EMG-Based Feature Extraction and Classification for Prosthetic Hand Control

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Abstract—In recent years, real-time control of prosthetic hands has gained a great deal of attention. In particular, real-time analysis of Electromyography (EMG) signals has several challenges to achieve an acceptable accuracy and execution delay. In this paper, we address some of these challenges by improving the accuracy in a shorter signal length. We first introduce a set of new feature extraction functions applying on each level of wavelet decomposition. Then, we propose a postprocessing approach to process the neural network outputs. The experimental results illustrate that the proposed method enhances the accuracy of real-time classification of EMG signals up to 95.5% for 800 msec signal length. The proposed postprocessing method achieves higher consistency compared with conventional majority voting and Bayesian fusion methods.

I. INTRODUCTION

In recent years, Electromyography (EMG) has received considerable attention due to its applications for the control of powered upper-limb prostheses. In these techniques, EMG signal captured by skin-mounted sensors resulting by muscle contraction is used to send control commands [1].

The early myoelectric hands controlled via EMG signals were limited to "on" or "off" states depending on the amount of mean absolute value of signals [2]. If the amount of mean absolute value of EMG signal is more than a specified threshold value, the output is "on" and a simple activation would occur; Otherwise, the output is "off" and no activation would happen. This technique causes prosthetic hands to perform limited movements much less than the expected actions done by human hand. Pattern recognition is one of the most promising approaches to provide flexibility for fingers movements. Due to the capability of EMG signals, many researchers have concentrated on finding appropriate features and classifiers to achieve high accuracy. Feature extraction from EMG signals is one of the vital part for the classification of fingers gestures. This feature extraction should be performed to find monotonic relation between related signal and that of its corresponding command. In general, three different type of features are used for EMG signals classification: time domain (TD), frequency domain (FD) and time-frequency domain.

Heydarzadeh et al. [3] performed spectral analysis on EMG signals and extracted reflection coefficients as their features.

For classification, the authors utilized support vector machine (SVM) as classifier. Azhiri et al. [4] extracted the same features of [3], but their classifier was extreme value machine (EVM), and improved the accuracy. Esa et al. [5] used Hudgins features, root mean square (RMS) and finally combination of all these features, and a SVM classifier. Authors in [6] used some combination of wavelet features and classified the EMG signal with optimized parameters of SVM to get high accuracy of this classifier. Reference [7] used statistical features like RMS, median, standard deviation, and variance combined with fast Fourier transform (FFT) and implemented gradient boosting (GB) as a classifier.

While high accuracies have been reported in literature, most of them targeted off-line processing which is impractical for real-time myoelectric control of prosthetics. Generally speaking, it is expected to contemplate that the accuracy of real-time classification is less than off-line technique. On real-time control of upper-limb prostheses, Khushaba et al. [8] extracted TD, autoregressive (AR) and Hjorth as their features and performed feature reduction with linear discriminant analysis (LDA). Finally, classification is done with KNN and library SVM (LIBSVM). Authors in [9] used wavelet packet transform as a generalized format of wavelet transform. They utilized principal component analysis (PCA) and self-organizing feature map (SOFM) for feature reduction, and then classified with multilayer perceptron (MLP) in real-time approach. Reference [10] applied filtering, rectifying and extracting features in time, frequency and time-frequency domains, and applying different parametric and nonparametric classifiers.

Wavelet transform is a promising approach for analyzing EMG signals. In this paper, we utilize db1 mother wavelet transform. After applying a wavelet transform on EMG signals, the features are extracted using conventional feature extraction functions that are applied on signals. While some feature extraction functions are conventionally used in the literature, we propose five new feature extraction functions to be applied at each level of wavelet decomposition. For classification, a neural network architecture with six hidden layers with 32 neurons at each layer is used. Moreover, a new postprocessing

[margin notes: - Calibrated by clients at beginning using an app; REAL TIME]

method is employed to combine and refine the results of the neural network classifier. The proposed method is based on the summation of probabilities for each class. This method is compared with the majority voting and Bayesian fusion technique.

This paper is organized as follows. In Section II, wavelet transform and feature extraction is explained. Section III discusses EMG processing methodology including preprocessing, neural network classifier, and postprocessing. In Section IV, experimental results are elaborated and discussed. Finally, concluding remarks are in Section V.

II. WAVELET TRANSFORM AND FEATURE EXTRACTION

Wavelet transform is an efficient method of capturing both time and frequency information of a signal. Wavelet transform has successfully been used for processing time-varying and non-stationary biomedical signals. Various wavelet decomposition techniques have been reported for EMG signal decomposition in the literature in terms of mother wavelet and decomposition level [11–16]. For analyzing a signal by wavelet transform, the type of wavelet and the level of decomposition have significant impact on the analysis. After choosing a suitable wavelet transform and determining the level of decomposition, a set of functions should be applied on the output signals of wavelet transform to extract features that are ultimately given to a classifier.

In EMG pattern recognition systems, a set of conventional functions are applied to extract some features in time domain. These features are appropriate for real-time systems satisfying required constrains and can also be implemented using a simple hardware. The conventional time domain features are usually calculated based on the statistics of the EMG signal or its first derivative. Table 1 tabulates the equations of these 12 conventional features.

We propose to add a set of new features that have not been previously applied for the EMG signal classification task. We were inspired to use these features by observing their effectiveness in filter design and mapping a signal by a concave or convex function. These five features are as follows:

1) Integrated Absolute of Second Derivative (IASD):

$$IASD = \sum_{n=1}^{N-2} |x'[n+1] - x'[n]| \tag{1}$$

where $x'[n] = x[n+1] - x[n]$. This feature captures the relative changes of the second derivative of a signal which behaves like a filter to reduce the noise.

2) Integrated Absolute of Third Derivative (IATD):

$$IATD = \sum_{n=1}^{N-3} |x''[n+1] - x''[n]| \tag{2}$$

where $x''[n] = x'[n+1] - x'[n]$. This feature captures the relative changes of the third derivative of a signal. Similar to IASD, the third derivative also filters out the noise.

3) Integrated Exponential of Absolute Values (IEAV):

$$IEAV = \sum_{n=1}^{N} \exp(|x[n]|) \tag{3}$$

This function amplifies the samples that are large and suppresses the samples that are small for all positive and negative samples.

4) Integrated Absolute Log Values (IALV):

$$IALV = \sum_{n=1}^{N} |\log(x[n] + T)| \tag{4}$$

where T is a threshold that must empirically be tuned. This function suppresses the samples that are large and amplifies the samples that are small.

5) Integrated Exponential (IE):

$$IE = \sum_{n=1}^{N} \exp(x[n]) \tag{5}$$

It is similar to IEAV while distinguishes between positive and negative samples, i.e., generally amplifies positive samples and suppresses negative ones.

III. EMG PROCESSING METHODOLOGY

Our proposed architecture, as shown in Figure 1, includes three parts: preprocessing, processing (feature extraction and neural network), and postprocessing.

III-A. Preprocessing

Due to the stochastic nature of EMG signals, instantaneous processing could not provide desired information for real-time control of prosthetic hands. Therefore, data windowing is required to examine EMG signals in batches of consecutive samples [21].

For feature extraction, the wavelet features are calculated for each window i.e., 100 msec, to discriminate disparate finger movements. These features are used as inputs for the neural network classifier.

III-B. Neural Network

There has been an increasing interest to employ neural networks for classification of EMG signals. This interest has emanated from the fact that the real-time control of prosthetic hands demands a large number of data samples which is impractical for the most of the conventional classifiers. Our neural network model includes six hidden layers with 32 neurons for each layer. The number of neurons in the input layer depends on the wavelet decomposition level, and the number of features extracted from each level. The output layer has ten neurons corresponding to ten gestures of dataset.
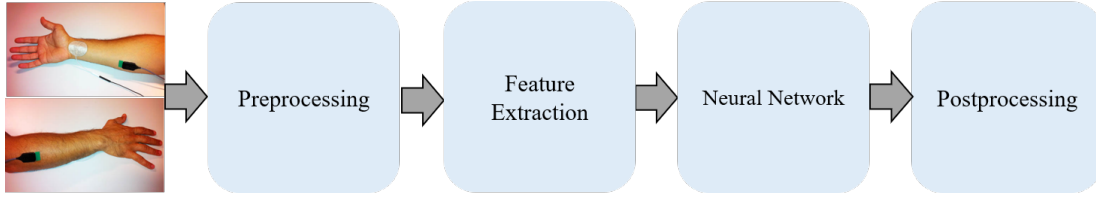
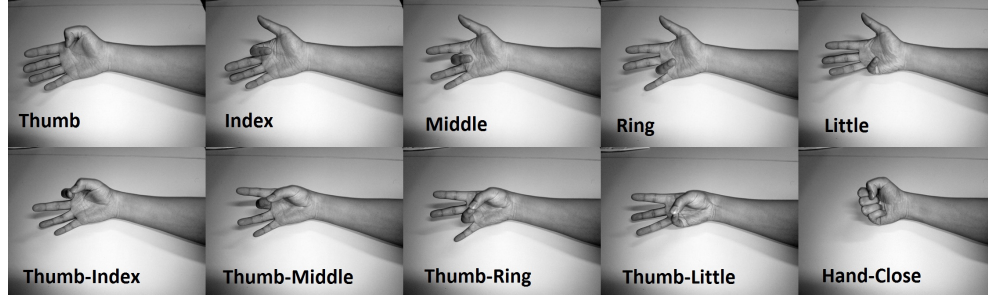Figure 1. The overall procedure of our proposed model.

Figure 2. Ten individual and combined finger movements [8]. Each finger movement corresponds to a class, i.e. Thumb: class 1, Index: class 2, Middle: class 3, Ring: class 4, Little: class 5, Thumb-Index: class 6, Thumb-Middle: class 7, Thumb-Ring: class 8, Thumb-Little: class 9, Hand-Close: class 10.

Table 1. Conventional Features.

Statistical Metric	Abbreviation	Formula
Integrated EMG [17]	IEMG	$\sum_{n=1}^{N} |x[n]|$
Mean Absolute Value [18]	MAV	$\frac{1}{N} \sum_{n=1}^{N} |x[n]|$
Simple Square Integrated [19]	SSI	$\sum_{n=1}^{N} x[n]^2$
Root Mean Square [19]	RMS	$\sqrt{\frac{1}{N} \sum_{n=1}^{N} x[n]^2}$
Variance [20]	VAR	$\frac{1}{N-1} \sum_{n=1}^{N} x[n]^2$
Myopulse Percentage Rate [19]	MYOP	$\frac{1}{N} \sum_{n=1}^{N} f(|x[n]|), \quad f(a) = \begin{cases} 1 & \text{if } a > T \\ 0 & \text{otherwise} \end{cases}$
Waveform Length [19]	WL	$\sum_{n=1}^{N-1} |x[n+1] - x[n]|$
Difference Absolute Mean Value [20]	DAMV	$\frac{1}{N-1} \sum_{n=1}^{N-1} |x[n+1] - x[n]|$
Second-Order Moment [20]	M2	$\sum_{n=1}^{N-1} (x[n+1] - x[n])^2$
Difference Variance Version [20]	DVARV	$\frac{1}{N-2} \sum_{n=1}^{N-1} (x[n+1] - x[n])^2$
Difference absolute standard deviation value [20]	DASDV	$\sqrt{\frac{1}{N-1} \sum_{n=1}^{N-1} (x[n+1] - x[n])^2}$
Willison Amplitude [19]	WAMP	$\sum_{n=1}^{N-1} f(|x[n+1] - x[n]|), \quad f(a) = \begin{cases} 1 & \text{if } a > T \\ 0 & \text{otherwise} \end{cases}$

III-C. Postprocessing

After classification by the neural network, we need a postprocessing method to combine the results obtaining from each window of an EMG signal. The purpose of this step is to refine the results of neural network classifier. For the postprocessing, we propose a new method that is based on the summation of probabilities of each class, i.e., we solve

$$\hat{c} = \arg\max_{i} \sum_{j} P(c_i|w_j), \quad (6)$$

where $p(c_i|w_j)$ denote the probability of class i given window j. We compare our postprocessing method with the Bayesian fusion method [8] that can be stated as:

$$\hat{c} = \arg\max_{i} P(c_i|w_1, w_2, \cdots, w_N)$$
$$= \arg\max_{i} \delta \prod_{j} P(c_i|w_j), \quad (7)$$

where δ is a normalization constant. Also, we compare these postprocessing methods with a simple majority voting method [8]. The main drawback of Eqn. (7) is for a situation in which the probability of a class given window w_k vanishes.
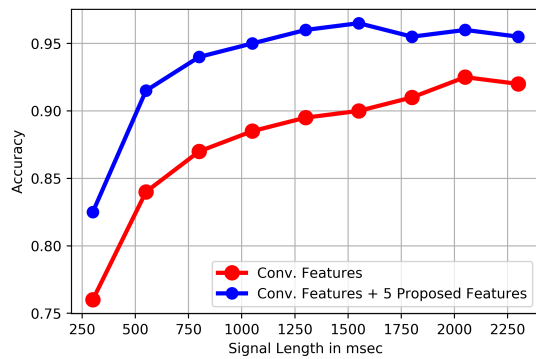
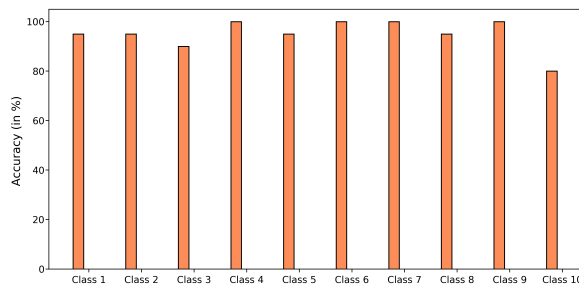Figure 3. Accuracy of features on the same EMG dataset.

Figure 4. The classification accuracy for each class.

The probability of this phenomena increases by increasing the number of windows. Our proposed postprocessing method in Eqn. (6) can overcome this problem by adding probabilities instead of multiplying them.

IV. Experimental Results

IV-A. Dataset

The proposed model is applied to the dataset provided by Center of Intelligent Mechatronic Systems at the University of Technology at Sydney [8]. Eight participants (six men and two women at the range of 25 to 30 years old) performing ten different finger movements consisting five individuals as Thumb (T), Index (I), Middle (M), Ring (R), Little (L) and five combined movement as Thumb-Index (T-I), Thumb-Middle (T-M), Thumb-Ring (T-R), Thumb-Little (T-L) and closed hands. In Figure 2, these fingers movements are illustrated. The data is recorded with two skin-mounted EMG channels at 4,000 Hz and then amplified to total gain of 1,000. Each movement of fingers is repeated six times. Each gesture took five seconds including rest and holding of each finger posture. We select the first four trials for the training of the classification and the last two for the test in order to check the accuracy of the classifiers.

IV-B. System Set up and Architecture

Each EMG signal contains 20,000 samples that have been sampled and recorded for 5 seconds with frequency sampling of 4,000 Hz. Therefore, we break down each training EMG signal into 99 training parts using a window of length 400 samples and overlap of 200 samples. Please note that for training the neural network, we only use our training dataset, and this training is done off-line. We consider a window size of 100 msec with an overlap of 50 msec. The overlapped windowing scheme provides higher classification accuracy than that of disjoint one. The wavelet transform is applied to each window of the original signal for feature extraction.

After applying a wavelet transform, a set of features are extracted; some are based on conventional feature extraction functions that are common for time-varying signals proposed in the literature. We also use our new feature extraction functions discussed in Section II, i.e. IASD, IEAV, IATD, IALV and IE. We consider a 2-level mother wavelet transform decomposition. The total number of features extracted from conventional and proposed feature extraction functions are 17 for each level of wavelet transform decomposition. We define the *signal length* as the length of the original signal that is used for classification in the postprocessing step. We have trained this model in python and ran it in a windows-based PC with 2.60 GHz CPU and 16 GB memory.

IV-C. Results

In Table 2, the effects of different features are shown. The accuracy of conventional features is significantly improved by our proposed features. Combination of all new proposed and conventional features enhance the classification accuracy up to 94.0% and 91.5% within signal length of 800 and 550 msec, respectively, while we use a simple majority postprocessing. Table 3 shows a comparison between conventional features and our proposed feature extraction methods in the presence of our proposed postprocessing. It can be seen that the classification accuracy increases to 95.5% and 92% within 800 and 550 msec signal length, respectively. In Figure 3, the effect of signal length and classification accuracy is depicted for various signal length at the output of the postprocessing. The simulation results show that after a specific signal length around 1,000 msec, the accuracy does not change significantly.

Figure 4 also shows the accuracy for each class for 800 msec signal length using the majority voting. Again, it is obvious that while high and uniform accuracy is gained by our architecture, the accuracy of the last class is not satisfying. This result could be related to the large nonlinear movement in the corresponding class [8]. This misclassification for this class could be addressed by defining different postprocessing windowing technique. Overall, the accuracy of eight classes is more than 95% which proves the capability and success of the proposed feature extraction functions.

Table 2. The accuracy (in %) of majority voting postprocessing method for various signal length.

Features	Signal Length msec							
	300	550	800	1050	1300	1550	1800	2050
Conv. Features	76.0	84.0	87.0	88.5	89.5	90.0	91.0	92.5
Conv. Features + 5 Proposed Features	**82.5**	**91.5**	**94.0**	**95.0**	**96.0**	**96.5**	**95.5**	**96.0**

Table 3. The accuracy (in %) of our proposed postprocessing meyhod for various signal length.

Features	Signal Length msec							
	300	550	800	1050	1300	1550	1800	2050
Conv. Features	75.5	83.5	88.0	91.0	92.0	92.5	91.5	90.5
Conv. Features + 5 Proposed Features	**84.5**	**92.0**	**95.5**	**97.0**	**96.5**	**97.5**	**97.5**	**96.5**

Table 4. Comparing the results of different approaches for the same EMG dataset.

Approaches	Features	Classifier	Classes	Condition	Avg. Acc (%)
[22]	TD+Hjorth+RMS	ANN	5	Off-line	96.7
[23]	AR + RMS	ANN+NMF	5	Off-line	92.0
[3]	Reflection Coefficients	SVM	10	Off-line	89.0
[8]	TD+AR+Hjorth	KNN+SVM+Fusion	10	Online	90.0
Ours	**Wavelet**	**NN**	**10**	**Online**	**95.5**

In Table 4, the performance of our proposed methods is compared with the results of other researchers on the same dataset. Comparing with other works, especially the results that are obtained on the real-time framework, the strength of our method is proved. Some of the previous works on this dataset have just concentrated on five classes [20, 22]. Also, some works have focused on pattern recognition in off-line mode [3]. Our architecture that benefits from wavelet transform, neural network, and a set of new feature extraction functions, and a new postprocessing method outperforms in term of classification accuracy in comparison to the existing works. As it is obvious in Figure 5, receiver operating characteristic (ROC) curve verifies the performance of added features and improves the capabilities of the classifier.

Finally, Figure 6 compares three proposed postprocessing methods with majority voting and Bayesian fusion methods in the presence of all features. This figure shows that our postprocessing method is consistent and does not suffer from the main drawback of Bayesian fusion method.

The delay time for the system is the result of feature extraction and process time required by the classifier to make the decision. Based on our hardware and our proposed architecture, for 800 msec signal length at postprocessing, delay time is about 5.7 msec for the feature extraction and 3.12 msec for the classification.

Finally, it is worth to mention that using neural network architectures such as Convolutional Neural Network (CNN) [24], Graph Convolutional Neural Network (GCNN) [25], and Recurrent Neural Network (RNN) [26] can significantly improve
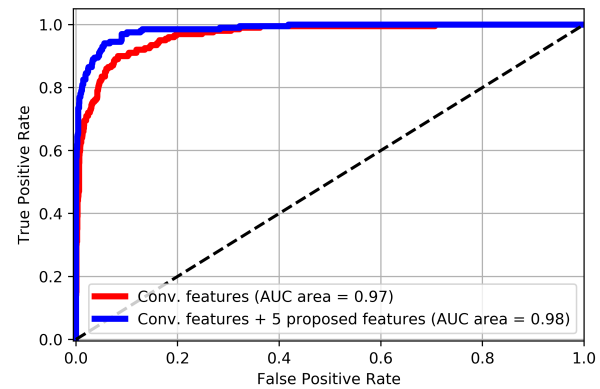

Figure 5. ROC of conventional features and all features including five proposed features.

the classification accuracy. Also, various optimization methods such as Particle Swarm Optimization (PSO) and Genetic algorithm [27, 28] can be applied to select a set of features with significant importance.

V. CONCLUSION

In this paper, we proposed an architecture that is used for real-time control of prosthetic hands. For the first time, we proposed five new feature extraction functions applying on each level of wavelet transform. The proposed features were compared with conventional features previously used in the literature. The proposed feature extraction method enhances the accuracy up to 8% approximately, and could achieve
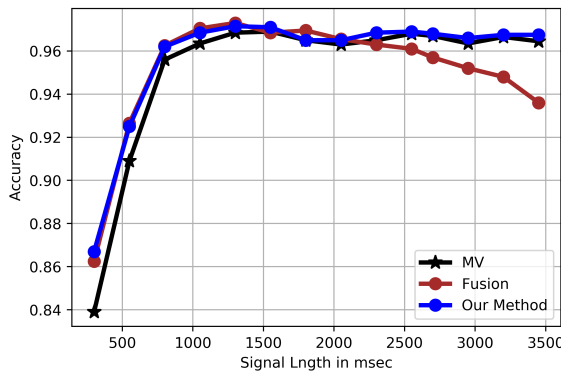
Figure 6. A comparison between accuracy of our proposed postprocessing method, majority voting, and Bayesian fusion on different signal lengths.

the accuracy of 94% within 800 msec signal length using a majority voting postprocessing. The proposed postprocesssing method also increased the accuracy to 95.5%. It was shown that the proposed postprocessing method is much better than Bayesian fusion and can compete with majority voting.

We intend to implement the proposed feature extraction functions with other neural network architectures and other conventional classifiers on various datasets. Specifically, we plan to apply the proposed features to analyse other biomedical signals and compare with other feature extraction methods.

REFERENCES

[1] M. Jafarzadeh, D. C. Hussey, and Y. Tadesse, "Deep learning approach to control of prosthetic hands with electromyography signals," *2019 IEEE International Symposium on Measurement and Control in Robotics (ISMCR)*, 2019, pp. A1–4–1–A1–4–11.

[2] A. D. Roche, H. Rehbaum, D. Farina, and O. C. Aszmann, "Prosthetic myoelectric control strategies: a clinical perspective," *Current Surgery Reports*, vol. 2, no. 3, pp. 1–11, 2014.

[3] M. Heydarzadeh, J. Birjandtalab, and M. Nourani, "Emg spectral analysis for prosthetic finger control," *2017 European Conference on Electrical Engineering and Computer Science (EECS)*, 2017, pp. 131–135.

[4] R. B. Azhiri, M. Esmaeili, M. Jafarzadeh, and M. Nourani, "Emg signal classification using reflection coefficients and extreme value machine," *arXiv preprint arXiv: 2106.10561*, 2021.

[5] N. M. Esa, A. M. Zain, and M. Bahari, "Electromyography (emg) based classification of finger movements using svm," *International Journal of Innovative Computing*, vol. 8, no. 3, 2018.

[6] A. Palkowski and G. Redlarski, "Basic hand gestures classification based on surface electromyography," *Computational and mathematical methods in medicine*, vol. 2016, 2016.

[7] C. K. Bhattachargee, N. Sikder, M. T. Hasan, and A.-A. Nahid, "Finger movement classification based on statistical and frequency features extracted from surface emg signals," *2019 International Conference on Computer, Communication, Chemical, Materials and Electronic Engineering (IC4ME2)*. IEEE, 2019, pp. 1–4.

[8] R. N. Khushaba, S. Kodagoda, M. Takruri, and G. Dissanayake, "Toward improved control of prosthetic fingers using surface electromyogram (emg) signals," *Expert Systems with Applications*, vol. 39, no. 12, pp. 10 731–10 738, 2012.

[9] J.-U. Chu, I. Moon, and M.-S. Mun, "A real-time emg pattern recognition system based on linear-nonlinear feature projection for a multifunction myoelectric hand," *IEEE Transactions on biomedical engineering*, vol. 53, no. 11, pp. 2232–2239, 2006.

[10] A. G. Jaramillo and M. E. Benalcázar, "Real-time hand gesture recognition with emg using machine learning," *2017 IEEE Second Ecuador Technical Chapters Meeting (ETCM)*. IEEE, 2017, pp. 1–5.

[11] D. Zennaro, T. Läubli, P. Wellig, D. Krebs, M. Schnoz, A. Klipstein, and H. Krueger, "A method to test reliability and accuracy of the decomposition of multi-channel long-term intramuscular emg signal recordings," *International journal of industrial ergonomics*, vol. 30, no. 4-5, pp. 211–224, 2002.

[12] D. Zennaro, P. Wellig, V. M. Koch, G. S. Moschytz, and T. Laubli, "A software package for the decomposition of long-term multichannel emg signals using wavelet coefficients," *IEEE Transactions on Biomedical Engineering*, vol. 50, no. 1, pp. 58–69, 2003.

[13] P. Wellig and G. S. Moschytz, "Analysis of wavelet features for myoelectric signal classification," *1998 IEEE International Conference on Electronics, Circuits and Systems. Surfing the Waves of Science and Technology (Cat. No. 98EX196)*, vol. 3. IEEE, 1998, pp. 109–112.

[14] R. Yamada, J. Ushiba, Y. Tomita, and Y. Masakado, "Decomposition of electromyographic signal by principal component analysis of wavelet coefficients," *IEEE EMBS Asian-Pacific Conference on Biomedical Engineering, 2003*. IEEE, 2003, pp. 118–119.

[15] X. Ren, H. Huang, and L. Deng, "Muap classification based on wavelet packet and fuzzy clustering technique," *2009 3rd International Conference on Bioinformatics and Biomedical Engineering*. IEEE, 2009, pp. 1–4.

[16] S. Rasheed, D. W. Stashuk, and M. S. Kamel, "A hybrid classifier fusion approach for motor unit potential classification during emg signal decomposition," *IEEE Transactions on Biomedical Engineering*, vol. 54, no. 9, pp. 1715–1721, 2007.

[17] M. Zardoshti-Kermani, B. C. Wheeler, K. Badie, and R. M. Hashemi, "Emg feature evaluation for movement control of upper extremity prostheses," *IEEE Transactions on Rehabilitation Engineering*, vol. 3, no. 4, pp. 324–333, 1995.

[18] B. Hudgins, P. Parker, and R. N. Scott, "A new strategy for multifunction myoelectric control," *IEEE transactions on biomedical engineering*, vol. 40, no. 1, pp. 82–94, 1993.

[19] A. Phinyomark, P. Phukpattaranont, and C. Limsakul, "Feature reduction and selection for emg signal classification," *Expert systems with applications*, vol. 39, no. 8, pp. 7420–7431, 2012.

[20] A. Phinyomark, F. Quaine, S. Charbonnier, C. Serviere, F. Tarpin-Bernard, and Y. Laurillau, "Feature extraction of the first difference of emg time series for emg pattern recognition," *Computer methods and programs in biomedicine*, vol. 117, no. 2, pp. 247–256, 2014.

[21] A. Krasoulis, "Machine learning-based dexterous control of hand prostheses," *The University of Edinburgh*, 2018.

[22] M. Ariyanto, W. Caesarendra, K. A. Mustaqim, M. Irfan, J. A. Pakpahan, J. D. Setiawan, and A. R. Winoto, "Finger movement pattern recognition method using artificial neural network based on electromyography (emg) sensor," *2015 International Conference on Automation, Cognitive Science, Optics, Micro Electro-Mechanical System, and Information Technology (ICACOMIT)*. IEEE, 2015, pp. 12–17.

[23] G. R. Naik and H. T. Nguyen, "Nonnegative matrix factorization for the identification of emg finger movements: Evaluation using matrix analysis," *IEEE journal of biomedical and health informatics*, vol. 19, no. 2, pp. 478–485, 2014.

[24] M. Jafarzadeh and Y. Tadesse, "Convolutional neural networks for speech controlled prosthetic hands," *2019 First International Conference on Transdisciplinary AI (TransAI)*. IEEE, 2019, pp. 35–42.

[25] M. Esmaeili and A. Nosratinia, "Semi-supervised node classification by graph convolutional networks and extracted side information," *arXiv preprint arXiv:2009.13734*, 2020.

[26] Y. Huang, Z. He, Y. Liu, R. Yang, X. Zhang, G. Cheng, J. Yi, J. P. Ferreira, and T. Liu, "Real-time intended knee joint motion prediction by deep-recurrent neural networks," *IEEE Sensors Journal*, vol. 19, no. 23, pp. 11 503–11 509, 2019.

[27] M. Esmaeili, N. Granpayeh, and M. Bozorgi, "A novel reliable optimization method for output beam forming of photonic crystal waveguide terminated with surface crow," *Optik*, vol. 126, no. 4, pp. 421–425, 2015.

[28] A. A. M. Lima, R. M. Araujo, F. A. G. d. Santos, V. H. Yoshizumi, F. K. H. de Barros, D. H. Spatti, L. H. B. Liboni, and M. E. Dajer, "Classification of hand movements from emg signals using optimized mlp," *2018 International Joint Conference on Neural Networks (IJCNN)*, 2018, pp. 1–7.