VOL. 15, NO. 23, DECEMBER 2020 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

www.arpnjournals.com

ANALYSIS BETWEEN ELM AND ANN IN EMG SIGNALS OBTAINED FOR THE CONTROL OF A ROBOTIC HAND PROSTHESIS

Yeisson David Claros Grandett[1], Nicolás Suarez Argote[1] and Ruthber Rodriguez Serrezuela[2]
[1]Programa de Ingeniería Electrónica, Universidad Surcolombiana, Colombia
[2]Programa de Ingeniería Industrial, Corporación Universitaria del Huila, Colombia
E-Mail: ruthber.rodriguez@corhuila.edu.co

ABSTRACT

Over the last decades, the robotics industry has evolved exponentially, and humanoid robots cannot only be made but also, they can perform the physical functions of people. From this point of view, robotic hands are vital for many people who suffer either from an amputation or from any other disease. The main objective of this research was to classify the Electromyography (EMG) signals received from the human arm of healthy people and then carry out the manual application with a robotic hand in a virtual environment. This is especially important to understand and classify the geometric structure of the object contained in robotic handheld applications. The classification time and the precision relationship between the Artificial Neural Networks (ANN) and the Extreme Learning Machines (ELM) used for this classification were investigated. For this, 10 characteristics were extracted and the classifications were tested using ANN and ELM. The successful classification results obtained were compared with each other and applied to a virtual robotic hand using the V-Rep program.

Keywords: robotic hand, artificial neural networks (ANN), extreme learning machine (ELM), EMG signals.

1. INTRODUCTION

Some people face such congenital problems, work accidents in daily life that cause loss of limbs. The smart robotics industry has enabled the development of humanoid robots that can perform people's physical functions. Today, robotic arms and hands have had a remarkable development. Robotic hands must be able to fulfill some basic skills, such as grasping objects and transferring from one place to another in a similar way as people do in daily life. Robotics becomes important to people who have lost their arm or been born without their arm. For example, in the field of image processing, images of different positions of the hand taken by the human hand have been worked on and the robotic arm has been able to perform these movements rapidly [1]. In another study, a hand movement recognition system was implemented using the Kinect sensor. Movement can be detected in the app to detect hand movements in any direction, especially when taking the direction of a 3D marker [2]. In addition to image processing, many signal processing operations have been performed. In the case of signal processing based on support vector machines, the surface EMG signal is taken for the opening and closing movements of the human hand and this signal is shown to be independent of the position of the arm, which is considered adequate for the control of active prostheses [3]. In a two-section study investigating the use of forearm surface electromyographic (EMG) signals for real-time control of a robotic arm, high-level control is also provided [4]. In another study, using EMG signal data, basic hand movements based on biomedical signal analysis were identified and classified using Empirical Mode Decomposition (DME) [5]. In this study, the characteristics of the EMG signal taken from the arm of a 25-year-old man in [5] were extracted and then classified into the Extreme Learning Machine (ELM) and Artificial Neural Networks (ANN). The results of the classification were compared, and it was observed that ELM is a better option than ANN. In the following parts of this document, ANN, ELM, and feature extraction will be briefly explained, then the experiments and the results obtained will be given. The final section will discuss the results and what can be done in the future.

2. MATERIALS AND METHODS

Currently, many robotic applications are being performed with signals from the human body. In this study, the experiments were carried out using free and repeated grasping of the various elements necessary for the identification of hand movements. The strength and speed of the grip made is deliberately left to the person's will. These data were collected using the Labview National Instruments (NI) program at a sampling rate of 500Hz. By using elastic bands and two surface forearm EMG electrodes to collect information on muscle activation that is maintained at the central reference electrode, these signals were transmitted to a two-channel EMG system using the Myoware EMG system [5]. These electrodes were connected to both sides of the forearm and received signals from the forearm while grasping. Then, these signals were transferred from the electrodes to the central reference electrode to which the electrode was connected to the Labview National Instrument (NI) program. This data transfer was performed using the EMG Myoware system. The ten patients were five men and five women in the range of 22 to 35 years, who were asked to hold the objects with the following six different grip patterns repeatedly Figure-1.

ARPN Journal of Engineering and Applied Sciences

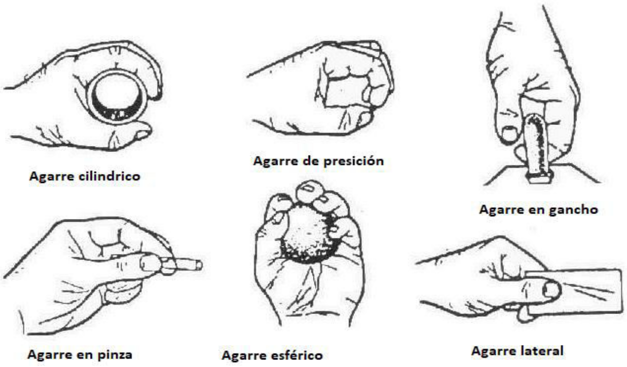

Figure-1. Six different grip types. [1]

a) Cylindrical: to hold cylindrical tools.
b) Precision: to hold small tools.
c) Hook: to support a heavy load.
d) Gripper: to grip with the palm towards the object.
e) Spherical: to hold spherical tools.
f) Side: to hold thin and flat objects.

The experiment consists of each subject performing 6 dams 100 times during 3 consecutive days. Therefore, at the end of the 3-day series, a total of 18,000 data measured from channel 1 and channel 2 were obtained from the device. Because each grasp is performed at 5-second intervals, 36,000 data is obtained for each grabbing operation, as this program operates at a frequency of 500Hz [5]. With all of this in mind, there are 100 cycles that take 5 seconds and are used to create the ANN and ELM. Therefore, 6,000 data is obtained for each grip and a total of 36,000 data is included per data matrix, respectively.

2.1 Artificial Neural Networks (ANN)

One of the subfields of artificial intelligence is ANN. The information processing is carried out through the neurons. The neurons are connected to each other by weighted connections, as shown in Figure-2.

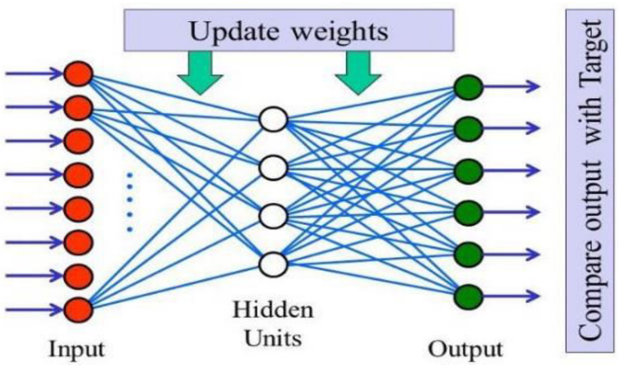

Figure-2. Structure of an ANN. Authors

An ANN consists of 3 basic layers. These are input, a hidden layer, and an output layer. The input data is applied directly to the input layer, so the number of neurons in the input layer equals the number of each input sample.

This data is then passed on from operations such as the addition, multiplication, and activation function that reaches the output layer. Finally, this data is given directly to the output layer. More than one hidden layer can be used in ANN depending on the complexity of the network. A hidden layer was used in our work. Multilayer perceptron- type optimization (MLP) is widely used in the field of artificial intelligence optimization.

Artificial neural networks of the (MLP) type were used in this study and the activation functions used between the layers were; a) Logarithmic sigmoid: Logsig b) Tan-Sigmoid and c) Purelin. Artificial neural networks can collect information on samples, generalize, and then decide on those samples using learned information compared to samples they have never seen before. Due to these learnings and generalizations, artificial neural networks find wide applications in many scientific fields and demonstrate their ability to solve complex problems successfully [6]. In this study, the ANN structure consists of input, output, and a hidden layer. The previously collected EMG signal data is delivered to the input layer, which is then updated by the trigger functions and transmitted to the output layer. The basic structure of ANN is presented. In each circle, a neuron is represented.

2.2 Extreme Learning Machine (ELM)

An ELM has an ANN network structure with a single hidden layer (see Figure-3) and the number of standard ELMs hidden layer neurons is usually more than 1000 [7]. Weights and thresholds are randomly assigned. These weights are not changed later. Operations are performed according to initial weights and threshold values. The entries in the ELM are features derived from the available data. The data used as output is also the target data. Since weights are also randomized, the main purpose here is to find the Beta coefficient. Beta coefficients are generated during the training phase, and then the same coefficient is used during the testing phase. The generalized Moore- Penrose inverse is used to find the beta coefficients [8]. As a result of obtaining the Beta coefficients, the network is trained. In other words, there is no iterative calculation in the ELM. For this reason, it has a great advantage in terms of training speed.

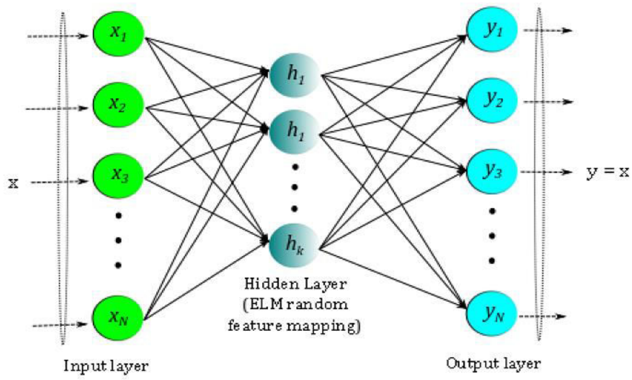

Figure-3. Structure of an Extreme Learning Machine. Authors

2.3 Feature Extraction

To classify the received data into ANN, it is necessary to extract the classification properties, and the training and testing procedures are performed according to these features. In this study, a total of 10 features were extracted, including time domain and frequency. In the time domain, five features were extracted: signal energy, standard deviation, absolute average, bias, and kurtosis value. To transfer the signal from the time domain to the frequency domain, the signal power spectral density (PSD) must be obtained by the method of Welch [9] or others and, therefore, the signal can be observed in the frequency domain. Six features were then extracted, including averages for this frequency, standard deviation, asymmetric kurtosis, power density between 0-50Hz, and 50-250Hz.

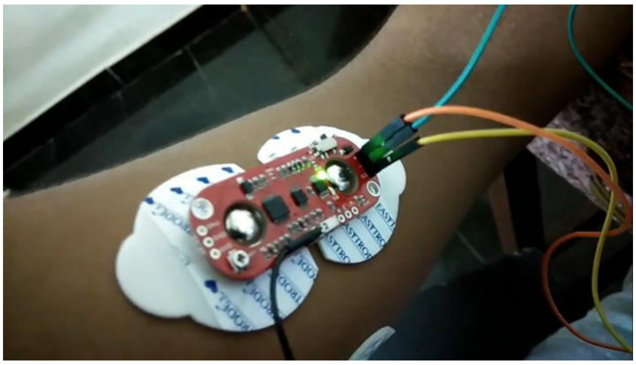

Figure-4. Extraction of myoelectric signals. Authors

2.4 Graphical User Interface (GUI)

The GUI is an interface that allows the user to interact with the program using visual objects (button, edit text, static text, graphics, etc.) [10]. In this study, the precision values of the ANN and ELM models were obtained using an interface and were represented graphically, and the developed GUI interface is shown in Figure-5, Figure-6 and Figure-7.

The interface was developed with the version of Labview 2019, it was installed on a Lenovo computer, with Intel Core 7i processor, 8650U Processor (8M Cache, up to 4.20 GHz), Turbo Boost 4.3, with 4.2 GHz, 8 GB memory of DDR4 SDRAM -2133, 1Tb hard drive.

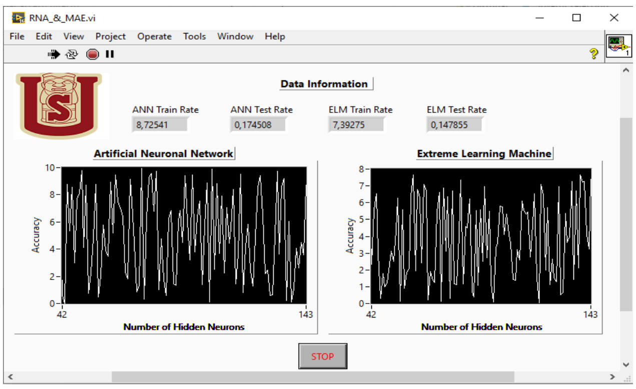

Figure-5. The front panel of the designed graphical user interface. Authors

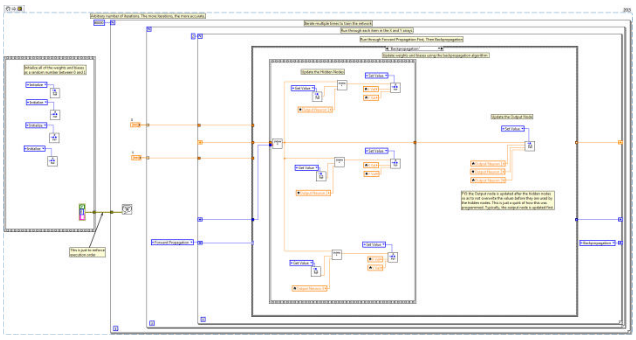

Figure-6. The blocks diagram of the designed graphical user interface. Authors

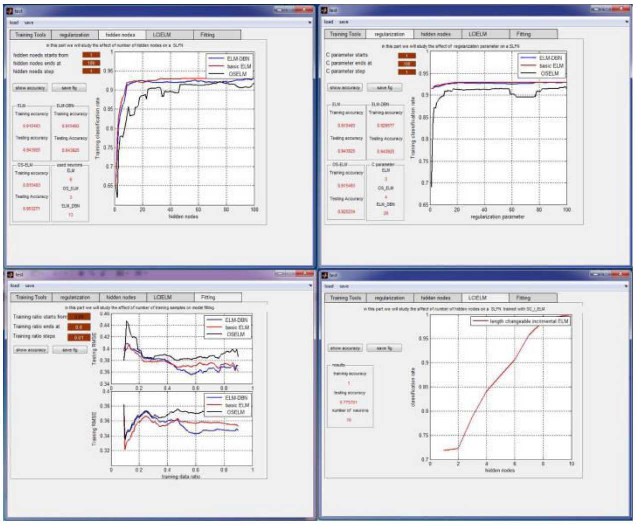

Figure-7. The blocks diagram of the designed graphical user interface. Authors

2.5 Training and Testing in ANN and ELM

The features extracted from the myoelectric data obtained are presented as training and test data to be implemented in artificial neural networks (ANN) and extreme learning machines (ELM). In this investigation, 80% of the data presented to ANN and ELM were taken as training and 20% as test data. The classification is made using the updates of the bias values and the weight according to the Newton- Raphson method [11] in ANN. ANN parameters were found according to the best precision and these parameter values were recorded in Table-1.

Table-1. Best ANN parameter found throughout the research. Authors.

Best ANN Parameter	
Number of hidden neurons	**12**
Número of epochs	500
Learning rate	0.45

ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

Impulse coefficient	0.15

12 training and testing procedures were carried out using these values. Because of these twelve tests, the ranking index averages were taken. A classification was achieved with an accuracy of between 98.7% and 99.47% as a result of tests in ELM and 88.32% -99.59% ANN. The accuracy rate and training time were given in Table-2.

Table-2. Comparison of ANN, ELM, and average accuracy rates. Authors.

	ANN			ELM		
	Training (%)	**Time (%)**	**Test (%)**	**Training (%)**	**Time (%)**	**Test (%)**
1	98,70	5,50	95,58	99,24	0,29	97,28
2	96,73	8,76	90,38	98,98	0,13	97,52
3	98,97	6,62	94,55	98,71	0,21	97,00
4	94,06	5,83	91,43	98,96	0,13	97,20
5	99,48	5,63	98,96	99,23	0,19	97,35
6	96,36	5,62	96,83	99,23	0,13	97,20
7	92,20	5,65	91,12	98,96	0,19	97,07
8	96,62	5,69	88,32	99,48	0,13	97,40
9	93,77	5,08	89,31	98,96	0,18	97,04
10	98,96	5,34	94,86	98,70	0,14	97,20
11	99,59	8,48	95,56	99,24	0,19	97,28
12	92,87	7,69	94,15	98,98	0,15	97,52
Average	96,53	6,32	93,42	99,06	0,17	97,26

3. RESULTS

Multiple hidden layers can be used in an ANN depending on the complexity of the processing. Using two hidden layers the best results were obtained. Likewise, some system parameters directly affect the classification in ANN, such as the learning rate, the impulse coefficient, the number of hidden neurons, and the number of iterations.

It is intended to minimize system error when varying the parameters. Figures 8, 9, and 10 graphically show the precision values obtained by changing these values within a certain range for ANN. We can see that in the graph of the accuracy rate according to the number of neurons the percentage does not exceed 96.56% on average, in the test an average of 93.42% was achieved, in a maximum of 12 hidden neurons. Likewise, the highest accuracy rate was obtained only when the lowest number of epochs existed in the ANN, reaching 98.96%, a value that agrees with the literature according to [7], [8].

ELMs are a method that does not depend on iteration. That is, there are no parameter limitations in the ELM method, although there are many parameter limitations in the ANN method. Therefore, the Beta (β) values of the ELM are calculated independently from the iteration. The number of hidden neurons is the factor that affects performance in the ELM method. The precision graph obtained by changing the number of hidden neurons within a certain range is shown in Figure-11.

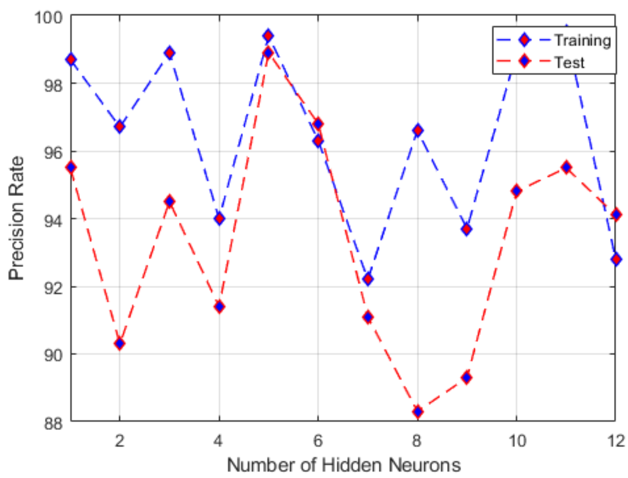

Figure-8. Accuracy rate according to the number of hidden neurons in ANN. Authors

VOL. 15, NO. 23, DECEMBER 2020 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

www.arpnjournals.com

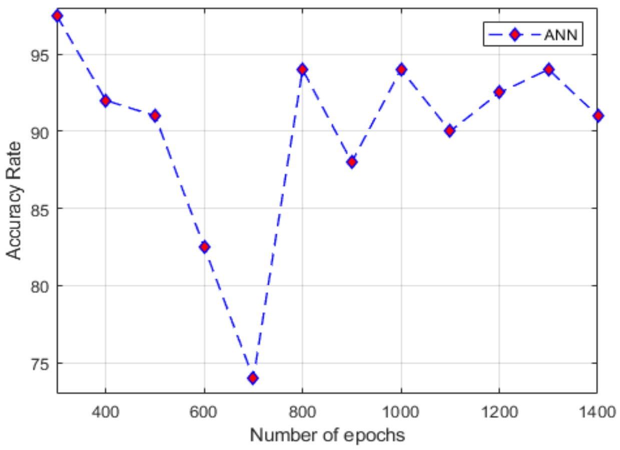

Figure-9. Accuracy rate according to the number of epochs in ANN. Authors

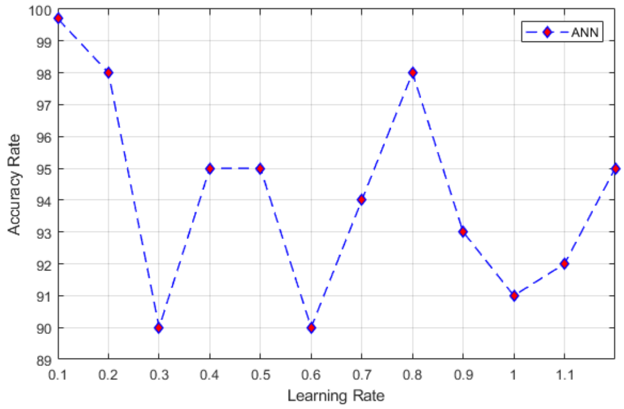

Figure-10. Accuracy rate according to the learning rate. Authors

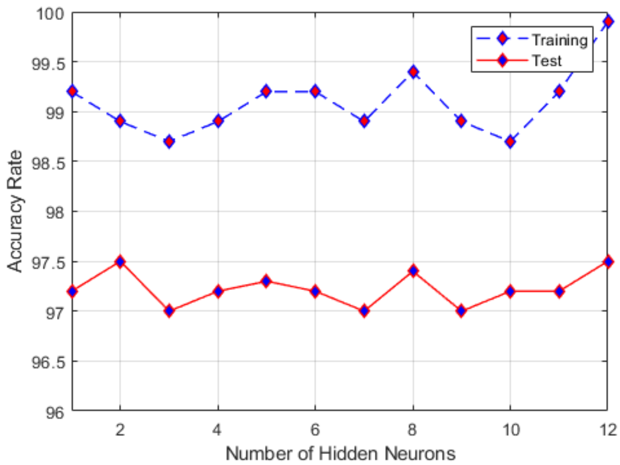

Figure-11. Accuracy rate according to the number of hidden neurons in ELM. Authors

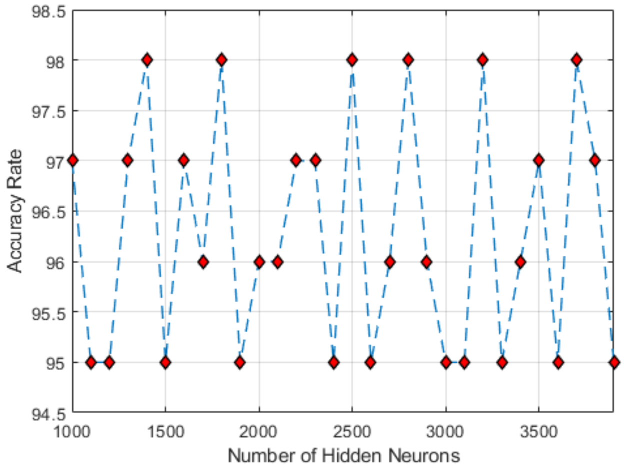

Figure-12. Accuracy values according to the number of hidden neurons for ELM. Authors

4. CONCLUSIONS

The average accuracy values are reached as 96.53% for ANN in the calculation time of 6.32 seconds and 99.06% for ELM in the calculation time of 0.17 seconds. When the mean value and the results obtained with the 12 tests are taken into account, the variance of the ELM accuracy rate is 0.0479, although the variance of the ANN accuracy rate is 6.6466. This suggests that the ELM will be more stable in the responses of the robotic arm. Also in real-time applications, the reaction time of the robotic arm is very important. Here, the learning speed of ELM is approximately 67 times faster than that of ANN. Therefore, ELM will be more effective in real-time applications. To conclude, it can be said that ELM is a better option than ANN in situations where the reactions are fast and precise.

Conflict of interests

The authors declare that there are no conflicts of interest regarding the publication of this document.

REFERENCES

[1] Rahim M. A., Islam M. R. & Shin J. 2019. Non-Touch Sign Word Recognition Based on Dynamic Hand Gesture Using Hybrid Segmentation and CNN Feature Fusion. Applied Sciences. 9(18): 3790.

[2] Mazhar O., Navarro B., Ramdani S., Passama R. & Cherubini A. 2019. A real-time human-robot interaction framework with robust background invariant hand gesture detection. Robotics and Computer-Integrated Manufacturing. 60, 34-48.

[3] Precup R. E., Teban T. A., Albu A., Borlea A. B., Zamfirache I. A. & Petriu E. M. 2020. Evolving fuzzy models for prosthetic hand myoelectric-based control. IEEE Transactions on Instrumentation and Measurement.

ARPN Journal of Engineering and Applied Sciences

[4] Xue J., Yang Y., Chen J., Jiang Y., Zhu C., Yokoi H. & Duan F. 2019. The Development of an Underwater sEMG Signal Recognition System Based on Conductive Silicon. In 2019 IEEE International Conference on Advanced Robotics and its Social Impacts (ARSO) (pp. 387-392). IEEE.

[5] Yavuz E. & Eyupoglu C. 2019. A cepstrum analysis-based classification method for hand movement surface EMG signals. Medical & biological engineering & computing. 57(10): 2179-2201.

[6] Cao J., Zhu J., Hu W. & Kummert A. 2019. Epileptic signal classification with deep EEG features by stacked CNNs. IEEE Transactions on Cognitive and Developmental Systems.

[7] Huang G., Huang G. B., Song S. & You K. 2015. Trends in extreme learning machines: A review. Neural Networks. 61, 32-48.

[8] Mirza B., Wang W., Wang J., Choi H., Chung N. C. & Ping P. 2019. Machine learning and integrative analysis of biomedical big data. Genes. 10(2): 87.

[9] Serrezuela R. R., Trujillo J. L. A., Delgado D. R., Benavides V. K. O., Zamora R. S. & Reyes E. M. 2018, September. Diseño e implementación de una prótesis de mano robótica antropomórfica subactuada. In Memorias de Congresos UTP. pp. 165-172.

[10] Rojas J. H. C., Serrezuela R. R., López J. A. Q. & Perdomo K. L. R. 2016. LQR hybrid approach control of a robotic arm two degrees of freedom. International Journal of Applied Engineering Research. 11(17): 9221-9228.

[11] Zhai J., Zhang S., Zhang M. & Liu X. 2018. Fuzzy integral-based ELM ensemble for imbalanced big data classification. Soft Computing. 22(11): 3519-3531.

[12] Broche-Vázquez, L., Torres-Quezada, M., Milanés-Hermosilla, D., González-Romero, D., Rodríguez-Serrezuela, R., & Sagaró-Zamora, R. (2020). Exoesqueleto robótico para la rehabilitación del miembro superior del paciente hemipléjico. Ingeniería Mecánica, 23(3).

[13] Serrezuela, R. R., Quezada, M. T., Zayas, M. H., Pedrón, A. M., Hermosilla, D. M., & Zamora, R. S. (2020). Robotic therapy for the hemiplegic shoulder pain: a pilot study. Journal of NeuroEngineering and Rehabilitation, 17, 1-12.

[14] Serrezuela, R. R., Zamora, R. S., & Reyes, E. M. (2020). Control Strategy for Underactuated Multi-Fingered Robot Hand Movement Using Electromyography Signal with Wearable Myo Armband. In Biosensor-Current and Novel Strategies for Biosensing. IntechOpen.

[15] Serrezuela, R. R., Chavarro, A. F. C., Cardozo, M. A. T., Toquica, A. L., & Martinez, L. F. O. (2017). Kinematic modelling of a robotic arm manipulator using Matlab. ARPN Journal of Engineering and Applied Sciences, 12(7), 2037-2045.

[16] Azhmyakov, V., Martinez, J. C., Poznyak, A., & Serrezuela, R. R. (2015, July). Optimization of a class of nonlinear switched systems with fixed-levels control inputs. In 2015 American Control Conference (ACC) (pp. 1770-1775). IEEE.

[17] Serrezuela, R. R., & Chavarro, A. F. C. (2016). Multivariable control alternatives for the prototype tower distillation and evaporation plant. International Journal of Applied Engineering Research, 11(8), 6039-6043.

[18] Azhmyakov, V., Rodriguez Serrezuela, R., Rios Gallardo, A. M., & Gerardo Vargas, W. (2014). An approximations based approach to optimal control of switched dynamic systems. Mathematical Problems in Engineering, 2014.

[19] Serrezuela, R. R., Villar, O. F., Zarta, J. R., & Cuenca, Y. H. (2016). The K-Exponential Matrix to solve systems of differential equations deformed. Global Journal of Pure and Applied Mathematics, 12(3), 1921-1945.

[20] Serrezuela, R. R., Cardozo, M. Á. T., Ardila, D. L., & Perdomo, C. A. C. (2018). A consistent methodology for the development of inverse and direct kinematics of robust industrial robots. ARPN Journal of Engineering and Applied Sciences, 13(01), 293-301.