

Genetic Algorithm Application to Feature Selection in sEMG Movement Recognition with Regularized Extreme Learning Machine*

Maurício C. Tosin, Leia B. Bagesteiro, and Alexandre Balbinot

Abstract — This paper presents a genetic algorithm (GA) feature selection strategy for sEMG hand-arm movement prediction. The proposed approach evaluates the best feature set for each channel independently. Regularized Extreme Learning Machine was used for the classification stage. The proposed procedure was tested and analyzed applying Ninapro database 2, exercise B. Eleven time domain and two frequency domain metrics were considered in the feature population, totalizing 156 combined feature/channel. As compared to previous studies, our results are promising – 87.7% accuracy was achieved with an average of 43 combined feature/channel selection.

I. INTRODUCTION

The study of electromyography has been the focus of many scientific studies since 1940s [1]. Algorithms for pattern recognition associated with surface electromyography (sEMG) for prosthetic movement control have been explored since the 1960s. This approach is based on the premise that an individual is capable of reproducing repeatable and distinct sEMG pattern for specific movements in the remained musculature [2].

Several studies were developed in this area in the past decades leading to a considerable advance in this research field [3]–[5]. Today there are commercially available myoelectric controlled prostheses with several degree of freedom. However, there is still a lack of natural, proportional and simultaneous control of the device movements [6]. Hence, there are many aspects of the design to be solved and improved, which guides the current work in the area.

In this context, a general sEMG pattern recognition system is based on the following steps: sEMG acquisition, signal pre-processing, feature extraction, feature selection and classification. Feature selection plays an important role in the process of EMG pattern recognition, since it eliminates redundant and irrelevant features that may impair the system performance. However, very few studies explored this viewpoint [7], as compared to EEG signal processing, for example, which explores data driven decomposition to enhance signal segmentation in specific frequency bands in a wider range of studies [8]–[10].

Despite the large amount of time domain (TD), frequency domain (FD) and time-frequency domain (TFD) features commonly used in the literature, the best feature or features set

to characterize the sEMG signal is still an open topic [2]. Phinyomark et al. [11] evaluated 37 TD and FD features to characterize six upper limb motions from five channels. They verified redundancy in most analyzed features. In our previous work [12], we proposed a feature selection algorithm based on Support Vector Machine Recursive Feature Elimination (SVM-RFE) method to find the best combined feature/channel set to enhance classification accuracy of the first 10 volunteers from Ninapro Database 2.

Motivated by this work, the aim of the current study is to present a new strategy based in Genetic Algorithm (GA) and Regularized Extreme Learning Machine (RELM) to select the best combined feature/channel. GA are very often used in optimization tasks mainly due to its great generalization and randomized global solution search strategy. In sEMG pattern recognition, stands out the work by Zhang and Shi [13], which used GA to optimize number of neurons and weights of a neural network to classify six hand movements.

Thus, the main goal of this paper is to propose a pre-processing stage to enhance the class separability and improve movement intent recognition using sEMG signals.

II. MATERIALS AND METHODS

The proposed algorithm is based on three steps: (1) 13 commonly used features are extracted; (2) the higher correlated combined feature/channel are removed from the dataset; (3) the remained dataset pass through a GA, where each individual combined feature/channel corresponds to a chromosome and the RELM classification accuracy defines the fitness of each individual chromosome chain (i.e. combined feature/channel set candidate). As an end of the GA processing the best combined feature/channel set and the respective classification accuracy is determined. Combined feature/channel is referred to each feature extracted in an individual channel. It is worth to note that the combined feature/channel pairs selection is performed for each volunteer individually (i.e. single user). A multiuser system is more complex than a single user approach due to the intrinsic signal variability among subjects, making the search of the global best set of feature/channel pairs an infeasible task.

A. Database

Database 2, Exercise B from Non-Invasive Adaptive Hand Prosthetics (Ninapro) repository was used in the present work.

* Research supported by National Counsel of Technological and Scientific Development (CNPq).

M. C. Tosin and A. Balbinot are with the Electro-Electronic Instrumentation Laboratory of the Electrical Engineering Department, Federal University of Rio Grande do Sul, Porto Alegre, Rio Grande do Sul

90040-060 Brazil (mauricio.ctosin@gmail.com, abalbinot@gmail.com). L. B. Bagesteiro is with NeuroTech Lab, Kinesiology Department, San Francisco State University, San Francisco, CA, 94132, USA. (lbb1108@gmail.com).

Ninapro is an internationally available database. It was developed by Atzori et al. [14] with a main goal of enabling results comparison among different studies based on a public available database. It is currently composed of eight distinct databases containing sEMG signals acquired in different exercises from amputees and non-amputee volunteers. sEMG signals acquired from 12 Trigno Wireless electrodes in 40 intact volunteers during execution of eight basic fingers movements and nine basic wrist motions (17 different movements) were selected as the dataset for the present work.

B. Feature Extraction

sEMG signals were segmented following sliding windows approach. Windows of 300ms with displacement of 75ms were defined to match the requirements for real time applications [15]. For each sEMG channel segment, 13 different features commonly used in the literature were extracted, resulting in 156 combined feature/channel (12 channel x 13 features).

Eleven (TD) features (Root Mean Square, Difference Absolute Means, Fractal Dimension, Higuchi Fractal Dimension, Mean Absolute Value, Maximum Fractal Length, Power, Signal Slope Changes, Standard Deviation, Waveform Length and Zero-Crossings) and two (FD) features (Frequency Mean and Frequency Waveform Length) were extracted using BioPatRec open source codes [16].

C. Correlation Analysis

Redundant features are undesirable in a dataset since they do not bring new information and generally impairs the classifier performance. Therefore, combined feature/channel with correlation metric above 0.9 were removed from the dataset. This threshold value was defined following previous research [12], [17]. Task complexity and the search field of GA are considerably reduced with the addition of this stage.

D. Genetic Algorithm

Genetic Algorithm (GA) is an optimization method based on the evolution theory, as introduced by Bagley [18] and Holland [19]. GA consists of five main steps: (1) Initial population definition; (2) Fitness analysis of each chromosome chain from population; (3) Selection of chromosome chains with higher fitness to cross and generate a new population; (4) Mutation of chromosome chains in the new population; (5) Fitness evaluation of new population. These five steps are executed iteratively until a stop criterion is reached.

We used GA to find the best set of feature/channel pairs. A chromosome chain is a binary vector where “1” indicates a feature/channel pair used and “0” is an unused feature/channel pair. Hence, the chromosome chain length is the number of feature/channel pairs that survives from correlation analysis. Classification accuracy of a RELM classifier expressed fitness. Elitism strategy was used to create the new generation and 1% of chromosomes were randomly selected to mutation stage. Figure 1 shows a block diagram of the proposed GA feature selection.

D. Regularized Extreme Learning Machine (RELM)

Extreme Learning machine is a non-iterative classification algorithm based in a Single Layer Feed-forward Neural Network [20]. The method consists of randomly assign values to hidden layer weights and then calculates analytically the

weights of output layer. Hence, the learning speed is much higher than traditional Artificial Neural Networks. Deng et al. [21] reported that ELM training speed could be hundreds times faster than back propagation learning method in some benchmark datasets.

The regularized form of ELM introduces a regularization factor to weight the empirical and structural risk minimization during learning stage, reducing the ripple in classification caused by outliers [3], [21], [22]. Equation 1 determines the output weights from RELM method.

$$\beta = \left(\frac{I}{C} + H^T H \right)^{-1} H^T T \quad (1)$$

where I is eye matrix, C is the regularization factor, H is the hidden layer output matrix, T is the class label vector and β is the output layer weights.

The RELM algorithm was selected due to its faster learning and descent results [3], [12], [23]. In addition, RELM has fewer parameters to be adjusted and presented better results when compared with other iterative methods as SVM and RLR (Regularized Logistic Regression) [3].

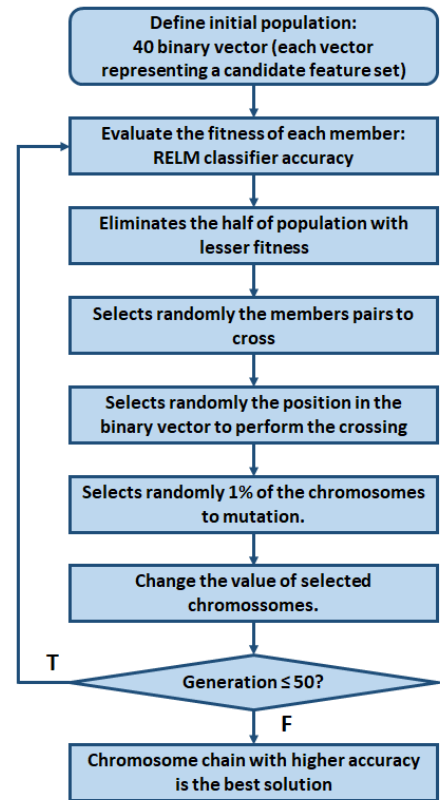


Figure 1. Proposed feature selection method based in GA.

III. RESULTS

Experiments were performed in MATLAB R2017b software. In order to perform a fair comparison and validate the proposed algorithm, the SVM-RFE based method and conditions presented in our previous work [12] was considered as baseline. In summary, Tosin et al. [12] feature selection method was based on four steps: (1) feature extraction, (2)

removal of feature/channel pairs higher correlated, (3) remained feature/channel pairs are ranked by importance through SVM-RFE method, and (4) best set of feature/channel pairs and classification accuracy are determined in a wrapper based feature selection algorithm with RELM classifier.

After the removal of higher correlated features, 75 feature/channel pairs on average, per volunteer, remained in the dataset. This number is less than half of the original set, indicating that there is redundancy in most (TD) and (FD) features considered, confirming results reported by Phinyomark et al. [11].

Remaining combined feature/channel were submitted to SVM-RFE and presented GA based method to best feature set selection. The parameters of SVM-RFE based method were adjusted according to previous work [12]. For GA based method, the number of chromosome chains of initial population is fixed in 40. This number was defined after preliminary tests to make the classification accuracy more stable along the generations. Stop criteria was defined when maximum number of generations (or iterations) reached 50. Accuracy did not increase after 50 generations, as observed after several simulations. This is evident in Figure 2, which shows volunteer #01 accuracy progression after 70 generations. The same behavior was obtained for all 40 volunteers. For classification, the dataset was divided in 70% for training and 30% for testing. It was decided not to perform cross validation since it was executed 40 trainings in each generation. RELM parameters' adjustment and SVM-RFE based method were set according to previous work [12].

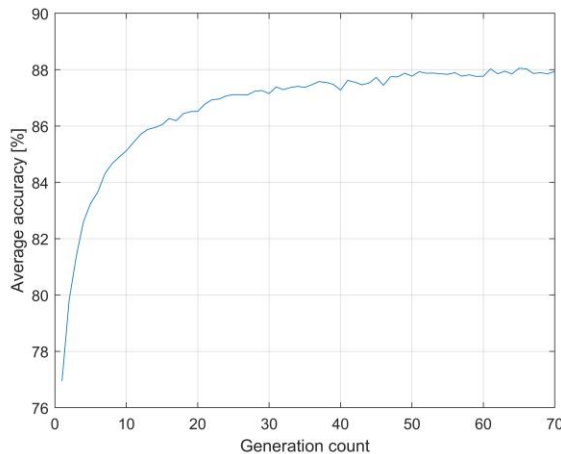


Figure 2. Classifier evolution with generations for volunteer #01.

Figure 3 shows the accuracy (i.e. average accuracy per movement) obtained with the best combined feature/channel set selected by each method (SVM-RFE and GA) for each volunteer. Accuracy associated to a specific movement was determined as the number of correctly classified instances divided by the total of instances labeled with that movement.

IV. DISCUSSION

As observed in Figure 3, the best combined feature/channel set selected by the proposed GA based method achieved higher average accuracy for almost all volunteers. Only subjects #20 and #26 showed SVM-RFE method outperforming GA, with only 0.2% difference. The higher difference in favor of GA method was observed for volunteers #27 and #32 (6.2 and 6.4%, respectively).

On average, the proposed GA based method achieved 87.7% per volunteer, whereas SVM-RFE resulted in 85.0%. This difference was verified as significant with 95% of confidence level based on ANOVA results. This is potentially related to the greater ability of GA to solve optimization problems. In addition, the proposed algorithm has fewer stages, presenting higher computational efficiency in preliminary tests. Thus, the GA based method showed a better effectiveness finding the best combined feature/channel set.

Regarding the number of combined feature/channel selected, GA method selected 43, on average, per volunteer, while SVM-RFE elected 35. This difference was significant with 95% of confidence level. This fact may indicate that the proposed algorithm refines the features set selection performed by SVM-RFE method by adding combined feature/channel that improves class separability.

V. CONCLUSION

The present study proposes a GA based method to select feature/channel pairs for the task of classifying hand-arm segment movements from sEMG signal, for that we employed signals from 40 volunteers from Ninapro Database 2. Classification procedure was performed as described in our our previous work [12] to enable a direct comparison between the proposed method and SVM-RFE approach.

The significant higher average accuracy achieved with the proposed algorithm indicates that it is an interesting strategy to sEMG signal pre-processing stage, justifying further work in the area.

As a next stage, the combined feature/channel set selected by the proposed algorithm will be further investigated. The GA based method will be tested with amputee data to validate the current results in a specific population. Repeatability of the best set of feature/channel pairs will also be evaluated using other database [23].

ACKNOWLEDGMENT

This study was partially financially supported by the *Coordenação de Aperfeiçoamento de Pessoal de Nível Superior - Brasil (CAPES) - Finance Code 001*.

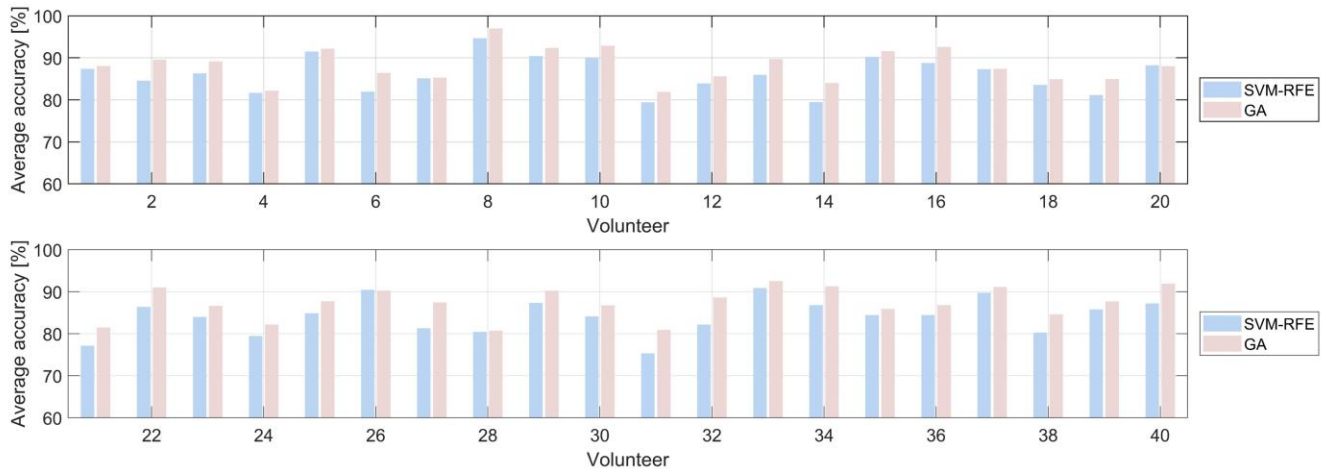


Figure 3. Average accuracy per movement obtained for each volunteer using SVM-RFE method and GA based one.

REFERENCES

- [1] L. Gillis, "Recent Advances in the Treatment of Arm Amputations, Kineplastic Surgery and Arm Prostheses," *Ann R Coll Surg Engl.*, vol. 3, no. 5, pp. 227–247, 1948.
- [2] H. M. Al-Angari, G. Kanitz, S. Tarantino, and C. Cipriani, "Distance and mutual information methods for EMG feature and channel subset selection for classification of hand movements," *Biomed. Signal Process. Control*, vol. 27, pp. 24–31, 2016.
- [3] V. H. Cene and A. Balbinot, "Enhancing the classification of hand movements through sEMG signal and non-iterative methods," *Health Technol. (Berl.)*, 2019.
- [4] A. Furui *et al.*, "A myoelectric prosthetic hand with muscle synergy-based motion determination and impedance model-based biomimetic control," *Sci. Robot.*, vol. 4, no. 31, p. eaaw6339, 2019.
- [5] K. de O. A. De Moura and A. Balbinot, "Virtual sensor of surface electromyography in a new extensive fault-tolerant classification system," *Sensors (Switzerland)*, vol. 18, no. 5, 2018.
- [6] M. Atzori and H. Müller, "Control capabilities of myoelectric robotic prostheses by hand amputees: A scientific research and market overview," *Front. Syst. Neurosci.*, vol. 9, no. Nov, pp. 1–7, 2015.
- [7] D. Zhou, Y. Fang, J. Botzheim, N. Kubota, and H. Liu, "Bacterial Memetic Algorithm based Feature Selection for Surface EMG based Hand Motion Recognition in Long-term Use," in *The 2016 IEEE Symposium Series on Computational Intelligence*, 2016, pp. 1–7.
- [8] P. Gaur, R. B. Pachori, H. Wang, and G. Prasad, "A multi-class EEG-based BCI classification using multivariate empirical mode decomposition based filtering and Riemannian geometry," *Expert Syst. Appl.*, vol. 95, pp. 201–211, 2018.
- [9] P. Gaur, R. B. Pachori, H. Wang, and G. Prasad, "An Automatic Subject Specific Intrinsic Mode Function Selection for Enhancing Two-Class EEG based Motor Imagery-Brain Computer Interface," *IEEE Sens. J.*, vol. 14, no. 19, pp. 1–10, 2019.
- [10] P. Gaur, K. McCreadie, H. Wang, and G. Prasad, "Tangent Space Features-Based Transfer Learning Classification Model for Two-Class Motor Imagery Brain – Computer Interface," *Int. J. Neural Syst.*, vol. 29, no. 10, 2019.
- [11] A. Phinyomark, F. Quaine, S. Charbonnier, C. Serviere, F. Tarpin-Bernard, and Y. Laurillau, "EMG feature evaluation for improving myoelectric pattern recognition robustness," *Expert Syst. Appl.*, vol. 40, no. 12, pp. 4832–4840, 2013.
- [12] M. C. Tosin, M. Majolo, R. Chedid, V. H. Cene, G. W. Favieiro, and A. Balbinot, "SEMG feature selection and classification using SVM-RFE," in *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*, 2017.
- [13] Q. Zhang and K. Shi, "A study on multi-motion pattern recognition of EMG based on genetic algorithm," in *Proceedings of the 2012 2nd International Conference on Instrumentation and Measurement, Computer, Communication and Control, IMCCC 2012*, 2012, pp. 168–171.
- [14] M. Atzori *et al.*, "Electromyography data for non-invasive naturally-controlled robotic hand prostheses," *Sci. data*, vol. 1, pp. 1–13, 2014.
- [15] F. Riillo *et al.*, "Optimization of EMG-based hand gesture recognition: Supervised vs. unsupervised data preprocessing on healthy subjects and transradial amputees," *Biomed. Signal Process. Control*, 2014.
- [16] M. Ortiz-Catalan, R. Brånemark, and B. Häkansson, "BioPatRec: A modular research platform for the control of artificial limbs based on pattern recognition algorithms," *Source Code Biol. Med.*, vol. 8, 2013.
- [17] J. Yin, J. Hou, Z. She, C. Yang, and H. Yu, "Improving the Performance of SVM-RFE on Classification of Pancreatic Cancer Data," in *IEEE International Conference on Industrial Technology (ICIT)*, 2016, pp. 956–961.
- [18] J. D. Bagley, "The Behavior of Adaptive Systems Which Employ Genetic and Correlative Algorithms," *Universidade de Michigan*, 1967.
- [19] J. H. Holland, *Adaptation in Natural and Artificial Systems*. MIT Press, 1975.
- [20] G.-B. Huang, Q.-Y. Zhu, and C.-K. Siew, "Extreme Learning Machine: A New Learning Scheme of Feedforward Neural Networks," *Proc. Int. Jt. Conf. Neural Networks*, vol. 2, pp. 985–990, 2004.
- [21] W. Deng, Q. Zheng, and L. Chen, "Regularized Extreme Learning Machine," *2009 IEEE Symp. Comput. Intell. Data Min.*, no. 60825202, pp. 389–395, 2009.
- [22] G.-B. Huang, H. Zhou, X. Ding, and R. Zhang, "Extreme Learning Machine for Regression and Multiclass Classification," in *IEEE Transactions on Systems, Man, and Cybernetics - Part B: Cybernetics*, 2012, vol. 42, no. 2.
- [23] V. H. Cene, M. Tosin, J. Machado, and A. Balbinot, "Open database for accurate upper-limb intent detection using electromyography and reliable extreme learning machines," *Sensors (Switzerland)*, vol. 19, no. 8, 2019.