K-NN with Frequency Domain Features for Identify Fingers Movement

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Abstract. Prosthetic hands, which make daily chores more accessible, are one of the improvements brought about by quick technology advancements. The study and use of technological, therapeutic, and diagnostic principles concerning human activity are known as biomechanics, and it has led to the development of new technology, such as electromyography (EMG). Human muscles contract or relax to produce EMG signals, which are signals. This study tries to pinpoint the human finger's opening and closing motion as detected by the Myo Armband sensor. The Myo Armband sensor is attached to the subject's right hand's forearm to receive signals from the EMG. FFT will be used to transfer the collected data to the frequency domain, and 70% of the EMG signal data will then be used as training data to determine the outcomes of each movement. 30% of the EMG signal data will be used to test the training results, which will then be K-Nearest Neighbor-classified. K-Nearest Neighbor classification techniques used in the study yielded a percentage of correct readings of 73.3%.

Keywords: EMG, Myo Armband, K-Nearest Neighbour

1 Introduction

Rapid technological advancements have resulted in numerous improvements to overcome existing problems, one of which is prosthetic arms. Prosthetic hands can help with everyday tasks like picking up or moving objects. There is a clinical discipline called biomechanics that studies human movement. The field of biomechanics studies and applies technology, treatment, and prognosis concepts related to human activities to provide a new era in the form of electromyography (EMG) [1].

Human muscles produce EMG indicators after they settle or relax. EMG has been widely used and implemented as a signal control device in various Human system Interface applications because it can be used to check the condition of muscles and nerve cells to assist in locating disturbances in nerves or muscle mass.

Researchers employ a variety of methods to detect this type of sign. The primary technique involves inserting an EMG sensor into the skin with a needle [2]. The second technique is to

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place the sensor on the skin's surface to detect the EMG signal [1]. The second approach is more convenient, even though the signal’s noise is higher.

There are three strategies for using this sign to recognize the arm movement pattern. There are time domains [1] and [3], frequency domains [4], and time-frequency domain names [5] and [6]. The frequency domain is more likely to be successful in recognizing actions. However, due to the higher computation cost of the frequency domain, this technique is slower than the time area technique [5] and [7]

Furthermore, numerous algorithms have been used to detect hand movement. Specifically, Support Vector Machine (SVM) [8], Neural network [4], Adaptive Neuro-Fuzzy Inference System (ANFIS) [9], Naive-Bayes, and K-Nearest Neighbours are used [1]. Most studies allow us to become aware of the movement of the fingers in the range of 60% to 90%.

One technique for generating judgments using supervised learning is K-Nearest Neighbor, where the outcomes of new input data are categorized based on the nearest in the value data. This algorithm is more straightforward than other algorithms, for example, naive Bayes [1]. The K-NN algorithm is a technique for classifying objects based on the learning data that is most similar to the thing. The results of the new query instance are classified using most of the K-NN algorithm's categories in the supervised learning algorithm K-NN. The class emerging from the categorization will be the class that appears the most. Metric distances, like the Euclidean distance, are used to define proximity.

The following section provides the examination's strategies. Occasionally, the outcomes and discussion section will include the experiment results. The findings are presented at the end, in the final section.

2 Methods

In this examination, the EMG signal was located using a Myo armband as a tool. These readings are processed on a personal computer with 8 Gb RAM and a middle-class i5 processor, as shown in figure 1. These sensors’ information is in the time domain and must be converted to the frequency domain. This method employs the fast Fourier rework (FFT) technique. For this observation, five aspects of the frequency indicators are used. Specifically, mean frequency, median frequency, peak frequency, mean power, and total power of the signal.

The average frequency, or mean frequency (MNF), is determined by multiplying the EMG power spectrum by the frequency and dividing the result by the total number of spectrum intensities. [10].

$$MNF = (\sum_{j=1}^{M} f_j P_j)/(\sum_{j=1}^{M} P_j) \qquad (1)$$

Where
Pj = the EMG power spectrum at frequency bin j,
fj = the frequency of the range at frequency bin j,
M = the frequency bin's length.

Median frequency (MDF) can be understood as half of the Total Power (TTP) feature or as a frequency and spectrum split into two parts of equal amplitude.

$$\sum_{j=1}^{MDF} P_j = \sum_{j=MDF}^{M} P_j = \frac{1}{2}\sum_{j=1}^{M} P_j \quad (2)$$

The frequency at which the maximum power is present is peak frequency (PKF).:

$$\text{PKF} = \max\left(P_j\right); j = 1, \dots, M \quad (3)$$

The EMG spectrum's average power is called mean power (MNP).

$$\text{MNP} = \frac{\sum_{j=1}^{M} P_j}{M} \quad (4)$$

TTP encompasses the complete EMG power spectrum.

$$\text{TTP} = \sum_{j=1}^{M} P_j = SM0 \quad (5)$$

Where: $SM0$ is Zero spectral moment

In the higher right hand of the task, Myo armbands are utilized. Figure 2 shows that the subject is wearing the tool. The subject is a right-handed male without neurological or physical issues. The center of the hand's lower back is approximately where sensor number four is located (see Figure 2). The subject is seated on a chair to receive the signals. He reaches across the desk in front of him with his hand. The subject acts on his hands at the exact moment. This study makes five finger motions simultaneously, as seen in figure 3. For each posture, the individual begins by extending all of their fingers and bending one of them. He holds this position for five seconds before returning to the starting position. The subject repeated ten times for each stance.

There are stages for this system to register the arms' movements. The machine's education component comes first, followed by the examination section. Seven facts from each position are used for the education facts, while three different pieces of information are used for the examination. In Figure 4, the flow chart for both processes is displayed. The raw signals are picked up when the subject moves his finger. These EMG signals are gathered from the sensors. Then the signals are transformed to the frequency region using the FFT equation. The training data are collected during the training phase and then applied in the test phase.

Fig. 1 Diagram block of the identified system

Fig. 2 Subject wears the sensors.

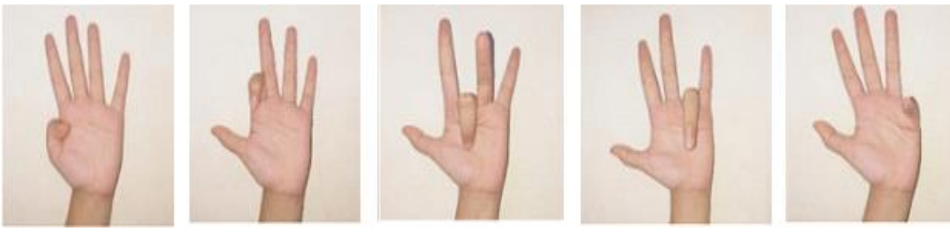


Fig. 3 Pose of the hand

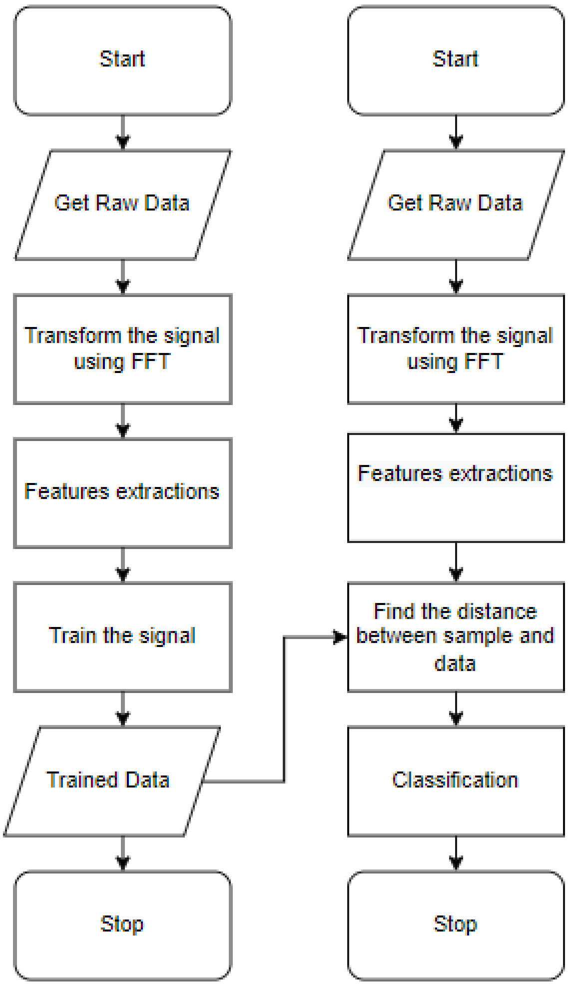


Fig. 4 The flow chart of the system

3 Result

The sensor's ability to gather EMG signals is enabled. Figure 5 displays the composite time-domain EMG signal from all the sensors for the thumb-finger position. Figure 6 shows the signal from each sensor for the same pose in comparison.

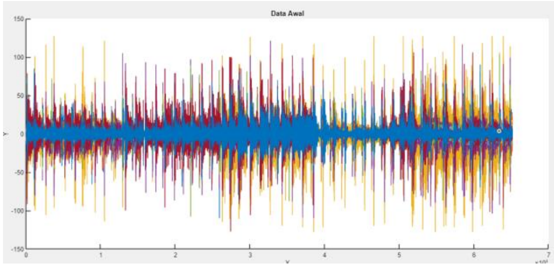
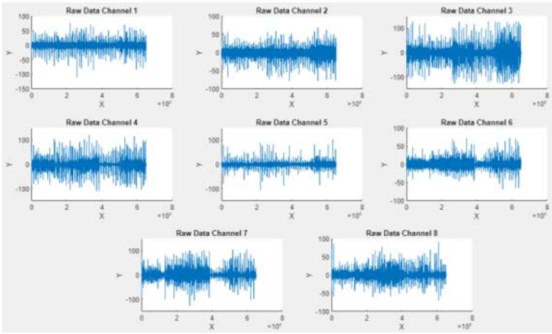


Fig 5. Graph of EMG raw data signal



Fig,6. Graph of EMG Raw data each sensors signal

FFT transforms the time domain into the frequency domain after the raw EMG data signals from each finger have been supplied. The FFT data for the EMG signal is displayed in Figure 7, with the frequency and amplitude of each sensor represented on the X and Y axes, respectively. The EMG data signal is then separated using the five extraction features for the thumb finger listed in Table 1: mean frequency, median frequency, peak frequency, mean power, and total power.

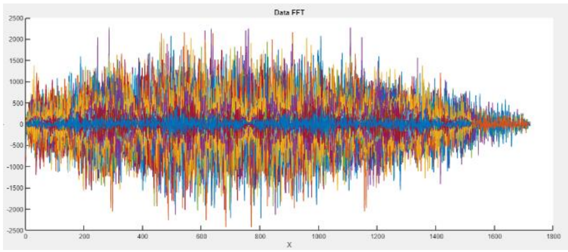


Fig.7. Graph of FFT Result of EMG Signal Data

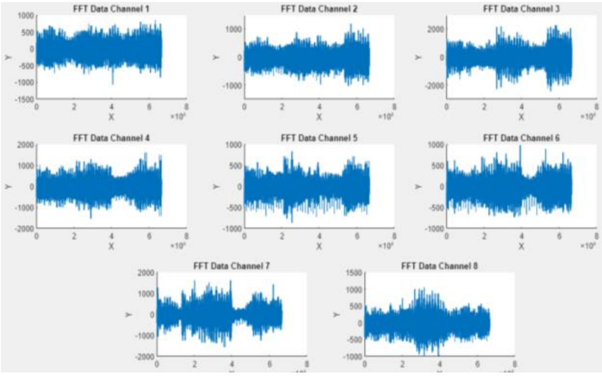


Fig.8. Graph of FFT Result of each sensor data EMG Signal Data

Table 1. Features of the thumb pose

	MEAN FREQ	MEDIAN FREQ	PEAK FREQ	MEAN POWER	TOTAL POWER
SENSOR 1	0.4339	-1695	386	-2.9973	-3390
SENSOR 2	0.4294	-1695	238	-2.9973	-3.39E+03
SENSOR 3	0.4558	-1695	485	-5.9947	-6.78E+03
SENSOR 4	0.4221	-1695	481	-2.9973	-3.39E+03
SENSOR 5	0.3945	-1695	407	-1.9982	-2.26E+03
SENSOR 6	0.4499	-1695	619	-3.9965	-4.52E+03
SENSOR 7	0.456	-1695	513	-3.9965	-4.52E+03
SENSOR 8	0.4541	-1695	759	-3.9965	-4.52E+03

Testing for the five fingers using the K-NN classification approach with various K values yielded the results in Table 2. This table shows that the highest accuracy occurs for K=3. Table 3 is the confusion matrix for K=3. According to matrix results, the system can recognize about 73.3% of this task. The determination of the middle, ring, and little fingers can be inaccurate. These mistakes occur because those fingers' movements also trigger other fingers.

Table 2. Accuracy for various K

K	Accuracy(%)
1	66.6
3	73.3
5	66.6
7	60
9	60

Table 3. Confusion matrix for K=3

Movement Pattern (actual data)	Experiment and result		
	1	2	3

Thumb	Thumb	Thumb	Thumb
Index	Index	Index	Index
Middle	Ring	Ring	Middle
Ring	Little	Ring	Ring-
Little	Little	Little	Ring

4 Conclusions

This study uses sEMG sensors and the K-NN algorithm to attempt to recognize finger gestures. This technology has the ability to recognize the finger poses of the subject. The percentage of this system that recognizes motions is up to 73.3%, according to the results. The implementation of this technology for real-time hardware control is in the future.

Acknowledgments

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