Prediction of orientation-aware sEMG gesture classification by a Hybrid Phase–Frequency Dynamical Map Framework with the FORS-EMG dataset

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Abstract

As an emerging research field, the recognition of gestures using surface electromyography (sEMG) has drawn significant attention in diverse applications such as assistive robotics, wearable human–computer interaction (wHCI), rehabilitation engineering, and prosthetic control. Nevertheless, accurate gesture classification is still difficult due to the high non-stationarity of the sEMG signals, and the inter-subject variability, forearm orientation, and electrode displacement. This paper introduces a new hybrid feature engineering approach for orientation-aware sEMG gesture classification using FORS-EMG dataset, which utilizes traditional time domain descriptors and a proposed Phase–Frequency Dynamical Map (PFDM) sEMG representation. The proposed method uses 160 features extracted from every signal epoch such as statistical time domain features and nonlinear features based on PFDM analysis including phase space and spectral descriptors. Four machine learning classifiers, Support Vector Machine (SVM), Random Forest (RF), K-Nearest Neighbors (KNN), and Naive Bayes (NB), are compared in regard to both subject-specific five-fold cross validation (5x5) and leave-one-subject-out (LOSO) validation. The experimental results show that the classification accuracy is high under the subject specific evaluation with SVM having the maximum mean accuracy of 96.32%. The proposed framework also shows the capacity to promise generalization in the cross subject validation. The results acquired suggest that the incorporation of nonlinear phase frequency dynamics towards conventional EMG descriptors could offer an understandable and a lightweight approach to robust wearable sEMG gesture recognition systems.

Keywords: Surface electromyography (sEMG); Hand gesture recognition; Phase–Frequency Dynamical Map (PFDM); Machine learning; Cross-subject classification; Wearable biosignal processing

1. Introduction

The surface electromyography (sEMG) is a non-invasive electrophysiological method for measuring the electrical activity produced by skeletal muscles when they contract. In the last few years, gesture recognition using sEMG has received enormous research interest due to its applications in control of prosthetic hand, rehabilitation systems, assistive robotics, exoskeletons, virtual reality interfaces, gaming systems, and human–computer interaction. With the growing number of low cost wearable EMG acquisition systems, the research has been pushed forward to further realize intelligent and real-time gesture decoding systems.

Although there have been significant advances in this research area, there is still much work to be done in the field of robust sEMG gesture recognition. The sEMG signals have highly nonlinear, stochastic and non-stationary properties unlike the conventional stationary physiological signals. They differ widely with muscle fatigue, electrode displacement, muscle contraction strength, the posture of the limbs, the angle of the forearm and inter-subject physiological differences. In particular, among these factors, forearm orientation variation is important as it can significantly affect muscle activation patterns and decrease the generalization ability of a gesture recognition system.

Most of the traditional sEMG gesture classification methods are based on the time domain features that are handcrafted, such as mean absolute value (MAV), root mean square (RMS), zero crossing (ZC), and slope sign change (SSC). The features are also computation-efficient and have been found to work well in various wearable applications. The method is also studied in the frequency domain and time–frequency domain using other approaches to enhance the robustness of the method to signal variability. Recently, deep learning techniques such as deep convolutional neural network (CNN), recurrent neural network (RNN), and long short-term memory (LSTM) have demonstrated classification ability. But most deep learning methods are complex, need large training sets and a high model complexity, which is a problem when used in lightweight wearable systems.

Another key shortcoming in the literature is the absence of orientation-aware datasets and evaluation approaches. Although there are many publicly available EMG datasets available, they are typically collected in a fixed posture of the limbs which is not representative of realistic wearable operating conditions. The FORS-EMG dataset overcomes this issue with several forearm orientations when acquiring gestures. This dataset comprises 19 subjects performing 12 gestures in three orientations (pronation, resting and supination) with an 8 channel sEMG acquisition system.

These challenges led to the development of a hybrid feature engineering framework combining conventional time domain descriptors and a Phase–Frequency Dynamical Map (PFDM) representation for the problem of gesture classification from sEMG for orientation. To tackle these challenges, this conference paper proposes a hybrid feature engineering framework, which combines conventional time domain descriptors and a Phase–Frequency Dynamical Map (PFDM) representation for orientation-aware sEMG gesture classification. The methodology proposed integrates statistical EMG features with non-linear phase space and spectral descriptors, which are able to characterize local amplitude properties and complex dynamics of sEMG signals. In contrast to purely deep learning-based systems, the proposed framework is not only computationally light but it is also interpretable and can be used in wearable implementations.

The proposed PFDM framework includes the following metrics based on the trajectories: phase-space descriptors, recurrence characteristics, spectral measures, and coupled phase-frequency interaction metrics. The extracted descriptors are combined with conventional time domain features together to form a complete feature representation for gesture classification. Four classifiers are used to evaluate the performance in the two settings – subject-specific and cross-subject: SVM, RF, KNN, and NB.

2. Methodology

2.1 Dataset Description

In this study, FORS-EMG data were used for the experiments. The dataset has been created with the goal of hand gesture recognition in different forearm orientations and serves as a representative ground truth for wearable EMG classifiers. The data consists of recordings of 19 able-bodied subjects performing 12 hand and wrist gestures with three different forearm orientations: pronation, neutral resting position and supination. Wearable EMG sensors around the forearm were used to collect 8-channel sEMG signals. Five repetitions for each gesture- orientation were done for each subject. The sampling rate of the acquisition system was 200 Hz. Thus, the database is complete and includes all orientation-specific EMG patterns, which can be used for subject-specific and cross-subject pattern generalization.

Table 1. FORS-EMG Dataset Configuration

Parameter	Value
Subjects	19
Gestures	12
Forearm Orientations	3
Trials per Gesture	5
EMG Channels	8
Sampling Frequency	200 Hz
Total Samples	3420

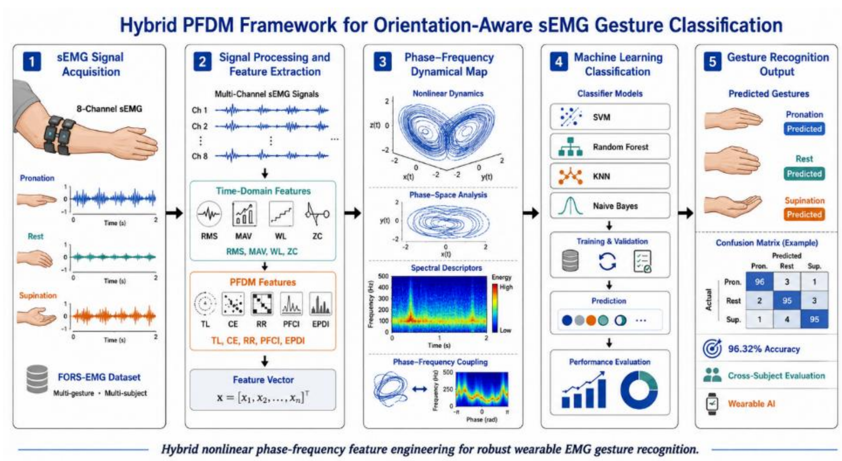


Fig 1: Overall Block Diagram of Proposed Methodology

2.2 Signal Processing Framework

The proposed methodology consists of signal acquisition, feature extraction, feature fusion, classification, and performance evaluation stages. Each EMG sample is processed independently across all eight channels. Hybrid features obtained from time-domain analysis and PFDM analysis are concatenated to generate the final feature representation.

2.3 Preprocessing

The extracted EMG feature matrices were normalized prior to classification using z-score normalization. Let X denote the extracted feature matrix. The normalized feature vector Xn is computed as:

$$X_n = \frac{X - \mu}{\sigma} \qquad (1)$$

where (μ) and (σ) represent the mean and standard deviation of the training features, respectively.

Normalization is particularly important for cross-subject classification because different subjects exhibit significant variability in EMG amplitude and signal distribution.

2.4 Time-Domain Feature Extraction

Conventional time-domain (TD) features were extracted independently from each EMG channel. Time-domain descriptors are computationally efficient and widely used in wearable EMG systems. The extracted TD features include Mean, Standard deviation, Variance, Root mean square (RMS), Mean absolute value (MAV), Zero crossing (ZC), Slope sign change (SSC), Waveform length (WL), Skewness, Kurtosis

The RMS feature is mathematically expressed as:

$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2} \qquad (2)$$

Similarly, MAV is computed as:

$$MAV = \frac{1}{N}\sum_{i=1}^{N} |x_i| \qquad (3)$$

where (x_i) represents the EMG sample and (N) denotes the total number of samples in the epoch.

2.5 Proposed PFDM Feature Framework

The proposed Phase–Frequency Dynamical Map (PFDM) framework integrates nonlinear phase-space dynamics with spectral descriptors to capture complex temporal and dynamical properties of sEMG signals.

The PFDM descriptors include Trajectory Length (TL), Curvature Entropy (CE), Phase Volume (PV), Recurrence Rate (RR), Mean Divergence (MD), Spectral Centroid (SC), Spectral Bandwidth (SB), Spectral Entropy (SE), Phase–Frequency Coupling Index (PFCI), Energy–Phase Dispersion Index (EPDI).

Table 2. Feature Categories Used in the Proposed Framework

Feature Group	Features
Time-Domain Features	Mean, Std, Variance, RMS, MAV, ZC, SSC, WL, Skewness, Kurtosis
PFDM Features	TL, CE, PV, RR, MD, SC, SB, SE, PFCI, EPDI

The phase-space trajectory of the EMG signal can be represented as:

$$P(t) = [x(t), x(t + \tau)] \qquad (4)$$

where (τ) denotes the embedding delay.
Trajectory Length (TL) is computed as:

$$TL = \sum_{i=1}^{N-1} \sqrt{(x_{i+1} - x_i)^2 + (y_{i+1} - y_i)^2} \qquad (5)$$

Spectral entropy is estimated as:

$$SE = -\sum_{k=1}^{K} p_k \log(p_k) \qquad (6)$$

where (p_k) represents the normalized spectral energy distribution.

The proposed PFCI descriptor captures the coupling between phase-space angular dynamics and frequency behavior. This descriptor is designed to characterize orientation-dependent variations in muscle activation patterns.

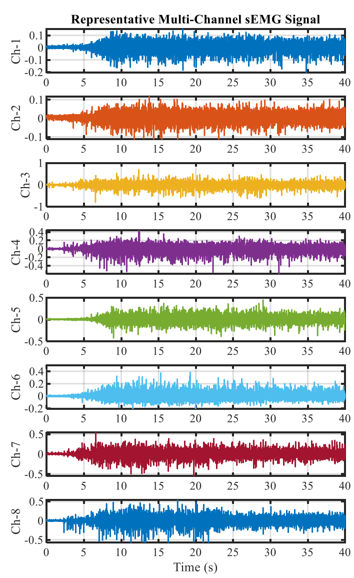
2.6 Feature Fusion

For each EMG channel, ten TD features and ten PFDM features are extracted. Since the dataset contains eight channels, the total feature dimensionality per signal epoch is:

$$8 \times (10 + 10) = 160 \qquad (7)$$

Table 3. Feature Dimensionality

Description	Count
TD Features per Channel	10
PFDM Features per Channel	10
Total Features per Channel	20
Number of Channels	8
Total Features per Epoch	160



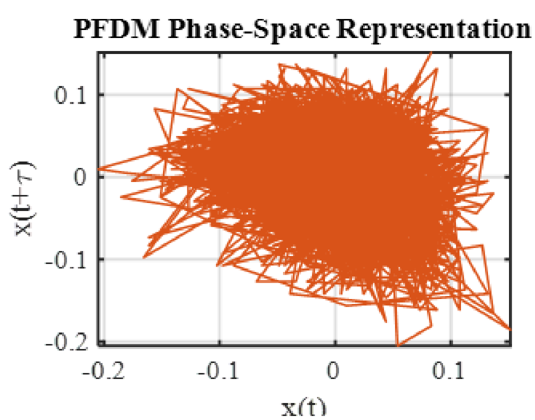


Fig 2: phase–Frequency Dynamical Map Representation

Fig 3: Representative Multi-Channel sEMG Signal

2.7 Classification Models

Four machine learning classifiers were employed for gesture classification.

Support Vector Machine (SVM): A linear multiclass error-correcting output code SVM classifier was used because of its strong generalization capability and computational efficiency.

Random Forest (RF): Random Forest classification was implemented using an ensemble of decision trees constructed using bootstrap aggregation.

K-Nearest Neighbors (KNN): KNN classification was performed using Euclidean distance with (k = 5).

Naive Bayes (NB): A probabilistic Naive Bayes classifier was employed to evaluate lightweight statistical classification performance.

2.8 Validation Protocols

Two evaluation strategies were considered.

Subject-Specific 5-Fold Cross-Validation: In this setting, training and testing were performed separately for each subject using five-fold cross-validation.

Leave-One-Subject-Out (LOSO) Validation: LOSO validation evaluates cross-subject generalization. During each iteration, one subject was used for testing while the remaining eighteen subjects were used for training.

2.9 Performance Metrics

Classification performance was evaluated using accuracy, precision, recall, and F1-score.

Accuracy is defined as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (8)$$

Precision and recall are computed as:

$$Precision = \frac{TP}{TP + FP} \quad (9)$$

$$Recall = \frac{TP}{TP + FN} \quad (10)$$

The F1-score is given by:

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (11$$

3. Results and Discussion

3.1 Subject-Specific Classification Performance

The proposed hybrid PFDM framework demonstrated strong classification performance under subject-specific five-fold cross-validation. Among the evaluated classifiers, SVM achieved the highest average classification accuracy of 96.32%, followed by Random Forest with 94.59%, Naive Bayes with 91.32%, and KNN with 90.50%.

Table 4. Subject-Specific Five-Fold Cross-Validation Performance

Classifier	Mean Accuracy (%)
SVM	96.32
Random Forest	94.59
KNN	90.50
Naive Bayes	91.32

The obtained results indicate that the proposed hybrid feature representation effectively captures orientation-dependent EMG characteristics. The superior performance of SVM suggests that the extracted feature space possesses good discriminative separability.

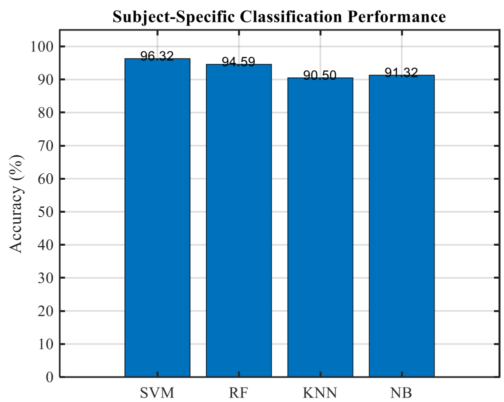


Fig 4: Subject-Specific Classifier Performance Comparison]

3.2 Cross-Subject LOSO Performance

LOSO evaluation was conducted to investigate model generalization across unseen subjects. Cross-subject gesture recognition is considerably more challenging because of inter-subject variability in muscle physiology and electrode placement.

The LOSO experiments demonstrate that the proposed methodology maintains promising generalization capability even under unseen-subject conditions. Although performance degradation was observed compared with subject-specific validation, this behavior is expected in practical wearable EMG systems.

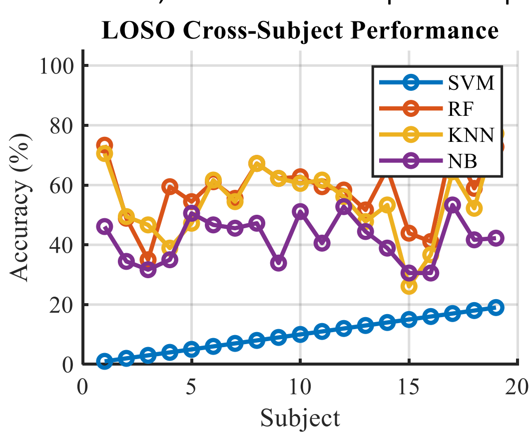


Fig 5: LOSO Per-Subject Performance

3.3 Reduced Feature Optimization Results

Preliminary feature reduction experiments were also conducted using optimized feature subsets.

Table 5. Reduced Feature Optimization Results

Classifier	Accuracy (%)
Bagged Trees	43.09
KNN	35.95
Decision Tree	29.76

The reduced-feature analysis demonstrates that aggressive feature reduction can significantly influence classification performance. These preliminary observations motivate future work involving advanced feature selection and dimensionality reduction strategies.

3.4 Discussion

There are a number of significant points to note about the proposed methodology. First, the use of nonlinear phase-space descriptors in conjunction with the conventional EMG features provides better representation capability of the extracted feature space. Second, the framework is not as compute-intensive as deep learning based methods and therefore is appropriate for wearable or embedded applications. The PFDM representation includes more information about the signal dynamics and phase-frequency interactions information that cannot be obtained from a conventional time domain representation. The results retrieved indicate that nonlinear descriptors can be useful in enhancing the performance of the orientation-aware gesture recognition. This idea of the proposed framework also is well-interpretable as the extracted descriptors have meaningful physical and statistical interpretation. This is a significant benefit when compared to lots of deep learning systems, which are considered black-box models. However, there are certain limitations with the present study. The existing research does not provide much analysis on feature selection, deep learning comparison, and cross-dataset benchmarking. Moreover, there was no detailed analysis performed on deployment analysis and optimization of computational complexity in real time. Future work involves optimization of advanced features, integration of hybrid Deep Learning, Cross Subject Transfer Learning and implementation of Advanced Features in Real time at Wearable Computer. Further research utilizing explainable artificial intelligence and adaptive EMG decoding methods could help to enhance the robustness of gesture recognition systems with orientation awareness.

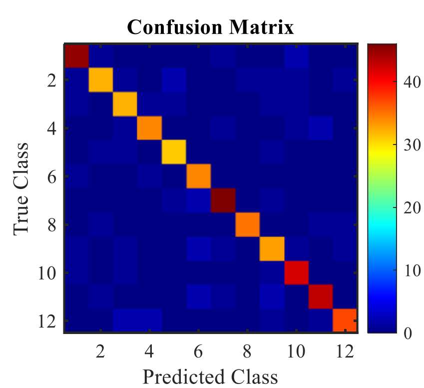


Fig 6: Confusion Matrix of Best Performing Classifier

4. Conclusion

This conference paper introduced a hybrid feature engineering approach that combines traditional time domain descriptors with a proposed Phase–Frequency Dynamical Map (PFDM) representation to classify sEMG based orientation-aware gestures with the FORS-EMG dataset. The proposed methodology combines statistical, nonlinear and spectral descriptors to capture the complex dynamics of the EMG under different forearm orientations.

Eight channel EMG records were taken of each epoch of each signal, from which a total of 160 features were extracted. Several machine learning classifiers were tested with both subject-specific and cross-subject validations. The classification results obtained from the experiments showed good classification with the best accuracy obtained by SVM which is 96.32% for a particular subject. The results obtained suggest that the proposed nonlinear phase space analysis along with conventional EMG descriptors can be an effective and easily interpretable solution for developing wearable gesture recognition systems. Furthermore, the proposed methodology is also lightweight in computation as compared to complicated deep learning architectures. The present work lays the groundwork for future research on feature optimization, dimensionality reduction, transfer learning and real-time embedded implementation. Future extensions will also feature full ablation analysis, cross-dataset benchmarking and sophisticated adaptive learning models for the robust cross-subject EMG gesture recognition.

References

[1] U. Rumman, A. Ferdousi, B. Saha, M. S. Hossain, M. J. Islam, S. Ahmad, M. B. I. Reaz, and M. R. Islam, "FORS-EMG: A Novel sEMG Dataset for Hand Gesture Recognition Across Multiple Forearm Orientations," arXiv preprint arXiv:2409.07484, 2024.

[2] A. Jaramillo-Yánez, M. Benalcázar, and E. Mena-Maldonado, "Real-Time Hand Gesture Recognition Using Surface Electromyography and Machine Learning: A Systematic Literature Review," Sensors, vol. 20, no. 9, p. 2467, 2020.

[3] Z. Zhang, Z. Yang, H. Yin, Z. Zhang, Y. Xiao, and H. Yang, "Real-Time Surface EMG Pattern Recognition for Hand Gestures Based on an Artificial Neural Network," Sensors, vol. 19, no. 14, p. 3170, 2019.

[4] T. Prabhavathy, M. A. Hossain, and S. A. Parah, "A Surface Electromyography Based Hand Gesture Recognition Framework Leveraging Variational Mode Decomposition Technique and Deep Learning Classifier," Engineering Applications of Artificial Intelligence, vol. 130, p. 107669, 2024.

[5] J. Shin et al., "Hand Gesture Recognition Using sEMG Signals with a Multi-Stream CNN Framework," Scientific Reports, vol. 14, 2024.

[6] M. R. K. Kadavath et al., "Enhanced Hand Gesture Recognition with Surface Electromyography Signals Using Machine Learning," Sensors, vol. 24, no. 16, p. 5231, 2024.

[7] M. R. Islam, D. Massicotte, P. Y. Massicotte, and W. P. Zhu, "Surface EMG-Based Inter-Session/Inter-Subject Gesture Recognition by Leveraging Lightweight All-ConvNet and Transfer Learning," arXiv preprint arXiv:2305.08014, 2023.

[8] A. S. M. Miah, N. Hassan, M. Maniruzzaman, N. Asai, and J. Shin, "EMG-Based Hand Gesture Recognition through Diverse Domain Feature Enhancement and Machine Learning-Based Approach," arXiv preprint arXiv:2408.13723, 2024.

[9] P. N. Aarotale and A. Rattani, "Machine Learning-based sEMG Signal Classification for Hand Gesture Recognition," arXiv preprint arXiv:2411.15655, 2024.

[10] R. Zhang et al., “Advances in Electromyography Armbands for Gesture Recognition,” iScience, 2025.
[11] Y. He et al., “Improved Fuzzy Adaptive Membership Function Algorithm for HD-sEMG Gesture Classification,” Journal of Advanced Computational Intelligence and Intelligent Informatics, vol. 29, no. 5, 2025.
[12] K. S. Prakash et al., “An Optimized Electrode Configuration for Wrist Wearable EMG-Based Hand Gesture Recognition System,” Expert Systems with Applications, 2025.
[13] W. Wei et al., “Surface-Electromyography-Based Gesture Recognition by Multi-View Deep Learning,” IEEE Transactions on Biomedical Engineering, vol. 66, no. 10, pp. 2964–2973, 2019.
[14] Y. Hu et al., “A Novel Attention-Based Hybrid CNN-RNN Architecture for sEMG-Based Gesture Recognition,” PLoS ONE, vol. 13, no. 10, 2018.
[15] L. Chen, J. Fu, Y. Wu, H. Li, and B. Zheng, “Hand Gesture Recognition Using Compact CNN via Surface Electromyography Signals,” Sensors, vol. 20, p. 672, 2020.
[16] K. Lakra et al., “Toward Fatigue-Aware sEMG Gesture Recognition for VR Applications,” Proceedings of ACM Symposium, 2025.
[17] R. Rajapriya and M. Rajeswari, “Forearm Orientation and Contraction Force Independent Method for Hand Gesture Recognition Using sEMG Signals,” IEEE Sensors Journal, 2020.
[18] A. Aydin et al., “EMG Based Hand Gesture Recognition Using Deep Learning,” 2020 International Conference Publication.
[19] P. S. Wawryka et al., “Intra- and Inter-Individual Spectral Pattern Variability of sEMG Signals,” 2026.
[20] R. Khushaba et al., “Temporal-Spatial Descriptors for Robust Myoelectric Pattern Recognition,” IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 25, no. 6, pp. 1–10.
[21] 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.
[22] S. 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.
[23] N. Jiang, S. Dosen, K. R. Muller, and D. Farina, “Myoelectric Control of Artificial Limbs: Is There a Need to Change Focus?” IEEE Signal Processing Magazine, vol. 29, no. 5, pp. 152–150, 2012.
[24] D. Farina and O. Aszmann, “Bionic Limbs: Clinical Reality and Academic Promises,” Science Translational Medicine, vol. 6, no. 257, 2014.
[25] S. Scheme and K. Englehart, “Electromyogram Pattern Recognition for Control of Powered Upper-Limb Prostheses: State of the Art and Challenges for Clinical Use,” Journal of Rehabilitation Research and Development, vol. 48, no. 6, pp. 643–660, 2011.