Comparison of Machine Learning Algorithms to Classify Hand Movements Recorded by sEMG Sensors

Tiago Lopes Rezende
ENSTA Paris
Palaiseau, France
Email: tiago.lopes@ensta-paris.fr

Frédéric Amiel
ISEP
Issy-les-Moulineaux, France
Email: frederic.amiel@isep.fr

Adam Wilheim
Myothesis
Issy-les-Moulineaux, France
Email: adam.wilheim@myothesis.com

Adriana Berger
Myothesis
Issy-les-Moulineaux, France
Email: adriana.berger@myothesis.com

Patricia Condes-Cespedes
ISEP
Issy-les-Moulineaux, France
Email: patricia.conde-cespedes@isep.fr

Maria Trocan
ISEP
Issy-les-Moulineaux, France
Email: maria.trocan@isep.fr

***Abstract*—This study explores several machine learning methodologies to effectively classify distinct hand gestures using data that were collected by a gauntlet embedded with multiple surface electromyography (sEMG) sensors placed to capture muscle activation patterns. Correlations between sensor data, filtering techniques, and a variety of machine learning algorithms are included in the analysis. These efforts had the goal of identifying approaches that could facilitate the development of a commercially viable device. By evaluating the classification accuracy and computational efficiency of each method during the validation phase, this study seeks to identify techniques for further refinement to be used in this kind of product.**

I. Introduction

The detection of body movements and signals is an area that is intensely researched due to the many possible applications it can provide, such as the control of different types of prostheses [1], as an interaction tool for machines or computational systems [2], or as a possible translator or teaching tool for sign languages [3].

The detection and classification of hand movements is a field that allows significant advancements and improvements to these types of applications, as well as the creation of new technologies and gadgets. A possible approach to the detection of hand gestures is the use of sEMG sensors, which can be placed in contact with the skin to detect voltage level changes caused by muscle contraction signals by placing those sensors near specific muscles. This could lead to the capture of the necessary information to feed machine learning methods with the purpose of classifying different hand movements. sEMG sensors are already in use to classify movements in the applications mentioned above and many others.[4].

The use of sEMG is a non-invasive technique that provides an optimal way to achieve these purposes, as it does not cause significant discomfort or inconvenience and essentially does not interfere with the user's natural movements. This makes it possible for people with disabilities or amputations to use, as it doesn't require the movement itself to detect the signals that coordinate the movements [5]. Additionally, it can be easily worn or removed if used in a device like a gauntlet, and can be comfortably and functionally used by different people. This versatility enables the creation of products incorporating this technology.

Many of the difficulties encountered in the development of movement recognition are attributed to the signal being very noisy [6]. This occurs because sensors receive interference from the electrical grid, other body signals—particularly from the heart—and various other sources [7]. Therefore, achieving accurate movement detection requires careful analysis of different types of filters.

Alongside this problem, the large amount of data creates challenges in implementing real-time applications of recognition or prediction algorithms. Today, there are already reliable implementations of gesture recognition systems [8], but faster and more reliable systems are always desired to build devices that could be transformed into products. This would allow the use of simpler and cheaper computational systems to enable the classification of movements.

This paper will analyze the potential of various machine learning techniques to assess their precision and the time taken to classify different hand gestures. The objective is to identify the most viable approaches for developing a system capable of recognizing hand movements in real time, which could be implemented as a practical product.

II. Data analysis and treatment

A. Data base

The data was collected by a bracelet composed of 12 sEMG sensors that measured the skin's voltage around the forearm. The bracelet is used in the center of the anterior forearm region, as shown in the Figure 1, where it can measure the voltage in the region of the muscles utilized in hand movements, such as the extensor carpi ulnaris, extensor digitorum, brachioradialis, flexor carpi radialis, palmaris longus, and flexor digitorum superficialis. The data is then read by a microcontroller as an analog signal and recorded on a computer. The sEMG sensors' sampling frequency was 2 kHz, and the data recorded for every movement repetition consists of the recorded voltage at the 12 points for 2 seconds, before, during, and after each movement.

Fig. 1. Bracelet position.

The data was collected using 4 units of this bracelet, worn by 39 different people. For this study, 4 different movements were analyzed: 'wrist extension', 'pronation', 'rest', and 'three', they are shown in the Figure 2. For the 'rest', the users were instructed to leave their elbows on the table and to keep their wrists elevated while keeping their hands in their natural resting position. Each movement was repeated 3 to 10 times by each person. All users were adults aged 19 to 61 years old, but the majority were heavily concentrated between 19 and 25 years old. All users, except for one, used the gauntlet on their right arm.

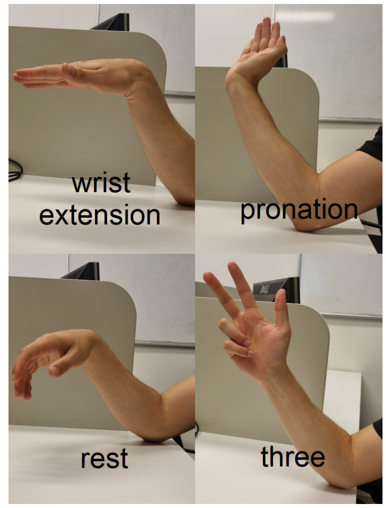

Fig. 2. Different movements.

B. Redundance in the data

The analysis of potential redundancies in the data is a crucial aspect, as it could lead to a reduction in the number of sensors and eliminate a portion of the data that will be processed by machine learning methods, as it was studied in [9]. It was believed that the data used in this work could present redundancies in the different sEMG sensors used. Since sensors that are near each other may detect the same, or a relevant proportion of, the voltage variation present in their neighbors sensors, it might be possible to retain the important information with a reduced number of sensors.To assess the importance of each sensor, the correlations between sensors were evaluated for each movement, and then averaged across all recordings of each movement type. The average matrix for each movement can be observed in the figures 3, 4, 5 and 6. The matrices reveal that there is not a strong correlation in the data collected by the different sensors for each observed movement.

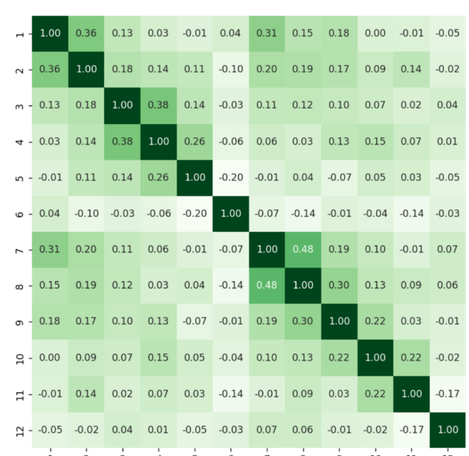

Fig. 3. Average correlation matrix for the movement "pronation".

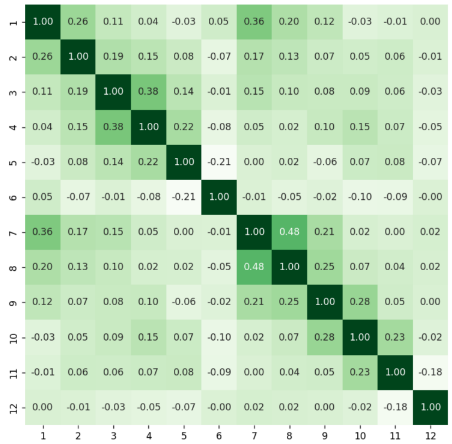

Fig. 4. Average correlation matrix for the movement ”rest”.

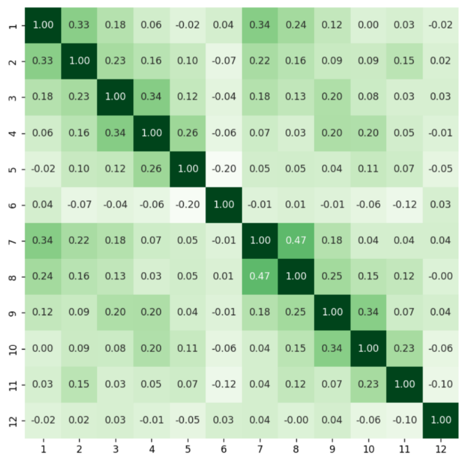

Fig. 5. Average correlation matrix for the movement ”three”.

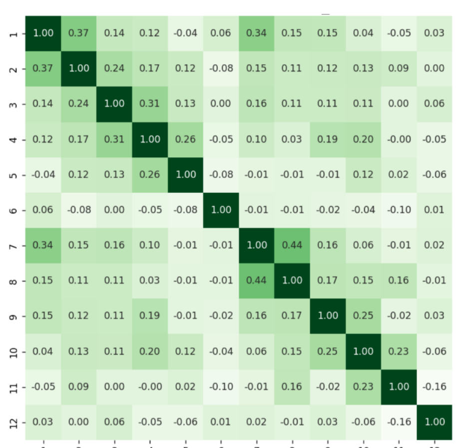

Fig. 6. Average correlation matrix for the movement ”wrist extension”.

C. Filtering

Different methods of filtering the data were analyzed, following those most commonly used by researchers. However, the chosen method to use in the data that would be feed to the machine learning methods was a 5th-order Butterworth band-pass filter, ranging from 100 Hz to 400 Hz, to eliminate the noise from the various sources previously mentioned. Additionally, after applying the Butterworth filter, only the absolute values of the data were considered to reduce the variance.

III. Machine learning methods

Four different machine learning methods are analyzed: SVC, Logistic Regression, Neural Network, and Gaussian Naive Bayes. They were all implemented using functions provided by the sklearn library. For all the models, the data was standardized to have an average of zero and a standard deviation of one, aiming to enhance the efficacy and convergence of the models.

For the SVC method, the gamma parameter was set to ’auto’, adjusting gamma to be inversely proportional to the number of features to fine-tune the model’s sensitivity. Additionally, the regularization parameter C was set to 10 to increase the penalty for misclassifications, aiming to improve generalization. All other configurations were kept as default.

In the Logistic Regression model, the inverse of the regularization strength parameter C was set to 10, indicating a stronger regularization to prevent overfitting. The maximum number of iterations was set to 1000 to ensure convergence of the optimization process.

For the Neural Network, the MLPClassifier function was employed with three hidden layers, each containing 200 neurons. The maximum number of iterations was set to 2000 to allow adequate training time for the model to converge and potentially enhance performance.

The Gaussian Naive Bayes model, in the sklearn library represented by the function GaussianNB, was utilized with its standard specifications, assuming a Gaussian distribution for the features and making the naive assumption of feature independence given the class.

The data was fed to the models as a single line composed of measurements from each sensor, organized sequentially one after another. The training and validation datasets were divided into 80% and 20% of the data, respectively. The individuals were separated such that some were used only for training, while others were used solely for validation.

IV. Results

The tables I, II, III, IV shows the results from the classification from diferents machine learning algorithimes and in the V the time it took to classifie the validation dataset.

TABLE I
SVM CLASSIFICATION REPORT

	precision	recall	f1-score	support
wrist extension	1.00	0.87	0.93	63
pronation	0.69	0.81	0.74	63
rest	0.92	0.90	0.91	63
three	0.82	0.79	0.81	63
accuracy			0.85	252
macro average	0.86	0.85	0.85	252
weighted average	0.86	0.85	0.85	252

TABLE II
LOGISTIC REGRESSION CLASSIFICATION REPORT

	precision	recall	f1-score	support
wrist extension	0.84	0.97	0.90	63
pronation	0.85	0.73	0.79	63
rest	0.92	0.89	0.90	63
three	0.78	0.79	0.79	63
accuracy			0.85	252
macro average	0.85	0.85	0.84	252
weighted average	0.85	0.85	0.84	252

TABLE III
NEURAL NETWORK CLASSIFICATION REPORT

	precision	recall	f1-score	support
wrist extension	0.87	0.97	0.92	63
pronation	0.84	0.92	0.88	63
rest	0.89	0.90	0.90	63
three	0.92	0.71	0.80	63
accuracy			0.88	252
macro average	0.88	0.88	0.87	252
weighted average	0.88	0.88	0.87	252

TABLE IV
NAIVE BAYES CLASSIFICATION REPORT

	precision	recall	f1-score	support
wrist extension	0.74	0.71	0.73	63
pronation	0.86	0.48	0.61	63
rest	0.55	0.90	0.68	63
three	0.35	0.29	0.31	63
accuracy			0.6	252
macro average	0.62	0.60	0.58	252
weighted average	0.62	0.60	0.58	252

TABLE V
THE TIME TAKEN BY EACH ALGORITHM

SVM	51.72613630000001 s
Logistic Regression	0.15876219999995556 s
Neural Network	0.20207809999999427 s
Naive Bayes	0.8029424000000063 s

The confusion matrices resulting from the different classification models are shown in the figure 7, 8, 9, 10.

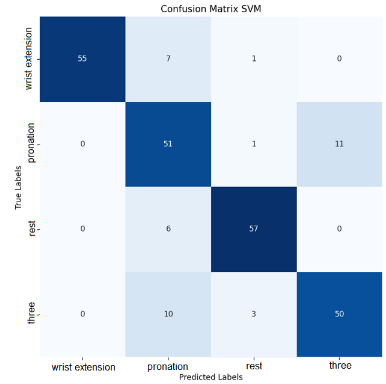

Fig. 7. confusion matrix SVM.

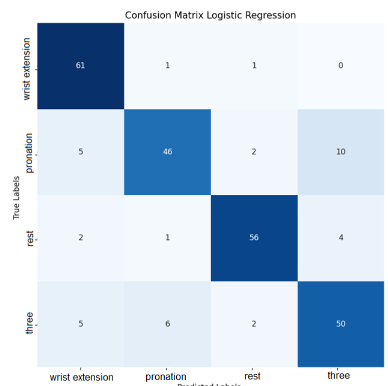

Fig. 8. confusion matrix logistic regression.

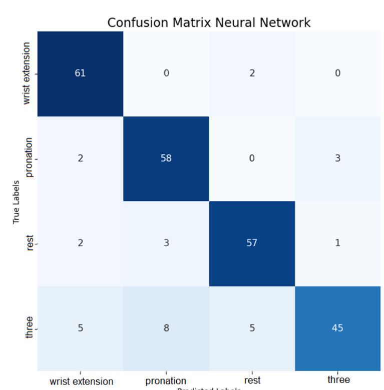

Fig. 9. confusion matrix neural network.

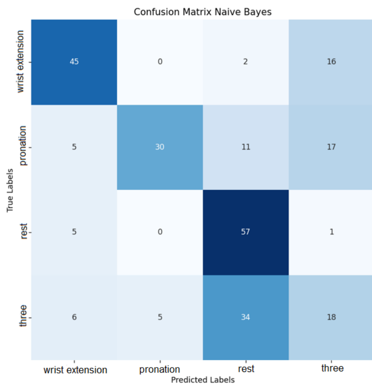

Fig. 10. confusion matrix naive bayes.

It is evident that the worst performing algorithm in terms of classification accuracy metrics is the Naive Bayes model, where two classes, 'three' and 'wrist pronation', had extremely low recall, which also led to poor precision in the other classes. Observing its confusion matrix, we can see that the movement 'three' was frequently misclassified by the algorithm as 'pronation' and 'wrist extension'. Some reasons that may explain the outstandingly poor classification performance of Gaussian Naive Bayes are the assumptions of independence of features, which is not true in this case, as there are relationships in the data collected for different types of movements. Another presumption is that the data would have characteristics with a normal distribution, which is also not true.

The other algorithms performed well for most classes, but it is important to note that the recall for the movement 'three' in the neural network and 'pronation' in logistic regression was somewhat bad. Meanwhile, the recall for 'three' in both the SVM and logistic regression models was marginally good.

In terms of classification time, considering that the validation stage involved classifying 252 movements, it is possible to affirm that, with the exception of SVM, the duration was short and could be considered suitable for real-time application. However, for the SVM, the time taken was significantly longer, and it would require substantial reduction to be viable for real-time application. Reducing the number of features to one reduced the validation time to 22.34663770000003 seconds, approximately a 40% decrease, however, the quality of the predictions was affected. A possible reason for the long time taken by the SVM classification is the Platt scaling used to convert scores into class probabilities. Dimensionality reduction techniques like PCA and ISOMAP were tested to try to reduce the time taken, but the quality of the predictions was affected.

V. Possible improvements

The development of a commercial product that classifies hand movements may require the recognition of a greater number of movements. The accuracy of the algorithm is reasonable for the number of movements studied in this article, but if this number is increased, the quality of the classification can be affected. Due to that, improvements would need to be implemented to enhance the classification. However, the time taken in the classification process should always remain an important factor.

To enhance the SVM model's ability to correctly classify the classes, the most evident approach is to use different hyperparameters. A higher C and gamma could improve the classification but could also lead to overfitting. However, the time was the biggest issue with this model, and different approaches to dimensionality reduction could help solve this issue. To combat the decrease in classification quality that the dimension reduction causes, a combination of dimensionality reduction methods with different hyperparameters could be effective. The same goes for logistic regression. It is also possible to try different hyperparameter configurations, which may lead to an increase in computation time and the risk of overfitting. Different regularization methods could also be tested to determine if they are more effective.

The neural network may be the algorithm with the most potential for improvement. Simply increasing the number of neurons, hidden layers, or learning rate could enhance classification accuracy, but employing more complex architectures, which is the most common approach for this type of classification today, could further improve the models. Long Short-Term Memory (LSTM) networks are widely used and can significantly increase classification accuracy, although they may also considerably increase the computational time required. The Naive Bayes algorithm has the least room for improvement since it classifies the data based on its proximity to the Gaussian distribution of the parameters. Therefore, changing the way data is captured and filtered could be a better approach.

VI. Conclusion

The analysis of different machine learning methods to classify hand gestures captured by sEMG sensors coupled in a gauntlet shows that, with the exception of the Naive Bayes method, the methods can classify the gestures with a precision that may be good enough to allow the generation of a viable product. Alongside this conclusion, there is the time analysis which, with the exception of the SVM method, shows that the time taken for the analysis is short, allowing possible real-time classification. Therefore, the algorithms with the most potential for real-time application are the Neural Network and the Logistic Regression. If the response time is not an issue, the SVC would be the most recommended one.

Acknowledgment

The authors would like to thank...

References

[1] C. Ferreira, L. P. Reis, and C. P. Santos, "Review of control strategies for lower limb prostheses," in *Robot 2015: Second Iberian Robotics Conference: Advances in Robotics, Volume 2*. Springer, 2016, pp. 209–220.

[2] R. Sharma, V. Pavlovic, and T. Huang, "Toward multimodal human-computer interface," *Proceedings of the IEEE*, vol. 86, no. 5, pp. 853–869, 1998.

[3] C. F. F. Costa, R. S. d. Souza, J. R. d. Santos, B. L. d. Santos, and M. G. F. Costa, "A fully automatic method for recognizing hand configurations of brazilian sign language," *Research on Biomedical Engineering*, vol. 33, no. 1, p. 78–89, Mar 2017. [Online]. Available: https://doi.org/10.1590/2446-4740.03816

[4] A. Sultana, F. Ahmed, and M. S. Alam, "A systematic review on surface electromyography-based classification system for identifying hand and finger movements," *Healthcare Analytics*, vol. 3, p. 100126, 2023. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2772442522000661

[5] N. Jarrassé, C. Nicol, A. Touillet, F. Richer, N. Martinet, J. Paysant, and J. B. de Graaf, "Classification of phantom finger, hand, wrist, and elbow voluntary gestures in transhumeral amputees with semg," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 25, no. 1, pp. 71–80, 2017.

[6] U. BAŞPINAR, V. Y. ŞENYÜREK, B. DOĞAN, and H. S. VAROL, "A comparative study of denoising semg signals," *Turkish Journal of Electrical Engineering and Computer Sciences*, vol. 23, no. 4, pp. 931–944, 2015.

[7] M. Boyer, L. Bouyer, J.-S. Roy, and A. Campeau-Lecours, "Reducing noise, artifacts and interference in single-channel emg signals: A review," *Sensors*, vol. 23, no. 6, 2023. [Online]. Available: https://www.mdpi.com/1424-8220/23/6/2927

[8] E. Kim, J. Shin, Y. Kwon, and B. Park, "Emg-based dynamic hand gesture recognition using edge ai for human–robot interaction," *Electronics*, vol. 12, no. 7, 2023. [Online]. Available: https://www.mdpi.com/2079-9292/12/7/1541

[9] P. Kang, J. Li, S. Jiang, and P. B. Shull, "Reduce system redundancy and optimize sensor disposition for emg–imu multimodal fusion human–machine interfaces with xai," *IEEE Transactions on Instrumentation and Measurement*, vol. 72, pp. 1–9, 2022.