Modeling Based on Computational Intelligence for Physiotherapeutic Rehabilitation Games

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Abstract. Over the last years, the use of computational environments, like serious games, has been one of the strategies to improve commitment and motivation of patients undergoing rehabilitation. Beyond providing motivation, these systems are able to simulate life activities and provide means to automatically monitor users interactions, assuring that the patient is performing the exercises correctly, thus allowing the user to perform the exercises without the need of constant monitoring by a health professional. The aim of this work is to develop a modeling for construction of serious games, whose interaction is given by gestures performed by hand and wrist. The model includes an automatic continuous evaluation of rehabilitation exercises executed by the patient and dynamic game balancing using computational intelligence methods.

Keywords: Rehabilitation, serious games, gesture recognition, Adaptive neuro-fuzzy inference system, assessment system

1 Introduction

Stroke is the leading cause of death and disability in Brazil: around 68.000 deaths caused by stroke are registered each year in the country. It is caused by the interruption of the blood supply to the brain, which results in brain damage. There are two types of stroke: ischemic and hemorrhagic. The first one, which occurs in 80 to 90% of the cases, is caused when a blood vessel is obstructed. The second type occurs when a blood vessel ruptures, and tends to be more severe. Although it is not necessarily fatal, stroke causes grave disabilities to the patient and is one of the conditions that most incapacitate individuals.

Upper limbs are the main body area afflicted by stroke [1], having a direct impact in the patient's quality of life. Particularly, the impairments caused to the hand can be highlighted, which compromises the execution of common daily activities, like holding a fork or lifting a cup. Overall, many rehabilitation sessions are required to recover the affected limbs' movements, requiring from the patient the execution of a series of repetitive movements. Due to this treatment characteristic, maintaining patient interest to keep performing the exercises is not an easy job. The lack of interest may cause the patient to be absent in the rehabilitation sessions, causing the treatment to be ineffective and possibly frustrating the patient [2].

Over the last years, one of the strategies being used to improve patient commitment and motivation is the use of computational environments, like serious games [3]. Beyond providing motivation, these systems are able to simulate life activities and provide means to automatically monitor user's interactions [2]. However, to be able to provide an automatic performance evaluation, the system needs to incorporate motion tracking devices, such as optical or magnetic trackers or exoskeletons [5]. These equipments require the use of sensors or special clothing, introducing aspects related to comfort, hygiene and user safety, which could compromise their experience with the systems and increase the system's cost.

The use of tracking equipment often requires a model to interpret data being captured into a gesture so the system can be aware of the user's actions. In rehabilitation environments, it is important to assess the user's performance so they can perform the exercises in a correct manner, in a way that the treatment is not compromised. So the use of tools to assess and monitor the user are a fundamental part of these systems.

The aim of this work is to develop a model for the construction of serious games whose interaction is given by gestures for hand and wrist rehabilitation. The model includes automatic continuous evaluation of the exercises executed by the patient and dynamic game balancing (processing of changing game parameters, according to patient's detected ability), using computational intelligence methods [6].

2 Serious Games for Rehabilitation

Stroke rehabilitation is often a long, repetitive and intense process which requires commitment. Maintaining patient interest on rehabilitation is a challenge, and one of the strategies being explored over the last years is the use of games, particularly serious games.

There are many definitions for the term "serious game". Although it generally refers to games where the "fun factor" is not the main concern, but aspects related to training, education, advertisement or simulation. The main difference between serious and entertainment games is the focus of the game. While in entertainment games the focus is the user experience and enjoyment, on serious games the focus is the passing of a concept or the stimulation of psychometric functions [7].

The use of games as a rehabilitation tool has the potential to help patients undergoing rehabilitation through the diminution of the monotony of performing several repetitive movements, through the introduction of the competitive and playful nature of the games on the treatment. Furthermore, the capacity of the games to provide performance feedback enhance the treatment quality and motivate the user to dedicate more time to performing the exercises [8].

Burke et al. [9] identified three aspects of game design that are relevant for rehabilitation games: meaningful play, failure management and challenge. Meaningful play refers to the interaction between the player and the environment, in which each action made by the user affects the state of the game. Actions and their results must be discernible and integrated to the context of the game, with not only immediate consequences, but also affecting the state of the game in the future.

Failure management is something that should be analyzed carefully in rehabilitation games. Since rehabilitation normally deals with elderly people, who usually have little to no experience with computers, dealing with failures in a encouraging and motivating way will diminish the chances of the patient getting frustrated or unmotivated with the game [10].

Challenge is as important in rehabilitation games as it is in regular games. Normally, games increase difficulty with time. One of the strategies normally used is the concept of levels. At initial levels, where the player is not familiarized with the game, the challenges are easier and gradually the level of difficulty is increased. The problem with this approach is that it presumes that all players have the same level of familiarity with the devices and abilities to perform the challenges. Due to the diversity of the injuries of the patients undergoing rehabilitation, that assumption may not be true in this context.

Since rehabilitation is a patient-centered process, the game must be shaped around the individual, evaluating his needs and adjusting the level of difficulty according with the result of the evaluation, the idea of adaptable challenges become important in these games. Games with that characteristic are able to adapt to the users' current ability level. For that, it needs to posses some way to measure the user ability, which is not always an easy task [11]. After an initial evaluation, the data collected can be used to assure that the game is not too trivial nor too difficult. According to Burke et al. [10] it is the best way to maintain a appropriate level of difficulty, avoiding frustrating the player.

2.1 Natural Interaction

The concept of natural interaction is being used as a simpler and more intuitive way of interaction. In this context, natural interaction can be defined a way of interacting with computational systems that, differently from the one made via keyboard and mouse, allows the user communication with the computational system through gestures, expressions and movements, among others [12].

Interfaces created based on the natural interaction principle are known as NUI (Natural User Interfaces). The idea behind NUIs is free the user from the necessity to hold a mouse ou any other interaction device. Instead, user expressions such as voice, gestures and body movements are tracked and interpreted by the system [13].

2.2 Gesture Recognition

Gestures are body expressions that convey a meaning through body parts such as fingers, hands, arms, head or face. NUIs can use gesture recognition to perform tracking of these gestures and to interpret their meaning. Gesture recognition has applications in sign language [14], patient rehabilitation [16], patient monitoring, navigation and object manipulation in virtual environments and distance learning [15].

To interpret a gesture, a device that performs the capture of the regions of interest to be analysed by the computer system is necessary. This process is called motion capture. There are different devices that perform motion capture, such as Kinect, Nintendo Wii, RGB cameras, among others. One of the most popular devices that use this type of interface is the Kinect, for allowing the player to control the game without the use of controls, making it through gestures and movements.

In rehabilitation applications, the correct execution of movements is essential for the treatment, so the existence of an evaluation system becomes necessary, aiming to provide greater security to the user. For that to be implemented, one needs to track the user movements. In this context, tracking gestures becomes important, allowing the system to capture users' movements performing exercises, and allowing the system to provide user feedback.

Automatic Continuous Evaluation of Exercises Performed by Patients Rehabilitation process involves the execution of multiple exercises such as flexing, extension of the wrist and fingers, among others. In these systems, monitoring and evaluating the users' gestures is essential, making sure that he is performing the exercises in a correct manner and also allowing the patient to perform them without the constant watch of a health professional.

One type of evaluation which can be applied in this context is the continuous evaluation [17]. This approach is a methodology in educational learning process. However, only recently it was applied in training based on virtual environments, such as virtual reality [18] or Web [19]. It is based on measures and data analysis from data collected from user's interactions, building a diagnostic in order to inform the trainees the areas in which they presented good and bad results, allowing them to concentrate on improving the skills where they performed the worst.

In the literature four models for Continuous Evaluation performed can be found for virtual environments. The first one was proposed in 2005 for training performed in virtual reality environments [18] and it was based on statistics tools and an expert system to construct an individual profile for each trainee. The statistical tools used are measures of describing center and spread of distributions, tables and statistical graphics (time dependent or not). Beyond the data collection, these tools provide information to the expert system for the profile composition throughout training process. Two reports are build by the system: an evaluation report as presented above and a continuous evaluation report. The evaluation report is able to inform the trainee his performance in the previous training, which contains a qualitative report (in the form of a scale previously calibrated by an expert) and the execution performance of specific tasks. The continuous evaluation report presents the trainee profile and shows, with statistical measures, tables, graphics and models, the historical of execution performance of specific tasks.

The second type was proposed for training performed by Web [19]. It is able to perform an automatic analysis of the training database using statistical measures, such as mean, median, mode, standard deviation, etc. Besides, statistical models based on regression analysis to perform linear and non-linear modeling or even statistical time series analysis can be used to perform better statistical models for relevant aspects of training executed by Web. Statistical measures and statistical parameters of models can be compared using appropriate statistical testing of hypothesis, according to statistical distribution of data. As results of these comparisons, statistical decisions about equality or difference between parameters and a measure of probability of significance is obtained. It is possible that some variables can be measured in an approximate way, then fuzzy sets can be used to perform modeling on them. Experts previously defined these fuzzy membership functions for those variables. A fuzzy rule based expert system combines logically all information about fuzzy and non-fuzzy (statistical) variables to provide decision making and reports about the last training and the historical ones.

The third type is quite similar to the second one, but it was proposed for training performed in virtual reality environments [20]. The last one was proposed for virtual reality based training too [17] and it is a complete fuzzy approach. Automatic fuzzy statistical tools are programmed to make analysis of the training database and construct fuzzy statistical measures, fuzzy statistical models and to produce fuzzy statistical hypothesis testing. Like the second one, a fuzzy rule based expert system combines all information in order to produce the two reports previously mentioned.

Dynamic game balancing of the physiotherapy exercises Dynamic game balancing is a way to classify gamers in degrees of skills and also change the game difficulty according to it. So, it is possible to raise difficulty level or decrease it [21]. For all kinds of games, there are at least two ways of changing their parameters. For example, it is possible to monitor the interactions of the user and use an intelligent tool to verify if it is possible to increment the difficulty level of the game for the next gaming. To do that, the user must be able to have a very good performance on that game level. Another way is to perform the same verification, but adjust the parameters during the game execution. This changing requires rigid control mechanisms in order to propagate the parameters changed for all game routines and consequently to avoid problems in the game execution [22].

Patients who need to perform physiotherapy exercises for rehabilitation can be psychologically affected by frustration, when they did not complete an exercise in a satisfactory way. These undesired patient emotions can be minimized changing the difficulty levels [23]. In order to avoid these emotions and provide a renewed stimulus to the patient, the last way of dynamic game balancing is more suitable to be used in this case.

3 Computational Intelligence Based Modeling

In this Section, a new model is proposed based on Computational Intelligence for psychotherapeutic rehabilitation games with natural user interface. The Fig. 1 presents the diagram of the elements which compose this proposal.

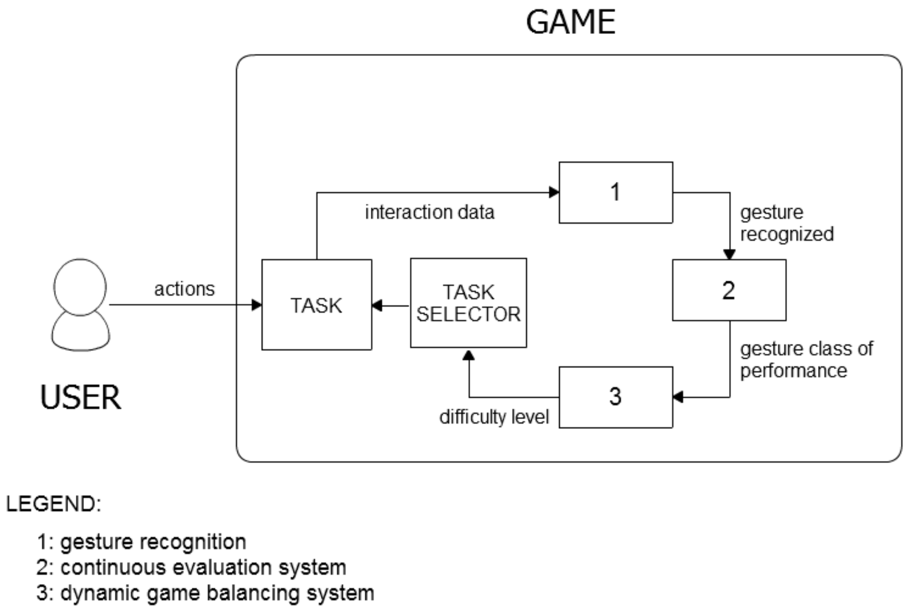

Fig. 1. Diagram of elements contained in the model.

The game has a parameter set which stores the actual difficulty level and other game parameters, such as random starting point, type of avatars (chosen by patient or not), colors used in that level, story places, etc. Those parameters allows the game to offer different scenarios for increasing patient's motivation and to minimize game repetitiveness, which can bore the patient.

In the first level, the gesture recognition is performed, i.e., the patients execute a specific gesture, as specified by the game. Of course, the gesture is part of the set of physiotherapeutic exercises required for their rehabilitation. A computational intelligence method is responsible for gesture recognition and must provide high accuracy in this recognition.

The gesture previously recognized is compared with a gestures databased stored in advance by an expert for a continuous evaluation system, in the second level. This system is also based on a computational intelligence method and it should provide a class of performance for that gesture. In contrast to the previous works, this system does not need provide reports at this moment, but it can be provide at the end of physiotherapeutic exercises set.

After evaluation of the last gesture executed by patient, the third level must analyze the class of performance for that gesture and predict the new difficulty level for the next exercise (observe that it is not the next set of exercises). So, three decisions are available: increase difficulty, decrease difficulty or maintain the same level of difficulty. This new level is sent to the Task Selector, in order to change the necessary parameters before the next exercise be presented to the patient.

3.1 Computational Intelligence Elements

In order to clarify which are the computational methods used for games development, some of them are presented in the following section. It is interesting to note that according to specific necessities and/or technologies available, different methods can be used to provide the characteristics mentioned above.

Gesture recognition For gesture recognition, the Adaptative Neuro-Fuzzy Inference System (ANFIS) [24] has been used with success [25]. It is a fuzzy integration model based on the Takagi-Sungeno architecture [32] where the fuzzy inference system is optimized by means of an artificial neural network. The Takagi-Sungeno architecture uses a linear input-output relation, allowing it to model dynamical systems[33].

ANFIS combines a multilayer feedforward network and fuzzy logic to map an input space to an output space. It has been in the most varied applications, such as forecasting [26], virus classification [27] and fault diagnosis [28]. It uses an adaptative network, which consists of a set of nodes connected via directional links, where each node possesses a function that processes the incoming signals from other nodes or parameters pertaining to that node and output a value.

To better understand the ANFIS architecture, consider the example presented in [24], where the fuzzy inference system has two inputs, x and y and one output z. And assume the following two rules, present on the rule base.

Rule 1: If x is A_1 and y is B_1, then $f_1 = p_1x + q_1y + r_1$
Rule 2: If x is A_2 and y is B_2, then $f_1 = p_2x + q_2y + r_2$

The architecture of this network is depicted in Fig. 2 and is composed of five layers, which is explained briefly in the following.

- **Layer 1**
  Every node in this layer has a function of type:

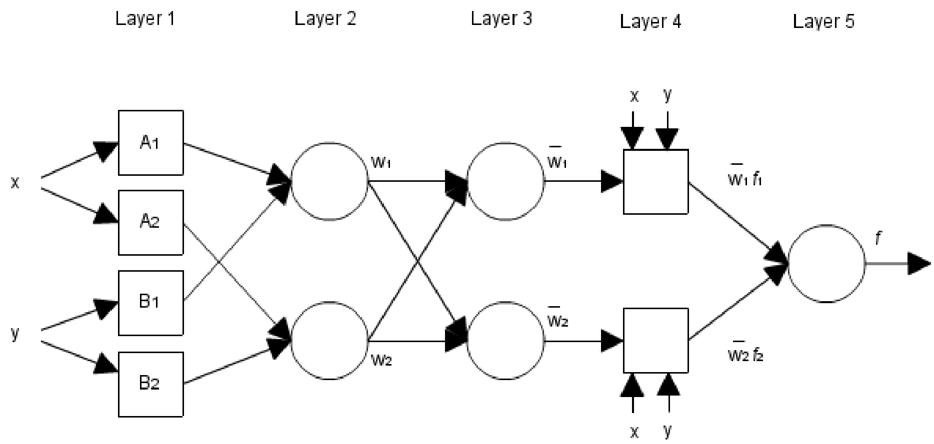

Fig. 2. ANFIS architecture.

$$O_i^1 = \mu_{A_i}(x), i = 1, 2 \tag{1}$$

where $\mu_{A_i}(x)$ is the membership function that will output how much the input x satisfies the linguistic variable A_i.

– **Layer 2**
The nodes in this layer multiply the incoming signals and sends the product as an output, representing the firing strength of a rule, which measures the degree of how the rule matches the inputs,

$$w_i = \mu_{A_i}(x) \times \mu_{B_i}(y), i = 1, 2 \tag{2}$$

– **Layer 3**
In this layer, each node calculates the firing strength of the input node firing strength divided by the sum of all rules' firing strengths:

$$\bar{w_i} = \frac{w_i}{w_1 + w2}, i = 1, 2 \tag{3}$$

– **Layer 4**
Every node in this layer has the following function:

$$\bar{w_i} f_i = \bar{w_i}(f_i = p_i x + q_i y + r_i) \tag{4}$$

where p_i, q_i, r_i is the parameters set for the function f_i.

– **Layer 5**
The single node in this layer sums all incoming signals, denoted by O^5, transforming the result in a crisp output.

$$O^5 = \sum_i \bar{w_i} f_i \tag{5}$$

To improve training efficiency and some problems from neural networks, such as the local minimum problem, a hybrid learning algorithm was created for this model, combining gradient descent and least squares. ANFIS possesses a good learning, construction and classification capability, as well as being capable of improving the complex expert's knowledge conversion to fuzzy systems. This model was chosen also because, on the initial tests, had the best results when recognizing gestures based on electromyographic data [25]. In rehabilitation applications, the correct execution of the movements is essential to the treatment, therefore, the existence of a evaluating system becomes necessary, making the treatment safer.

Continuous Evaluation System Continuous evaluation is a technique in which user data is stored in each session of an activity and used to monitor their progress and evolution in time. A continuous evaluation system can be built using a variation of a fuzzy rule-based expert system proposed in [20], in which statistical measures and parameters are inputs used to automatically contruct an user profile by their multiple interactions on the several executions of the application. In a rehabilitation game, the continuous evaluation system should monitor the specific features related to the activity. In this case, may be not necessary to provide realtime feedback during the game, but only at the end of each rehabilitation session executed with the game. Therefore, the system will use the previous results (last rehabilitation game sessions) to construct an evolution report. Other interesting adaptation could be transforming the classes of performance of the last gesture in additional points for patient in the game, showed on the screen, as a way of stimulation. Another approach could be showing on the screen messages, as in dance games, such as "perfect", "good", or "try again". Possibly, both approaches can be used at same time.

Dynamic game balancing system It is possible to change game parameters, according to patient's detected ability and this can be accomplished by several methods like probabilistic approach [29], particle filtering [30], agents, genetic algorithms or neural networks [31]. It is easy to notice that several of those methods belong to the Computational Intelligence.

So, anyone of those methods could be applied in order to provide dynamic game balancing. However, as the previous methods proposed in this paper are fuzzy systems, would be interesting to keep the same methodological approach. Thus, the information provided by Continuous Evaluation System to the dynamic game balancing system is basically the fuzzy class of performance of last gesture (as for example: "perfect", "good", "almost good", "regular", and "try again"). As an example, a small set of three fuzzy rules could be enough to predict the next difficulty level for the physiotherapy exercise, as such as:

R_1: If *Fuzzy Class of Performance* is *Perfect* OR *Good* Then *Next Difficulty Level* is *Increased*;

R_2: If *Fuzzy Class of Performance* is *Almost Good* Then *Next Difficulty Level* is *Same*;

R_2: If *Fuzzy Class of Performance* is *Regular* OR *Try Again* Then *Next Difficulty Level* is *Decrease*.

The computation of this fuzzy rule-based system is fast and it is performed in real time.

4 Conclusions

In this paper it was proposed a modeling for physiotherapeutic rehabilitation games. This approach uses three levels, in which gesture recognition, continuous evaluation of activities and dynamic game balancing are based on Computational Intelligence methods. It was designed specially to attend specificities of rehabilitation games with NUIs.

After suffering a stroke, the rehabilitation process should be started immediately. An adequate rehabilitation can minimize patient's incapacities, avoiding sequelae and and allowing patient's return to his/her normal activities. However, the rehabilitation process requires that patients perform a series of activities in the same repetitive way, which could cause a loss of interest with the treatment.

Beyond providing motivation to the patient, serious games can allow the treatment take place in the patient's home. Home-based rehabilitation has potential to help in the patient's recovery through proximity of familiar places and decreasing the monotony of performing several times the same set of exercises. A serious game which incorporate a continuous evaluation system allows performing them without constant observation from a professional.

The goal of serious games for rehabilitation based on this proposal is to offer better experiences for the patient. They will be able to monitor his/her progress during the treatment, and to adjust difficulties levels according to the patient's abilities progress. This approach can help to avoid patient's frustration, and as a game can help to make this treatment more pleasurable.

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References

1. Williams, L.S., Weinberger, M., Harris, L.E., Clark, D.O., Biller, J.: Development of a stroke-specific quality of life scale. Stroke. 30, 1362-1369 (1999)
2. Betker, A.L., Desai, A., Nett, C., Kapadia, N., Szturm, T.: Game-based exercises for dynamic short-sitting balance rehabilitation of people with chronic spinal cord and traumatic brain injuries. Phys. Ther. 87, 13891398 (2007)
3. Ma, M., Bechkoum, K.: Serious games for movement therapy after stroke. IEEE Int. Conf. Syst. Man Cybern. 1872-1877 (2008)

4. Boian, R., Sharma, a., Han, C., Merians, a., Burdea, G., Adamovich, S., Recce, M., Tremaine, M., Poizner, H.: Virtual reality-based post-stroke hand rehabilitation. Stud. Health Technol. Inform. 85, 64-70 (2002)
5. Lange, B., Chang, C.Y., Suma, E., Newman, B., Rizzo, A.S., Bolas, M.: Development and evaluation of low cost game-based balance rehabilitation tool using the microsoft kinect sensor. Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. EMBS. 2011, 1831-1834 (2011)
6. Rutkowski, L.: Computational Intelligence. Springer (2008)
7. Moraes, R.M., Machado, L.S., Nunes, F.D.L.S., Costa, R.M.E.M.: Serious Games and Virtual Reality for Education, Training and Health. Handb. Res. Serious Games as Educ. Bus. Res. Tools. 315-336 (2012)
8. Alankus, G., Lazar, A., May, M., Kelleher, C.: Towards customizable games for stroke rehabilitation. Proc. 28th Int. Conf. Hum. factors Comput. Syst. CHI 10. 2113-2122 (2010)
9. Burke, J.W., McNeill, M.D.J., Charles, D.K., Morrow, P.J., Crosbie, J.H., McDonough, S.M.: Augmented Reality Games for Upper-Limb Stroke Rehabilitation. 2010 Second Int. Conf. Games Virtual Worlds Serious Appl. 75-78 (2010)
10. Burke, J.W., McNeill, M.D.J., Charles, D.K., Morrow, P.J., Crosbie, J.H., McDonough, S.M.: Serious Games for Upper Limb Rehabilitation Following Stroke. Games Virtual Worlds Serious Appl. 2009. VS-GAMES 09. Conf. 103-110 (2009)
11. Schuytema, P.: Design de games: uma abordagem prtica. Cengage Learning. (2008)
12. Valli, A.: The design of natural interaction. Multimed. Tools Appl. 38, 295-305 (2008).
13. Boehm, J.: Natural User Interface Sensors for Human Body Measurement. ISPRS - Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci. XXXIX-B3, 531-536 (2012)
14. Vogler, C., Metaxas, D.: A Framework for Recognizing the Simultaneous Aspects of American Sign Language. Comput. Vis. Image Underst. 81, 358-384 (2001)
15. Lisetti, C.L., Schiano, D.J.: Automatic facial expression interpretation: Where human-computer interaction, artificial intelligence and cognitive science intersect. Pragmat. Cogn. 8, 185-235 (2000).
16. Chang, Y.-J., Chen, S.-F., Huang, J.-D.: A Kinect-based system for physical rehabilitation: A pilot study for young adults with motor disabilities. Res. Dev. Disabil. 32, 2566-2570 (2011)
17. Moraes, R.M., Machado, L.S.: Fuzzy Continuous Evaluation in Training Systems Based on Virtual Reality. Proc. 2009 IFSA World Congr. 102-107 (2009)
18. Moraes, R.M., Machado, L.S.: Continuous Evaluation in Training Systems Based on Virtual Reality. Proc. Glob. Congr. Eng. Technol. Educ. 1048-1051 (2005)
19. Moraes, R.M., Machado, L.S.: Continuous Evaluation in Training Systems Based on Web. Proc. World Congr. Comput. Sci. Eng. Technol. Educ. 223-227 (2006)
20. Machado, L.S., Moraes, R.M.: Continuous Evaluation in Training Systems Based on Virtual Reality Using Fuzzy Rule Based Expert Systems. VI Int. Conf. Eng. Comput. Educ. 8-11 (2009)
21. Andrade, G., Ramalho, G., Gomes, A.S., Corruble, V.: Dynamic game balancing: An evaluation of user satisfaction. Proc. Second Artif. Intell. Interact. Digit. Entertain. Conf. (2006)
22. Crawford, C.: Chris Crawford on Game Design. New Riders Publishing (2003)
23. Tijs, T.J.W., Brokken, D., IJsselsteijn, W.A.: Dynamic game balancing by recognizing affect. In: Fun and Games. pp. 88-93. Springer Berlin Heidelberg (2008)
24. Jang, J.R.: ANFIS: adaptive-network-based fuzzy inference system, Systems, Man and Cybernetics, IEEE Transactions on, 665–685 (1993)

25. Batista, T. V. V., Moraes, R. M., Machado, L. S., Valena, A. M. G.: Evaluating User Gestures in Rehabilitation from Electromyographic Signals. Revista IEEE América Latina, 14, 1387–1392 (2016).
26. Moosavi, V., Vafakhah, M., Shirmohammadi, B., Behnia, N.: A Wavelet-ANFIS Hybrid Model for Groundwater Level Forecasting for Different Prediction Periods. Water Resour. Manag. 27, 1301-1321 (2013).
27. Dogantekin, E., Avci, E., Erkus, O.: Automatic RNA virus classification using the Entropy-ANFIS method. Digit. Signal Process. A Rev. J. 23, 1209-1215 (2013).
28. Lau, C.K., Ghosh, K., Hussain, M.A., Che Hassan, C.R.: Fault diagnosis of Tennessee Eastman process with multi-scale PCA and ANFIS. Chemom. Intell. Lab. Syst. 120, 1-14 (2013).
29. Hunicke, R., Chapman, V.: AI for Dynamic Difficulty Adjustment in Games. Proc. of the 19th National Conference on Artificial Intelligence, 91–96 (2004).
30. 1. Hawkins, G., Nesbitt, K., Brown, S.: Dynamic difficulty balancing for cautious players and risk takers. Int. J. Comput. Games Technol. 2012, (2012)
31. Carvalho, C.V.: Dynamic Serious Games Balancing. SGAMES 2015, LNCIS, 161, 21–27 (2016).
32. Takagi, T., Sugeno, M.: Fuzzy Identification of Systems and Its Applications to Modeling and Control. IEEE Trans. Syst. Man Cybern. SMC-15, 116-132 (1985).
33. Joh, J., Chen, Y.-H., Langari, R.: On the Stability Issues of Linear. IEEE Trans. Fuzzy Syst. 6, 402-410 (1998).