Gesture Classification from sEMG Signals using Machine Learning Approaches

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***Abstract*—In this paper, the open-access sEMG dataset [2] is utilized to classify hand motor movements to the respective gesture they represent, using machine learning approaches. This is done as a prospective benchmark for fast and efficient communication in cases of disability, where the gesture class can be replaced with a letter in the alphabet, to form a sentence from a combination of gestures. The Machine Learning approaches tested in this paper are Logistic Regression, Random Forest, and Bagging Classifier algorithms. All approaches will be tested for their accuracy in classifying the sEMG data. The Bagging classification algorithm had the highest accuracy score, followed by Random Forest and Logistic Regression.**

Keywords—Electromyogram, Machine Learning, Bagging, Random Forest.

I. Introduction

Communication comes in many forms, whether verbal or non-verbal, to express oneself, feelings, ideas, and frustrations, or even to form pivotal familial and social relationships. It is unimaginable to lose the ability to speak and communicate with those around you. Other than speech, sign language is often utilized for communication. This is why it is very important to improve and refine communication mechanisms in cases of disability, where verbal communication becomes obsolete. To be able to execute a combination of specific gestures, and have them associated with a list of output letters, forming a word or sentence, read out loud by a device, would serve as a benchmark for communication among all individuals. This paper takes inspiration from the work of Jiang et. al., that use hand-movement High Density Surface Electromyogram (HD-sEMG) recordings [1] to create a "neuromuscular password" in which a combination of hand movements represents a letter. In this paper, Surface Electromyogram (sEMG) data, obtained by performing a list of unique gestures to complete a "Pacman" task [2], is used with the intended purpose of classifying each signal to a unique gesture label, that can be replaced by a corresponding letter in the alphabet in later works. The goal is that in practice, a list of gestures completed in a specified sequence would result in a sentence that the user can communicate to others in a fast and efficient manner. What about cases in which motor hand movement is not possible? Thankfully, even in such cases, the nerve and muscle endings are still able to provide electrical signals that can be recorded by the sensor for classification. Throughout this paper, the data is first obtained and filtered before it is passed into a feature extraction algorithm and classified into the specific gesture it represents. Three main methods of classification are compared for their classification accuracy and complexity.

II. Methods and Materials

A. Dataset

Many different datasets were surveyed for use in this paper, all of which consisted of different formats of multichannel EMG signals of multiple gestures. The decided upon data, [2], was a set of 13 males and 24 females of differing levels of physical activity, and no experience with sEMG recordings. The experiment itself consisted of sEMG data recorded from a MYO Thalmic bracelet worn on the subject's forearm, while completing a "Pacman" inspired gaming task. The game's goal was to reach a target "cherry" by implementing several gestures outlined in **Table 1**, each representing a different movement towards the target. Each hand movement was performed for 3 seconds, with a relaxation period in-between consecutive gesture for an additional 3 seconds. This was all recorded once by each of the 8 channels on the bracelet and stored in its own folder for each subject and trial. The data was made up of 10 columns, with the first column representing the time in milliseconds, columns 2 to 9 representing the signals from channels 1 through 8, and the tenth column being the gesture label (0-7, as seen in **Table 1**). The dataset chosen was of the first subject.

B. Preprocessing

The first subject's dataset was loaded into Python, and a plot of the signals from all the channels was constructed, as seen in **Fig. 1**. To prepare the sEMG data for feature extraction and gesture classification, filtering was performed. A notch filter, which rejects frequencies within a narrow band, was adapted. This is because of the variance in the frequencies of the signals from each gesture, making it difficult to choose an appropriate cut-off frequency that would optimize all

Gesture label	**Hand movement**	**Movement in game**
0	unmarked	N/A
1	Hand at rest	None (relaxation)
2	Palm clenched	Mouse left-click
3	Wrist flexion	Left
4	Wrist extension	Right
5	Radial deviation	Up
6	Ulnar deviation	Down
7	Palm extended	Mouse right-click

Table 1. Different gestures recorded by the MYO armband and their corresponding representation in the task completed by the subjects.

signals. It is much simpler to chose a narrow band of signals to attenuate. The signal was rejected between 0.0002 and 0.0003. This was decided upon through experimental results. The filtered signal can be seen in **Fig. 2**.

C. *Feature Extraction*

After filtering the signals, a feature extraction algorithm, adapted from the open access GitHub repository by Sebastian Restrepo [3], was implemented. To extract the features of the signal, a sliding window of 200ms and a step size of 100ms were utilized, with a sampling frequency of 1000 Hz, as implemented by the original paper [2].

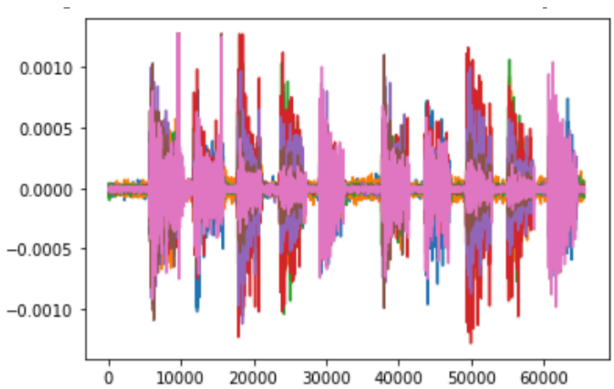

Fig. 1. sEMG signal of subject 1 from all 8 channels for all recorded gestures in the time series signal.

Out of the 18 features that were successfully extracted from the signal data, the time domain feaure chosen to be used in the classification algorithm is the root mean square, described by Equation (1); where n represents the number of datapoints and x is the sEMG data. This metric was chosen as it seems to be the most commonly used parameter across the literature for classification of EMG signals [1]-[4].

The feature extraction algorithm was slightly altered in order to output an additional gesture array. This was done by utilizing a count function that returns the variable occurring most in an array, and then assigning that gesture to the signal in the current window.

Then, to extract the features from each channel, a function of embedded loops was composed. This functions task is to take the 8-channel sEMG signals, and extract features for each channel, and retrieve its gesture data, separately, by setting the index of feature extraction to 3000 ms with the assumption that the data acquisition procedures were accurate, and there truly was a pause of 3 seconds between consecutive hand gestures. The feature array was later retrieved and split for each channel in preparation for the classification algorithms.

$$RMS = \sqrt{\frac{1}{n}\sum_i x_i^2} \qquad (1)$$

D. *Classification*

The classification procedures were fairly straightforward. First the features array was assigned as the independent variable, and the gestures were assigned as the reference variable. Then, Python sklearn's model selection packages were utilized to split the data into 80% training and 20% testing. For classification, sklearns Logistic Regression, Random Forest, and Bagging classifiers were implemented, with the accuracy score metric utilized.

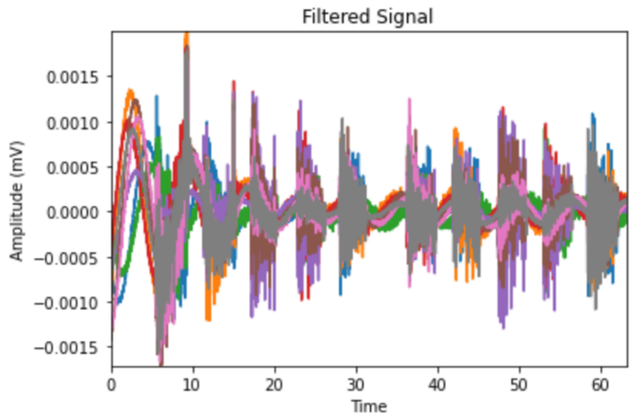

Fig. 2. sEMG signal of subject 1 from all channels following notch filtering.

III. Results

All three classifier were successful at predicting the gesture classes with above a 50% accuracy. The bagging classifier was the most suitable for this task, as it resulted in an 87.3% classification accuracy on the testing set, with random forest following closely at 85.6%, and regression performing poorly, at 63.5%. These results are expected, as a logistic regression model is better suited at classifying binary (0 or 1) data, and bagging classifiers are well suited for models with a high variance which is prevalent in sEMG signals.

When the signal is unfiltered, the classification results decrease significantly for both the bagging and random forest algorithms, to 77.1 and 80%, respectively. The logistic regression results remained fairly similar with an unfiltered signal (64%).

IV. Conclusion

The results of this paper illustrate that the task of classifying gestures from filtered sEMG signals is possible and carried out best by a bagging classifier. A hurdle encountered in most studies is the data is very clean and does not reflect real day to day gesture data. However, due to the nature of the data collection process, where subjects in the experiment were required to complete a task, instead of simply performing the gesture after weeks of training, the data retrieved is in fact real-life data. Improvements to these papers procedures might include implementing a cross-validation algorithm to further increase the accuracy of classification, along with conducting a channel importance analysis to identify which channel's data is the most useful for the classification problem.

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