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Enhancing Myoelectric Signal Classification Through Conditional Spectral Moments and Wavelet-Enhanced Time-Domain Descriptors

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ABSTRACT

This study underscores the imperative role of feature extraction and classification in the domain of electromyography (EMG) signals. The efficacy of myoelectric pattern recognition hinges upon the judicious selection of pertinent features. In this research endeavor, we introduce a novel approach that leverages two distinct feature sets: conditional spectral moments and refined time-domain descriptors, tailored to augment the precision of myoelectric signal classification. The conditional spectral moments, derived from the time-frequency distribution of EMG signals, encapsulate nuanced variations in muscle activity and movement dynamics. This augmentation facilitates seamless differentiation of hand gestures, a pivotal advancement in the context of prosthetic applications. Concurrently, we enhance the time-domain descriptors by convolving them with wavelet filter coefficients, thereby extracting both spatial and temporal characteristics of muscle activity. The extracted features are subjected to classification using Support Vector Machines (SVM), K-Nearest Neighbor (KNN), Decision Tree (DT), and Ensemble Bagging classifiers. To elucidate the efficacy of our proposed features, comprehensive experiments are conducted employing the benchmark databases Ninapro DB1 (comprising 52 classes) and DB2 (comprising 49 classes). Our findings underscore the superiority of the proposed features, particularly when applied in conjunction with ensemble classifiers. Specifically, the classification accuracies of the modified time-domain descriptor feature exhibit substantial enhancements, achieving 87.1% and 85.3% accuracy rates for Ninapro DB1 and DB2, respectively. Notably, the conditional spectral moments outperform with remarkable classification accuracies of 92.9% and 90.8% for Ninapro DB1 and DB2, respectively. This marked improvement in EMG signal classification corroborates the enhanced precision in decoding hand movements, thus imparting significant advancements in the realm of hand prosthesis control.

1. INTRODUCTION

Myoelectric is a term that refers to the electric properties of muscles, and myoelectric-controlled prostheses utilize the electrical signals emanating from muscles [1]. The EMG acquired from the muscles in the residual limb is used by the myoelectric prostheses to control its functionality. Electromyography is a diagnostic procedure used to assess the health of muscles and the nerve cells that control them. EMG non-invasively measures muscle activity and extracts reliable information from the muscles, making it commonly used by researchers to determine discriminative information. Pattern recognition (PR) techniques extract insightful information from the EMG signals and interpret the neural control signals into movement commands for movement recognition. Prosthesis controllers receive commands to implement movements using EMG patterns based on pattern classification. This allows users to manage their myoelectric prosthesis more easily and with more control using the EMG-PR technique [2]. It is challenging to operate artificial hands with the same degree of dexterity and complexity as biological hands. Nevertheless, PR has long been used for controlling myoelectric prosthetic devices. PR enables more intuitive control that is easier for both humans and computers to learn. It also allows the independent control of numerous degrees of freedom (DOF), viz., simultaneous, sequential, or semi-sequential control, bringing the prosthesis closer to natural arm functions. The limb movement can be accurately decoded and used to control a prosthetic hand using a suitable PR-based and signal-processing technique combined with machine learning algorithms. There have been many studies that show that the pre-processing of EMG signals, the choice of good features, and the right classification methods are very important to the overall performance of myoelectric systems [3-5].

Several feature extraction schemes have been proposed for EMG feature extraction and classification. Kuzborskij et al. [6] utilized time domain features like mean absolute value (MAV), wavelength, and histogram for classifying large-scale data sets. Waris et al. [7] investigated time-domain features like MAV, Zero Crossing (ZC), Willison Amplitude

(WAMP), Slope Sign Changes (SSC), Waveform Length (WL), Cardinality (CARD), and Myopulse Rate (MYOP) for intuitive control for upper-limb prosthesis. A combination of time-domain features by Hudgins et al. [8], namely the Hudgins Time Domain feature set, paved the way for multifunction myoelectric control. Khushaba et al. [4] derived the Time-Dependent-Power Spectral Descriptor (TD-PSD) feature from the power spectral descriptors, which was proven to find the muscular activities. Phinyomark and Scheme [9] have proposed the mean prominence of local peaks and valleys, which excel in the HTD feature set. Frequency domain features like autoregressive model coefficients proposed by Al-Timemy et al. [10] and the logarithm of Fourier transform (FT) moments feature proposed by Al-Timemy et al. [5] for multifunction prosthesis are available for EMG classification. Wavelet transform-based feature by Chu et al. [11], wavelet-based iterative feature, namely, ternary pattern by Turker et al. [12], energy features by Karnam et al. [13], and variational mode decomposition (VMD)-based feature extraction methods [14] were developed for efficient EMG classification. A spatiotemporal feature developed by Jabbari et al. [15], namely spatiotemporal warping (STW), outperformed the traditional features.

A classifier is required to determine the gesture label of the signal after feature extraction. Several classifiers have been suggested and tested, including linear discriminant analysis (LDA), SVM [16], MLP [17], and KNN [18]. Techniques known as ensemble machine learning combine the findings of numerous learners to produce better results [19].

EMG pattern recognition can be widely categorized into traditional and deep learning (DL) methods, while the former depends on feature engineering and the latter on feature learning [20]. Wei et al. [21] proposed a Multi-View Convolutional Neural Network (CNN) framework with DL techniques for hand gesture classification. An improved DL-based framework was framed by Pancholi et al. [22] for myoelectric prosthesis control. An EMG signal classification model using CNN was presented by Atzori et al. [23], with results comparable to state-of-the-art machine learning techniques. Tsinganos et al. [24] used temporal CNN to classify EMG signals into 52 classes. Côté-Allard et al. [25] utilized the transfer learning technique with CNN to classify EMG signals.

Despite the fact that quite a few state-of-the-art approaches are available for feature extraction and classification of EMG signals, the robustness of the classification technique poses a challenge to the researchers. There are a lot of challenges in classifying hand gestures with multiple degrees of freedom [26, 27], and getting the model to work with a lot of different motions, like moving the upper and lower limbs, is important for making prosthetic control better [28]. Although notable progress has been made in DL methods for EMG-based hand gesture classification, it is essential to recognize that these achievements often entail considerable computational expenses. These expenses stem from the extensive data needed for training deep learning models such as CNN and the relatively large number of parameters that have to be learned. The number of model parameters varies widely, ranging from 34k to 95k [29], 104k to 30k [30], and 30k to 549k [31], extending to several million parameters. Hence, a straightforward and resource-efficient model suitable for operation on constrained platforms is a crucial element in the development of machine-learning-based prosthetic devices. Moreover, robust feature extraction and classification have to be developed to classify EMG signals.

The contributions of this research are:

(1) To extract conditional spectral moment features from the EMG signal for capturing the variations of different hand gestures.

(2) To obtain a modified TD-PSD by convolving the low-pass decomposition filter coefficients of the wavelet transform with the TD-PSD [5].

(3) To classify the features extracted from the EMG signals with SVM, KNN, DT, and Bagged Ensemble DT classifiers.

A feature extraction and classification framework has been proposed to improve the classification accuracy of EMG signals for hand prostheses to address the above-mentioned challenges. The conditional spectral moment and TD-PSD were extracted from the EMG signal. Spectral moments seem to be a potential strategy for EMG classification and have been employed in several applications [24, 25]. The conditional spectral moment is a morphological feature and is more noise-resistant, which has been extracted from the spectrogram of the EMG signal [32]. Dynamic hand movements that involve muscle activations in different sequences with varying intensities result in asymmetric EMG signal distribution. The conditional spectral moments identify and differentiate patterns of muscle activity that exhibit asymmetric distributions.

In the context of EMG-based hand gesture classification, it is important to recognize that individual hand gestures give rise to unique patterns of muscle activity. TD-PSD is a useful method for measuring how sensitive a signal is to changes in time. This lets us tell the difference between and describe the different patterns of muscle activity that are linked to different hand gestures. In the current work, the TD-PSD proposed by Al-Timemy et al. [5] is utilized as the base feature for EMG classification. These features are derived directly from the time domain through the use of FT and Parseval's theorem. The derivatives utilized in the power spectral moments are susceptible to noise interference; hence, it becomes crucial to apply feature value normalization to mitigate noise effects. To achieve this, a normalization step is incorporated by exponentiating the log-scaled amplitudes to an appropriate power [5]. The TD-PSD feature was mixed with wavelet transform filter coefficients to include both the spatial and temporal aspects of hand gesture EMG signals. This made the modified TD-PSD feature representation. When you combine the base feature set with wavelet transform filter coefficients, you get feature values from the combination of channels that were thought about, which helps with spatial focus. The rationale for integrating the wavelet filter coefficients with the time domain descriptors is to combine the information from both the time and wavelet domains. Also, this approach captures temporal and frequency-related characteristics. This is due to the fact that the EMG signals encompass frequency components associated with muscle activity and motion. The fusion of these frequency components with the statistical characteristics of time-domain descriptors enhances the discriminative capability of the extracted features. During muscle contractions or movements, the primary power of the EMG signal is concentrated within the 20 Hz to 500 Hz frequency range. The low-pass decomposition filter is adept at noise removal while retaining the essential signal components. This study introduces a changed TD-PSD feature that takes advantage of the benefits of wavelet transform filter coefficients and power spectral descriptors.

This work is illustrated as follows: The EMG dataset used for this research is detailed in Section 2.1. In Section 2.2, the proposed conditional spectral moments and the modified TD-PSD features are elaborated. The feature sets utilized from the literature for comparing the accuracy of the proposed features are detailed in Section 2.3. The details of the classifiers employed for classifying the extracted features are given in Section 2.4. The classification outcomes achieved using the proposed features with the Ninapro databases, as well as the corresponding discussions, are presented in Section 3. Section 4 describes the conclusion and outlines future work.

2. MATERIALS AND METHODS

2.1 EMG dataset

The proposed feature is evaluated with two databases, Ninapro DB1 [33] and DB2 [34], a widely used benchmark dataset for myoelectric prostheses. A collection of 52 movements were selected from the DB1, which were split up into three exercises, namely A, B, and C. Exercise A is comprised of 12 basic finger movements; Exercise B incorporates 17 hand postures and basic wrist movements; and Exercise C contains 23 functional and grasping movements of the hands correlated with daily life actions. DB2 comprises 49 hand gestures from 40 subjects and includes finger gestures and functional and grasping movements. The details of the datasets utilized are summarized in Table 1. OttoBock MyoBock 13E200 sEMG electrodes were used to record the surface EMG (SEMG) data. These electrodes amplified, filtered, and rectified the signals. We used MyoBock 13E200-50 electrodes to measure the muscle activity of DB2 in 40 healthy individuals. sEMG signals were gathered from 12 electrodes placed on the forearm, flexor Digitorum Superficialis, muscle extensor Digitorum Superficialis, triceps brachii, and biceps brachii.

Table 1. Details of the dataset

Parameter	Ninapro DB1	Ninapro DB2
No. of subjects, classes	27, 52	40, 49
No. of repetitions	10	6
No. of channels	10	12
Sampling frequency (Hz)	100	2000
Duration (sec)	5	5
Total patterns	14040	11760
Training patterns	8424	7840
Test patterns	5616	3920

2.2 Proposed feature extraction

2.2.1 Conditional spectral moment

Figure 1 depicts the work carried out in this paper. The raw, multichannel EMG signal undergoes a pre-processing stage, a feature extraction stage, and finally the classification stage. The conditional spectral moment of a non-stationary EMG signal is obtained from the EMG signal spectrum. This is taken from the time-frequency distribution, $P(t, \omega)$ of the signal and is given by:

$$\langle \omega^i \rangle_t = \frac{1}{P(t)} \int \omega^i P(t, \omega) d\omega \tag{1}$$

$P(t)$ defines the marginal distribution and describes the order.

Eq. (1) is termed the 'instantaneous frequency' or mean. The variance, or 'instantaneous bandwidth' is given by:

$$\sigma^2_{\omega/t} = \int (\omega - \langle \omega \rangle_t)^2 \ P(\omega|t) d\omega \tag{2}$$

Skewness and kurtosis are the third and fourth-order moments, respectively. This is described as:

$$C_{\omega/t} = 1\sigma^3_{\omega/t} \int (\omega - \langle \omega \rangle_t)^3 \, P(\omega|t) d\omega \tag{3}$$

$$K_{\omega/t} = 1\sigma^4_{\omega/t} \int (\omega - \langle \omega \rangle_t)^4 \ P(\omega|t) d\omega \tag{4}$$

The first four moments mentioned above, namely mean, variance, skewness, and kurtosis, are extracted from the EMG signal for the Ninapro DB1 and DB2 for each class of movements.

2.2.2 Modified TD-PSD

In the work TD-PSD [5], an improvement in classification accuracy of 6% to 8% was reported. In the current work, a modified TD-PSD feature is proposed and obtained from the TD-PSD by convolving each descriptor $(f_1, f_2, f_3, f_4, f_5, f_6)$ mentioned in Figure 1 with the low-pass wavelet filter coefficients of the input EMG signal.

The time domain descriptors $(f_1, f_2, f_3, f_4, f_5, f_6)$ are extracted from the pre-processed EMG signal, and each feature takes the shape of $(1 \times M)$, $wherein\ M$ is the length of the EMG channel. These features are reshaped into an array of sizes $(a \times b)$, such that the product of a and b gives M. The wavelet filter coefficient is obtained by wavelet decomposing the input EMG with a decomposition level of 2. The reshaped feature array $(R_1, R_2, \ldots, R_6)$ is convolved with the filter coefficient L, which is further flattened and concatenated, forming a new feature $F4$.

The EMG signal is decomposed with a wavelet transform, which uses the Daubechies wavelet family, 'db44'. The reason behind the selection of 'db44' is that it possesses more resemblance in the signal and mother wavelet function. Most biological signals like EMG possess sharp spikes, which can be analyzed with Daubechies wavelets since these wavelets experience asymmetric spikes. Thus, 'db44' seems to have a similar function to EMG amid the 324 mother wavelets [35]. The time domain descriptors are derived from the relation obtained by Parseval's theorem and are given in the Appendix.

Let L denote the filter coefficients obtained by wavelet decomposing the input EMG signal to a decomposition level of 2. The coefficients in general can be expressed as:

$$L = \begin{bmatrix} l_1 & l_2 \\ l_3 & l_4 \end{bmatrix} \tag{5}$$

The modified TD-PSD is obtained as follows:

$$r_1 = R_1 * L; r_2 = R_2 * L; r_3 = R_3 * L \tag{6}$$

$$r_4 = R_4 * L; r_5 = R_5 * L; r_6 = R_6 * L \tag{7}$$

$$F_4 = concatenate[r_1; r_2; r_3; r_4; r_5; r_6] \tag{8}$$

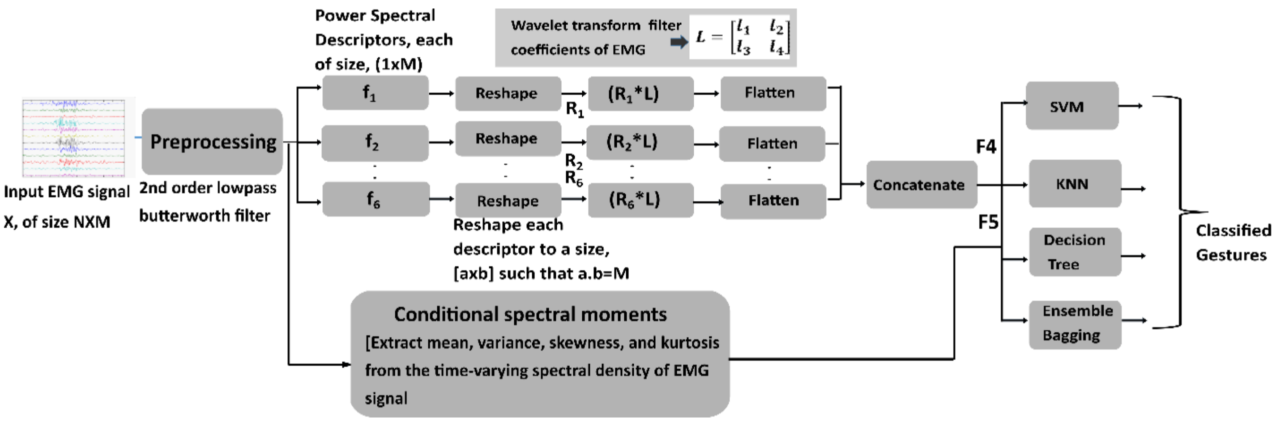

Figure 1. Proposed feature extraction and classification

2.3 Feature sets for investigation

The following feature sets were also taken from the literature to compare the effectiveness of the proposed feature.

AR-HTD [36]: This is the combination of 6th-order autoregressive coefficients and Hudgins Time Domain features MAV, IAV, RMS, WL, SSC, and ZC.

AR-RMS [37]: Combination of autoregressive coefficients of 6th order and RMS value.

MWTD [38]: The multisignal wavelet transform decomposition coefficients can be extracted from the wavelet transform coefficients of each node, including energy, variance, standard deviation, waveform length, and entropy. The entire set of feature sets for investigation is mentioned in Table 2.

Table 2. Features used for classification

Features under Investigation	
AR-HTD	F1
AR-RMS	F2
MWTD	F3
Modified TD-PSD	F4
Conditional spectral moments	F5

2.4 Classification of EMG signals

The proposed feature was investigated with four different classifiers: SVM, KNN, Decision Tree Classifier, and Decision Tree Ensemble with Bagging. The pseudocode for the feature extraction and classification is given in Table 3. SVM represents a category of supervised machine learning techniques employed in tasks involving classification and regression [18]. They are well-suited for classifying hand gestures with EMG signals. The objective of this classification algorithm is to find an optimal hyperplane within the feature space, effectively distinguishing various classes of hand movements. Training the SVM model involves utilizing a labeled dataset of EMG signals, each associated with a specific hand gesture, which enables the SVM to identify the most suitable hyperplane for separating the distinct hand gesture classes [19]. In KNN, data points with similar features tend to have the same class labels. When classifying a new data point, KNN looks at the class labels of its nearest neighbors in feature space and assigns the majority class as the predicted label. When classifying a new EMG signal corresponding to a hand gesture, KNN calculates the distance between the feature vector and all feature vectors in the training dataset. The decision tree algorithm navigates through the tree structure, comparing the feature values of the EMG signal to the criteria at each node. The path followed through the tree leads to a leaf node, which represents the predicted hand gesture class. If the data is high-dimensional and if the single classifier fails to perform well, ensemble classifiers provide better results. Decision trees with ensemble bagging classifiers combine the principles of decision trees and ensemble learning, which involves aggregating the predictions of multiple individual models to improve accuracy and robustness. The feasibility of the bagging and boosting ensemble classifiers for basic hand movement recognition is evaluated using EMG signals captured during grasping actions with different objects for the six hand movements [39].

Table 3. Pseudo code for the proposed feature extraction

Pseudocode: sEMG signal classification scheme with the proposed feature extraction
Input: n×m sEMG signals $x_{n\times m}(i)$, each with class labels 1. for each n = 1 to N, m = 1 to M. 2. for winsize = 250ms, wininc = 75ms. 3. Compute f_1=m_0, f_2=m_2, f_3=m_4, f_4=Sparseness, f_5=IRF, f_6=WL. 4. Wavelet decompose $x_{n\times m}(i)$, with 'db44' & extract the filter coefficients by decomposing $x_{n\times m}(i)$: L= Wavelet filter coefficients 5. R_1=Reshape(f_1), R_2=Reshape(f_2), R_3=Reshape(f_3), R_4=Reshape(f_4), R_5=Reshape(f_5), R_6=Reshape(f_6). [features of size (1×M) are reshaped into the shape a×b, such that multiplication of a and b gives the channel M. 6. Convolution: R_1*L, R_2*L, R_3*L, R_4*L, R_5*L, R_6*L 7. Flatten and concatenate → Feature F4. 8. Compute the first four conditional spectral moments using Eqs. (1), (2), (3), and (4), feature F5. 9. Classify features with SVM, KNN, Decision Tree, and Ensemble Bagging.

3. RESULTS AND DISCUSSION

3.1 EMG data pre-processing model training

This research was conducted on an HP DESKTOP-F26D10N running Windows 10 Pro 64-bit, equipped with an AMD A8-5500B APU featuring Radeon HD Graphics with a 3.20 GHz processor and 8.00 GB of installed RAM. The data pre-processing, feature extraction, and classification were done in MATLAB 2022 software to obtain both the training and testing datasets. Each dataset undergoes different preprocessing procedures. The Ninapro DB1 is sampled at 100 Hz, and wavelet denoising using the Daubechies wavelet of order 44 ['db44'] wavelet is applied. NinaPro DB2 was sampled at 2 kHz. It undergoes low-pass filtering with a 500 Hz cutoff, line noise filtering at 50 Hz, and wavelet denoising using the 'db44' wavelet since the 'db44' family of wavelets possesses similar characteristics as the EMG signal. Ten-fold cross-validation is performed to obtain a robust estimate of the model performance and also for better generalization capability. All the classifiers were trained with 70% cross-validation and 30% test sets for all the exercises. Both the training and testing datasets are standardized, ensuring that the resulting data exhibits a mean of zero and a variance of one. Let TP and TN denotes the True positive and True Negative values, FP and FN denotes the False Positive and False Negative values, the classification accuracy is given by:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{9}$$

3.2 Results of Ninapro DB1 and DB2

The proposed features (F4 and F5) are evaluated on the two benchmark datasets, Ninapro DB1 and DB2. Ten-fold cross-validation is used, in which the data is randomly divided into ten equal parts, ensuring that each class is represented proportionally as it appears in the entire dataset. The Ninapro DB1 includes 52 hand gestures, which are categorized into 3 exercises, namely E1 (12 classes), E2 (17 classes), and E3 (23 classes), respectively. Ninapro DB2 contains 49 hand gestures, which are categorized into 3 exercises: E1 (17 classes), E2 (23 classes), and E3 (9 classes). Two experiments were conducted on the aforementioned datasets:

(1) Model evaluation for 12, 17, and 23 classes: The choice of window length and overlap impacts the temporal resolution of feature extraction, influencing the ability to capture detailed temporal aspects. Hence, evaluating the proposed features F4 and F5 with different window lengths and overlaps [(250 ms, 75 ms) and (200 ms, 50 ms)] for the classifiers SVM, KNN, DT, and Bagged Ensemble DT and exploring the best feature-classifier combination. The analysis is conducted separately on three exercises within each dataset to reveal the implications of classification accuracy across different numbers of gestures.

(2) Model evaluation for 52 classes: evaluating the proposed features for all the hand gestures in Ninapro DB1 and DB2.

3.2.1 Model evaluation for 12, 17, and 23 classes

The classification accuracy of Ninapro DB1 for window lengths of 250 ms and 200 ms and overlap of 75 ms and 50 ms is tabulated in Table 4 for all the features mentioned in Table 2. The features F4 and F5 provide better classification accuracy with a bagged ensemble classifier for the window length and overlap of 250 ms and 75 ms, respectively. Similar results are found for all the features. The feature sets F1, F2, and F3 give higher classification accuracy with a bagged ensemble classifier for window length and overlap of 250 ms and 75 ms, respectively. The accuracy of the KNN classifier is higher than that of the SVM for features in F1 and F2. A statistical significance test was conducted for all feature combinations and classifiers and found that the bagged ensemble classifier with features F4 and F5 significantly outperformed all other classifiers (p<0.01).

Table 4. Classification accuracies of Ninapro DB1for 12, 17, 23 classes

Feature	Exercise	(Win Len, Overlap)	Classification Accuracy (%)			
			SVM	KNN	DT	Ensem. Bagg.
	E1		69.6	68.3	74.6	82.5
F1	E2	(250ms,75ms)	66	67.8	72.9	80.4
	E3		65.2	65.8	72.2	77.5
	E1		66.3	68.1	73.9	81.4
F1	E2	(200ms,50ms)	65.8	66.3	72	80.1
	E3		63.7	65.2	71.6	76.4
	E1		76.7	82.3	80.1	84.1
F2	E2	(250ms,75ms)	74.8	81.4	78.6	82.9
	E3		73.5	80.7	78.1	81.4
	E1		76.1	81.8	79	83.6
F2	E2	(200ms,50ms)	73.9	81.3	78.1	81.8
	E3		73.2	79.1	76.4	80.3
	E1		67.3	65.9	76.2	83.2
F3	E2	(250ms,75ms)	65.4	64.8	74.8	83
	E3		64	64.2	73.3	81.2
	E1		66.8	65.3	75.8	83.1
F3	E2	(200ms,50ms)	63.9	64.2	74.2	82.6
	E3		63.7	63.8	72.8	80.1
	E1		88.7	87.8	80.4	89.3
F4	E2	(250ms,75ms)	88.1	84.1	78.1	87.1
	E3		85.4	83.3	86.3	87.2
	E1		82.6	87.5	80	88.1
F4	E2	(200ms,50ms)	81.8	83	77.8	86.3
	E3		79	82.6	76	85.3
	E1		79.3	83.1	85.8	**95.2**
F5	E2	(250ms,75ms)	77.1	81.8	84.1	94.6
	E3		76.3	80.9	82.1	93.2
	E1		79	81.8	84.3	**94.8**
F5	E2	(200ms,50ms)	76.8	80.1	83.6	93.7
	E3		75.1	80.3	81.8	91.8

Table 5. Classification accuracies of Ninapro DB2 for 12, 17, 23 classes

Feature	Exercise	(Win Len, Overlap)	Classification Accuracy (%)			
			SVM	KNN	DT	Ensem. Bagg.
F1	E1	(250ms,75ms)	66.3	70.4	72.4	79.7
	E2		64.8	68.6	71.6	78.6
	E3		64.2	68.3	68.3	76.3
F1	E1	(200ms,50ms)	65.9	70.1	71.8	78.4
	E2		63.6	68.3	71.1	77.1
	E3		62.1	67.1	70.3	76.1
F2	E1	(250ms,75ms)	73.2	80.2	77.4	84.9
	E2		71.4	78.6	77.1	84.2
	E3		71.1	79	74.3	82.6
F2	E1	(200ms,50ms)	72.1	79.1	76.3	84.3
	E2		70.2	78.1	76.1	84.1
	E3		70	78.3	73.3	81.3
F3	E1	(250ms,75ms)	68.5	65	73.1	75.9
	E2		67.1	64.1	72.6	75.1
	E3		66.8	63.2	70.3	74.6
F3	E1	(200ms,50ms)	67.7	64.2	72.1	74.8
	E2		66.3	63.6	71.9	74.9
	E3		65.9	62.2	70.1	73.2
F4	E1	(250ms,75ms)	82.9	85.8	81.4	87.2
	E2		81.3	84.6	78.3	85.6
	E3		80.8	84.1	78.1	85.5
F4	E1	(200ms,50ms)	81.7	84.7	80.2	86.7
	E2		80.7	83.5	77.9	85.5
	E3		80.2	83.9	7.5	85.3
F5	E1	(250ms,75ms)	79.5	83.4	82.4	91.9
	E2		77.6	82.1	80.3	91.1
	E3		76.2	80.9	80.1	90.3
F5	E1	(200ms,50ms)	79.5	83	82.1	91.3
	E2		77	81.9	80.1	90.9
	E3		76.1	80.7	79.4	89.7

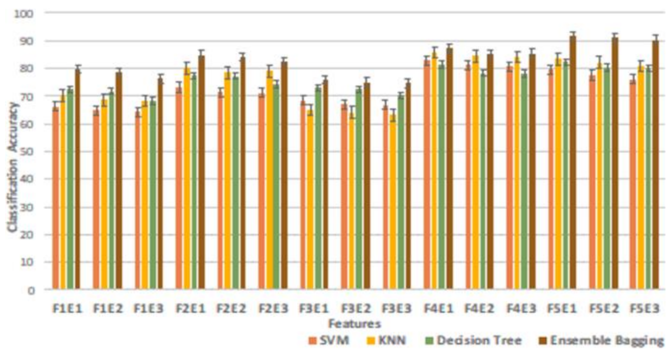

Figure 2. Comparison chart of classification accuracies for Ninapro DB1 for different feature sets

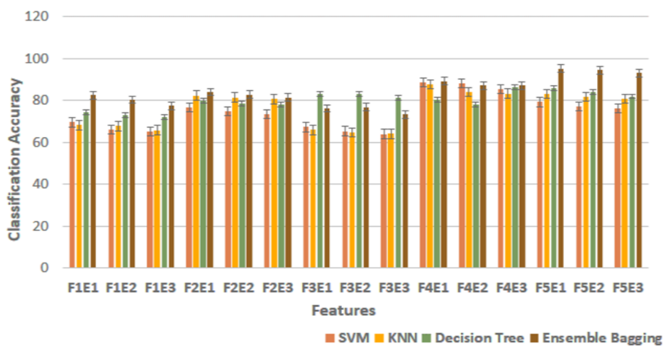

Figure 3. Comparison chart of classification accuracies for Ninapro DB2 for different feature sets

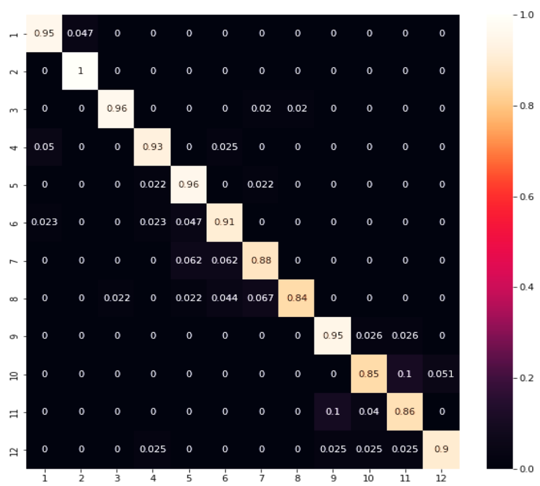

Figure 4. Confusion matrix for 12 gestures of Ninapro DB1

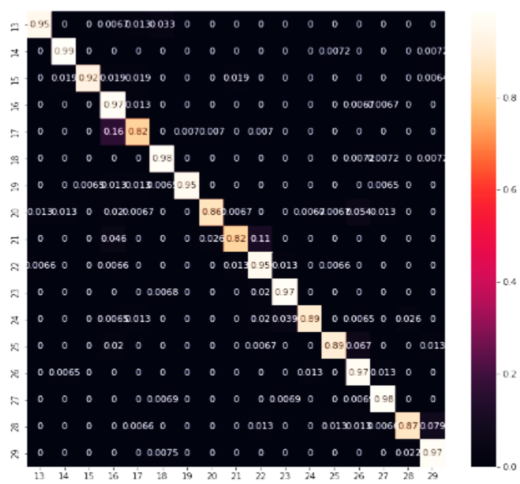

Figure 5. Confusion matrix for 17 gestures of Ninapro DB1

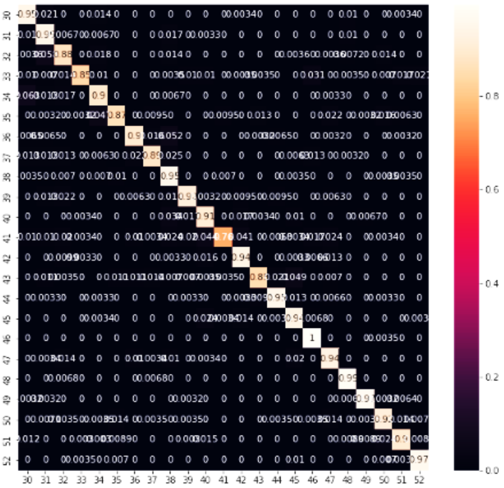

Figure 6. Confusion matrix for 23 gestures of Ninapro DB1

The classification accuracy of Ninapro DB1 for window lengths of 250 ms and 200 ms and overlap of 75 ms and 50 ms is tabulated in Table 5 for all the features mentioned in Table 2. For Ninapro DB2, the features F4 and F5 give the highest classification accuracy for the bagged tree ensemble classifier compared to the features F1, F2, and F3. The performance of the KNN classifier is better than that of SVM for features F1, F2, F4, and F5. The SVM classifier is better than KNN for feature F3. A statistical significance test was conducted for all the feature-classifier combinations; the bagged ensemble classifier for the features F4 and F5 significantly outperformed ($p<0.01$) the other feature sets. The classification accuracy of the DT classifier for feature sets F1, F2, and F3 is higher than that of the SVM and KNN classifiers. For F4 and F5, the accuracies of SVM and KNN are higher than DT classifiers. Figures 2 and 3 show the classification accuracies of Ninapro DB1 and DB2.

The confusion matrix of Ninapro DB1 for the three exercises is given in Figures 4-6. This depicts the model performance for the feature F5 classified with the Ensemble Bagging classifier. In exercise E1, gesture number 8 is misclassified along with neighboring gestures. In exercise E2, gestures 17 and 21 are misclassified. In exercise E3, gestures 33 and 41 are misclassified along with neighboring gestures. All other gestures show better performance. The effect of window length on classification accuracy, according to the work done by Menon et al. [40], was investigated by adopting different window sizes for feature extraction. From the results based on the window length and overlap, a window length of 250 ms and 75 ms works better than a window length of 200 ms and 50 ms. The studies focused on classifying finger and wrist movements, which include the most complex muscle activations. To best utilize the processing capability of the prosthetic device, the overlapping windowing approach was proposed, in which the analysis window is increased by the processing delay, which is the time it takes to extract features and to make a decision. Also, this model can be compared with deep learning (DL) models with respect to its classification performance and the ability to extract both spatial and temporal information.

3.2.2 Model evaluation for 52 classes

The classification accuracies of Ninapro DB1 and DB2 for the 52 classes of movements for the window length of 250 ms and overlap of 75 ms are tabulated in Table 6. Using Ninapro DB1 and DB2, the features F4 and F5 show more promising results for the bagged ensemble classifier. The highest classification accuracy is reported for feature F5, followed by feature F4. The performance of SVM is better than the KNN classifier for the features F1, F2, F4, and F5 for Ninapro DB1. For feature F3, the KNN classifier gives better accuracy than SVM. For Ninapro DB2, for all the features, the performance of the SVM classifier is better than that of the KNN classifier.

Table 6. Classification accuracies of Ninapro DB1 and DB2 for 52 classes

Feature	Ninapro DB1				Ninapro DB2			
	SVM	KNN	DT	Bagged Ensemble	SVM	KNN	DT	Bagged Ensemble
F1	78.5	76.3	80.9	83.4	76.4	73.9	80.3	81.4
F2	75.3	72.4	77.3	80.3	73.9	71.3	78.6	80.1
F3	76.4	79.3	81.4	84.9	77.4	72.9	80.1	82.9
F4	84.5	81.3	86.3	**87.1**	80.3	77.3	81.7	**85.3**
F5	87.6	85.7	90.1	**92.9**	86.6	83.4	88.3	**90.8**

Table 7. Computation time for different feature extraction schemes

Feature	Computation Time (sec)
F1	0.723
F2	0.752
F3	0.536
F4	0.874
F5	0.793

3.3 Computation time

The computation time for the feature extraction of the EMG signals is given below in Table 7.

The computation time for extracting F4 and F5 is higher than F1, F2, and F3. Efforts to mitigate this limitation could involve exploring advanced hardware acceleration techniques, parallel processing strategies, or implementing more efficient algorithms for feature extraction. The increased computational requirements may impact the real-time applicability of the system, particularly in situations where low latency is essential. Despite the current computational time constraint, the study lays the foundation for future research endeavors aimed at improving the efficiency of EMG-based hand gesture classification systems. Incorporating multi-modal data, such as combining EMG signals with other sensor data like accelerometers or inertial sensors, can potentially enhance the robustness and accuracy of prosthesis control systems.

3.4 Comparison with the literature

The proposed feature extraction is compared with the literature as given in Table 8. Atzori et al. [23] have proposed an EMG classification with Ninapro DB1 and DB2 and provided an accuracy of 75.32% and 75.27%, respectively. Wei et al. [21] utilized the same dataset for gesture classification and came up with an accuracy of 88.20% and 83.70%. Karnam et al. [13] utilized energy features and attained an accuracy of 88.8% for energy features. Pancholi et al. [22], by utilizing Ninapro DB1, achieved an accuracy of 92.18%. The modified time domain descriptor feature provides classification accuracies of 87.1% and 85.3% for Ninapro DB1 and DB2. The conditional spectral moments provide classification accuracies of 92.9% and 90.8% for Ninapro DB1 and DB2, respectively, which are higher than the literature.

Table 8. Comparison of the proposed features with the literature values

Authors	Database	Classes	Accuracy (%)
Atzori et al. [23]	Ninapro DB1	50	75.32
	Ninapro DB2	49	75.27
Wei et al. [21]	Ninapro DB1	52	88.20
	Ninapro DB2	50	83.70
Karnam et al. [13]	Ninapro DB1	52	88.8
Pancholi et al. [22]	Ninapro DB1	53	92.18
Proposed Feature	Ninapro DB1	52	92.9
F5 (Ensemble Bagging)	Ninapro DB2	50	90.8

4. CONCLUSION

In this work, the feature extraction and classification of myoelectric signals, with a primary focus on enhancing the accuracy of classifying hand gestures with multiple DoF for prosthetic applications, have been presented. The pivotal role of feature extraction in the success of myoelectric pattern recognition has been underscored, and in this work, two features, namely conditional spectral moments and an enhanced time-domain descriptor, have been proposed to achieve improved classification performance. The conditional spectral moments, derived from the time-frequency distribution of EMG signals, effectively captured variations in muscle activity and movement, providing valuable insights for the classification of intricate hand gestures. Furthermore, the enhanced time-domain descriptor obtained through convolution with wavelet filter coefficients successfully extracted both spatial and temporal characteristics of muscle activity, contributing to a more robust representation of the myoelectric signal. Ninapro DB1 and DB2 were used to evaluate the efficacy of the enhanced time domain descriptors and conditional spectral moment features by using the classifiers SVM, KNN, DT, and ensemble bagging. The classification accuracies for the proposed TD-PSD and conditional spectral moment feature have improved significantly, with 87.1% and 92.9%, respectively, for Ninapro DB1 and 85.3% and 90.8% for Ninapro DB2, respectively. These findings showcase the ability of the features to capture spatial and temporal information from the EMG signal and provide multiple DoFs for prosthetic users. By incorporating feature selection and dimensionality reduction, the extensive computation time for feature extraction can be reduced, making the model more practical and scalable. This study can be further extended for more complex movements with multiple degrees of freedom to handle intricate hand gestures and diverse movement patterns. The feature engineering in myoelectric applications thus paves the way for more accurate and effective prosthetic control systems.

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NOMENCLATURE

k	Frequency index
Δ	Derivative
db44	Daubechies wavelet function
p	Probability under assumption

APPENDIX

Let $X[k]$ represent the corresponding Discrete Fourier Transform of the EMG input signal. It states that the sum of the square of $x[j]$ equals the sum of the square of $X[k]$. It can be described by the equation:

$$\sum_{j=0}^{N-1} |x[j]^2| = \frac{1}{N}\sum_{k=0}^{N-1} |X[k]X^*[k]| = \sum_{k=0}^{N-1} P[k] \quad (10)$$

$P[k]$ is the phase-excluded power spectrum derived from the multiplication of $X[k]$ by its conjugate, and 'k' is the frequency index. The power spectral density cannot be directly accessed from the time domain, both positive and negative frequencies should be dealt with, in significance with the symmetry property, and statistically, all the odd moments become zero. The n*th*-order moment m of $P[k]$ is given by the following equation:

$$m_n = \sum_{k=0}^{N-1} k^n\, P[k] \quad (11)$$

Eq. (10) uses Eq. (11) for n = 0 and non-zero values, it utilizes the time-differentiation property. According to this property, the n^{th} derivative corresponds to multiplying the spectrum by k^n for a discrete-time signal in the time domain.

Mathematically, this can be given as:

$$F\left[\Delta^n x[j]\right] = k^n X[k] \quad (12)$$

The zero-order moment (power in frequency domain) or the strength of muscle contraction is stated as:

$$f_1 = m_0 = \sqrt{\sum_{j=0}^{N-1} x[j]^2} \quad (13)$$

Accordingly, the second and fourth-order moments can be given by the equations:

$$f_2 = m_2 = \sqrt{\sum_{k=0}^{N-1} k^2 P[k]} = \sqrt{\frac{1}{N}\sum_{j=0}^{N-1} \Delta x[j]^2} \quad (14)$$

A repetition of this yields the fourth-order moment.

$$f_3 = \sqrt{\sum_{k=0}^{N-1} k^4 P[k]} = \sqrt{\frac{1}{N}\sum_{j=0}^{N-1} (\Delta^2 x[j])^2} \quad (15)$$

Sparseness is a feature that states how much energy is packed within a few components. It is represented by:

$$f_4 = \log\left(\frac{m_0}{\sqrt{(m_0 - m_2)(m_0 - (m_4)}}\right) \quad (16)$$

The Irregularity Factor (IF) can be defined from the number of Zero Crossings (ZC) and the Number of Peaks (NP). Both the measures can be expressed merely by their spectral moments. The IF can be demonstrated expressively by:

$$f_5 = \log\left(\frac{ZC}{NP}\right) = \log\left[\frac{\sqrt{\frac{m_2}{m_0}}}{\sqrt{\frac{m_2}{m_2}}}\right] = \log\,(\frac{m_2}{\sqrt{m_0 m_4}}) \quad (17)$$

The Waveform Length Ratio (WL) feature can be obtained by summing the absolute value of the EMG signal derivatives. It can be expressed mathematically as:

$$f_6 = \log\left(\frac{\sum_{j=0}^{1}|\Delta x|}{\sum_{j=0}^{1}|\Delta^2 x|}\right) \quad (18)$$