Design and Implementation of a Time–Frequency Metaheuristic Framework for Automated Limb-Movement Classification

Dr Syeda Husna Mehanoor [1], Dr. Shashi Kant Gupta [2]

[1] Postdoctoral Researcher, Lincoln University College, Malaysia; pdf.syeda@lincoln.edu.my

[2] Adjunct Professor, Lincoln University College, Malaysia, Founding Professor, Translational Research, Lincoln Innovation Hub (LIH), Malaysia; shashigupta@lincoln.edu.my

Abstract:

Reliable limb-movement classification using surface electromyography (sEMG) remains challenging due to signal non-stationarity, inter-subject variability, and high feature redundancy. While prior studies have emphasized classifier design, comparatively less attention has been paid to the systematic formulation of robust experimental methodologies that ensure generalization and feature stability. This paper presents a structured research design and experimental framework for sEMG-based limb-movement recognition, focusing on time–frequency feature representation and large-scale metaheuristic feature selection.

The proposed framework integrates standardized preprocessing, time–frequency decomposition using STFT, EWT, and TQWT, and comprehensive feature extraction encompassing time-domain, spectral, and hybrid descriptors. Feature selection is performed using a diverse set of 44 metaheuristic optimization algorithms, with a composite fitness function balancing classification accuracy and feature compactness. Ensemble-based stability analysis is employed to identify consistently informative features across optimizers and validation folds. Classification performance is evaluated using multiple machine-learning models under both within-subject and cross-subject validation schemes, including Leave-One-Subject-Out testing.

The experimental design is validated on benchmark sEMG datasets, with expected outcomes including substantial feature reduction, improved classification performance, and enhanced generalization. The proposed methodology establishes a reproducible and extensible foundation for robust EMG-based movement recognition.

Keywords: Surface electromyography, Time–frequency analysis, Metaheuristic feature selection, Limb-movement classification, Cross-subject validation

1. Introduction

Surface electromyography (sEMG) has emerged as a critical biosignal for interpreting neuromuscular activity in human–machine interfaces, rehabilitation systems, and assistive robotics. Despite extensive prior research, reliable limb-movement classification remains challenging due to non-stationary signal characteristics, inter-subject variability, muscle fatigue, and redundant feature representations. The first phase of this research identified the limitations of conventional time-domain pipelines and single-optimizer feature selection approaches, particularly in terms of generalization and stability [1], [2], [3].

This second conference paper focuses on translating the identified research problem into a concrete and testable experimental methodology. The emphasis is placed on the systematic design of preprocessing, time–frequency feature extraction, multi-optimizer feature selection, and robust validation strategies. Rather than proposing a new classifier, this work prioritizes methodological rigor and experimental transparency [4].

This paper presents the systematic methodology and experimental framework for achieving robust and generalizable EMG-based limb-movement recognition.

2. Research Design

2.1 Datasets and Data Acquisition

Two publicly available benchmark datasets are employed to ensure methodological generalizability:

1. FORS-EMG Dataset: Multi-channel sEMG recordings acquired from healthy subjects performing controlled upper-limb movements. Signals were recorded at a sampling frequency of 2 kHz using bipolar electrode configurations [5].
2. UCI sEMG Dataset: A widely used dataset consisting of multi-subject forearm muscle activity recordings sampled at 1 kHz, covering multiple hand and wrist gestures [6].

Both datasets include multiple subjects, repetitions, and movement classes, enabling evaluation under both within-subject and cross-subject conditions.

2.2 Data Organization and Splitting

The data are segmented subject-wise and organized into training, validation, and testing partitions. Two validation protocols are adopted:

- 10-Fold Cross-Validation (CV): Applied within subjects to assess classification consistency under controlled conditions [7].

- Leave-One-Subject-Out (LOSO): Used to evaluate cross-subject generalization, where data from one subject are held out entirely for testing [8].

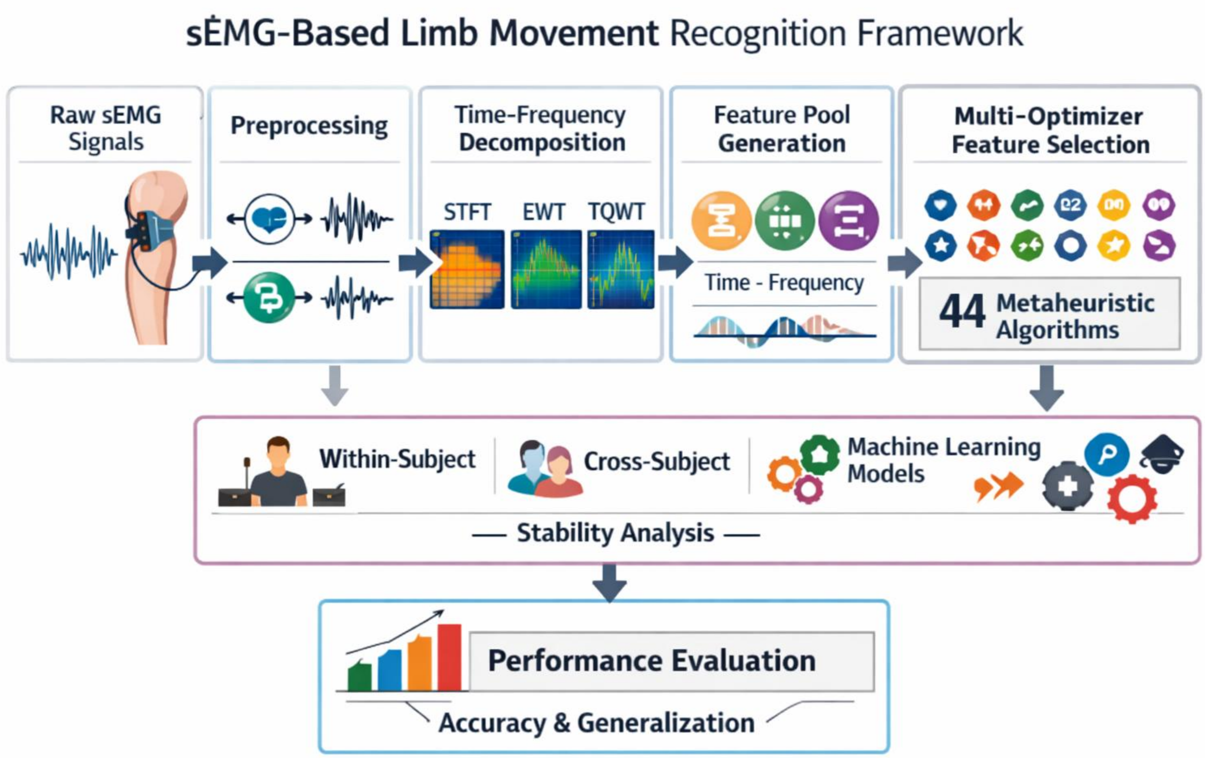

Fig. 1. The framework for sEMG based limb movement classification

2.3 Evaluation Metrics

Performance is quantified using multiple complementary metrics [9]:

- Classification Accuracy
- F1-score
- Matthews Correlation Coefficient (MCC)
- Feature Stability Index (FSI), measuring selection consistency across optimizers and folds

This multi-metric evaluation avoids biased interpretations based solely on accuracy.

3. Methodology Framework

3.1 Signal Preprocessing

Raw sEMG signals are first subjected to a fourth-order Butterworth bandpass filter in the range of 20–450 Hz to suppress motion artifacts and high-frequency noise. Power-line interference is removed using a notch filter at 50 Hz or 60 Hz, depending on dataset origin.

Signals are amplitude-normalized using z-score normalization to reduce inter-session variability. Window-based segmentation is then applied using overlapping windows of 200–250 ms with 50 percent overlap. This window length balances temporal resolution with physiological relevance [10].

3.2 Feature Extraction

To capture both temporal and spectral characteristics, time–frequency decomposition is performed using multiple techniques [7], [8], [11]:

- Short-Time Fourier Transform (STFT)
- Empirical Wavelet Transform (EWT)
- Tunable Q-factor Wavelet Transform (TQWT)

From each sub-band, a comprehensive feature pool is extracted, including:

- Time-domain features: Mean absolute value, variance, waveform length, and Hjorth parameters [12].
- Spectral features: Band power, spectral entropy, and spectral centroid.
- Hybrid features: Energy entropy and log-transformed power ratios.

In selected experiments, the Hilbert transform is applied to obtain instantaneous frequency and amplitude envelope features, enhancing sensitivity to muscle activation dynamics.

3.3 Feature Selection Using Metaheuristic Optimizers

A central contribution of this work is the use of 44 metaheuristic optimization algorithms for feature selection, covering swarm-based, evolutionary, physics-inspired, and math-inspired categories. Examples include Particle Swarm Optimization (PSO), Grey Wolf Optimizer (GWO), Whale Optimization Algorithm (WOA), Arithmetic Optimization Algorithm (AOA), and Harris Hawks Optimization (HHO) [13], [14].

Each optimizer searches for an optimal feature subset by maximizing a composite fitness function [11]:

$$[Fitness = \alpha \times Accuracy + (1-\alpha) \times Compactness] \quad [1]$$

where compactness penalizes larger feature subsets. To improve robustness, ensemble-based feature stability is achieved through voting and intersection strategies across optimizers and validation folds. The summary of these optimizers is given in Table 1.

Table 1. Summary of metaheuristic optimizers

Category	Optimizer	Abbreviation	Key Control Parameters
Swarm-based	Particle Swarm Optimization	PSO	Population size, inertia weight, cognitive and social coefficients
Swarm-based	Grey Wolf Optimizer	GWO	Population size, control parameter *a*
Swarm-based	Whale Optimization Algorithm	WOA	Population size, spiral constant, control parameter *a*
Swarm-based	Harris Hawks Optimization	HHO	Population size, energy parameter
Swarm-based	Ant Lion Optimizer	ALO	Population size, random walk bounds
Swarm-based	Artificial Bee Colony	ABC	Colony size, limit parameter
Physics-inspired	Gravitational Search Algorithm	GSA	Population size, gravitational constant
Physics-inspired	Charged System Search	CSS	Population size, charge coefficient
Physics-inspired	Archimedes Optimization Algorithm	AOA	Population size, density and acceleration coefficients
Evolutionary	Genetic Algorithm	GA	Population size, crossover rate, mutation rate
Evolutionary	Differential Evolution	DE	Population size, mutation factor, crossover probability
Evolutionary	Evolution Strategy	ES	Population size, mutation step size
Mathematics-inspired	Arithmetic Optimization Algorithm	AOA	Population size, arithmetic control parameters
Mathematics-inspired	Sine Cosine Algorithm	SCA	Population size, frequency parameter
Mathematics-inspired	Golden Eagle Optimizer	GEO	Population size, attack and cruise coefficients
Hybrid / Recent	Slime Mould Algorithm	SMA	Population size, weight updating parameters
Hybrid / Recent	Marine Predators Algorithm	MPA	Population size, step size control

3.4 Classification Models

The selected feature subsets are evaluated using multiple classifiers to avoid model-specific bias:

- k-Nearest Neighbors (KNN)

- Support Vector Machine with RBF kernel
- Random Forest
- Light Gradient Boosting Machine (LightGBM)

Performance is evaluated under both within-subject and LOSO settings, emphasizing generalization rather than peak accuracy.

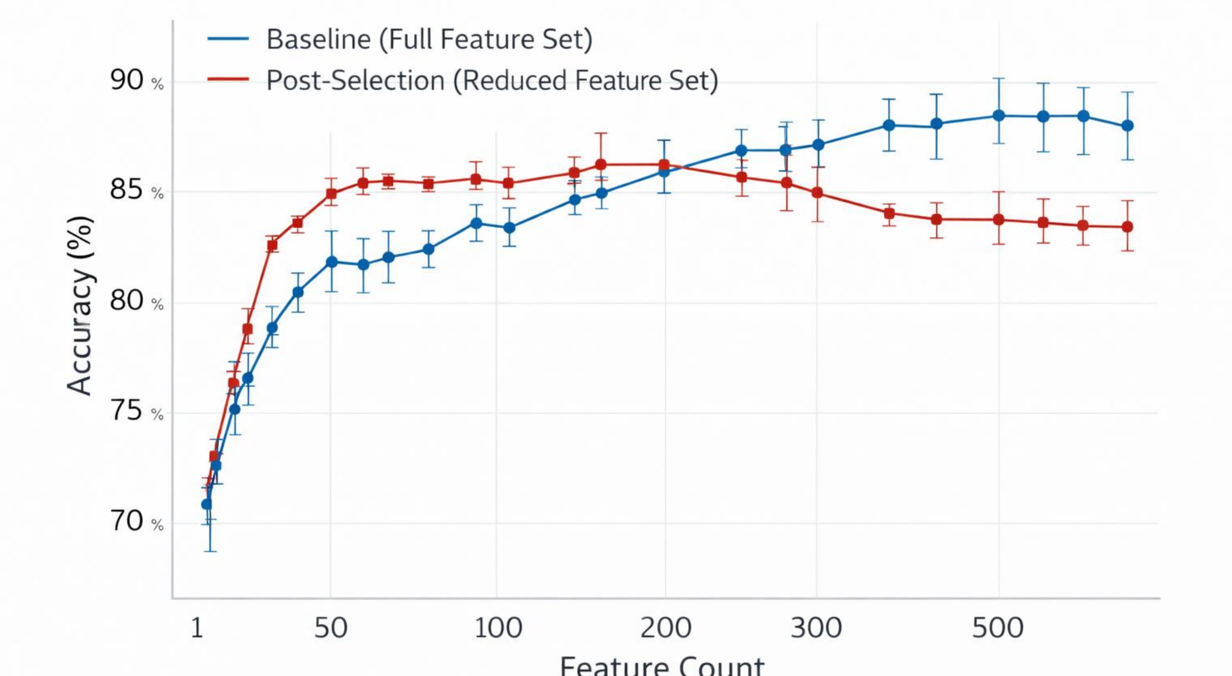

Figure 2. Accuracy versus feature count before and after feature selection

4. System Flow Diagram

The complete processing pipeline adopted in this study is illustrated in Fig. 1. The framework begins with the acquisition of raw sEMG signals, which are first subjected to preprocessing to remove noise, suppress artifacts, and normalize signal amplitudes. The preprocessed signals are then transformed into the time–frequency domain using appropriate decomposition techniques, enabling the capture of both temporal and spectral characteristics of muscle activity. From these representations, a comprehensive pool of time-domain, spectral, and hybrid features is generated.

Subsequently, a multi-optimizer feature selection stage is employed to identify compact and discriminative feature subsets, reducing redundancy while preserving classification performance. The selected features are finally provided as input to machine-learning classifiers, and system performance is quantitatively assessed using standard evaluation metrics. As shown in Fig. 1, this modular pipeline allows each processing stage to be analyzed independently and provides flexibility for future extensions, including the integration of deep learning models or adaptation for real-time deployment [15].

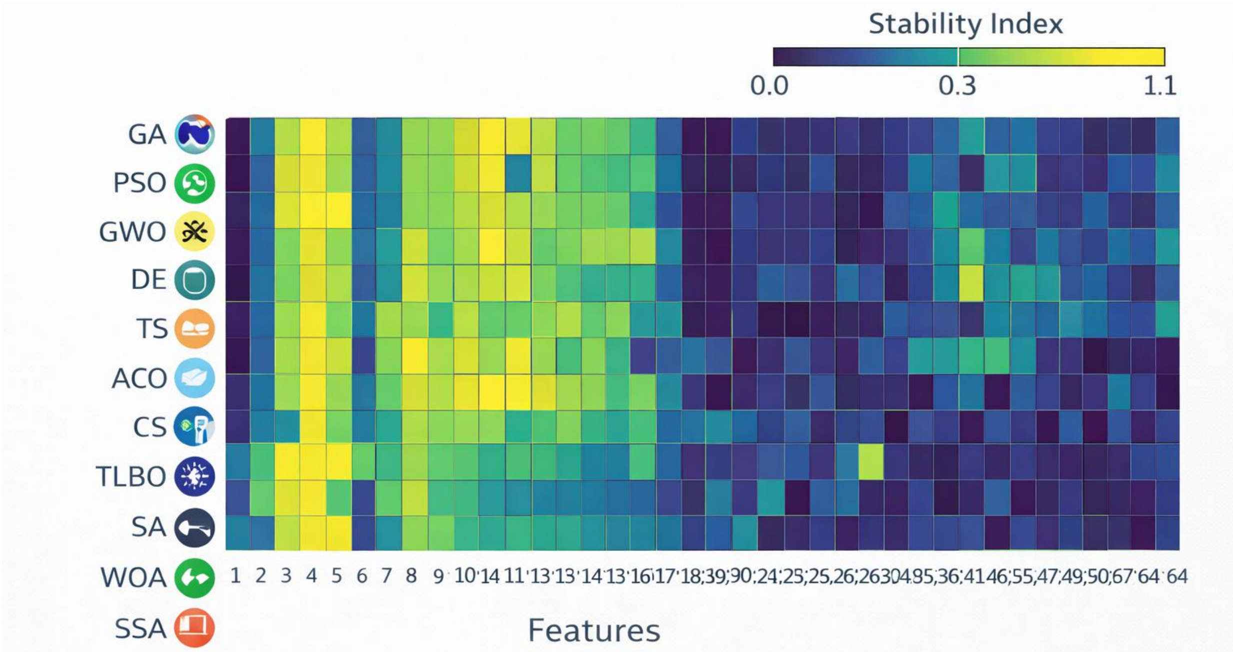

Figure 3. Optimizer-wise feature selection stability chart

5. Experimental Plan and Tools

All experiments are implemented using MATLAB 2023. Signal preprocessing and feature extraction rely on the Signal Processing Toolbox and Wavelet Toolbox. Metaheuristic optimizers are implemented using custom scripts validated against standard benchmark functions.

Experiments are conducted on a Windows-based workstation equipped with an Intel i7 CPU, 32 GB RAM, and SSD storage. Computational time and convergence behavior are recorded for comparative analysis [16].

6. Expected Results and Validation Strategy

The proposed framework is expected to achieve a 60–70 percent reduction in feature dimensionality without loss of discriminative power. Compared to baseline full-feature models, classification accuracy improvements of approximately 5–10 percent are anticipated.

Stability analysis is expected to demonstrate consistent feature selection across optimizers, particularly for physiologically meaningful features such as signal energy and frequency-band power. Statistical significance will be assessed using paired t-tests or Wilcoxon signed-rank tests, depending on data normality. Figure 2 depicts the accuracy versus feature count before and after feature selection Figure 3 shows optimizer-wise feature selection stability chart

Confusion matrices will be used to analyze per-class performance and misclassification patterns.

7. Conclusion

This paper presents a carefully designed and experimentally grounded methodology for EMG-based limb-movement classification. By integrating time–frequency analysis with large-scale metaheuristic feature selection and rigorous validation protocols, the proposed framework systematically addresses signal variability, feature redundancy, limited generalization, and computational inefficiency. The emphasis on methodological transparency and stability positions this work as a strong foundation for subsequent journal-level extensions and real-world biomedical applications.

Reference

[1] A. Sultana, F. Ahmed, and Md. S. Alam, "A systematic review on surface electromyography-based classification system for identifying hand and finger movements," *Healthcare Analytics*, vol. 3, p. 100126, Nov. 2023, doi: 10.1016/j.health.2022.100126.

[2] S. Abbaspour, M. Lindén, H. Gholamhosseini, A. Naber, and M. Ortiz-Catalan, "Evaluation of surface EMG-based recognition algorithms for decoding hand movements," *Med Biol Eng Comput*, vol. 58, no. 1, pp. 83–100, Jan. 2020, doi: 10.1007/s11517-019-02073-z.

[3] H. Hellara, R. Barioul, S. Sahnoun, A. Fakhfakh, and O. Kanoun, "Comparative Study of sEMG Feature Evaluation Methods Based on the Hand Gesture Classification Performance," *Sensors*, vol. 24, no. 11, p. 3638, Jan. 2024, doi: 10.3390/s24113638.

[4] H. She, J. Zhu, Y. Tian, Y. Wang, H. Yokoi, and Q. Huang, "SEMG Feature Extraction Based on Stockwell Transform Improves Hand Movement Recognition Accuracy," *Sensors*, vol. 19, no. 20, p. 4457, Jan. 2019, doi: 10.3390/s19204457.

[5] I. Kyranou, K. Szymaniak, and K. Nazarpour, "EMG Dataset for Gesture Recognition with Arm Translation," *Sci Data*, vol. 12, no. 1, p. 100, Jan. 2025, doi: 10.1038/s41597-024-04296-8.

[6] A. T. Christos Sapsanis, "sEMG for Basic Hand movements." UCI Machine Learning Repository, 2013. doi: 10.24432/C5TK53.

[7] S. I. Khan and R. B. Pachori, "Empirical Wavelet Transform-Based Framework for Diagnosis of Epilepsy Using EEG Signals," in *AI-Enabled Smart Healthcare Using Biomedical Signals*, IGI Global Scientific Publishing, 2022, pp. 217–239. doi: 10.4018/978-1-6684-3947-0.ch012.

[8] S. I. Khan and V. Ahmed, "Study of effectiveness of stockwell transform for detection of coronary artery disease from heart sounds," in *2016 2nd International Conference on Contemporary Computing and Informatics (IC3I)*, Dec. 2016, pp. 725–728. doi: 10.1109/IC3I.2016.7918056.

[9] "Analysis of Normal and Adventitious Lung Sound Signals Using Empirical Mode Decomposition and Central Tendency Measure | IIETA." Accessed: Feb. 10, 2026. [Online]. Available: https://iieta.org/journals/ts/paper/10.18280/ts.380320

[10] C. Cabezaolias, R. Raya, C. Sanchez, R. Rodriguez, and E. Urendes, “Effect of focal muscle vibration on sEMG activity during repeated elbow movements in healthy adults,” *J NeuroEngineering Rehabil*, vol. 23, no. 1, p. 2, Nov. 2025, doi: 10.1186/s12984-025-01816-4.

[11] S. I. Khan and R. B. Pachori, “Derived vectorcardiogram based automated detection of posterior myocardial infarction using FBSE-EWT technique,” *Biomedical Signal Processing and Control*, vol. 70, p. 103051, Sep. 2021, doi: 10.1016/j.bspc.2021.103051.

[12] S. I. Khan and R. B. Pachori, “Automated Bundle Branch Block Detection Using Multivariate Fourier–Bessel Series Expansion-Based Empirical Wavelet Transform,” *IEEE Transactions on Artificial Intelligence*, vol. 5, no. 11, pp. 5643–5654, Nov. 2024, doi: 10.1109/TAI.2024.3420259.

[13] J. Barrera-García, F. Cisternas-Caneo, B. Crawford, M. Gómez Sánchez, and R. Soto, “Feature Selection Problem and Metaheuristics: A Systematic Literature Review about Its Formulation, Evaluation and Applications,” *Biomimetics*, vol. 9, no. 1, p. 9, Jan. 2024, doi: 10.3390/biomimetics9010009.

[14] T. Stephan, P. S, C.-C. Lin, and S. Agarwal, “A Comprehensive Study of Grey Wolf Optimizer Variants for Optimizing Feature Selection in High-Dimensional Data,” *Applied Artificial Intelligence*, vol. 40, no. 1, p. 2601378, Dec. 2025, doi: 10.1080/08839514.2025.2601378.

[15] S. I. Khan and V. Ahmed, “Study of Adventitious Lung Sounds of Paediatric Population using Artificial Neural Network Approach,” *International Journal of Current Research and Review*, May 2017, Accessed: Feb. 10, 2026. [Online]. Available: https://ijcrr.com/abstract.php?article_id=818

[16] “Signal Processing Toolbox.” Accessed: Feb. 10, 2026. [Online]. Available: https://in.mathworks.com/products/signal.html