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sEMG Signals Classification using CNN Features Extraction as a Reliable Method

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Abstract: sEMG (Surface electromyography) signals are essential in several applications, such as in prosthetic control. These signals are collected and analyzed to produce the expected actions through corresponding pattern recognition. In this sense, feature extraction plays a critical role in achieving good accuracy during the classification process. In recent years, with the interesting results obtained through convolutional filters and supervised learning, it is possible to extract properties that best distinguish and classify images. Therefore, this research work uses a CNN network to extract these features that will be later applied in conventional classifiers. The obtained results allowed to verify that the proposed methodology guarantees better results when compared to the works that use traditional characteristics for the classification process.

Resumo: Sinais sEMG (do inglês, *Surface electromyography* ou eletromiografia de superfície) são essenciais em diversas aplicações, tal como no controle de próteses. Esses sinais são coletados e analisados para produzir as ações esperadas por um reconhecimento de padrão correspondente. Sendo assim, a extração de características desempenha um papel crítico na obtenção de uma boa acurácia durante o processo de classificação. Nos últimos anos, com resultados interessantes obtidos através de filtros convolucionais e aprendizado supervisionado, tornou possível realizar a extração de propriedades que melhor distinguem e classificam imagens. Portanto, este trabalho de pesquisa utiliza uma rede neural convolucional para a extração de características de sEMG que posteriormente serão aplicadas em classificadores convencionais. Os resultados obtidos permitiram verificar que a metodologia proposta garantiu melhores valores de acurácia quando comparado aos trabalhos que utilizam características tradicionais para o processo de classificação.

Keywords: Convolutional Neural Networks; Feature Extraction; Machine Learning; Pattern Recognition; sEMG.

Palavras-chaves: Aprendizado de Máquina; Extração de características; Reconhecimento de padrões; Redes neurais convolucionais; sEMG.

1. INTRODUCTION

According to Phinyomark et al. (2020), electromyography (EMG) is the technique of measuring the electrical activity produced by muscles using electrodes on the surface of the skin or inserted in the muscle. Controlling prosthesis through the use of EMG signal is widely spread in recent years. Surface electromyography (sEMG) acquisition technique is essential in many applications, such as the controlling of prosthetic devices. The process happens in the following way. A person with some disability contracts a specific muscle and the nerve produces EMG signals, which are collected and analyzed to produce expected actions through pattern recognition methods, as stated by Li and Feng (2019). The obtained features are submitted to a dimensionality reduction and then classified by a machine learning algorithm, such as in Rabin et al. (2020).

The extraction of features is a way to distinguish each sEMG signal. Initially, this differentiation was made by analyzing features in the domain of time or frequency, as explained in the work of Phinyomark et al. (2012). After a few years, results were achieved by merging these two sources of characteristics, as shown in Pizzolato et al. (2017). The choice of which features to use is particularly important for success in classification.

The authors of Thiamchoo and Phukpattaranont (2019) stated that the classification of sEMG signals could be divided into four main stages: signal acquisition, feature extraction, pattern recognition or classifier modeling, and performance evaluation.

Regarding the extraction of characteristics, a large number of different methods are noted to recognize and classify sEMG signals. For instance, Sapsanis et al. (2013) used eight features in the time domain to classify six hand movements that were stored in a public database: Integrated Electromyagram (IEMG), Zero Crossing (ZC), Variance (VAR), Slope Sign Changes (SSC), Waveform Length (WL), Wilson Amplitude (WAMP), Kurtosis e Skewness. Gu et al. (2017) proposed a previous decomposition of the signal using the method called Empirical Mode Decomposition (EMD) to improve the accuracy values. After this pre-processing stage, the authors used the same extraction algorithms for the characteristics mentioned above. Finally, they reduced the size of the problem through Principal Component Analysis (PCA). Another work that analyzed this database was Ramírez-Martínez et al. (2019). The authors innovated by adding features in the time domain and a methodology called Burg Reflection Coefficients to obtain more information from the signals. However, given a large number of characteristics, the authors were concerned with implementing a way of selecting the most representative features of the signal so that it would not be considered redundant and irrelevant aspects that would harm the classification.

Luo et al. (2017) introduced, in its work's set of features, properties corresponding to the frequency domain as a way to improve its training accuracy. In addition to this new features, six properties in the time domain were also used (i.e., RMS, WL, VAR, ZC, SSC, IEMG, already mentioned), and two more new ones: Mean Absolute Value (MAV) and Mean Absolute value slope (MAVS). The signals were classified using a Multi-Layer Perceptron (MLP) Neural Network.

The work presented in Donati et al. (2019) classified three distinct signals by analyzing the spikes present in each one. Besides, they presented a structure based on Neural Networks and PCA to classify results in devices aiming at lower power consumption. There are eight sensor channels available in this database, and the authors chose only four to perform the classification. This decision can directly affect the results, since relevant information may be lost. The authors obtained an accuracy rate of 84% using the signals' peaks related features.

It is important to note that the number of features used to classify a signal does not always increase the classifier's accuracy. As an example, the work of Sharma and Gupta (2019) presented a study stating that the increase of the characteristics used in machine learning was favorable to the accuracy until the use of a certain amount of features. After that point, the results got worse when new features were added to the machine learning algorithm training. Therefore, given the number of characteristics and methods available to use, this abundance of possibilities can arise a problem that must be carefully managed when preparing an sEMG classifier.

In recent years, the Convolutional Neural Network (CNN) has surpassed many traditional methods in the field of machine learning. Some of the most interesting CNNs results were in works involving computer vision, as can be seen in Kim et al. (2016) and Cireşan et al. (2011). It is possible to extract features that self distinguish the best ones from convolutional filters and supervised learning. Such implementations for image classification can be seen in the works of Hong et al. (2017) and Aboutalib et al. (2018). Recently, CNN has also been used successfully in analyzing time signals. For example, to increase the robustness between different users, the work of Park and Lee (2016) developed a method of decoding the intention of the movement based on a Deep Learning model that uses characteristics of human biosignal electromyography. In Atzori et al. (2016), the authors obtained a satisfactory result using a simple Convolutional Neural Network. Therefore, CNN can be implemented for signals classification in general, eliminating the need to search for the best properties of sEMG.

Given this previous context, it is clear that a large number of well-known features can characterize a signal. The selection of the best set of features depends on many factors, as the type of movement or subject. The efforts in searching for the best problem-fitted characteristics can be a problem. A reliable method capable of analyzing the data and extracting the features that will better discriminate the EMGs signals effectively still stands as an ongoing problem.

1.1 Main Contributions

This research's main contribution is the development of a methodology capable of finding relevant characteristics in EMG signals without the need for careful search in algorithms that extract distinct properties from the signal. This work uses a Convolutional Neural Network to extract characteristics that will later be applied in conventional machine learning classifiers. Feature extraction methods currently used in the scientific literature were chosen to compare the results with the one achieved by using the method presented in this paper, proving the effectiveness of the proposed method. The database of this work is the same used by Donati et al. (2019) and consists of three hand movements with eight sensor channels. The other contributions can be summarized as follows:

- Increase in the accuracy value when compared to results found in the other work that uses the same database;
- The proposition of a robust methodology for extracting characteristics of sEMG signals in a more general way;
- Performance presentation of the features extracted under the influence of several conventional classification methods.

1.2 Work Organization

The remaining content of this paper is divided as follows. Section 2 details the methodology developed for extracting characteristics in sEMG signals, and it presents a brief explanation for each of the classifying methods. Section 3 shows the performed experiments with an appropriate discussion. The conclusions and ideas for future works are shown in Section 4.

2. PROPOSED METHODOLOGY

Figure 1 presents an overview of the proposed method. Initially, the signals presented in the database are sent to a feature extraction algorithm. In this work, a Convolutional Neural Network is applied to this pre-processing stage. Afterward, the results are passed through to some classical classification algorithms.

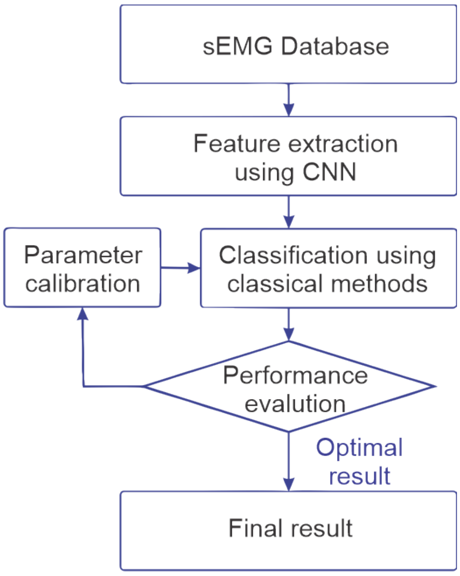
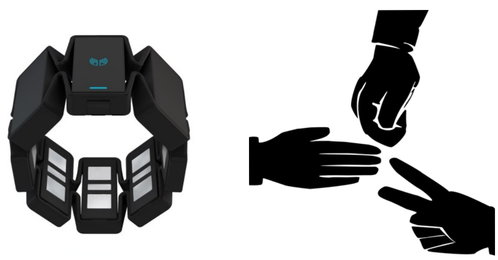


Figure 1. Flowchart of the proposed method.

2.1 Database

The database is composed of 45 samples (for each subject) collected by a Myo Armband (Figure 2(a)). For more details, the authors refer to Donati et al. (2019). This device is equipped with a set of 8 non-evasive sensors that involve the human arm to detect sEMG signals from the muscles. It is possible to send the acquired data to a remote device via wireless communication.

The acquisition protocol was applied to 10 able-bodied subjects (3 females and 7 males). Each of these people made three hand gesture movements called a stone, paper, and scissors (Roshambo game). The tests were divided into three sections. In each of them, the subjects performed five repetitions of each movement with a relaxation phase of 1 second. When a change in the type of movement is performed (stone, paper, or scissors), the defined rest was 2 seconds. Figure 2 details this database.



(a) (b)

Figure 2. Database details. (a) Myo armband. (b) Hand gestures.

The sensors set used to detect the sEMG can be seen in Figure 2(a) and the three gestures to be performed are illustrated in Figure 2(b).

2.2 Traditional Features

This research considered seven characteristics that were the reason for the good results in works already published in the literature: RMS, VAR, ZC, MAV, SSC, WL e IEMG. However, considering these seven characteristics together does not guarantee a high-accuracy classification. In the search for good results, it would be necessary to implement some method of choosing the most relevant features for the three-hand gestures. Also, as seen in Guo et al. (2015), characteristics may vary from subject to subject, increasing the level of complexity in choosing the best features.

The original signal was divided into windows, as shown in Sapsanis et al. (2013), with a window of 100 samples, where 20 samples are overlapping the others. Then, all methods of extracting features were applied to each of the partitioned signals. Then, the PCA reduction method was also applied to the vector that aggregates all features from all windows.

2.3 CNN used to Extract Features

The eight channels present in the sEMG signal of the studied database are treated in parallel in the CNN input structure. This network has convolutional filters that pass through the signal so that relevant attributes are highlighted. Subsequently, they will be analyzed by conventional classifiers. The processing gain of convolutional neural networks is observed in obtaining filters, which previously had to be implemented manually to be able to extract features. This pre-processing of filters' construction generally takes a lot of time, so CNN is responsible for learning which filters will best characterize the data in training LeCun et al. (1995). Given this situation, it is possible to replace the filters of a trained network by the traditional features in the classification of sEMG signals.

The gains of 2D filters are initialized randomly and they are updated using the Adam Kingma and Ba (2014) stochastic optimization algorithm. Note that max-pooling (MP) and dropout structures were considered in our network to avoid overfitting problems. In order to guarantee the treatment to process nonlinearities, activation functions were added between each layer *ReLU*. The implemented network structure can be seen in Figure 3.

The convergence of the system was considered from the minimum error value stagnation. After completing the training, we eliminate the structure after *Flatten* (the neurons). Note that in order to train the machine learning methods, all the signals from the training set are passed through the structure of the remaining network (before *flatten*), and then, the PCA is applied to observe only the first two components. Thus, the data is prepared to be trained and classified.

2.4 Traditional Classifiers

After extracting the signal features, it is necessary to apply the results obtained in the machine learning classifiers. In

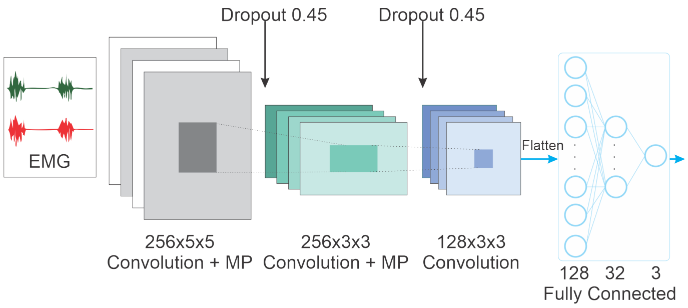


Figure 3. Structure of the implemented convolutional network.

this stage, conventional, simple, and consolidated methods in the literature were chosen. The first is called Support Vector Machine (SVM). SVM creates hyperplanes to delimit the different classes of the experiment and maximizes the distance among them to obtain better accuracy values (Cai et al. (2019)). Generally, SVMs work well with small training sets Raczko and Zagajewski (2017), such as the database in this article. The separation hyperplanes can be built in a linear (SVM-L) and non-linear (SVM-NL) way, depending on the complexity of the data.

Another Machine Learning algorithm used for classifications is the KNN (an acronym for K-Nearest Neighbors), which uses a defined metric that allows the classification of samples through comparisons with others that belong to the training set. The K parameter corresponds to the number of samples that the algorithm should consider close to the new sample that will be predicted. In some cases, it is superior to SVM in the sEMG classification, as seen in Bhusari et al. (2019).

This work also uses the machine learning algorithm called decision trees (D.T), which allows data to be treated more generally. The data's features are submitted to the rules that will guide the flow until the final's tree, where the classification will be predicted. The deepest the tree, the higher will be its probability to overfit the learning over the data. Note that a variant of the method, called Random Forest (R.F.), can be implemented to solve this problem. This algorithm adds random features in the construction of machine learning rules. Palermo et al. (2017) and Bian et al. (2017) proved that the Random Forest technique could be useful in classifying movements based on sEMG signals.

As seen in the introduction, MLPs can also be used to classify sEMG signal (Luo et al. (2017)). The inputs (i.e., neurons) of these networks correspond to the features that were obtained in the extraction process. Each neuron present in the posterior layers will be dependent on the sum of all the other neurons. In order that each neuron reacts to the different features, so that it is possible to classify the movement from the input, it is necessary to apply weights and activation functions during layer transitions. The weights are adjusted using an optimization algorithm implemented in the method. It should be noted that the classifications involving CNNs are formed by a feature extraction phase, characterized by convolutions, which will later be connected to a traditional MLP (second phase). In this research, the convolution phase was used to extract characteristics. Then, the operation was evaluated with several machine learning algorithms, including MLP.

Finally, there is the classification algorithm Naive Bayes (N.B.), whose simplicity and quickness makes its application viable in several works. The main characteristic of this method is the "naive" behavior of how each feature is treated, that is, for this machine learning algorithm, the obtained characteristics do not correlate with each other. The output of this classifier is a set of probabilities that indicates to which class the sample that was tested belongs. Thus, the sample that has the highest probability among all others is chosen. Jamaluddin et al. (2019) presented a work that classifies sEMG generated by muscle fatigue using the Naive Bayes algorithm.

In this work, all the presented methods were implemented through the Python programming language using the sickit-learn Pedregosa et al. (2011)) library. Besides, to evidence the good extraction of features from CNN, there was no concern in performing hyperparameter adjustments for each of the methods, that is, the default values from the library were used for each method of machine learning.

3. RESULTS AND DISCUSSIONS

To certify the results, 9 samples were separated from the 45 available for each subject to be the set of tests. The other 36 are the training and validation set, where applicable. The results were obtained through cross-validation, whose sets of validations and training were randomly shuffled in the proposed methodology.The mean accuracy value and the standard deviation of the classifications were calculated for all subjects. Figure 4 presents the results regarding the accuracy of the classifiers that use traditional features and the proposed methodology.

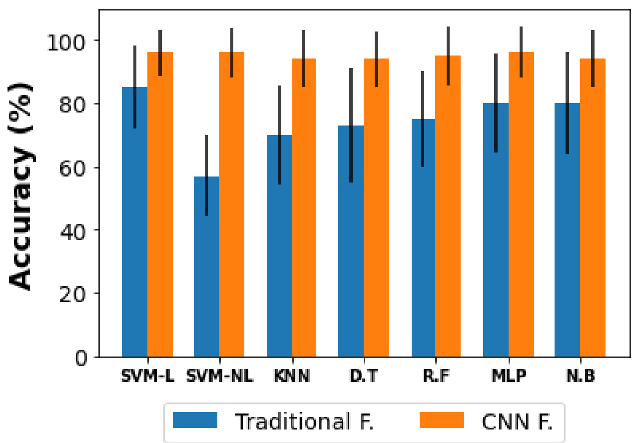


Figure 4. Average accuracy of all classifiers.

For the proposed methodology, it is noted the lowest average accuracy value among each of the machine learning algorithms, such as the smallest standard deviation. It is important to emphasize that the conventional approach should not be defined as worse than the one presented by this work when comparing the accuracy. However, the complexity and efforts in the search for characteristics that better discriminate the movements also tend to increase, requiring more specialist knowledge in solving the problem.

Another important point is the results of standard deviations since the database offers a few samples. Note that small variations in the number of correct classifications significantly change the accuracy. For example, considering that all samples in the test set were classified correctly, the accuracy is 100%. However, if only one sample receives the prediction erroneously, the accuracy in this situation drops to approximately 89%.

Figures 5 and 6 graphically represent the results for the classification using the non-linear SVM of the tests' set with the extraction of conventional features and the proposed methodology, respectively. It is noteworthy that both results presented in these figures correspond to the signals generated by the same subject.

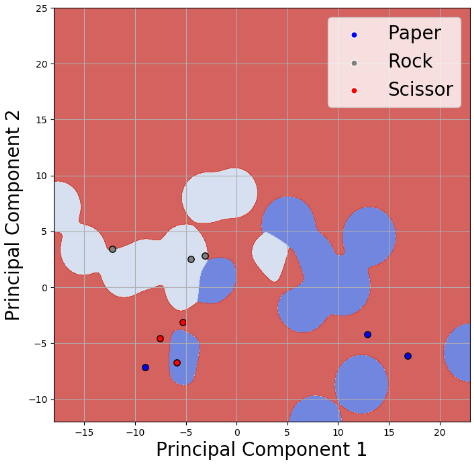


Figure 5. Classification using conventional features.

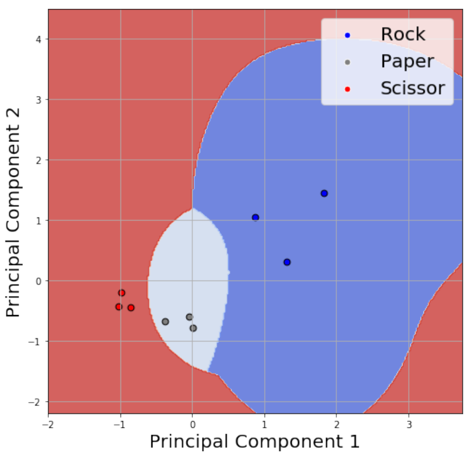


Figure 6. Classification Using CNN Features.

Note the higher incidence in the wrong areas of the test data in Figure 5 compared to Figure 6. The areas defined for each class can be seen at the figure's background and are generated by the training step of the machine learning algorithms. It is clear that the conventional features that were extracted are not very representative, since the areas present random and diffuse aspects, leading to an overfitting outcome. This result is shown by Figure 7.

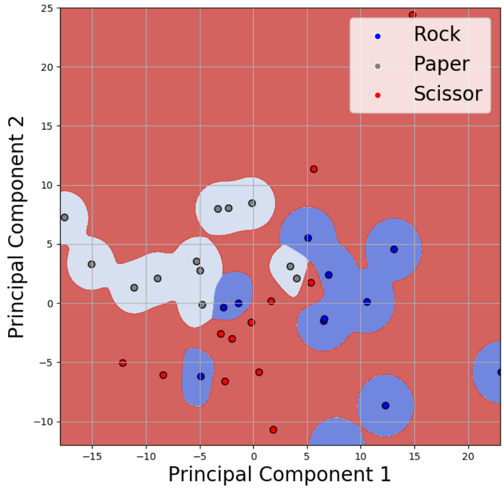


Figure 7. Training set classification.

Figures 8 and 9 show the classification of the non-linear SVM training set for two different subjects to demonstrate the effectiveness of the proposed methodology. It is possible to notice that the relevant characteristics of the first subject are not the same for another one. This comparison shows the main difficulty in defining fixed features for the classification of these sEMG signals. Therefore, based on these scenarios, CNNs become the best option, where the main feature is found in the extraction of the most relevant properties of each signal produced by the movement of each subject's hand.

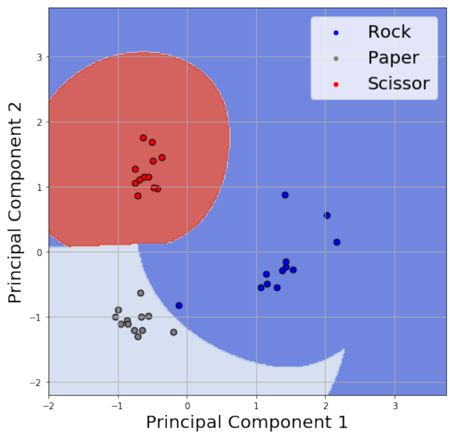


Figure 8. Training set classification (subject 4).

The values of Figure 4 are represented in Table 1, which is filled with standard deviations (STD) and the average accuracy for each of the classification algorithms: Conventional Features (Conventional-F) and the features extracted by the CNN (CNN-F).

Regarding the work that used this same database (Donati et al. (2019)), it was seen that the best result presented by the authors in the classification of movements was 84%. In the methodology proposed by this article, the worst value was observed by the KNN algorithm with a rate of 94.2%.

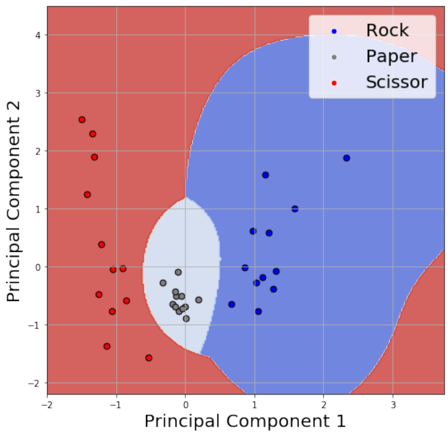


Figure 9. Training set classification (subject 8).

Table 1. Average accuracy and standard deviations.

	Conventional-F		CNN-F	
	Accuracy (%)	STD.	Accuracy (%)	STD.
SVM-L	0.856	0.132	0.962	0.072
SVM-NL	0.578	0.130	0.960	0.078
KNN	0.700	0.158	0.942	0.090
D. T.	0.731	0.182	0.948	0.089
R. F.	0.757	0.150	0.951	0.092
MLP	0.800	0.155	0.960	0.080
N. B.	0.800	0.163	0.944	0.090

4. CONCLUSIONS AND FUTURE WORK

The sEMG signal acquisition technique is essential in many applications. These signals are collected, processed, and analyzed to be interpreted for different functions. A pattern recognition algorithm is used, which is responsible for classifying the movement performed. Note that a large amount of data characterizes a movement, so to be able to discriminate each signal, we must extract characteristics. The choice of extracting features is particularly important for successful classification. Recently, CNN networks have outperformed most traditional machine learning methods, and have been used successfully in the analysis of temporal signals.

Therefore, this research work presented a robust methodology for extracting features from sEMG signals. After the extraction process, the obtained results are applied in conventional and simple classifiers consolidated in the literature. Note that the development of this methodology allows us to find characteristics in the sEMG without a deeper search in algorithms that extract properties that will distinguish the signals. Besides, it was possible to observe that the use of convolutional networks for this application obtained better results compared to classifiers that use traditional features.

As future works, the authors intend to apply the feature extraction methodology in other databases. It is also intended to merge the characteristics found by the CNN network with traditional features, seeking to improve data classification.

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