Machine Learning-based Method to Label Signals from People with Neurological Injuries

João Pedro Moreto Lourenção
Postgraduate Program in Electrical Engineering and Industrial Informatics (CPGEI) – UTFPR-CT
jlourencao@alunos.utfpr.edu.br

André Eugênio Lazzaretti
Postgraduate Program in Electrical Engineering and Industrial Informatics (CPGEI) – UTFPR-CT
andrelazzaretti@gmail.com

Cristian Veggian Matias
Postgraduate Program in Electrical Engineering and Industrial Informatics (CPGEI) – UTFPR-CT
cristianveggian@gmail.com

María Verónica González Méndez
Postgraduate Program in Electrical Engineering and Industrial Informatics (CPGEI) – UTFPR-CT
mariaveronica@alunos.utfpr.edu.br

José Jair Alves Mendes Júnior
Postgraduate Program in Electrical Engineering and Industrial Informatics (CPGEI) – UTFPR-CT
jjjunior@utfpr.edu.br

ABSTRACT

Interfaces that use sEMG signals face the challenge of correctly identifying the signal while distinguishing it from noise or interference. Although classical techniques like visual inspection and machine learning methods exist, most studies focus on signals from healthy individuals. There is a lack of data and methods suitable for signals from individuals with neurological conditions, such as cerebral palsy and post-stroke. This study analyzes sEMG data from individuals with neurological injuries, using machine learning methods to identify muscle contractions and rest without pre-processing. The data were acquired from people with neurological diseases, such as cerebral palsy and post-stroke. They were extracted using sEMG from *triceps brachii* and *extensor carpi radialis* muscles. The signals were not preprocessed and were input as segmented time windows to three proposed classifiers: Support Vector Machine, Random Forest and an Ensemble Voting classifier. All three classifiers reached around 99% accuracy and F1-Score on typical sEMG data, but the results on abnormal data were inconclusive.

KEYWORDS

Onset Detection, Machine Learning, sEMG, Support Vector Machine, Random Forest

1 INTRODUCTION

Technological advancements and globalization have facilitated the development of Assistive Technology, which includes tools and strategies to enhance the autonomy and quality of life for individuals with disabilities [1]. Globally, 15% of the population has some form of disability [2], and in Brazil, 8.9% of individuals are affected, with 1.4% experiencing difficulties in manual tasks such as handling objects [3]. A 2021 study by *The Lancet Neurology*, in collaboration with the World Health Organization, reported that over three billion people worldwide live with neurological conditions, including stroke, neonatal encephalopathy, migraine, dementia, diabetic neuropathy, meningitis, epilepsy, autism spectrum disorder, and nervous system cancers [4].

The myoelectric signal (electromyography, EMG) is a synthetic behavior of compound action potentials (APs) generated by a series of motor units (MUs) being electrically or neurologically activated [5]. While myoelectric signals can be detected invasively using needle electrodes, this method could present some discomfort to the user during the acquisition [6]. Instead, an alternative way called surface electromyography (sEMG) allows the capture of the signals in surface skin, acquiring the signals generated by motor unit action potentials propagating through skeleton muscles [7]. It provides insights into the specific movements those muscles execute [8].

Taking as a reference people with neurological diseases, several assistive technologies are developed to aid in their needs [9, 10]. In some of them, sEMG signals are used to control activities, such as an interface that allows commands to be sent to everyday electronics such as a television, a radio, lamps [11], and even electrical stimulation to help them to perform activities of daily living. In this last case, there are some developments in interfaces that joint sEMG signals with the trigger of Functional Electric Stimulation pulses, targeted to a specific area of a muscle. These interfaces help people move limbs that are not often used by people with this condition to prevent muscle atrophy and provide more fluid and natural movements [12].

In the case of interfaces that work with the activation of the sEMG signals, there is a challenge in correctly identifying the sEMG signal as opposed to non-activation or noise or interference present in the signal itself [5]. The problem of correctly identifying the sEMG signal is not new, and there are several classic techniques and methods such as visual inspection (gold method), threshold-based, statistical, machine learning-based, among others. However, most cases focus on signals from databases of healthy people, without the presence of injuries or conditions such as cerebral palsy and post-stroke. Therefore, there is a gap both in the availability of data that can be used in studies and in methods that can be applied to signals from these individuals, which involve greater difficulty.

For instance, Gallon proposes a methodology for automatically detecting muscular activity by denoising, extracting features, and classifying healthy surface electromyography (sEMG) signals. Additionally, digital signal processing methods were applied before the machine learning algorithms were utilized [13]. Ghislieri et al. presents a novel approach for automatic muscle activity detection using long short-term memory (LSTM) recurrent neural network. They used simulated and real data both healthy individuals and patients affected by neurological or orthopedic pathologies, during walking tasks. The main difference is that it used and deep-learning algorithm, which is not the purpose of this study [14].

In this context, we present an analysis of surface electromyography data collected from individuals with neurological injuries in a hospital environment. This work aims to use signals from people with neurological conditions to observe the behavior of a machine learning-based method to label these signals and demarcate where muscle contractions and rest occur.

2 METHODS

In this section, the data acquisition protocol and the signal processing are presented.

2.1 Data Acquisition

The sEMG signals used in this work were acquired using the neural interface developed by [15], which consists of a neuro-orthosis that applies pulses of Functional Electrical Stimulation (FES) after the detection of muscle contraction. It is sensed by a sEMG sensor based on AD8232 integrated [16]. An ESP32 microcontroller was used as collection system, receiving and storing data on an SD card, with a sampling rate of 1 kHz. The data were acquired from the Health Complex Pequeno Cotolengo in people with neurological diseases. This project was approved from the Ethical Committee of Research of Human Being, number 55850722.2.0000.5231.

The data was collected from people with cerebral palsy or post-stroke. Some of them had all their limbs affected and others only some limbs. The signals obtained, shown on Table 1, were named Pre fist, Pre reach, Pre elbow, Post fist, Post reach and Post elbow, where the 'pre' term refers to the signals acquired before the use of the electrical stimulation and 'post' refers to the signals acquired after the electrical stimulus application.

Table 1: Data for each patient

Patient	Pre fist	Pre reach	Pre elbow	Post fist	Post reach	Post elbow	Total
P1	7	7	5	8	7	9	43
P3	1	1	1	1	1	1	5
P4	6	7	7	11	11	13	46
P5	2	0	4	5	0	2	13
P6	1	1	1	1	0	0	4
Total							111

The sEMG signals were acquired using bipolar electrodes in two different muscles: *triceps brachii* and *extensor carpi radialis*. The electrodes were placed in the volunteers as demonstrated in the Figure 1 and Figure 2. In both acquisitions, the reference electrode was placed on the bony protrusion of the elbow. For the *triceps brachii*, the electrodes were placed on two to three fingers above the reference electrode. To acquire the *extensor carpi radialis*, the electrodes were placed on the forearm, three fingers below the reference electrode.

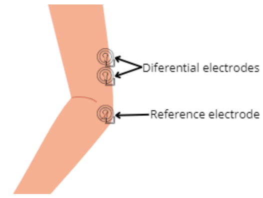


Figure 1: Positioning of electrodes to obtain the *triceps brachii* signals

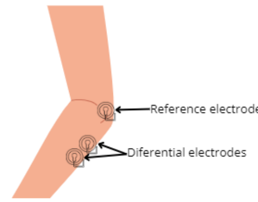


Figure 2: Positioning of electrodes to obtain the *extensor carpi radialis* signals

The data were acquired from three conditions: elbow evaluation, wrist evaluation, and reach evaluation. Moreover, they were collected in a functional activity, which consisted of volunteers reaching and grasping a bottle of water, placed 10 cm from the trunk region. For each condition, volunteers were asked to perform an activity for five seconds, rest, and then perform the same movement again for five seconds. In elbow evaluation, it was requested that the volunteer perform an elbow extension, where it was acquired the data from the *triceps brachii*. It was requested that the volunteer open the hand for wrist evaluation and for reach evaluation, it was requested to extend the arm as far as possible. In this lasts, both were acquired from the *extensor carpi radialis*.

Figure 3 shows a collected signal that has well-defined contraction and rest regions. This signal was collected from participant P3, from *triceps brachii*. It contains 45 seconds sampled at 1 kHz, which means 45000 samples.

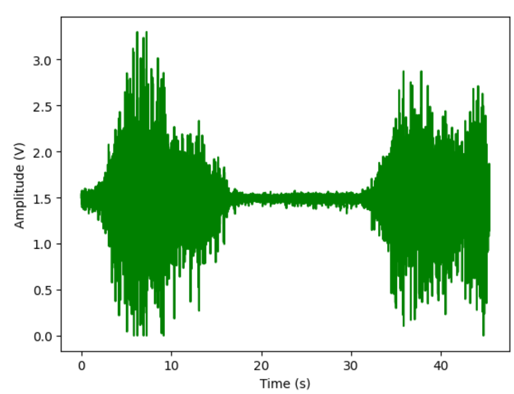


Figure 3: Signal with resting and contraction phases

2.2 Signal Processing

In this work, we propose a machine learning methodology for the segmentation and classification of sEMG signals of people with neurological conditions, employing a set of classifiers (ensemble) and separately evaluating the performances of Random Forest (RF) and Support Vector Machine (SVM). The main flow of the steps used in this work is presented in Figure 4.

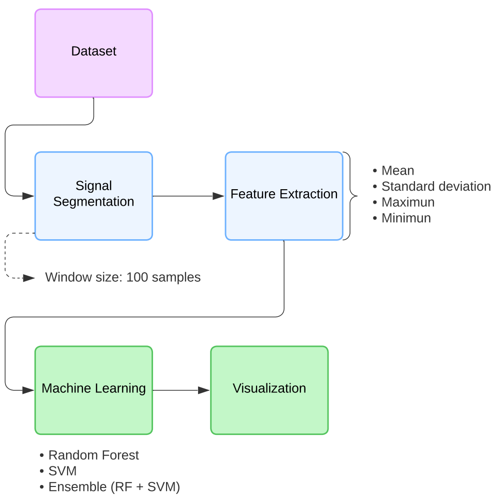


Figure 4: Operating flowchart

The data segmentation was made manually, setting the window size to 100 samples. In Figure 5 we can see the size of the window chosen close to the captured signal range, which means 0,1 s of the signal. For each signal window, statistical features were extracted to describe the signal properties. The features considered were mean, standard deviation, maximum value and minimum value, as they provide a simple but effective description of the signal fluctuations, which is crucial to distinguish between different classes of muscle activity (rest and contraction) [17].

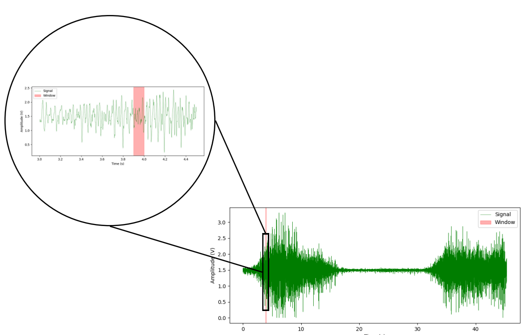


Figure 5: Window size close to the signal

The extracted features were normalized using MinMaxScaler to ensure consistency in the data scale. Subsequently, we used the K-means clustering algorithm to categorize the data into two distinct groups, corresponding to the resting and contraction states of the muscles. This initial clustering helps in identifying the phases of muscle activity in the sEMG signal.

The k-fold cross-validation was used to evaluate the performance of the machine learning models used in this study, allowing a robust validation and a reliable estimate of the generalization capacity. In the validation process, the data were divided into k subsets (in this case, 5), where, at each iteration, one subset was used as a test set and the other k-1 subsets were used for training. This approach was applied within Grid Search, which performs an exhaustive search for the best parameters of the Random Forest and SVM models, ensuring that the hyperparameter selection was performed efficiently and robustly. The use of k-fold cross-validation in Grid Search ensures that the model does not overfit the training data, providing an accurate assessment of the classifier performance, minimizing the risk of overfitting and allowing a fair comparison between the different parameter configurations.

We used two distinct classifiers for the analysis: Random Forest (RF) and Support Vector Machine (SVM) [18]. For both, we performed a grid search ("GridSearchCV") in order to optimize their hyperparameters, ensuring the best possible performance. Each classifier was evaluated individually to determine its effectiveness in the task of classifying sEMG signals.

To improve the performance of the classification model, we combined the Random Forest and SVM classifiers in an ensemble using a VotingClassifier. The ensemble was configured to perform a majority vote between the two models, where the final class of each signal window was determined by the most voted class. In tie situations, majority voting ensures that the tiebreaker is resolved consistently. In the specific case of a tie between variations of two models, VotingClassifier chooses the label that appears most frequently among the differences. This ensemble combined the strengths of both models, taking advantage of the robustness of Random Forest and the generalization capabilities of SVM.

The model performance was evaluated using three main metrics: accuracy, Jaccard index, and classification report. Accuracy was calculated as the proportion of correct classifications in relation to the total samples. The Jaccard index was used to assess the similarity between the predicted and true classes in the classification tasks, especially considering that the problem involves multiple classes and anomaly detection. The Jaccard index measures the intersection between the predicted and true classes, normalized by the union of these classes, and is given by the equation:

$$J(A,B) = \frac{|A \cap B|}{|A \cup B|} \tag{1}$$

where A represents the samples of a true class and B the samples of the predicted class. A higher Jaccard value indicates a greater similarity between the classes, and this metric was especially useful for evaluating the model's performance in the contraction and rest classes, which are the most common in sEMG signals. Furthermore, the Jaccard index provided a performance measure for the analysis of unbalanced classes.

The performance of the models was visualized through graphs, in which the original signal was plotted over time, with areas corresponding to rest and contraction highlighted in different colors. This visualization allowed a qualitative analysis of the effectiveness of the muscle activity states, facilitating the interpretation of the results and the identification of possible failures or areas of improvement.

3 RESULTS AND DISCUSSION

The sections of the signal labeled by the developed algorithms are colored following the colors below:

- Green: contraction;
- Blue: rest.

The output of the algorithm is a graph that has the sEMG signal with the areas painted according to their classification, as shown in Figure 6. In it, we can observe that there is a clear distinction between what is rest and what is contraction when the signal is well-defined. There is no large difference between the three approaches when the signal is in a typical state.

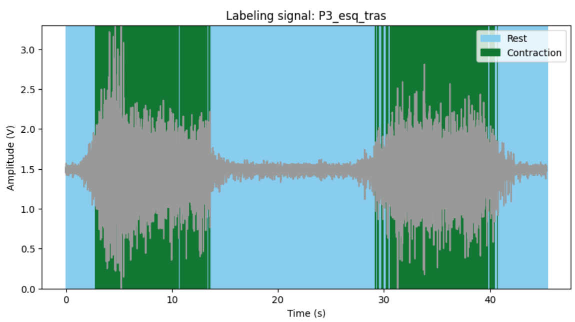


Figure 6: Output containing a labeled signal.

In addition to the machine learning-based method, an algorithm based on Detection of Transition On State (DTOS), which is the gold standard method, was developed to validate the visual inspection, using the signal energy. The thresholds were based on the mean energy and the standard deviation of the energy. An adaptive threshold is then defined by adding the mean energy to n (threshold_factor, in this case, 1,5) times the standard deviation. The algorithm runs through the list of energies and checks the first window where the energy exceeds the threshold. Figure 7 shows the result of the developed DTOS method. Analyzing the two images, we can observe that the moment of detection of the first muscle activation is very close, which corroborates the effectiveness of the developed model.

The times when the onsets were detected by both methods are also calculated. The developed machine learning method determined the onset for participant P3, shown on Figure 7, at 3,2 seconds and the DTOS method detected the onset at 3,3 seconds. With a difference of 0,1 seconds, we can see that the developed classifier is very close to what is considered the gold standard for onset detection. However, when we compare the developed method with visual inspection, Figure 8a, we observe that there is a considerable difference between them. While the developed method determined the onset in 3,2 seconds, visual inspection determined it in 1,58 seconds.

The same occurs for signals from participants P1 and P4. For the signal from P1, we obtained 1,8 seconds by the developed method, 1,91 s by the DTOS and 1,47 s for visual inspection, as explained in

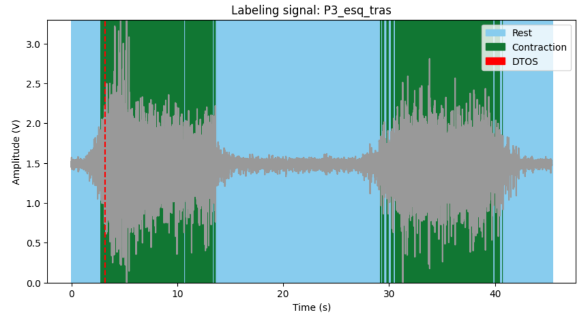


Figure 7: Onset detection using DTOS.

Figure 8b. From the signal from P4, we obtained 2 s by the developed method, 0,64 s by DTOS and 2,92 s by visual inspection, as identified in Figure 8c. In all these cases, the developed method was delayed in comparison with the visual inspection but had a better result than DTOS.

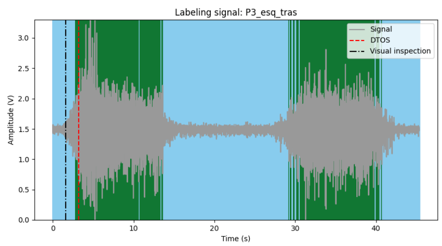
Comparing with a simple amplitude threshold algorithm, as we can see in Figure 9, the detection is close to the machine learning method developed and DTOS. However, in the case of the amplitude threshold we have to define the value of the threshold factor manually. Thus, the developed method determines the start without the need to define this factor manually, which prevents errors caused by an incorrect determination from occurring.

The developed methods were also evaluated regarding metrics such as confusion matrix, Average Accuracy, Average Precision, Average Recall, Average F1-score, Average Jaccard index. The confusion matrices, shown in Figure 10, are concerning the number of signal windows. We can notice that the SVM method confuses the two classes. When the ensemble is made, the confusion is greater when it predicts rest. However, there is a great agreement between Random Forest and SVM.

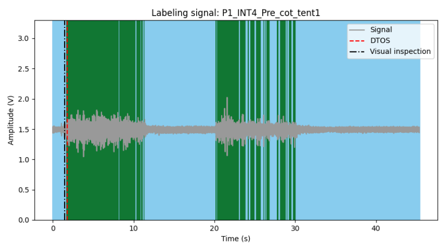
Regarding the other metrics, in Figure 11, we see that they are very close, being slightly lower in the SVM classifier. In fact, it is also in the SVM that we see the lowest Jaccard index, which indicates that there is less similarity between the set of predicted labels and the set of true labels. This ends up affecting the ensemble made with Random Forest, causing it to become more confused in determining the contraction.

Nevertheless, when the contraction is not so clear or there is some anomaly in the signal, the developed methods failed in the classification, as can be seen in Figure 12. In no case where there was any anomaly in the signals was the labeling done correctly, making it clear that this is a limitation of the work. It is then necessary to use anomaly detection methods in future work, to interpret an anomaly and not allow it to interfere with the classification of the rest of the signal, in addition to also labeling it. However, for the model, this type of signal - which contains anomalies - wasn't classified incorrectly, since the model understands that the anomaly is rest and everything above it is classified as a contraction. This can only be considered an error when using visual inspection to analyze the signal.

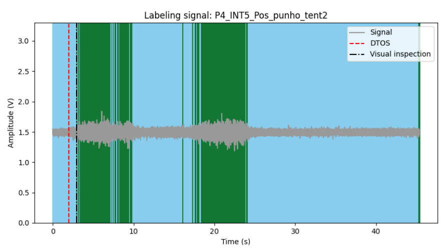
Comparing with similar works, Gallón et al. [13] proposed a methodology that utilizes the Discrete Wavelet Transform (DWT)



(a)



(b)



(c)

Figure 8: Visual inspection comparison with the developed method. In (a), the comparison for a signal from participant P3 is presented. The comparison for participant P1 is presented in (b). In (c), is presented the comparison for participant P4.

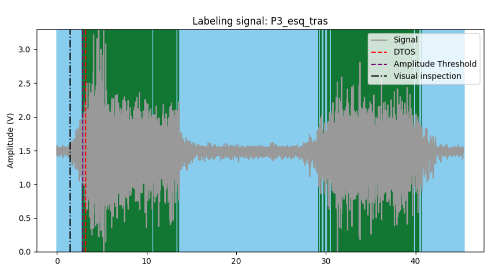
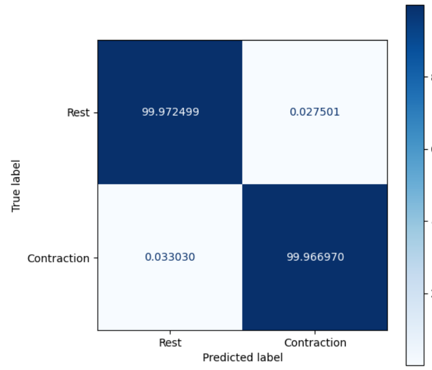
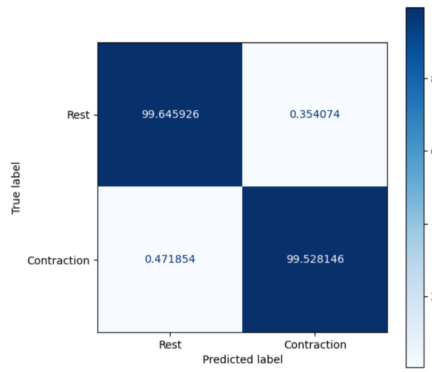


Figure 9: Onset detection using a simple amplitude threshold.

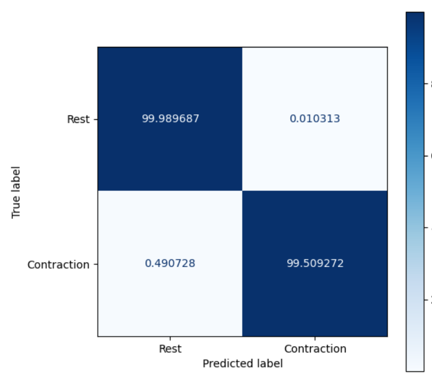
and Willison's Amplitude Algorithm (WAMP) for feature extraction. Five classification methods, including Neural Networks (NN), Classification Vector, XGBoost, Light Gradient Boosting Machine (LGBM), and ExtraTree, were evaluated using F-Measure, Precision,



(a)



(b)



(c)

Figure 10: Confusion matrices. In (a), the confusion matrix for Random Forest is presented. The confusion matrix for SVM is presented in (b). In (c), is presented the confusion matrix for the ensemble.

and Recall as performance metrics. In this case, they were not concerned with identifying anomalies, only with finding the activation time. The result was positive, managing to correctly determine when the contraction began and ended. The classifiers used and the preprocessing methods could be used in future works to improve the anomaly and contraction detection.

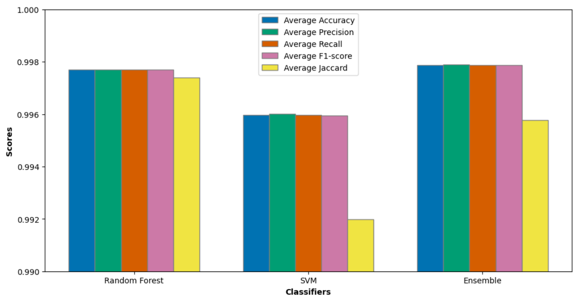


Figure 11: Performance Comparison of Classifiers

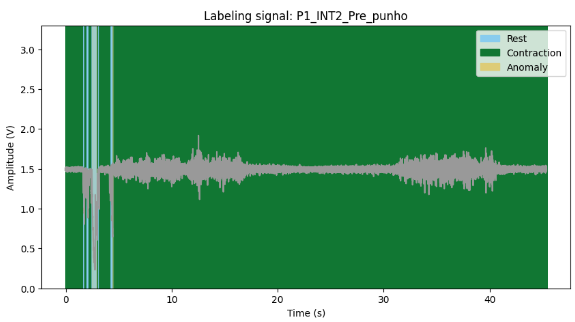


Figure 12: Labeled signal affected by an anomaly

In the work of Ghislieri et al., the authors tested several LSTM models directly on surface electromyography (sEMG) signals, without the need for feature extraction steps. The methodology involved dividing the datasets into training, validation, and test sets, and the evaluation of the model's performance was performed using metrics such as precision and recall. The main focus was on the accurate detection of muscle activation intervals, revealing an absolute bias of less than 6 ms in the identification of the activation start and end moments. The results demonstrated that the LSTM-MAD detector outperformed traditional methods, such as the Teager–Kaiser Energy Operator (TKEO) and the double-threshold statistical detector, suggesting that the approach can be a valuable tool for applications that require accurate recognition of muscle activity in noisy environments [14].

The main difference in this study is that, instead of performing onset detection on electromyography signals from healthy individuals, the detection was performed on signals from individuals with neurological injuries. While other studies focus on performing this analysis on healthy or even simulated signals, this study performed the analysis on sEMG signals affected by neurological injuries, collected from a rehabilitation project and with a real application, and achieved a good result in identifying contraction and rest signals. Even without performing filtering, rectification and linear envelope extraction, the methods were able to distinguish between the sections.

This provides valuable understanding for studies that require the evaluation of signals from people with neurological conditions. Furthermore, with improvements and enhancements, it can, for example, be integrated with MES-FES interfaces, in order to improve the onset of the application of functional electrical stimulation in rehabilitation applications.

Future applications include anomaly detection to avoid model confusion and testing the effectiveness of the model in an online embedded environment, collecting real data, and validating the application of this method working together with the neuro orthosis used in the initial collection of data used in this study.

4 CONCLUSION

This work used a dataset of surface EMG data collected in a health complex of people with neurological conditions. The objective was to find where there was a contraction and rest areas on those signals using machine learning algorithms. The developed method was compared to the gold standard Double Threshold Onset Detection (DTOS) and visual inspection to determine its precision. The muscle activity detection was successful when there is no anomaly on the signal analyzed. But, when there is an anomaly, the whole signal is mistaken either for contraction or rest.

In future work, hyperparameter adjustment and testing of different algorithms and classifiers will be highlighted topics to improve separation and reduce errors. In addition, including anomaly detection methods is essential, since when dealing with sEMG signals from people with neurological injuries, the signals are very susceptible to noise, electrode displacement and movement artifacts. This analysis will allow identifying and preventing these anomalies from interfering with the classification of the rest of the signal. Preprocessing the signals can help the methods to better differentiate what each thing is, including improving the detection of anomalies and preventing the entire signal from being confused with just one class.

Furthermore, this work proposes to make the data and algorithms developed available, to provide another type of analysis, in addition to being able to receive improvements. It is available at https://github.com/Joao-Pedro-ML/Machine-Learning-based-method-to-label-signals-from-people-with-neurological-injuries.git.

ACKNOWLEDGMENTS

The authors would like to thank CNPq - National Council for Scientific and Technological Development - for financial support.

REFERENCES

[1] E. N. Garcia and A. M. D. P Vieira. *Desafios Contemporâneos: O Uso da Tecnologia Assistiva Como Instrumento Facilitador da Aprendizagem.* 2018. doi: 10.37885/221211538.

[2] World Health Organization, The World Bank, and World Report on Disability. World report on disability, 2011. URL https://www.who.int/publications/i/item/world-report-on-disability. (accessed: 01.26.2024).

[3] Ministério dos Direitos Humanos e da Cidadania. O brasil tem cerca de 18,9 milhões de pessoas com deficiência, 2023. URL https://www.gov.br/mdh/pt-br/navegue-por-temas/pessoa-com-deficiencia/estatisticas.

[4] World Health Organization. Over 1 in 3 people affected by neurological conditions, the leading cause of illness and disability worldwide, mar 2024. URL https://www.who.int/news/item/14-03-2024-over-1-in-3-people-affected-by-neurological-conditions--the-leading-cause-of-illness-and-disability-worldwide.

[5] Dapeng Yang, Huajie Zhang, Yikun Gu, and Hong Liu. Accurate emg onset detection in pathological, weak and noisy myoelectric signals. *Biomedical Signal Processing and Control*, 33:306–315, 3 2017. ISSN 17468108. doi: 10.1016/j.bspc.2016.12.014.

[6] Manuela Besomi, Paul W. Hodges, Jaap Van Dieën, Richard G. Carson, Edward A. Clancy, Catherine Disselhorst-Klug, Aleš Holobar, François Hug, Matthew C. Kiernan, Madeleine Lowery, Kevin McGill, Roberto Merletti, Eric Perreault,

Karen Søgaard, Kylie Tucker, Thor Besier, Roger Enoka, Deborah Falla, Dario Farina, Simon Gandevia, John C. Rothwell, Bill Vicenzino, and Tim Wrigley. Consensus for experimental design in electromyography (cede) project: Electrode selection matrix. *Journal of Electromyography and Kinesiology*, 48:128–144, October 2019. ISSN 1050-6411. doi: 10.1016/j.jelekin.2019.07.008. URL http://dx.doi.org/10.1016/j.jelekin.2019.07.008.

[7] Lara McManus, Giuseppe De Vito, and Madeleine M. Lowery. Analysis and biophysics of surface emg for physiotherapists and kinesiologists: Toward a common language with rehabilitation engineers. *Frontiers in Neurology*, 11, 2020. ISSN 1664-2295. doi: 10.3389/fneur.2020.576729. URL https://www.frontiersin.org/journals/neurology/articles/10.3389/fneur.2020.576729.

[8] D. F. Lovely. *The Origins and Nature of the Myoelectric Signal*, pages 17–33. Springer Berlin Heidelberg, Berlin, Heidelberg, 2004. ISBN 978-3-642-18812-1. doi: 10.1007/978-3-642-18812-1_2. URL https://doi.org/10.1007/978-3-642-18812-1_2.

[9] Shefali Gupta, Chitvan Mishra, Pragya Katyayan, and Nisheeth Joshi. Assistive technology for neurological disorders. *SSRN Electronic Journal*, 2018. ISSN 1556-5068. doi: 10.2139/ssrn.3166499. URL http://dx.doi.org/10.2139/ssrn.3166499.

[10] Carlos Bandeira de Mello Monteiro, Helen Dawes, Nancy Mayo, Johnny Collett, and Fernando Henrique Magalhães. Assistive technology innovations in neurological conditions. *BioMed Research International*, 2021:1–2, February 2021. ISSN 2314-6133. doi: 10.1155/2021/6846120. URL http://dx.doi.org/10.1155/2021/6846120.

[11] Alexandre L.C. Bissoli, Mariana M. Sime, and Teodiano F. Bastos-Filho. Using semg, eog and vog to control an intelligent environment. *IFAC-PapersOnLine*, 49 (30):210–215, 2016. ISSN 2405-8963. doi: https://doi.org/10.1016/j.ifacol.2016.11.169. URL https://www.sciencedirect.com/science/article/pii/S2405896316326313. 4th IFAC Symposium on Telematics Applications TA 2016.

[12] C. Marquez-Chin and M. R. Popovic. Functional electrical stimulation therapy for restoration of motor function after spinal cord injury and stroke: a review. *BioMedical Engineering OnLine*, 19, 2020. URL https://api.semanticscholar.org/CorpusID:218873586.

[13] Valentina Mejía Gallón, Stirley Madrid Vélez, Juan Ramírez, and Freddy Bolaños. Comparison of machine learning algorithms and feature extraction techniques for the automatic detection of surface emg activation timing. *Biomedical Signal Processing and Control*, 94:106266, August 2024. ISSN 1746-8094. doi: 10.1016/j.bspc.2024.106266. URL http://dx.doi.org/10.1016/J.BSPC.2024.106266.

[14] Marco Ghislieri, Giacinto Luigi Cerone, Marco Knaflitz, and Valentina Agostini. Long short-term memory (lstm) recurrent neural network for muscle activity detection. *Journal of NeuroEngineering and Rehabilitation*, 18(1), October 2021. ISSN 1743-0003. doi: 10.1186/s12984-021-00945-w. URL http://dx.doi.org/10.1186/s12984-021-00945-w.

[15] Paulo Broniera Junior André Eugenio Lazzaretti Larissa Gomes Sartori Daniel Prado Campos, José Jair Alves Mendes Junior and Eddy Krueger. Non-invasive muscle-machine interface open source project: wearable hand myoelectrical orthosis (mes-fes). *Assistive Technology*, 0(0):1–10, 2024. doi: 10.1080/10400435.2024.2382857. URL https://doi.org/10.1080/10400435.2024.2382857. PMID: 39324974.

[16] José Mendes Júnior, Daniel Campos, Lorenzo Biassio, Pedro Passos, Paulo Júnior, André Lazzaretti, and Eddy Krueger. Ad8232 to biopotentials sensors: Open source project and benchmark. *Electronics*, 12:833, 02 2023. doi: 10.3390/electronics12040833.

[17] Sidi Mohamed Sid'El Moctar, Imad Rida, and Sofiane Boudaoud. Time-domain features for semg signal classification: A brief survey. *HAL Open Science*, 2023. https://hal.science/hal-04199535v1.

[18] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay. Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research*, 12:2825–2830, 2011.