to the generation of task features for the subsequent level of the game. It should be decided which task type is better to choose.

6. Simulations and Results

In order to evaluate the artificial intelligence in the game and collect some preliminary results, simulations were performed on three groups of students: i) Students with Learning Deficit (DAP), ii) with Gradual Learning (APG) and iii) Students with Consolidated Learning. (APC).

The system was tested in a teaching unit containing fifteen words used by GEIC and with the same educational structure. The fifteen words used in this work are: *bolo* (cake), *tatu* (armadillo), *vaca* (cow), *bico* (beak), *mala* (bag), *tubo* (tube), *pipa* (kite), *cavalo* (horse), *apito* (whistle), *luva* (glove), *tomate* (tomato), *vovô* (grandpa), *muleta* (crutch), *fita* (tape) and *pato* (duck).

Of the fifteen words were correspond to the teaching session known as pre-test, we analyzed the learning of five words. These five words used in this work are: *bolo* (cake), *tatu* (armadillo), *apito* (whistle), *tomate* (tomato) *and muleta* (crutch).

For the AGP and APC, the result of simulation indicates that the words was learned. In the DAP, the result of simulation indicates that the IA ranking the word as learned for read and no-learned for the write. These data confirms the simulations done by the psychologists, in particular to the behavior of DAP.

The simulations generated graphs for every single word in the three behaviors. As an example there is a graph in Figure 10 with the tasks for the teaching of the word "*bolo*", both for writing and for reading in the experiment of learning deficit. Each task has a representation of right or wrong, as indicated. Also in Figure 10 is displayed a task with decreased difficulty, represented by a "*", which was generated by the AI based on historical errors of this student.

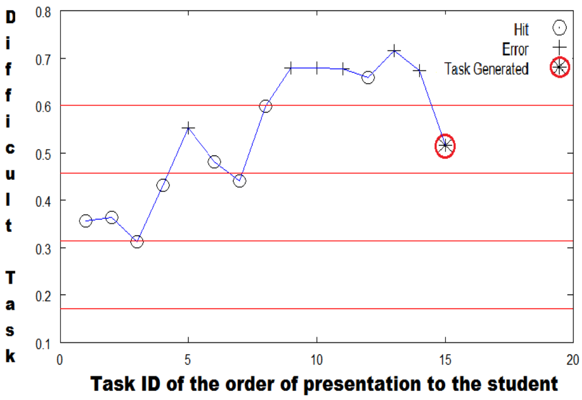


Figure 10: Graphs with the teaching tasks of teaching the word "bolo" in the Learning Deficit group.

For validate the data generated by the IA, questionnaires were submitted to a group of psychologists containing a sequence of teaching tasks for every word of the experiment for each simulated behavior. The questionnaires had two goals. The first objective is identify the difficulty level for each teaching task in a scale (very easy = 1, easy = 2, regular = 3, difficult = 4, very difficult = 5). The second point is, through five tasks as alternatives, the psychologists should be able to answer the question: “What task the student should do based on previous tasks?”, where one of the alternatives generated by the task was the AI. An average level of difficulty was calculated taking into consideration the answers given by psychologists, as seen in the following tables 6 and 7.

The result generated by the AI and the result of the questionnaire was compared and show in Table 6. The lines correspond to the tasks presented to psychologists, and the columns represent the word taught by tasks. The table values mean the difference between the level of difficulty of the task chosen by the psychologist in relation to the level of difficulty of the task generated by the AI. Values near 0 indicates that the tasks generated by the IA and by the psychologists are the same, while values near 5 indicates that the tasks are very different. For example, task 1 (row 1) teaches that the word “*bolo*” (column 1) has difficulty level rated by AI 3,5. Psychologists, through the survey, rated the task difficulty level of 2,0. The difference between the value generated by AI and the value selected by psychologists was equal to 1,5.

Table 6: Difference of the level of difficulty of each task from the difficulty chosen by the AI and the difficulty chosen by the psychologist. Lower values are better.

	bolo	tatu	apito	tomate	muleta
Task 1	1,5	1,5	0,5	2,5	1,5
Task 2	0,5	1,5	2	1	2
Task 3	0,5	0,5	0,5	0,5	0,5
Task 4	1	0,5	0,5	1	0,5
Task 5	1	0	0	1	0
Task 6	1	0,5	0,5	1,5	0,5
Task 7	1	0,5	0,5	0	0,5
Task 8	4	4	2,5	3,5	3,5
Task 9	1	0,5	0,5	1	1
Task 10	1	1	0,5	0,5	0,5
Task 11	0	0	0	1	1
Task 12	2	0,5	0,5	1	0,5
Task 13	0	0,5	1,5	0,5	0,5
Task 14	1	0,5	0,5	0	0

According to Table 6 it can be seen that:

- Tasks considered as complex by the AI were also considered complex by the psychologists.
- In all the words on task 8, the difference in the difficulty level was equivalent or near 4. This is because these task are "Copy" type task, where the model is a text and the choices are syllables (CE type). As an improvement for this task type, it should be revised to set the weight for that type and fit it to the opinions of experts.
- 14.28% of the tasks were classified equally by the psychologists and AI, with the same level of difficulty, meaning that the difficulty level selected by the psychologist was the same as the system-generated difficulty.
- 64.28% of the tasks have been classified with a difference between 0 and 1 point (rounding up or down), which means that a small

difference is acceptable between the choice of the AI and the psychologists for the task.
- 78.56% of the tasks are similar and acceptable by the psychologists and the AI.

The Table 7 shows the data collected with the opinions of the psychologists about the difficulty level of the chosen task as appropriate for the student based on tasks previously performed and the difficulty level generated by the AI. The data was arranged by groups of students obtained from the simulation that had been proposed. The average difficulty levels for the chosen tasks defined by the psychologists and stated in Table 7 were also calculated. The closest the value generated by the AI to the value given by the Psychologists, the better the result.

Table 7: Difficulty level of the generated tasks, given the difficulty generated by the AI and the task chosen by the psychologists grouped by student's behavior.

	DAP		APG		APC	
	AI	Psychologists	AI	Psychologists	AI	Psychologists
Bolo	4	2,5	4	3,5	5	5
Tatu	4	2	4	4,5	5	5
Apito	5	2,5	5	3,5	4	3,5
Muleta	2	2	5	4,5	4	4,5

According to data collected with this simulation it was concluded that the difficulty of the tasks generated by the AI are close to the options chosen by experts.

The experts analyzed the options of tasks choosing how much that they attend the needs of the students. Regarding the tasks generated by the AI, which were hidden among the others, 25% were considered optimal, 41.66% were considered satisfactory and 33.34% were considered far from ideal.

7. Conclusion

This paper presents a game with AI techniques for helping children learn how to read and write in a more entertaining way. Artificial intelligence has been divided into identification of learning (Machine Learning) and task generation (Fuzzy System), which is a part of the system that aim to make decisions about the real need that of a person in order to perform a given type of task.

By the data analysis and feedback of experts after completion of the questionnaires, the artificial intelligence system was effective in what it intended to accomplish, making the system able to be tested with students in the classroom. With some improvements, mainly in the types of tasks, it will be possible to balance the weight of these tasks types with the opinions of psychologists. It is noted that the data of the experts in the behavioral analysis field are in agreement with the data output of the machine learning system and the task generation system, thereby validating its output values.

In the next step is intended to cover the tests with larger numbers of students, and add different types of mini-games to increase the player's motivation.

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