sEMG signal analysis for hand gesture prediction using ML models

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1. Abstract:

This paper presents a machine learning approach to classify ten hand gestures using sEMG data from Mendeley repository which includes recordings of 40 participants. I have filtered the noise in the data using bandpass and notch filters. Then, extracted time and frequency domain features using moving window with 50% overlap. After exploratory data analysis and processing to address outliers and data transformations, optimal features are selected using methods like correlation, feature importance analysis and wrapper methods. Then, four classification models Decision Tree, Random Forest, XG Boost, and Support Vector Machine (SVM) – were trained with hyperparameters optimized via grid search. Additionally, a binary classifier was developed to distinguish rest (no movement) from active gestures. The proposed approach achieved good multi-class classification accuracy, with XG Boost (82.6% accuracy). The binary rest-versus-activity classification reached up to 90% accuracy. These results demonstrate the effectiveness of combining robust preprocessing and feature extraction for sEMG-based gesture recognition.

2. Introduction:

sEMG signals are electric signals generated by muscles during movements. Since these signals are collected from surface of skin, they are called surface EMG signals. Human hand gesture recognition using sEMG signals have various applications in healthcare, robotics and human computer interaction. Reliable recognition can enable intuitive control of prosthetic limbs, help in rehabilitation experience human computer interfaces and virtual reality applications [4]. Gopal et al [7] demonstrates the use of sEMG signals to restore the function of lost limbs using prosthetics. However, classifying gestures using sEMG signals is challenging due to nonlinear, non-stationary nature of muscle signals and high inter subject variability [1]. Building sEMG gesture recognition systems involve multiple processing stages like signal processing, segmentation, feature extraction and classification [1]. Over past decades researchers have developed various methods to improve the accuracy and robustness of gesture prediction.

3. Literature Review:

Recent advances in sEMG gesture predictions showcase a blend of traditional and modern computational techniques aimed at enhancing accuracy and application scope. Phinyomark *et al.* [11] highlighted the efficacy of time-domain and frequency-domain features such as mean absolute value (MAV) and waveform length (WL) when utilized with linear discriminant analysis, demonstrating robust upper-limb motion recognition. Asfour *et al.* [3] introduced an innovative approach by optimizing feature pairing, significantly simplifying model architectures while maintaining high accuracy, especially with larger segment windows. The advent of deep learning has further transformed the field, with studies like that of Byun et al. [8] showing superior performance of artificial neural networks over traditional models like SVMs in recognizing nuanced hand and finger gestures. In another study Liu et al. [9] incorporated a CNN-Transformer hybrid approach, enhancing feature extraction and integration capabilities, thus improving the gesture prediction accuracy. M. A. Ozdemir *et al.* [5] explored the potential of using signal processing techniques like short time Fourier transform, image processing and deep learning to achieve reliable results. Similar method was used by Fatayer *et al.* [6] where they further enhanced using a method called ALR-CNN which helps in refining the noisy labels while optimizing the

CNN performance. This demonstrate that combination of signal processing, image processing, ML and DL models have potential to improve the performance of the models.

4. Methodology

4.1. Data Overview:

The data was sourced from Mendeley repository. It is created by Izmir Katip Celebi University, Department of Biomedical Engineering [10]. The sEMG dataset consists of 10 distinct hand and wrist gestures (including a neutral “rest” state) performed by 40 healthy participants. Each participant repeated each gesture five times under controlled conditions. The signals were recorded using a BIOPAC MP36 system with 4 bipolar channels of surface Ag/AgCl electrodes placed on four different areas on the forearm. The sampling rate was 2000 Hz. This multi-subject, multi-gesture dataset provides a broad basis to evaluate the generality of the classification methods.

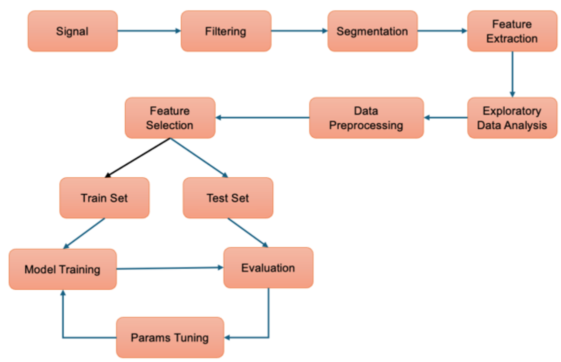

Figure (1) Overview of the methodology

4.2 Time Domain Analysis:

I have analyzed the time series data to find the patterns in different gestures. Used signal plots, spectrograms and correlation matrices to find the patterns. Found that channel 1,2,3 have a correlation around 0.25 to 0.3 and channel 4 has almost 0 correlation with other channels. The spectrograms plot showed extension have high PSD and rest has the least PSD.

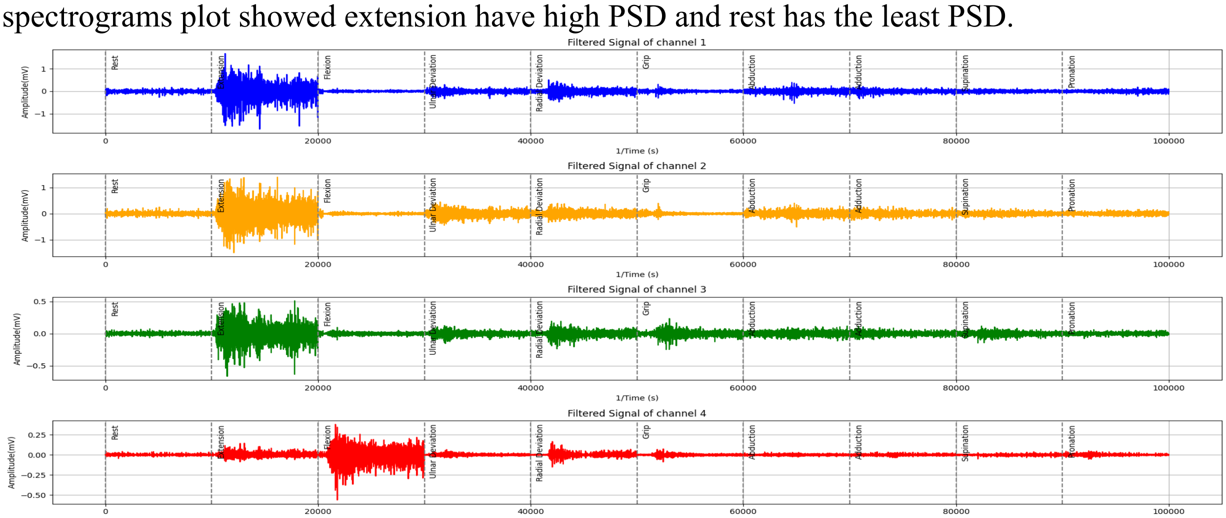

Figure (2) Shows the four channel signals for different gestures in the data. We can see Extension and Flexion showed complete opposite effects.

4.2 Signal Filtering

The sEMG signals are collected from the surface of skin using electrodes. So, there are high chances of low frequency noise and high frequency noise being added to the signal because of the electrode movements, cable movements, etc. And the electric supply at 50Hz adds its own noise to the signal. Hence, it is important to filter these noises. The human muscle movements have a frequency range of 5-500Hz [10]. Hence, I have used 6^{th} order butterworth bandpass filter available in scipy python package to remove this noise. Then, I have applied second order notch filter to attenuate the 50Hz frequency. The results can be seen in the figure.

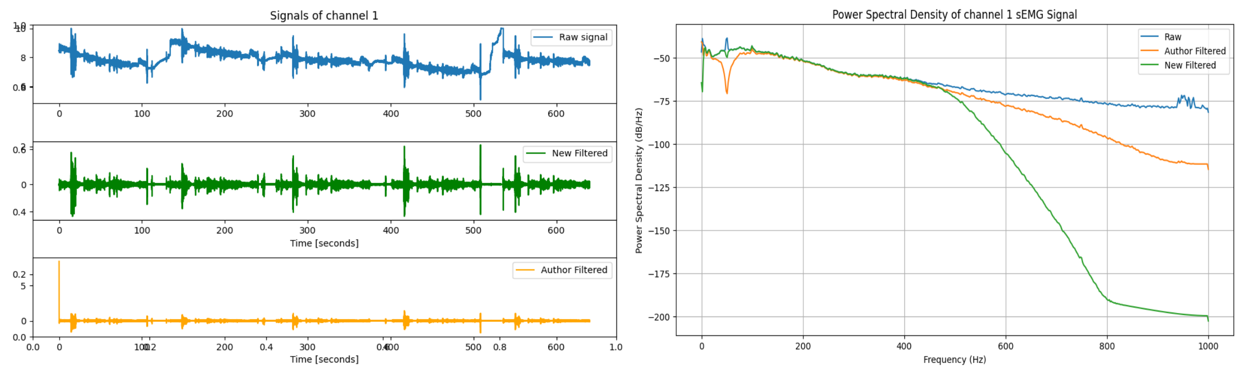

Figure 3 (a) Raw signal shows the effect of noise. The new filtered is the signal I filtered using scipy package showing clean signal compared to authors. (b) shows the effect noise in power spectral density curve. See the new filtered noise better than authors at both 50Hz and 500Hz

4.3 Data Segmentation

Data segmentation is important to extract the features from the data. I have applied moving window technique with an overlap of 50% to segment the signals. The moving window ensures the continuous patterns in the signals are captured. I have used a moving window of 250ms, we can experiment with other window sizes to check the effect of window size. [3] stated that window size can pay a major role in capturing the relevant information improving the accuracy.

4.4 Feature Extraction:

I have extracted time 24-time domain and frequency domain features for each channel in the data [11]. So, 24*4=96 features for each segment. Key time-domain features included mean absolute value , root mean square, variance, standard deviation, waveform length , zero-crossing count , slope sign changes, Willison amplitude, and integrated EMG. These features quantify signal amplitude, signal complexity, and temporal frequency of sign changes, which relate to muscle contraction intensity and firing patterns. Higher-order statistical features such as skewness and kurtosis were computed to capture the distribution shape of the EMG amplitude. I have also calculated Hjorth parameters (Activity, Mobility, and Complexity) which describe the signal's statistical properties in terms of variance and frequency content. Additionally, several frequency-domain features were extracted by computing the power spectral density (PSD) of each segment (via FFT). From the PSD, we derived features including mean frequency, median frequency, peak frequency, total signal power, and spectral entropy. These frequency features reflect muscle fiber conduction velocity and fatigue state indicators. We also included Teager–Kaiser energy (TKEO) as a nonlinear energy measure and a mean absolute slope to capture rapid changes.

4.5 Exploratory Data Analysis

I have analyzed the patterns in the data for different gestures for all features. Used stacked histogram plots, box plots to check the spread of each gesture. Then used scatter plots and correlation matrices to analyze the relationship between the features. The goal here is to identify the features that can better differentiate the gesture which can be used as a good predictor for the model. These also helped in understanding the relations between the features. These plots also gave a good idea about the distribution of feature and need to transform some of the features because of their high skewness.

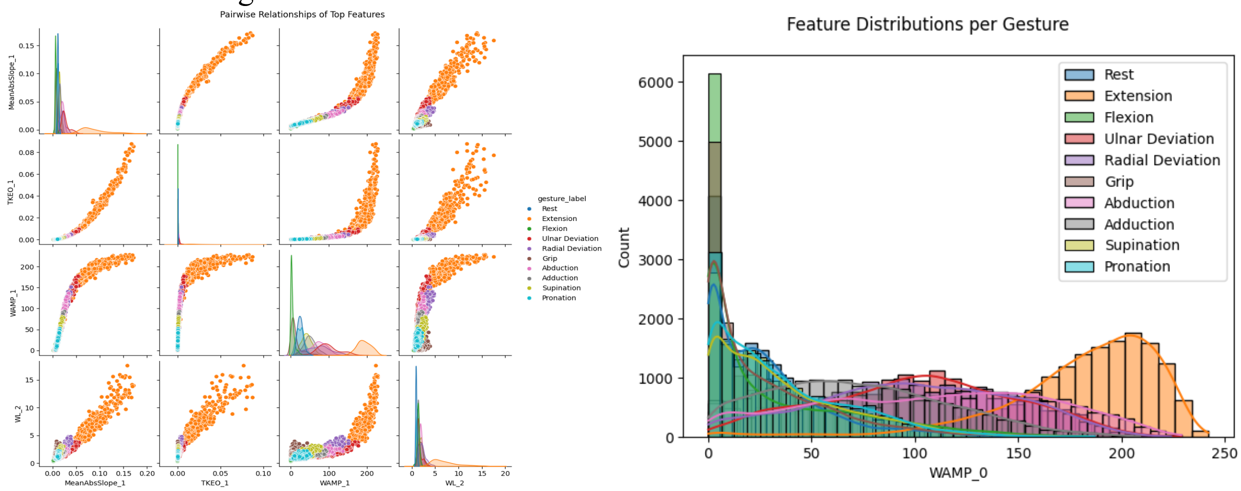

Figure 4 (a) Pair plot of some features (b) Distribution of gestures in WAMP_0

I have also plotted the data on a 2D feature space using PCA and t-SNE plots to find the spread of gestures on the feature space. Like our observation from time series, extension and flexion have separate clusters meaning these classes are easier to be classified. The close clustering of other gestures makes it difficult for classifiers to predict them. Considering this, it gives an idea that distance-based algorithms might not work well for the data. But, by using some transformation methods, we could still project the data into a different space making it easier for modelling.

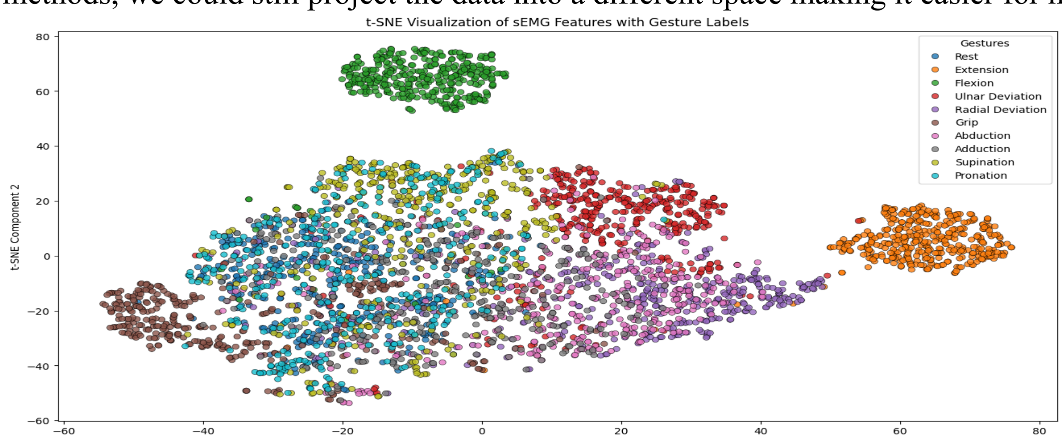

Figure (5) Spread of gestures on feature space

I have also analyzed the outliers in the features using IQR method and box plots. Instead of considering outliers on a feature level, I have considered them on a gesture level which helps in retaining the properties of certain gestures having peaks in the data. The outlier plot clearly shows that certain gestures like extension, flexion have peaks in the data which are often outside the IQR range.

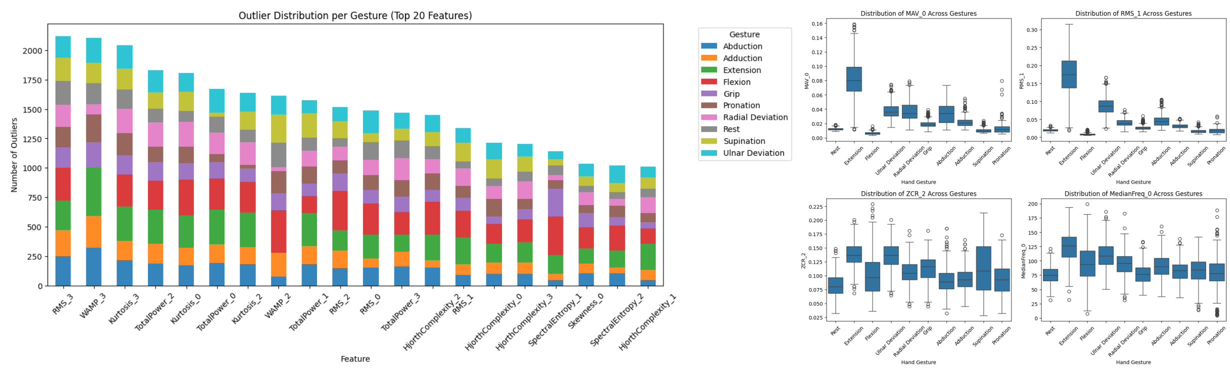

Figure (6) Distribution of outliers in each gesture over features.

Since all the features are extracted from the same signals, the extracted features have multi collinearity. I have used scatter plots and confusion matrix to find the correlated variables. Then, removed 44 variables with high corrrelations (above 0.9).

4.6 Data Preprocessing.

I have handled the outliers in the data on a gesture group level. Certain gestures are expected to have spikes so checked for outliers in gesture group for the feature, then replaced those outliers (values < Q1-1.5*IQR, values > Q3+1.5*IQR, IQR = Q3-Q1) with the 99^{th} percentile value of the group. This makes sure the gesture level patterns in the data are still in place even after minimizing the effect of outliers.

Many columns in the data are highly right skewed. So, I have used log transformations and square root transformations to reduce the skewness in the distributions. After that, I have checked for the distribution of the data and applied standard normalization for features with gaussian distribution and min max normalization for the other. [2] stated that applying min max normalizations for all features with min=-1 and max=1 helped in improving the performances of the models, we could test it out in the next experiments.

4.7 Feature Selection:

The data have many pairs with high correlations. It is important to handle them using feature selection methods to reduce the multicollinearity. First, a correlation-based filtering was applied and features with pairwise Pearson correlation above 0.90 were considered highly collinear and one of each highly correlated pair was removed. Next, I have analyzed feature importances from ensemble tree models to find the features contributing more to the model. We have also applied wrapper based filtering and backward elimination methods to identify the most significant features for the models. Notably, features related to signal energy and waveform complexity ranked highly – for example, RMS and total power from all four channels, WAMP from all channels, and Hjorth mobility and kurtosis from specific channels were among the top features selected.

4.8 Train test split:

The dataset contains the recordings of 40 participants. If we perform, random splitting on the overall dataset, there will be high chances of data leakage because of similar participants in train and test data. Hence, I have randomly split 40 participants into train and test data creating train set containing 32 participants data and test set containing 8 participants data.

4.9 Model Training:

I have evaluated four supervised machine learning algorithms for multi class classification: Decision trees, Random forests, XG Boost and SVM. The models' parameters are tuned via grid search using cross validation on the training data. For example, decision trees are trained for different max depths, min samples split, min samples leaf and criterion. I could not perform grid search for SVM model since it was computationally expensive and was taking a lot of time. It explains the poor performance of the model in the results while SVM is a popular choice of modelling in sEMG signal analysis. The results of modelling showed XG Boost model giving the best overall accuracy among all classifiers. Individual performances of the classifiers are discussed in results.

4.10 Binary Classification (Rest Vs Activity):

In addition to the multi class classification, I have also analyzed the rest vs activity (gestures other than rest) patterns in the data. This study has a potential application in monitoring the movements of coma patients and can also help in rehabilitation. I have performed a high-level analysis of the data distributions and found certain features like WAMP, RMS being the best predictor for the modelling. I have trained four models, decision trees, random forests, XG Boost and SVM. After performing some feature selection and parameter optimization, I have found almost all the models giving similar results with accuracy scores around 90%.

5 Results:

The performance of the models are evaluated for accuracy, precision and recall. XGBoost achieved the highest accuracy of 82.6% followed by random forests with 70.6%. It shows the ensemble methods have clear edge over other models for predictive modelling. The SVM model with rbf kernel performed the worst on the dataset with 58% accuracy.

Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**
Decision Tree	65.3	65.1	65.3	65.1
Random Forest	70.6	70.9	70.6	70.5
XGBoost	**82.6**	**82.6**	**83.0**	**83.0**
SVM (RBF kernel)	58.0	58.0	58.0	57.0

Table (1) Table showing overall metrics for multi class gesture classification

For the rest vs activity classification(binary), almost all models showed similar performance after some parameter tuning. Here as well, XG boost showed the best performance with 90% accuracy. The notable observation is the decision trees performing on par with random forests. It proves that the classification is rather simple for tree based model. A better finetuning of random forests could improve the performance better. Also it can be noted that almost all the models have AUC scores 97% which shows these models are performing quite well in distinguishing rest from activity classes.

Metric	**Decision Trees**	**Random Forest**	**XG Boost**	**SVM**
Accuracy	89.37	89.0	**90.0**	85.7
F1-Score	87	92.3	**92.9**	89.7
AUC	97.12	97.0	**97.7**	91.2

Table (2) Table showing metrics for binary classification (Rest vs Activity)

Model	**Class**	**Rest**	**Extension**	**Flexion**	**Ulnar Deviation**	**Radial Deviation**	**Grip**	**Abduction**	**Adduction**	**Supination**	**Pronation**	**Overall**
XGBoost	Precision	78	96	100	86	84	91	81	62	81	70	82.64
XGBoost	Recall	85	98	99	90	85	89	70	68	76	66	83
XGBoost	F1	81	98	99	88	85	90	75	65	79	68	83

DT	Precision	66.9	86.0	94.1	66.4	69.0	69.4	52.7	43.5	54.8	47.8	65.1
DT	Recall	67.2	96.6	93.2	65.2	71.1	65.0	45.2	44.9	54.2	52.4	65.2
DT	F1	67.0	91.0	93.6	64.4	70.0	67.2	48.7	44.2	54.5	50.0	65.1
RF	Precision	66.2	85.1	97.0	75.6	75.5	82.2	67.8	51.5	61.2	46.6	70.9
RF	Recall	74.5	98.4	94.1	70.6	78.8	73.6	52.2	50.0	58.4	54.5	70.6
RF	F1	70.1	91.3	95.5	73.0	77.1	77.7	59.3	50.8	59.7	50.2	70.5
SVM	Precision	36	77	78	60	56	75	55	43	50	51	58
SVM	Recall	62	94	93	63	62	59	45	37	42	21	57
SVM	F1	45	84	85	62	59	66	49	40	46	30	57

Table (3) Table showing gesture level metrics for each model

6. Discussion

The experimental results demonstrate the efficiency of using a well-designed feature extraction and preprocessing pipeline for sEMG gesture prediction. The XG Boost emerged as top performer for both multi class and binary classification problem. This outcome is in line with expectations, as XGBoost's boosted trees can capture complex nonlinear relationships among features and are relatively robust to noise and redundant features. The poorer performance of SVM (58% accuracy on 10 classes) was somewhat surprising, since SVMs have been used successfully in prior EMG studies. One major reason is lack of parameter optimization because of system limitations. One other reason for its poor performance is the close clustering the gestures in the feature space which make it difficult for distance-based algorithms like SVM to distinguish between classes. It can be seen in the class level metrics that gestures like Extension and Flexion that are spaced away from other clusters have got the highest scores. And gestures like Adduction and pronation that are closely spaced have got the least accuracy. It shows the importance of data transformation to project the features into a space where the classes are easy to classify.

7. Conclusion

In this paper, I have presented the pipeline for working with time series signals like sEMG signals for gesture prediction. It presents ideas on the filtering methods to be used, feature extraction, outlier handling and feature selections. It shows by leveraging feature extraction and some rigorous feature transformation and model optimizations, we can improve the accuracy of the models. It also showed that signal amplitude and power features like RMS, TotalPower are key features for modelling the data. Among the evaluated models, XG Boost provided the best performance followed by random forests.

These models have practical applications in healthcare, HCI and robotics. The binary rest vs activity classifier is particularly useful to monitor the movements of coma patients. The hand gesture study results can be used to develop prosthetic arms and gesture-based machine controls.

8. Future Work

There is a lot of potential for this study area. I could analyze the effects of gender, height, weight on hand gestures. I could also reduce the number of classes to wrist movements, finger movements or hand movements for better classifications.

We could also explore the application of deep learning models for modelling hand gesture predictions and feature selections. They can also be used for feature extraction instead of classic approach. One interesting area would be to extract the features using neural networks and apply them to machine learning models to improve the performance of the model.

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