JTE HCMUTE
ISSN: 2615-9740

JOURNAL OF TECHNICAL EDUCATION SCIENCE
Ho Chi Minh City University of Technology and Education
Website: https://jte.edu.vn
Email: jte@hcmute.edu.vn

Controlling an Upper-Limb Rehabilitation Robot by EMG Signals

Quoc Thanh Trinh[1], Minh Nhut Nguyen[2], Thanh Nha Nguyen[1], Quoc Thanh Truong[3], My Ha Le[1], Duc Thien Tran[1*]

[1]*Ho Chi Minh City University of Technology and Education, Vietnam*
[2]*Samsung HCMC CE Complex, Vietnam*
[3]*Ho Chi Minh City University of Technology, VNU-HCM, Vietnam*

[*]Corresponding author. *Email: thientd@hcmute.edu.vn*

ARTICLE INFO

Received:	17/01/2025
Revised:	05/02/2025
Accepted:	18/02/2025
Published:	

KEYWORDS

Rehabilitation robot;

Upper limb exoskeleton;

EMGs;

Kalman filter;

Jacobian.

ABSTRACT

This paper presents a method for controlling the motion of a 6-DOF upper limb rehabilitation robot based on electromyography (EMG) signal. A kinematic model has been determined by Denavit - Hartenberg (D-H) method. Due to the complexity of the robot mechanical structure, the inverse kinematics is addressed using the Jacobian method. Besides, the EMG signal is a physiological signal generated during muscle contraction, which is collected from a low-cost sensor interacted on the human arm, but noise is inevitable in the extracted data. Therefore, the method treats EMG signal noise using Butterworth filter and proposes a method to predict elbow joint angle based on EMG using zero crossing and Kalman filter. Finally, the proposed method is evaluated through simulation on MATLAB Simulink and experiments on a 6-DOF robot arm model. The experimental results show that the EMG signal processing method proposed is significantly effective and the upper limb rehabilitation robot based on EMG signals is feasible.

Doi: https://doi.org/10.54644/jte.2025.1783

1. Introduction

Nowadays, with the outstanding development of science and technology, the application of Robots in all aspects of life is of interest. According to statistics from the Vietnamese Ministry of Health in 2022, there will be about 200,000 people suffering from strokes due to various causes, so the need for rehabilitation is very necessary [1], [2]. Rehabilitation robots come in many different types, depending on the mechanical design of the skeleton that can be attached to the upper limb as robot ARMin, robot CADEN7, actuator, control approach, the transmission mechanism is made by cable, can move in large spaces to enhance human mobility [3]-[5]. In the medical field, robots perform repetitive motion exercises for injured limbs. However, the structure of exoskeleton robot is special, so the calculation of robot's kinematics is of interest, for robots with different configurations, the authors used the Jacobian method along with the D-H axis placement method to solve the inverse kinematics problem for the robot [6]-[8]. Another approach based on human limb analogs, author Shuo Pei used the Pseudo-Inverse method together with the gradient descent algorithm to perform inverse kinematic calculations using the Jacobian matrix with directional priority and achieved results with the directional error of the actuator falling to 10^{-3} rad [9]. The method of solving inverse kinematics using Jacobian matrix with constraints on the motion of robot joints, the kinematic solution method uses the inverse from the Pseudo-Inverse equation, reducing the Gradient Descent to constrain the motion of the joints, the result achieved with the maximum error of the system is only about 0.05 degrees [10]. Besides, the remote robot control is also of interest, the control signal by EMGs is considered one of the most intuitive methods, directly describing the operation from natural human limbs based on the collected biological signals [11], [12]. In Yunxia Huo's 2023 study on EMG-based robot control intervention, it was shown that EMG based control intervention is more effective than conventional methods, focusing on identifying factors of muscle stiffness, adjusting intensity, and limiting overactivity during exercise [13]. The issue of research and development of remote-control systems, integrating EMG control signals in Robotics Operating

System (ROS) to perform motion control, estimating joint angles using mathematical models of human limbs in the problem of rehabilitation robots is also of interest [14]-[16]. The authors performed control of exoskeleton robot mechanisms with inverse kinematics solution method for multi-level serial robots, performed open-loop control of robot using CAN bus communication method to study control of a robot joint using EMGs signal, measure and process uncertain signals.

The structure of this paper is organized as follows: describing the rehabilitation robot system, calculating the kinematics for the robot in section 2. Section 3 presents the EMG signal processing with noise filtering using a Butterworth filter and joint angle estimation using Kalman filter. Section 4 presents the experimental results of verifying the motion, EMG signals with a real robot model. Section 5 presents the conclusion of the proposed method.

2. System description

2.1. System model

The overall model of the system includes two main functional blocks, master and slave which communicate with each other via the CAN network. The master block has the function of collecting and processing data collected from all external fields. The EMGs DFMotion robot sensor collects electromyographic signals attached to the skin or areas in contact with the muscle bundles to be measured. The Arduino Mega 2560 microcontroller collects analog signals received from the sensor and performs active noise filtering. The slave will take on the function of executing commands from the master, performing tasks in the user system interface, exporting and processing control values via Jetson Nano embedded computer.

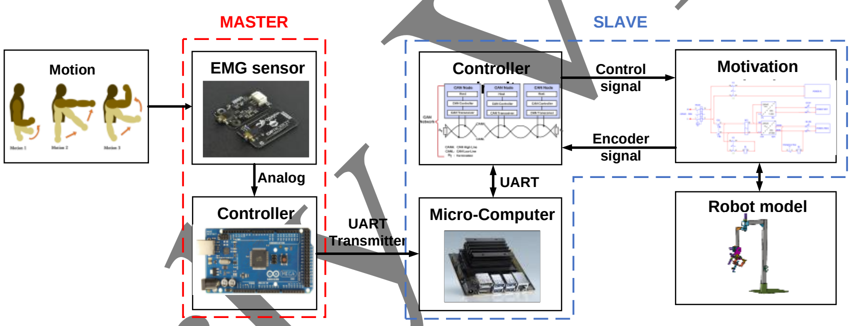


Figure 1. *System overview illustration*

2.2. Kinematic Analysus of Robots

2.2.1. Forward Kinematics

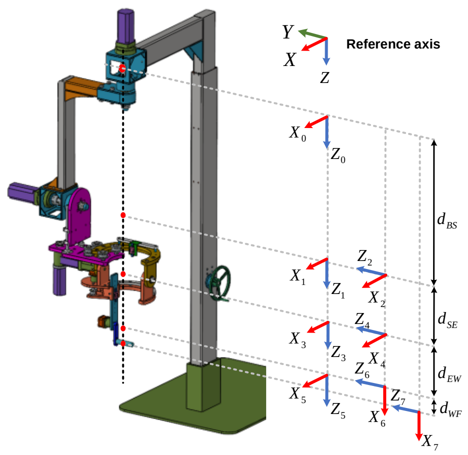


Figure 2. *Image of placing the internal axis in the robot space.*

Table 1. *DH parameter table*

i	α_{i-1}	a_{i-1}	d_i	θ_i
1	0	0	d_{BS}	θ_1
2	-90	0	0	θ_2
3	90	0	d_{SE}	θ_3
4	-90	0	0	θ_4
5	90	0	d_{EW}	θ_5
6	-90	0	0	$\theta_6 - 90$
7	0	d_{WF}	0	0

JTE
HCMUTE
ISSN: 2615-9740

JOURNAL OF TECHNICAL EDUCATION SCIENCE
Ho Chi Minh City University of Technology and Education
Website: https://jte.edu.vn
Email: jte@hcmute.edu.vn

In rehabilitation robot system, the commonly used approach by researchers is the D–H parametric method and forward kinematics as shown in Figure 2. After establishing the joint coordinate system, the D–H parameter (Table 1) of each joint was determined using the adjacent joint coordinate system.

2.2.2. Inverse Kinematics

In this study, the Pseudo-Inverse method is used to solve the inverse kinematics for the 6-DOF robot exoskeleton arm and the Damped-least square (DLS) algorithm is used to improve the robot's workspace with the high frequency of singularities in the workspace. In addition, the application of the Gradient Descent (GD) method is an accompanying method that also helps to improve the computation time.

Step 1: Determine the input values of the system: parameters of position and direction of the actuator

Step 2: Calculate the error between the current position and the desired position of the actuator

$$x_e = X_d - X_c \tag{1}$$

Where X_d is the desired set value of the actuator, consisting of three parameters of position and direction.

Step 3: Perform an update of the Jacobian matrix with size R^{6x6}

Step 4: Invert the Jacobian matrix with Pseudo-Inverse and Damped Least Square methods

$$J^{\dagger} = J^T (JJ^T + \lambda^2 I) \tag{2}$$

Step 5: Determine motion constraints with the Gradient Descent algorithm

$$H(\theta) = \frac{1}{6}\sum_{i=1}^{i=6}\left(\frac{\theta_i - a_i}{a_i - \theta_{iMax}}\right)^2 \tag{3}$$

Where $a_i = \left(\frac{a_{\max} - a_{\min}}{2}\right)$ is the average value of the working space corresponding to the 6 joints mentioned. From there the Gradient of equation (3) has the following form:

$$\nabla H(\theta) = \left(\frac{\partial H(\theta)}{\theta_1} \quad \frac{\partial H(\theta)}{\theta_2} \quad \dots \quad \frac{\partial H(\theta)}{\theta_6}\right)^T \tag{4}$$

Step 6: Update the angle of change of the Jacobian solution

$$\dot{\theta} = J_v^{\dagger +} x_{ev} + k\left(I - J_v^{\dagger} J_v\right)\left(\nabla H(\theta) + J_w^{\dagger} x_{ew}\right) \tag{5}$$

Step 7: Perform condition check if not satisfied go back to step 1.

3. EMG signal processing

To perform EMG signal application in conditions with a lot of interference from environmental noise, we need to perform the procedures described in Figure 3 consisting of three stages: determining the sensor location, processing noise in the system, and building a joint angle estimator.

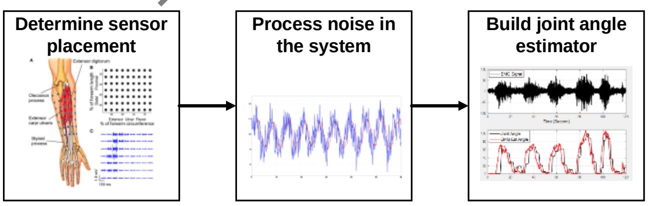
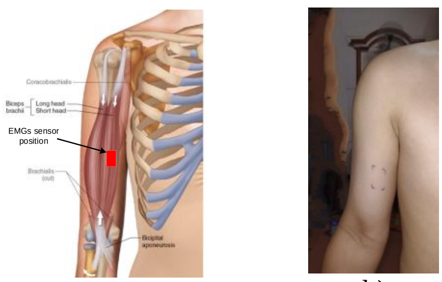


Figure 3. *Electromechanical signal processing procedure*



a) b)

Figure 4. *Sensor location a) Drawing by Dr. Joe Muscolino, Excellence in online anatomy education; b) EMGs sensor placement.*

3.1. EMG signal noise processing

3.1.1. Determine sensor placement

The sensor placement will start from the head of the shoulder blade where the Biceps muscle and the shoulder blade connect, the EMGs sensor will be placed about 13-15cm from the clavicle and is placed above the long head muscle bundle of the biceps branchia muscle.

3.1.2. Processing noise signals on sensors

EMG signals were collected at the Biceps muscle bundle during the elbow flexion/extension posture. The sampling frequency was 2000Hz for 40 seconds. The raw EMG signals were collected by Arduino Uno, and the data were stored by MATLAB 2022b software via UART communication. The signals obtained from the collection process included the raw EMG signal and two Fourier transforms before and after filtering. Figure 5b, the raw electromechanical signal has a useful frequency range of 20-250Hz. The band-pass filter is designed based on this frequency range by combining a 4th order Butterworth high-pass filter with a cut-off frequency of 20Hz and a 4th order Butterworth low-pass filter with a cut-off frequency of 250Hz. The electromechanical signal after filtering in the time domain and the signal frequency spectrum after filtering noise are shown in Figure 6.

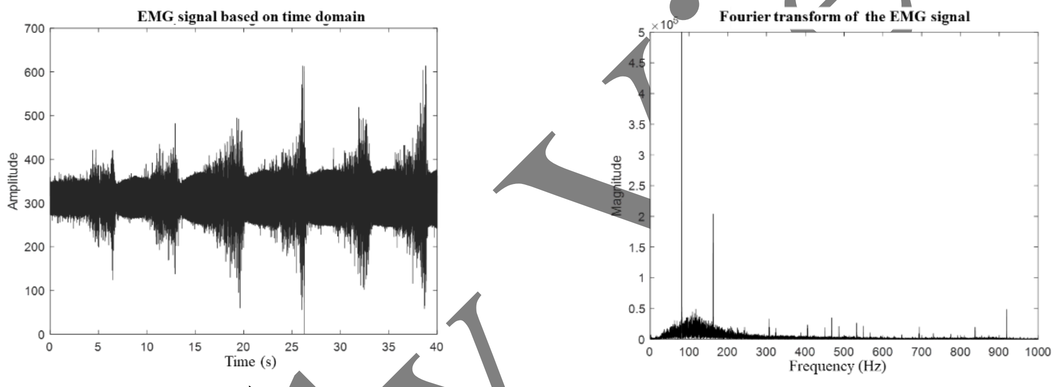


Figure 5. *Raw signal spectrum analysis a) In time domain; b) Frequency spectrum analysis*

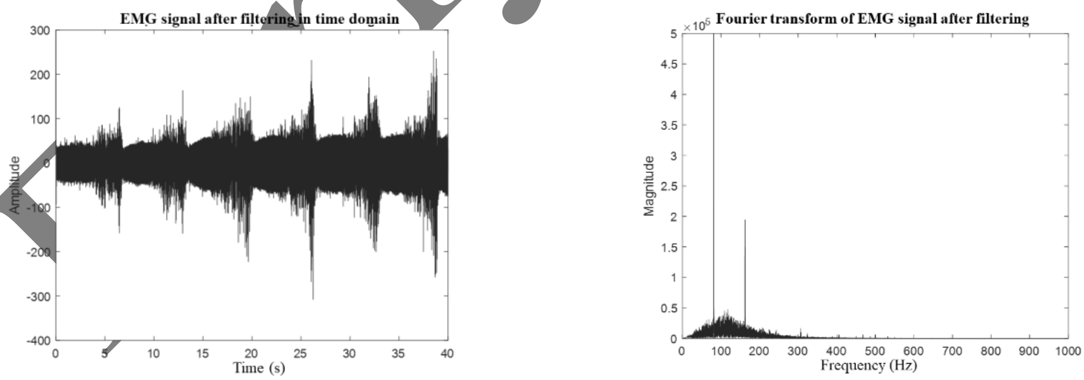


Figure 6. *Frequency spectrum analysis of the filtered signal a) In the time domain; b) Signal frequency spectrum*

3.1.3. Design of digital Butterworth noise filter for experimental model

The Fourier series analysis for raw electromechanical signals and determine the frequency range carrying useful information in the range of 20-250Hz. The digital filter is designed for signals using Arduino Mega 2560 to simultaneously perform two tasks of signal collection and processing, based on the sampling frequency in the process of collecting and processing electromechanical signals [17], [18].

Step 1: Determine the pre-distortion frequency

$$\partial = \tan\left(\frac{180 f_c}{f}\right) \tag{6}$$

Step 2: Determine the filter transfer function

$$H(s) = \frac{1}{D(s)} \tag{7}$$

Step 3: Discretize the signal, where $s = \dfrac{z-1}{z+1}$

$$H(z) = \frac{Y(z)}{X(z)} = \frac{b_0 + b_1 z^{-1} + b_2 z^{-2} + \ldots}{1 + a_1 z^{-1} + a_2 z^{-2} - \ldots} \tag{8}$$

Step 4: Inverse transform in discrete domain

$$y[n] = -a_1 y[n-1] - a_2 y[n-2] - \ldots + b_0 x[n] + b_1 x[n-1] + b_2 x[n-2] + \ldots \tag{9}$$

Where y[n], x[n] is the current output and input signal at time n; y[n-1], x[n-1] is the current output and input signal at time n-1. From the above general steps, we have:

Expression of 4th order low pass Butterworth filter, cut-off frequency $f_c = 250Hz$

$$\begin{aligned} y(4) &= -1{,}159y(3) - 0{,}913y(2) - 0{,}304y(1) + 0{,}047y(0) \\ &+ 0{,}214x(4) + 0{,}856x(3) + 1{,}284x(2) + 0{,}856x(1) + 0{,}214x(0) \end{aligned} \tag{10}$$

Expression of 4th order high-pass Butterworth filter, cut-off frequency $f_c = 20Hz$

$$\begin{aligned} y(4) &= -1{,}159y(3) - 0{,}913y(2) - 0{,}304y(1) + 0{,}047y(0) \\ &+ 0{,}031x(4) - 0{,}124x(3) + 0{,}186x(2) - 0{,}124x(1) + 0{,}031x(0) \end{aligned} \tag{11}$$

3.2. Estimating and processing EMG

Zero Crossing method is one of the time domain signal feature extraction methods used to analyze the characteristics of electromechanical signals. Kalman Filter can be used as a signal value predictor at a certain time. The steps in Kalman Filter implementation are as follows:

Step 1: Perform reading of the required data sample (200 samples) from the sensor

Step 2: Determine the values of the sgn() and diff() functions from expressions (12) and (13)

$$\operatorname{sgn}(x) = \begin{cases} 1, \; if \rightarrow x \geq threshold \\ 0, \quad otherwise \end{cases} \tag{12}$$

$$diff(x) = \begin{cases} 1, \; if \rightarrow x \geq threshold \\ 0, \quad otherwise \end{cases} \tag{13}$$

Step 3: Zero-crossing feature was described, where, ZC is the total number of times the signal amplitude changes in accordance with the preset condition, N is the number of samples in each segment, $Threshold$ is the level of amplitude limitation, x_i is the $i-th$ sample and sgn is the sign function of the product of x_i, x_{i+1}.

JTE
HCMUTE
ISSN: 2615-9740

$$ZC = \sum_{i=1}^{N-1}\left[\operatorname{sgn}(x_i x_{i+1}) \cap diff\left(\left|x_i - x_{i+1}\right|\right)\right] \quad (14)$$

Step 4: The prediction step by updating the system's covariance matrix and prediction error (P) according to formulas (15) and (16), respectively.

$$\hat{x}_k^- = A\hat{x}_{k-1} + Bu_k + w_k \quad (15)$$

$$P_k^- = AP_{k-1}A^T + Q \quad (16)$$

Where A is transition matrix which relates current x_k and previous estimation x_{k-1}. B is matrix which relates current x_k and previous estimation. Q is a process noise and P_k^- is a linear addition between prior error covariance P_{k-1}.

Step 5: The measurement parameter updates with Kalman gain, estimated output value and update the value of covariance P respectively according to formulas (17), (18) and (19)

$$K_k = P_k^- H^T (HP_k^- H^T + R)^{-1} \quad (17)$$

$$\hat{x}_k = \hat{x}_k^- + K_k\left(z_k - H\hat{x}_k^-\right) \quad (18)$$

$$P_k = (I - K_k H)P_k^- \quad (19)$$

Where R is the measurement noise with $R = 0.01$, P_k is the covariance at time k, P_k^- is prediction error covariance, $\hat{x}_k$ is the estimated joint angle value at time k, $\hat{x}_k^-$ is the predicted joint angle value at time k, z_k is a measurement value obtained from the extracted value of EMG signal data over time using the Zero Crossing method, H is the system state matrix with $H = 1$, K_k is Kalman gain

Step 6: Extract the estimated angle value from the filter and repeat step 1.

4. Simulation and experimental results

4.1. System simulation

4.1.1. Trajectory planning simulation for Robot

The research team performed motion trajectory analysis for the robot based on a specific robot motion exercise. The experiment was implemented with the following simulation model as Figure 7. From the calculation results, the points that need to be planned in the space where the orbital response is matched will be performed with the responses shown in the following Figure 8. Figure 9 shows a respond to the position to achieve the set requirements and Figure 10 shows a final actuator error in simulation.

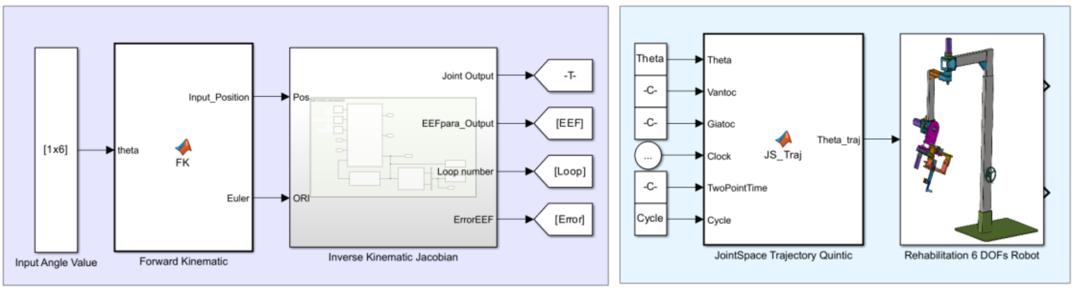


Figure 7. *Trajectory planning program verified in simulation*

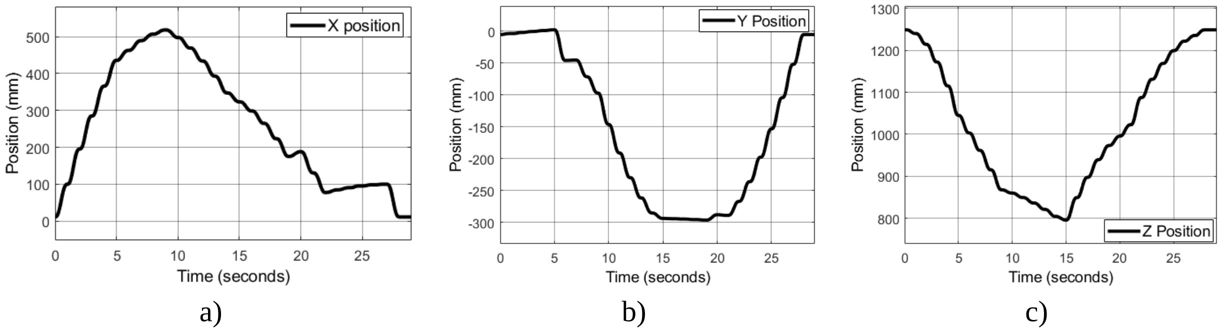
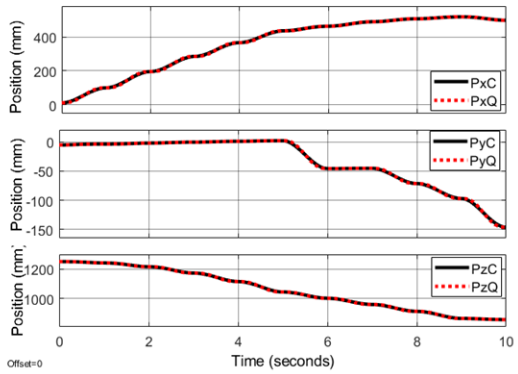


Figure 8. *Robot responses in simulation with final actuator*



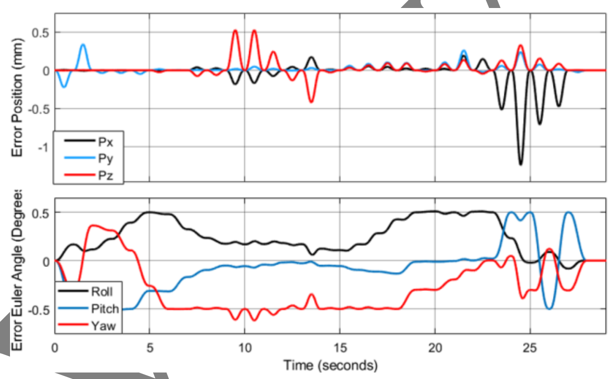
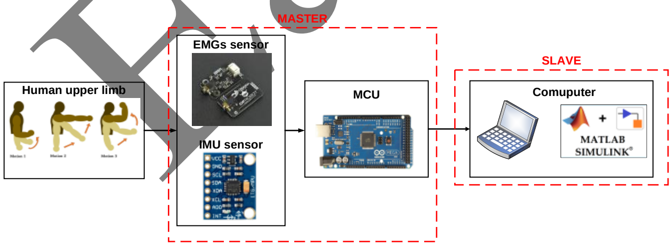


Figure 9. *Robot position response in planning*

Figure 10. *Final actuator error in simulation*

4.1.2. Simulation validation with EMGs signals

In Figure 12 show as signal before and after noise filtering and estimated angle between EMG signal and reference signal. From the experimental EMGs results, the response of EMGs signals was found, but there was still a discrepancy between the estimated angle and the actual angle collected by the IMU sensor. The use of EMG sensors basically shows the biological responses of the body during the movement of the limbs. It shows that EMG signals are often used in diagnostic methods rather than being used to control an object, so we can use EMGs sensors for diagnosis in the medical field.



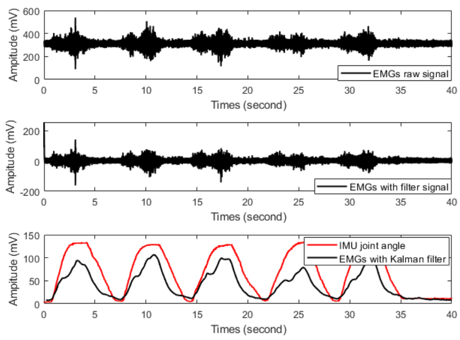


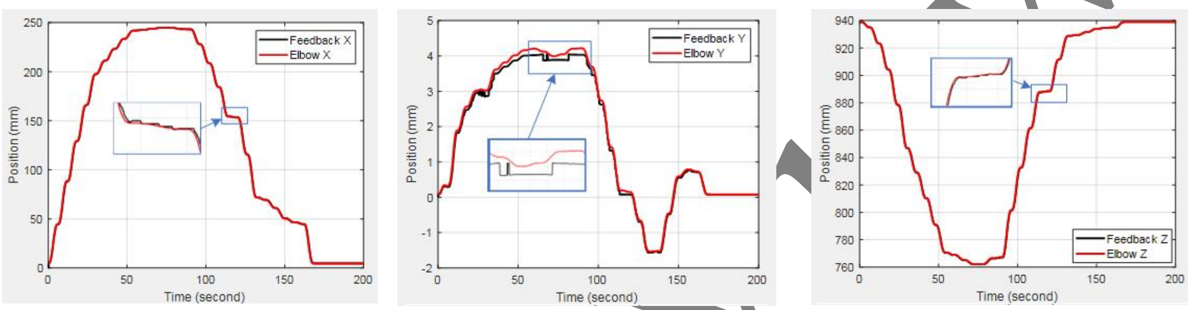
Figure 11. *Simulation process of estimation method and evaluation of EMGs signal processing results.*

Figure 12. *Validation of EMGs signals with the collected data set with Biceps muscle bundle.*

4.2. Experimental results

4.2.1. Experimental verification of robot motion

Experiments compare the simulation results of the position of the elbow joint (joint 4) with the response results from the actual robot as shown in Figure 13. To evaluate the response of the robot model to the reference value in motion, the RMS method of least squares is used to evaluate the error in the model's motion. The tests are repeated 5 times with the trajectory unchanged. The data files will be exported and evaluated together with the data obtained from the simulation to find the error in 3 parameters of the position of the elbow joint in space. Based on Figure 13a, Figure 13b, Figure 13c, Figure 14, Figure 15, Figure 16, the robot's system responses in practice mostly meet the desired movements. Through RMSE evaluation, during the trajectory execution, the errors when compared on the Y coordinate axis have the least deviation, the errors mostly have results below 1mm in each coordinate system. When considering the position of the elbow joint in the Y direction in Figure 13b, the results have a large deviation in the time from 40-100s. This influence can be examined more closely in Figure 16 when considering the factors of the velocity and acceleration of the joint in the Y direction, in the time from 65-85s. There are still phenomena of jerking in velocity even though there is no big change in movement, on the contrary, in the X and Z directions of the elbow joint, the results are closest to reality. In Figure 14 and Figure 16 when considering the moving velocity, the gripping responses are like the velocity amplitude in the simulation even though the chattering phenomenon is still present.



a) b) c)

Figure 13. *Position response between actual and simulated elbow joint in direction a) X; b) Y; c) Z*

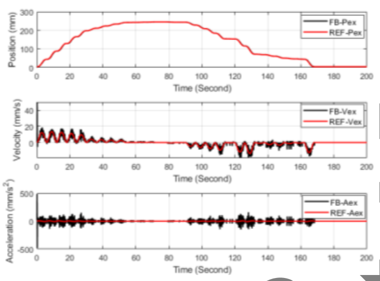


Figure 14. *Response in the x-direction of the elbow joint: a) position; b) velocity; c) acceleration*

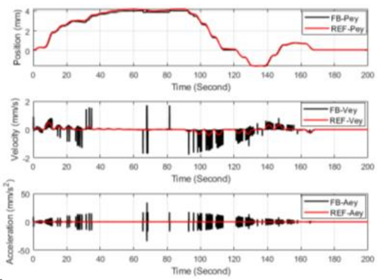


Figure 15. *Responses were compared a) Position; b) Direction; c) Y-axis acceleration of the elbow joint*

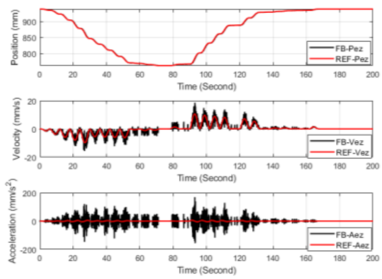


Figure 16. *Responses were compared in terms of a) Position, b) Direction and c) Z-axis of the elbow joint*

4.2.2. Experimental verification of EMG signals on Robot model

Experimental verification of EMG signals on real tissue is shown through flowchart Figure 17.

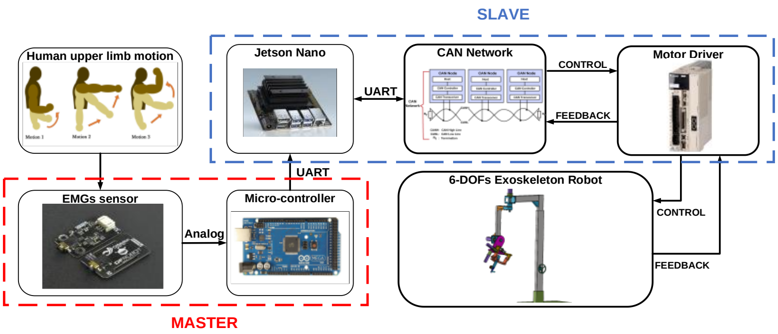


Figure 17. *Flowchart for performing EMGs signal verification on real model*

JTE HCMUTE
ISSN: 2615-9740
JOURNAL OF TECHNICAL EDUCATION SCIENCE
Ho Chi Minh City University of Technology and Education
Website: https://jte.edu.vn
Email: jte@hcmute.edu.vn

Basically based on the EMG signals collected, the robot's responses are almost the same amplitude, the signals show the delay as proposed. The value of the estimated angles has a value similar to the signal collected from the IMU sensor, although there is still a large error as Figure 18. The result, a sensor using EMG signal is often used as a therapy accompanying the support device in old medicine, such as rehabilitation robot models, helping to detect and diagnose muscle strength during the recovery process.

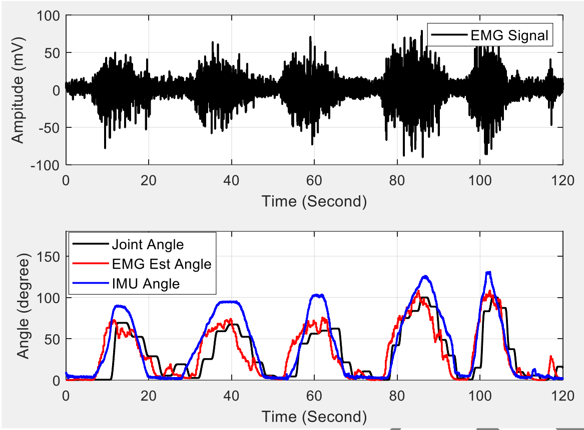


Figure 18. *Estimated signal from EMG sensor and joint angle response from model*

5. Conclusion

This paper presents the evaluation of EMG signals in a 6-DOF rehabilitation robot. Besides, the kinematics of the robot are calculated following the D-H method. Because of the complexity of the mechanical structure, the Jacobian method is used to calculate the inverse kinematics for the robot. To handle the noise and estimate the joint angle value, the Klaman filter and the zero crossing method are used. Experimental control of the robot using EMG signals and exercises to evaluate the feedback signal from the robot. The research results demonstrate that sensors using EMG signals are often used as a therapy with assistive devices in medicine, specifically rehabilitation robot models, to help detect and diagnose muscle strength during the rehabilitation process.

Acknowledgments

This research was studied at the Robotics and Intelligent Control Laboratory (RIC Lab), Faculty of Electrical and Electronics Engineering, HCMC University of technology and Education, Vietnam.

Conflict of Interest

The authors declare no conflict of interest.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

REFERENCES

[1] “Statistics on Stroke in Vietnam,” (in Vietnamese), 2022. [Online]. Available: https://tinyurl.com/29k7g6dr
[2] Viet Nam Ministry of Health, “Shortage of rehabilitation human resources in Vietnam,” (in Vietnamese), *Viet Nam Ministry of Health Portal*, 2023.
[3] L. Marchal-Crespo and R. Riener, “The effectiveness of robotic training depends on motor task characteristics,” *Exp. Brain Res.*, vol. 235, no. 5, pp. 1307–1315, 2017, doi: 10.1007/s00221-017-5099-9.
[4] J. C. Perry and J. Rosen, “Isotropy of an upper limb exoskeleton and the kinematics and dynamics of the human arm,” *Appl. Bionics Biomech.*, vol. 6, no. 2, pp. 175–191, 2009, doi: 10.1080/11762320902920575.
[5] M. Dežman, A. Ude, and A. Gams, “Mechanical design and friction modelling of a cable-driven upper-limb exoskeleton,” *Mech. Mach. Theory*, vol. 170, p. 104701, 2022.
[6] N. N. Thanh, T. P. Manh, N. N. Minh, T. T. Quoc, and T. D. Thien, “Modeling, kinematic analysis, and simulation for a 6-DOF upper limb rehabilitation robot,” in *Computational Intelligence Methods for Green Technology and Sustainable Development*, Cham, Switzerland: Springer, 2024, pp. 12–24.
[7] M. A. Gull, S. H. Bengtson, M. Mohammadi, L. N. S. A. Struijk, T. B. Moeslund, T. Bak, and S. Bai, “A 4-DOF upper limb exoskeleton for physical assistance: Design, modeling, control and performance evaluation,” *Appl. Sci.*, vol. 11, no. 15, p. 7139, 2021.

[8] L. Hang, R. Ren, and J. Wang, "Design and analysis of an upper limb rehabilitation robot based on multimodal control," *Sensors*, vol. 23, no. 21, p. 8801, 2023, doi: 10.3390/s23218801.

[9] S. Pei, J. Guo, H. Yin, and Y. Yao, "A human-like inverse kinematics algorithm of an upper limb rehabilitation exoskeleton," *Symmetry*, vol. 15, no. 9, p. 1657, 2023, doi: 10.3390/sym15091657.

[10] D. T. Tran, T. D. Nguyen, M. K. Tran, and K. K. Ahn, "Development of a hardware-in-the-loop platform for a teleoperation flexibility robotic system," *Appl. Sci.*, vol. 14, no. 5, p. 2207, 2024, doi: 10.3390/app14052207.

[11] A. M. Simon, L. J. Hargrove, B. A. Lock, and T. A. Kuiken, "Target achievement control test: Evaluating real-time myoelectric pattern-recognition control of multifunctional upper-limb prostheses," *J. Rehabil. Res. Dev.*, vol. 48, no. 6, pp. 619–628, 2011.

[12] Y. Tao, S. Guo, Y. Li, X. Li, and F. Xi, "Review of sEMG for robot control: Techniques and applications," *Appl. Sci.*, vol. 13, no. 17, p. 9546, 2023, doi: 10.3390/app13179546.

[13] Y. Huo, W. Zhao, H. Hu, and L. Li, "Effects of EMG-based robot for upper extremity rehabilitation on post-stroke patients: A systematic review and meta-analysis," *Front. Physiol.*, vol. 14, p. 1172958, 2023, doi: 10.3389/fphys.2023.1172958.

[14] S. Bisi, B. Shrestha, Z. Yang, and V. Gandhi, "Development of an EMG-controlled mobile robot," *Robotics*, vol. 7, no. 3, p. 36, 2018, doi: 10.3390/robotics7030036.

[15] M. Pang, Q. Huang, H. Ishihara, and H. Hirata, "Electromyography-based quantitative representation method for upper-limb elbow joint angle in sagittal plane," *J. Med. Biol. Eng.*, vol. 35, no. 3, pp. 356–364, 2015.

[16] T. Tuncer and A. Subasi, "Surface EMG signal classification using ternary pattern and discrete wavelet transform-based feature extraction for hand movement recognition," *Biomed. Signal Process. Control*, vol. 58, p. 101872, 2020, doi: 10.1016/j.bspc.2020.101872.

[17] G. Naik, *Biomedical Signal Processing: Advances in Theory, Algorithms and Applications*. Cham, Switzerland: Springer, 2019.

[18] M. S. H. Reaz, F. M. Y. Mohamed, and M. I. B. Hussain, "Techniques of EMG signal analysis: Detection, processing, classification and applications," *Biol. Proced. Online*, vol. 8, pp. 11–35, 2006, doi: 10.1251/bpo115.

Quoc Thanh Trinh received the B.S and M.S. degrees in the Faculty of Electrical and Electronics Engineering, Ho Chi Minh University of Technology, Vietnam, in 2017, 2019, respectively. He works as a lecturer at Ho Chi Minh City University of Technology and Education (HCMUTE), Vietnam. Currently studying as a PhD student at the Faculty of Electrical and Electronics Engineering, Ho Chi Minh City University of Technical Education, Vietnam. His research interests include robotics, rehabilitation robot, automation, nonlinear control and intelligent technique.

Email: thanhtq.ncs@hcmute.edu.vn. ORCID: https://orcid.org/0009-0001-1379-6461

Minh Nhut Nguyen is a graduate student at the Faculty of Electrical and Electronics Engineering, Ho Chi Minh University of Technology and Education, Vietnam, in 2024. He works as a Samsung HCMC CE Complex, Ho Chi Minh, Vietnam. His research interests include serial robot, parallel robot, nonlinear control, and intelligent control.

Email: nhut.nguyenminh318@gmail.com. ORCID: https://orcid.org/0009-0004-7947-9735

Thanh Nha Nguyen received the Bachelor's of engineer majoring in automation and control engineering from the Faculty electrical and electronics engineering, Ho Chi Minh City University of Technology and Education, Vietnam, in 2023. He works as a Robotics and Intelligent Control Lab member in the Department of Automatic Control, Ho Chi Minh University of Technology and Education, Vietnam. His research interests include robotics, parallel robot, rehabilitation robots, nonlinear control, and intelligent control.

Email: ntnha0639@gmail.com or 2341104@student.hcmute.edu.vn. ORCID: https://orcid.org/0009-0004-1302-5378

Quoc Thanh Truong received the BSc. degree in the department of Mechanical Engineering from Ho Chi Minh City University of Technology in 1998, and the MSc. degree from the master program of mechanics under Inter-University Cooperation Program between Liege University (Belgium) and HCMUT (Vietnam) in 2000. After that, he finished the PhD. degree at the University of Ulsan (Korea) in 2009. From 2000 to 2004 and from 2009 to now, he worked as a lecturer in the mechanical department of Ho Chi Minh City University of Technology (HCMUT). His research interests focus on designing, modelling, simulating and manufacturing of new actuators. Otherwise, he is also focusing on vibration control theory and application theories.

Email: thanhtq@hcmut.edu.vn. ORCID: https://orcid.org/0009-0002-7530-1740

My Ha Le received the B.S and M.S. degrees in the Department of Electrical Engineering, Ho Chi Minh City University of Technology, Vietnam, in 2005, 2009, and the Ph.D. degree from University of Ulsan in 2020, respectively. He works as a deputy head of faculty of electrical and electronics engineering, Ho Chi Minh City University of Technology and Education (HCMUTE), Vietnam. His research interests include artificial intelligence, computer vision and robotic.

Email: halm@hcmute.edu.vn. ORCID: https://orcid.org/0009-0009-7943-0444

Duc Thien Tran received the B.S and M.S. degrees in the Department of Electrical Engineering, Ho Chi Minh City University of Technology, Vietnam, in 2010, 2013, and the Ph.D. degree from University of Ulsan in 2020, respectively. He works as a lecturer with the Department of Automatic Control, Ho Chi Minh City University of Technology and Education (HCMUTE), Vietnam. His research interests include robotics, variable stiffness system, fluid power control, disturbance observer, nonlinear control, adaptive control, and intelligent technique.

Email: thientd@hcmute.edu.vn. ORCID: https://orcid.org/0000-0002-6684-0681