A Fuzzy Inference System as a Tool to Measure Levels of Interaction

Ricardo Rosales(✉), Margarita Ramírez-Ramírez, Nora Osuna-Millán, Manuel Castañón-Puga, Josue Miguel Flores-Parra, and Maria Quezada

Autonomous University of Baja California, 22390 Tijuana, Mexico
{ricardorosales,maguiram,nora.osuna,puga,mflores31, maria.quezada}@uabc.edu.mx

Abstract. The interaction between humans and their environment is a current research area. Technology has been part of the environment with which humans have forged their progress, making this socio-technical phenomenon a field of study of interest in the field of research and technological development. In this paper, we present a FIS as a Tool to Measure Levels of Interaction during human-machine interaction. The proposal describes a system that bases its reasoning on user performance during user-exhibition interaction context in an interactive museum. Thte performance is determined by levels of interaction derived from intercativity actions and situations within the user-exhibition context. The FIS objective is to improve the user experience by managing the interaction process in user-exhibition relationships.

Keywords: Levels · Interaction · Fuzzy inference system

1 Introduction

The use of technology focused on information and communication systems is increasingly common in everyday activities. The current technological devices help users in their tasks during the day, providing an effective way of interaction that improves their experience in achieving goals. However, although interaction seems to be a fundamental aspect in the design of such technology, how can such interaction be modeled? Is it possible to incorporate the evaluation of the interaction itself as part of this technology? What impact would these improvements have?

Much suggests that the interaction is a complex phenomenon that depends largely on the subjective evaluation of the observer, so Gayesky and Williams [1] propose a theory based on levels based on some parameters they consider important. Some of the aspects to be considered are presence, interactivity, control, feedback, creativity, productivity, communication and adaptation.

By identifying the level of interaction by observing how the users experience the systems, it could help to design new forms of action that consider their

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preferences. Evaluating the interaction requires knowing criteria based on the qualitative aspects of user behavior.

In this paper, we develop a Fuzzy Inference System (FIS) [2] as an intelligent system that implements an evaluation system that infers the level of interaction according to the Gayesky and Williams scale. A system is described that bases its reasoning on the user's performance determined by levels of interaction. Once the level of interaction is inferred, this information can be used to improve the user experience through a feedback system.

We exemplify these levels of interaction as the result of interactive actions and situations that are presented within the user-exhibition context in an interactive museum. The example system uses the inputs present in the interaction to properly configure and feedback to it. The objective is to improve the user experience by managing the interaction process in user-exhibition relationships.

The concept of interaction can be difficult to represent. However, interactions often occur as well as important aspects of behavioral science. The interaction involves at least two entities or can be a product of communication between these entities, e.g., the user and the system; both are complex, are not similar to each other, interact and communicate given the domain, actions, tasks, goals, and objectives. The interaction represents the interface. Therefore it must efficiently translate the messages among those involved helping in the fulfillment of goals of an application domain [3]. Therefore, the interaction helps to have dynamic cooperation and an end of cooperation between an entity and another entity or between several entities to achieve the objectives of the individual entities or to achieve some collective objective. The interaction often uses distributed artificial intelligence behaviors, as well as behaviors based on the multi-agent system, to propose tasks or perform tasks [4].

How can the interaction be represented? To answer this question you have to know the meaning of representation that the representation is the act or instances that represent an image or ideas of something or someone in mind, things that are not known. Otherwise, it is pure imagination or disfigurement of reality.

A description takes advantage of the conventions of a representation to describe something in particular. The representation is good because they show the restrictions of the problem, the representation of the interaction can be by mathematical Formulation [5], Analysis of the simple effects in factorial models [6,7], Contrast of interaction [8–10], Patterns of interaction [2,11,12], Fuzzy inference system [2,13,14].

2 Related Work

Nowadays, to provide services or information to the user, it is necessary to measure interaction levels based on their performance. In general, the most common measurements of interaction levels are based on numerical and metric values, such as some clicks, feedback, logins to a system, etc. This measurement practice involves the following reflection: Does a metric allow measuring the level of interaction of a user? On the other hand, helping the user with a guide can be essential for the improvement of the interaction. Therefore, it is desirable to have interactive activities specific to the level reached by the user, helping to measure the interaction.

The measurement of the interaction takes place in the natural environment of the user often interrupted by the lack of controlled conditions and the inadequate replication of the problems caused by the user's interaction. In [15], he explains the idea that multiple measurement effects should be studied as isolated effects of a single variable.

There are investigations on the measurement of interaction levels focusing on measurable quantitative variables. For example, in [16] proposes a novel framework with characteristics to measure interactions quantitatively, quantifying the contribution made by each variable as well as the interactions involved.

Wachs et al. [17] proposes a framework of analysis to measure the human-computer interaction with four quantitative variables: ease of use, time of realization, the number of errors and the accuracy of the recognition, as well as with two variables qualitative "individual interview" to obtain feedback on experiences using a vision based on an interface compared to a conventional joystick, and the second "interview of questions", which focuses mainly on determining what features of the interface based on gestures of the hand are the most important and determine what additional features would be especially important.

The fuzzy logic [2,13,14], can help us to represent the levels of interaction of the user, just as it can help us to model the approximate fuzzy reasoning during the interaction. The relations between elements and sets follow a transition between belonging and non-belonging that is gradually represented by values of intermediate belonging between the true and the false in classical logic.

Jiang and Adeli [18] use the fuzzy logic to study investigate complexities and chaotic behavior in such systems. The fuzzy logic is used to for determining the embedding dimension a fuzzy c-means clustering approach is proposed for finding the optimum embedding dimension accurately.

Joelianto et al. [19] use an ANFIS to determine a time series estimation on Earthquake. An algorithm in the backward pass by using a mapping function maps the inputs to all corrected values obtained via error correction rules in the first layer by means of an interpolation of the inputs.

Pozna et al. [20] applied to fuzzy modelling in terms of mapping them to fuzzy inference systems. An example expressed as two applications dealing with modelling of fuzzy inference systems. A framework for the symbolic representation of data represented by the signatures and suggested a data configuration referred to as signatures offering possibilities of symbolic representation and of symbolic manipulation of fuzzy inference systems when the fuzzy modelling of MIMO systems is involved.

Nowakova et al. [21] present a novel method for fuzzy medical image retrieval (FMIR) using vector quantization (VQ) with fuzzy signatures in conjunction with fuzzy S-trees. The method is going to be added to the complex decision support system to help to determine appropriate healthcare according to the experiences of similar, previous cases.

3 Case Study

The case study is based on observation where scenes of interactive environments are analyzed, researched and modeled, to represent real examples of interaction. Interactive museums have a wide variety of interactive exhibitions and show various situations that arise due to the presence of interaction in groups of people. To understand the dynamics present in a context of interaction, the facilities of the interactive museum El Trompo, located in Tijuana, Mexico, with an annual attendance of 154,070 visitors per year is a magnificent place for the case study. The Fig. 1 shows some detail of the museum.

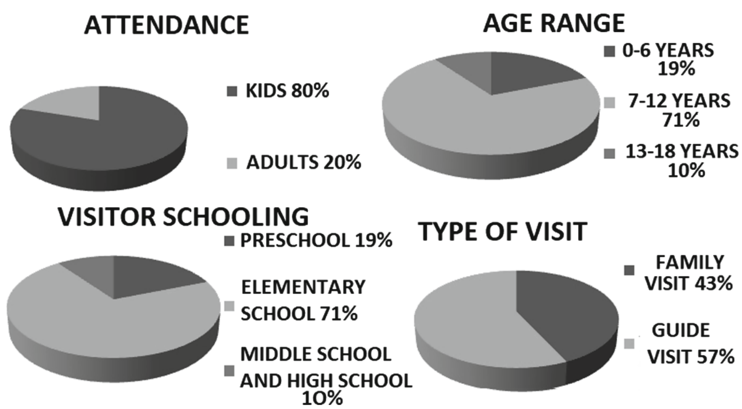

Fig. 1. Percentage of attendance, age, schooling and type of visits of users of the interactive museum El Trompo.

Because it is a museum dedicated to education, its main objective is to provide an interactive place where users can play while they learn. The museum was an ideal place to observe the behavior of users, especially of children and adolescents, being these the central objective of the research.

The behavioral patterns of the interactive museum environment were analyzed such as displacements, trajectories, place of interaction, those who are part of the interaction, interaction time, reading time of information labels, family, fatigue, social behavior, repeat visits, Information learning impact of exhibitions, attitudes, behaviors, and interests.

This information is crucial for the construction of models to help design the presentation format of the exhibition modules, signage, media design, and content information. Likewise, this information improves the measurement methods, the analysis to evaluate the behavior, performance, actions of the visitor, as well as the impact in the short, medium and long-term of the experiences of interaction, participation, patterns of social behavior and assistance.

3.1 Observation and Analysis of Users

To analyze the behavior patterns of the users, the exhibition modules (content, objective, media interface, etc.) were studied, particularly an interactive module with interactive features was chosen, which allowed obtaining the necessary data for analysis performed. The name of this display module is "move domain" The educational and interactive experience of this exhibition is that users play in four stations, where each teaches how to manipulate a means of transport (car, plane, motorcycle and hot air balloon). These show a virtual world simultaneously on all four screens, providing users with experiences of the four modes of transport as they travel through the simulated virtual world.

4 Proposed Fuzzy Inference System

Unlike other models that use different paradigms through heuristics, the research proposal adopts a theory of fuzzy sets to build the knowledge that an accredited user possesses. The FIS was built with the help of the MATLAB Diffuse Logic Toolbox [22]. The configuration of the FIS was carried out through an empirical process.

The inputs of the proposed FIS are the variables that are perceived by the display using sensors; these variables are the performance information of the user interaction which is: Presence, Interactivity, Control, Feedback, Creativity, Productivity, Communication, and Adaptation. Each of these variables was

Table 1. Inputs of the fuzzy inference system (Interaction level)

Inputs	Parameters (Values)					
	Very Bad	Bad	Regular	Good	Very Good	Excellent
Presence	0.085 3.5e−18	0.085 0.2	0.085 0.4	0.085 0.6	0.085 0.8	0.085 1
Interactivity	0.085 3.5e−18	0.085 0.2	0.085 0.4	0.085 0.6	0.085 0.8	0.085 1
Control	0.085 3.5e−18	0.085 0.2	0.085 0.4	0.085 0.6	0.085 0.8	0.085 1
Feedback	0.085 3.5e−18	0.085 0.2	0.085 0.4	0.085 0.6	0.085 0.8	0.085 1
Creativity	0.085 3.5e−18	0.085 0.2	0.085 0.4	0.085 0.6	0.085 0.8	0.085 1
Productivity	0.085 3.5e−18	0.085 0.2	0.085 0.4	0.085 0.6	0.085 0.8	0.085 1
Communication	0.085 3.5e−18	0.085 0.2	0.085 0.4	0.085 0.6	0.085 0.8	0.085 1
Adaptation	0.085 3.5e−18	0.085 0.2	0.085 0.4	0.085 0.6	0.085 0.8	0.085 1

Table 2. Outputs fuzzy inference system (Level of interaction)

Outputs	Parameters (Values)	
	Low	High
Level 0	0.05 0	0.3 1
Level 1	0.05 0	0.3 1
Level 2	0.025 0	0.3 1
Level 3	0.025 0	0.5 1
Level 4	0.025 0	0.5 1
Level 5	0.05 0	0.3 1

Table 3. Fuzzy inference rules (Interaction level)

Num.	Fuzzy inference rules
1	If (Presence is VeryBad) and (Interactivity is VeryBad) and (Control is VeryBad) and (Feedback is VeryBad) and (Creativity is VeryBad) and (Productivity is VeryBad) and (Communication is VeryBad) and (Adaptation is VeryBad) then (level0 is High)(level1 is Low)(level2 is Low) (level3 is Low)(level4 is Low)(level5 is Low)
2	If (Presence is Bad) and (Interactivity is Bad) and (Control is Bad) and (Feedback is Bad) and (Creativity is Bad) and (Productivity is Bad) and (Communication is Bad) and (Adaptation is Bad) then (level0 is Bad)(level1 is High)(level2 is Low) (level3 is Low)(level4 is Low)(level5 is Low)
3	If (Presence is Regular) and (Interactivity is Regular) and (Control is Regular) and (Feedback is Regular) and (Creativity is Regular) and (Productivity is Regular) and (Communication is Regular) and (Adaptation is Regular) then (level0 is Low)(level1 is Low)(level2 is High) (level3 is Low)(level4 is Low)(level5 is Low)
4	If (Presence is Good) and (Interactivity is Good) and (Control is Good) and (Feedback is Good) and (Creativity is Good) and (Productivity is Good) and (Communication is Good) and (Adaptation is Good) then (level0 is Low)(level1 is Low)(level2 is Low) (level3 is High)(level4 is Low)(level5 is Low)
5	If (Presence is VeryGood) and (Interactivity is VeryGood) and (Control is VeryGood) and (Feedback is VeryGood) and (Creativity is VeryGood) and (Productivity is VeryGood) and (Communication is VeryGood) and (Adaptation is VeryGood) then (level0 is Low)(level1 is Low)(level2 is Low) (level3 is Low)(level4 is High)(level5 is Low)
6	If (Presence is Excellent) and (Interactivity is Excellent) and (Control is Excellent) and (Feedback is Excellent) and (Creativity is Excellent) and (Productivity is Excellent) and (Communication is Excellent) and (Adaptation is Excellent) then (level0 is Low)(level1 is Low)(level2 is Low) (level3 is Low)(level4 is Low)(nivel5 is High)

described in the previous section. In the case of the output variables, the interaction levels discussed above were taken.

In the case of entries, it was partitioned into 6 Gaussian membership functions, since it was desired to have a partition for each existing exit in the FIS, to facilitate the construction of the FIS knowledge system. The parameters chosen for these functions were configured through the MATLAB Fuzzy Logic Toolbox.

This Toolbox has a function of adding an amount "x" of membership functions, and it distributes them evenly, in the range selected for each entry.

In the case of the outputs, it was partitioned into only two linguistic values (Low and High) for each of the outputs, as well as the entries the membership function selected was the Gaussian type. Initially, the parameters were calculated in the same way as the inputs. Only the outputs were subjected to a small process of empirical adjustment.

The parameters for the output inputs can be observed in the Tables 1 and 2.

The proposed FIS is defined by 6 rules of fuzzy inference, the Table 3 shows the base rules; this is the representation of our knowledge base.

To verify the performance of the users according to their inputs and that they have the corresponding level of interaction, the output that is the reunification of the resulting level is evaluated. In this way, users move from one level to another, that is, when their membership function value is close to the nearest integer, the corresponding value is taken, e.g., if the level is 0.2 it belongs to level 0 of interaction, but if the level is 0.9 it belongs to level 1 of interaction, therefore the system updates the knowledge base for the next interaction.

Therefore, the values obtained form the basis of the behavior and knowledge of the users in the context of interaction, on the other hand, these values can change dynamically, and the values of their membership functions can be modified, characterizing from a greater uncertainty to a lower uncertainty considering the user's performance. Once the level of interaction is known, information or services could be sent according to the level of interaction that results.

5 Experiments and Results

From a sample of 500 users, an evaluation of the interaction of each of them was made with the interactive module present in the museum. According to the parameters described above, values were generated that served as input to validate the proposed FIS.

The evaluations obtained showed a great variety of interaction ranging from very low interaction to an extremely high one. These results allowed us to obtain a universe of different user-exhibition interaction scenarios.

The Table 4 is a sample of some of the results obtained from the level of interaction evaluated by the expert. The final interaction level is calculated simply by the average of the values multiplied by the maximum number of interaction levels according to Eq. (1).

$$\begin{aligned} InteractionLevel = Average(&Presence, Interactivity, Control, Feedback, \\ &Creativity, Productivity, Comunication, Adaptation) * 5 \end{aligned} \tag{1}$$

To verify the percentage that was correctly classified, the results of the classification made by the evaluator were compared with the classification made by the FIS through a confusion matrix. The results of the confusion matrix are shown in the Fig. 2.

Table 4. Results obtained from the interaction level evaluated

Subject	Presence	Interactivity	Control	Feedback	Creativity	Productivity	Communication	Adaptation	Level of interaction
1	0.5	0.4	0.5	0.3	0.3	0.2	0.1	0.2	1
2	0.4	0.4	0.4	0.5	0.3	0.3	0.5	0.4	2
3	0.7	0.8	0.8	0.6	0.5	0.5	0.6	0.6	3
4	1	1	1	1	0.8	0.8	1	0.7	4
5	1	1	1	1	1	1	1	1	5
6	0.1	0.1	0.1	0	0	0	0	0	0
...	...	...	...	...	...	...	...	...	...
500	0.4	0.3	0.6	0.2	0.1	0.3	0.5	1	3

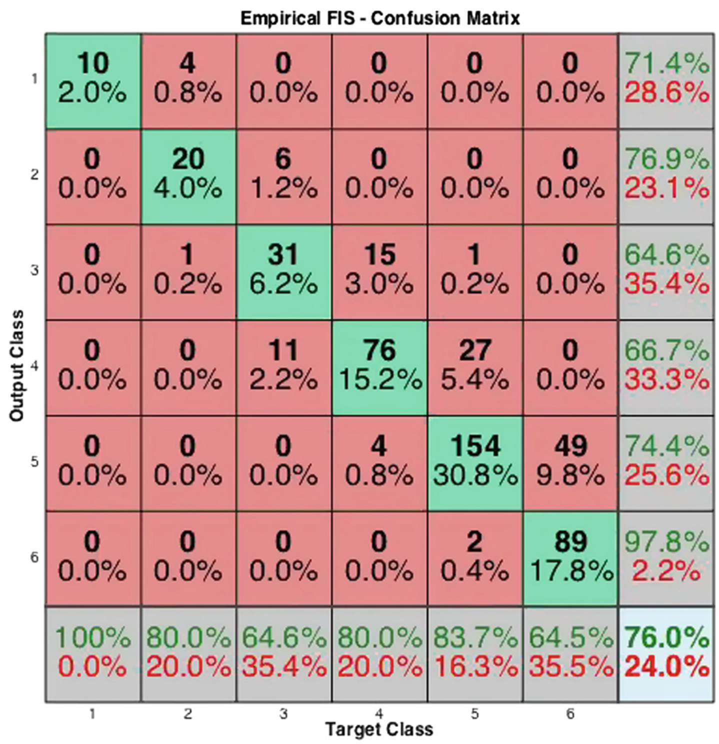

Fig. 2. Confusion matrix.

From the sample of 500 users, it was divided into two equal parts, 250 as a basis to configure the FIS and 250 to perform the tests.

The choice of the elements of the sample was made through the randperm method of MATLAB. This method allows choosing randomly the 250 elements of each sample. The configuration of the FIS was carried out with the help of the base sample, that is, this sample served as the basis for obtaining the configuration through an empirical process.

In the case of entries, it was partitioned into 6 Gaussian membership functions, since it was desired to have a partition for each existing exit in the FIS, to facilitate the construction of the FIS knowledge system. The parameters chosen for these functions were configured through the MATLAB Fuzzy Logic Toolbox.

This Toolbox has a function of adding an amount "x" of membership functions, and it distributes them evenly, in the range selected for each entry.

As mentioned in previous sections, visitors were evaluated, based on this observation, each of them was rated in each of the input variables with a score of 0 to 1, according to these ratings was classified at a level of interaction. The results of this classification made by an expert were used to compare concerning the results obtained from the FIS from a confusion matrix. The percentages obtained in each of the classifications were used to know which outputs needed an adjustment in the parameters to be able to make a classification as similar to that of the expert. The parameters of the outputs obtained are displayed in the Table 2.

6 Conclusion and Future Work

In this work, a Mamdani Type 1 Diffuse Inference System was presented that evaluates and classifies the interaction conditions in a Human-Computer Interface (HCI). This evaluation is carried out according to the levels proposed by Gayesky and Williams [1] which basically consists of a set of qualitative observations based on their experience and research.

The configuration of the system was also described and showed how it could be built using the MATLAB Fuzzy Logic Toolbox. This is a well-known tool that is commonly used in research.

An exhibition inside an interactive museum was shown as an example of application. In this case, the system observes the user evaluating the level of interaction to offer later new possibilities that help to maintain their attention. This intelligent system could help improve the user experience by keeping your attention captive.

To validate the model, a comparison was made between the response of the system and assessments made by humans. The system showed that the output of the system is similar to the evaluation done, obtaining an approximate 76% accuracy between the predicted values and the test values, being that precision is to some extent acceptable.

We will expand the sample of users to at least 1000 to have a more meaningful sample that helps refine the tool obtaining a level of interaction according to the user's interaction.

Although the validation obtained a minimum acceptable approach, as future work, we believe that the accuracy of the system can be improved if it could be generated using a data mining process based on the real data. It could also be improved by changing from a type 1 Mamdani system to type 2, or a Sugeno type to consider the uncertainty.

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