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Electromyography Feature Analysis to Recognize the Hand Motion in a Prosthetic Hand Design

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Abstract. The increasing need for prosthetic hands for people with disabilities is one reason for innovation in the field of prosthetic hands to create the best prosthetic hand technology. In the design of EMG-based prosthetic hands, this is determined by several things, among others, the selection of features. The selection of the right features will determine the accuracy of the prosthetic hand Therefore, the purpose of this study is to analysis the time domain feature to obtain the best feature in classifying the hand motion. The contribution of this work is able to detect 4 movements in real time, namely hand close, flexion, extension, and relax. The Electromyograph signal is tapped using an electromyograph (EMG) dry electrode sensor in which there is a circuit of EMG instrumentation amplifier. Furthermore, the analog EMG signal data is processed through the ADC (Analog to Digital Converter) by using MCP3008 device. EMG signal data is processed in Raspberry Pi. A feature extraction process is applied to reduce data and determine the characteristics of each hand movement. Feature extraction used is MAV (mean absolute value), SSI (sign slope integral), VAR (variance), and RMS (root mean square). From the results of the four-time domain feature, then the best feature extraction is determined using scatter plot and Euclidean distance. The results that have been carried out on ten people with each person doing ten sets of movements (hand close, flexion, extension, relax), showing the best Euclidean distance results, is the RMS feature, with a value of 2608.07. This data is the result of the best feature extraction analysis through the method of calculating the distance of feature extraction data using Euclidean distance. This analysis of time domain feature is expected to be useful for further experiment in machine learning implementation so that it can be obtained an effective prosthetic hand.

Introduction

Persons with disabilities with physical limitations have limitations in carrying out daily activities, such as for work, sports, and physical activities. With these limitations, we need tools that can support the activities of persons with disabilities in carrying out daily activities. 0. With advances in increasingly sophisticated technology, assistive devices for people with disabilities are also made with the latest and increasingly sophisticated technology, especially for prosthetic hand aids that are used for people with disabilities with physical disabilities. Based on the results of the 2015 Inter-Census Population Survey (SUPAS) [1], the percentage of people over the age of 10 who have difficulty using or moving their hands or fingers is 2.61 percent, with a condition of 1.08 percent of men and 1.53 percent of women with gender. By looking at these data, the need for robot hand tools or prosthetic hands in Indonesia should be increasingly increased. The development of prosthetic hand technology is increasingly sophisticated. Increasingly sophisticated technology is certainly supported in terms of high costs. The development of prosthetic hands in Indonesia must certainly be supported by costs that are in accordance with the conditions of people in developing countries. In contrast to the development of prosthetic hands that exist abroad, which uses advanced technology at a high cost. Prosthetic hand technology in Indonesia is expected to have a sophisticated design, easy to use, and supported by affordable costs.

In several studies, mostly, prosthetic hands are controlled using the EMG signal. In some studies, EMG signals are processed conventionally by comparing a certain motion based on a threshold or by looking at its amplitude. The difference in a movement when the muscles contract affects the size of the amplitude produced. However, identification of EMG signals using amplitude cannot detect any differences in motion because it only utilizes differences in reference voltages. In the study [2] discusses prosthetic hand control using a threshold and is able to detect the movement of 5 fingers. However, it still uses disposable electrodes for EMG leads. In the study [3] discusses making inexpensive prosthetic hands with EMG signal control, but only detects movement between the thumb and the other four fingers. In the study [4] discusses prosthetic hand control using EMG signals with the ability to detect objects to be held. But can only do grasping movements. In the study [5] discusses prosthetic hand control via EMG signals with RMS feature extraction, but the result of feature extraction is determined threshold distinguish two movements. Research [6] discusses prosthetic hand control using EMG signals by feature extraction and classification. However, it can only detect three movements and use disposable electrodes. The research [7] discusses prosthetic hand control using EMG signals with feature extraction processing and classification, but can only detect slight movements. Some subsequent studies discuss prosthetic hand control by feature extraction. In various studies discuss the comparison of various extraction features used in EMG signal processing. The extraction feature used is based on the time domain. In the comparison of various time-domain extraction features, the accuracy level varies with each movement performed. However, the extraction processing is done on a personal computer or on a microcontroller, which cannot be used directly and is portable. Data from the EMG signal is entered into a computer or microcontroller and then processed and identified its characteristics and accuracy. Accuracy results used for prosthetic hand control have not yet entered the embedded system, which is then used online for a portable control device. In the study [8] discusses the processing of EMG signal feature extraction to analyze the contraction strength of patients with amputation hands. But not they are yet used for embedded systems and control. Research [9] discusses prosthetic hand control using EMG signals with feature extraction processing but uses a complex wireless system and electrodes. Research [10] discusses EMG signal processing using feature extraction but has not yet been used in embedded systems. Research [11] discusses EMG signal processing using feature extraction for 6 movements, but not yet used in embedded systems. Research [12] discusses EMG signal processing using time-domain feature extraction but has not yet been applied to embedded systems. Research [13] discusses EMG signal processing using time-domain feature extraction and then analyzed for classification. But not she is yet applied to prosthetic hand control and embedded systems. In research [14] it discusses EMG signal processing using time-domain feature extraction but only analyzed using neural networks not yet used for control devices.

Based on the previous problems, the purpose of this study is to analyse the EMG features in order to recognize the hand motion and obtained the best feature. Additionally, this study identifies four movements, namely hand close, relax, flexion, and extension. The development was carried out by processing the two EMG channels and extract the EMG signal using the time-domain feature. Additionally, in this study, we result in the characteristics of each hand close, relax, flexion, and extension movements based on the EMG features. Furthermore, the feature extraction results are processed using scatter and Euclidean distance to determine the best feature extraction.

The rest of this paper is composed of five sections; namely, section introduction described the problem and state of the art method; section two describes the material and methods used in this study. The result of this study was explained in result section. Section discussion showed the interpretation and study comparison. Finally, section five concluded the overall study.

Materials and Methods

Experimental Setup. In this study, EMG signal data collection was performed on ten subjects aged 21-22 years. Subjects were taken randomly, and each subject was doing ten sets of movements starting from HC (Hand Close), FL (Flexion), EX (Extension), and relax at every movement transition. A set of movements takes 19 seconds. The EMG signal is then tapped by a dry electrode and enters the MCP3008 ADC IC for processing analog data into digital data, then enters the Raspberry for feature extraction processing (Figure 1).

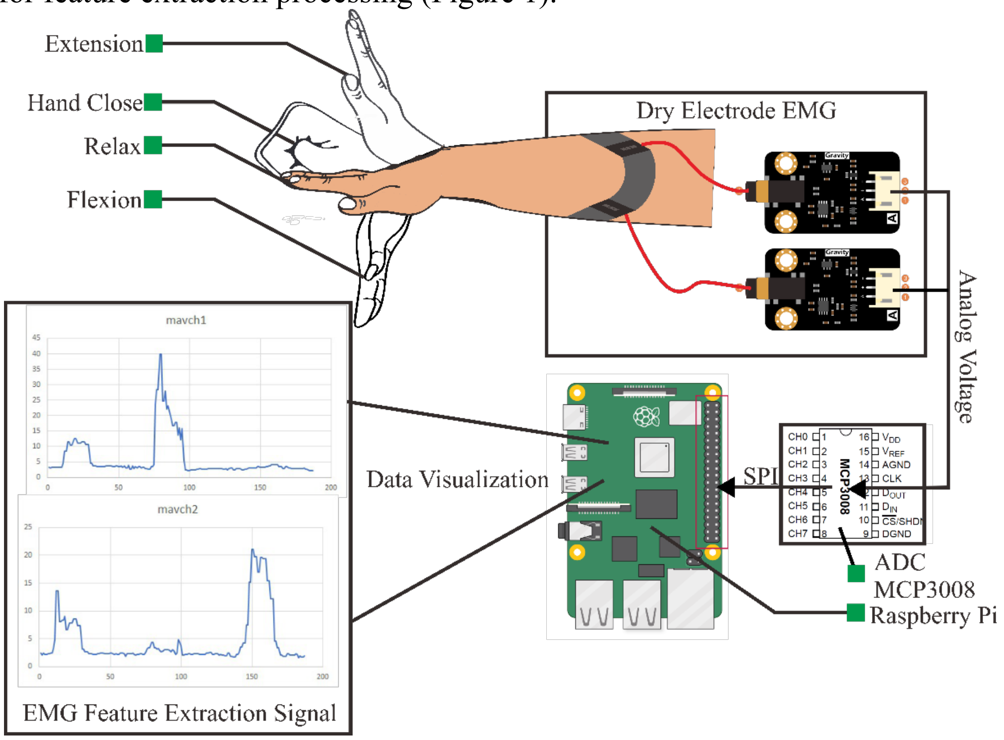


Fig. 1. Design of EMG Signal Processing Materials and Device

In this study, the recording of the EMG signal used dry electrode EMG Sensor OY Motion SKU: SEN0240 (DF Robot, China). Notch filter to reduce the frequency noise 50 Hz. Raspberry Pi (Model 3B+, United Kingdom) with processor Broadcom BCM2837B0 for data processing. Raspbian Buster Linux operating system (last installed in version February 2020). IC MCP3008 is used to convert data from analog to digital. The external ADC was required because the Raspberry Pi did not support the ADC feature.

Fig. 2. EMG Sensor OY Motion

Figure 2 shows the dry electrode along with the front amplifier circuit. In this study, the dry electrode was chosen because it can be used repeatedly so that it is more economical during development.
In Figure 2, an OY Motion EMG Sensor with SKU: SEN0240 was produced by DF Robot. This sensor consists of a pair of dry electrodes and an instrumentation circuit. This sensor requires a 5V power supply and ground. Additionally, the output of this circuit produces an analog data. In this study, we used two sets of EMG sensors because we collected the EMG signal from two muscle groups.

Figure 3 shows the interfacing circuit of notch filters and ADC on the Raspberry Pi board. This shield circuit is integrated Raspberries with other supporting circuits. This shield is used to make an easy connection to the raspberry GPIO pin.

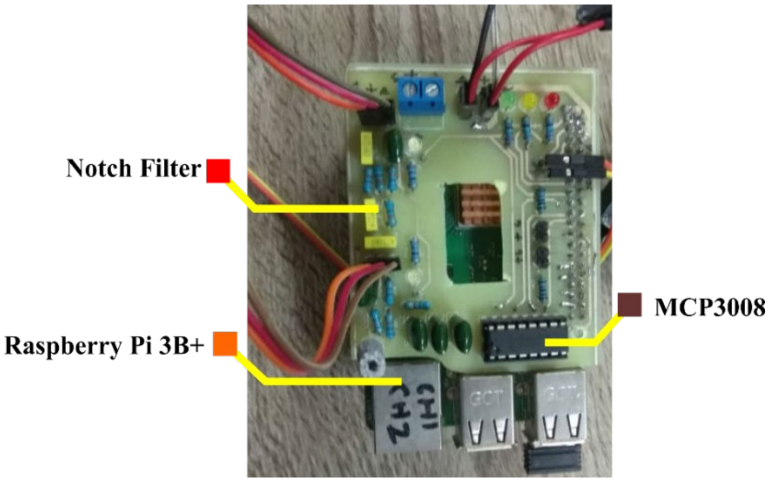


Fig. 3. Raspberry, ADC, and notch filter

In Figure 3, the passive notch filters circuit and ADC were placed on processing analog EMG sensors and then converted into digital data. The Raspberry Pi does not provide ADC features; therefore, in this study, an ADC MCP3008 must be added. In Figure 3, at the bottom of the shield circuit, the Raspberry Pi type B + board was placed.

Experiment. In this study, researchers processed the EMG signal for feature extraction. In this stage, the feature extraction used is based on time-domain using MAV, SSI, VAR, RMS [12][15]. Furthermore, after the feature extraction process, the distribution of data was viewed using scatter. Moreover, the separability of the feature was calculated using Euclidean distance. Figure 4 shows the placement of the electrodes in the forearm. As seen in the figure, the type of electrode used is a dry electrode.

Fig. 4. Dry Electrode Placement

In Figure 4, is the placement of dry electrodes on the wrist flexor and extensor muscle. This research uses a 2-channel system so that there are two electrodes attached.

MAV (Mean Absolute Value) is a formula for calculating average values and windowing values calculated in absolute values [6],[12],[13]. The MAV calculation formula is as follows.

$$MAV = \frac{1}{N}\sum_{I=1}^{N} |x_i| \tag{1}$$

SSI (Simple Square Integral) can be defined as an energy index. The value can be calculated by the equation [16],[12],[13],[17].

$$\text{SSI} = \sum_{i=1}^{N} xi^2 \tag{2}$$

VAR (Variance of EMG) is a strength index. VAR is defined as the average value of the square of the deviation. The average value of the EMG signal is close to zero. The formula of VAR is as follows [16],[12],[17].

$$\mathrm{VAR} = \frac{1}{N-1}\sum_{i=1}^{N} xi^2 \quad (3)$$

RMS (Root Mean Square) is the relationship between constant force and contraction without fatigue [16],[12],[13],[11]. The RMS formula is as follows.

$$\mathrm{RMS} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} xi^2} \quad (4)$$

Euclidean Distance is a method of analyzing data by calculating the distance between data. In this study, using two-dimensional distance Euclidean data analysis methods. The formula for calculating Euclidean distance is as follows [18],[19],[20],[21].

$$d = \sqrt{\sum_{i=1}^{n}(P_i - Q_i)^2} \quad (5)$$

The Diagram Block. Figure 5 shows the diagram block of this study. It consists of three parts, namely, input, process, and output. This block diagram explains the control mechanism in research. First of all, the EMG signal is collected by a dry electrode (OY Motion, SKU SEN 0240), and then the EMG signal entered into the instrumentation amplifier (OY Motion, SKU SEN 0240). Moreover, the dry electrodes and instrumentation amplifier produced an analog signal. In order to reduce the 50 Hz interference, the notch filter is applied. Analog to Digital Converter (ADC) MCP 3008A functions to convert analog data into digital data. This ADC was connected to Raspberry through serial communication (transmitter and receiver pin). The EMG signal is extracted using time-domain features. This feature extraction process is performed to obtain the EMG feature, which represents the flexion, extension, grasp, and relaxes motion. The feature extraction process was carried out in the Raspberry system. In this study, four-time domain features were used to extract the EMG signal (MAV, SSI, VAR, and RMS). Then the feature extraction results are processed using a scatter plot to see the clustering of data. In this stage, therefore, we can find the best feature for the classification process. Furthermore, Euclidean distance was applied to measure the distance between the clustering data in each feature extraction. Based on the Euclidean distance value, it can be seen as the best feature extraction for the classifier machine.

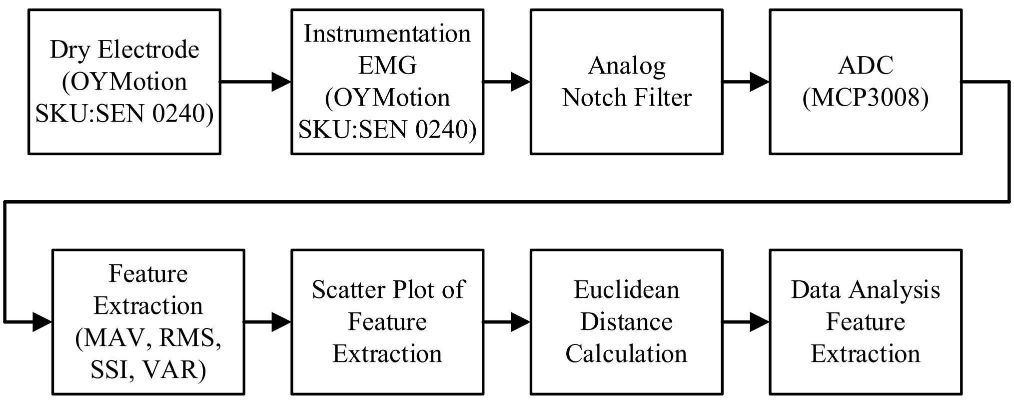


Fig. 5. The diagram blocks of data acquisition and feature extraction process

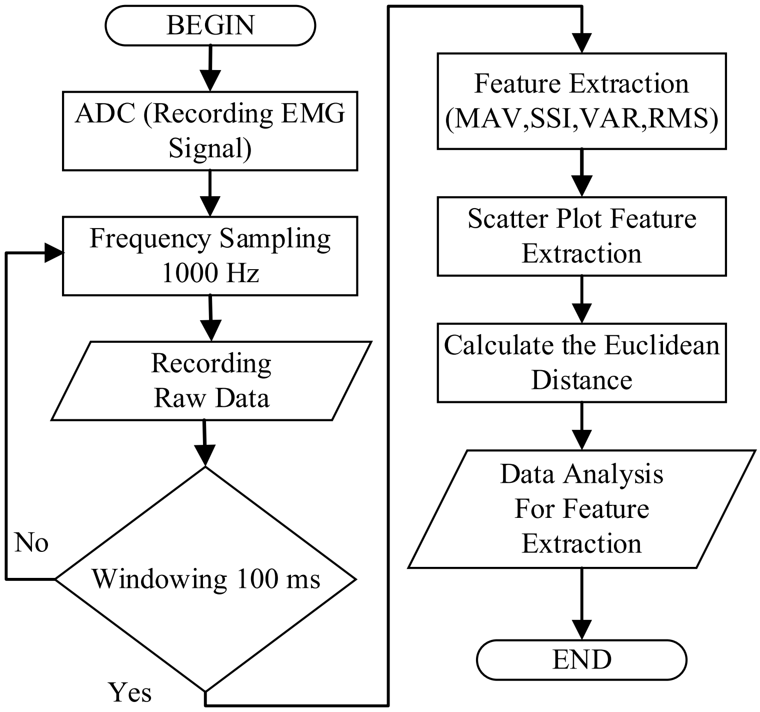


Fig. 6. The Flowchart EMG signal processing and extraction feature

The Flowchart. Figure 6 shows a flow chart of the data acquisition process and feature extraction of the EMG signal tapped at two measurement points. In the data acquisition process, the ADC records the EMG analog signal to be converted into digital form. The ADC recording process is controlled via the Raspberry Pi B +. The data collection process was carried out with a sampling frequency of 1000 Hz (1 ms period). EMG data from the two channels is stored in a variable for further analysis or feature extraction. In the feature extraction process option, the EMG signal is segmented every 100 ms, which is then carried out by the feature extraction process.

The feature extraction process is carried out sequentially, starting from the MAV, SSI, VAR, and RMS features. Furthermore, to see the grouping of features based on movement (flexion, extension, graph, and relax), a scatter plot process is carried out for each pair of movements and the variations of the existing features.

The distance between groups on a scatter plot can be measured using Euclidean Distance. Furthermore, all results are analyzed to get recommendations for the right features for the pattern recognition process on machine learning resistance.

Circuit. This section will reveal about hardware. Additionally, this part will describe in detail the circuit used for data acquisition purposes. This section consists of discussing the notch filter circuit, ADC, and the interface to the Raspberry Pi.

Circuit of Notch Filter. In general, Figure 7 describes a passive notch filter circuit that is built using resistor and capacitor components. The output of the two EMG sensors enters the passive notch filter circuit with 49 Hz cut-off frequency. The notch filter functions to cut or reduce at one particular frequency that is 50 Hz frequency with attenuation of 60 dB. Both passive notch filter circuits have the same cut-off frequency and component values. Furthermore, in this study, the passive notch filter is used to suppress the frequency of the line power, which interference with the circuit during the data acquisition process with a frequency of 50 HZ. Even though in this study, we powered the circuit using a battery; however, the 50 Hz interference coming from the power line always exists.

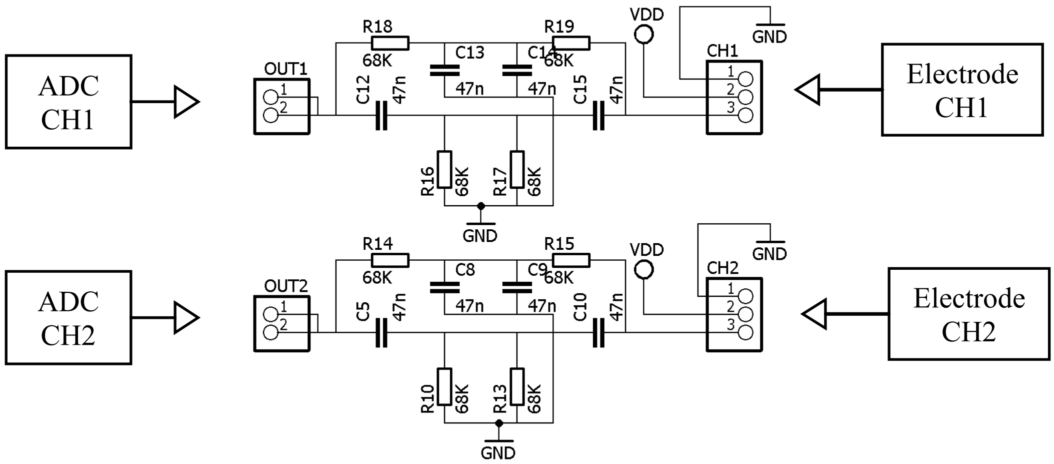


Fig. 7. Circuit of notch filter with frequency cut off 49 Hz

Raspberry Pi. This section consists of the main circuit, namely the Raspberry Pi 3B + (Figure 8). This board is connected to several other supporting circuits, namely led indicator circuits, switch circuits, ADC circuits, and servo motor circuits. The LED indicator functions to indicate when the Raspberry start to collect the EMG data from ADC for each movement. Additionally, switch buttons are used to start and end movements when the system is run online. Moreover, in this study, the programming language used is based on Python using a software version 3.6. In order to run the program, several libraries were used in this study include Pandas, NumPy, Sklearn, Scatter, and Matplotlib. In detail, the circuit configuration is as follows:

GPIO 17, 22, and 27 are connected to the LED indicators to indicate the movement. GPIO 05 and 06 are connected to the switch circuit to start and end the program while the system is running online. GPIO 19 and 26 are connected to the LED indicator to detect the maximum magnitude of the EMG signal during a muscle contraction. The SCL and SDA pins are connected to the PCA9685 servo driver. This servo is used to move the prosthetic hand in flexion and extension.

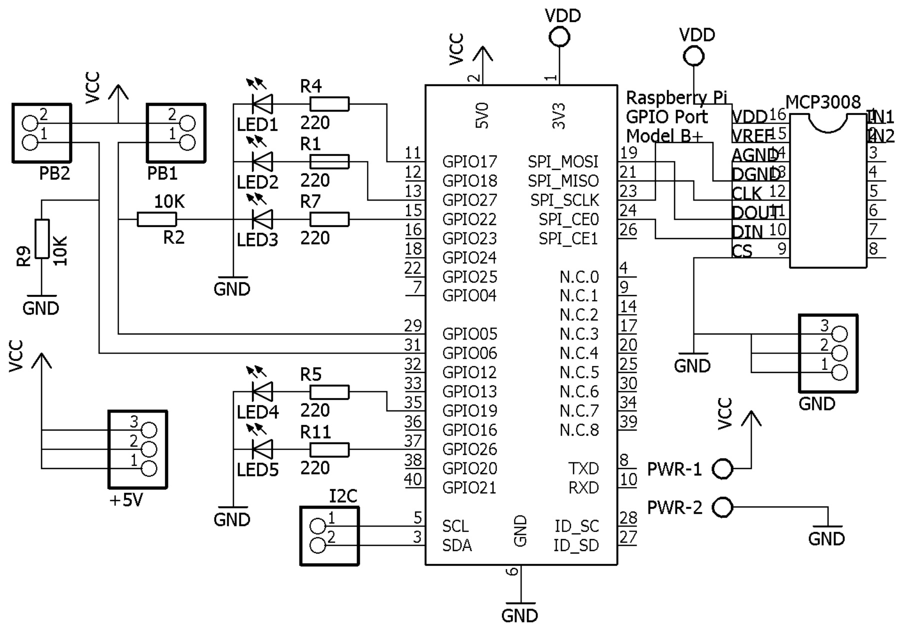


Fig. 8. Circuit of Raspberry Pi for data processing

Result

This section will describe the results obtained in the study. In general, this section discusses several algorithms, including the data acquisition process algorithm, the feature extraction process, the scatter data plot process, and the calculation of the value of Euclidean Distance.

Algorithm of ADC EMG and filter digital. This algorithm is used for processing EMG signals from analog data into digital data and then filtered using a digital bandpass filter with a cut-off frequency of 20-500 Hz. Digital data that enters the raspberries are then processed with a digital filter to ensure that the resulting signal is a true EMG signal, with frequency characteristics between 20-500 Hz. The digital filter used is IIR (Infinite Impulse Response) with order six and the type of bandpass filter with cut-off frequencies is 20 and 500 Hz. Then after going through a digital filter, the signal enters the windowing phase with 100 ms or per 100 data. The results of windowing are then used for the next process, namely feature extraction.

Algorithm 1: filtering the EMG data using a notch filter.

Init: b =[0.78429785289303577; -4.7057871173582146; 11.764467793395536; -15.685957057860715; 11.764467793395536; -4.7057871173582146; 0.78429785289303577]; a =[1; -5.5145351211661646; 12.689113056515138; -15.593635210704097; 10.793296670485377; -3.9893594042308824; 0.6151231220526282]; orde = 6; range = 100;
Input: EMGch1; EMGch2
Output: EMGch1filter; EMGch2filter
WHILE (LEN(EMGch1filter)<range AND LEN(EMGch2filter)<range)
FOR n→0 TO orde DO
xch1[n]= xch1[n-1]
xch2[n]= xch2[n-1]
ych1[n]= ych1[n-1]
ych2[n]= ych2[n-1]
    FOR n→0 TO orde DO
        y1=b[n]*xch1[n]-a[n]*ych1[n]
        ych1+= y1
        y2=b[n]*xch2[n]-a[n]*ych2[n]
        ych2+= y2
        EMGch1filter APPEND (ych1)
        EMGch2filter APPEND (ych2)
        CLEAR (EMGch1filter)
        CLEAR (EMGch2filter)
END

Algorithm of Extraction Feature. The below algorithm functions to create a new CSV file and create a column with a predetermined title to hold the extraction signal data. For the extraction formula, directly call the library and entered into the calculation. Data were obtained from the previous process of data retrieval, with windowing per 100 data. The time needed for extraction of a set of movements is 19 seconds, so the amount of data from one extraction file is 190 for each extraction.

Algorithm 2: Feature extraction process

Init: range = 100;
Input: EMGch1filter; EMGch2filter
Output: EMGch1mav; EMGch2mav; EMGch1rms; EMGch2rms; EMGch1ssi; EMGch2ssi; EMGch1var; EMGch2var
WHILE (LEN(EMGch1filter)==range AND LEN(EMGch2filter)==range)
EMGch1mav = MEAN(ABS(EMGch1filter))
  EMGch1ssi = SUM(EMGch1filter**2)
  EMGch1var = SUM(EMGch1filter**2)/(range-1)
  EMGch1rms = SQRT(SUM(EMGch1filter**2)/(range))
  EMGch2mav = MEAN(ABS(EMGch2filter))
  EMGch2ssi = SUM(EMGch2filter**2)

```
  EMGch2var = SUM(EMGch2filter**2)/(range-1)
  EMGch2rms = SQRT(SUM(EMGch2filter**2)/(range))
  WRITE (EMGch1mav, EMGch2mav, EMGch1rms, EMGch2rms, EMGch1ssi,
EMGch2ssi, EMGch1var, EMGch2var)
END
```

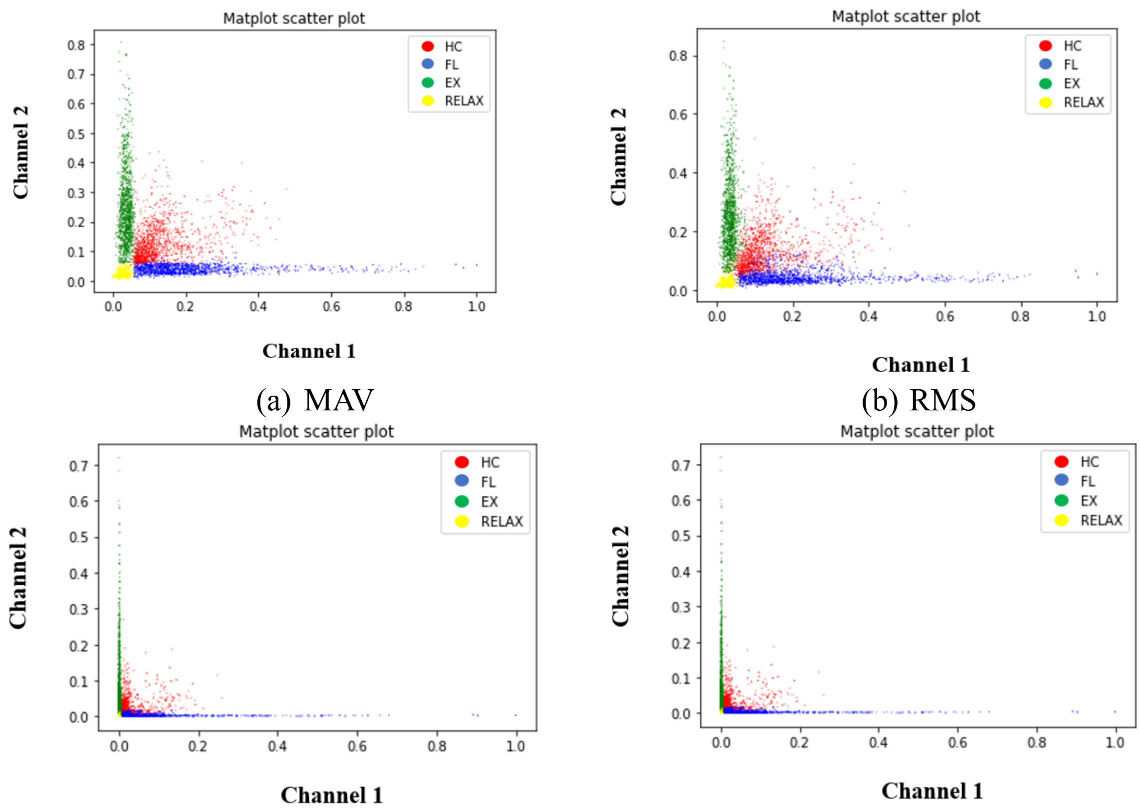
Algorithm of Euclidean Distance. Algorithm 3 describes the algorithm for Euclidean distance. Euclidean distance program is built using a Python program to calculate the distance between movements based on scattering data. Data that has been displayed on the scatter then the distance distribution is calculated.

Algorithm 3: Procedure to calculate the Euclidean Distance

```
Init:  EDcount =0; i =0; k =0;
Input: EMGch1[p1]; EMGch2[p2]; EMGch1[q1]; EMGch2[q2];
Output: EDtotal
WHILE (EDcount <LEN(EMGch1) AND EDcount <LEN(EMGch2))
WHILE (i <LEN(EMGch1) AND i <LEN(EMGch2))
A = (EMGch1[p1][EDcount], EMGch2[p2][EDcount])
B = (EMGch1[q1][i], EMGch2[q2][i])
ED = distance.euclidean (A,B)

EDSUM =+ (ED*ED)
i += 1
        EDcount += 1
        i = 0
        IF (EDcount >= LEN(EMGch1) AND EDcount >= LEN(EMGch2))
        THEN EDtotal = SQRT(EDSUM)
        END
```

Plotting Scatter. Figure 9 shows the scatter plot for the four-movement patterns. The scatter is plotted based on the channel number, type of motion, and EMG features, namely MAV, SSI, RMS, and VAR. Generally, each movement represents a different pattern.



(a) MAV (b) RMS (c) SSI (d) VAR

Fig. 9. The scatter plot from (a) MAV, (b)RMS, (c) SSI, and (d) VAR features

In Figure 9 (a) is the result of scattering MAV feature extraction. Seen in the picture for the distribution of data is quite visible and does not coincide with the data. Figure 9(b) is the result of RMS feature extraction. Evidently, it showed that there are some data that coincide or are mixed in other areas of movement. However, the euclidean distance value for the highest RMS is due to the high amount of data, so it affects the euclidean distance value. Data with high value compared to data with coincidence is greater in the number of high-value data. Figure 9(c), and Figure 9(d), are the results of SSI and VAR extraction scatter. Both extractions have the same normalization value, so the results of the scatter are the same and the same Euclidean distance value. After the data is collected, then it is normalized to determine the standard values of all data. If it is not normalized, then data comparisons between extractions cannot be made because the range values of each extraction are different [22].

Euclidean Distance. Table 1 shows the Euclidean distance values of ten subjects, with each subject doing ten sets of movements, starting from the preparation (relax), HC (Hand Close), FL (Flexion), and EX (Extension). The results of data retrieval are then seen by the distribution of the data and calculated the distance of each movement using Euclidean distance (Figure 10). There are six possible calculations of euclidean distance between movements, namely HC with FL, HC with EX, FL with EX, HC with R, FL with R, and EX with R. The possibility of movement is taken from the probability of 4 movements, namely HC (Hand Close), FL (Flexion), EX (Extension) and Relax. All possible gestures apply to each feature extraction. After the sixth data of possible movement is collected, then the total distance of data distribution is calculated in each feature extraction and produces the total in the rightmost column.

Table 1 The value Euclidean distance from feature extraction with 6 possible hand movement

No.	Feature Extraction	Hand Movement						
		HC-FL	HC-EX	FL-EX	HC-R	FL-R	EX-R	TOTAL
1.	MAV	373.15	387.465	589.835	318.112	422.863	460.364	2551.79
2.	RMS	379.714	398.989	597.556	329.946	430.25	471.612	2608.07
3.	VAR	220.605	202.511	304.533	90.8351	224.281	209.622	1252.39
4.	SSI	220.605	202.511	304.533	90.8351	224.281	209.622	1252.39

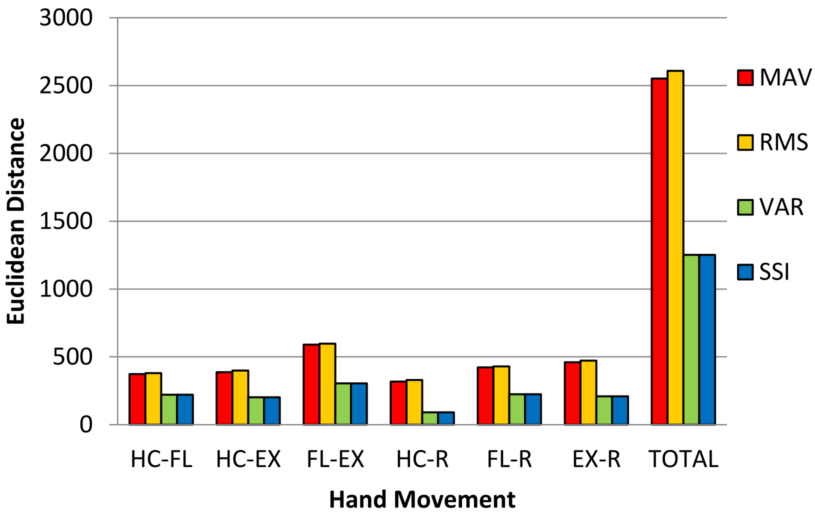


Fig. 10. Euclidean Distance with six-position of hand movement

Discussion

In this study, there is a difference between the amount of data from the ADC process with the actual sampling data, where the –data generated for a set of movements for 19 seconds is 18.539, while the data should be 19000 with a sampling time of 1000 ms. The resulting difference of 461 data is then calculated with an error rate of 2.43%. For feature extraction with a windowing of 100 ms, it should produce 190 data amounts in 1 second. However, this study only produced 187-188 data for each feature extraction. Then the difference in the amount of extraction data is calculated and produces an error of 2-3% for each feature extraction data. The error value is due to the speed of processing the feature extraction by the raspberry processor, which is unable to reach the actual data.

Table 1 is the result of data separability values calculated using Euclidean distance. The data shows the value of the distance of data separations between 6 possible movements (HC-FL, HC-EX, FL-EX, HC-R, FL-R, EX-R) for each feature extraction. From Table 1, it appears the total value obtained from the sum of all possible motions in one feature extraction. The total value is then compared. Figure 10 shows a graph of Euclidean distance obtained from the data in table 1. The graph aims to facilitate the comparison of the results of Euclidean distance in each feature extraction by looking at six possible movements. There is a total overall graph to illustrate the number of Euclidean distance values for each feature extraction. Red colour charts are MAV, yellow RMS, green VAR, and blue SSI.

The largest euclidean distance value is the RMS feature extraction with a value of 2608.07, followed by the MAV feature extraction with a value of 2551.79 and the lowest value for the extraction of the SSI and VAR features with the same value of 1252.39. In research [13] discusses the comparison of time-domain feature extraction by processing the KNN and SVM classification algorithm with matrix confusion. The study [20] discusses the use of the Euclidean Distance method used to analyze the index of muscle fatigue during contractions. Whereas in this study, the euclidean distance was used to determine the best feature extraction from EMG signals.

We have discussed the effect of time domain feature to extract the EMG signal. However, so far, we did not consider the effect of muscle fatigue in the EMG signal. Evidently, muscle fatigue could effect the EMG signal in frequency and amplitude [23].

Conclusion

The purpose of this study was to determine the best time domain feature for four hand motion. The time-domain features used in this study are MAV, SSI, VAR, RMS. Furthermore, the highest Euclidean distance values indicate the best feature. In this study, we found that the highest Euclidean distance value is the RMS feature extraction (ED=2608.07). Further experimental investigations are needed to look for comparisons of other time-domain feature extractions for better accuracy in the machine learning.

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