Novel Design of a Robotic Arm Prototype with Complex Movements Based on Surface EMG Signals to Assist Disabilities in Vietnam

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***Abstract*—In recent years, surface electromyography (sEMG) signals have been recognized as a type of signal with significant practical implications not only in medicine but also in the field of science and engineering for functional rehabilitation. This study focuses on understanding the application of surface electromyography signals in controlling a robotic arm for assisting disabled individuals in Vietnam. The raw sEMG signals, collected using appropriate sensors, have been processed using an effective method that includes several steps such as A/D converting and the use of band-pass and low-pass filters combined with an envelope detector. To demonstrate the meaningful effectiveness of the processed sEMG signals, the study has designed a robotic arm model with complex finger movements similar to those of a human. The experimental results show that the robotic arm operates effectively, with fast response times, meeting the support needs of disabled individuals.**

Keywords—Disabilities; sEMG; signal processing; human arm; robotic arm

I. Introduction

Vietnam has a historical association with significant national defense wars, resulting in a substantial population of veterans and disabled individuals. Additionally, Vietnam is presently a developing nation with a considerable demand for unskilled labor, alongside an underdeveloped transportation infrastructure. This reality has led to a relatively high incidence of disability due to labor and/or traffic accidents. According to statistics, Vietnam is a country with a high number of disabled people, accounting for 7.8% of the population (equivalent to 7.2 million disabled people aged five years and older), of which the rate of disabled children is about 28.3% (equivalent to nearly 1.3 million children with disabilities). The two most common types of disabilities are mobility disabilities and neurological and/or intellectual disabilities, followed by visual disabilities. The other types account for less than 10% of the total number of people with disabilities [1]. The large number of people with disabilities presents a significant challenge for society and the Vietnamese government in providing support and ensuring their rights. This Fig. 1 highlights the extension of the disability problem to the country. Therefore, designing and manufacturing prosthetic devices to assist disabled individuals in restoring mobility function is one of the urgent issues in Vietnam today.

EMG signals are biological signals obtained by measuring voltage related to the current generated in a muscle during contraction, providing a measure of muscle nerve activity [2]. Methods for collecting EMG signals include invasive and non-invasive techniques. Invasive electromyography (*i*EMG) is a method of measurement that involves inserting a needle into the skin. Non-invasive methods, also known as surface electromyography (*s*EMG), collect data through electrodes attached to the skin [3]. This method is more widely used than the invasive counterpart due to its safety and ease of use. Surface electrodes are divided into two types: wet and dry ones. Wet electrodes, mainly containing Ag/AgCl ions, have better quality and lower electrode-skin impedance. However, these wet electrodes can irritate the skin and their quality may decrease over time due to the gel drying out. On the other hand, dry electrodes, although they have higher electrode-skin impedance, have the ability to capture stronger sEMG signals and are easier to use, without requiring surface preparation procedures like wet electrodes. For these reasons, the majority of sEMG sensor studies have used dry electrodes [4].

The placement of sEMG electrodes is crucial for successfully distinguishing different finger movements. Therefore, it is necessary to understand the muscle structure involved in controlling the fingers in order to determine the placement of the sEMG electrodes.

In the forearm, the main muscles involved in finger control are the flexor and the extensor muscles. These muscles are located on both sides of the wrist and forearm. The flexor muscles are primarily located on the front side of the forearm and are responsible for flexing the joints in the wrist and fingers. These muscles help to curl the fingers and the wrist. Examples of major flexor muscles include the flexor digitorum profundus and the flexor digitorum superficialis. Meanwhile, the extensor muscles are located on the back side of the forearm and play a role in extending the joints in the wrist and fingers. The extensor digitorum and the extensor digiti minimi are important muscles in the extensor group. Both of these muscle groups often work together to produce complex movements of the wrist and fingers. When the flexor muscles contract, they cause the extensor muscles to relax, and vice versa. Therefore, in order to obtain the sEMG signals of finger activities, the electrodes should be placed on the flexor and extensor muscle groups. Additionally, the electrodes should be located in the middle of these muscle groups to capture the strongest signals.

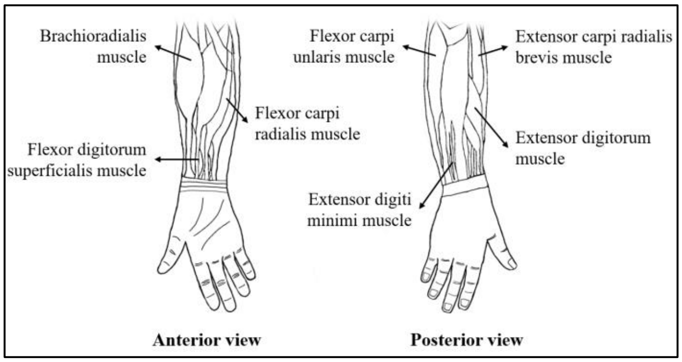

Fig. 1. The structure of muscles in the human arm.

II. Related Work

Recently, with the development of semiconductor technology, there have been many successful studies in developing EMG sensors that are increasingly compact, consume less power, and are more accurate [5-13]. For example, in study [7], the authors implemented a high-frequency and low-power sEMG signal acquisition system. The results showed that the EMG signal samples from the proposed system had a correlation coefficient of up to 99.5% compared to commercial systems, while the power consumption could be reduced by up to 92.72% and the battery life extended up to 9,057 times. The study in [8] proposed an integrated sEMG sensor with a signal reading circuit, MCU, and BLE for human-machine interface (HMI) applications, achieving an accuracy and stability of over 95%. This sensor is flexible, durable, and lightweight, making it suitable for different individuals or for use with different muscle groups, as it is constructed on a multi-layer polyimide-coated copper sheet. In study [10], the authors developed a high-stability capacitive EMG sensor. The sensor is particularly suitable for the Otto Bock standard prosthetic limb in real-world applications, providing comfort when worn and avoiding skin irritation.

There have been numerous studies using various algorithms to classify hand gestures through sEMG signals, with the most common ones being Artificial Neural Networks (ANN), Linear Discriminant Analysis (LDA), Support Vector Machine (SVM), etc. In the past decades, ANN tools have garnered significant attention from researchers in the field of EMG signal classification. ANN has several advantages in EMG signal classification, such as the ability to learn from examples, high noise tolerance, and generalization capabilities in high-dimensional input spaces [14-20]. In one experiment [14], researchers meticulously examined a surface electromyography (sEMG) signal classification system based on Deep Neural Networks (DNN). The results, focusing on eight gestures, demonstrated that the DNN-based system outperformed other classifiers (with an average accuracy of 98.88%), including SVM, kNN, Random Forest, and Decision Tree. In study [15], machine learning (ML) algorithm is employed to process shoulder and upper limb muscle signals, enabling the recognition of motion patterns and real-time control of an upper arm exoskeleton. The results demonstrate high accuracy, particularly with the SVM algorithm achieving 96 ± 3.8% accuracy offline and 90 ± 9.1% accuracy online, showcasing the reliability of ML in pattern recognition and exoskeleton motion control. Another study introduced a real-time hand gesture recognition model employing sEMG with a feedforward Artificial Neural Network (ANN), achieving an average recognition rate of 98.7% and an average response time of 227.76 milliseconds across twelve subjects, each performing five gestures [16]. Furthermore, in study [17], the authors applied a Fuzzy Inference System and Long Short-Term Memory network to analyze EMG signals for classifying the four main gestures of the hand. The classification results achieved an accuracy of 91.3% for the four - dimensional actions (Forward/ Reverse/ GripUp/ RelDown), 95.1% for the two-dimensional actions (Forward/Reverse), and 96.7% for the two-dimensional actions (GripUp/RelDown). In study [18], the authors employed Neural Network and Fuzzy Logic to classify hand movements using two channels of sEMG. The data were collected from ten subjects, and the procedure involved preprocessing, feature extraction, dimensionality reduction, and pattern recognition. The average classification accuracies were 96.08 (±0.9)% and 90.56 (±3)% for Neural Network and Fuzzy Logic, respectively. The study [19] introduces a novel interval type-2 fuzzy classifier based on an explainable neural network for surface electromyogram (sEMG) gesture recognition. Achieving a categorization accuracy of 95.04% for 52 gestures and demonstrating high performance in real scenarios, the proposed method holds promise for applications such as human intent detection and manipulator control. In [20], fuzzy neural networks were employed to represent the different elements affecting the primary muscles when the shoulder-elbow joint of the upper arm was positioned differently. This model utilizes multiple-channel sEMG signals as its input and translates them into the torque exerted on the human upper limb joints.

This paper focuses on developing a robotic arm model with complex movements controlled by surface electromyography (sEMG) signals to assist individuals with disabilities in Vietnam. To address this issue, the current research concentrates on utilizing sEMG signals to control the movements of the robotic arm. This work deals with simulating and analyzing the sEMG signals collected from the arm muscles, and then applies them to accurately control the robot's movements. The remaining sections of the article are organized as follows. After Section II presenting related studies, particularly on robotics and EMG sensors, a detailed overview of the system, from EMG sensors to control units and EMG signal processing, will be presented in Section III. Sections IV and V will present the experimental results, system performance evaluation and relevant discussion. Finally, the main points and future research directions are summarized in Section VI.

III. Materials and Methods

A. System Overview

A detailed description of the components of the proposed system is presented in Fig. 2. The relevant explanation for this diagram is as follows:

1) The surface EMG sensors: The Gravity Analog EMG Sensors have been introduced through a collaboration between DFRobot and OYMotion. The sensor consists of two components, a module containing electrodes and a module integrating filtering and amplification circuits. The EMG sensor, similar to Gravity sensor (see Fig. 3), amplifies surface EMG signals 1000 times and reduces noise through a differential input and a similar filtering circuit. The amplified EMG signals are sampled using a 10-bit analog-to-digital converter (ADC) through the MCU's analog input.

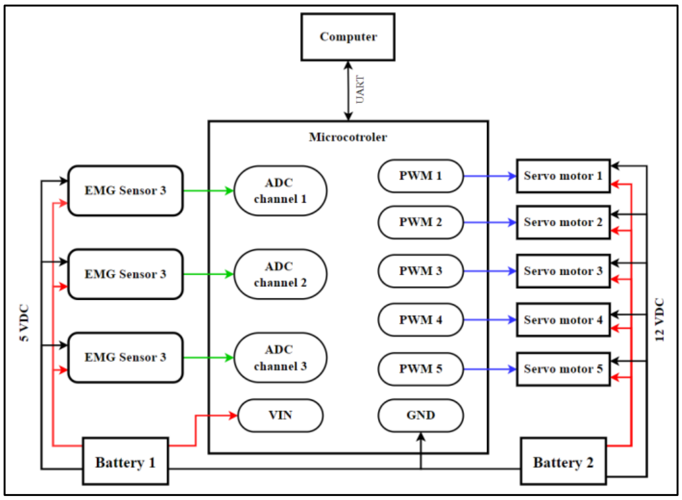

Fig. 2. General system diagram

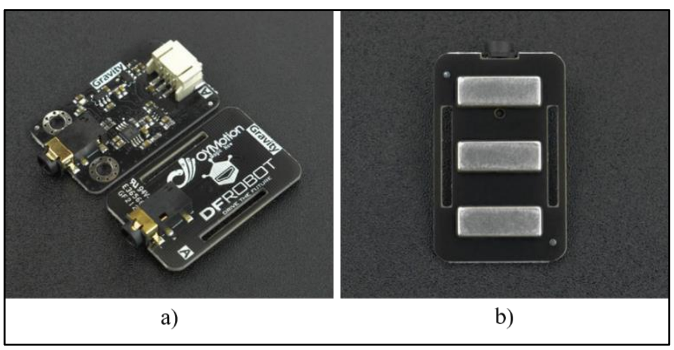

Fig. 3. Gravity Analog EMG sensor

2) ATMEGA2560 Microcontroller: Processes EMG signals from the sensor, sends processed signals to the computer, and simultaneously receives control signals from the computer to control finger gestures, corresponding to 5 Servo motors.

3) Computer: Battery 1, Battery 2: Power supply for the sensors, microcontroller (5 VDC - battery 1), and 5 servo motors (12 VDC - battery 2).

B. EMG Signal Processing

The EMG sensor, similar to Gravity, amplifies surface EMG signals 1000 times and reduces noise through a differential input and a similar filtering circuit. The sensor's output is an analog voltage signal ranging from 0 to 3.0V (corresponding to muscle contraction intensity). This analog signal is converted to a digital signal by the 10-bit ADC of the microcontroller, with a sampling frequency of 1kHz. The digital signal then passes through a second-order Butterworth high-pass filter. Finally, the signal goes through an envelope detection algorithm, resulting in the final processed signal (see Fig. 4).

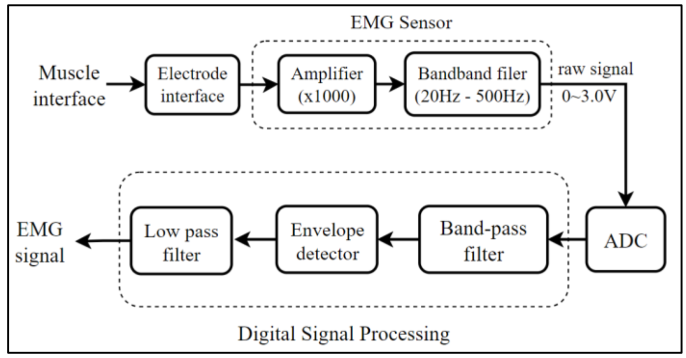

Fig. 4. Surface EMG signal processing.

In signal processing, the function of a digital filter is to remove unwanted components of the input signal or extract useful parts of the signal. A digital filter uses digital processing to perform mathematical operations on the input signal in order to reduce or enhance specific aspects of the signal. There are two types of digital filters: infinite impulse response (IIR) filters and finite impulse response (FIR) filters. For a FIR filter, the output depends only on the current and previous inputs, and the general form of a FIR filter is:

$$y(n) = b_0x[n] + b_1x[n-1] + b_2x[n-2] + \cdots + b_Nx[N] \tag{1}$$

On the other hand, IIR filters are recursive, meaning that the output depends not only on the current and previous inputs but also on the previous output. Therefore, the general form of an IIR filter is:

$$\sum_{m=0}^{M} a_m y[n-m] = \sum_{k=0}^{N} b_k[n-k] \tag{2}$$

A digital filter can be designed as an IIR filter or an FIR filter. The advantage of IIR filters over FIR filters is that they often meet specific technical specifications with a much lower filter order compared to the corresponding FIR filter. For these reasons, the authors of this study used IIR filters to process EMG signals. A common method for designing IIR filters is to design a similar analog filter and then convert it into an equivalent digital filter. There are various types of similar low-pass filters, such as Butterworth, Chebyshev, and Elliptic filters. These filters differ in their nature of intensity and phase response. Designing similar filters other than low-pass filters is based on frequency transformation techniques, creating high-pass filters, band-pass filters, or band-stop filters equivalent to the prototype low-pass filter of the same type. The similar IIR filter is then converted into an equivalent digital filter using the same transformation method. There are three main conversion methods: impulse invariant method, backward difference method, and bilinear z-transform. In the article, a second-order IIR Butterworth digital filter is used to filter EMG signals. The low-cut frequency is set at f_{cl} = 50Hz (to remove low-frequency noise) and the high-cut frequency is set at f_{ch} =150Hz (to remove high-frequency noise). The sampling frequency of the filter is 1kHz, based on references [11-13] which suggested that a sampling frequency between 400Hz and 500Hz is sufficient for measuring EMG signals. The transfer function of the filter is shown in the equation below:

$$H(z) = \frac{Y(z)}{X(z)} = \frac{0{,}106s - 0{,}212z^{-1} + 0{,}106z^{-2}}{1 - 0{,}754z^{-1} - 0{,}392z^{-2} + 0{,}754z^{-3} + 1{,}006z^{-4}} \quad (3)$$

The final low-pass filter in the EMG signal processing is used to smooth the output signal of the envelope detector algorithm. This work has designed a first-order IIR digital low-pass filter with a cut-off frequency of f_c = 10 Hz and a sampling frequency of f_s = 1kHz. The transfer function of the filter is presented in (4).

$$G_{LP}[z] = \frac{Y[z]}{U[z]} = \frac{b[0]}{a[0] + a[1]z - 1} \quad (4)$$

where, U_z is the input and $Y[z]$ is the output. It is assumed to set a = [1, -c] and b =[c] to represent the storage elements. The parameters of the first-order delay elements are adjusted according to the time constant T and the cut-off frequency f_c as follows:

$$T = \frac{c\Delta t}{1-c} = \frac{1}{2\pi f_c} \quad (5)$$

Therefore, the factor c can be calculated in (6).

$$c = \frac{1}{1+\frac{\Delta t}{T}} = \frac{1}{1+2\pi f_c \Delta t} \quad (6)$$

Applying the signal processing for the sEMG as proposed above, the results can be successfully obtained. Fig. 5 represents three types of the sEMG signal: raw signal, high-pass filter output and envelope signal. The last one can be obviously used for the control of a robotic arm which will be presented in the next section.

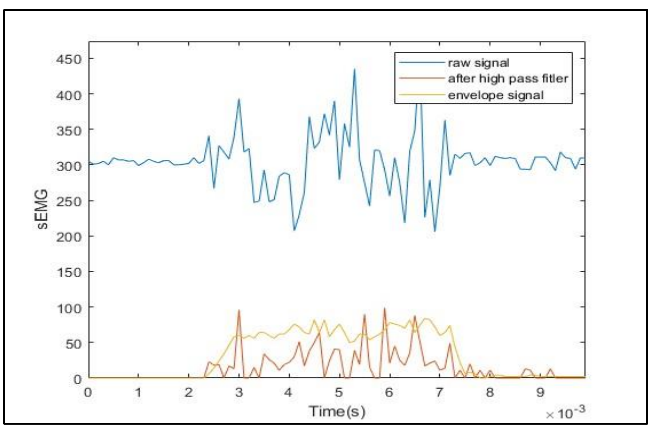

Fig. 5. Results of the sEMG signal processing.

IV. Results

The placement of the actual electrodes is shown in Fig. 6. In this figure, electrode 1 is responsible for measuring the maneuverability activity of the index finger, electrode 2 measures the motion activity of the middle finger and index finger, and electrode 3 measures the mobility activity of the thumb.

This work utilizes the open-source design of the InMoov robot hand, created by Gael Langevin. With its 3D-printed structure as shown in Fig. 7, this hand is not only aesthetically pleasing but also capable of mimicking natural hand movements. InMoov is not just limited to being a sophisticated robot product but also an open-source project, encouraging community involvement in its development and customization. The sEMG signal-controlled system makes it an excellent tool for learning and research in the field of assistive robotics.

When the muscles of the fingers are relaxed, the raw sEMG signals obtained from the three sensors maintain a small oscillation at the reference voltage threshold (1.5V). This oscillation frequency is lower than the high-cut frequency of the digital high-pass filter, so these signals are attenuated. As a result, both the output signals from the bandpass filter and the envelope signals have values of zeros.

When the fingers contract, the raw signals from the sEMG sensors will fluctuate with a higher amplitude at a higher frequency. The bandpass filter is used to allow these signals to pass through. By applying an edge detection algorithm, we can obtain an envelope signal that represents the level of muscle contraction, with the magnitude depending on the degree of contraction of the corresponding muscle. Fig. 8 with various movements of the wrist and fingers illustrates the states of the EMG signal channels when performing basic motor tasks. Experiment results are totally acceptable in control of a robotic arm.

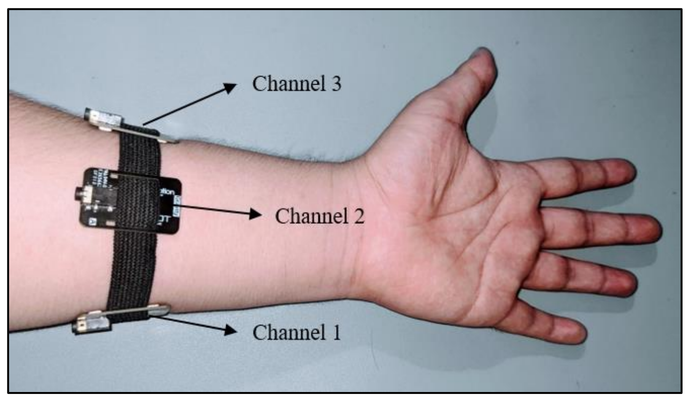

Fig. 6. Actual placements of the electrodes.

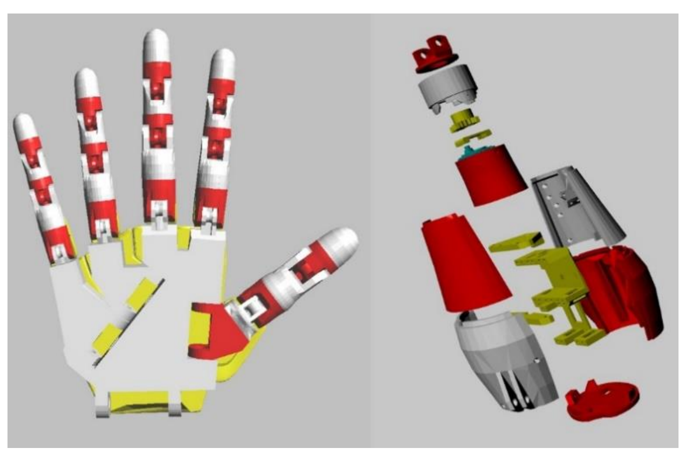

Fig. 7. The design of a 3D – robotic arm (InMoov).

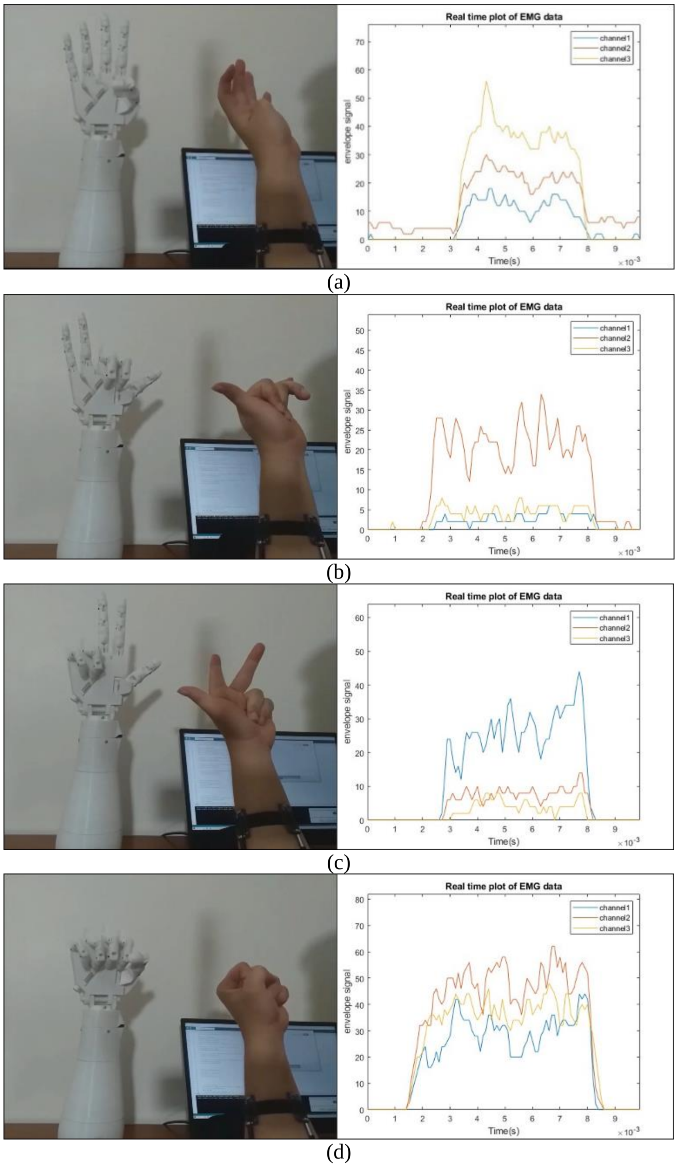

Fig. 8. The experimental results on the robotic arm model applied sEMG signals. (a) Thumb control, (b) Control of the index and middle fingers, (c) Control of the pinky and ring fingers, (d) Hand grasp control.

The results of the study above have demonstrated the effectiveness of the sEMG signal processing system and robot arm model in supporting individuals with disabilities. The sEMG signal processing system has verifed the ability to accurately and stably collect and convert sEMG signals into control signals for the robot arm. Filters and signal processing algorithms help eliminate noise and create precise control signals that respond quickly and flexibly to muscle movements.

The robot arm model has been able to perform complex movements of the fingers accurately and flexibly. The response time of the robot arm is fast, responding promptly to control signals from sEMG signals. Test results have demonstrated that the robot arm model operates effectively and stably under real conditions.

V. Discussion

The results of this study contribute to the field of developing sEMG signal-controlled robotic arms to assist individuals with disabilities. Using an effective method of collecting and processing sEMG signals, this work has successfully designed a robot arm model that can perform complex movements similar to those of humans. One of the notable points is that the application of filters and signal processing algorithms has allowed us to accurately and efficiently collect and convert sEMG signals into control signals for the robot arm. Experimental results have demonstrated that the robot arm is capable of stable operation and quick response, properly meeting the support needs of disabled individuals.

However, although this study has achieved positive results, there are still a number of further research directions that can be explored. Specifically, a significant integration of wrist rotations, as well as arm bending and extension, will complete the complex movements of the robot arm model. This will increase the flexibility and applicability of the robot arm in real-life tasks. In addition, the research can also be expanded to apply machine learning and artificial intelligence methods to improve the precise recognition and control of robot arms based on sEMG signals [14-20]. Developments in this area will bring significant advances in supporting and enhancing the quality of life of individuals with disabilities.

VI. Conclusion

This paper presents in detail the steps of collecting and processing sEMG signals effectively. These sEMG signals have been applied to control a robotic arm model with complex movements of each finger. The experimental results (see Table I of Appendix) confirm that the model works stably and efficiently. The future work inspired from this research will focus on incorporating additional wrist rotation, as well as flexion and extension of the forearm, to complete the complex movements of the robotic arm model. In this scenario, the model has been fully designed for commercialization and widely applied in a developing country like Vietnam.

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APPENDIX

TABLE I. PARAMETERS OF THE MAIN COMPONENTS USED TO DESIGN THE EXPERIMENTAL ARM ROBOT MODEL

No.	Component	Specifications
1	Gravity Analog EMG	**Supply voltage**: + 3.3V ~ 5.5V **Supply current**: >20mA **Operating voltage**: +3.0V **Detection range**: +/- 1.5mV **Output voltage**: 0 ~ 3.0V **Reference voltage**: +1.5V **Gain**: x1000 **Effective spectrum range**: 20Hz ~ 500Hz
2	MG996R Servo Motor	**Motor type**: DC motor servo **Operating range**: 0-180 degrees **Operating voltage**: 4.8V ~ 7.2 VDC **Runing current:** 500mA ~ 900mA (6V) **Stall current**: 2.5A (6V) **Stall torque**: 9.4 kgf·cm (4.8 V), 11 kgf·cm (6 V) **Operating speed**: 0.17 s/60º (4.8 V), 0.14 s/60º (6 V) **Dead band width:** 5 µs **Weight:** 55 g **Dimension**: 40.7 x 19.7 x 42.9 mm approx **Temperature range**: 0° ~ 55℃
3	ATMEGA32U4-MU	**CPU Family:** AVR RISC **Core Size**: 8 bit **Program Memory Size (KB):** 32 **RAM (bytes):** 2560 **Data EEPROM (bytes):** 1024 **Frequency:** 8 Mhz (2.7V), 16 Mhz (4.5V) **Number of Terminations:** 44 **Number of I/Os:** 26 I/O **Operation Voltage (V):** 5.5 (Max), 2.7 (Min) **Supply Current-Max:** 15 mA **Max ADC Resolution (bits):** 10 **Number of ADC Channels:** 12 **Number of PWM Channels:** 8 **Number of Timers/Counters**: 5 **Number of USB Channels:** 1 **Interface:** I2C, SPI, UART/USART, USB **Temperature range:** -40 ~ 85℃