Time Domain Analysis of EMG Signals using KNN and SVM Techniques

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Abstract: The EMG signals that have been processed can mimic human movements. For this study, raw EMG data obtained when the hands are in repose (rest), in a clasp, and when the wrist is buckled and stretched were used to categorise four distinct forms of hand gestures using a MATLAB-based intelligent framework (open access data set). Statistical-time-domain features are applied to sort various hand gestures in this investigation. The K-Nearest-Neighbor (KNN) and Support-Vector-Machine (SVM) classifiers are used for classification and comparison. Furthermore, our method outperforms a state-of-the-art method on other data sets of hand gestures.

Keywords: Hand gesture recognition, Support-Vector-Machine, K-Nearest-Neighbour, Electromyography, Empirical Mode Decomposition, Kaggle Database

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1. Introduction

Individuals who have their upper limbs amputated go through a terrible experience. Limb loss affects around 0.0017 billion people in the United States, or about one out of every 200 people. Every year, 50,000 new amputation cases are reported to the National Center for Health Statistics. The most prevalent are partial hand amputations, which result in the loss of one or more fingers. Amputations can occur for a variety of reasons. Peripheral arterial disease, or impaired circulation caused by injury or constriction of the arteries, is the most common cause. If there isn't enough blood flow, the human body's cells won't get the oxygen and nutrition they require. If the damaged tissue doesn't get enough oxygen, it starts to die, and infections might develop. Severe injuries are another factor. Other causes include severe injuries sustained in traffic accidents, combat, severe burns, explosions, malignant tumours in the muscles or bones of the limbs, and infections that are resistant to treatment.

Human bioelectric signals have been widely studied and used in a number of therapeutic and psychological research studies. A bio-electrical signal is a signal acquired from any organ that exhibits an important physical property. A bio-electric signal is a time-dependent signal that may be characterized in terms of frequency, amplitude and phase. The EMG has recently been used in the rehabilitation of individuals who have had amputations in the form of robotic prostheses. EMG is a highly helpful instrument since it gives a natural way of sensing and identifying various body motions.

Electromyography (EMG) is a biological signal that is used to evaluate muscle responses or electrical signals generated by skeletal muscles. Electrical signals termed impulses are sent from the nerves to the muscles, and these impulses may be detected and studied using EMG sensors. The EMG's amplitude and spectrum are affected by the skin's temperature and thickness, the fat layer between the skin and muscles, the rate of blood flow, and the sensors' placement. Muscle function and EMG signals deteriorate as a result of fatigue, ageing, and neuromuscular disorders. Depending on the type of sensor, there are two types of EMGs. One is related to the surface, whereas the other is intramuscular. Electromyography (EMG), which records electrical activity in muscles, should be considered an add-on to the clinical exam. It can differentiate between neurogenic and myopathic muscular weakness. This can detect abnormalities in clinically normal muscles, such as chronic denervation and fasciculation. It can differentiate between focal nerve, plexus, and radicular diseases and give supporting evidence of the pathophysiology of peripheral neuropathy, such as axonal degeneration or demyelination, by detecting the distribution of neurogenic abnormalities. In motor neuron disease, electromyography (EMG) is required to show widespread denervation and fasciculation, which is necessary for a correct diagnosis.

2. Problem Formulation

Nikitha Anil [6] employed wavelet decomposition, a signal processing approach in which signals are decomposed into wavelet coefficients with spatial and temporal localization. The dataset is made up of these coefficients, which are categorized using Support Vector Machines (an ML technique). In this study, to reduce the number of features in EMG data, Principal Component Analysis (PCA) and Uncorrelated Linear Discriminated Analysis (ULDA) were used, while SVM was used to discriminate unique movements in real-time. After extracting five Eigen values in the temporal domain, the scientists utilised a Neural Network (NN) to detect six motions. In their suggested model, they got 93% accuracy.

Jingxiang Chen, et al. (2019)[4] propose two methods for combining information from the Leap Motion and Myo sensors, resulting in significantly improved hand tracking accuracy for the operator. They also use the Myo sensor's EMG data in conjunction with convolution neural networks to solve Leap Motion's problems of reliably recognising the active fingers.

Ahsan et al.[9] proposed a study that combines an EMG signal with an Artificial Neural Network to recognise motions (ANN). It discusses a comprehensive investigation of EMG signals and the development of a human-computer interface (HCI) to assist the elderly and crippled. With a success rate of 88.4%, hidden layers of 10 neurons generated the best result out of a dataset of 204 samples. To categorise the hand motions produced by the MYO armband, the author employed the k-nearest neighbour and dynamic temporal warping methods. They also integrated a muscular activity detector, which reduces processing time and increases identification accuracy. Finally, they calculated an accuracy of 89.5 percent and concluded that their model surpasses both MYO's and other systems. They used two hand movements: a relaxed hand and a closed hand, according to them. They extracted statistical time domain characteristics and utilised KNN and SVM classifiers to recognise them (mean, variance, kurtosis, and skewness). They eventually achieved 96.58 percent accuracy.

Andi Dharmawan; CaturAtmaji; DanangLelono; AgusHarjoko,[22] Artificial Neural Networks (ANNs) and long-short-term memories, as well as the foundations of finger motion classification with four electrodes, were used to compare the variation of characteristics that would be used for classification in the time domain or frequency domain (LSTM). According to the findings of this investigation, using time domain data for classification with artificial neural networks (ANNs) produces more accuracy than using LSTM. This is due to the movement's brief period of only two seconds in this investigation. When using the frequency domain feature, the results demonstrate that using LSTM improves accuracy, especially in terms of mean-power and median-frequency characteristics.

Apiwat Junlasat, et al.[18], presented finger movement detection based on several EMG locations. EMG signals were recorded using Myoware muscle sensors. In a low-cost computational processing unit, the recorded EMG signals are gathered and analysed.

Michele Barsotti et al.[19] suggested a minimally supervised, online myocontrol system for proportional and simultaneous finger force estimate utilizing just individual finger tasks, based on ridge regression and training..They compared the system's performance using two feature sets taken from high-density electromyography (EMG) recordings: EMG linear-envelope (ENV) and non-linear EMG to muscle activation mapping (ACT). On eight participants with intact limbs, they used online target-reaching tasks.

3. Problem Solution

3.1 Proposed Methodology

The study technique utilised to categorise EMG-based hand movements is depicted in Figure 1. The collection of raw data was the first step in the development of our system. We collected EMG signals from diverse hand motions using an open-access data set [2]. Before conducting classification, the next step is to preprocess the datasets and eliminate the noise components from the signal (segmentation). We did this using Empirical Mode Decomposition (EMD), which not only segregates our research region but also eliminates the undesired high-frequency components (0–500Hz). Following that, we extracted the time domain characteristics from the segmented EMG signals and classified them for gesture detection using a k-nearest neighbour classifier.

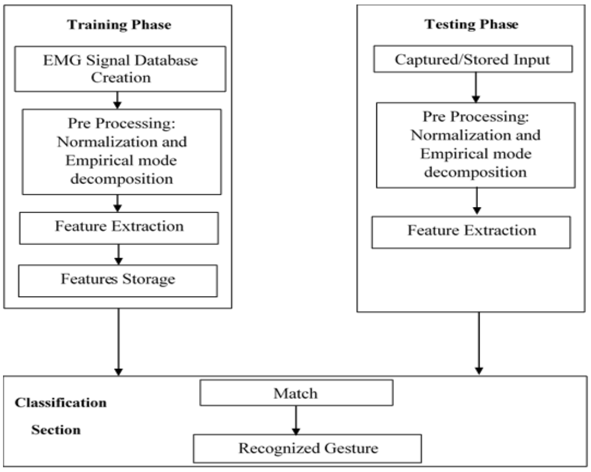

Fig 1. Proposed block diagram.

3.1.1. Dataset

The Kaggle Machine Learning Repository dataset [2] was used in our research. They used a MYO thalamic bracelet with eight separate sensors that collected myography signals over eight channels to collect EMG data. We observed 36 people performing six different hand motions, but we only looked at three of them: "hand at rest," "hand clenched in a fist," and "wrist extension." Each move lasted three seconds, followed by a three-second break.

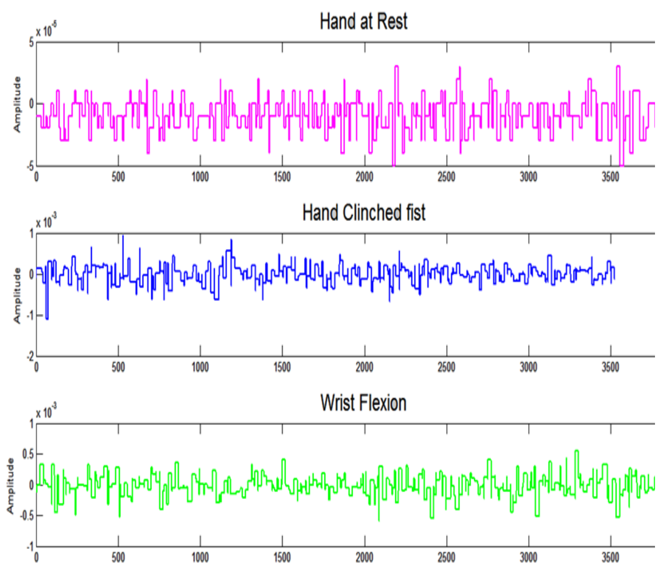

Fig 2. Unprocessed EMG signals of hand gesture.

3.1.2. Pre-Processing and ROI extraction

Instrument noise and baseline interference are the most common types of noise detected in EMG data. Thus, we will first remove variance from this dataset in order to ensure that all signals have the same range, and then use the Empirical Mode Decomposition (EMD) techniques to filter out any unprocessed EMG signals affected by these disturbances. EMD decomposes the signal into IMFs with varying resolution scales, similar to wavelet analysis. In EMD, a pre-designed mother wavelet that is selected before the investigation determines the fundamental functions for the different scales, whereas in wavelet analysis, the basic functions for the various scales are dictated by a pre-designed mother wavelet that is chosen before the research.

As a result, IMF is better able to describe the local properties of a signal and adjust to its oscillation patterns over time. As a consequence, EMD is appropriate for studying nonlinear and non-stationary signals as a consequence of this advantage, and may thus be used for EMG analysis. Following decomposition, the IMFs were formed in order, with each IMF having a lower frequency and a residual signal than the one before it. Mathematically,

$$\mathrm{EMG}_{\mathrm{normalize}} = \frac{\mathrm{EMG} - \mathrm{EMG(min)}}{\mathrm{EMG(max)} - \mathrm{EMG(min)}} \qquad (1)$$

$$\mathrm{EMG}_{\mathrm{segmented}} = \sum_{k=1}^{M} \mathrm{R_f} + \mathrm{IMF_k} \qquad (2)$$

Because our major purpose was to denoise and distinguish ROI rather than decomposing the unprocessed EMG signals into distinct IMFs. Selecting IMFs with lower frequency(LMFs) components and eliminating all IMFs with higher frequency components accomplishes this.

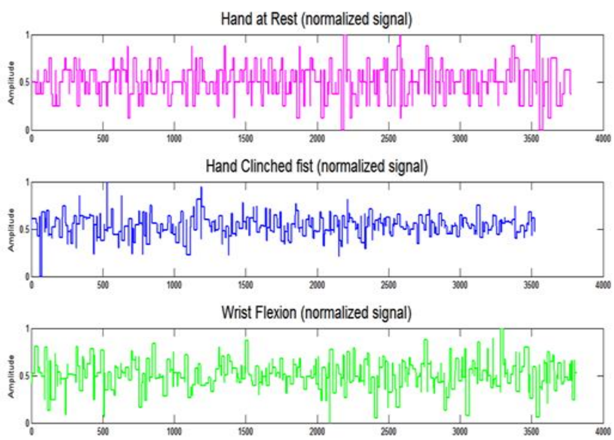

Fig 3. Standardized EMG signals of hand gesture.

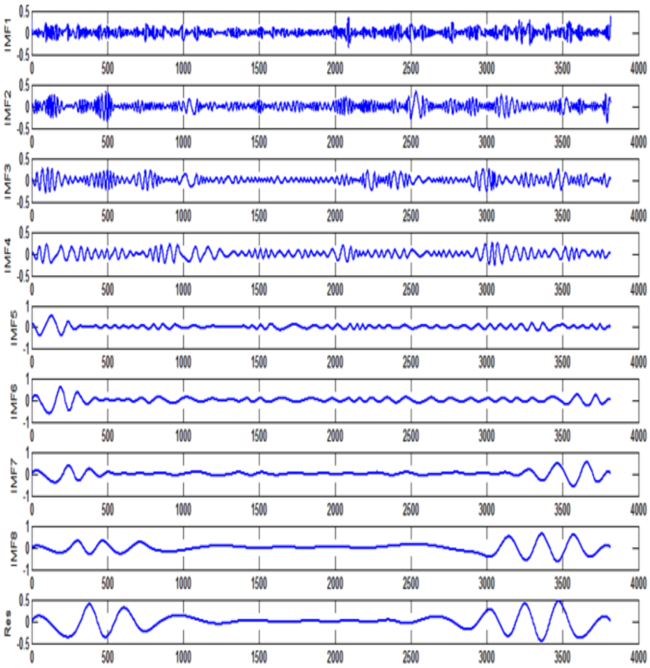

Fig 4. Segmented EMG signal when Hand at rest

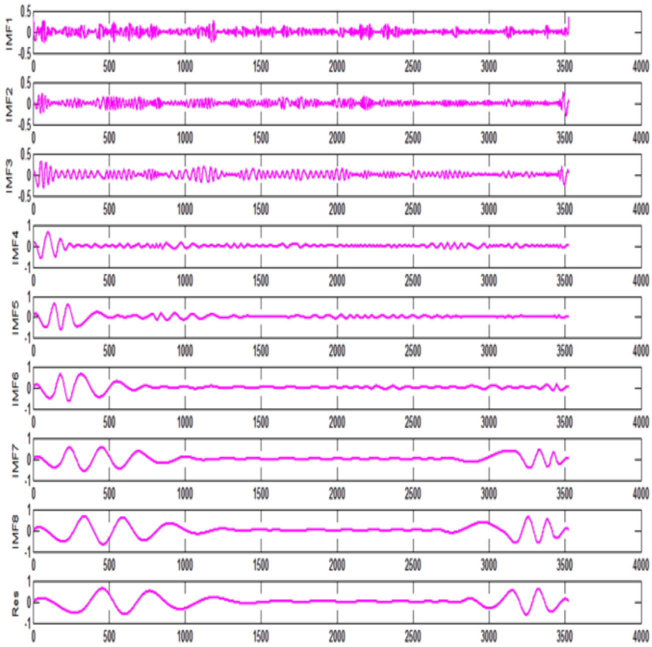

Fig 5. Segmented EMG signal when Hand at clinched fist

3.1.3. Feature Extraction

Feature extraction is a technique for obtaining attributes from EMG data. Mean-Absolute-Value (MAV), Root Mean Square (RMS), Variance (VA), and Simple Square Integral (SSI) were computed for each movement. Because EMG signals are in TD, they are referred to as time-domain (TD) features. The feature extraction value will be utilised as an input to the classification model.

3.1.4. Mean-Absolute-Value (MAV)

The absolute average of the EMG signal is designated as MAV. The MAV is the computer-calculated corresponding average revised value (ARV). The MAV is referred to as a time-domain variable because it is measured as a f(t), i.e. as a function of time.It shows the area beneath the EMG signal after it has been rectified, which means that all (-ve) negative voltage values have been transformed to (+ve) positive voltage values. The MAV is used to determine the amplitude of the EMG signal. The following formula is used to compute it:

$$\mathrm{MAV} = \frac{1}{N}\sum_{k=1}^{N} |X_k| \quad (3)$$

Where N denotes the signal's whole length andXkrepresents the EMG signals.

3.1.5. Root Mean Square

The RMS is the square-root of the average power of the EMG signal (RMS). The RMS represents constant force and nonfatiguing contraction, and it's characterised as an amplitude modulated Gaussian (AMG) random process. Because it represents the physiological activity in the motor unit during contraction, its level has been used to measure the electrical signal.

It's worded like this:

$$\mathrm{RMS} = \sqrt{\frac{1}{N}\sum_{k=1}^{N} X_k^2} \qquad (4)$$

3.1.6. Variance

The power density of an EMG signal is measured using EMG Signal Variance. The value of the EMG signal variance might be zero. Since EMG signals are based on white Gaussian noise (AWGN).

The following formula may be used to compute it:

$$\mathrm{VAR} = \frac{1}{N}\sum_{k=1}^{N} (X_k - \overline{X})^2 \qquad (5)$$

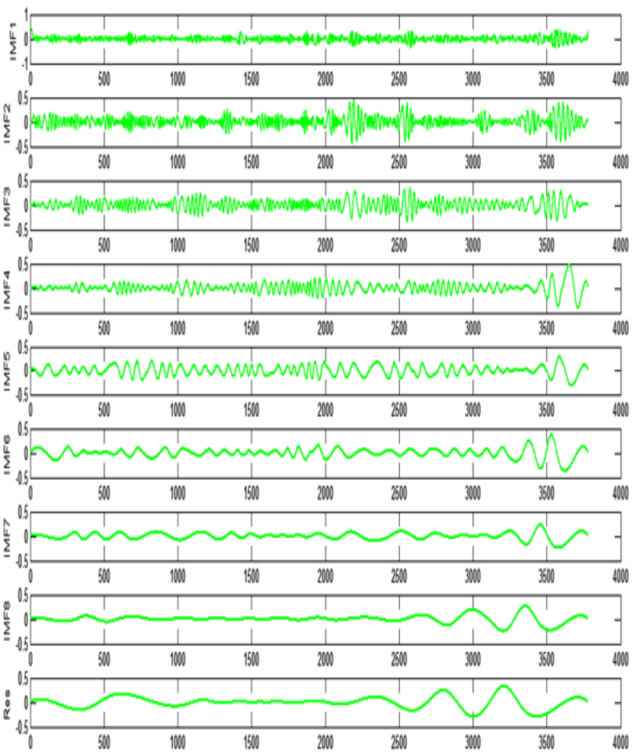

Fig 6. Segmented EMG signal when Wrist flexion

3.1.7. Simple Square Integral (SSI)

The EMG signal energy is measured by the SSI. It's comparable to ZC, another approach for displaying EMG signal frequency data. This is how it's spelled out:

$$\mathrm{SSI} = \sum_{k=1}^{N} |X_k^2| \qquad (6)$$

a. Classification

Comparison of the test EMG [9] feature vectors to the learned EMG feature vectors is performed using distance and similarity metrics. The closest sample from the training set was determined to be the unidentified test sample. While measuring distance, the lowest value is utilized, when measuring similarity, the highest value is used. This strategy is simple yet ineffective. Instead of just selecting a nearby training set sample, accuracy may be enhanced by analyzing a group of neighboring feature vectors. This is known as the K-Nearest Neighbor (KNN) approach. K best-matching neighbors are selected to classify the unknown sample into the specific class. K might be anything from one to the total number of images in the training sets. The K value utilized determines the accuracy of recognition. As the value of K increases, we compare matching to non-matching neighbors in the training sets.

3.2.1.K-NN model

For a given query instance, the K-NN algorithm functions as follows:

$$y_t = \underset{c\epsilon\{c_1,c_2,\dots\dots c_m\}}{\arg\max} \sum_{x_i \epsilon N(x_t,k)} E(y_i, c) \qquad (7)$$

Wherey_t, is the expected class for the query objectx_t, c is a class number, and mis the class number of a data. $N(x_t, k)$the set of nearest neighbors.

$$E(a,b) = \begin{cases} 1 \text{ if min ED} \\ 0 \text{ if max ED} \end{cases}$$

Where Euclidean distance between query instance vector a and trained vectorb.

$$\mathrm{ED} = \sqrt{\sum_{i=1}^{n} (a_i - b_i)^2} \qquad (8)$$

b. Results and Discussion

Simulation has been carried out in MATLAB for the detection and categorization of diverse EMG-based hand motions, we used normalization, empirical mode decomposition, and KNN. For evaluating the efficacy of parameters, we employed numerous performance metrics generated from the testing dataset, including sensitivity (Se), specificity (Sc), false value (Fn), true value (Tp), accuracy (Ac), and precision (Pp). From the confusion matrix, determine the classification's accuracy, sensitivity, and specificity.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \times 100 \qquad (9)$$

$$\text{Sensitivity} = \frac{TP}{TP + FP} \qquad (10)$$

$$\text{Specificity} = \frac{TN}{TN + FN} \qquad (11)$$

Table 1: The proposed work is compared to other Classifiers

Model	Accuracy	Sensitivity	Specificity	Execution Time (Sec)
Proposed (K-NN)	98.45	98.02	0.0134	1.92
RBF Network	96.63	98.33	0.0787	2.78
Naive Bayes	96.92	97.79	0.0581	5.66
Random Forest	97.76	98.52	0.0465	4.55

4. Conclusion

In this research, we provide a thorough and groundbreaking method for categorising hand motions using EMG data. Normalization was performed to eliminate variation after empirical mode decomposition was used to segment raw EMG signals. After a comprehensive analysis, the best classifier for gesture classification was selected. Finally, the best features of dimension 1x4 were used to train and evaluate K-NN, resulting in an accuracy of 98.45%, a specificity of 98.02%, and a sensitivity of 99.66% with a margin of error of less than 2%.

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Contribution of individual authors to the creation of a scientific article

Prakash M B, has carried out Design and implementation of Algorithm, Simulation of Results
Niranjana Kumara M has organized and executed the results.
Harish H M was responsible for collecting related information about hand gestures, Kaggle database Statistics collection of data