Finger Movements Recognition Using Naive Bayes Algorithm in Frequency Domain

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Keywords: EMG, Myo Armband, Naïve Bayes, Recognition.

Abstract: Rapid technological developments have led to various innovations to overcome existing problems, one of which is prosthetic hands to facilitate daily activities. The field of biomechanics studies and applies the concepts of technology, treatment, and diagnosis related to human activities, resulting in new technology in the form of electromyography (EMG). EMG signals are signals originating from human muscles when they contract or relax. This study aims to identify the Myo Armband sensor's movement pattern of the human fingers. The Myo Armband sensor is placed on the forearm of the subject's right hand to receive signals from the EMG. The data obtained will be converted to the frequency domain using FFT, then 70 percent of the data from the EMG signal is used as training data to get the results of each movement. The training results will be tested using 30 percent of the EMG signal data and classified using the Naive Bayes algorithm. The study's results show that this system manages to identify the gesture around 80%.

1 INTRODUCTION

Rapid technological developments have led to various innovations to overcome existing problems, one of which is prosthetic hands. Prosthetic hands can facilitate daily activities such as picking up or moving items. In the medical field, there is a field of biomechanics that studies human movement. The area of biomechanics studies and applies the concepts of technology, treatment, and diagnosis related to human activities to produce new technology in the form of electromyography (EMG) (Pamungkas et al., 2020).

EMG signals come from human muscles when they contract or relax. EMG has been widely used and applied as a signal control system in various applications of the Human Machine Interface because it can be used to check the condition of muscles and nerve cells to help detect disturbances in nerves or muscles.

To detect this type of signal, there are several methods that researchers use. The first method uses a needle to place the EMG sensor inside the skin (Dy et al., 2021). The second method is the sensor location on the skin's surface to sense the EMG signal (Pamungkas et al., 2020). The second method is more convenient, even though the signal's noise is higher.

Three methods can be used to apply this signal for recognizing the pattern of the movement of the fingers. There are time domains (Pamungkas et al., 2020), (Esa et al., 2018), frequency domains (Andrean et al., 2019) (Yousif et al., 2019), and a combination of time and frequency domains (Pancholi & Joshi, 2020)(Guo et al., 2004). The frequency domain tends to obtain higher success in recognizing the movements. However, this method is slower than the time domain method because the computation cost of the frequency domain is higher (Nossier et al., 2020).

Moreover, several algorithms have been used to identify the movement of the hand. Namely, Support Vector Machine (SVM) (Dela et al., 2022), Neural Network (Andrean et al., 2019), Naïve Bayes, and K-Nearest Neighbours (K-NN) (Pamungkas et al., 2020). Most of the research enables us to identify the movement of the fingers from around 60% to 90%.

The naive Bayes classification method is a simple probability classification method using a set of probabilities. In this study, the frequency domain features are used. The surface EMG (sEMG) sensors are utilzed. Myo armband is an sEMG type, and it has eight EMG sensors. While the Naive Bayes algorithm is used. This method is expected to obtain the results better than others.

Pamungkas, D. and Dharmayani, N.
Finger Movements Recognition Using Naive Bayes Algorithm in Frequency Domain.
DOI: 10.5220/0011880100003575
In *Proceedings of the 5th International Conference on Applied Science and Technology on Engineering Science (iCAST-ES 2022)*, pages 777-780
ISBN: 978-989-758-619-4; ISSN: 2975-8246

The methods of the study are presented in the following section. Afterward, the results of the experiments are provided in the results and discussion section. Finally, in the last section, the conclusions are delivered.

2 METHODS

In this study, we utilized a Myo armband as a device to detect the EMG signal. Those signals are processed in a PC with core i5 and 8 Gb RAM, as seen in figure 1. The signals from the sensors are in the time domain and need to be transformed into the frequency domain. The Fast Fourier Transform (FFT) method is used for this process. Five features of the frequency signals are used for this study. Namely mean frequency, median frequency, peak frequency, mean power, and total power of the signal.

Myo armbands are used in the upper right hand of the subject. Figure 2 shows that the subject wears the device. The subject is a right-hand male without disorders in neurological and muscular. The location of sensor no 4 is approximately in the back of the hand's middle (see figure 2). To obtain the signals, the subject is sitting in a chair. His hand is placed on the desk in front of him. At the same time, the subject moves their fingers. Five hand gestures are conducted simultaneously in this study, as shown in Figure 3. For every pose, the subject start by opening all the fingers and bending the finger, then hold for 5 seconds and goes back to the initial position. For each pose, the subject repeated ten times.

There are two phases for this system to identify the movements of the fingers. First is the training phase, then the test phase of the system. From each pose, seven data are used for the training data, while three other data are used for the test. The flow chart of both steps can be seen in Figure 4. The raw signals are obtained when the subject moves his finger. Signals EMG from the sensor on the subject are transformed to the frequency domain using the FFT equation next step is to acquire features of the transformed signal. The training data are obtained in the training phase and then used in the test phase.

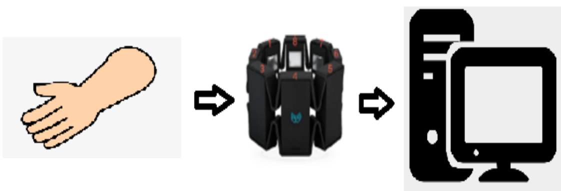

Figure 1: Diagram block of the identified system.

Figure 2: Subject wears the sensors.

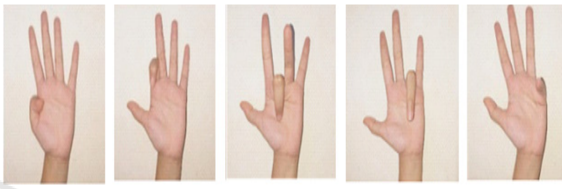

Figure 3: Pose of the hand.

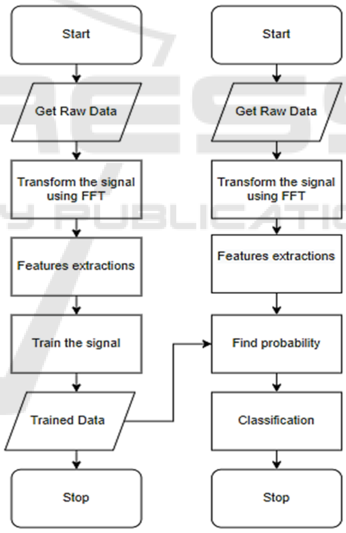

Figure 4: The flow chart of the system.

3 RESULTS AND DISCUSSION

The EMG signals are enabled to collect from the sensor. Figure 5 shows the combination EMG signal from all the sensors in the time domain for the thumb finger pose. In comparison, each sensor's signal can be seen in Figure 6 for the same pose.

After each finger's raw EMG data signal has been input, FFT converts the time domain into the frequency domain. The FFT data EMG signal is shown in Figure 7, where the X axis is the frequency, the Y axis is the amplitude, and the FFT of each sensor data is shown in Figure 8. Then the EMG data signal is extracted using five extraction features: mean frequency, median frequency, peak frequency, mean power, and total power contained in Table 1.

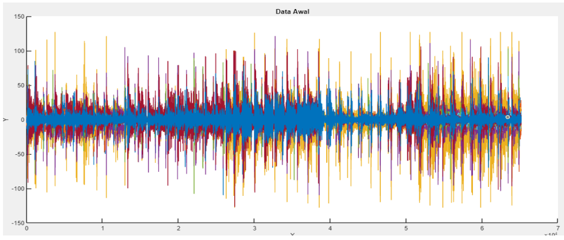

Figure 5: Graph of EMG raw data signal.

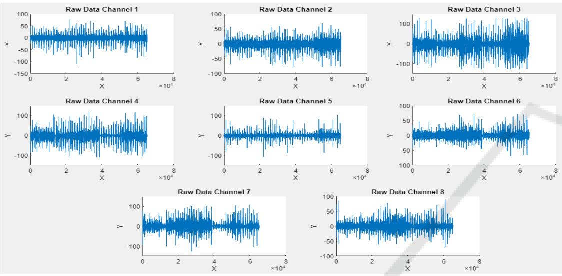

Figure 6: Graph of EMG Raw data each sensor signal.

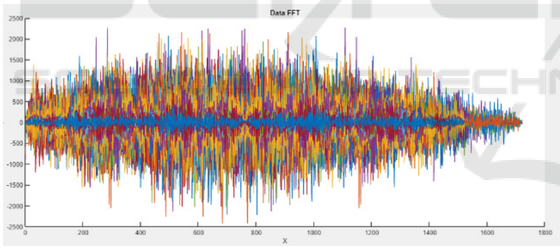

Figure 7: Graph of FFT result of EMG signal data.

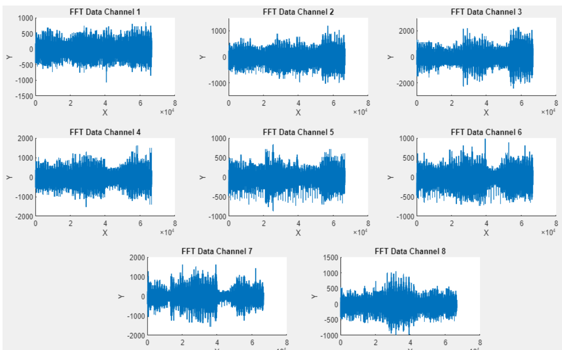

Figure 8: Graph of FFT result of each sensor data EMG signal data.

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
Sensor 1	0.5675	2.06E + 03	505	2.9978	4.11E + 03
Sensor 2	0.5283	2.06E + 03	899	6.9949	9.60E + 03
Sensor 3	0.7422	2.06E + 03	277	0.9993	1371
Sensor 4	6.81E + 12	2.06E + 03	739	1.99E - 15	2.73E-12
Sensor 5	0.2888	2.06E + 03	1	-0.9993	-1.37E + 03
Sensor 6	0.7042	2.06E + 03	1	0.9993	1.37E + 03
Sensor 7	0.4403	2.06E + 03	481	-2.9978	-4.11E + 03
Sensor 8	0.5875	2.06E + 03	1	1.9985	2.74E + 03

In the naive Bayes classification method, testing for the five fingers obtained results, as shown in Table 2. From this confusion, matrix results show that the system enables to identify of around 80%. Some errors occur in determining the middle, ring, and little fingers. Those failures are because the movement of those fingers also activates others fingers.

Table 2: Confusion matrix of the result.

Movement Pattern (actual data)	Experiment and Result		
	1	2	3
Thumb	Thumb	Thumb	Thumb
Index	Index	Index	Index
Middle	Middle	Ring	Middle
Ring	Little	Ring	Ring
Little	Little	Little	Ring

4 CONCLUSIONS

This study attempts to recognize the fingers' gestures using sEMG sensors and the Naive Bayes algorithm. This system is capable of identifying the poses of the subject's fingers. Results show that the percentage of this system is 80% to acknowledge gestures. In the future, this system will be used in real time and implemented for controlling hardware.

ACKNOWLEDGMENTS

The DRPM research fund funded this research.

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