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An expert system for detection of key pinch and tripod hand grip based on sEMG signals

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Abstract

This work presents a system to recognize key pinch and tripod hand grips using surface electromyography. This system made use of sEMG signals collected from 8 subjects for training and testing, making use of a 4-channel system designed to recognize Key Pinch and Tripod Pinch hand grips. Signals were pre-processed using band pass filter and notch filter, and a time domain feature extraction was performed from these signals, namely Mean Absolute Value, Standard Deviation and Wilson Amplitude. This work implements and compares 5 different classifications techniques namely Random Forest, Decision Tree, Logistic Regression, KNN and Adaboost. Random Forest provided the highest testing accuracy of gesture recognition at 88.68% and a precision of 88.88%. The system correctly recognizes key pinch and tripod hand gestures.

Subject Classification: *Primary 94A12, Secondary 62H15.*

Keywords: *Statistical analysis, Electromyography (EMG), Machine learning, Prosthetic arm.*

I. Introduction

The use of EMG signals has gained increased traction across many different applications [1], spanning from clinical or biomedical use to

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prosthesis. Amputation of limbs brings an activity in their daily life. This makes realization of control for prosthetics in addition to exoskeletons to support other medical conditions crucial for their welfare. Converting these signals [2] into adequate control signals needs high computational power and involves complex processes. In the past, insufficient features for machine learning techniques caused the prosthetics to move abnormally. However, significant improvements in hardware systems and development of large datasets of EMG in the past decade has made deep learning a viable option. The first end-to-end deep learning architecture [3] demonstrated the vital role of Convolutional Neural Network for achieving high accuracy in sEMG classification. As a result of its high accuracy [4], CNN has an edge over other existing traditional machine learning algorithm. Nevertheless, there are challenges to overcome; the lack of robustness in grip recognition and control along with noise in the EMG signal that can make it difficult for users to read and interpret signals without professional assistance.

II. Literature survey

The systems looked at relied on signals from a synthesis of different sensors and sampling frequencies in addition to sEMG/EMG signals. K. Yang et al. [5] used a myo armband which placed sEMG sensors on the forearm muscles sensing its movement, direction, and rotation. This experiment was performed on 5 subjects, who showed no signs of muscle dystrophy. Mean Absolute Value (MAV), Slope Sign Change (SSC), Waveform Length (WL) and Root Mean Square (RMS) features based on Time domain were used. Each grip took two seconds to acquire, and the samples collected were 30, at a frequency of 200 Hz through 8 channels. Maria Claudia et al. [6] recorded four subject's sEMG signals 16/30 with 1000 Hz sampling rate and a 20-500 Hz filtering range. Five channel system was used with the sensors placed on the muscles of forearm: the extensor digiti minimi, palmaris longus, abductor pollicis longus, and extensor communis digitorum, the flexor digitorum superficialis. [7] used a Camera-EMG sensor fusion to acquire sEMG signals with sampling frequency fixed at 200 Hz. The system made use of 2-time domain features namely the MAV and RMS. The 4-channel system placed the sensors on flexor carpi radialis, flexor carpi ulnaris, abductor pollicis and flexor pollicis brevis. Xu Zhang et al. Accelerometer-EMG fusion was implemented with a sampling frequency of 20-450Hz. Implementation of a system with a multi-sensor fusion approach increased accuracy and robustness with the tradeoff being high computational and monetary costs. The sEMG signals were recorded from 4 subjects. The system showcased classical linear classifiers (Linear Bayesian Classifier) low computing complexity and consistent recognition made them more suitable for applications in real-time. Studying the feature extraction techniques, use of time domain features was prevalent due to low computational complexity. MAV, SD, SSC and WL were the four most common features, with MAV being the most frequently implemented, as seen in works [8]. [9] used sEMG signals extracted from six subjects as the general grip EMG feature extraction network using a CNN structure. The system employed a successful Transfer Learning strategy, this module in the solution enables strong generalization with little training burden, and it is claimed that using a transfer learning technique enhances accuracy by 10-38 percent. [10] used the k-NN algorithm as the classifier giving an accuracy of 94%. [11] used a 4-channel system with the sensors placed on the muscles of forearm; extensor pollicis brevis, flexor digitorum profundus and extensor digitorum. The system recorded a comparative analysis between RNN using LSTM recurrent units and Gated Recurrent Unit and showed that classifiers trained with a stepwise learning rate and a bidirectional recurrent layer made up of LSTM units that employed the attention mechanism performed better than all other evaluated RNN classifiers. [12] demonstrated to obtain more time-varying frequency characteristics. [13] retrieved a set of features allowing for the merging of sensor channels as well as a visual assessment of its utility for hand grip differentiation. [14] demonstrated a hybrid deep learning architecture for detecting hand movements using sEMG inputs. Literature demonstrated a tensor-based system for hand grip recognition using a multilinear singular value decomposition (MLSVD). [15] used sEMG signals through an 8-channel system with the sensors placed on the forearm muscles. [16] made use of clustering methods. [17] demonstrated a hands-free HMI, using just two channels and an SVM classifier to classify five-foot movements. [18] Found PSD and ZCR features of physiological signals to be highly relevant towards class discrimination. [19] Used wavelet decomposition technique for information security. [20] Implemented open pose model with a limitation of recognition of occluded joints as it causes information loss. Sliding window technique for the signals captured from sensors embedded in wearable clothing is implemented. The obtained features classified by neural networks yielded 92.6% accuracy of posture classification [21].

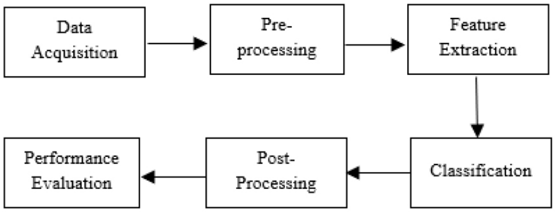

Figure 1

Proposed hand grip recognition framework

III. Methodology

General flow of the proposed solutions procedure to carry out hand grip recognition is given in Figure. 1.

A. *Dataset and Pre-Processing*

Surface EMG signals were recorded using the Clarity medical EMG machine with 2000 Hz sampling rate The electrode distance required was 20mm apart. The electrode montage for the activity was identified and 4 electrodes were positioned to record. The participants were sat with their arms 90 degrees bent and their forearms resting. First the neutral position, then the key pinch, next grip was the tripod pinch with index, middle and thumb, fourth being hand close and the last was with hand open position were the fundamental finger grip hand motions that were recorded. Each grip lasted for more than a second, and there were thirty repetitions of each action in a random order. The solution worked on this project is concerned with the recognition of the pinch and tripod pinch.

The data collection was done on 8 subjects, 6 used for training and 2 for testing. 4 electrodes were used channel 1 being on the palmaris longus

Figure 2

Tripod Pinch Grip

Figure 3

Key Pinch Grip

which is responsible for flexion in the wrist, channel 2 being the Extensor digitorum responsible for hand contraction, channel 3 being the Flexor capri ulnaris responsible for hand abduction and finally channel 4 being the Flexor capri radialis responsible for Hand adduction.

Figures 2 and 3 show the subject being recorded doing the tripod pinch and the key pinch respectively.

B. Feature Extraction

It is observed that signals recorded for subject 1 show more variation in amplitude than subject 2. The average amplitude in subject 1 is higher than the mean band amplitudes shown in Figure 4.

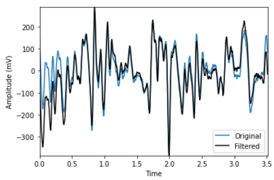

Figure 4

Filtered signal

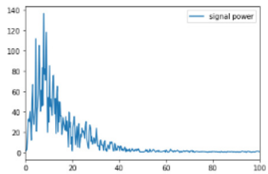

Figure 5

PSD Key Pinch

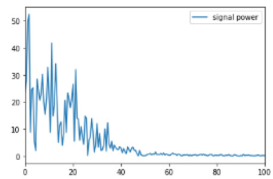

Figure 6

PSD Tripod Pinch

It was observed that the mean signal power of subject 1 to be far higher than subject 2. As shown in Figure 5 and 6 the power spectral density plot is distinctly different for the features of 2 different grips key pinch and tripod.

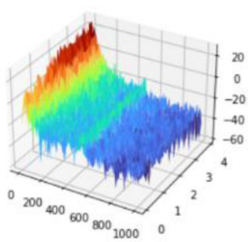

Figure 7

Key pinch

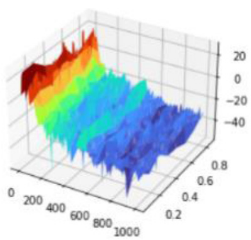

Figure 8

Tripod pinch

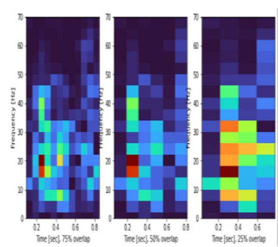

Figure 9

Sliding window overlap

Figure 7 depicts the spectrogram of key pinch, Figure 8 depicts the spectrogram of Tripod pinch. The windowing technique is implemented to create small subsets of data. When choosing the window, the sample frequency was set at 2000 Hz. Sliding window technique with 75%, 50% and 25% overlap is studied and the resulting feature variety is seen in Figure 9. The window with 500 data points and 50% overlapping is chosen for further analysis. The signals are put through a wavelet transform function, which is regarded as a time scale density and provides details on the relative energy associated with various frequency bands. By manipulating the scaling and shifting components of a single wavelet function, this mathematical approach decomposes the signal into numerous lower resolution levels. The main advantage this technique is its ability to extract the local spectral as well as temporal feature values. This is especially important in practical applications regarding EMG signals. This solution made use of two filtering techniques: the notch filter, and the Band Pass filter. Notch filtering is used to reduce power line and harmonic interference, which can taint sEMG signals. These filters are regularly incorporated in EMG recording equipment and are frequently utilized during clinical recording sessions. BP is used to eliminate low and high frequencies from a raw signal before it is digitized. The features of time domain that were used were MAV, SD, and WAMP. The MAV is analogous to the ARV. It may be computed using the moving average of the preprocessed EMG. To put it another way, it is determined by averaging the absolute value of the sEMG signal. Because of how simple it is, it is a common myoelectric application for detecting the intensity of muscle contraction. MAV is represented in equation (1).

$$MAV = \frac{1}{n}\sum_{a=1}^{n}|x_m| \tag{1}$$

SD simply measures the degree of variance or dispersion in the EMG signals. Standard Deviation is represented in equation (2).

$$S = \sqrt{\frac{(x_i - x)^2}{n-1}} \tag{2}$$

The WAMP is a measure of how often the difference in amplitude between two successive amplitudes exceeds a threshold of magnitude. WAMP is represented in equation (3).

$$WAMP = \sum_{i=1}^{N} u(|x_{i+1} - x_i| - T) \tag{3}$$

The overall length of the waveform across a segment is called the waveform length (WL). It provides the comprehensive information about the frequency, amplitude and duration of the input signal and its equation is shown in equation (4).

$$WL = \sum_{i=1}^{N} |x_i - x_{i-1}| \quad (4)$$

Algorithm 1: EMG Signal feature extraction

Input: Raw EMG Signals

Output: Feature description vector

Init:

1: **for** file in folder **do**
2: Filter using band stop/notch to remove noise
3: Select the frequency range using the filter
4: Windowing technique to generate short sample
5: Extraction of features
6: Normalize and append to feature vector
7: **end for**
8: **return** feature descriptor vector

The sum of times the slope's sign changes is known as Slope Sign Change (SSC), a property that describes a signal's frequency information. Equation (5) describes SSC

$$SSC = \sum_{n=2}^{N-1} [f[(x_n - x_{n-1}) * (x_n - x_{n+1})]] \quad (5)$$

A signal's RMS value is calculated as the result of the constant force and the contraction of the muscle for non-fatiguing state. RMS is a method that is computationally quick and efficient, equation (6) describes RMS.

$$RMS = \sqrt{\frac{1}{N} \sum_{i=1}^{N} |x_i^2|} \quad (6)$$

The frequency median (FMD) is a technique for extracting features that is based on the power spectral density (PSD). When it comes to PWD signals there are generally two types: Parametric and Non-Parametric. FMD is the frequency whose spectrum is divided into two equal parts and is described in equation (7).

$$FMD = \frac{1}{2} \sum_{i=1}^{M} PSD \quad (7)$$

C. Analysis of EMG- signal

The wavelet transforms of actions- key pinch and tripod hand grips of subject 1 is shown in Figure 10 and 11 respectively. A three level DWT

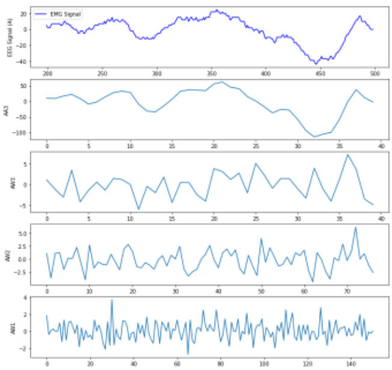

Figure 10

Wavelet – Key Pinch

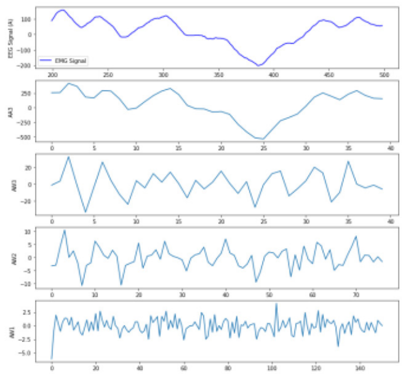

Figure 11

Wavelet – Tripod

composition is used. The Daubechies wavelet are written as dbN where db is the wavelet and N is the order. Here we use 'db4' where 4 is the order of the wavelet. The wavelet transforms also extract local spectral and temporal information.

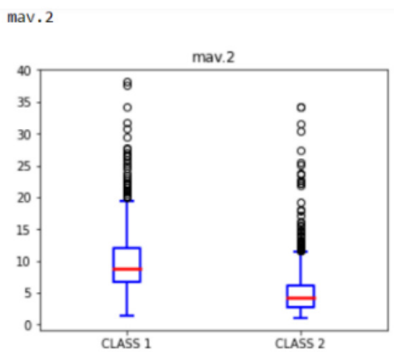

Figure 12

MAV of channel 2

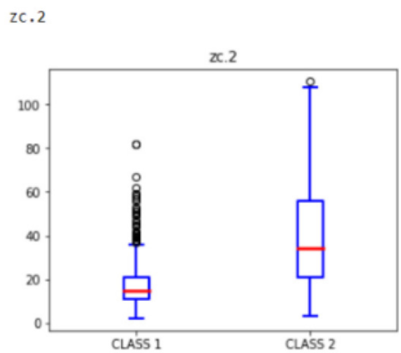

Figure 13

Zero Crossing of channel 2

MAV and Zero Crossing are the features taken into consideration shown in the Figure 12 and 13. Class 1 and Class 2 represent tripod and key pinch respectively. Distribution of data explained with boxplot showing lower and upper quartile and median. A clear discrimination as denoted by the red line is seen in both mav.2 and zc.2 between class 1 and class 2.

D. Classification Techniques for recognition of tripod and key pinch

The proposed machine learning model explored five supervised classifiers for binary classification namely Decision Tree (DT), Random Forest (RF), K Nearest Neighbors (KNN), Logistic Regression (LR), AdaBoost (AB)

The first classifier used is a decision tree. Feature of the vectors define the decision rule and thus form the branches of tree. The leaf nodes represent the outcome based on entropy. In this model an entropy attribute is used with a maximum depth of 13. The DT algorithm's greatest benefit is that it considers every possibility. Entropy is given in equation (8)

$$S = \sum_{i=1}^{c} -p_i \log_2(p_i) \tag{8}$$

Pi here is the probability of class i.

Algorithm 2: Detection of Hand Grip Detection

Input: Raw EMG Signals

Output: Reduced feature vector

1. For each Subject in Directory:

2. Feature Extraction of subject's signals;

   Feature reduction

3. Reduced feature vector(F_d);

4. End For

5. Initialise Accuracy ;

6. List Classifiers

7. For each classifier

8. Train test split

9. Model = Classifier(data);

10. New_Perf = Evaluation (Model);

11. **If** New_Perf >= Perf:

12. Perf = New_Perf;

13. Save (Model);

14. **End If**

15. End For

16. Return Prediction based on Model

Information gain in each node of the decision tree id the entropy function. The RF classifier comprises several decision trees in different subparts of the dataset. The final class of the item is then determined by averaging the outcomes from each decision tree. It uses Mean Squared Error to branch data from each node as given in equation (9).

$$TS = \frac{1}{N}\sum_{i=1}^{N}(ki - li)^2 \tag{9}$$

N being the datapoint number, *ki* being the value returned by the model and *li* being the value for datapoint *i.* KNN classifier finds the similarity of the test data with the group. The model in this case considered the seven nearest neighbors. Predictions were based on Euclidian distance. Minkowski distance parameter with a p-value equal to 3 was used. The Minkowski distance is given by the equation (10).

$$d(x, y) = \left(\sum_{i=1}^{n}|x_i - y_i|^p\right)^{1/p} \tag{10}$$

LR predicts categorical dependent variable. These depend on the set of independent variables. It provides probabilistic interpretation which lies from 0 to 1. Here, the single input value's (x) coefficient is represented by b2, while the bias or intercept term is represented by b1 in equation (11).

$$y = \frac{e^{b_1 + b_2}}{(1 + e^{(b_1 + b_2 * x)})} \tag{11}$$

AB or adaptive boost classifier combines many classifiers. This method, known as an iterative ensemble technique. It validates and uses a combination of weak classifiers to create a strong classifier. The key idea is optimize the classifier weights in each iteration. such that accurate predictions of odd observations are made.

IV. Results

It is observed that RF gives a promising testing accuracy of 88.68% along with precision 88.88%, Recall 88.68% and F1 score 88.64%. It also gives the precision, recall and F1 scores of these 5 classifiers where RF performs the best out of the five different classifiers that are implemented. Visual representation of performance is given in Figure 14. The visualization of Receiver Operating Characteristics (ROC) for trained data of RF classifier is shown in Figure 15. The classifier yields ROC score of 0.935. Table 1. shows the accuracies of the 5 classifiers implemented.

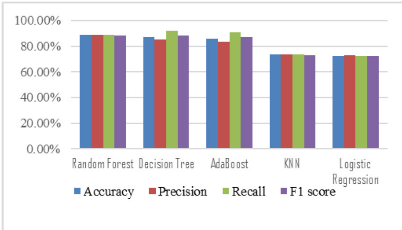

Figure 14

Classifier performance

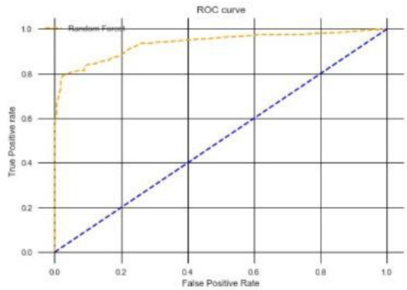

Figure 15

ROC curve for RF Classifier

Table 1

Performance of classifiers

Classifiers	Accuracy	Precision	Recall	F1 score
RF	88.68%	88.88%	88.68%	88.64%
Decision Tree	87.22%	85.25%	91.72%	88.37%
AB	85.76%	83.54%	91.03%	87.12%
KNN	73.35%	73.60%	73.35%	73.11%
LR	72.62%	72.90%	72.62%	72.62%

V. Conclusion

Electromyography (EMG) based approach is presented in this work for classification and detection of tripod and key pinch grips. A four-channel system with two classes is recommended in order to meet the primary objective. Notch (49 Hz- 51 Hz) and Bandpass (10Hz- 500 Hz) filters were used for preprocessing of raw EMG signals. The experimental results show that by placing the electrodes on targeted muscle - flexor carpi radialis, extensor carpi ulnaris, abductor pollicis brevis, and flexor pollicis brevis, a highly accurate recognition of two grips, Tripod and Key pinch, can be achieved. This type of electrode arrangement is appropriate for recording numerous grips, given its testing accuracy of 88.68%. The experimental results show that muscle activity obtained at the four electrode sites offers useful information for categorization of Tripod and Key pinch. This system is part of the development of bionic prosthetic arm.

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