Optimizing PID-Based Controller Utilizing Hybrid Evolutionary Algorithmn in Electric Motor-Driven Exoskeletons for Therapeutic Locomotion of Stroke Patients

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***Abstract*— Wearable robots have become increasingly significant in rehabilitation treatments aimed at improving patients suffering from walking gait abnormalities. The effectiveness of these robots depends on their ability to accurately track trajectories. This paper proposes a hybrid technique for tuning a PID controller in a wearable lower limb rehabilitation robot (WLLR). The combination of GA and PSO, termed HGAPSO, is utilized to acquire PID parameters for the hip and knee joints, with the aim of minimizing overshoot and tracking error. Notably, the percentage overshoot recorded by HGAPSO for the hip and knee is superior to that of conventional ZN, GA, and PSO methods, with percentages of 4.9% and 0.42%, respectively. Furthermore, the maximum error (ME) and average error (AE) between desired and actual trajectories recorded for a range of motion (ROM) and walking conditions do not exceed 0.05, which are deemed acceptable errors. The maximum root mean square error (RMSE) recorded for both ROM and walking conditions is 0.028 and 0.043, respectively. Additionally, the coefficient of determination (R^2) for both conditions is more than 99%, indicating a close fit between desired and actual trajectories under various conditions.**

Keywords—Lower Limb Robot, Exoskeletons, PID Controller, Genetic Algorithm, Locomotion, Particle Swarm Optimization

I. Introduction

In recent years, there has been an increase in stroke patients and the aging population experiencing abnormal walking gaits [1]. Consequently, the demand for wearable robots in rehabilitation treatments has become more pronounced [2]. Researchers have thus focused more on designing and developing wearable rehabilitation robots to restore muscle strength and address walking gait abnormalities. Additionally, these robots assist patients who have lost their ability to perform daily tasks due to conditions such as accidents and spinal cord injuries (SCI). Wearable lower limb rehabilitation robots (WLLRs) operate alongside human limbs, aiming to rehabilitate patients who are unable to walk [3-6]. Furthermore, WLLRs function as gait training robots requiring controllers to minimize steady-state errors and improve tracking performance. Various methods and algorithms for controlling WLLRs have been explored [7-8].

The Proportional-Integral-Derivative (PID) controller is widely used in position tracking control due to its simplicity, robustness, and successful practical applications. Galvan et al. [9] designed a PID controller for WLLRs that exhibited good joint angle tracking performance despite disturbances. Similarly, Sanngoen et al. [10] utilized PID to control the WAR robot, demonstrating consistent footpath and actual foot trajectory patterns. The accuracy of the position tracking control algorithm depends on precise controller tuning, which enhances the robot's ability to track input signals while minimizing position tracking errors. The conventional Ziegler-Nichols (ZN) method is a popular approach for tuning PID controllers due to its speed, simplicity, and ease of implementation. Several studies have reported tuning WLLR positions using conventional ZN [11-12]. However, this method still has drawbacks, such as the need for further fine-tuning to improve transient response and tracking errors. Additionally, the PID closed-loop system is highly sensitive to parameter variations, resulting in large overshoots and oscillatory responses. Thus, there is ongoing research interest in improving controller accuracy and reducing position tracking errors.

To address these challenges, optimization techniques such as genetic algorithms (GA) and Particle Swarm Optimization (PSO) have been introduced to tune PID parameters. GA is an evolutionary optimization technique that employs concepts of natural selection, crossover, and mutation [13]. Meanwhile, PSO is a metaheuristic technique inspired by biological behaviors such as swarming, bird flocking, and fish schooling [14]. Elbayomy et al. discussed PID controller tuning using GA for the Electro-Hydraulic Servo Actuator System (EHSAS), showing improved PID performance compared to conventional tuning methods [15]. Similarly, Cuellar et al. [16] combined Gain Phase Margin (GMP) with GA to tune the

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PID controller, while Azar et al. [17] utilized GA to optimize controller parameters for a six-bar Steward parallel robot. PSO has also been employed in various applications, including tuning PID control for lower-limb human exoskeletons. Although PSO converges faster than GA in achieving globally optimal solutions, it is susceptible to getting trapped in local optima.

In this study, our contribution lies in implementing a hybrid technique that combines genetic algorithms and particle swarm optimization, termed hybrid HGAPSO, to acquire PID controller parameters for WLLR joints. Our motivation behind this hybrid technique is to enhance the chances of minimizing control overshoot and reducing tracking errors across both ranges of motion (ROM) and walking gait conditions. We derived the transfer function of a dynamic model for the hip and knee joints using Lagrangian formulation and Kirchoff's Law, based on mathematical modeling approaches [18]. A decentralized closed-loop control system is utilized in the tuning process, where GA is initially run with random initial values, and the results guide PSO to find optimal PID parameters for the control system. We simulate a three-dimensional model (3D) of the WLLR using MATLAB Simmechanics software to analyze the proposed controller's behavior under different experimental conditions, including ROM and walking gait conditions

II. Methodology

A. Development of Controller

A closed-loop control algorithm implemented for the WLLR is represented in Fig. 1, in which the left/right hip and knee joint is controlled by PID separately. The and represent the desired and actual trajectory of the control system. A PID controller is used for controlling the joints of the WLLR due to its potential in providing satisfactory results and comfort of operation [19]. Besides, the PID controller's characteristic is simple, easy to implement, robust and practical in a wide range of application. The closed-loop transfer function of the PID controller is expressed in (1).

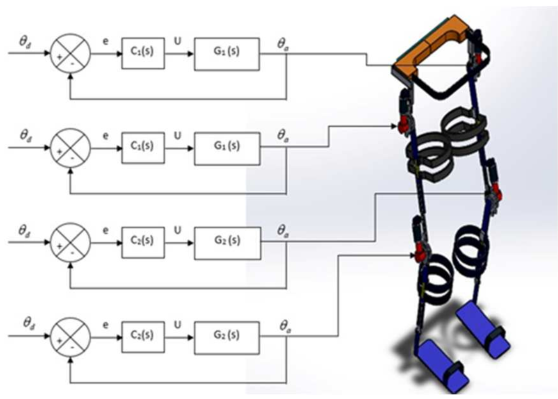


Fig. 1: Closed Loop Control Algorithm for hip and knee joint

$$\frac{\theta_{a_i}(s)}{\theta_{d_i}(s)} = \frac{C_i(s)G_i(s)}{1+C_i(s)G_i(s)} \quad (1)$$

The transfer function of a dynamic model is present by while i =1, 2 represents the femur and tibia respectively. is the transfer function of the PID controller written as in (2).

$$C_i(s) = \frac{U}{e} = K_p + \frac{1}{s}K_i + K_d s \quad (2)$$

Kp, Ki, and Kd respectively present proportional, integral, derivative parameter. The tracking error is different between desired and actual trajectory expressed in the following equation.

$$e_i(s) = \theta_{d_i}(s) - \theta_{a_i}(s) \quad (3)$$

where and is the desired and actual trajectory of the WLLR motion. is denoted as the input error to the PID controller while (s) is the controller output and input to the dynamic model. The objective function of optimization is determined by fixed the control system input as a step response (= 1) while i=1,2,3,4 represent right hip, left hip, right knee and left knee, respectively. Therefore, by substitution of (1) in (3), the error is expressed in (4).

$$e_{obj_i}(s) = 1 - \frac{C(s)_i G_i(s)}{1+C(s)_i G_i(s)} \quad (4)$$

In this study, the objective function is determined based on Integral Time Absolute Error (ITAE) [5], which is the summation of absolute error, weighted by time and sample time is expressed as in the following equation;

$$ITAE = f_{obj_i} = \int_0^\infty t\,|e_{\mathrm{obj}_i}(t)|\mathrm{dt} \quad (5)$$

where is the error of the control system in the time domain and is the elapsed time. This section details the methodology employed in the research. The modeling of WLRR is detailed out in []It is focused on the designing the controller, and will further elaborate on the utilization of a hybrid algorithm for tuning the PID controller.

B. Hybrid Algorithm for PID-Based Controller

The PID tuning is set as an optimization problem and solved by the combination of genetic algorithm(GA) and Particle Swarm Optimization(PSO) in series, called HGAPSO (Hybrid technique). GA is an evolutionary optimization technique based on the concept of natural selection, crossover and mutation [20]. Meanwhile, PSO is a metaheuristic technique called population-based optimization strategy, inspired by the biological behaviour of swarms, birds flocking, and fish schooling [21]. The tuning process stated by the GA optimization algorithm and the optimized parameters of Kp, Ki, and Kd values obtained used as initial values of the PSO algorithm. Hence, GA provides search space or initial value for the PSO algorithm. The PSO then converges the PID parameters to the optimal solution. In this technique, the PSO resembles GA in setting the initial population and finding the best solution iteratively. However, there is no mutation and crossover. PSO has been implemented in various types of problem and proven to converge faster than GA in achieving a globally optimal solution, but easy to trap in local optima [22-23]. The design variables of the optimization problem are three parameters of the PID controller. Fig. 2 illustrates the configuration of the first population, in which each gene consists of 30 sets of random values for PID parameters. After creating the initial population, each gene is evaluated by the objective function. The genes are then arranged based on the objective function value by sorting from the lowest to the highest. The generation is created by crossover, mutation and some of them evaluated as the best gene remains unchanged called "elite genes"[24]. Crossover extracts the genes from the population and recombines them to increase the chance of finding the best result. Mutation remains the diversity of GA from one generation to the next one.

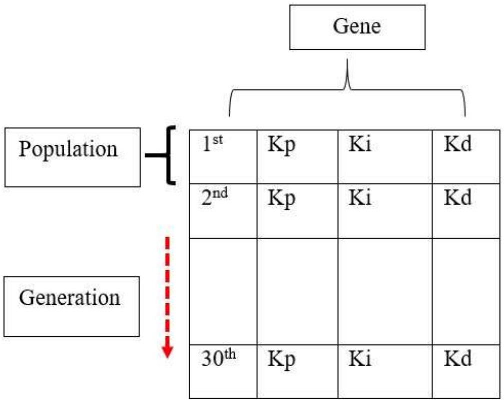


Fig. 2. Initial Population Configuration

Creating the next generation consists of keeping 5% of the previous population unchanged as elite genes. These genes should have the best results after evaluation. In this study, crossover and mutation probabilities are set to 0.8 and 0.2. It means that 80% of the remain population are selected via a crossover, and the rest 20% be filled using mutation. The adaptive feasible is selected as a method for mutation. The GA parameters setup in MATLAB is shown in Table I. The optimization and evaluation cycle continues until the generation of GA terminated. It means that the GA achieved the optimal solution. The output of GA is shown as in (6);

$$X_{GA} = [K_p, K_i, K_d] \tag{6}$$

The optimization process then continues by the PSO algorithm, in which each particle carries the PID parameter values, as shown in (7).

$$X_{1,j} = rand([X_{GA} - y, X_{GA} + y]) \tag{7}$$

Where y is defined as parameter tolerance. The population of the next generation is created as in (8).

$$X_{i,j} = X_{i-1,j} + V_{i,j} \tag{8}$$

TABLE I. GA TUNING PARAMETERS

GA Property	***Value/Method***
Population Size	30
Number of Generation	Hip:60 Knee:60
Objective Function	ITAE
Selection Function	Tournament
Probability of Crossover	0.8
Crossover Function	Arithmetic
Mutation Function	Adaptive Feasible
Probability of Mutation	0.2
Elite Genes	0.05

Where Vi, j represents the next generation particle and x i −1, j is the particle of the previous generation. Generally, the velocity equation in PSO is written as follows:

$$V_{i,j} = \omega_i x V_{i-1,j} + c_1 x\ rand_1 x\ p_{best,i-1} - c_2 x\ rand_2 x\ g_{best} - x_{i,j} \tag{9}$$

where rand 1 and rand 2 are the random values between 0 and 1, C1 and C2 are positive coefficients of the self-recognition component and social components respectively, usually, the value is set as 2 . Pbest, i and g best are defined as the best position of each population and global best of them respectively while ωi is called as the inertia weight where its value readjusted as the following equation per each iteration:

$$\omega_i = \omega_{damp} x\ \omega_{i-1} \tag{10}$$

ω damp is set as 0.05. In each generation, the objective function is determined to evaluate the particles. Each particle with a minimum value of the objective function is stored as p best, i. Among the stored value of p best, i, the lowest value is selected as global best, which shown as g best. The PSO tuning parameters setup in MATLAB is shown in Table II. The particle of g best is chosen as the final result of the HGAPSO algorithm.

TABLE II. PSO TUNING PARAMETERS

GA Property	***Value/Method***
Population Size	30
Number of Generation	Hip:40 Knee:40
Objective Function	ITAE
Self Recognition Component (C1)	1.5
Social Component (C2)	2
Initial Weight	0.05

In this technique, the total number of generation setup is 100. It means that, for the hip, 60 generations is run by using GA tool box in MATLAB and 40 generations continued by using PSO code developed in MATLAB. Similarly for knee, 60 generations is run by GA and the rest 40 generation is run by PSO to obtain the optimal solution. The optimization block diagram of GA, PSO and HGAPSO in MATLAB is shown as in Fig. 3.

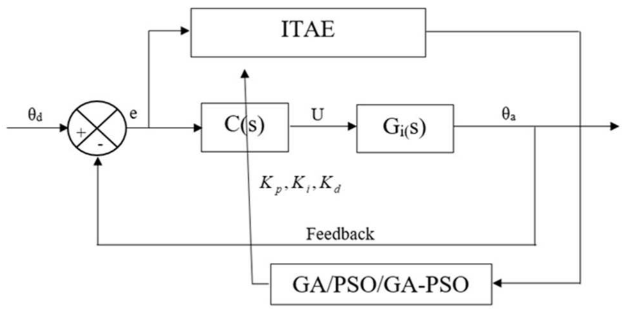


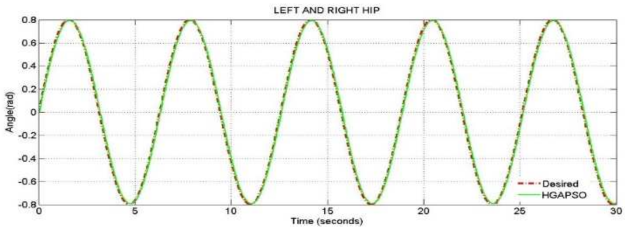
Fig. 3: Optimization Block Diagram in MATLAB

III. RESULTS AND DISCUSSIONS

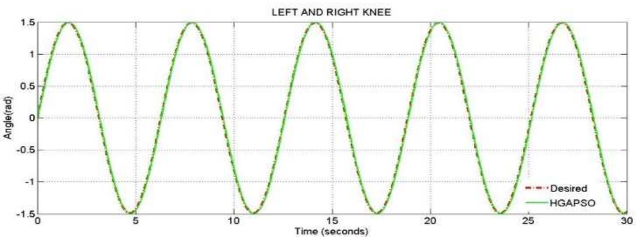
In order to verify the controller performance, PID parameters tuned via HGAPSO has been added to the simulation model as shown in Fig. 1. The WLLR model was tested to validate the performance of the controller in two different simulation experiments, which are ROM and walking gait condition. In ROM condition, only one joint is moved while the other joints are fixed [9]. The ROM trajectory applied to the hip and knee joint shown in Table III. Fig. 4 compares the desired and actual trajectory performance of WLLR controlled by PID via HGAPSO in ROM condition. Fig. 4(a) illustrated the right and left hip, while Fig. 4(b) illustrated the right and left knee.

TABLE III. PID PARAMETERS (HIP)

	MROM (radian)	*MROM (degree)*	*MS (rad/s)*
Hip Flexion/Extension	-0.8 to 0.8	-45.84 to 45.84	1
Knee Flexion/Extension	-1.49 to 0	-85.37 to 0	1



(a)

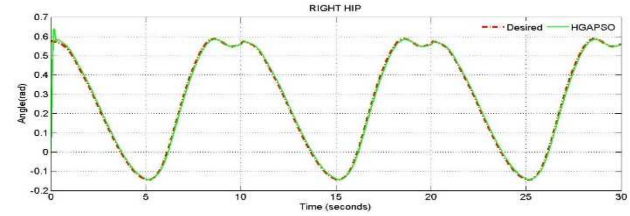


(b)

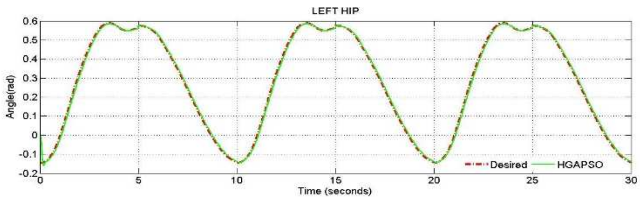
Fig. 4: Tracking Performance of PID-HGAPSO in ROM Condition (a) Right and Left Hip (b) Right and Left Knee

Statistical analysis was carried out in order to validate the data result. The statistical analysis of the PID tuned via HGAPSO performance in ROM which is ME, AE, RMSE, and R^2 represent the maximum error, average error, root-mean-square and coefficient of determination, respectively. The results discovered that ME and AE recorded for ROM condition are still not exceeding 0.05, which are still acceptable for ROM. Besides, the maximum of root means square error(RMSE) is only 0.028 while R^2 of all joints are more than 99 %. These statistical results indicating that the desired ROM trajectory nearly fitted to all variability of the actual ROM trajectories.

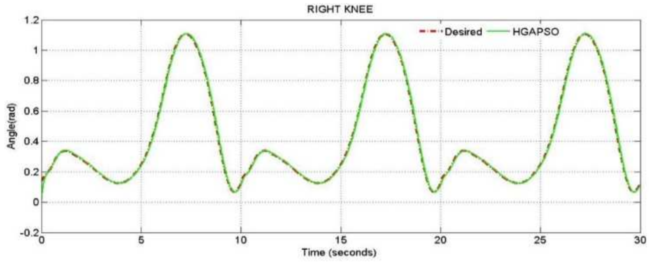
In walking condition, hip and knee joints for both left and right leg moved simultaneously to test the controller performance. Human gait was adopted as input for motion trajectory. However, some modification was made in order to fix the gait data to the simulation model. The walking gait result illustrated as in Fig. 6, which is Fig. 5(a) and Fig. 5(b) represent right and left hip, while Fig. 5(c) and Fig. 5(d) represent right and left knee, respectively. Similarly ROM, Statistical analysis was also carried out to validate the data result. The results revealed that ME and AE for walking condition are also not exceeding 0.05, which are still acceptable for walking motion. Furthermore, the maximum of RMSE is only 0.043 while R^2 of all joints are more than 99 %, indicating that the desired precisely fitted to all variability of the actual walking trajectories.



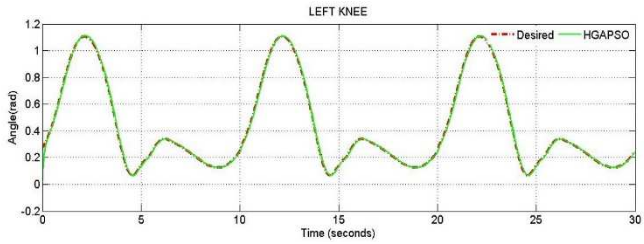
(a)



(b)



(c)



(d)

Fig. 5: Tracking Performance of PID-HGAPSO in Walking Condition (a) Right hip (b) Left hip (c) Right Knee (d) Left knee

IV. CONCLUSION

The dynamic of the WLLR is derived using Lagrangian formulation and Kirchhoff's law based on a mathematical modelling approach. The optimized PID parameters Kp, Ki, and Kd, were tested in the 3D model in MATLAB Simmechanic for two different experiments which are ROM and walking gait conditions. The results showed that the PID control tuned via HGAPSO is better than the conventional PID tuning in term of overshoot and tracking performance. The tuning process started with a genetic algorithm (GA), and the result obtained provides search space for particle swarm optimization(PSO) to converge the optimal solution for the PID parameters. This technique can be used to tune PID control for WLLR in order to help stroke patients in lower limb training. However, the limitations of this study are the controller only tested on the fixed structure and not tested on the actual structure of the WLLR. Besides, the influences of disturbance of the human are not considered in this study. Based on these limitations, an adaptive control system based on PID tuned via HGAPSO can be extended in future works to wind stand against disturbance and flexible to the adjustable frame of the WLLR. This analysis is essential as a preliminary stage before further development of adaptive control for WLLR.

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