A PSO Based Online Adaptive PID Controller for Assistive Lower Limb Exoskeleton

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***Abstract*—Robotic exoskeletons have demonstrated excellent performance in gait assistive tasks for the elders. However, the design of the exoskeleton controller still cannot meet the requirements of fast convergence rate and environment with uncertain perturbations. In this paper, we proposed a PSO based online PID controller for driving a 9-DOF lower limb exoskeleton to track the given joint trajectory. An improved PSO algorithm is proposed for online adaptive PID controller, which is used for the torque generation. By the human walking simulation experiment, we demonstrate that the angle tracking error at the hip joint, knee joint, and ankle joint is no more than 0.0013 rad/s, which surpasses the classical PID controller and the conventional offline PSO based PID controller. There are only few parameters to be predetermined, which has large potential in complex environment control problems, where the complicated human-robot interaction modelling, the unpredictable, stochastic perturbations from human efforts, environmental changes and other external disturbances appears as unavoidable challenges.**

Keywords—PSO, exoskeleton, trajectory tracking

I. INTRODUCTION

The aging of the global population has become one of the most serious problems for modern human society. In China, the proportion of people over 65 expects to increase from 13.5% in 2021 to 24% in 2050, reaching the total cost of 429 million Yuan, just for the inpatient care of the 80+ population [1]. For the elders, aging can result in deterioration of various cognitive organs as well as the onset of physical illnesses [2]. Gait disorders and lower-limb impairment are comment and often devastating companions of aging [3]: studies showed that 35% of people over 70 are troubled by gait disorders, and the percentage soared to 80% for the elderly over 85 [4]. Moreover, gait disorders and lower-limb impairment have been recognized as one of the biggest risk factors for the elderly falls, which are responsible for bone fractures and severe head trauma [5].

Robotic exoskeletons have been propose as an excellent solution by scholars and doctors to assist seniors affected by gait disorders and lower-limb impairment in the past 20 years. An exoskeleton is a wearable robot that can provide support, assistance, or protection through interaction with human limbs. For individuals with limited mobility or requiring gait rehabilitation, walking with exoskeletons can be a promising way of reducing muscle fatigue, metabolic expenditure, or injury rates [6].

One of the most important factors that affects an exoskeleton's performance is the control strategy. Various controllers, such as PID controller [7], fuzzy controller [8], central pattern generator (CPG) based controller [9], and impedance/admittance controller [10], have been implemented and evaluated for driving the device. PID control, which is wildly applied in industrial manipulators, is the simplest and most effective method for exoskeleton driving with the absence of robot knowledge. But tuning the parameters in conventional PID algorithm for multi-joint exoskeletons can be a difficult and time-wasting task [11]. Wang et al. proposed a fuzzy self-tuning PID algorithm to change PID parameters online and evaluated their method in a lower limb soft exosuit [8]. However, the determination of fuzzy rules is supported by substantial priori knowledge and extra complicated robust modification needs to be applied to assure stability with respect to uncertainties [12]. The same challenge occurs in CPG and impedance/admittance controller, where the hyper-parameters can only be determined previously by priori knowledge or parameter identification. In [13], 60 Gaussian functions were used as kernel of the non-linear filter in CPG controller. Moreover, there is no online adaptive CPG or impedance/admittance controller implemented for lower-limb exoskeletons yet.

On the other hand, heuristic algorithms have been integrated with conventional controllers for performance improvement. Among various metaheuristics, the particle swarm optimization (PSO) algorithm possesses unique merits in that it is robust, simple to realize, and have very few parameters to be tuned. Hence, the PSO algorithm is capable of dealing with complex high-dimensional nonlinear systems and dynamic optimization problems of various backgrounds [14-17]. Amiri et al. developed an intelligent PID controller for a 4-DOF exoskeleton, where the particle swarm optimization (PSO) algorithm was employed to effectively determine the PID gains [18]. In spite of its potentials, the limitations of PSO algorithms that impede its further applications cannot be overlooked: compared with other methods like CPG and impedance control, the convergence time of the conventional PSO algorithm is too long to be implemented online, and undesired chattering phenomena may be induced. Additionally, in the scenario of robotic exoskeleton, the complexities in human-robot interaction modelling, and the unpredictable, stochastic perturbations from human efforts, environmental changes and other external disturbances, make it challengeable for all control strategies [11].

In this paper, we proposed a PSO based online PID controller that drives a 9-DOF lower limb exoskeleton to track the given joint trajectory. An improved PSO algorithm is proposed for online adaptive PID controller, which is used for the torque generation. We demonstrate the excellent tracking performance and the rapid convergence of the exoskeleton, with only few parameters to be predetermined. The rest of this paper is organized as follows. Section II presents the exoskeleton and analyze the dynamic model of the exoskeleton. Section III describes the procedure of the proposed PSO based online adaptive PID controller. Section

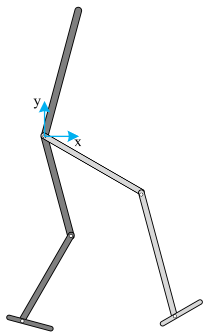

Fig. 1. The 2-dimensional exoskeleton model

IV shows the experiment that demonstrate the feasibility and effectiveness of the control scheme. Finally, section V discusses the results and draws conclusions based on the experimental results.

II. Lower Extremity Exoskeleton

A. System Design

Figure (1) shows the 2-dimensional human-exoskeleton system model. The 9-DOF exoskeleton, consisting of a trunk and two legs, is designed for human gait assistance. By generating assistive torque in each powered joint, the exoskeleton can cooperate the user to maintain a normal, stable gait during walking.

Each leg of the exoskeleton is further divided into three components: a thigh, a shank and a foot. They are connected to each other by 1-DOF joints, namely hip joint (connecting hip with thigh), knee joint (connecting thigh with shank), and ankle joint (connecting shank with foot). The joint connecting trunk and hip have three DOF: the trunk of the exoskeleton can not only rotate around the hip link in sagittal plane, but translate along the x and y directions. In sum, the exoskeleton has a total of 9 DOF. All the joints are equipped with a motor, generating torque by PID controllers given coefficients K_p, K_i and K_d. The 27 parameters are determined and optimized in real time by improved PSO algorithm. n the 2-dimensional model of the exoskeleton, the trunk, thigh, and shank are simplified into rigid rods, and the foot is simplified into a T-type rigid component.

B. Dynamic modelling

In this model we aim to reconstruct as much detailed constraints of human-exoskeleton interaction in the real world as possible [11]. Let $\mathbf{q}$ be assigned as vector $\mathbf{q} = (x, y, q_{\mathrm{B}}, q_{\mathrm{TL}}, q_{\mathrm{TR}}, q_{\mathrm{SL}}, q_{\mathrm{SR}}, q_{\mathrm{FL}}, q_{\mathrm{FR}})^{\mathrm{T}}$, and according to the Lagrange Equation of the first kind, we have

$$\mathbf{M}(\mathbf{q})\ddot{\mathbf{q}} + \mathbf{C}(\mathbf{q},\dot{\mathbf{q}})\dot{\mathbf{q}} + \mathbf{N}(\mathbf{q}) = \boldsymbol{\tau}_{\mathrm{M}} + \boldsymbol{\tau}_{\mathrm{I}} + \mathbf{F}_f + \mathbf{G} \tag{1}$$

where $\mathbf{M}(\mathbf{q})$, $\mathbf{C}(\mathbf{q},\dot{\mathbf{q}})$, and $\mathbf{N}(\mathbf{q})$ indicate the mass matrix, the damping matrix and the stiffness matrix of the exoskeleton, respectively; $\boldsymbol{\tau}_{\mathrm{M}}$ indicates the assistive torque generated by motors; $\boldsymbol{\tau}_{\mathrm{I}}$ indicates the human-exoskeleton interactive force; $\mathbf{F}_f$ indicates the friction between human and ground; $\mathbf{G}$ is the gravity compensation term.

III. PSO Based Online Adaptive PID Controller

One of the key strengths of the proposed PSO based online adaptive PID control method is that it can guide the lower-level PID controller to modify its parameter in real time. The method combines the advantages of PSO algorithm and PID controller: compared to the conventional PID controller, CPG controller and impedance/admittance controller, the PSO based PID controller needs only few hyper-parameters to be predetermined; additionally, instead of determining the global optimized parameter offline, the PSO based PID controller can adapt its parameter in real time according to the condition of the exoskeleton and other perturbations, and thus be more stable and more adaptive to the unknown environment. Compared to the traditional PSO algorithm, the proposed adaptive PSO algorithm is able to converge much rapidly for its particular modification for online optimization, which will be described in detail in the following subsections.

A. PSO based PID control scheme

As introduced in section II, the exoskeleton is equipped with 9 motors, each controlled by an independent PID controller for trajectory tracking task, where the parameters K_p, K_i and K_d can be optimized by PSO method in real time. Figure (2) displays the diagram of the proposed PSO based PID control scheme.

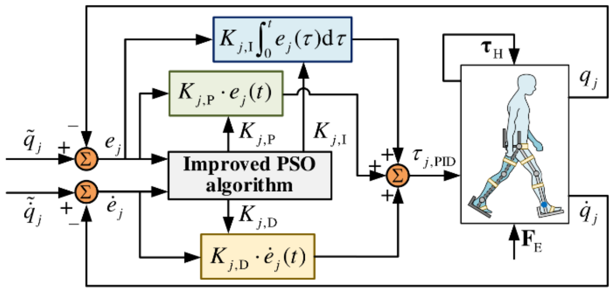

Fig. 2. Diagram of the proposed control scheme

As shown in the diagram, the human-exoskeleton system is affected by four forces during walking at time t: the motor drive force $\boldsymbol{\tau}_{\mathrm{M}}$, the human-exoskeleton interaction force $\boldsymbol{\tau}_{\mathrm{I}}$, the friction and propel force $\mathbf{F}_f$ between the system and ground, and the gravity force $\mathbf{G}$. The consequent angle q and angular velocity $\dot{q}$ can thus be calculated based on the dynamic model we constructed in section II in simulation. The kinematic data can also be collected by sensors on the device in practice. Then the angle error e and angular velocity error $\dot{e}$ are obtained by comparing the calculated/measured data with the desired trajectory $\tilde{q}$ and $\dot{\tilde{q}}$ (the desired trajectory is obtained from experiment data of normal human walking). Thus the PID controller, using the angle error and angular velocity error as input, generates assistive torque $\boldsymbol{\tau}_{j,\mathrm{PID}}$ for the next torque cycle; meanwhile, the PSO algorithm evaluate the performance of the controller and modify the parameter configuration for the next iteration.

B. The Proposed online PSO algorithm

The core advantage of the PSO based PID controller that surpass conventional PID controller, CPG controller or impedance/admittance controller is that the parameters can be adaptively optimized online with fast convergence rate, which has a great potential in real world where the perturbations are uncertain and the environment is complex and time-variant. This is achieved by the online PSO algorithm. The mechanism of online PSO is different from that of traditional offline PSO: in online PSO algorithm, optimization procedure is guided chronologically, which means the environment of every particle and every iteration is not the same.

The overall procedure of the online PSO algorithm is summarized as Algorithm 1 and each step of the algorithm is described below in detail:

1) Initialize the population

A population is a set of N particles with D dimensions, which have their own position and velocity. The position $\mathbf{x}^k$ and velocity $\mathbf{v}^k$ of the kth particle p^k, k = 1, 2, …, N, are the D-dimensional vectors as follows:

$$\mathbf{x}^k \in \mathbb{R}^D, \mathbf{v}^k \in \mathbb{R}^D \tag{2}$$

In practice, in order for better performance and faster convergence rate, the initial position of every particle in the population can be set either according to priori knowledge or by offline PSO algorithm. To better show the performance of our algorithm, here we randomize the position and zeroize the velocity of every particle in the population.

The fitness of the kth particle is calculated according to the fitness function f_k, which can be represented as follow:

$$f_k = \frac{1}{\Delta t}\sum_{t_0}^{t_0+\Delta t}\sqrt{\alpha\sum_j e_j^2(t) + (1-\alpha)\sum_j \dot{e}_j^2(t)} \tag{3}$$

where Δt is the control period of kth particle, t_0 is the time kth particle starts to control the motors, j = 1, 2, …, 9 refers to the 9 motors on the exoskeleton, $e_j(t)$ and $\dot{e}_j(t)$ are the angle error and angular velocity error of jth motor. α is weight coefficient, indicating the importance of the angle error relative to angular velocity error. We let $\alpha = 0.5$ and $\Delta t = 0.002$. Obviously the lower the value of fitness function is, the more preferable the particle is.

The personal best parameter configuration of the kth particle $\mathbf{X}_{pb}^k$ and the global best parameter configuration $\mathbf{X}_{gb}$ is

$$\begin{aligned}\mathbf{X}_{pb}^k &= \arg\min_{\mathbf{x}^k} f_k\left(\mathbf{x}^k\right)\\ \mathbf{X}_{gb} &= \arg\min_{\mathbf{X}_{pb}^k} f_k\left(\mathbf{X}_{pb}^k\right)\end{aligned} \tag{4}$$

which means $\mathbf{X}_{pb}^k$ is the local best position of kth particle from the beginning till now, while $\mathbf{X}_{gb}$ is the global best position of the population with the lowest fitness function value from the beginning till now. Obviously, for the first iteration, we have

$$\mathbf{X}_{pb}^k = \mathbf{x}^k, \mathbf{X}_{gb} = \arg\max_{\mathbf{x}} f_k(\mathbf{x}) \tag{5}$$

2) Drive the control system to walk

To ensure the instantaneity of the algorithm, instead of evaluating all particles in the population simultaneously, only one particle was injected into the human-exoskeleton system for control and evaluated according to the fitness function. The torque generated by motors satisfies the classical PID control law:

$$\tau_{\mathrm{PID},j}(t) = K_{p,j}e_j(t) + K_{i,j}\int_{t_{0,j}}^{t_{0,j}} e_j(s)\,\mathrm{d}s + K_{d,j}\dot{e}_j(t) \tag{6}$$

where $K_{p,j}$, $K_{i,j}$ and $K_{d,j}$ are the PID parameters of the jth motor. Hence, within each control period, only one particle is put into use for the control system. This is one of the key point in which the online PSO optimization algorithm differ to other offline algorithm: the parameter configuration doesn't necessarily converge to the optimal/ suboptimal one before the control procedure begins. The "working particle" is evaluated in real time, and its fitness function is updated based on (3).

3) Update the population

After all particles in the population have been put into control, the personal best parameter configuration of each particle and the global best parameter configuration is updated according to (4). Then the population can be updated, given by

$$\begin{aligned}\mathbf{v}_{i+1}^k &= w\mathbf{v}_i^k + c_1 r_1\left(\mathbf{X}_{pb}^k - \mathbf{x}_i^k\right) + c_2 r_2\left(\mathbf{X}_{gb} - \mathbf{x}_i^k\right)\\ \mathbf{x}_{i+1}^k &= \mathbf{x}_i^k + \mathbf{v}_i^k\end{aligned} \tag{7}$$

where w, c_1 and c_2 are constants, xi and vi is the velocity of kth particle after ith iteration. The pseudo code is displayed as Algorithm 1.

Algorithm 1: PSO based online PID controller

```
Start
Initialize desired trajectory q_d, control frequency f_s, loop number n
and other experimental configurations
Initialize particle number m, constant w, c_1, c_2, α, Δt
Randomize the position, and zeroize the velocity of the m particles
for j = 1 : n do
  for i = 1 : m do
    Put the particle x_i into control system
    while lasting time < Δt do
      Calculate control torques using (6)
      Apply torques, then calculate the system response by (1)
      Measure angle error and angular velocity error
    end while
    Update fitness function f_i of ith particle by (3)
  end for
  Update personal best and global best parameter configuration
by (4)
  Update the velocity and position of each particle by (7)
end for
End
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IV. Human Walking Simulation and Results

This section examines the performance of the proposed PSO based online adaptive PID controller. The controller is used to drive the motors on a 9-DOF exoskeleton to generate assistive torque for human walking. The aim for the controller is to track the desired joint trajectory as fast and precise as possible. The population has 100 particles with 27 dimensions each. The control frequency is 10kHz, and Δt is set as 0.02 s. The initial constant w, c_1 and c_2 are 1, 2, 2, respectively, but w decays chronologically from 1 to 0.3 in a linear form. The position of the particles is randomized with the feasible region and the velocity is set to zero initially.

Figure (3) shows the torque generated hip joint, knee joint and ankle joint on both sides. We select these 6 joints out of 9 since the hip, knee, and ankle joints are the most effective joints in human walking procedure [19]. We can see that at the first the torques oscillated unstably, but within 2 seconds the value of all joints converged two a relatively small range, and torque vibrates stably and periodically. From the supplementary video we can also see the similar phenomenon: at the first two seconds, the human walked with his body shaking at a small, visible range, but in no time the human was able to walk stably and normally. We can confirm that the sable vibrating period exactly corresponds to the human gait cycle.

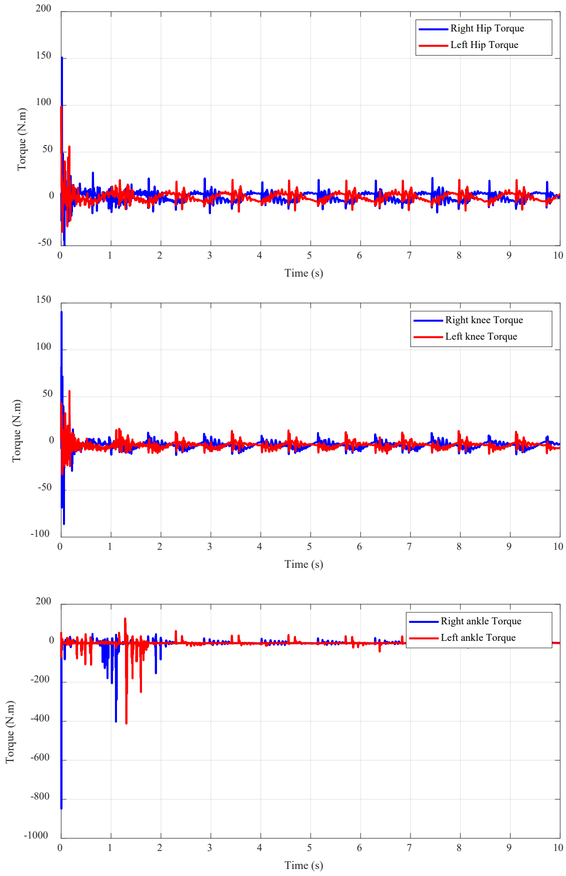

Fig. 3. Torque generated by hip, knee and ankle

The parameter configuration of hip joint, knee joint, and ankle joint is displayed in Figure (4). The angle tracking performance and the angle error of the considered three joints are shown in Figure 5. Also in this way we demonstrate the feasibility and the fast convergence rate of the proposed method: combine Figure (4) with Figure (5), we can see that the parameters were able to converge to its optimal or suboptimal value after approximately 3 seconds with maximum angle error at hip joint, knee joint, and ankle joint being 0.013 rad/s, 0.008 rad/s, 0.004 rad/s, respectively.

V. Conclusion

In this paper, we proposed a PSO based online PID controller for driving a 9-DOF lower limb exoskeleton to track the given joint trajectory. An improved PSO algorithm is proposed for online adaptive PID controller, which is used for the torque generation. By the human walking simulation experiment, we demonstrate that the angle tracking error at the hip joint, knee joint, and ankle joint is no more than 0.0013 rad/s, which surpasses the classical PID controller and the conventional offline PSO based PID controller. There are only few parameters to be predetermined, which has large potential in complex environment control problems, where the complicated human-robot interaction modelling, the

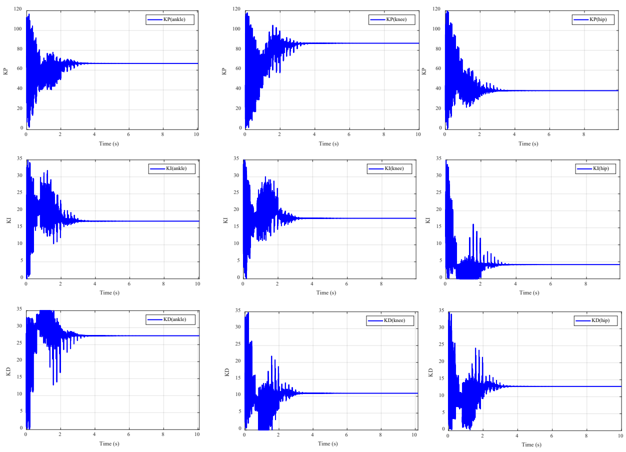

Fig. 4. The procedure of parameter configuration optimization of hip, knee and ankle

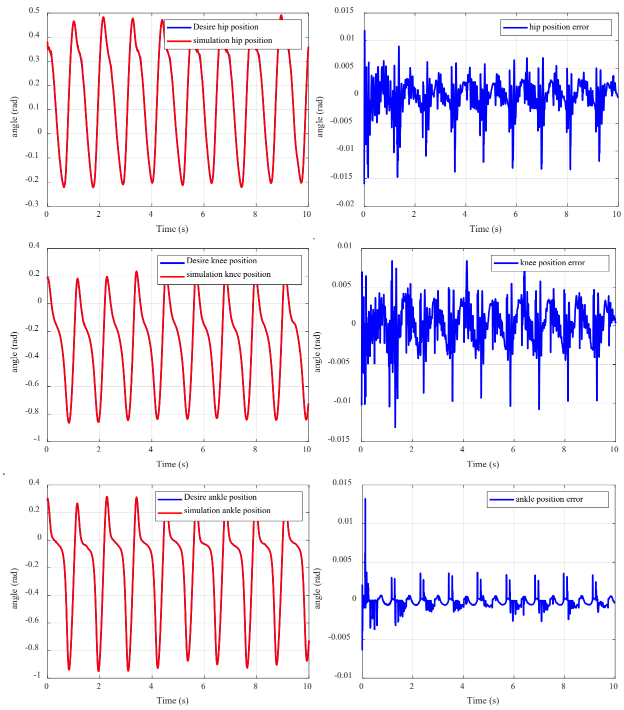

Fig. 5. The angle tracking performance and angle error during human walking simulation

unpredictable, stochastic perturbations from human efforts, environmental changes and other external disturbances appears as unavoidable challenges. Further studies may be more comparison with model-based PID controller, CPG based controller, impedance/admittance controller and other forms of modern controllers to demonstrate the performance and the convergence rate of the proposed method.

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