Article Journal of Computational Systems and ICTs
June 2019 Vol.5 No.15 35-42

Evaluation of a hierarchical fuzzy system, using fuzzy composite concepts in computer assisted therapy systems

Evaluación de un sistema jerárquico difuso, utilizando conceptos compuestos difusos en sistemas de terapia asistida por computadora

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DOI: 10.35429/JCSI.2019.15.5.9.13 Received March 18, 2019; Accepted May 30, 2019

Abstract

Fuzzy logic systems provide a set of proven tools and methods to imitate or emulate human basic reasoning, that is, transform it into instructions that the computer can understand or transform into binary instructions. Based on the structure with multiple layers, subsystems and varied topologies that in previous research have shown that fuzzy hierarchical systems have been used to improve the interpretability, in this research work the objective is to design a fuzzy hierarchical system using fuzzy composite concepts artificial intelligence compounds to measure the efficiency of simulated scenarios. As a fundamental part of the present investigation, an analysis is made of the sensitivity of the results of the fuzzy system with respect to its inputs and with a set of membership functions, in a virtual scenario; which allows demonstrating the advantages obtained by applying a fuzzy hierarchical system to systems oriented to the area of health.

Fuzzy Composite Concepts, Fuzzy Hierarchical System, Fuzzy Logic Systems, Intelligent Environments, Affective Computing, Expert System, Interpretability, Fuzzy Logic Systems of Type 1

Resumen

Los sistemas de lógica difusa proporcionan un conjunto de herramientas y métodos comprobados para imitar o emular el razonamiento básico humano, es decir, transformarlo en instrucciones que la computadora pueda entender o transformar en instrucciones binarias. Con base a la estructura con múltiples capas, subsistemas y topologías variadas que en investigaciones anteriores han demostrado que los sistemas difusos jerárquicos se han utilizado para mejorar la interpretabilidad, en este trabajo de investigación el objetivo que se propone es diseñar un sistema difuso jerárquico utilizando conceptos compuestos difusos de la inteligencia artificial para medir la eficiencia de los escenarios simulados. Como parte fundamental de la presente investigación, se realiza un análisis de la sensibilidad de los resultados del sistema difuso con respecto a sus entradas y con un conjunto de funciones de membresía, en un escenario virtual; lo cual permite demostrar las ventajas que se obtienen al aplicar un sistema difuso jerárquico a sistemas orientados al área de la salud.

Conceptos Compuestos Difusos, Sistema Difuso Jerárquico, Sistemas de Lógica Difusa, Ambientes Inteligentes, Cómputo Afectivo, Sistema Experto, Interpretabilidad, Sistemas de Lógica Difusa de Tipo 1

Citation: MORALES-NAVA, Renato, ZAMUDIO-RODRIGUEZ, Víctor Manuel, NAVARRO-BARRÓN, Francisco Javier, GUTIERREZ-HERNANDEZ, David Asael, BALTAZAR-FLORES, María del Rosario and PUGA-SOBERANES, Héctor José. Evaluation of a hierarchical fuzzy system, using fuzzy composite concepts in computer assisted therapy systems. Journal of Computational Systems and ICTs. 2019, 5-15: 35-42.

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Introduction

Inadequate attention to health and safety regulations in the workplace causes approximately 2 million work-related deaths per year (Manriquez et al., 2018). Consequently, as part of this research project, we focus on imitating a very basic skill which is the ability to generalize and integrate a wide range of information sources into a series of simple concepts that can be called compound concepts (Hagras, Aysenur, Hagras, & Shreyas, 2014). A simple example of such compound is the quality of the weather, or simply "the weather" as we refer to it daily. Statements such as "The weather is pleasant today" are universally known without having to refer to the intrinsic properties of what "good weather" really encompases.

In fact, as humans we rely on a great body of world (experience, personal background, education, etc.) which provides us with an understanding of the relevant factors in terms of qualifying, for example, the weather. As such, by saying: "The weather is pleasant today", we mean and incorporate a wide range of sources of information, like temperature, cloudiness, rain, etc.; Fuzzy Logic Systems (FLS) provide a proven toolset to mimic human reasoning. (Hagras, Aysenur, Hagras, & Shreyas, 2014).

Fuzzy Composite Concepts (FCC) are based on standard FLS and extend them transparently to provide intuitively interpretable rules bases and improve the ability to recover and reuse FLS in general. Currently, one of the core problems related to FLS is how to reduce the total amount of rules involved and their corresponding computing requirements.

Unlike computers, humans have common sense, which allows them to reason in a world where things are only partialities of the truth. Fuzzy logic is a branch of artificial intelligence that helps computers represent the full range of common sense images in a world full of uncertainties.

Expert System (ES)

An Expert System (SE) is a computer application that, on a Knowledge Base (BC), has information from one or more experts to solve a set of problems in a specific area.

The BC is a special type of Database (DB) for knowledge management, which has a considerable capacity for deduction from the information it contains. The difference between the DB and the BC is that the former stores only facts (statements that serve to represent concepts, data, objects, etc.) and the functions of the DB engine are those of editing and consulting the data. The latter can store, in addition to facts (basis of facts that describe a problem), a set of rules. A rule is a conditional structure that logically relates the information contained in the part of the antecedent with other information contained in the part of the consequent (Tabares Ospina & Monsalve Llano, 2013).

Emotion

Among the elements which a person can generate in an environment, it is considered that there are expressions generated by people that are called emotion, which is defined as a “short-term commotion that activates and directs our behavior” (Cruz Parada , Modeling emotions in intelligent environments, 2019). Therefore, emotions are considered as an element of influence in people's behavior and depend on a specific moment. This is related to the understanding of a situation or the event that is experienced by different feelings, for example anger, fear, joy or surprise. These emotions stimulate and intervene in the conduct, which causes behavioral and physiological alterations.

Affective computing

Affective computing is the field of machine design that can recognize, express, communicate and respond to human beings through the use of emotions. Affective computing, which is the subject related to the design of emotionally intelligent machines, has been an area of growing interest in the field of human-computer interactions. The objective of Affective Computing is to use the positive and affective communication found in human-human interaction and apply it to human-computer interaction (Schwark, 2015). The principles of Affective Computing rest within the field of human factors in the topic of human-computer interaction and the finding that humans interact socially with computers and machines, similar to how humans interact with other humans (Schwark, 2015).

Although we may be far from a computer feeling emotions like humans, Picard says: "Affective computers need only express emotions, not feel them" (Manriquez Santos, et al., 2018).

Once the computers are able to measure the current affective state of the user, the next step is to generate an affective change in the user. The purpose of affective computating can change dramatically depending on the context, but similarity is the goal of using affection to improve some aspects of user interaction (Schwark, 2015).

Background

The communities of opinion interaction and human-agent interaction currently approach the analysis of sentiment from different perspectives which include, on the one hand, the disparate phenomena related to feeling and computational representations, and on the other hand, different methods of dialogue detection and management. The sentiment/opinion detection methods used in the human-agent interaction are very specific and, when used, are not different from those used in an opinion set and consequently are not designed for socio-affective interactions (temporal interaction restriction, sentiment analysis as an input and an output of interaction strategies).

Fuzzy Logic Systems (FLS) provide a proven toolset to mimic human reasoning. FCCs provide intuitively interpretable rules bases and improve the resilience and reuse of FLS in general.

This paper provides a general description of the philosophical concepts behind the FCC and their applicability is discussed. Additionally, in this work the domain of application is affective computing (Schwark, 2015), which has gained relevance in recent years due to its social and economic impact; Stress and sadness are some of the factors that affect people's quality of life, therefore inadequate attention to health and safety regulations at work causes approximately 2 million work-related deaths per year (Manriquez Santos, and others, 2018).

The fuzzy technique is evaluated in terms of its ability to model affective states compared to other existing machine learning approaches.

Type-1 Fuzzy Logic Systems

In a type 1 fuzzy logic system (T1 FLS), the inference engine combines rules and provides an allocation of the input T1 FLS to the output T1 FLS. The multiple antecedents in the rules are connected by the -standard (corresponding to the intersection of sets). Membership qualifications in the input sets are combined with those in the output sets using the sup-star composition. Multiple rules can be combined using the operation corresponding to the union of sets or during defuzzification by weighted sum (Gupta, 2014).

In a T1 FLS, the defuzzifier produces a clear output of the fuzzy set that is the output of the inference motor, that is, an 0-type (crisp) is obtained from a 1-type set.

Type-2 Fuzzy Logic Systems

The concept of a type 2 fuzzy logic system (T2 FLS) was introduced by Zadeh (Hooman & Alireza, 2017), as an extension of the concept of an ordinary fuzzy set. Such sets are fuzzy sets the membership qualifications of which are T1 FLS sets; they are very useful in circumstances where it is difficult to determine an exact membership function for a fuzzy set; therefore, they are useful for incorporating linguistic uncertainties, for example, the words used in linguistic knowledge can mean different things to different people. The T2 FLS sets can be used to convey the uncertainties in the membership functions of the T1 FLS sets due to the dependence of the membership functions on the available linguistic and numerical information. Linguistic information (for example, expert rules), in general, does not provide any information on the forms of membership functions (Hooman & Alireza, 2017).

FLS Interpretability

Interpretability indicates the ease with which humans can understand an FLS. In recent years, researchers' interest in obtaining more interpretable fuzzy models has increased.

However, the choice for an appropriate interpretability measure remains an open discussion due to its subjective nature and the large number of factors involved. Substantial research on interpretability measures (Razak, Garibaldi, C., A., & Soria, 2017).

Hierarchical Fuzzy Systems (HFS)

Hierarchical Fuzzy Systems (HFS) consist of several fuzzy systems of low dimension in a hierarchical form and which have the advantage that the total number of rules increases only linearly with the number of input variables (Luis , 2018).

This architecture is represented in Figure 1 (a) and (b) with 4 (n=4) input variables and 5 (m=5) membership functions, it is obtained that each fuzzy system of low dimension consists of 5^2 (m^2) rules and therefore the total number of rules is $3\times5^2=75[(n-1)m^2]$, which represents a linear function of the n input variables. In contrast, we can verify that the number of rules of the conventional fuzzy system in Figure 1 (c) is $5^4=625$ rules and therefore, conclude that the total number of fuzzy rules is considerably reduced under the scheme of fuzzy hierarchical systems.

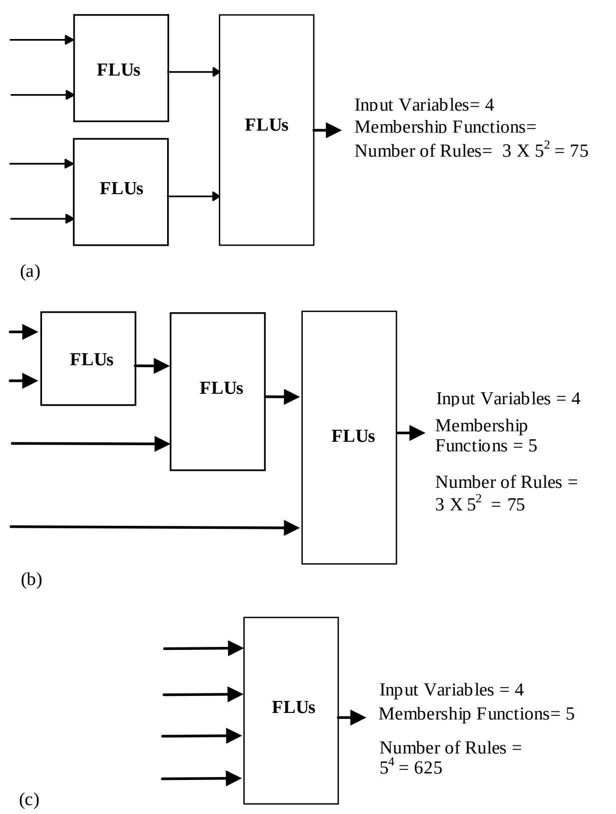

Figure 1 (a) and (b) Representation for the hierarchical fuzzy logic system; (c) representation for the conventional single-layer fuzzy logic system

The design of HFS is developed in such a way that one can easily design the fuzzy rules involved in the intermediate layers of the hierarchical structure. The design of fuzzy controllers is commonly a time-consuming activity which involves the acquisition of knowledge, the defining of the controller's structure, the defining of rules and other parameters of the controller.

Currently, one of the important problems in FLS is how to reduce the total amount of rules involved and their corresponding computing requirements. In a standard fuzzy system, the number of rules increases exponentially with the number of increases in the variables. In fact, the complexity of a problem increases exponentially with the number of variables involved, called "curse of dimensionality," is not exclusive to fuzzy systems. Therefore, to deal with the "curse of dimensionality" and the problem of rule explosion, it can be found that the total number of rules is greatly reduced under the structure of HFS (Luis, 2018).

Additionally, interpretability in HFS is extremely important because it allows us to understand, design, and interpret the rules more easily in contrast to other paradigms, for example in systems based on neural networks.

Dimensionality

Specifically, this problem called curse of dimensionality established with the use of **n** variables and **m** sets defined by each variable, it takes m^n fuzzy rules to build a complete fuzzy controller, as **n** grows, the rule base quickly overloads the memory of any computing device, making the fuzzy controller difficult to implement, in addition to defining an impossible response time for fast real-time processes (Luis, 2018).

IBM Watson

IBM Watson began a deep natural language processing system, achieving accuracy when trying to evaluate as much context as possible. His objective was based on achieving precision while trying to evaluate as much context as possible when processing information that is not structured, but that is related to a topic of prior knowledge (Cruz Parada, et al., 2018).

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The system is becoming a tool in the form of a collection of services that use language information analysis, voice, vision, and data information to develop applications. Each Watson service works with an API for their interaction.

Active Mind

It is a software for prevention, detection, evaluation, and monitoring of elderly adults with cognitive impairment and dementia. The software allows cognitive stimulation through the use of interactive games specially designed by psychologists, running on computers with touch screens and multimedia elements (Navarro, and others, 2018).

Occupational Stress

Stress is a mental state which affects the human body, and it is listed as one of the most frequent conditions in modern society. In Europe it was determined as one of the most important occupational diseases of the 1990s. In a survey conducted between 1995 and 1996, more than 60% of workers suffered stress for more than half of the workday (Manriquez Santos, and others, 2018).

Burnout

Burnout syndrome occurs frequently in workers who have contact with users or clients, and is defined as a state of physical, emotional, and mental exhaustion as a result of the worker being exposed for multiple periods of time to multiple demands on the work (Manriquez Santos, and others, 2018).

Problems

In this work, a fuzzy hierarchical system is considered, where the number of rules grows exponentially with the variables involved, making them difficult to interpret, this can happen in high-impact scenarios such as the health area, and in particular, work stress, where expert systems are used. It is noted that HFS are used effectively in this context, reducing the number of rules and maintaining system interpretability. In this context, FCC have been introduced as models to exploit and spread uncertainty within hierarchical systems showing great potential.

However, this capacity to take advantage of information has not been explored within the context of T2 FLS, which, when using type 2 fuzzy sets, have a greater capacity for modeling uncertainty with respect to the T1 FLS.

Therefore, in the development of this work, 2 fuzzy systems FLS 1 and FLS 2 were considered, which are briefly described below.

FLS 1. Fuzzy Inference System for the Estimation of Energy and Pleasure from Multiple Emotions.
System based on fuzzy logic which facilitates the interpretability of the emotional factor, considering as inputs the scores of 5 emotions that are the result of the analysis of a phrase made by a user and generating 2 output variables which are: Energy and Pleasure (Cruz Parada , Modeling emotions in intelligent environments, 2019).

FLS 2. Interactive cognitive stimulation program.
System based on fuzzy logic in order to evaluate all user interaction with the system and recommend exercises that mainly take into account areas to improve with a new, more appropriate difficulty (Barrón, 2014).

Below is a fuzzy hierarchical system on 2 levels, which integrates 3 fuzzy logic systems (FLS 1, FLS 2) of 5 inputs each and a (FLS 3) of 4 inputs, as shown in the Figure 2 Block diagram.

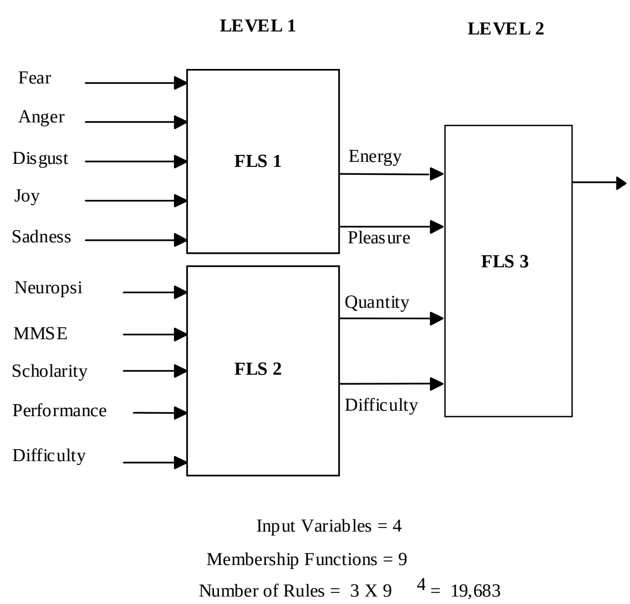

Figure 2 Block diagram

ISSN 2444-5002

If it were a conventional fuzzy logic system, the representation would be as shown in Figure 3 Diagram of a single FLS, where a system with 10 inputs would be represented.

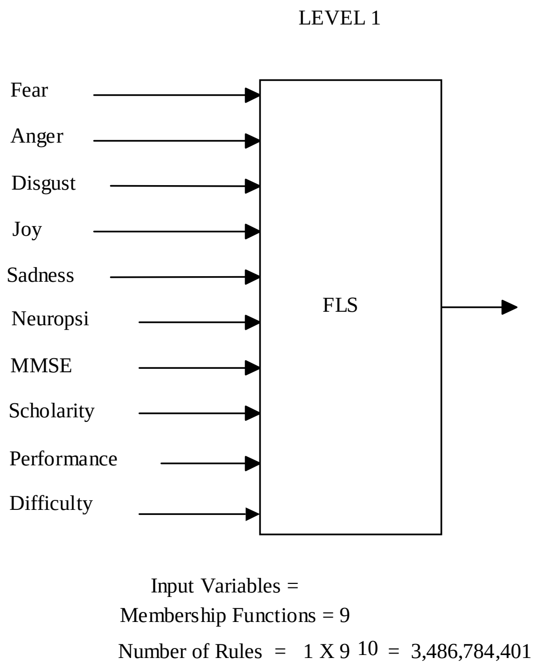

Figure 3 Diagram of a single FLS

So far we can show a quantitative comparison of the two FLS systems, since in the fuzzy hierarchical model the number of rules decreases considerably, but choosing the internal structure of fuzzy systems is crucial. Usually, there is a set of inputs available and the objective is to propose an adequate structure, not only decreasing the total number of rules, since it may be that the structure is not adequate to model real systems and that it is not well organized regarding the physical meaning of simple fuzzy subsystems. Therefore, the best way is to define the structure of the fuzzy system based on the knowledge of the modeled system (Luis, 2018). Inputs with the same fund or related to the same output must be connected to the same fuzzy subsystem where we can conclude in a quantitative and qualitative evaluation of the structure of the resulting model.

Considering Figure 2 Block diagram, the outputs of the FLS 1 fuzzy logic system are Energy and Pleasure, this can be encapsulated to an output that we will call Attitude, which will be used to generate a proposed HFS model, as it is shown in Figure 4 Diagram 3 outputs, where the inputs of each of the FLS corresponding to the generation of the new model are represented.

In this investigation, we are using new technologies designed by IBM, such as IBM Watson, and with the help of this tool, the proposal to detect user emotions in human-agent interactions is being considered.

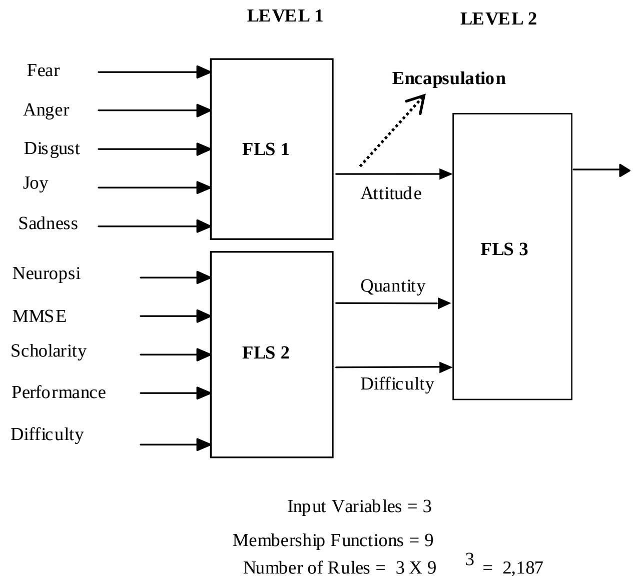

Figure 4 Diagram 3 outputs

For which a fuzzy hierarchical system is proposed to generate a scenario through an expert system that controls the input rules and can process the system outputs through an objective function.

The system evaluates the emotions of patients or agents and calculates performance scores for different health areas. The system will contain a finite number of agents that will be simulated in a virtual scenario to test or verify the levels of stress in the work environment and therefore obtain a measurable value of the quality of life at work.

Methodology

We describe the implementation of the FCC and demonstrate their benefits using real-world examples based on our work in Smart Environments. The performance of the proposed effect modeling methodology is tested by the deployment of a personalized learning system and a series of experiments in virtual scenarios.

There are research initiatives that aim to predict, detect and intervene when dangerous conditions are found, although there is little research focused on obtaining and processing emotional information derived from work actions in real life.

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Fuzzy Logic is proposed to model the parameters, characteristics and dependencies of imprecise and uncertain heterogeneous data of the proposed system. A particular characteristic of fuzzy systems is their capacity for interpretation and responsibility ("why does employee X do Y activity?). T2 FLS, provide key advantages in their ability to model complex uncertainty (noise and subjectivity) present in the data parameters (user opinion, environmental and physiological parameters) without increasing the complexity of the system (for example, by increasing the number of rules).

FLS include both adaptation models, when the values of the model parameters are dynamically adapted to include new information from the data sources and the evolution of the model, when, according to the characteristics of the new data, the structures of the new model must be built by themselves.

An analysis of infrastructure performance on data processing, analysis and storage will be carried out, illustrating its feasibility for large-scale data processing tasks in expert systems for a more complete diagnosis.

Effective verbal and feeling language is the oldest and most universal of all our media. It seems that the time has come for computer machinery to understand it too.

Discussion and analysis

Most of the methods are based on the analysis of the conventional fuzzy model, the model for the design of the fuzzy hierarchical system proposed in this document requires the development of the initial fuzzy model that is usually large and very complex.

The presented model overcomes this problem by the components of the sequential generation layer of the hierarchical fuzzy system from data, since the most problematic part of the hierarchical fuzzy system is the connections between layers to obtain the data set and fuzzy clustering in superior levels.

The inputs that enter the lower level are grouped in the input space by encapsulating output data, which means that the data is divided into the desired number of groups, and let us remember that not only decreasing the total number of rules, since the structure may not be adequate to model real systems and it is not well organized with respect to the physical meaning of simple fuzzy subsystems and that each sample of data is assigned to some of these groups and this information is passed to the following levels. Interconnections during model design are the weak point of the method.

The design proposed in Figure 4 Diagram 3 outputs is considered as future work. The challenge is to be able to encapsulate two outputs as shown in Figure 2 Block diagram, and obtain an output as shown in Figure 4 Diagram 3 outputs, without affecting the functionality of the same system.

Conclusions

Based on the research work carried out, the hierarchical fuzzy system not only aims to minimize the number of membership rules or functions, but also to optimize the operation of fuzzy logical system, thus improving the ability to implement two systems in one, generating a system that allows the control of output rules through an expert system that can process the outputs through an objective function, that is, that the system contains a finite number of rules that emulate the behavior of patients to achieve a result that will be more sensitive and optimal for users. The system may calculate the performance levels of the inputs in its different test scenarios that control a finite number of inputs to the system.

It is important that in terms of modeling accuracy of a new expert system, based on fuzzy hierarchical systems and fuzzy composite concepts, the interpretability of the new system which can calculate the performance levels and the finite number of inputs in its different scenarios test that control it is guaranteed.

References

Cruz Parada, P. (2019). Modelado de emociones en ambientes inteligentes. (Master's Thesis). Intituto Tecnologico de Leon, Leon, Gto; Mex.

ISSN 2444-5002

Cruz Parada, P., Zamudio Rodriguez, V. M., Lino Ramirez, C., Navarro Barron, J., Baltazar, R., Gutierrez Hernandez, D., & Faiyaz, D. (2018). Identification and Analysis of Emotions in a Game Based Therapy for Patients with Cognitive Impairment. En Intelligent Environments 2018 (pags. 506-515). © 2018 The authors and IOS Press.

Gupta, N. (2014). Comparative Study of type-1 and Type-2 Fuzzy Systems . International Journal of Engineering Research and General Science, 198(4), 195.

Hagras, H., Aysenur, B., Hagras, H., & Shreyas, U. (2014). An Adaptive Ambient Intelligent Platform for Recommending Recipes using Computing With Words . IEEE Computer Society, 372-377.

Hooman, T., & Alireza, S. (2017). Zadeh's Separation Theorem to Calculate Operations on Type-2 Fuzzy Sets. IEEE International Conference on Fuzzy Systems (FUZZ-IEEE), 122.

Luis, M. (2018). Designing interpretable Hierarchical Fuzzy Systems. IEEE International Conference on Fuzzy Systems.

Manriquez Santos, J. J., Zamudio Rodriguez, V. M., Lino Ramirez, C., Navarro Barron, J., Baltazar, R., Gutierrez Hernandez, D., & Faiyaz, D. (2018). Towards an Innovative Architecture to Monitor and Handle Emotions in Work Scenarios. En Intelligent Environments 2018 (Vol. 1, págs. 25-35). © 2018 The authors and IOS Press.

Navarro Barrón, F. J. (2014). Sistema inteligente para el monitoreo y generacion de tareas en escenarios de terapia para adultos mayores. (Master's Thesis). Instituto Tecnologico de Leon., Leon, Gto; Mex.

Navarro, J., Doctor, F., Zamudio, V., Rahat, I., Arun, K., & Lino, C. (2018). Fuzzy Adaptive Cognitive Stimulation TherapyGeneration for Alzheimer's Sufferers: Towards a Pervasive Dementia Care Monitoring Platform. Elsevier, 479-490.

Razak, T. R., Garibaldi, J. M., C. W., A. P., & Soria, D. (2017). Interpretability Indices for Hierarchical Fuzzy Systems. in IEEE International Conference on Fuzzy Systems., Institute of Electrical and Electronics Engineers Inc., 2017.

Schwark, J. D. (2015). Toward a Taxonomy of affective Computing.

Tabares Ospina, H., & Monsalve Llano, D. (2013). Expert System Model for Educational. Tecno. Lógicas, 30(ISSN 0123-7799), 51-70.