Gesture Recognition via Estimation of Information Exchange between Muscles

Alicia Falcon-Caro and Saeid Sanei
Department of Computer Science
Nottingham Trent University
Nottingham, UK

Abstract—**A new approach based on exploitation of the information exchanged by human muscles is proposed for recognition of the resulting hand gesture. Such information can be realized through estimation of the causality between the multichannel surface electromyography (sEMG) signals over short signal windows. These measures can then be classified effectively not only to accurately identify the hand gesture but also to study the human motion dynamics, which can be effectively used for rehabilitation purposes. In our experiment, we see that this approach can achieve an overall classification accuracy as high as 90.3% even with a small data size, which can be hardly achieved by traditional methods with the same classifiers.**

Index Terms—**Causality, directed transfer function, electromyography, gesture recognition, hand gestures.**

I. Introduction

Surface electromyography (sEMG) is a non-invasive technique used to record the electrical activity of the muscles and nerves when a motor movement is performed. This allows researchers to study the myoelectric output of muscles and investigate on the identification of individual motor units (MUs). Electromyography signals (sEMGs) have been extensively used in the rehabilitation field for different purposes [1]–[4] and, in recent years, its use in the development and improvement of prosthetic limbs has extensively increased [5]–[7]. Although the use of other biological signals, such as electroencephalograms (EEGs), to control prostheses has been investigated [8], [9], so far sEMGs seem to provide the highest accuracy while having the lowest computational cost for the system and risks for the prosthetic user. sEMGs have also been used in the implementation of human-machine interfaces (HMIs) [10], [11]. However, its use in HMI applications is limited since sEMGs are non-stationary and highly affected by individual differences and external factors, making it difficult for an HMI to easily adapt to multiple subjects while maintaining a high gesture recognition accuracy. This is one of the main challenges that researchers are facing when implementing sEMG-based systems [12], [13].

Gesture recognition is a subset of gait analysis traditionally performed using either vision-based [14] or sensor-based [15] (mainly with the use of accelerometers [16]) methods. Most of these methods rely on the study of muscle activation time during motor activity and techniques that study the amplitude of the EMGs for each gesture, signal processing techniques, signal representation and modeling techniques, and time-frequency features studies [17]. Although these techniques have been able to obtain some good classification accuracy, none of them allows the study of the human motion dynamics. Moreover, they require a high number of data points in order to obtain a good accuracy. Collecting datasets with such amount of data can be tedious, time consuming and hard to achieve. Therefore, having to rely on a big enough dataset for these techniques to give a good classification accuracy can also be considered another challenge in the use of sEMG to control prostheses and in the development of HMIs, particularly for data-driven classification methods. To overcome these challenges, we propose to estimate the causalities between the channels of a multichannel sEMG and use them as the feature vector for our classifier.

Information flow studies that analyse the information exchanged between different regions of the human brain have been extensively used when analysing biological signals such as electroencephalography (EEG) [18], [19] or magnetoencephalography (MEG) [20]. However, its use in the analysis of sEMGs is still very limited. Although some information flow analysis has been previously applied to sEMGs to classify muscular disorders [21], [22], an information flow analysis between the muscles has never been used as the feature vector for hand gesture classification thanks to multichannel EMG recordings. The new technique presented in this paper is used to extract the individual characteristics of multiple hand gestures. These characteristics allow us to investigate the dynamic of the gestures and are used as the feature vector for our classification model. This method results in a higher classification accuracy, even with a lower number of subjects, than those achievable by other gesture recognition methods.

The main contributions of this paper are: (1) application of information exchanged between human muscles for hand gestures classification; (2) development of a method that allows us to investigate the human motion dynamics; (3) accurate gesture classification model less affected by individual differences.

The following sections explain how the information flow between a set of human muscles is estimated and used as the feature vector for a classification model in order to decode a set of hand gestures. The publicly available putEMG dataset [13] is used to validate our method.

979-8-3503-3959-8/23/$31.00 ©2023 IEEE

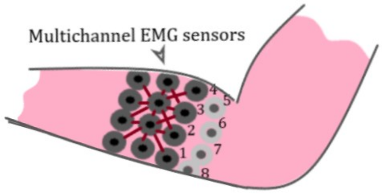

Fig. 1. A set of sEMG electrodes distributed around and along the forearm. The red, thick lines connecting some of the electrodes represent the network formed between the sEMGs.

II. Methodology

Our proposed model relies on the estimation of features which best describe the information exchanged between a set of muscles which generate the hand gestures.

Information flow analysis via estimation of mutual information has been used to study the dynamics of connections between different nodes of a connected network. In this analysis, the aim is to evaluate the causal relation between those nodes. This information flow can be estimated from a multivariate autoregressive (MVAR) model of temporally correlated time series. A number of techniques have already been developed to evaluate such MVAR-based causality, such as the directed transfer function (DTF) [23], [24].

Here, we propose the use of a connected network where each node k of the network is represented by each sEMG electrode, as shown in Fig. 1. When a motor movement is performed, a set of muscles need to work in synchrony and in a specific order to perform the movement. During such movement, the information is exchanged between the nodes of the network depending on the dynamic of the gesture being performed. We use DTF to evaluate the information exchanged between the set of sEMGs at different time instants t during the completion of each gesture. This allows us to define each gesture based on the information exchanged between the muscles, resulting in a set of parameters that can characterise the gesture less affected by differences between the subjects.

In order to perform the information exchanged evaluation, given N sEMG signals, which can be considered as channels, consider a multichannel MVAR model of the form:

$$\mathbf{x}_t = \sum_{m=1}^{p} \mathbf{A}_m \mathbf{x}_{t-m} + \mathbf{e}_t \tag{1}$$

where $\mathbf{x}_t = [x_1(t), x_2(t), ...x_N(t)]$ is the vector of sEMG k-channel process, p denotes the model order, $\mathbf{A}_m$ is an $N \times N$ matrix containing the time-varying coefficients of the model and $\mathbf{e}_t$ is the multivariate error vector at time instant t.

We transform this equation to the frequency domain and obtain the transfer matrix of the system which describes the model between the sEMGs in the frequency domain in the form [25]:

$$H(f) = \left[\sum_{m=0}^{p} \mathbf{A}_m e^{-j2\pi f \Delta_t} \right]^{-1} \tag{2}$$

where Δ_t is the sampling interval.

Given the transfer function of the MVAR model, we obtain the normalised DTF (between [0 1]) as [26]:

$$DTF^2_{k \to l}(f) = \frac{|H_{l,k}(f)|^2}{\sum_{q=1}^{N} |H_{q,k}(f)|^2} \tag{3}$$

DTF allows us to estimate the casual influence of each channel k on another channel l in the frequency domain. The output of this equation is an $N \times N$ matrix containing the normalised mutual influences. These parameters are then used to classify each gesture.

Gesture recognition process contains three main steps: preprocessing, feature extraction, and classification.

A. Preprocessing

The raw sEMG signals are preprocessed by applying an appropriate bandpass filtering, rectification and smoothing to remove noise. Then, the signals are segmented into fixed-length overlapping windows. The length of the window depends on the duration of the gestures segmented to a limited number of windows.

Some of the latest gesture recognition techniques, particularly deep learning-based methods such as convolutional neural networks (CNNs), require to apply data augmentation techniques during the preprocessing of the signals for the good performance of the method. However, the use of data augmentation increases the computational cost and involves some possible issues that could affect the accuracy and reliability of the model. Nonetheless, our proposed gesture recognition technique can obtain a good performance even without the use of data augmentation.

B. Feature extraction

Once the preprocessed segmented signals are obtained, the causality coefficients are calculated. For each signal window, the MVAR model as in (1) is calculated. Then, the obtained MVAR coefficients are applied to (2) and (3) to obtain an $N \times N \times f$ matrix containing the DTF coefficients for each signal window, where N represents the number of signals and f the frequency points. The average over f is calculated to reduce the dimensionality of the matrix, obtaining an $N \times N$ matrix for each signal window.

C. Classification

A number of classifiers have been proven to give good results for EMG applications, such as artificial neural networks (ANN), fuzzy classifiers, linear discriminant analysis (LDA), support vector machines (SVM) and decision trees [11]. The previously obtained $N \times N$ DTF matrix for each signal window is applied as input for the chosen classifier.

III. Experiments

In this section, we make best use of causality-related features to classify a set of hand gestures. We used the publicly available putEMG dataset. This dataset contains data from two experiments, one for hand gestures and another for a force

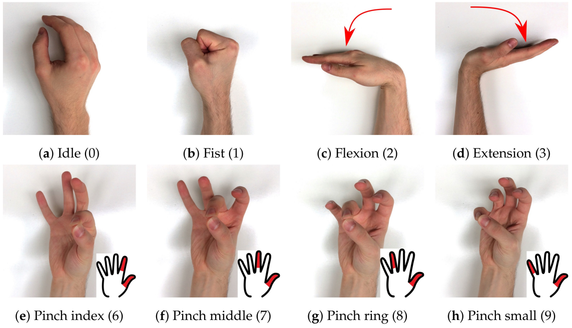

Fig. 2. Representation of the set of hand gestures contained in the analysed putEMG dataset. The figure is taken from [13].

experiment. Only the hand gestures data is used in this paper. The hand gestures recorded in this dataset are: relax, idle, fist, flexion, extension, pinch thumb-index, pinch thumb-middle, pinch thumb-ring and pinch thumb-small, as shown in Fig. 2. The dataset contains three different sessions for each subject: a long repetition sequence, a short repetition sequence and a sequential repetition sequence. Each subject performed each session twice. The data from 44 subjects were obtained for this dataset. The sEMGs were recorded from 24 electrodes located around the subject forearm using three elastic bands at a sampling rate of 1520 Hz (for more information on the dataset, refer to [13]). The location of the electrodes favors the creation of our sEMG network, forming a similar network to the one depicted in Fig. 1.

In this paper, three datasets are analysed using the proposed gesture recognition technique: one set containing data from 2 subjects, one from 10 subjects and one from 30 subjects. The three datasets have been preprocessed and analyzed using the same techniques.

Preprocessing: We lowpass filtered the data at 50 Hz and downsampled them by a factor of 3. The segments associated with relax or idle time, where the subjects were asked to move the hand freely or not move it at all, were removed from the signals. This is mainly because they cannot be recognised as an specific gesture and may, therefore, be considered as noise. Fig. 3 shows a preview of the masked signals of the first subject before and after preprocessing.

Feature extraction: In order to study the dynamics of each hand gesture, a window of 0.5s with a 25% overlap slides over the signals. For each signal window, the MVAR model is calculated with the help of ARfit [27] and BioSig [28] toolboxes. The optimum MVAR model order is estimated applying the Schwarz-Bayesian criterion [29]. Then, the steps defined in II-B are followed to obtain the feature vector for our model.

Classification: To assess the performance of our proposed feature extraction technique, we selected three different relatively low computational classifiers that usually have a good performance for sEMG hand gesture recognition: a weighted K-nearest neighbor (KNN) with 10 neighbors [30], a kernel SVM [31], and a CNN with three fully connected layers, each with 10 neighbors, with ReLU as the activation function [32].

The results obtained for the above three classifiers for each dataset are given and explained in section IV.

IV. Results

In this section, we present the results of applying the above classifiers to the causality features for three datasets: one containing data from 2 subjects (a.k.a dataset 1), one from 10 subjects (a.k.a dataset 2) and one from 30 subjects (a.k.a dataset 3).

To better validate and compare our proposed approach against other low computational cost gesture recognition techniques, the same datasets are also analyzed applying the same preprocessing and classification techniques, which means that no data augmentation is applied to maintain the low computational cost. In order to still obtain some reasonably acceptable results when using the competing method, the mean absolute value (MAV), which is still currently one of the predominant feature extraction techniques for sEMG-based gesture recognition, is used as the feature extraction technique for the competing method to obtain the feature vector used for the classifiers.

To assess the classification accuracy of each feature extraction followed by classification approach, the following equation is used to obtain the percentage of positive predictive values (PPV) for each hand gesture:

$$PPV(\%) = \frac{TP}{TP + FP} \times 100 \quad (4)$$

where TP represents the number of true positives and FP represents the number of false positives.

Table I shows the accuracy obtained for each hand gesture for each dataset for the two feature extraction techniques (the proposed method based on DTF and the competing method that uses MAV) during the testing of the classification systems. The overall accuracy of the systems during the training and testing, calculated using (4), is also included. As expected, the accuracy for both systems decreases for the second and third datasets as compared to the first dataset, and increases again for the third dataset with respect to the second dataset. Given the small amount of data used for the first dataset, there is a possibility that the good classification performance obtained for this dataset is due to a high similarity between the data used for the training and testing of the system. The second and third datasets however, contain data from several subjects instead of only two, avoiding such similarity. Given this, the results still show that our proposed feature extraction technique leads to a higher classification accuracy in overall than the competing feature extraction technique while using the same classifiers. Results also show that our proposed approach provides considerably better results even when used over a small number of subjects, even for some of the hard to classify hand gestures such as individual finger movements.

Other papers have shown considerable similar results to the ones obtained for our proposed method when analyzing a dataset of similar or bigger size as the third dataset analyzed in

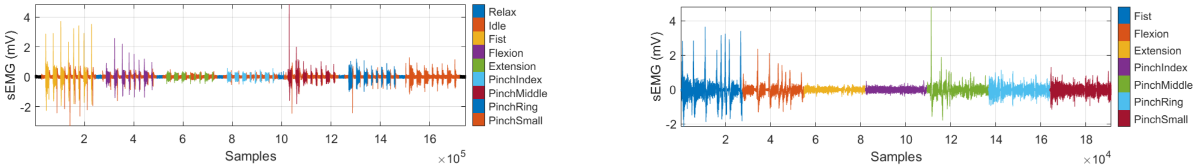

Fig. 3. Masked representation of the sEMGs of the first subject recorded during the long sequence session. (a) before preprocessing and (b) after preprocessing.

TABLE I
CLASSIFICATION ACCURACY OVER A NUMBER OF CLASSIFIERS FOR THREE DATASETS AND TWO FEATURE EXTRACTION TECHNIQUES.

		Feature extraction Technique					
		DTF			**MAV**		
Dataset	**Hand Gesture**	**Kernel SVM**	**KNN**	**CNN**	**Kernel SVM**	**KNN**	**CNN**
Dataset 1	Fist	94.8%	94.7%	88.3%	82.6%	88.1%	86.4%
	Flexion	100.0%	100.0%	96.0%	75.0%	83.3%	88.2%
	Extension	98.5%	99.5%	84.8%	96.3%	90.6%	88.5%
	Pinch Index	84.5%	82.5%	77.3%	83.0%	82.8%	76.6%
	Pinch Middle	87.9%	83.0%	72.1%	77.1%	85.9%	89.3%
	Pinch Ring	83.1%	82.6%	76.2%	78.6%	76.9%	80.2%
	Pinch Small	86.5%	84.5%	84.4%	89.9%	92.5%	88.8%
Overall Accuracy (training)		90.0%	90.2%	83.5%	83.8%	86.1%	86.3%
Overall Accuracy (testing)		**90.3%**	89.0%	82.6%	83.0%	85.5%	85.2%
Dataset 2	Fist	93.2%	93.4%	77%	50.0%	70.4%	69.4%
	Flexion	97.7%	98.7%	87.1%	51.2%	81.0%	73.4%
	Extension	97.0%	97.0%	90.2%	67.3%	90.5%	83.4%
	Pinch Index	71.4%	69.5%	53.8%	54.2%	54.0%	54.8%
	Pinch Middle	77.6%	78.3%	54.4%	52.7%	56.8%	46.7%
	Pinch Ring	80.5%	84.0%	53.2%	54.2%	62.0%	48.0%
	Pinch Small	87.8%	88.9%	65.5%	64.8%	63.9%	56.6%
Overall Accuracy (training)		85.4%	85.9%	66.8%	56.3%	67.5%	59.5%
Overall Accuracy (testing)		85.8%	**86.4%**	68.3%	56.1%	67.4%	60.8%
Dataset 3	Fist	91.3%	92.8%	91.2%	53.0%	75.4%	59.4%
	Flexion	96.0%	98.2%	98.2%	51.5%	83.1%	64.9%
	Extension	96.7%	96.8%	96.5%	59.3%	89.7%	78.6%
	Pinch Index	71.8%	70.7%	69.9%	48.4%	56.7%	41.1%
	Pinch Middle	75.6%	76.7%	74.5%	54.7%	60.1%	44.1%
	Pinch Ring	81.3%	84.7%	84.9%	56.2%	72.2%	47.0%
	Pinch Small	85.7%	89.7%	90.6%	59.3%	69.3%	46.7%
Overall Accuracy (training)		84.4%	85.9%	85.5%	52.9%	69.0%	53.6%
Overall Accuracy (testing)		85.1%	**86.4%**	85.8%	54.6%	71.4%	54.2%

this paper. This provides a good performance comparison for our method against some of the latest developed hand gesture recognition methods. In [33], they obtained an overall best accuracy of 89.76% when analyzing the Ninapro dataset [34] using a temporal convolutional networks (CTN) method. Although their accuracy is slightly higher than the one obtained from our system, this could be due to the differences in the preprocessing as well as the gestures recorded in the dataset. The Ninapro dataset also includes 54 participants compared to our third dataset that consists on 30 subjects. In [13], the full putEMG dataset with 44 participants is analysed using several methods. The best overall classification accuracy reported was approximately 90%. Other hand gesture recognition methods might show a higher accuracy but they rely on the analysis of EMG-images as opposed to our method, that analyzes time series data.

V. CONCLUSION

In this paper, we proposed a new approach to gesture recognition by using the causality parameters, which exploits the cooperation and information exchange between muscles for performing a gesture, as features. This method has been proven to give a higher accuracy than methods which process each sEMG channel separately even when analysed over a small data size. The proposed technique also allows estimation of human motion dynamics, opening new possibilities for the use of sEMG in rehabilitation and in new HCI applications. To better assess the efficiency of the proposed technique for new HCI applications, the proposed technique could also be validated with sEMGs from patients with muscular disorders or upper-limb amputees. An adaptive EMG segmentation such as in [35] may also enhance the performance.

REFERENCES

[1] I. Campanini, C. Disselhorst-Klug, W. Z. Rymer, and R. Merletti, "Surface EMG in clinical assessment and neurorehabilitation: barriers limiting its use," *Frontiers in Neurology*, p. 934, 2020.

[2] R. Pilkar, K. Momeni, A. Ramanujam, M. Ravi, E. Garbarini, and G. F. Forrest, "Use of surface EMG in clinical rehabilitation of individuals with SCI: barriers and future considerations," *Frontiers in Neurology*, vol. 11, p. 578559, 2020.

[3] H. Türker and H. Sze, "Surface electromyography in sports and exercise," *Electrodiagnosis in New Frontiers of Clinical Research*, pp. 175–194, 2013.

[4] C. Fang, B. He, Y. Wang, J. Cao, and S. Gao, "EMG-centered multisensory based technologies for pattern recognition in rehabilitation: state of the art and challenges," *Biosensors*, vol. 10, no. 8, p. 85, 2020.

[5] C. Castellini and P. Van Der Smagt, "Surface EMG in advanced hand prosthetics," *Biological Cybernetics*, vol. 100, pp. 35–47, 2009.

[6] S. Sudarsan and E. C. Sekaran, "Design and development of EMG controlled prosthetics limb," *Procedia Engineering*, vol. 38, pp. 3547–3551, 2012.

[7] N. Parajuli, N. Sreenivasan, P. Bifulco, M. Cesarelli, S. Savino, V. Niola, D. Esposito, T. J. Hamilton, G. R. Naik, U. Gunawardana, and G. D. Gargiulo, "Real-time EMG based pattern recognition control for hand prostheses: A review on existing methods, challenges and future implementation," *Sensors*, vol. 19, no. 20, p. 4596, 2019.

[8] G. Lange, C. Y. Low, K. Johar, F. A. Hanapiah, and F. Kamaruzaman, "Classification of electroencephalogram data from hand grasp and release movements for BCI controlled prosthesis," *Procedia Technology*, vol. 26, pp. 374–381, 2016.

[9] X. Li, O. W. Samuel, X. Zhang, H. Wang, P. Fang, and G. Li, "A motion-classification strategy based on sEMG-EEG signal combination for upper-limb amputees," *Journal of Neuroengineering and Rehabilitation*, vol. 14, no. 1, pp. 1–13, 2017.

[10] D. Esposito, J. Centracchio, E. Andreozzi, G. D. Gargiulo, G. R. Naik, and P. Bifulco, "Biosignal-based human–machine interfaces for assistance and rehabilitation: A survey," *Sensors*, vol. 21, no. 20, p. 6863, 2021.

[11] M. R. Ahsan, M. I. Ibrahimy, and O. O. Khalifa, "EMG signal classification for human computer interaction: a review," *European Journal of Scientific Research*, vol. 33, no. 3, pp. 480–501, 2009.

[12] W. Li, P. Shi, and H. Yu, "Gesture recognition using surface electromyography and deep learning for prostheses hand: state-of-the-art, challenges, and future," *Frontiers in Neuroscience*, vol. 15, p. 621885, 2021.

[13] P. Kaczmarek, T. Mańkowski, and J. Tomczyński, "putEMG—a surface electromyography hand gesture recognition dataset," *Sensors*, vol. 19, no. 16, p. 3548, 2019.

[14] T. K. Lee, M. Belkhatir, and S. Sanei, "A comprehensive review of past and present vision-based techniques for gait recognition," *Multimedia Tools and Applications*, vol. 72, pp. 2833–2869, 2014.

[15] S. Sanei, D. Jarchi, and A. G. Constantinides, *Body sensor networking, design and algorithms*. John Wiley & Sons, 2020.

[16] D. Jarchi, J. Pope, T. K. Lee, L. Tamjidi, A. Mirzaei, and S. Sanei, "A review on accelerometry-based gait analysis and emerging clinical applications," *IEEE Reviews in Biomedical Engineering*, vol. 11, pp. 177–194, 2018.

[17] A. D. Chan and G. C. Green, "Myoelectric control development toolbox," *CMBES Proceedings*, vol. 30, 2007.

[18] A. Zandbagleh, S. Mirzakuchaki, M. R. Daliri, P. Premkumar, and S. Sanei, "Classification of low and high schizotypy levels via evaluation of brain connectivity," *International Journal of Neural Systems*, vol. 32, no. 04, p. 2250013, 2022.

[19] P. Modares-Haghighi, R. Boostani, M. Nami, and S. Sanei, "Quantification of pain severity using EEG-based functional connectivity," *Biomedical Signal Processing and Control*, vol. 69, p. 102840, 2021.

[20] J. Escudero, S. Sanei, D. Jarchi, D. Abásolo, and R. Hornero, "Regional coherence evaluation in mild cognitive impairment and Alzheimer's disease based on adaptively extracted magnetoencephalogram rhythms," *Physiological Measurement*, vol. 32, no. 8, p. 1163, 2011.

[21] R. Latif, S. Sanei, C. Shave, and E. Carter, "Classification of temporomandibular disorder from electromyography signals via directed transfer function," in *2008 30th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*. IEEE, 2008, pp. 2904–2907.

[22] R. Latif, S. Sanei, and K. Nazarpour, "Classification of elbow electormyography signals based on directed transfer functions," in *2008 International Conference on BioMedical Engineering and Informatics*, vol. 2. IEEE, 2008, pp. 371–374.

[23] M. Eichler, "On the evaluation of information flow in multivariate systems by the directed transfer function," *Biological Cybernetics*, vol. 94, pp. 469–482, 2006.

[24] M. Kamiński, M. Ding, W. A. Truccolo, and S. L. Bressler, "Evaluating causal relations in neural systems: Granger causality, directed transfer function and statistical assessment of significance," *Biological Cybernetics*, vol. 85, pp. 145–157, 2001.

[25] M. J. Kaminski and K. J. Blinowska, "A new method of the description of the information flow in the brain structures," *Biological Cybernetics*, vol. 65, no. 3, pp. 203–210, 1991.

[26] K. J. Blinowska, "Review of the methods of determination of directed connectivity from multichannel data," *Medical & Biological Engineering & Computing*, vol. 49, pp. 521–529, 2011.

[27] T. Schneider and A. Neumaier, "Algorithm 808: ARfit—a matlab package for the estimation of parameters and eigenmodes of multivariate autoregressive models," *ACM Transactions on Mathematical Software (TOMS)*, vol. 27, no. 1, pp. 58–65, 2001.

[28] C. Vidaurre, T. H. Sander, and A. Schlögl, "BioSig: the free and open source software library for biomedical signal processing," *Computational Intelligence and Neuroscience*, vol. 2011, 2011.

[29] G. Schwarz, "Estimating the dimension of a model," *The Annals of Statistics*, pp. 461–464, 1978.

[30] K. S. Kim, H. H. Choi, C. S. Moon, and C. W. Mun, "Comparison of k-nearest neighbor, quadratic discriminant and linear discriminant analysis in classification of electromyogram signals based on the wrist-motion directions," *Current Applied Physics*, vol. 11, no. 3, pp. 740–745, 2011.

[31] D. C. Toledo-Pérez, J. Rodríguez-Reséndiz, R. A. Gómez-Loenzo, and J. C. Jauregui-Correa, "Support vector machine-based EMG signal classification techniques: A review," *Applied Sciences*, vol. 9, no. 20, p. 4402, 2019.

[32] N. Duan, L.-Z. Liu, X.-J. Yu, Q. Li, and S.-C. Yeh, "Classification of multichannel surface-electromyography signals based on convolutional neural networks," *Journal of Industrial Information Integration*, vol. 15, pp. 201–206, 2019.

[33] P. Tsinganos, B. Cornelis, J. Cornelis, B. Jansen, and A. Skodras, "Improved gesture recognition based on sEMG signals and TCN," in *ICASSP 2019 - 2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 2019, pp. 1169–1173.

[34] M. Atzori, A. Gijsberts, S. Heynen, A.-G. M. Hager, O. Deriaz, P. Van Der Smagt, C. Castellini, B. Caputo, and H. Müller, "Building the Ninapro database: A resource for the biorobotics community," in *2012 4th IEEE RAS & EMBS International Conference on Biomedical Robotics and Biomechatronics (BioRob)*. IEEE, 2012, pp. 1258–1265.

[35] H. Azami, H. Hassanpour, J. Escudero, and S. Sanei, "An intelligent approach for variable size segmentation of non-stationary signals," *Journal of Advanced Research*, vol. 6, no. 5, pp. 687–698, 2015.