Automated Classification of Limb Movements Using Time–Frequency Features and Multi-Optimizer Ensemble Framework

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Abstract: The electromyography (EMG) signals used in the recognition of limb-movements are crucial to intelligent prosthetic and rehabilitation systems. The existing techniques have the drawbacks of signal instability, overlapping features and poor extrapolative capability between subjects and orientations. This paper suggests a time-frequency meta-heuristic optimizer based machine-learned pipeline to automatically classify limb motions. The framework first displays time frequency separation in order to recover dynamic contents of non-stationary EMG signals. It then uses a collection of 44 different meta-heuristic optimizers in order to identify stable and discriminative subsets of features. A strategy based on voting picks the features, which uniformly enhance performance over optimizers. Two public datasets, FORS -EMG (8 channels, 12 gestures, 3 orientations) and UCI sEMG Basic Hand Movements (2 channels, 6 gestures) are tested on the proposed method through cross-subject and cross-orientation validation. Through the results, it is found that the model has a better classification accuracy, greater feature stability, and lower computational complexity than the current single-optimizer methods. The size and weight of the framework are small enough to fit the framework in real-time applications of embedded prosthetic control and rehabilitation devices. This study introduces a general and decipherable course of action of EMG-based limb-movement recognition frameworks that can be customized to various individuals and recording scenarios.

Keywords: Electromyography (EMG); Limb-Movement Classification; Time–Frequency Analysis; Metaheuristic Optimization; Feature Selection Ensemble; Prosthetic Control Systems.

1. Introduction:

Limb-movement recognition connects the activities of human muscles with intelligent machines. It is aimed at recognizing voluntary activities comparing the electric signals that can be generated by muscles in the course of movement [1]. These signals are referred to as surface electromyography (sEMG), which displays the intention of the user in real time. The interpretation of sEMG signals allows the machines prosthetic limbs, rehab devices, assistive robots etc. to react to human instructions in a natural manner [2]. EMG is a requirement in the field of prosthetic technology to provide natural, intuitive control of the limbs. It measures the muscle activity of the residual limb and translates it into artificial hands or arm signals. Amputees are also able to move their artificial legs to a direction that is close to the desired direction. The outcome is enhanced movement, response and control in daily activities [3].

In the course of rehabilitation, the EMG monitors the work of the muscles and helps trace the progress of the patients. It also enables therapists to visualize the muscles that become active and their functionality levels following a trauma or surgery. EMG provides real-time feedback when combined with robotic or virtual rehab systems to increase the accuracy of training and promote the speed of functional recovery [4].

In human-computers, EMG signals create systems that react to the activity of muscles as opposed to conventional inputs. These interfaces also enable the user to operate computer, wheelchair, or robots using simple gestures. EMG HCI in particular is useful with individuals who have limited mobility, enabling them to communicate and have fine control alone.

EMG is preferred in movement detection since it measures muscle activity in a non-invasive and safe way. Electrodes are applied to the skin surface that does not cause discomfort or risk. EMG provides a first-hand experience of muscle movements, as one can notice whether it is planned motion before it occurs. It is also capable of detecting fine gestures that may not be detected by cameras or motion sensors. EMG systems are easy to operate in clinics, labs and in everyday environments due to compact and portable sensors[5].

Even with advances, EMG based systems have reliability problems. Users and sessions differ significantly in signals leading to inconsistency in performance of the model. The signals are non-stationary and feature sets usually contain redundant information, which increases the complexity but does not increase the accuracy. Most models are not able to generalize to new subjects. All these issues demonstrate that more sophisticated techniques are required that will integrate time-frequency analysis with meta-heuristic feature selection in generating compact and stable features to be used to determine movements precisely and adaptively[6].

2. Problem Background

EMG signal-based classification is a automated frame-work that converts raw muscle movement signals into usable movement data. It begins with the signal acquisition, in which the electrodes on the skin detect minute electrical potentials under muscle contractions. The signal is then processed by preprocessing to remove noise and other artifacts attributed to skin movement, power-line interference and electrode instabilities. The extracted features, which are the important characteristics that have been captured in the time, frequency or time-frequency domain, are then taken out of the filtered signals. These characteristics characterize the patterns of muscle activity and feed into the classification step, during which machine-learning systems like Support Vector Machines (SVM), K -Nearest Neighbors (KNN) or neural networks identify the kind of movement being executed. The performance is still affected by a number of constraints despite the progress. A lot of the available systems are based on highly handcrafted features, which implies that designing features is based on human skills and experience. This restricts the scope of capture signal characteristics and is usually not able to adapt to different users or recording environments. One of the issues is that feature-selection strategies are not robust. The majority of the studies apply a single metaheuristic optimizer or simple statistical ranking, which may pick redundant or unstable features that are not very generalizable across subjects. A large number of reported models are also prone to overfitting when they are evaluated in subject-dependent fashion. They do well on data of the same individuals that they have been trained on and poor with new users. This is a poor generalization that restricts their applicability in the real world. A consistent and interpretable feature-selection framework is necessary to deal with such problems. This type of structure should be able to cope with signal fluctuation. Time-frequency representations are especially useful in the representation of the non-stationary character of EMG signals, and with the aid of metaheuristic optimization, can result in simple, trustworthy, and generalized movement classifications models[7].

3. Related work

The classification of limb-movements based on electromyography (EMG) signals has recently advanced rapidly due to improved signal processing, feature engineering and machine learning methods. A recent review indicates three predominant themes: (1) feature extraction techniques, (2) feature selection techniques and (3) datasets benchmarking of reported performance trends. All the themes assist in identifying the weaknesses and the strengths to fuel the current study [8].

3.1 Features Extraction methods in Movement Classification of EMG.

The feature extraction converts raw noisy EMG signals to some useful representations. There are traditional approaches, which are time-domain, frequency-domain, and time-frequency domain approaches. Attributes that are popular due to their simplicity and cheapness to compute are time-domain characteristics like the mean absolute value, zero crossings and length of the waveform. They however are noise and electrode movement sensitive.

FFT provides timing-independent information about power-distribution. In order to achieve time and frequency resolution, Discrete Wavelet Transform (DWT) and Short-Time Fourier Transform (STFT) were invented. DWT separates the signal into various levels of resolutions, and it allows us to examine low- and high-frequency information. The STFT provides an absolute time frequency resolution and is effective with short and quasi-stationary windows.

Recent developments are Empirical Mode Decomposition (EMD), Empirical Wavelet Transform (EWT) and Tunable- Q-Factor Wavelet Transform (TQWT). They are adaptive splitting the signal into intrinsic modes or subbands and retain both temporal and spectral content. EWT, as an example, constructs wavelets in the signal spectrum, and TQWT, flexibly measures periods of oscillations. These techniques are effective on non-stationary EMG signals, in which the frequencies vary with time.

Hybrid schemes take multiple time frequency representation to obtain more dynamic information. There are others which combine STFT with EMD or TQWT to enhance discrimination. Hierarchical features are learned automatically in deep approaches, which may use spectral grams or wavelet scalograms as input (convolutional neural networks). However, they typically require substantial amounts of data and expensive computation, and are not useful in a lightweight or real-time application.

Even though these breakthroughs were made, there is still a fundamental gap. In the majority of studies, decomposition is applied to one domain only where it is either time-frequency or spectral and is not tested on robustness across the domains. EMG signals are complex and dynamic in nature and thus characteristics of one domain do not usually generalize to new subjects or sessions. It is necessary to have structures that provide a combination of many feature views and remain interpretable and effective.

Table 1: Existing approaches for limb movement classification

Year	Paper (short)	Dataset / Setting	Methods (features / FS / model)	Eval notes	Reported result
2024	**VMD + ReliefF for sEMG hand motion**	**UCI sEMG Basic Hand Movements** (2-ch, 6 gestures)	**VMD** + **ReliefF** + classic classifiers	Split specifics matter; often	**Acc ≈ 99.14%** (paper claim). (PMC)[9]

				subject-mixed	
2024	**Enhanced hand gesture recognition with sEMG (Sensors)**	**Myo armband** EMG (multi-subj)	Feature eng. + ML pipeline	Addresses practical Myo signals	Performance strong; details per fold in paper. (PMC)[10]
2024	**Online cross-session EMG hand gesture recognition**	Cross-session EMG (gesture)	Online adaptation strategies	Focus on session shift robustness	State-of-the-art cross-session benchmarks. (ScienceDirect)[11]
2024	**Electromyography-based hand gesture classification**	Generic EMG hand gestures (prosthetic use)	End-to-end pipeline (ML/DL)	Intro + experimental examples	Baselines and practicalities discussed. (PMC)[12]
2025	**EMG dataset with arm translation (Sci Data)**	New EMG+kinematics dataset with arm translation	Dataset and benchmarks	Emphasizes positional variation	Provides reproducible resource. (Nature)[13]
2019	**UCI EMG Data for Gestures (Myo 36 subj)**	**UCI Myo** (36 subjects, 8 channels)	Raw EMG benchmark	Widely used for cross-subject tests	Dataset reference entry. (UCI Machine Learning Repository)[14]
2024	**Human hand movement classification (3 gestures)** [15]	Small EMG set (3 gestures)	Feature extractor comparison	Didactic but recent	Results per feature family reported. (Biomed Pharma Journal)

3.2 Feature Selection Processes.

The feature selection eliminates redundancy and enhances accuracy. Principal Component Analysis (PCA), Minimum Redundancy Maximum Relevance (mRMR) and ReliefF are classical algorithms used in EMG classification. PCA dimensions are reduced linearly, but can ignore nonlinear muscle-activation patterns: mRMR and ReliefF rank features according to their relevance to class labels and redundancy: these methods are heuristic and dataset-dependent [16].

Researchers overcome these limits with the help of metaheuristic algorithms. Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Grey Wolf Optimizer (GWO), Whale Optimization Algorithm (WOA), and Arithmetic Optimization Algorithm (AOA) want to find the best feature subsets. They are imitations of natural or physical processes in order to discover the most suitable combination which maximizes classification performance[17].

Metaheuristics are capable of enhancing relevance and dimensionality reduction, however, the performance is affected by peculiarities of datasets and parameter optimization. All optimizers possess their own search logic, which can either find out the informative features prematurely or overlook them. Therefore, the dataset is of paramount importance to performance. In most studies, the optimizer is single and hardly any study ever combines and votes on the stabilities of various optimizers to get common features. This absence of ensembles or voting restricts strength and reproducibility[17].

Multi-optimizer voting approach has the threat of increasing stability. When we use the output of multiple metaheuristics, we are able to pick features that appear to provide consistent accuracy across runs and datasets. This ensemble balances exploration and exploitation resulting in more generalizable and interpretable sets of features.

3.3 Performance Benchmark and Reported Results.

Public datasets are very important in testing EMG classification frameworks. Studies of limb-movements usually involve two benchmarks.

UCI sEMG of Basic Hand Movements captures two forearm EMG channels during 6 hand gestures. It is easily implemented and commonly used in benchmarking. A time-frequency analysis with handcrafted and statistical features resulted in an approximate accuracy of 82 0.047 Reaz et al. (2024). Nonetheless, majority of assessments are subject-dependent, i.e. training and test data is of the same subject. This breathes life into accuracy and fails to reflect the real world variability.

The dataset proposed by Nguyen et al. (2024), which is called FORS-EMG, is more difficult. It also has eight EMG channels of nineteen participants, who make twelve movements with three positions of the forearm. The highest scoring model received F1 -score of 88.58 per cent with the use of linear discriminant analysis and spectral features. This data shows the issue of dependence on orientation, in which the accuracy decreases as the training and test orientation becomes different.

The two datasets have two weaknesses in common, namely, absence of cross-subject assessment and poor explainability. Most publications indicate high accuracy but do not consider the extension to unknown subjects or examine the features that are driving the decisions. Consequently, the results are difficult to replicate or comprehend.

These observations put strong emphasis on the necessity of strong frameworks that integrate multi-domain feature extraction and ensemble-based feature selection. This strategy can enhance stability and generalization, resulting in the enhanced performance on realistic EMG data and providing more articulate information about muscle activity during movement of the limbs.

4. Research gap

Numerous researches have been conducted on EMG-based limb-movement classification, but various gaps are still present. The existing methods generally involve a single meta-heuristic optimizer to feature selection which gives different outcomes across different datasets and they are not stable. There is no systematic scheme that integrates multiple meta-heuristics to access stable and repeated feature subsets. Similarly, time frequency analysis though it offers the non-stationary behavior of EMG, there is little literature that combines hybrid time-frequency characteristics with the multi-optimizer choice to enhance resilience and interpretability.

The other major limitation is the poor emphasis on cross-subject and cross-orientation generalization. Most of the models are effective when validation is dependent on the subject, although the accuracy decreases dramatically when they are used with new users or other signal orientations. This prevents real life implementation and particularly in prosthetic and rehabilitation systems that need to be able to adjust to the differences. Moreover, the vast majority of the methods are computationally intensive and cannot be used in the real-time or embedded context.

Thus, it is evident that a need exists to have a lightweight and automated pipeline that combines time-frequency feature extraction with a multi-optimizer ensemble. With this system, generalizable, accurate and deployable limb-movement recognition would be achieved.

5. Problem Statement

Current EMG-based limb-movement classification frameworks lack robustness and interpretability due to redundant features, single-optimizer bias, and poor cross-subject generalization. There is a need for a unified, time–frequency and metaheuristic-driven machine learning pipeline that can yield high accuracy with reduced feature dimensionality and computational cost.

6. Research Objectives

The research will construct a hybrid time frequency feature extraction system of EMG signals, a multi optimizer ensemble will be used, and a lightweight machine-learning pipeline will be developed. Moreover, it will also cross-subject and cross-orientation test performance using publicly available EMG data to improve the generalization.

7. Expected Outcomes

The framework must provide a small and stable set of features enhancing the accuracy and stability of classification across subjects. It is anticipated to scale more to realistic conditions and maintain low computational expenses which make its use in practitioner prosthetic control and rehabilitation systems possible.

Conclusion

The objective of the work is to create a single strong, lightweight EMG-based limb-movement classification system, which makes use of both time-frequency feature extraction and multi-optimizer ensemble feature selection. The major flaws of current approaches such as unstable feature subsets, low cross-subject generalization, and high computational cost, hybrid time-frequency analysis with metaheuristic optimizers are combined. The resultant system must offer small, decipherable, and sound attributes that can be used in real-time to facilitate the development of prosthetic and rehabilitation apparatuses that can effectively react to the users.

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