Impact of Architecture and Genetic Algorithm Application in Neural Pattern Recognition

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***Abstract*— The surface electromyography is a non-invasive recording of biopotentials muscles signals. In the rehabilitation field, myoelectric prosthesis can be controlled by the features extracted from the signal and enable the devices adjustable for residual limb anatomy. In order to avoid the prosthesis abandonment, an efficient classification of these features is essential. In this way, this study analyzes 5 sEMG features classification of 8 isotonic and isometric hand movements. Thus, observing the behavior from 1 to 5 hidden layers in a Neural Pattern Recognition Network, the optimization of synaptic weights with Genetic Algorithm and their impact in accuracy. The results presented that the number of layers impact directly into algorithm accuracy. The best accuracy was an architecture of 4 hidden layers with an optimization of synaptic weights in pre-training reaching 73.10% of accuracy.**

Keywords — Recognition Pattern, Neural Pattern Recognition, Genetic Algorithm

I. Introduction

Currently, there are many studies that aim to improve the control of prostheses, especially in the upper limbs [1,2,3]. Amputations can occur with traumatic or non-traumatic etiologies and the myoelectric control of the prostheses is based on the muscles of the remaining limb. This fact makes categorizing surface electromyography patterns a more difficult task [4].

During daily activities, the anatomical structure of the hand, with the arm and forearm, perform various movements in three-dimensional space [5]. The focus of the use of prostheses is, partially or totally, the recovery of motor skills lost with the amputation. Subsequently, goaling the hability of the prosthesis control as similar as possible to the biomechanical movement [4].

For efficient myoelectric control analysis, it is usual to classify the characteristics of surface electromyographic (sEMG) signals, which are biopotential from the depolarization of the muscle membrane and induce contraction. They are extremely important to unveil the individual's movement intentions [1,6]. Neural pattern recognition (NPR) network is an artificial neural network type for features classification through a network training [1,7] and it can be used to classify the sEMG signal characteristics of limb movements. And, further, developing EMG-based control interfaces [8,9].

On the other hand, Genetic Algorithms (GA) are globally optimized logical algorithms that are based on genetic and natural selection mechanisms. These algorithms are commonly used in separation of biological electrical potentials as blind sources, estimation of torque and power of movement, also in approach of protheses gravitational point of balance, among other areas [10-13].

When is thought at a succesfully rehabilitation after an injury on the limb (amputation), the focus is on fast and efficient prosthesis control. The action classification time is also extremely important since an anatomical movement takes around 100 ms to occur [14]. First of all, if movement classification or movement action takes a longer interval than natural body behavior, the tendency of abandonment in use of prostheses increases. The reason is it does not meet expectations compared to conditions under natural body biomechanics [4].

In this way, this study aims to analyze the behavior of different algorithm architectures and, also, the influence of application of GA in optimization of the synaptic weights in NPR training. It makes possible understand if GA is a beneficially tool and in which conditions it might be inserted on network training for future prosthesis control.

II. Methodology

A. Database

First, electromyography features data were extracted from a public and academic purposes dataset provided by [15]. In this database, it was selected ten right-handed able-bodied subjects. From the recording of sEMG signal, the volunteers executed 8 isometric and isotonic hand configurations as shown by Fig. 1.

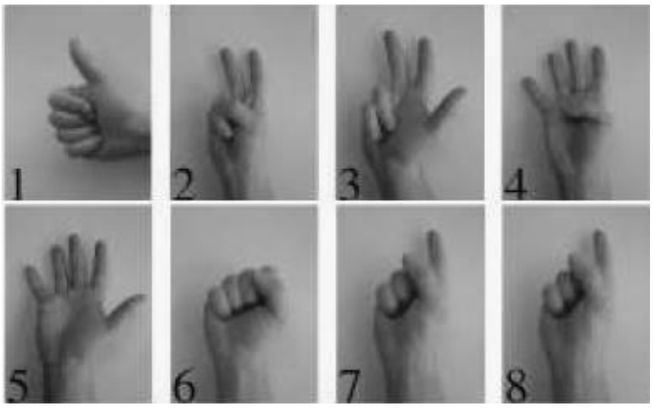

Fig. 1. Isotonic and isometric hand movements labeled from 1 to 8. Target movements classified from the neural pattern recognition network.

The twelve electrodes were non-invasive and equally spaced which 8 were positioned around the forearm corresponding the radio humeral joint, 2 electrodes were placed on the main spots of the biceps and of the triceps. Finally, 2 last were place on the main spots of the flexor. All electrodes around the forearm were fixed using their standard adhesive bands.

During the acquisition, the volunteers were asked to repeat the movements with the right hand, in a total of 8 different movements executed six times. In addition, each movement repetition was followed by three seconds of rest. The sEMG signals were sampled at a rate of 2 kHz. The data used in this study contained data files with synchronized variables.

B. *Data Processing*

The feature analysis from the sEMG signal consisted in the extraction of :

- Root Mean Square (RMS)
- Mean Absolute Value (MAV)
- Discrete Wavelet Transform (DWT)
- Wave Length (WL)
- Slope Sign Changes (SSC)

The selected features were chosen by the most relevant features analyzed from sEMG in the literature [16-18].

The NPR network was backpropagation and it is a widely used algorithm for training feedforward neural networks. Once the features were extracted, the times executions NPR network training consisted in a total of 10 runs. In order to analyze the architecture impact, an amount of 60 neurons were spread into hidden layers, from 1 to 5. An algorithm compilation is called run.

For one in a couple run, it was applied the GA optimization of synaptic weights. In other words, Run 1 and 2, NPR network was composed by one hidden layer with 60 neurons. In the subsequent Run 3 and 4, there were two hidden layers with 30 neurons each. Run 5 and 6 had three hidden layers with 20 neurons each. Followed by Run 7 and 8 with four hidden layers with 15 neurons each. And, finally, Run 9 e 10 with five hidden layers had 12 neurons each. In the even run number, the GA was applied.

The fitness function used was normalized mean square error (NMSE). The NMSE is used in order to avoid bias towards the model and it gives an overview of the model performance [19].

III. Results

Regarding the best accuracy in the analysis, the Fig. 2 shows the accuracies, in percentage, from all algorithm executions. The main result is the behavior of Run 8, an application of GA category with four hidden layers. This run reaches 73.10% of accuracy in the classification, which more than 70% was regarding movement 1. In view of other movements accuracies were around 0.15%. Excepted from target 1, the algorithm had difficulty to distinct fine different movements from index to little fingers. Considering the initially runs, 1 and 2, had the worse accuracies from the total 10. These runs had only one hidden layers and were not functionally efficient.

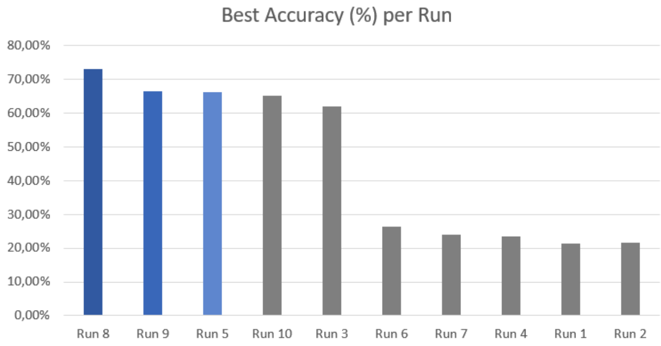

Fig. 2. Best accuracy of targets, in percentage, per run. The Run 8, 9 and 5 reaches the highest accuracies, respectively, from all trainings.

The Fig. 3 reveals the median target classification error from all targets, which is considered the absolute median values. The median variable is selected because an outlier error value from any movement does not interfere in hole complete analysis of the algorithm execution. In addition, the Run 9 had the lowest median under 0,0930.

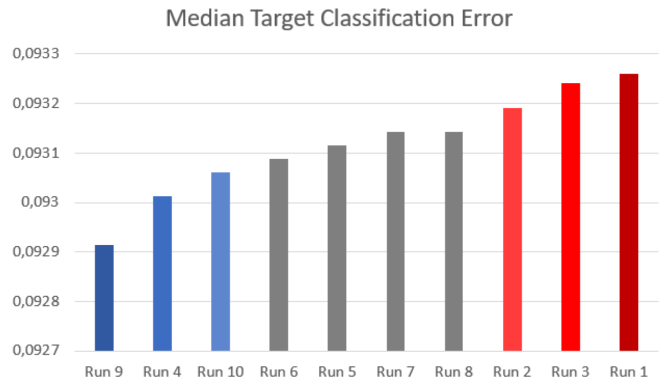

Fig. 3. Median target classification error among 10 runs which presents the worse meadian runs, 2,3 and 1 and better median runs, 10,4 and 9, respectively.

The Fig. 4 shows a complete observation of behavior regarding the algorithms with and without GA optimization and the number of hidden layers. Until to three hidden layers, the algorithm without GA appeared a better classification, from four hidden layers, the GA infers a better accuracy. It is important to notice that for four hidden layers the optimized algorithm had half computational time in comparative without GA.

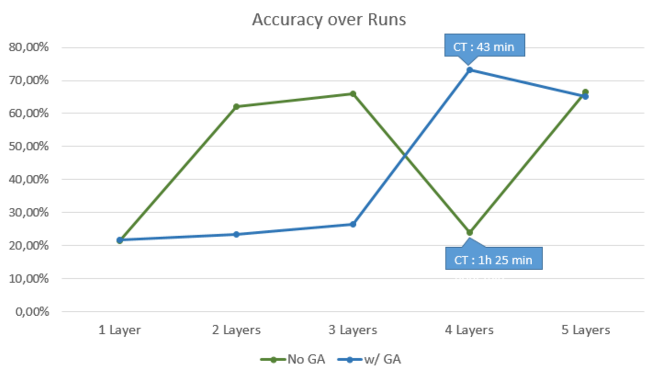

Fig. 4. Accuracy over runs, a comparison between the architecture from 1 to 5 hidden layers and the application or not of GA in synaptic weights of neural network. Highlight at 4 hidden layers where the algorithm reaches 73.10% of accuracy with optimization. CT: Computational Time.

In sum, according to computational time proportional to no optimization compared to the application of GA, the optimization of synpatic weights reduces an interval in average of 30% less computational time. Considering relation between computational time and the algorithm architecture, four hidden layers (Run 7 and 8) demand 2 hours summed. Related to the second and third best accuracies, the hidden layers were five and three with no GA, respectively. The relation between computational time and network accuracy is illustrated by Fig. 5. Three best accuracies in all trainings. The computational time influence in diameter of bubble graphic, the X axis is the number of hidden layers and Y axis is the accuracy in percentage. Green bubbles are runs without optimization and colored blue, with GA optimization.

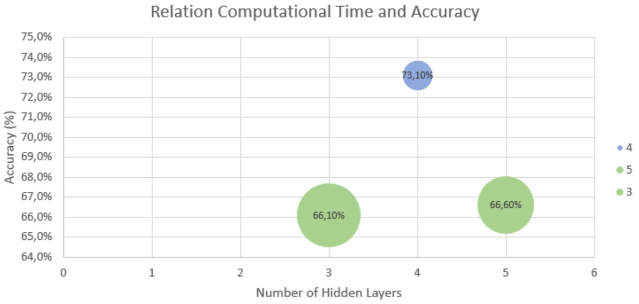

Fig. 5. The three best performances in all runs. The bubble diameter depends on computational time. Green bubbles are runs without optimization and blue, with GA optimization. The best performance reaches 73.10% of accuracy.

IV. Discussion and Conclusion

Considering the various tridimensional space anatomy conformations combining hand, arm and forearm, the difficulty level at classification of each movement increases. As noticed, the analysis classification worked on offline system. On the other hand, for a functional use in daily living, the subject will work with an online system which will be feedforward with new data [20].

This is the reason which optimization in network at higher accuracy of movement classification with lower computational cost as possible are essential. In view of the results obtained, it is possible to verify that the number of hidden layers interfere directly in the training and classification of the network. Fewer hidden layers, e.g. one or two hidden layers, lead to higher target error classifications as seen at Fig. 3. And, on the other hand, four and five hidden layers expose better results corresponding better accuracies from all architectures.

From the confusion matrices acquired in the study, it was noticed that moviments between target 1 and 7, the algorithm had difficulty to classify differences of thumb and index finger configurations. As same, it appears problems to classify movements between targets from 2 to 8 which isotonic position fingers – index to minimum – change. These movements are considered fine fingers movements, compute extra dificultty in pattern recognition and subsequent high error classification. It is important to emphasize the fact that, from second to fifth digits, there is the same flexor and extensor muscles, which are flexor digitorum superficialis, flexor digitorum profundus and extensor digitorum. Subsequently, tendon portions branch out over each metacarpal head [21]. In fact, it is a plausable reason regarding the difficulty in diferentiate fine movements of hand fingers. Concerning the opposable thumb, it has two exclusive extensor muscles, extensor pollicis brevis and longus, and a flexor muscle, flexor pollicis brevis. The possibility of the model has been suffered underfitting is not excluded. In the literature, researches focus on classification of fine fingers movements above 90% accuracies in high quality prosthesis control [18, 22-24].

The best accuracy founded in this study is not proper for a high quality control, as considered in the literature, above 90% [18]. Although, it shows that an optimization in synaptic weights in pre-training of neural pattern network has impact in final accuracy and in less computational time interval. From an overview, the GA does not bring benefits, according to Fig. 4, because it is only better with 4 hidden layers. But, although this general view, the best result show up with application of genetic algorithm. Then, the behavior of a model with the implementation of GA depends on the algorithm architecture.

In conclusion, the number of layers interfere directly into algorithm accuracy. Observed better beahviour of spreading an amount of 60 neurons into four hidden layers (12 neurons each) than one hidden layer with 60 neurons in total. The opmitization of synaptic weights, with GA, reduces the computational time in training the model with 4 hidden layers architecture. Finally, for future incorporation in this study, the focus is on improving the fitness function in optimization at pre-training stage of neural pattern recognition. Aiming a greater accuracy and better classification results for the targets selected in this study, followed by an expansion in the number of movements analyzed.

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List all authors' names up to six authors; is there are more than six authors, use "et al.".

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