Conference Paper

Human Muscle State Machine Using Electromyography Classification with Machine Learning

George Lyssas[1,*], Konstantinos Mitsopoulos[1], Dimitris Zantzas[2], Anestis Kalfas[2] and Panagiotis D. Bamidis[1]

[1] Lab of Medical Physics & Digital Innovation, School of Medicine, Faculty of Health Sciences, Aristotle University of Thessaloniki (AUTH), Thessaloniki, Greece.
[2] Laboratory of Fluid Mechanics and Turbomachinery, Department of Mechanical Engineering, Aristotle University of Thessaloniki (AUTH), Thessaloniki, Greece.

[*] Corresponding Author Email: georgios.lyssas@gmail.com

ABSTRACT

This research aims to create a tool that can recognize the state of the human skeletal muscle from surface Electromyography (sEMG) signals. The goal of this muscle state machine is for use in the functional rehabilitation of people suffering from Spinal cord injury and for stroke survivors who have lost mobility in their upper body limbs. The use of machine learning techniques for the classification of these muscle states brought forth the need for database creation to train the generated ML model. For the data collection process, an experimental protocol was proposed, and tests were conducted in healthy individuals with a Nexus MKII medical device. Following the data collection, a signal analysis procedure was performed to extract features from the sEMG signals that directly relate to the muscle state. In addition to the signal analysis, a Machine Learning classification model was created to recognize and classify the sEMG signals in different states of the muscle. This classification had a high enough accuracy of producing the correct result, given that the training and sampling size of the database was considerably small provided that in similar cases of ML classifying models the size of the Databases includes way more samples than the one in this research. The future steps for this research are the creation of a more extensive and diverse database and using this model in real-time situations.

Keywords—*Electromyography, Machine learning, Signal classification.*

INTRODUCTION

People who suffer from Spinal Cord Injury or are stroke survivors experience a loss in their mobility as an aftereffect of their condition.[1] To combat these aftereffects, functional rehabilitation is used. In cases of movement loss, the activation of the muscles is not visible in most cases, this is a problem that is impacting rehabilitation practitioners and a solution needs to be proposed. In this research, a solution to this problem was explored with the creation of a Machine Learning model that is trained to recognize and categorize the Electromyography signals that are produced from the activation of the skeletal muscles. This model simulates a state machine of the human skeletal muscle and the states recognized were the state of no activation, the activation state, and the muscle fatigue state. These states were selected due to their high importance in the procedure of patient rehabilitation. To train the model for recognizing the muscle states an extensive database of electromyography signals must be produced.[2]

MATERIALS AND METHODS

In this research there were no open-source databases that were relevant to the recognition of the muscle states, therefore the creation of such a database was imminent. For the creation of a database, a measurement protocol was made and introduced in this research with the scope of measuring the states of the human skeletal muscle. This protocol targeted the muscles of the upper extremities specifically the bicep and triceps muscles of both arms as it is illustrated in Figures 1 and 2. The exercises introduced were a set of 10 isometric contractions of the muscle without any external weight for measuring the baseline activation of the muscle, a continuous maximum contraction of the muscle that was held for 10 seconds so that the maximum contraction signal could be measured and lastly, a set of isometric contractions with an external weight of 5 kg until the subject was unable to continue, which was the start of muscle fatigue. In the last set of exercises, the goal was to have an electromyography signal that included all the muscle states and the transition between those states. Those exercises were performed for both the bicep and tricep muscles of both arms of the subjects. The number of subjects that participated in this procedure was 20. 13 of which were male and 7 were female with a mean age of 27, and the subjects that were a part of this research were selected. The measurements were recorded by a Nexus MKII medical device, and the files of the measurements were later extracted for a signal processing sequence that created the final database for training the machine learning model.[3]

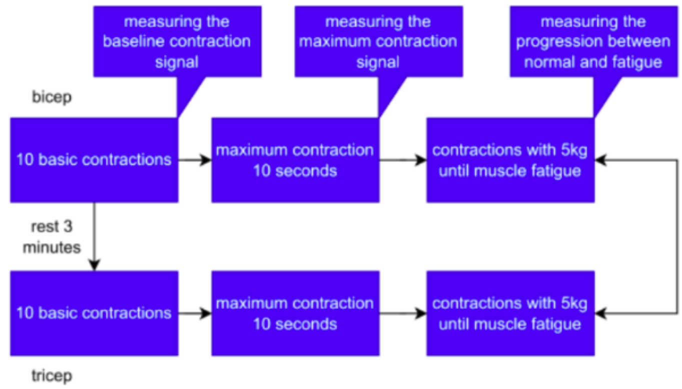

FIGURE 1. Measurement protocol.

FIGURE 2. Example of measurement.

After the extraction of the files of the measurements the procedure followed is shown in Figure 3, the timeline of the signal is in the form of a Raw-EMG signal, this form includes noise from the recording and measuring process and it is imminent to denoise the signal, for the features and the information of the signal to be clear and readable, the creation of the envelope of the signal was the result of

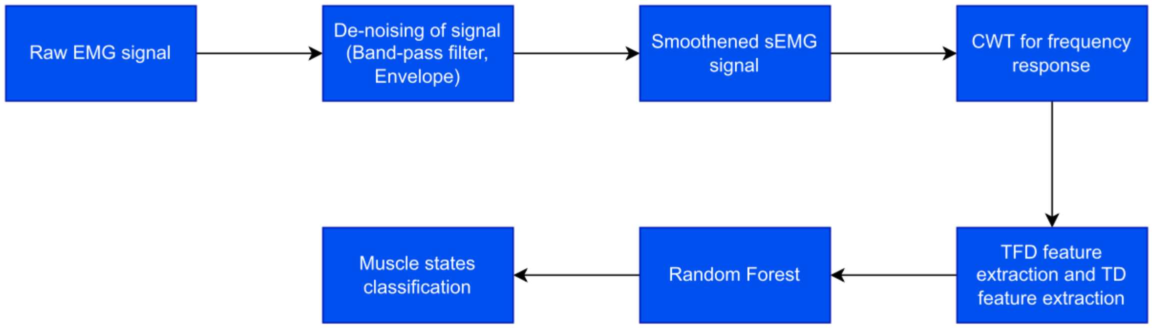

FIGURE 3. Signal analysis procedure.

the denoising procedure. Having completed the denoising procedure the signal was later separated into parts that contained an event in the timeline of the signal; those parts are referred to as epochs and are the data points of the database that was created. From the epochs created features of high importance to the classification of muscle states were extracted, those features were based on the time and frequency domain and parameters of the signal shape. Those parameters were the mean and median frequency, the mean Amplitude, the Hjorth Parameters (activity, mobility, complexity), the skewness and kurtosis of the signal, and also the Continuous Wavelet Transform of the epochs.[4–6] The features underwent a power analysis the results of which can be seen in Figure 4. All those features were later introduced to the Machine Learning model for the creation of the classifier (Figure 4).

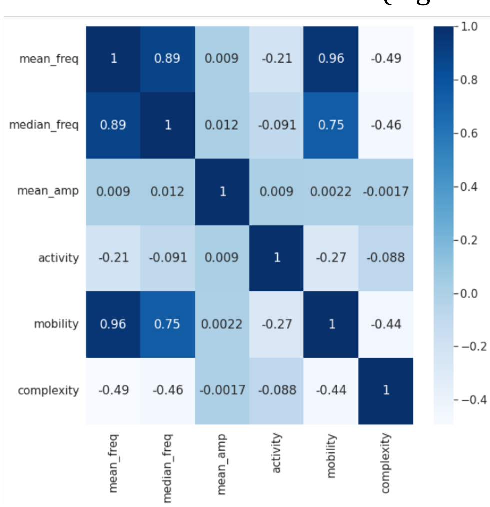

FIGURE 4. Signal features power analysis.

After the creation of the database three machine learning techniques were implemented and compared. The techniques used were a Random Forest classifier[7] model (a representation of a tree can be seen in Figure 5), an SVM model, and a Shallow Neural Network, which were created with Python programming language and with the use of the SciKit Learn and Tensorflow Keras libraries. Those models were trained with the created Database and their speed and reliability in their results were measured so that the optimal between the three models could be chosen as the Muscle state machine.[8]

RESULTS AND DISCUSSION

For the comparison between the efficiency and reliability of the machine learning models the use of metrics is the discerning factor between those models. The metrics that were used can be seen in Figure 6 where it is apparent that The Random Forest classifier model achieved the highest score among the other models.

DISCUSSION

In conclusion, the reliability and the adaptability of the Random Forest model is the best choice for the recognition and classification of EMG signals to muscle states, in this application with a small sample size. Although these results show that the Random Forest model is the best choice among the other models the effective database for the training of these models was quite limited and the accuracy with which those models recognize the muscle states is certainly influenced. This leads to the need for the creation of a completed and reliable Electromyography signals database to further encourage the use of ML in Biomedical applications.

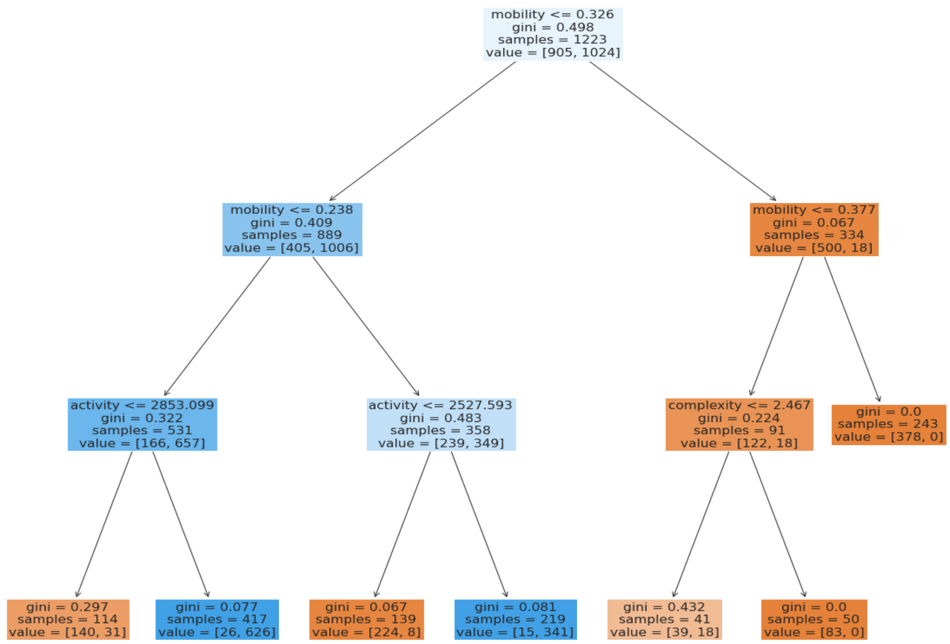

FIGURE 5. Visualization example of a random forest tree.

Metrics	Accuracy	F1-score	ROC-AUC	Precision Score	Recall Score
Random Forest (Training) [%]	91.3	92.4	0.908	89	96.12
Random Forest (Validation) [%]	84	89	0.7719	80.3	100
SVM (Polynomial) (Training) [%]	54	70	0.5	54	100
SVM (Polynomial) (Validation) [%]	50.4	70.7	0.5	55	100
SVM (Sigmoid) (Training) [%]	72	66.11	0.74	98	50
SVM (Sigmoid) (Validation) [%]	50.42	66.11	74.32	98	50
Shallow NN (Training) [%]	79.77	n/a	n/a	n/a	n/a
Shallow NN (Validation) [%]	77	80.88	76.92	76.16	86.22

FIGURE 6. Result of comparison with metrics (closer to 100% is better).

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