Signal Classification and Electromyography (EMG)
Instrumentation Design as Basic Electronic Control System

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Abstract— Human body naturally contains complex electrical signals ranging from the mechanism of the brain, heart, and muscles. Electromyography (EMG) is the development of biomedical engineering devices used to record electrical signal activity produced by muscles. The signal produced by the muscle has a very small amplitude, therefore, an amplifier circuit is required to read the signal using microcontroller. In this study, EMG signal amplification was carried out periodically to reduce errors that might occur if only charged to one signal amplifier. Signal reading was performed by conducting 5 different basic hand movements. Muscle signal activity during relaxed conditions had an amplitude of 0.05 V. Moreover, it conveyed an amplitude of 0.27 V up to 2.62 V with a signal gain of 10.350 when the muscle did different movements. The K-NN algorithm was used to classify EMG signals and determined the hand motion output used as a basic electronic control system. Results showed success rate of 88%. Failures when carrying out basic electronic control was due to the signal classification processes that had not met the parameters and the signal amplitude that was almost similar to another signal.

Keywords: EMG, classification, muscle signal, K-NN, signal amplifier

1. Introduction
Naturally, human body has complex electrical mechanisms ranging from brain, heart, muscles, nervous system, and bone growth mechanisms. The body's electrical system has a very important role in medical field. There are two electricity aspects known in medical field namely electricity that occurs in the human body and that is used for the surface skin. Biomedical engineering is the development of medical technology used to support medical science in diagnosing and preventing a disease. Recently, it has developed rapidly as an artificial control system using signals produced by the human body.

Electromyography is the development of biomedical engineering devices used as a process of recording electrical signal activity produced by muscles. The frequency revealed from various activities carried out by the muscles will show different results [1][2][3][4]. To record muscle signal activity that can be read by a microcontroller, EMG instrumentation is designed with signal amplifier and filter circuits to ward off noisy signals during the muscle signal recording process. The recording results are then classified to be used as the basic electronic control system. The K-Nearest Neighbor (K-NN) algorithm is considered as the reference of EMG signal classification. Moreover, the K-NN algorithm is used to classify objects based on learning data that is closest to the object. The most emerging class will later be the resulting class classification [5],[11].

2. Method
2.1 Electromyography Instrumentation
Electromyography (EMG) was a technique used to record electrical activity produced by skeletal muscles. The signal produced by the muscles had a very small signal amplitude. As a result, several steps were required by EMG instrumentation to get the EMG signal that could be read by a microcontroller. The EMG instrumentation stages covered instrumentation amplifier, wave rectifier,
signal filter, and final signal amplifier. Figure 1 depicts the block diagram of the EMG instrumentation.

![Block Diagram of EMG Instrumentation](image)

**Figure 1** Block Diagram of EMG Instrumentation

### 2.2 Electrode Placement

The installation process of the electrodes was carried out through surgery, which was less preferred and avoided. In this study, the electrodes used were Ag / AgCl type. The electrodes were placed on the bicep muscle to record the signal activity produced by the hand muscles. The electrodes were arranged in bipolar set; where two active electrodes were placed adjacent to the desired muscles and compared with the condition of the ground electrode placed separately from the electrodes 1 and 2.

![Placement of Electrode Sensors](image)

**Figure 2** Placement of Electrode Sensors

### 2.3 Wave rectifier

The full wave rectifier circuit served to pass EMG signals with positive polarity and convert EMG signals with negative polarity into those with positive polarity [10]. A wave rectifier was needed to change the polarity of an EMG signal from an instrumentation amplifier that naturally had a positive or negative average value close to zero [14]. The simple circuit of the active wave rectifier had two Op-Amps (see Figure 4). One rectifier operated in the positive input section and the other one operated in the negative input section. The input gain could be controlled using an R1 resistor.

![Wave rectifier circuit](image)

**Figure 4** Wave rectifier circuit

In accordance with Figure 4, a 0.01 μF capacitor functioned as a signal damper from the EMG instrumentation amplifier. The circuit configuration used the values of R1, R2, R3, R4, and R5, which was 150 kΩ. The input gain can be revealed by the formula equation:

### 2.4 Algorithm System
The initial process began from signal recognition from EMG instrumentation through serial communication. The data received were recorded and stored as the reference signal data for each hand motion. The selected reference signal data were stored on the reference signal bus data. Each new signal data input was compared with the reference signal bus data to determine the signal distance similarity using Euclidean Distance formula. The signal count results were then sorted based on the closest distance to determine the signal classification based on the K-NN algorithm.

### 3. RESULTS AND DISCUSSION

#### 3.1 Circuit Design and Testing

##### 3.1.1 Instrumentation Amplifier

Instrumentation amplifiers designed had a $R_G$ value of 240 Ω. The resulted signal amplification can be revealed by the following formula:

\[
Gain = 1 + \frac{49.4 \times \Omega}{240 \times \Omega} = 207
\]

#### 3.2 Circuit Testing

The circuit testing was carried out by giving input voltage to the instrumentation amplifier circuit. Positive input was disclosed at pin 3 and ground on pin 2 IC AD8221.
The input of the circuit testing was 24 mV (see Figure 8), which resulted in a voltage output of 1.2 V (see Figure 9). The following equation was to find the amplification amount existing in the EMG instrumentation with $R_f$ given to the final amplifier of 270 kΩ.

$$A_v = \frac{V_{out}}{V_{in}} = \frac{1.2}{0.024} = 50 \text{ (real gain)}$$

$$Gain = 207 \left( \frac{R_f}{R_{in}} \right) = 207 \left( \frac{0.27 \text{ kΩ}}{1 \text{ kΩ}} \right) = 55.89 \text{ (theoretical gain)}$$

The circuit testing results were almost similar between the real and theoretical gain values. The difference was caused by the tolerance of the circuit existing in the EMG instrumentation.

### 3.3 EMG Instrumentation Testing

EMG instrumentation testing was conducted by reading the EMG signal activity from the middle muscle sent from EMG instrumentation through serial communication. The transmitted signal was then displayed on the desktop interface using Delphi software. Signal reading was carried out with five different basic hand movements (see Figure 10):

![Figure 10 Input 5 Basic Hand Motion](image)

From the test results, a different signal graph was displayed for each hand motion. The difference of the signal graph was influenced by the changes in the amplitude of the EMG signal that resulted in different amplitude for each hand motion. Table 1 shows the conversion result from the EMG analog signal to voltage at the EMG instrumentation trial with 10.350 amplification.

| Trial | Initial Condition | Condition 1 | Condition 2 | Condition 3 | Condition 4 | Condition 5 |
|-------|-------------------|-------------|-------------|-------------|-------------|-------------|
| 1     | 0.06 V            | 0.32 V      | 0.61 V      | 1.22 V      | 1.66 V      | 2.62 V      |
| 2     | 0.05 V            | 0.27 V      | 0.58 V      | 0.99 V      | 1.50 V      | 2.15 V      |
| 3     | 0.07 V            | 0.29 V      | 0.75 V      | 1.21 V      | 1.68 V      | 2.38 V      |
| 4     | 0.05 V            | 0.33 V      | 0.63 V      | 1.45 V      | 1.55 V      | 1.95 V      |
| 5     | 0.05 V            | 0.31 V      | 0.75 V      | 1.21 V      | 1.53 V      | 1.97 V      |

The test was carried out by taking muscle signals from five people producing different signal outputs in the same conditions. The difference in muscle signal output could be affected by the electrode position or the recorded bicep muscle texture.

### 3.4 Signal Classification

Signal classification testing used the K-Nearest Neighbor (K-NN) method in classifying EMG signals to determine the hand motions used as a basic electronic control system. The distance of K-NN neighbors was calculated based on Euclidean Distance, which could be calculated using the following formula:
\[ d_i(x, y) = \sqrt{\sum_{i=1}^{N} (x_i - y_i)^2} \]

Notes: \( x_i \) = Training sample, \( y_i \) = Sample, \( d_i(x, y) \) = Euclidean Distance

### Table 2 Testing Results of Signal Data Distance

| Hand Position | Reference Values | Testing Results |
|---------------|------------------|-----------------|
| Condition 1   | 55               | 282             |
| Condition 2   | 120              | 217             |
| Condition 3   | 230              | 107             |
| Condition 4   | 310              | 27              |
| Condition 5   | 420              | 83              |

Based on Table 2, the following formula was an example of calculating the distance of the buckling hand position using a systematic Euclidean Distance formula:

\[ \text{Condition 4} = \sqrt{\sum_{i=1}^{4} (310 - 337)^2} = \sqrt{729} = 27 \]

The smaller the distance generated between the two training sample data (reference value) and the sensor data sample, the greater the similarity between the two data.

In accordance with Figure 11, Condition 4 showed almost similar data closest to the resulted signal. After the classification results obtained, the character "D1" was sent as a basic electronic control. Among the 25 testing results with 5 different people, 22 of them conveyed successful EMG signal classification and basic electronic control. The existing failure was due to the classification process of signals that had not met the parameters. Moreover, the signal amplitude was almost similar to other signal classes.

**CONCLUSION**

Based on the above results and discussion, this study concludes that:

1. Muscle signal activity has a different signal amplitude when doing different activities. During relaxed conditions, the signal amplitude is around 0.05 V. However, when the muscles make different motions, the muscle signal has an amplitude of 0.27 V up to 2.62 V with 10.350 signal amplification.
2. Each person has different muscle signal amplitude, which can be influenced by the electrode type and position as well as the recorded muscle texture.
3. The results of 25 tests with five different people show success rate of 88%. Failure when carrying out basic electronic control is due to the signal classification process that has not met the parameters. In addition, the signal amplitude is almost similar to other signal classes.

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