TELKOMNIKA Telecommunication Computing Electronics and Control
Vol. 24, No. 6, December 2026, pp. 2230~2242
ISSN: 1693-6930, DOI: 10.12928/TELKOMNIKA.v24i6.27850

A proportional integral derivative controlled rehabilitation glove for post-stroke hand therapy

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Article Info

Article history:

Received Feb 4, 2026
Revised Oct 7, 2026
Accepted Oct 11, 2026

Keywords:

Glove
Proportional integral derivative control
Rehabilitation
Repetitive
Stroke

ABSTRACT

This study presents a proportional integral derivative (PID)-controlled rehabilitation glove designed to assist post-stroke hand therapy through automated and repetitive finger flexion and extension. The glove integrates flex sensors for finger-angle measurement, servo motors for finger actuation, and an ESP32 microcontroller implementing a PID control system to regulate finger movements according to predefined target angles. Individual linear calibration models are applied to convert flex sensor readings into finger angles, while the PID controller minimizes the error between the measured and desired angles to improve motion stability. System performance is evaluated using the integral of absolute jerk (IAJ) to quantitatively assess motion smoothness at target angles of 30°, 45°, 60°, and 75°. Experimental results demonstrate substantial improvements in motion smoothness, with average IAJ reductions of 72.56%, 69.17%, 63.98%, and 61.29% at the respective set points, resulting in an overall average reduction of 66.75% compared with the uncontrolled system. Functional testing also achieved 100% accuracy in repetition counting for operation durations of 1, 5, and 10 minutes. These results demonstrate that the proposed PID-controlled rehabilitation glove provides stable and repeatable finger movements for post-stroke hand rehabilitation.

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1. INTRODUCTION

Post-stroke hand impairment is a major challenge in restoring upper-limb motor function and independence in daily activities. Hand weakness and spasticity can interfere with essential activities such as grasping, eating, and dressing, creating a need for intensive and repetitive rehabilitation [1]-[4]. Repetitive task-oriented exercises, including grasping and releasing movements, are widely used to stimulate neuroplasticity and support motor relearning through continuous sensorimotor feedback [5]-[7]. However, maintaining sufficient exercise frequency and intensity during independent rehabilitation remains difficult because of limited supervision, low motivation, and uncertainty regarding movement correctness [8]. These challenges have encouraged the development of robotic and wearable assistive devices that can provide repetitive finger movements with greater consistency and support rehabilitation outside conventional clinical settings.

Robotic rehabilitation devices offer promising support for post-stroke hand therapy, but their design must balance motion control, portability, usability, and system complexity. Conventional rehabilitation methods and commercial robotic devices have been associated with limitations in portability, ease of use, and

motion stability [9]. For example, robotic hand exoskeletons such as Gloreha may require relatively complex infrastructure and specialized training, which can limit their suitability for independent home-based therapy [10]. In addition, inconsistent therapy and discomfort associated with assistive devices can affect rehabilitation adherence [11]. Rehabilitation systems based on machine learning or electromyography (EMG) may also require more complex processing and expert-dependent calibration, potentially limiting independent use [12]. These limitations highlight the need for wearable rehabilitation systems that can provide controlled and repeatable finger movements while maintaining a relatively simple hardware and control architecture.

Recent studies have investigated a variety of low-cost and wearable approaches for post-stroke hand rehabilitation. A rehabilitation device presented in [13] combines polylactic acid (PLA), springs, servo motors, and an Arduino Uno to develop exoskeleton fingers with multiple degrees of freedom. Soft wearable systems have also been developed using bending and rotating actuators integrated into fabric-based gloves, together with flexible strain and force sensors and hybrid force/position proportional integral derivative (PID) control for pressure regulation [14]. Pneumatic actuation has been explored through wearable robotic hands driven by pneumatic muscle–torsion spring (PM-TS) mechanisms, with adaptive control strategies such as echo state network (ESN)-based PID controllers used to address nonlinear system behavior and improve tracking accuracy [15]. Other studies have investigated kinematic and dynamic modeling approaches for single-degree-of-freedom mechanisms capable of generating coordinated finger flexion and extension for neurological rehabilitation [16]. Sensing-based systems have also employed 24-electrode sleeves positioned over extensor muscles and artificial neural networks for signal processing and control [17]. More recent approaches include soft robotic gloves using shape memory alloy (SMA) actuators with PID-based control [18], soft pneumatic gloves with multiple rehabilitation postures and assisted grasping modes based on segmented PneuNets actuators [19], and stretchable epidermal surface electromyography (sEMG) systems combined with convolutional neural networks (CNNs) for hand gesture recognition and rehabilitation [20]. Open-source hand exoskeletons with wireless bilateral control have further emphasized accessibility and usability through lightweight designs and wireless fidelity (WiFi)-based communication [21].

Although these approaches demonstrate the potential of robotic and wearable technologies for hand rehabilitation, there remains a practical need for systems that combine wearable sensing, actuation, and closed-loop motion control within a relatively simple and computationally efficient architecture. In particular, controlled finger rehabilitation requires the actuator to follow predefined target angles while responding to differences between the desired and measured finger positions. PID control is suitable for this purpose because it provides a relatively simple closed-loop method for regulating actuator movement based on the control error, without requiring computationally intensive algorithms. In the proposed system, flex sensors provide measurements of finger bending, which are converted into finger joint angles through individual calibration models. The measured angle is then compared with the desired set point, and the resulting error is processed by the PID controller to regulate the servo motor response [22]. This approach enables the system to provide controlled finger flexion and extension while maintaining a comparatively simple implementation.

Based on this motivation, this study proposes a PID-controlled rehabilitation glove designed to support controlled and repeatable hand rehabilitation exercises for post-stroke therapy. The glove integrates an ESP32 microcontroller, five servo motor actuators, and five flex sensors, with each sensor positioned on an individual finger. A tendon-driven mechanism using nylon strings transfers the servo motion to the fingers, enabling assisted flexion and extension. The system is designed to accommodate both left and right hands. To account for differences among fingers and sensor-mechanical configurations, individual linear calibration models are applied to convert flex sensor measurements into finger angles. The PID controller is tuned using a trial-and-error approach under defined experimental conditions [22].

The performance of the proposed system is evaluated through technical experiments focusing on motion smoothness and functional operation. The integral of absolute jerk (IAJ) is used as a quantitative metric to assess the smoothness of finger movement, with lower IAJ values indicating reduced abrupt changes in motion [23]. System response is evaluated at target angles of 30°, 45°, 60°, and 75° with and without PID control, while functional testing evaluates repetition performance during operation periods of 1, 5, and 10 minutes. In addition, a Telegram-based monitoring system is incorporated to track repetition performance in real time and support the potential use of the device in home-based rehabilitation.

Accordingly, the main contributions of this study are: (i) the development of a compact wearable rehabilitation glove integrating flex-sensor-based finger-angle measurement, servo actuation, an ESP32 controller, and a tendon-driven mechanism; (ii) the implementation of a PID-based closed-loop control strategy for regulating finger movements according to predefined target angles; (iii) the application of individual linear calibration models to improve the conversion of flex-sensor measurements into finger angles; and (iv) the technical evaluation of motion smoothness using IAJ together with functional repetition testing. The evaluation in this study is limited to technical validation and does not include clinical or user-based assessment. Therefore, clinical validation and more systematic controller-tuning methods remain important directions for future work.

2. METHOD

2.1. System architecture

The proposed rehabilitation glove consists of four main components: a wearable glove mechanism, actuator mechanisms, sensor units, and a PID-based control module. The overall system operates as a closed-loop control system, in which finger bending is measured by flex sensors, converted into finger angles through calibration, and compared with predefined target angles. The resulting error is processed by the PID controller to regulate the servo motors and produce the desired finger movement.

As illustrated in Figure 1, the system begins with an initialization process in which the flex sensors, PID parameters, and predefined target angle are configured. The flex sensors continuously acquire analog signals corresponding to finger bending. These signals are converted into finger joint angles using individual calibration models. The difference between the measured finger angle and the predefined set point is then calculated as the control error. The proportional, integral, and derivative components of the PID controller process this error to generate the control action for the corresponding actuator.

The system operates continuously in a closed-loop configuration. The measured finger position is repeatedly fed back to the controller so that the actuator response can be adjusted according to the current error. The operation continues until the system is stopped by the user through the push button. This architecture enables the glove to provide controlled finger flexion and extension while continuously monitoring the resulting finger movement.

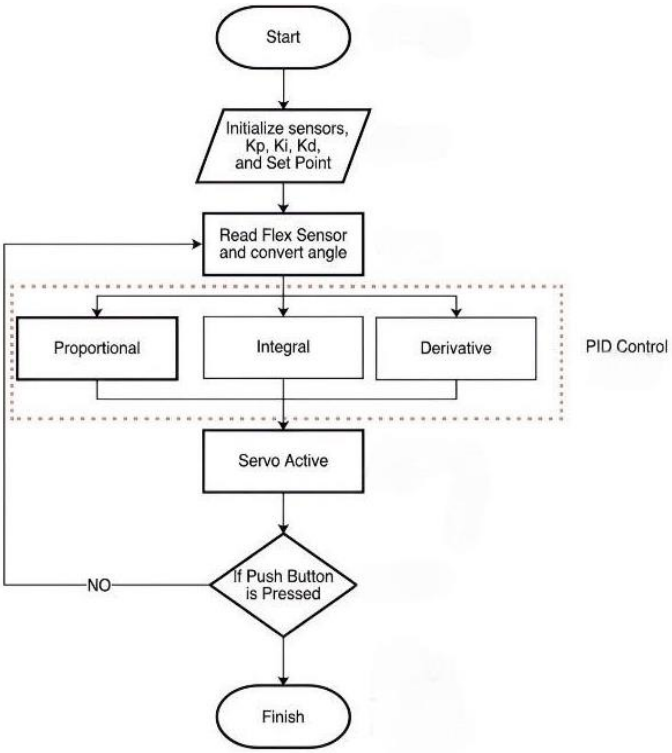


Figure 1. Flowchart of system operation

2.2. Hardware design

The electronic hardware configuration of the proposed system was modeled using Fritzing, as shown in Figure 2. The ESP32 microcontroller serves as the central processing and control unit. It receives the flex-sensor measurements, calculates the corresponding finger angles, executes the PID control algorithm, and generates control signals for the servo motors. A push button is also integrated into the system to provide a user-operated start and stop function.

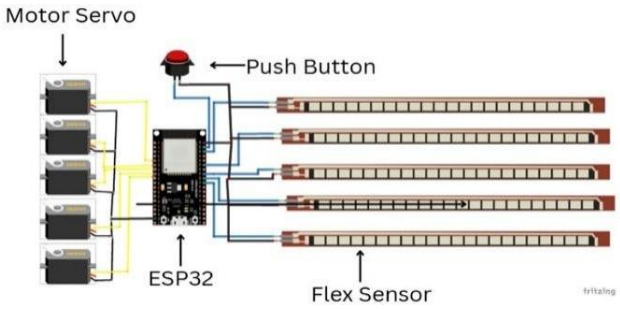


Figure 2. Device schematic

Five TowerPro MG995 servo motors are used as the primary actuators. Each servo motor is assigned to one finger to generate the required finger flexion movement. The five fingers are driven independently through a tendon-based mechanism using nylon strings. The tendon mechanism transfers the rotational movement of each servo motor to the corresponding finger, allowing the glove to produce assisted flexion and extension.

Five flex sensors are installed on the dorsal side of the glove, with one sensor assigned to each finger: thumb, index, middle, ring, and little finger. The sensors measure changes in finger bending and provide feedback to the ESP32 controller. The arrangement of the servo motors and flex sensors is designed to support independent sensing and actuation of each finger while maintaining a coordinated wearable configuration.

The three-dimensional design and physical arrangement of the rehabilitation glove are presented in Figures 3(a) to (c). The design incorporates the glove, servo motors, flex sensors, and enclosure into a wearable system. The configuration is intended to support both left-and right-hand use.



(a) (b) (c)

Figure 3. Rehabilitation glove design: (a) outer view, (b) glove, and (c) top view of the enclosure

2.3. Proportional-integral-derivative controller

PID controller is a combination of three main components, namely proportional, integral, and derivative, which can be applied either simultaneously or individually depending on the desired response of a system or plant. Based on the function of each component, the general equation of the PID controller can be formulated as follows [24]. The PID control equation can be expressed in (1):

$$u(t) = K_p e(t) + K_i \int_0^t e(t)\, dt\, K_d \frac{de(t)}{dt} \quad (1)$$

In this context, $u(t)$ represents the control variable, while $e(t)$ denotes the error value obtained from the difference between the reference input and the system output. The parameters K_p, K_i, and K_d act as the coefficients of the proportional, integral, and derivative controllers, respectively, and must be properly tuned to ensure optimal system performance.

This study applied a structured testing procedure to evaluate the performance and stability of the proposed smart rehabilitation glove (SRG) under repetitive operation. Based on previous post-stroke hand rehabilitation studies [25], finger flexion–extension exercises were conducted with training durations of 1, 5, and 10 minutes to represent different rehabilitation intensities and to assess PID controller robustness. Prior to system-level testing, flex sensors were calibrated at predefined angles of 0°, 30°, 45°, 60°, and 75°, and the recorded analog-to-digital converter (ADC) values were mapped to joint angles using a linear regression model as the control reference. The system was then evaluated through PID parameter tuning using a trial-and-error approach at a target angle of 75°, followed by response analysis at multiple reference angles (30°, 45°, 60°, and 75°) under conditions with and without PID control. Functional testing was subsequently performed at a fixed angle of 75° using the three training durations, with repeated trials to examine motion accuracy, stability, and repeatability.

2.4. IAJ analysis

To evaluate the performance of the proposed rehabilitation glove system, this study employs the IAJ as the primary evaluation metric to assess motion smoothness [26]. Unlike conventional control-performance metrics, IAJ is widely used in motion analysis and rehabilitation studies to quantify the smoothness and stability of joint movements based on kinematic properties. The selection of IAJ is particularly relevant to the proposed rehabilitation glove because achieving the desired finger angle alone does not necessarily indicate that the generated movement is smooth. In rehabilitation applications, abrupt changes in finger motion may be undesirable even when the target angle is reached accurately.

Other commonly used performance metrics, such as root mean square (RMS) error, rise time, and overshoot, evaluate different aspects of system performance. RMS error primarily measures the tracking accuracy between the actual and reference angles, while rise time characterizes the speed at which the system reaches the reference angle. Overshoot indicates the extent to which the response exceeds the desired reference angle. Although these metrics are useful for evaluating tracking and transient performance, they do not directly quantify the smoothness of the motion trajectory. In contrast, IAJ extends the jerk concept by integrating the absolute jerk over the entire motion duration, thereby quantifying the accumulated irregularity of the movement trajectory [26], [27]. A lower IAJ value indicates a smoother motion with fewer abrupt changes in angular movement. Therefore, IAJ was selected as the primary metric for evaluating motion smoothness, while the angular response was used to assess the overall control behavior of the system.

In a discrete-time implementation with a constant sampling interval, the IAJ calculation is performed through successive numerical differentiation of the angular position, resulting in angular velocity, angular acceleration, and jerk, followed by integration as defined in (2)-(5):

$$v(t) = \frac{d\theta(t)}{dt} \tag{2}$$

$$a(t) = \frac{dv(t)}{dt} \tag{3}$$

$$j(t) = \frac{da(t)}{dt} \tag{4}$$

$$IAJ = \sum_{i=0}^{N-1} | j_i | \Delta t \tag{5}$$

where $v(t)$ is the angular velocity obtained from the first derivative of the angular position $\theta(t)$ with respect to time, $a(t)$ is the angular acceleration defined as the derivative of angular velocity, and $j(t)$ is the jerk calculated as the derivative of angular acceleration. The IAJ is computed by summing the absolute jerk values $| j_i |$ over all motion samples and multiplying them by the sampling interval Δt, where Ndenotes the total number of samples.

Motion quality can be evaluated by analyzing time-based changes in position, where velocity, acceleration, and jerk serve as first- to third-order kinematic descriptors [27]. High jerk values indicate abrupt acceleration changes, which are commonly associated with vibration, instability, or discomfort during movement [26], [27].

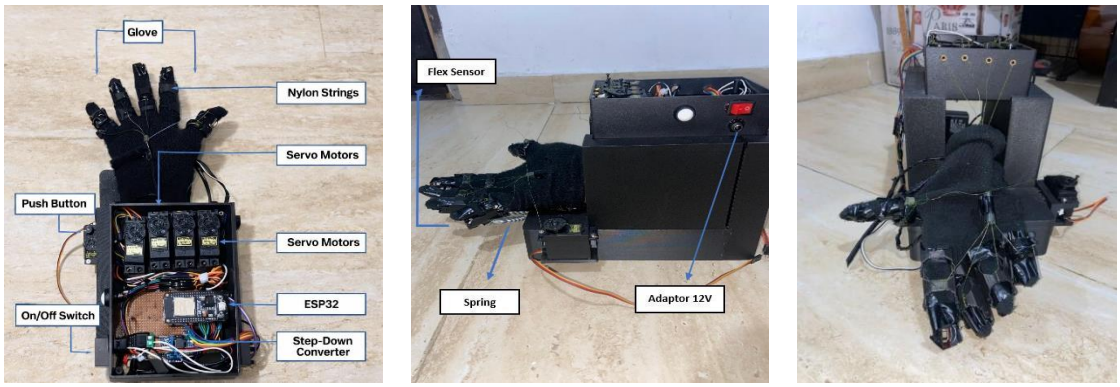
3. EXPERIMENTAL RESULTS AND DISCUSSION

3.1. Hardware implementation

This study proposes a SRG designed to assist post-stroke hand rehabilitation through controlled repetitive finger movements. The system architecture consists of three main components: sensing, actuation,

and control and monitoring. An ESP32 microcontroller is employed as the central processing unit due to its sufficient computational capability, integrated Wi-Fi module, and compatibility with real-time control and Internet of Things (IoT) applications.

Finger motion is actuated using TowerPro MG995 servo motors, which provide adequate torque to support passive finger flexion and extension. Five flex sensors are mounted on each finger (thumb, index, middle, ring, and little finger) to measure finger bending angles in real time, as presented in Figure 4(a)-(c).



(a) (b) (c)

Figure 4. Implementation hardware: (a) top view, (b) side view, and (c) front view

3.2. Flex sensor acquisition

Flex sensor calibration is a crucial step in ensuring the accuracy of the system in detecting and interpreting finger movements [28]. The calibration process is performed by bending the flex sensor at predefined angles measured using a protractor, namely 0°, 30°, 45°, 60°, and 75°, which represent the functional range of motion of the human finger. Each angle is measured ten times to obtain stable and representative ADC values for each flex sensor.

The data obtained from this calibration process are used to determine the relationship between the finger bending angle and the ADC value, which is subsequently implemented in the PID control algorithm to drive the servo motor. Calibration measurements of the flex sensor at different angles are illustrated in Figure 5. To convert raw ADC values into meaningful finger bending angles, a linear regression-based calibration approach was applied individually to each finger [29]. Due to differences in finger length, sensor placement, and mechanical characteristics, a single global calibration equation was not used.

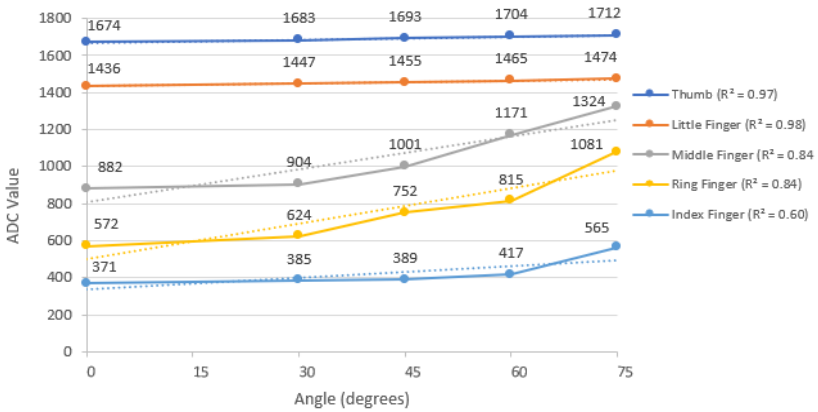


Figure 5. Graph of flex sensor ADC values versus finger angle variations

3.3. Tuning PID controller

The PID parameters were initially determined using an experimental trial-and-error procedure [30]. Rather than selecting the parameters arbitrarily, the tuning process was performed by systematically adjusting

the proportional, integral, and derivative gains while observing the angular response of the rehabilitation glove. The reference angle of 75° was selected as the tuning condition because it represents the largest reference angle evaluated in this study and therefore provides a relatively demanding operating condition for the tendon-driven mechanism. The proportional gain was first adjusted to obtain a sufficiently fast response while maintaining stable finger motion. The integral gain was subsequently introduced to reduce the steady-state error, while the derivative gain was adjusted to reduce excessive oscillation and improve the smoothness of the angular response. The resulting parameter combination was evaluated experimentally based on the ability of the system to reach and maintain the reference angle without excessive oscillation. Following this procedure, the final PID parameters were set to (K_p = 0.4), (K_i = 1.0), and (K_d = 0.1), and the same parameter set was applied to all five fingers.

Figure 6 shows the robotic glove response without PID control, where finger movements are unstable with noticeable initial fluctuations and inconsistent responses among fingers. The thumb and index finger approach the set point at around 11 seconds, while the middle, ring, and little fingers do not reach the reference angle within 15 seconds. This indicates steady-state errors, particularly in the ring and little fingers, demonstrating insufficient error correction without PID control. In this study, the PID parameters are tuned using a trial-and-error approach to obtain a stable response under the given experimental conditions. A single set of PID parameters is applied to all fingers to simplify the control implementation, although differences in mechanical characteristics and load across fingers may affect the uniformity of the response.

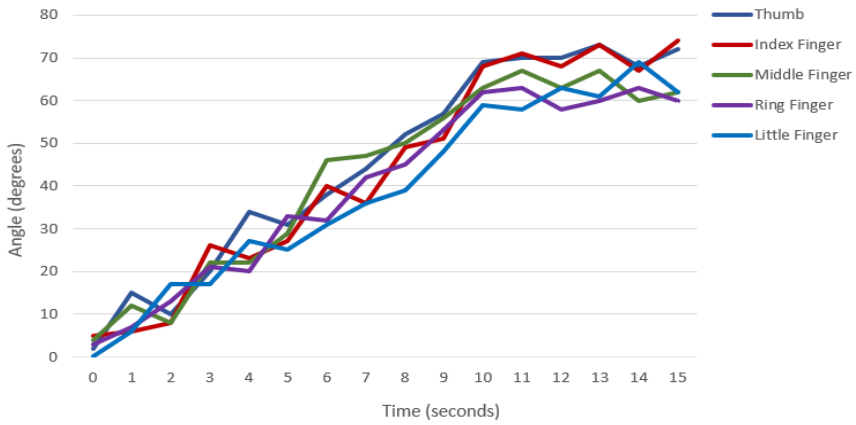


Figure 6. System response without PID

The Figure 7 illustrates the system response under proportional control with $K_p = 0.4$, while the integral and derivative terms are disabled ($K_i = 0$, $K_d = 0$). This stage aims to obtain a stable proportional gain before adding other control components. Under this configuration, all fingers move toward the set point with a more stable response. However, after approximately 7 seconds, the response reaches a steady condition at around 60–70°, failing to achieve the desired set point. This indicates a significant steady-state error, which occurs because pure proportional control produces a control signal that decreases as the error approaches zero, making it insufficient to overcome mechanical loads and actuator resistance. As a result, the system cannot drive the finger positions to the target angle.

The Figure 8 shows the system response after adding integral control with $K_p = 0.4$ and $K_i = 1.0$, while the derivative term remains inactive. The integral component is introduced to eliminate the steady-state error observed under pure proportional control. The results indicate that all fingers are able to reach and slightly exceed the 75° set point without stagnation. The thumb, index, and middle fingers reach the set point at approximately 8 seconds, while the ring and little fingers do so around 9 seconds. A slight overshoot up to about 80° is observed, caused by the accumulation of error in the integral term, which continues to generate control action after the target angle is reached.

The proportional gain K_p was increased first to obtain a faster initial response, followed by tuning of the integral gain K_i to reduce steady-state error. Subsequently, the derivative gain K_d was introduced to suppress excessive oscillations. The final tuning was performed using a full PID configuration with parameter values of $K_p = 0.4$, $K_i = 1.0$, and $K_d = 0.1$. The system response to this parameter combination was directly evaluated based on the flex sensor output data, is shown in Figure 9, to assess the effectiveness of the tuning process in improving control performance.

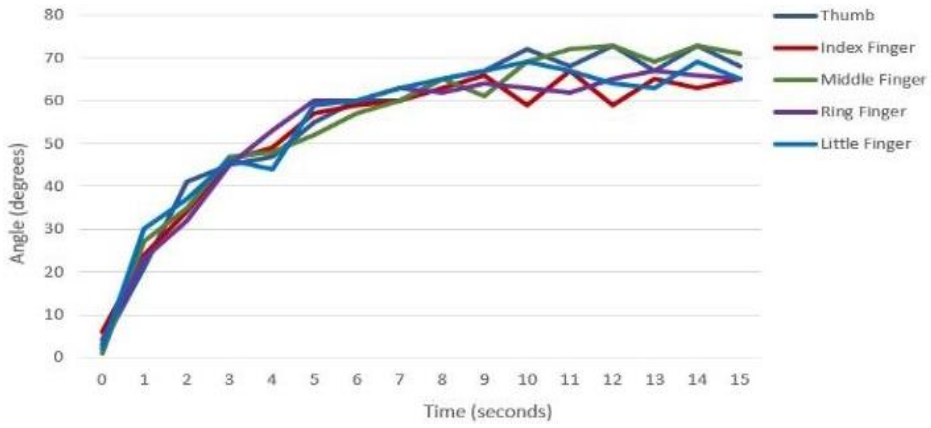


Figure 7. System response with $K_p = 0.4$, $K_i = 0$, and $K_d = 0$

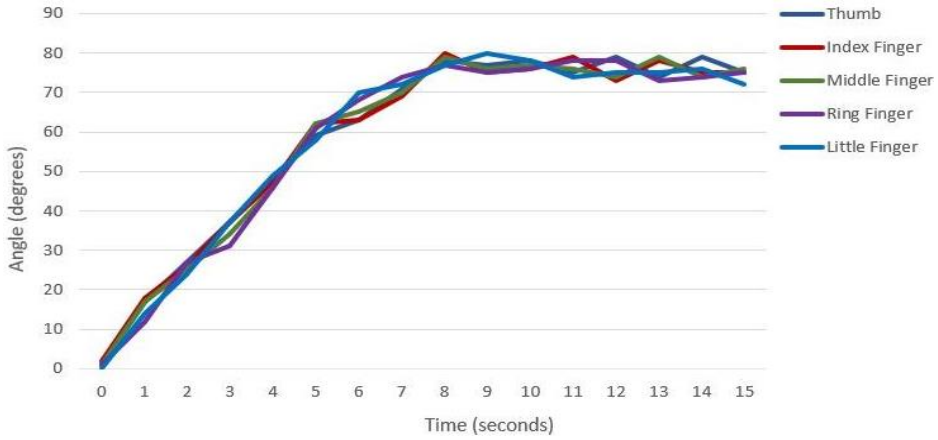


Figure 8. System Response with $K_p = 0.4$, $K_i = 1{,}0$, and $K_d = 0$

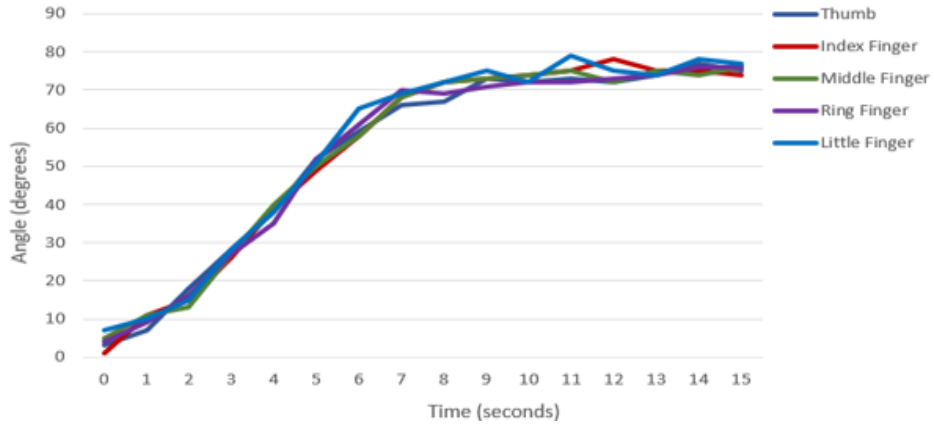


Figure 9. System response with $K_p = 0.4$, $K_i = 1.0$, and $K_d = 0.1$

3.4. System testing

System testing in this study was conducted to analyze the motion response of the robotic glove and to evaluate the effectiveness of the PID controller in improving finger movement stability and smoothness. The PID control parameters used in this experiment were set to $K_p = 0.4$, $K_i = 1.0$, and $K_d = 0.1$. The testing procedure began with observing the system response without PID control at several set-point angle variations of 30°, 45°, 60°, and 75°, which served as baseline conditions to characterize the system's motion

behavior before any corrective mechanism was applied to compensate for errors and disturbances. Subsequently, the PID controller was implemented at the same set-point angles of 30°, 45°, 60°, and 75°. For each test condition, the system response was evaluated based on the angular displacement over time and the IAJ value, which was used as a quantitative indicator of motion smoothness.

As depicted in Figures 10 and 11, at a 30-degree set point, the implementation of the PID controller was shown to significantly improve the smoothness of finger movements. The thumb exhibited a reduction in IAJ from 551.2 before PID to 152.4 after PID, corresponding to a decrease of 398.8 points or 72.35%. The index finger also demonstrated substantial improvement, with the IAJ value decreasing from 523.6 to 125.9, resulting in a reduction of 397.7 points or 75.95%. For the middle finger, the IAJ value was reduced from 434.8 to 146.9, representing a decrease of 287.9 points or 66.21%. The ring finger showed relatively high motion irregularity prior to PID control, with an IAJ value of 641.7; however, after PID implementation, this value decreased to 196.2, indicating a reduction of 445.5 points or 69.42%. Meanwhile, the little finger experienced the largest reduction, from 648.2 to 137.1, corresponding to a decrease of 511.1 points or 78.85%.

Figures 12 and 13 illustrate that the implementation of the PID controller significantly improves the smoothness of finger movements at a 45-degree set point. The thumb showed a reduction in IAJ from 542.4 to 175, representing a decrease of 367.4 points or 67.74%. The index finger experienced a notable improvement, with the IAJ value decreasing from 652.5 to 147.2, resulting in a reduction of 505.3 points or 77.44%. The middle finger exhibited a decrease in IAJ from 664 to 195.3, corresponding to a reduction of 468.7 points or 70.59%. The ring finger's IAJ value was reduced from 661.6 to 254.9, indicating a decrease of 406.7 points or 61.47%. Similarly, the little finger showed a reduction in IAJ from 696.7 to 218.7, corresponding to a decrease of 478 points or 68.61%.

The improvement in motion smoothness at a 60-degree set point with PID control can be observed in Figures 14 and 15, the increase in the operating angle resulted in higher initial IAJ values in the uncontrolled system. Nevertheless, after applying the PID controller, all fingers exhibited significant reductions in IAJ. The thumb showed a decrease from 558 to 260, corresponding to a reduction of 298 points or 53.41%. The index finger experienced a reduction in IAJ from 696.7 to 196.2, representing a decrease of 500.5 points or 71.84%. For the middle finger, the IAJ value decreased from 726.4 to 295.3, resulting in a reduction of 431.1 points or 59.35%. The ring finger showed a reduction from 784.4 to 291, corresponding to a decrease of 493.4 points or 62.90%. Meanwhile, the little finger demonstrated a decrease from 724.5 to 200, representing a reduction of 524.5 points or 72.39%.

The comparison of system responses in Figures 16 and 17, at the 75-degree set point, the uncontrolled system produced the highest IAJ values due to increased mechanical load and system dynamics. Following PID implementation, significant reductions in IAJ were observed across all fingers. The thumb exhibited a decrease in IAJ from 636.6 to 352.3, corresponding to a reduction of 284.3 points or 44.66%. The index finger showed a substantial improvement, with the IAJ value decreasing from 791.2 to 222.7, resulting in a reduction of 568.5 points or 71.85%. The middle finger experienced a decrease in IAJ from 823.3 to 313.9, corresponding to a reduction of 509.4 points or 61.87%. The ring finger demonstrated a reduction from 891.8 to 309.2, representing a decrease of 582.6 points or 65.33%. The little finger's IAJ value decreased from 734.9 to 273.8, corresponding to a reduction of 461.1 points or 62.74%.

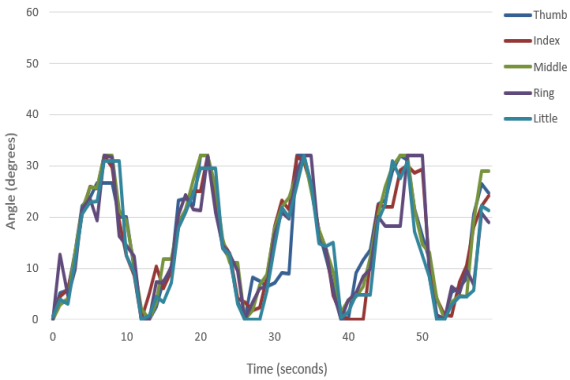


Figure 10. System response 30° angle before PID

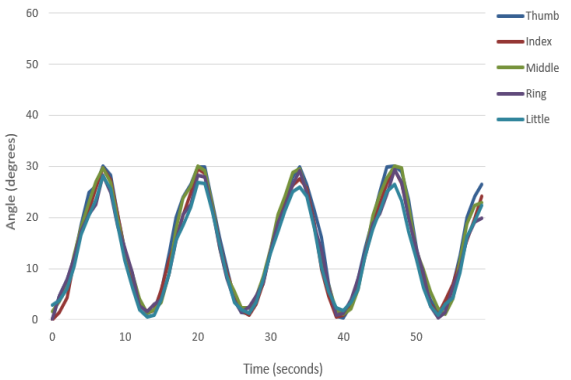


Figure 11. System response 30° angle after PID

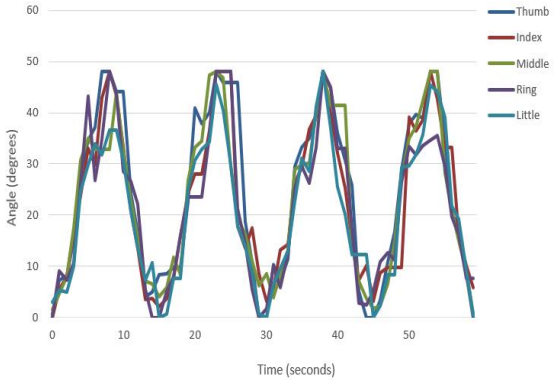


Figure 12. System response 45° angle before PID

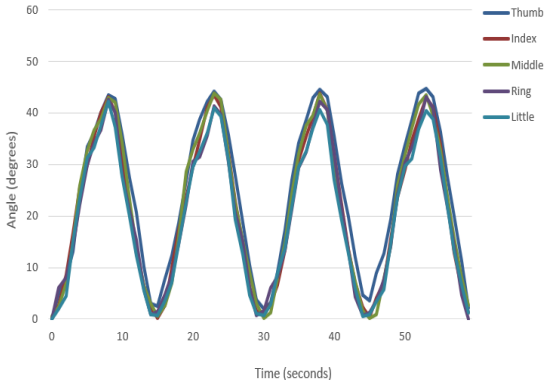


Figure 13. System response 45° angle after PID

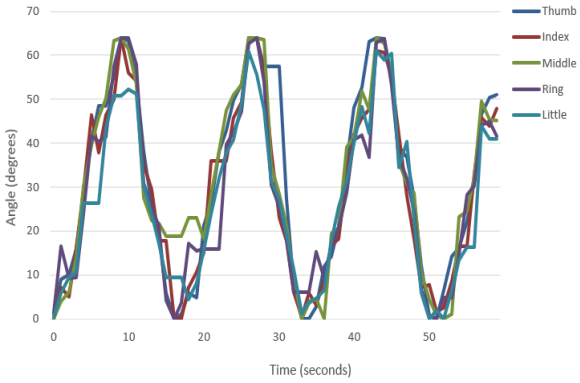


Figure 14. System response 60° angle before PID

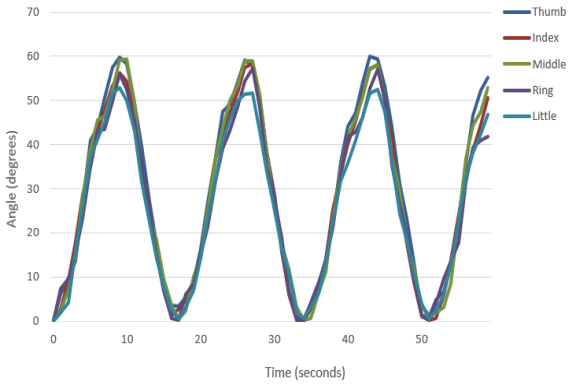


Figure 15. System response 60° angle after PID

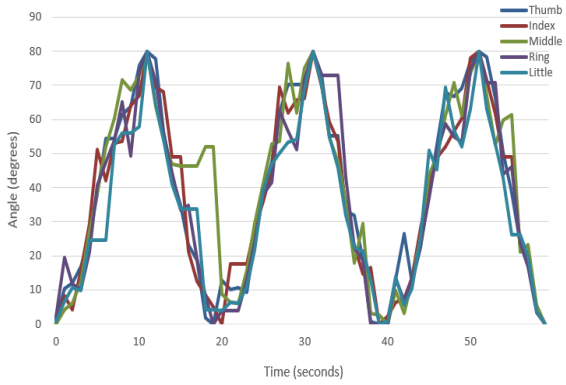


Figure 16. System response 75° angle before PID

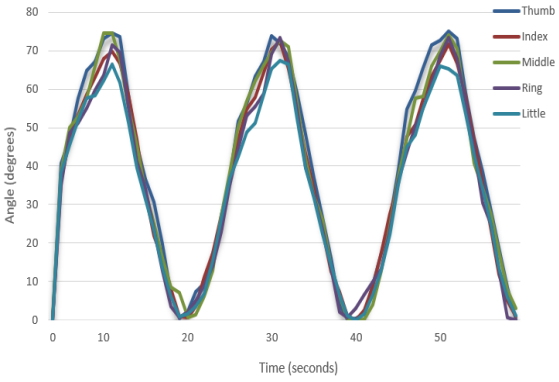


Figure 17. System response 75° angle after PID

4. CONCLUSION

The proposed PID-controlled rehabilitation glove demonstrated stable and repeatable finger movements for the tested rehabilitation exercises. Using the final PID parameters of ($Kp = 0.4$), ($Ki = 1.0$), and ($Kd = 0.1$), the system achieved 100% repetition success during functional tests conducted for 1, 5, and 10 min at a target angle of 75°. The motion smoothness analysis also showed substantial reductions in the IAJ compared with the uncontrolled condition, with average reductions of 72.56%, 69.17%, 63.98%, and 61.29% at target angles of 30°, 45°, 60°, and 75°, respectively. The overall average IAJ reduction was 66.75%, indicating that the PID controller improved the smoothness and stability of finger movements under the tested conditions.

These results indicate that the proposed system can provide controlled and repeatable finger movements and therefore has potential to support post-stroke hand rehabilitation exercises, particularly for

repetitive flexion and extension training. However, the present study was limited to technical validation of the robotic system and did not include clinical trials, patient-specific evaluation, or assessment of therapeutic outcomes. Future work should therefore investigate the system through clinical trials involving stroke patients, develop adaptive or patient-specific control strategies, and optimize the system according to individual hand characteristics and rehabilitation requirements

FUNDING INFORMATION

The authors declare that no funding was received for this research

AUTHOR CONTRIBUTIONS STATEMENT

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Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
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Achmad Zuchriadi				✓	✓					✓		✓		

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

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

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