Classification of Hand Gestures Essential for Activities of Daily Living (ADLs) Using Surface Electromyography (sEMG) Signals

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***Abstract*—This study presents a methodology for classifying hand gestures essential for Activities of Daily Living (ADLs) using surface electromyography (sEMG) signals. The dataset comprises recordings from 40 subjects performing ten distinct hand gestures. The analysis incorporates time-domain statistical features, frequency-domain statistical features from Fourier and wavelet transforms, and the creation of a comprehensive feature dataframe. After applying feature engineering, machine learning-based classification was conducted. This work lays a foundation for future advancements in sEMG-based gesture classification.**

I. Introduction

Hand gestures play a vital role in performing Activities of Daily Living (ADLs). Automating the classification of these gestures can significantly enhance applications in rehabilitation, prosthetics, and human-computer interaction. Surface electromyography (sEMG) signals are widely used for such tasks due to their non-invasive nature and ability to capture muscle activity.

This study focuses on the classification of ten hand gestures using sEMG signals from 40 subjects. The methodology involves extracting time-domain statistical features, frequency-domain statistical features from Fourier and wavelet transforms, and creating a comprehensive feature dataframe. Feature engineering and machine learning classification techniques are then applied to achieve accurate gesture recognition. Detailed explanations are provided to ensure replicability and to pave the way for future advancements in sEMG-based gesture classification.

II. Dataset Description

The dataset used in this study, *Dataset for multi-channel surface electromyography (sEMG) signals of hand gestures*, consists of sEMG signals recorded from 40 subjects. Each subject performed ten distinct hand gestures. Key details of the dataset are:

- **Number of Channels/Muscles:** 4
  - Channel 1: Extensor Carpi Ulnaris
  - Channel 2: Flexor Carpi Ulnaris
  - Channel 3: Extensor Carpi Radialis
  - Channel 4: Flexor Carpi Radialis
- **Sampling Rate:** 2000 Hz
- **Protocol:** For each subject:
  - 5 cycles of gestures
  - 30 seconds of rest between cycles
  - Each cycle: 104 seconds, comprising:
    - 4 seconds of rest at the beginning
    - 10 gestures of 6 seconds each, interleaved with 4 seconds of rest

Figures 1 and 2 illustrate the structure of the dataset for one subject.

III. Methodology

The methodology is divided into four main steps:

A. Data Preprocessing and Compilation

I consolidated the sEMG data from all subjects into a single DataFrame. The data was clean and free of noise. Exploratory Data Analysis (EDA) was performed to identify null values or inconsistencies, which were found to be absent. Labels such as `activity_id`, `cycle_id`, and `subject_id` were added to facilitate analysis. The final preprocessed data was saved as a CSV file for ease of access.

B. Feature Extraction: Statistical Methods

I extracted statistical features from the preprocessed data using a 250 ms sliding window. These features included mean, standard deviation, skewness, and kurtosis. The assumption was that a 250 ms window captures sufficient information for classifying the gestures. The resultant DataFrame containing extracted features was saved for further analysis.

C. Classification Using Machine Learning

I applied machine learning models to the extracted statistical features. Models such as Random Forest, Gradient Boosting, Logistic Regression, Support Vector Classifier (SVC), k-Nearest Neighbors (k-NN), and Decision Tree were ev aluated for their classification performance.

D. Wavelet Transform Analysis

I applied wavelet transforms to the sEMG data. He experimented with different mother wavelets to identify the optimal one for sEMG signal processing. Feature extraction using wavelet coefficients was performed, and the resulting features were used for classification.

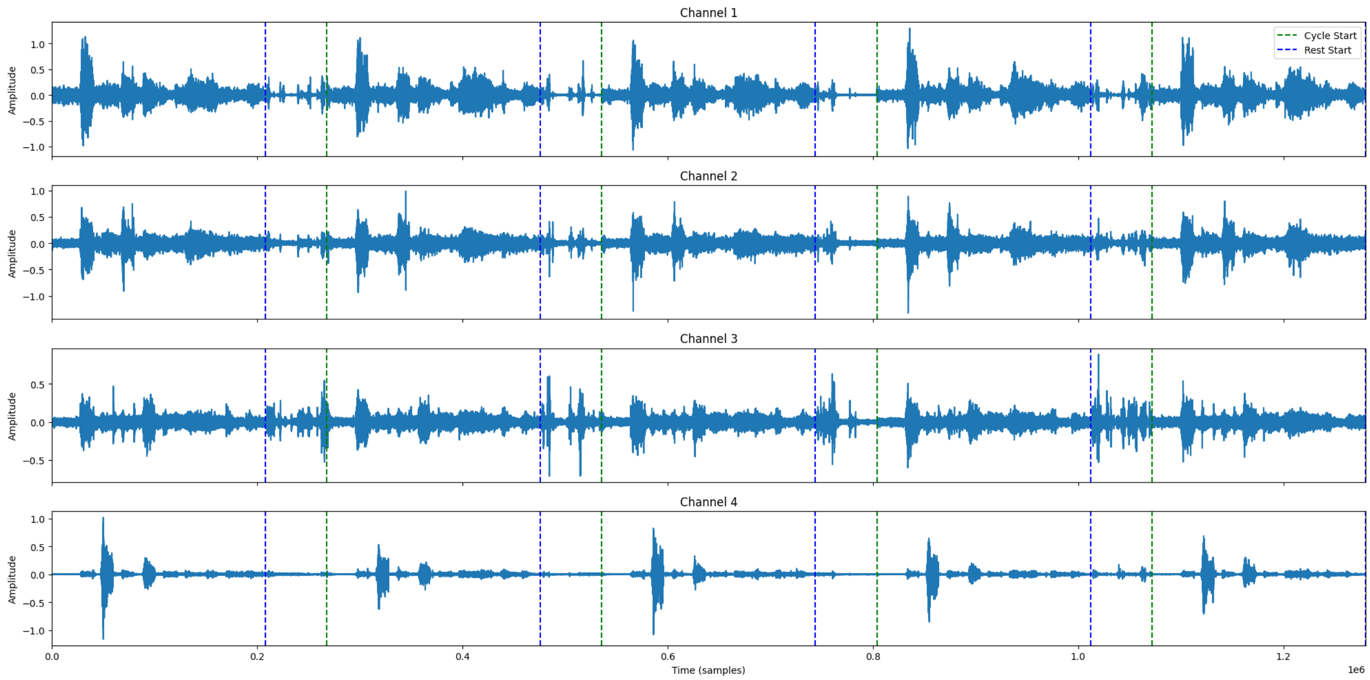

Fig. 1. sEMG data of all cycles for one subject.

IV. Feature Extraction Methodologies

sEMG signal analysis for gesture classification relies on robust feature extraction methodologies. For this study, two approaches were employed: Time-Domain Statistical Inference and Discrete Wavelet Transform (DWT). Features were extracted for each of the four channels separately, capturing distinct signal characteristics.

A. Time-Domain Statistical Inference

Time-domain statistical features provide insights into the temporal characteristics of the sEMG signals. For each channel, the following features were extracted:

- Mean (μ)
- Median
- Variance (σ^2)
- Skewness
- Kurtosis
- Root Mean Square (RMS)
- Mean Absolute Value (MAV)
- Zero Crossing (ZC)
- Waveform Amplitude (WAMP)
- Average Amplitude Change (AAC)
- Log Detector (LogD)
- Simple Square Integral (SSI)
- Integrated EMG (IEMG)
- Signal Energy (SE)
- Autoregressive Coefficients (AR1, AR2, AR3, AR4)

These features were computed for each of the four sEMG channels, resulting in a feature vector of 64 attributes per sample (16 features per channel $\times$ 4 channels). These features capture both low-level and higher-order statistical properties of the signals, enabling robust classification of hand gestures.

1) Classification Results Using Statistical Features: Table I summarizes the accuracy achieved by various classification models trained on the time-domain statistical features.

TABLE I
ACCURACY OF CLASSIFICATION MODELS USING STATISTICAL FEATURES

Model	**Accuracy (%)**
Random Forest	67
Decision Tree	63
Logistic Regression	54
Support Vector Classifier	58
k-Nearest Neighbors	51

B. Discrete Wavelet Transform (DWT) Analysis

Wavelet transform is a powerful technique for time-frequency analysis, particularly for non-stationary signals like sEMG. For this study, the Discrete Wavelet Transform (DWT) was used.

1) Mathematical Framework: DWT decomposes a signal into approximation and detail coefficients using a set of wavelet functions. The process involves:

- Selecting a mother wavelet, $\psi(t)$
- Decomposing the signal into multiple levels of detail (resolution)

The mathematical representation of DWT is given by:

$$c_{j,k} = \int_{-\infty}^{\infty} x(t)\psi_{j,k}(t)\,dt$$

where $c_{j,k}$ represents the wavelet coefficients for scale j and position k.

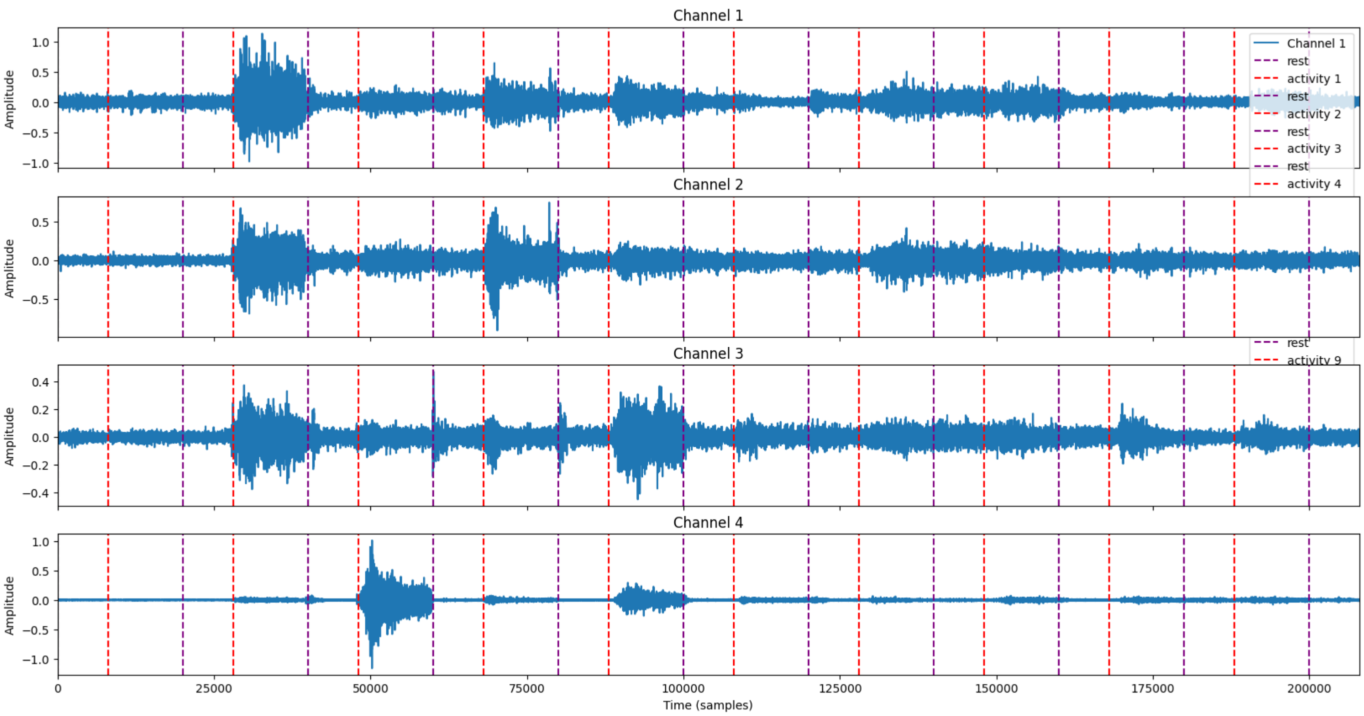

Fig. 2. sEMG data of one cycle showing activities and rest periods.

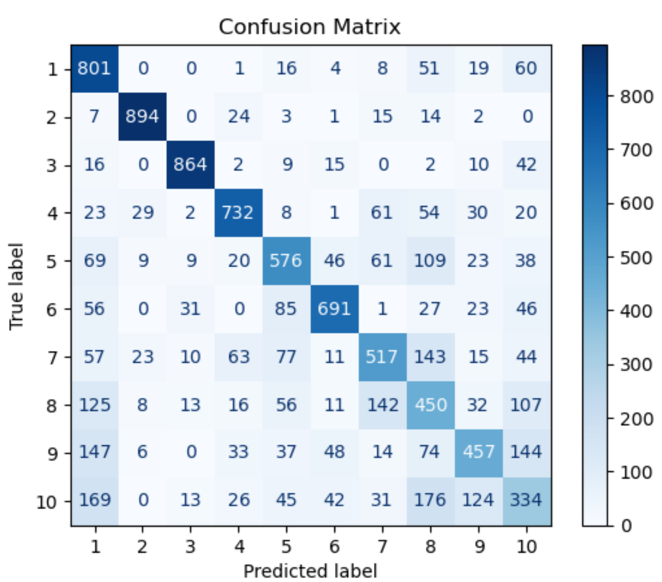

Fig. 3. Statistical Inference Result

2) Feature Extraction Using DWT: The following steps were performed for feature extraction:

- Signals from all four channels were decomposed using different mother wavelets (e.g., Daubechies, Symlets).
- Features such as energy distribution, entropy, and statistical measures of wavelet coefficients (mean, variance, skewness, and kurtosis) were calculated for each level of decomposition.

Table II shows the accuracy of a Random Forest classifier trained on wavelet-based features using different mother wavelets and decomposition levels.

V. NEW METHOD AND FINAL WORK AFTER FEEDBACK

A. Feature Extraction

I extracted statistical features from the preprocessed data using a sliding window technique. A 500 ms window, corresponding to 1000 instances, was selected for feature extraction. To ensure overlap and continuity, the next window was defined with a 125 ms (250 instances) overlap. For instance, the first window covered the index range [0, 1000), while the next window covered [750, 1750). This approach ensured that each window had a common overlapping segment with the subsequent one. The extracted statistical features included mean, standard deviation, skewness, kurtosis, and others from the time-domain signal, Fourier transform of the signal, and wavelet transform of the signal to generate a comprehensive feature dataframe. The resultant DataFrame containing the extracted features was saved for further analysis.

B. Data Preprocessing

I applied a standard scaler to normalize the data, ensuring all features had a consistent scale. The data instances with `cycle_id = 5` were designated as the test set. Additionally, a label encoder was used to encode the target column `activity_id` into numerical format suitable for classification algorithms.

TABLE II
CROSS-VALIDATION RESULTS FOR DIFFERENT MOTHER WAVELETS AND DECOMPOSITION LEVELS USING RANDOM FOREST

Wavelet	Level	Test Accuracy (%)	Train Accuracy (%)	Test Precision	Test Recall	Test F1
bior2.2	2	52.14	94.78	0.5674	0.5214	0.5232
coif3	4	56.41	98.48	0.5871	0.5641	0.5625
coif4	2	55.11	98.36	0.5735	0.5511	0.5504
coif5	2	54.27	71.66	0.5672	0.5427	0.5418
db6	2	54.55	93.43	0.5703	0.5455	0.5454
db8	2	54.59	85.70	0.5698	0.5459	0.5453
sym4	2	54.92	98.54	0.5723	0.5492	0.5485
sym6	2	53.65	71.75	0.5602	0.5365	0.5352
sym8	2	54.66	93.97	0.5704	0.5466	0.5459

C. Model Training and Classification Results

I employed the Random Forest classifier for classification, with the following best hyperparameters determined through grid search:

- **Bootstrap:** True
- **Class Weight:** Balanced
- **Max Depth:** 20
- **Min Samples Leaf:** 1
- **Min Samples Split:** 2
- **Number of Estimators:** 200

The classification results are summarized in Table III:

TABLE III
CLASSIFICATION REPORT

Class	Precision	Recall	F1-Score	Support
0	0.72	0.88	0.79	640
1	0.95	0.95	0.95	640
2	0.96	0.93	0.94	640
3	0.82	0.84	0.83	640
4	0.78	0.72	0.75	640
5	0.87	0.82	0.84	640
6	0.73	0.64	0.68	640
7	0.53	0.62	0.57	640
8	0.77	0.68	0.72	640
9	0.56	0.55	0.56	600

Overall performance metrics for the model are as follows:

- **Accuracy:** 76.31%
- **Weighted F1 Score:** 0.763
- **Weighted Precision:** 0.768
- **Weighted Recall:** 0.763

VI. LEAVE ONE SUBJECT OUT

I applied a leave-one-subject-out (LOSO) cross-validation approach to evaluate the model's generalization performance. For each iteration, the model was trained on data from 39 subjects and tested on the subject left out. The average results across all subjects are as follows: accuracy = 0.584, F1 score = 0.564, precision = 0.642, and recall = 0.584. These results are summarized in Table IV.

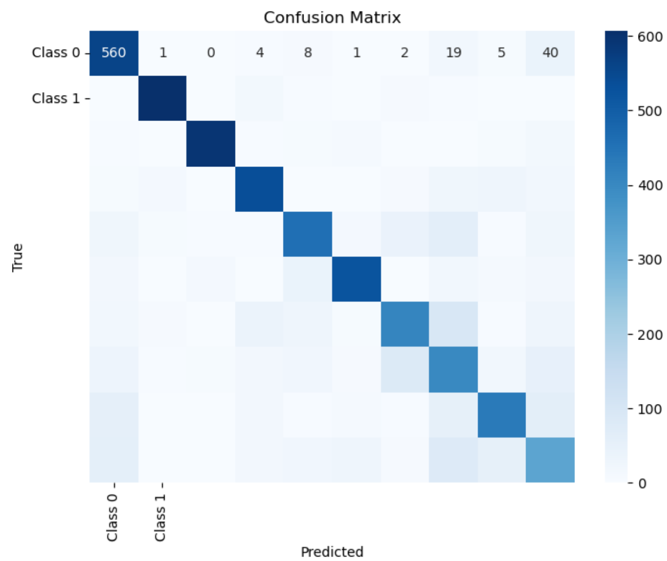

Fig. 4. Classification Report for Combined Features Derived from Frequency and Time Domains.

VII. RESULTS

The Random Forest classifiers trained on wavelet-transformed features showed varied performance across different mother wavelets. The highest accuracy was achieved with the `coif3` wavelet, followed by `coif4` and `sym4`, demonstrating the importance of wavelet selection in sEMG signal classification.

Building on this, statistical features extracted using a sliding window approach from time-domain, Fourier, and wavelet transforms further improved model performance. A Random Forest classifier with the following optimal hyperparameters (bootstrap: True, max depth: 20, estimators: 200) achieved an overall accuracy of 76.31% and a weighted F1 score of 0.763.

To evaluate the model's generalization performance, a leave-one-subject-out (LOSO) cross-validation approach was applied. For each iteration, the model was trained on data from 39 subjects and tested on the subject left out. The average results across all subjects are as follows: accuracy = 0.584, F1 score = 0.564, precision = 0.642, and recall = 0.584.

TABLE IV
LEAVE-ONE-SUBJECT-OUT CROSS-VALIDATION RESULTS

Subject ID	Accuracy	F1 Score	Precision	Recall
1	0.6503	0.6565	0.7273	0.6503
2	0.6478	0.6158	0.6131	0.6478
3	0.5283	0.5102	0.6358	0.5283
4	0.5258	0.4509	0.7908	0.5258
5	0.6943	0.6804	0.6845	0.6943
6	0.6415	0.6268	0.6613	0.6415
7	0.7396	0.7265	0.7808	0.7396
8	0.5434	0.5437	0.6353	0.5434
9	0.7447	0.7415	0.7691	0.7447
10	0.4302	0.4178	0.5359	0.4302
11	0.6126	0.6062	0.6253	0.6126
12	0.5597	0.5145	0.5164	0.5597
13	0.5509	0.5037	0.6168	0.5509
14	0.6465	0.6520	0.7327	0.6465
15	0.6239	0.6109	0.6888	0.6239
16	0.5874	0.5369	0.5117	0.5874
17	0.4050	0.3677	0.5687	0.4050
18	0.4138	0.3809	0.4818	0.4138
19	0.6654	0.6619	0.6870	0.6654
20	0.7283	0.7376	0.7933	0.7283
21	0.4428	0.4353	0.5153	0.4428
22	0.6252	0.5876	0.7187	0.6252
23	0.5245	0.5014	0.5702	0.5245
24	0.5635	0.5265	0.6039	0.5635
25	0.5019	0.4837	0.6570	0.5019
26	0.6226	0.6138	0.6482	0.6226
27	0.6830	0.6780	0.7162	0.6830
28	0.6604	0.6454	0.7309	0.6604
29	0.6805	0.6702	0.7155	0.6805
30	0.5157	0.4747	0.4916	0.5157
31	0.6013	0.5896	0.6447	0.6013
32	0.5874	0.5573	0.6755	0.5874
33	0.4642	0.4257	0.5373	0.4642
34	0.6000	0.6067	0.6536	0.6000
35	0.5673	0.5689	0.7722	0.5673
36	0.6214	0.5811	0.5939	0.6214
37	0.3572	0.3051	0.3516	0.3572
38	0.5346	0.5173	0.6573	0.5346
39	0.5648	0.5527	0.6439	0.5648
40	0.7220	0.7039	0.7314	0.7220

The detailed classification metrics for combined features are summarized in Table III, and the performance is visualized in Figure 4, highlighting the improved classification results derived from integrating multiple feature domains.

VIII. CONCLUSION

This study presents a comprehensive framework for classifying hand gestures using sEMG signals, incorporating both time-domain statistical features and wavelet-based features, alongside machine learning models. The results demonstrate the effectiveness of wavelet transforms, particularly when using mother wavelets like `coif3`, in improving gesture classification performance. Additionally, the inclusion of statistical features extracted via a sliding window approach further enhanced the model's accuracy and F1 score.

The application of a leave-one-subject-out (LOSO) cross-validation approach provided valuable insights into the model's generalizability. While the LOSO evaluation achieved moderate performance metrics (accuracy = 0.584, F1 score = 0.564, precision = 0.642, and recall = 0.584), it highlights the challenges associated with inter-subject variability and the need for further refinement.

The combination of these features with machine learning algorithms, such as Random Forest, offers promising results for reliable gesture recognition systems. Future research will focus on enhancing model robustness and generalizability by exploring advanced techniques and addressing inter-subject variability to improve performance across diverse populations.

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