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Optimal PID Controller Autotuning Design for MIMO Nonlinear Systems Based on the Adaptive SLP Algorithm

Jirapun Pongfai, Chrissanthi Angeli, Peng Shi, Xiaojie Su, and Wudhichai Assawinchaichote*

Abstract: In this paper, an adaptive swarm learning process (SLP) algorithm for designing the optimal proportional integral and derivative (PID) parameter for a multiple-input multiple-output (MIMO) control system is proposed. The SLP algorithm is proposed to improve the performance and convergence of PID parameter autotuning by applying the swarm algorithm and the learning process. The adaptive SLP algorithm improves the stability, performance and robustness of the traditional SLP algorithm to apply it to a MIMO control system. It can update the online weights of the SLP algorithm caused by the errors in the settling time, rise time and overshoot of the system based on a stable learning rate. The gradient descent is applied to update the weights. The stable learning rate is verified based on the Lyapunov stability theorem. Additionally, simulations are performed to verify the superiority of the algorithm in terms of performance and robustness. Results that compare the adaptive SLP algorithm with the traditional SLP, a neural network (NN), the genetic algorithm (GA),the particle swarm and optimization (PSO) algorithm and the kidney-inspired algorithm (KIA) based on a two-wheel inverted pendulum system are presented. With respect to performance and robustness, the adaptive SLP algorithm provides a better response than the traditional SLP, NN, GA, PSO and KIA.

Keywords: Autotuning, inverted pendulum, learning algorithm, multiple-input/multiple-output (MIMO), optimal control, PID controller, swarm algorithm.

1. INTRODUCTION

In many industrial applications, proportional integral and derivative (PID) controllers are used extensively to improve the transient of the system because of their simple structure, robustness, high performance and easy maintenance [1–10]. A PID controller is governed by its 3 tunable parameters, i.e., proportional gain (K_P), integral gain (K_I) and derivative gain (K_D), which determine the performance of the PID controller. However, these parameters cannot determine performance by themselves, especially in nonlinear systems. The common procedure used in industry to tune the parameters is matching the parameters with the operating conditions and tuning the parameters for all conditions [5]. However, normal industrial process control is dynamic and thus unpredictable, with unmodeled fallibility and sudden changes in conditions. The procedure is improperly used because requires a retuning of parameters to achieve the required control.

Therefore, in recent decades, artificial intelligence (AI) has been extensively used to overcome the PID tuning problem in nonlinear control systems and improve the control performance via autotuning with, for example, a genetic algorithm (GA) [11, 12], a neural network (NN) [13], fuzzy logic (FL) [14], particle swarm optimization (PSO) [15–17], a kidney-inspired algorithm (KIA) [18], or a bee colony algorithm (ABC) [19]. Although many AI techniques have been proposed to autotune the PID parameter, they remain the limitation on implementation and execution; i.e., an NN needs more convergence time for learning and more memory capacity for data recording that is necessary for the learning process. The performance of an NN depends on the amount of data for training [1, 6]. FL improperly adds to the complexity of the

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Jirapun Pongfai is with the Department of Electronic and Telecommunication Engineering, Faculty of Engineering, King Mongkut's University of Technology Thonburi, Bangkok, Thailand (e-mail: jirapun.p@mail.kmutt.ac.th). Chrissanthi Angeli is with the Department of Electrical and Electronics Engineering, Faculty of Engineering, University of West Attica, Athens, Greece (e-mail: c_angeli@otenet.gr). Peng Shi is a professor at the University of Adelaide, and Victoria University, Australia (e-mail: peng.shi@adelaide.edu.au). Xiaojie Su is with the College of Automation, Chongqing University, Chongqing, China (e-mail: suxiaojie@cqu.edu.cn). Wudhichai Assawinchaichote is with the Department of Electronic and Telecommunication Engineering, Faculty of Engineering, King Mongkut's University of Technology Thonburi, Bangkok, Thailand (e-mail: wudhichai.asa@kmutt.ac.th).
* Corresponding author.

system because it needs the experience of a designer to analyze the data for the tuning model [1, 6, 19]. GA and PSO need more memory capacity and have high computation costs [6]. Practically, the memory capacity and computation require a high-speed computer [20]. Pongfai *et al*. [21] proposed the swarm learning process (SLP) algorithm has been proposed to autotune the PID parameters for convergence and control performance improvement. SLP can achieve the convergence and control performance for single-input single-output (SISO) systems and nonlinear systems. In fact, the common processes in industry are multiple-input-multiple-output (MIMO) systems [23, 23–28] because in large systems, MIMO provides easy loop failure maintenance, multidirectional stimulation, straightforward implementation and wide coverage [29–31]. In this system, the variant inputs can affect too many output variables and it is still more complex and difficult to control than a SISO system [25,29,30,32]. Therefore, this paper proposes a PID controller autotuning design to improve the stability, performance and robustness of MIMO systems. It mixes the traditional SLP algorithm with varying online weights caused by the error, the settling time, the rise time and the overshoot with respect to the stable learning rate. The adequate condition of closed-loop stabilization is proven via the Lyapunov method. It is well known that the inverted pendulum control system is a common example for confirmation of a control algorithm because of its instability, nonlinearity and significant application in practical uses, such as robotics, space boosters, satellites and automatic aircraft [34–38]. The superior performance and robustness of the proposed controller design are verified based on the two-wheeled inverted pendulum (TWIP) by comparing the simulation with traditional SLP, GA, NN, PSO and KIA [18].

Many algorithms have been proposed to autotune the PID parameter. Nearly all of them apply to SISO systems. In most practical applications, the system is MIMO [23–28]. Therefore, the goal of this study is to propose an adaptive SLP algorithm to design the optimal PID parameter for a MIMO control system, based on the stable learning rate. The contributions of this paper are primarily in two aspects.

1) The adaptive SLP algorithm is proposed to improve the traditional SLP algorithm for a MIMO system based on the stable learning rate. The stability is verified according to the Lyapunov stability theorem.

2) The superiority of performance and robustness are verified by comparing the transient response and the convergence with traditional SLP, GA, NN, PSO and KIA [18], based on the TWIP system. They are verified with 2 case studies, i.e., the TWIP without noise and the TWIP with noise.

This paper is organized as follows: The PID controller autotuning design for MIMO systems is described in Section 2. Section 3 presents the adaptive SLP algorithm. Then, an illustrative example is described in Section 4. The conclusions and discussion are presented in Section 5.

2. PID CONTROLLER AUTOTUNING DESIGN FOR A MIMO SYSTEM

Considering a MIMO system, as shown in Fig. 1, $r(t) \in \mathbb{R}^s$, $x(t) \in \mathbb{R}^n$, $u(t) \in \mathbb{R}^p$, $e(t) \in \mathbb{R}^q$ and $y(t) \in \mathbb{R}^m$ are the reference input vector, the state vector, the control vector, the error vector and the output vector, respectively [38]. The plant and controller of the system are $P(t)$ and $C(t)$, respectively. $C(t) \in \mathbb{R}^{p\times q}$ is expressed as follows:

$$C(t) = \begin{bmatrix} C_{11}(t) & \dots & C_{1q}(t) \\ \vdots & \ddots & \vdots \\ C_{p1}(t) & \dots & C_{pq}(t) \end{bmatrix}. \tag{1}$$

For this study, $C(t)$ is the PID controller; its equation is as follows:

$$C_{pq}(t) = K_P e(t) + K_I \int e(t)dt + K_D \tfrac{de(t)}{dt}, \tag{2}$$

where $\{K_P, K_I, K_D\} \in \mathbb{R}^{p\times q}$ is the matrix of the proportional gain, the integral gain and the derivative gain. Normally, the conventional PID controller is applied to the SISO system without considering the disturbance and nonlinearity of the system [20], while the proposed controller design is an online adjustment. It adjusts in response to the effect of disturbing, unmodeled and uncertain factors in the MIMO system. A block diagram of the proposed controller is shown in Fig. 2.

As shown in Fig. 2, the PID autotuning controller for a MIMO control system modifies the structure of the MIMO system as shown in Fig. 1. The autotuning process ($A(t)$) provides K_P, K_I and K_D to the controller by considering

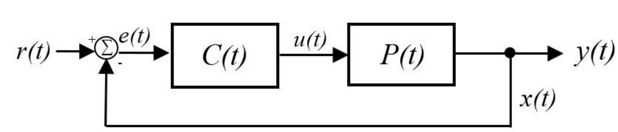

Fig. 1. Basic block diagram of a feedback PID control system.

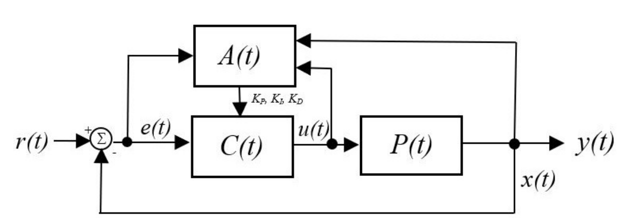

Fig. 2. Block diagram of the PID autotuning controller for a MIMO control system.

the previous control signal, the error and the output of the system. The values of K_P, K_I and K_D depend on the number of control signals. This study uses the adaptive SLP algorithm to autotune the PID parameters [21].

3. ADAPTIVE SLP ALGORITHM

The SLP algorithm is a stochastic algorithm that is inspired by the way the students learn in the classroom by separating the students into 2 groups, i.e., the good students and the bad students [21]. The good students will self-study until they become the perfect students who gain all criteria. In the opposite situation, the bad students will do the self-correction and back track to correct the error themselves to be the good students. In case of the bad students who cannot improve themselves to be the good students such that they become the worsen students, they will be sorted out. Then, the new students will be established. It is noted that the new students are established based on the knowledge of the good students. From the implementation point of view, it is shown that if a student's score meets the criteria, the student passes; a student whose score does not meet the criteria will stay in the classroom and study until its score meets the criteria. The students in the classroom are classified into 2 groups, the good score group and the bad score group. The students in the good score group can learn from another student with a good score, or they can learn by themselves. The students in the bad score group need the teacher or another student with a good score to teach them.

In the algorithm, the criterion for evaluating each student is the cost function. The score for each student is represented by the cost function calculation. Each student is K_P, K_I and K_D. Members of the good score group learn from themselves. Members of the bad score group learn from other students who have good scores. Good score learning can be written as follows:

$$X(K) = \frac{W(K)\sum_{c}^{N} x_i(K)}{N}, \tag{3}$$

where $X(K)$ is a student; K is K_P, K_I and K_D; x_i is the score for each student; N is the number of students; and $W(K)$ is the tuning weight for each student. Bad score learning can be written as follows:

$$X(K) = \frac{W(K)(X_{Bad}(K) + X_{Good}(K))}{2}, \tag{4}$$

where X_{Good} is the best score of the good student group and X_{Bad} is the score of the bad students who need to learn.

During student learning, the students are evaluated at every time to assess whether their score continues to meet the criteria of learning in that classroom. The students who do meet the criteria are taken out of the classroom, and a new student is established as follows:

Algorithm 1: SLP algorithm.

```
procedure SLP()
    The students X(K) are initialized randomly
    The scores for each student are calculated
    while the student's score ≤ the criteria do
        for Student's score ≤ Criteria do
            The student is moved out of the room
            The new student's weight is adjusted (W(K))
            The new student is established as (5)
        end for
        The student's score are sorted
        The students having good scores and bad scores are classified
        for the group of good score do
            The weights for the good score group are adjusted (W(K))
            A new student is crested as (3)
        end for
        for the group of bad score do
            The weights for the bad score group are adjusted (W(K))
            A good score is selected (X_Good)
            A bad score is selected (X_Bad)
            The new student is created following (4)
        end for
    end while
end procedure
```

$$X(K)_{new} = \frac{W(K)\sum_{i=1}^{N} f_i(K)x_i(K)}{N}, \tag{5}$$

where $X(K)_{new}$ represents the new student and $f_i(K)$ represents the frequency of $x_i(K)$ in the search space.

The goal of this study is to propose a PID controller design to minimize the transient response between the setpoint and the output of the system. This design is unlike the normal controller design that minimizes the error only. The general cost function is the integral of time multiplied square error (ITSE), the integral time absolute error (ITAE), the integral square of the error (ISE), and the integral absolute error (IAE), which are complex and time-consuming for an analysis [14]. This study uses a cost function from the literature [14] that focuses on the settling time (Ts), the rise time (Tr), the error (Ess) and the maximum overshoot (Mp) as follows:

$$\begin{aligned} J(t) =& (1 - e^{-\beta})(Mp(t) + Ess(t)) \\ &+ e^{-\beta}(Ts(t) - Tr(t)), \end{aligned} \tag{6}$$

where β is the weight factor that influences the transient response of the system. If β is set to greater than 0.7, the steady state error and maximum overshoot are reduced. Otherwise, the settling time and rise time are reduced [15].

For a PID controller to perform well in a MIMO system, this study proposes the adaptive SLP algorithm for autotuning. This algorithm improves the traditional SLP by applying the gradient descent to update the weights online. Traditional SLP algorithm is adjusted by random processes. In the dynamic system, the weigh with random process can affect the system which may be difficult to approach the steady state or take long time to approach it. However, the weight adjustment based on the gradient descent method does not need to be trained a priori. Weights are adjusted when the PID parameter needs changing because of the uncertainty, unmodeled effects or nonlinearity of the system. The rule of online adjustment is as follows:

$$W_i(t+1) = W_i(t) - \eta_i(t)\nabla W_i(t), \tag{7}$$

where $\eta_i(t)$ is the learning rate of the i^{th} student. It is adjusted corresponding to (8) for SISO system and (9) for MIMO system. $\nabla W_i(t) = \frac{\partial J_i(t)}{\partial W_i(t)}$ where $J_i(t)$ is the cost function at i^{th} iteration.

Theorem 1: In a SISO system, at sampling time t, the closed-loop control system with the adaptive SLP algorithm is stable if $Ess_J(t) \neq 0$, and $\eta_i(t)$ is generated as follows:

$$\sum_{i=1}^{N}\left(\frac{2NEss_i(t)}{J_I(t)Ess_J(t)}\right) < \eta_i(t) \leq 0;\ \ Ess_i(t) < 0, \tag{8}$$

or

$$0 \leq \eta_i(t) < \sum_{i=1}^{N}\left(\frac{2NEss_i(t)}{J_I(t)Ess_J(t)}\right);\quad Ess_i(t) \geq 0, \tag{9}$$

where $J_I(t) = \frac{\partial J_i(t)}{\partial W_i(t)}$, $Ess_J(t) = \sum_{j=1}^{N}\frac{\partial Ess_j(t)}{\partial W_i(t)}$ and N is the number of students.

Proof: To verify the stability of applying the adaptive SLP algorithm to a closed-loop control system, the Lyapunov stability theorem is applied. Practically, the system is dynamic. If there exists the sudden condition of operation changing and fast operation, the error in each operation may be very significant [25-28]. Thus, this paper presents the adjustment of the $\eta_i(t)$ based on the error of the system. From Fig. 1, the system can be written as follows:

$$Ess(t) = r(t) - x(t), \tag{10}$$

where $r(t)$ is the reference input and $x(t)$ is the output of the system. The Lypunov function is defined as follows:

$$V(t) = \frac{1}{2}\sum_{i=1}^{N}Ess_i^2(t), \tag{11}$$

where Ess is the error of response of the system and N is the number of student.

The change in a Lyapunov function is thus as follows:

$$\begin{aligned}\Delta V(t) =& V(t+1) - V(t) & (12)\\ =& \frac{1}{2}\sum_{i=1}^{N}(Ess_i^2(t+1) - Ess_i^2(t)) & (13)\\ =& \frac{1}{2}\sum_{i=1}^{N}((Ess_i(t+1)+Ess_i(t))(Ess_i(t+1) \\ & - Ess_i(t))) & (14)\\ =& \frac{1}{2}\sum_{i=1}^{N}((2Ess_i(t)+\Delta Ess_i(t))(\Delta Ess_i(t)))). & (15)\end{aligned}$$

From the structure of the SLP algorithm described by (3)-(5), the error of the system can be performed as

$$\begin{aligned}\Delta Ess_i(t) =& \Delta W_i(t)\frac{\sum_{j=1}^{N}\frac{\partial Ess_j(t)}{\partial W_i(t)}}{N}\\ =& \Delta W_i(t)\frac{Ess_J(t)}{N}, \end{aligned}\tag{16}$$

where $Ess_J(t) = \sum_{j=1}^{N}\frac{\partial Ess_j(t)}{\partial W_i(t)}$ and $\Delta W_i(t) = W_i(t+1) - W_i(t)$. Using (7), (16) can be written as follows:

$$\Delta V(t) = \sum_{i=1}^{N}\left(\frac{(\eta_i(t)J_I(t)Ess_J(t))^2}{2N^2} - \frac{\eta_i(t)Ess_i(t)J_I(t)Ess_J(t)}{N}\right). \tag{17}$$

From the Lyapunov stability theorem, if $\Delta V(k) \leq 0$ at any sampling time t, the stability of applying the SLP algorithm to a closed-loop system is verified. From (17), an adequate condition for $\Delta V(k) \leq 0$ is that η_i satisfies (8) and (9). □

Theorem 2: For a MIMO system, at sampling time t, the closed-loop control system with the adaptive SLP algorithm is stable if $Ess_K(t) \neq 0$, and $\eta_{ij}(t)$ is generated as follows:

$$\sum_{i=1}^{N}\sum_{j=1}^{p}\left(\frac{2NEss_{ij}(t)}{J_{IJ}(t)Ess_K(t)}\right) < \eta_{ij}(t) \leq 0;\quad Ess_{ij}(t) < 0, \tag{18}$$

or

$$0 \leq \eta_{ij}(t) < \sum_{j=1}^{N}\sum_{i=1}^{p}\left(\frac{2NEss_{ij}(t)}{J_{IJ}(t)Ess_K(t)}\right);\quad Ess_{ij}(t) \geq 0, \tag{19}$$

where $J_{IJ}(t) = \frac{\partial J_{ij}(t)}{\partial W_{ij}(t)}$, $Ess_K(t) = \sum_{k=1}^{N}\frac{\partial Ess_{ijk}(t)}{\partial W_{ij}(t)}$. p is the number of control signals and N is the number of student.

Proof: From Fig. 1, the number of errors (q) is assumed that corresponds with a number of control signals (p). So,

$e(t) \in \mathbb{R}^p$ and $C(t) \in \mathbb{R}^{p\times p}$ which is expressed as

$$C(t) = \begin{bmatrix} C_{11}(t) & \dots & C_{1p} \\ \vdots & \ddots & \vdots \\ C_{p1}(t) & \dots & C_{pp} \end{bmatrix} \tag{20}$$

with respect to PID controller, where $C(t)$ is performed as

$$C_{pp}(t) = K_P e_{pp}(t) + K_I \int e_{pp}(t)dt + K_D \frac{de_{pp}(t)}{dt}, \tag{21}$$

where $e_{pp}(t)$ is the error of signal matrix sequence at ppth. When the adaptive SLP algorithm is applied for autotuning of $\{K_P, K_I, K_D\}$, it needs N students per a control signal (p) for learning system. In the system for which each control signal is dependence, a control signal $u(t)$ can affect the other control signal. So, the Lyapunov function which is applied to verify the stability of applying the adaptive SLP algorithm to a closed-loop control system is defined as follows:

$$V(t) = \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{p} Ess_{ij}^2(t), \tag{22}$$

where $Ess_j(t) = e_{pp}$, N is the number of students and p is the number of control signals. Therefore, the change in a Lyapunov function is as follows:

$$\Delta V(t) = V(t+1) - V(t) \tag{23}$$

$$= \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{p}(Ess_{ij}^2(t+1) - Ess_{ij}^2(t)). \tag{24}$$

From Fig. 1,

$$Ess_{ij}(t) = r_j(t) - x_j(t), \tag{25}$$

so,

$$Ess_{ij}^2(t) = (r_j(t) - x_j(t))^2, \tag{26}$$

and

$$Ess_{ij}^2(t+1) = (r_j(t+1) - x_j(t+1))^2. \tag{27}$$

From (24), it can be performed as

$$\Delta V(t) = V(t+1) - V(t) \tag{28}$$

$$= \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{p}((r_j(t+1) - x_j(t+1))^2 - (r_j(t) - x_j(t))^2) \tag{29}$$

$$= \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{p}((2(r_j(t) - x_j(t)) + \Delta(r_j(t) - x_j(t))\Delta(r_j(t) - x_j(t))). \tag{30}$$

Consider the error of system based on the structure of SLP algorithm as (3), that is $X(K) = \Delta(r_j(t) - x_j(t))$ and $x_i(k) = (r_j(t) - x_j(t))$. So, $\Delta(r_j(t) - x_j(t))$ can be performed as follows:

$$\Delta(r_j(t) - x_j(t)) = \Delta W_j(t)\frac{\sum_{k=1}^{N}\frac{\partial(r_{jk}(t) - x_{jk}(t))}{\partial W_j(t)}}{N} = \Delta W_j(t)\frac{Ess_K(t)}{N}, \tag{31}$$

where $Ess_K(t) = \sum_{k=1}^{N}\frac{\partial(r_{jk}(t) - x_{jk}(t))}{\partial W_j(t)}$ and $\Delta W_j(t) = W_j(t+1) - W_j(t)$. From (7), (31) can be written as follows:

$$\Delta V(t) = \sum_{i=1}^{N}\sum_{j=1}^{p}\left(\frac{(\eta_{ij}(t)J_{IJ}(t)Ess_K(t))^2}{2N^2} - \frac{\eta_{ij}(t)Ess_{ij}(t)J_{IJ}(t)Ess_K(t)}{N}\right). \tag{32}$$

According to the Lyapunov stability theorem, if $\Delta V(k) \leq 0$ in any sampling time of t, the stability of applying SLP algorithm to closed-loop system is verified. From (32), an adequate condition for $\Delta V(k) \leq 0$ is that η satisfies (18) and (19).

Remark 1: Note that the adaptive SLP algorithm will autotune the PID parameter by considering the current response of the system while the traditional SLP, GA, NN, PSO and KIA [18] adjust the PID parameter based on random processes and initial value. That means if the initial value is far from the optimal value, they may take time to approach the optimal value or sometimes cannot approach the optimal value in case of system with high dynamic.

4. ILLUSTRATIVE EXAMPLE

In this study, a TWIP system is used to verify the performance and robustness of the proposed method. From the block diagram of the control system shown in Fig. 2, the controller is separated into 2 looped controllers for position control and angle control. The outputs of both controllers provide the control signal input to the system. For the TWIP control system, it is the voltage of a DC motor because the TWIP is modeled with a DC motor. To verify the performance and robustness of the proposed method, the adaptive SLP algorithm is compared by simulation with traditional SLP, NN, GA, PSO and KIA [18] by the minimizing cost function shown in (6).

4.1. Two-wheel inverted pendulum model

The TWIP comprises a pendulum and a wheel. During movement, the pendulum angle is changed, while the wheel rotation is used to change the pendulum. The position and balance control of the pendulum are the main problems in the controller design as it moves to the target position. The structure of the TWIP is shown in Fig. 3(a).

From Fig. 3(b), the moment and the force in the vertical direction are as follows:

$$m_p\ddot{x} = 2F_x + m_p l\ddot{\theta}^2\sin\theta - m_p l\ddot{\theta}\cos\theta, \tag{33}$$

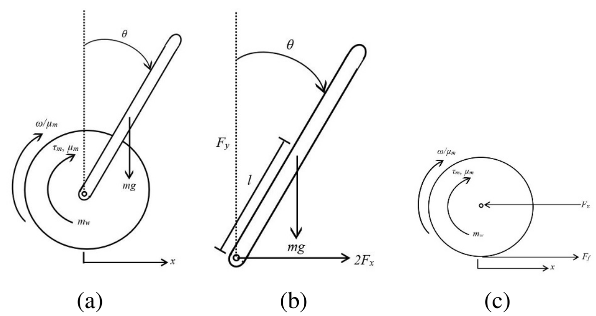

Fig. 3. TWIP diagram [3]. (a) is a structure of the TWIP, (b) is a diagram of the wheel and (c) is a diagram of the pendulum.

$$J_p\ddot{\theta} = 2F_y l\sin\theta - 2F_x l\cos\theta - d\dot{\theta}, \tag{34}$$

where θ is the angle of the pendulum, m_p is the mass of the pendulum, J_p is the moment of inertia of the pendulum, l is the length of the pendulum, and d is the damping coefficient of the pendulum. A balance of the pendulum in the vertical direction is the goal of the controller; therefore, the θ in (33) and (34) is 0. Hence, $\sin\theta \approx 0$, $\cos\theta \approx 1$ and $\dot{\theta}^2 \approx 0$.

$$2F_x = m_p\ddot{x} + m_p l\ddot{\theta}, \tag{35}$$

$$\ddot{\theta}(J_p + m_p l^2) = m_p g l\theta - m_p l\ddot{x}. \tag{36}$$

From Fig. 3(c), the force and the torque applied to the wheel can be written as follows:

$$F_f - F_x = m_w\ddot{x}, \tag{37}$$

$$\mu_m\tau_m - rF_f = \frac{J_w\ddot{x}}{r} = \frac{J_w\dot{\omega}}{\mu_m}, \tag{38}$$

where x is the position; m_w is the mass of the wheel; F_f is the frictional force; J_w is the moment of inertia of the wheel; F_x is the force of the reaction; r is the radius of the wheel; τ_m is the torque of the motor, which is modeled with a direct current (DC) motor; μ_m is the reaction ratio of the motor; ω is the angle position of the motor; and ω/μ_m is the angular position of wheel. From (37) and (38), F_x of wheel can be derived as follows:

$$F_x = (\frac{I_w}{r^2} + m_w)\ddot{x} - \frac{\mu_m\tau_m}{r}. \tag{39}$$

The DC motor equation consists of 2 parts, i.e., the electrical part and the mechanical part. The equation for the electrical part is in (40); for the mechanical part, it is in (41) as follows:

$$V_t - k_t\dot{\omega} = R_a i_a + L_a\frac{di_a}{dt}, \tag{40}$$

$$J_m\ddot{\omega} = k_t i_a - \tau_m, \tag{41}$$

where V_t is the supply voltage, k_t is the torque constant, R_a is the armature resistance, i_a is the armature current, L_a is the armature inductance and J_m is the inertial moment of the motor. Because the time constant (L_a/R_a) is small, the inductance of the motor can be neglected. Hence, the motor torque is as follows:

$$\tau_m = \frac{k_t V_t}{R_a} - \frac{k_t^2}{R_a}\dot{\omega} - J_m\ddot{\omega}, \tag{42}$$

where $\dot{\omega} = \dot{x}(\frac{\mu_m}{r})$. From (42), the force of the wheel in (39) can be rearranged as follows:

$$F_x = (\frac{J_m}{r^2} + m_w + \frac{J_m\mu_m^2}{r^2})\ddot{x} + \frac{k_t^2\mu_m^2}{r^2 R_a}\dot{x} - \frac{k_t\mu_m}{rR_a}V_t. \tag{43}$$

According to the force and moment equations of the wheel and the torque and force equations of the pendulum, the differential equation of the TWIP system is as follows:

$$\ddot{x} = -\frac{2k_t^2\mu_m^2}{r^2 R_a\alpha}\dot{x} + \frac{mgl}{\alpha}\theta + \frac{2k_t\mu_m}{rR_a\alpha}V_t, \tag{44}$$

$$\ddot{\theta} = \frac{2k_t^2\mu_m^2}{r^2 R_a\alpha\varphi}\dot{x} - \frac{mgl - g\alpha\varphi}{\alpha\varphi^2}\theta - \frac{2k_t\mu_m}{rR_a\alpha\varphi}V_t, \tag{45}$$

where $\alpha = 2\frac{J_w + J_m\mu_m^2}{r^2} + \frac{m_p l}{\varphi} + 2m_w$ and $\varphi = \frac{J_m}{m_p l} + l$.

Apply (44) and (45) to state space and replace the parameters of the TWIP as shown in Table 1; then, the state space of the TWIP for the simulation is as follows:

$$\begin{bmatrix}\dot{x}\\ \ddot{x}\\ \dot{\theta}\\ \ddot{\theta}\end{bmatrix} = \begin{bmatrix}0 & 1 & 0 & 0\\ 0 & -69.087 & 0.004 & 0\\ 0 & 0 & 0 & 1\\ 0 & 684.034 & 96.584 & 0\end{bmatrix}\begin{bmatrix}x\\ \dot{x}\\ \theta\\ \dot{\theta}\end{bmatrix} + \begin{bmatrix}0\\ 0.266\\ 0\\ -2.640\end{bmatrix}u, \tag{46}$$

$$y = \begin{bmatrix}1 & 0 & 0 & 0\\ 0 & 1 & 0 & 0\\ 0 & 0 & 1 & 0\\ 0 & 0 & 0 & 1\end{bmatrix}\begin{bmatrix}x\\ \dot{x}\\ \theta\\ \dot{\theta}\end{bmatrix} + \begin{bmatrix}0\\ 0\\ 0\\ 0\end{bmatrix}u. \tag{47}$$

Table 1. The parameter of TWIP system [3].

Symbol	Value
k_t (Nm/A)	0.24
J_w (Kg.m^2)	15.48×10^{-5}
r (m)	0.04825
J_p (Kg.m^2)	0.0125
l (m)	0.1
μ_m	50
J_m (Kg.m^2)	3×10^{-4}
m_w (kg)	0.113
R_a (Ω)	3
g (m/s^2)	9.8
m_p (kg)	3

Table 2. The initial PID parameter for autotuning (Angular control).

Dataset	K_P	K_I	K_D
1	0.682	0.712	0.621
2	0.122	0.286	0.963
3	0.744	0.023	0.215
4	0.406	0.055	0.516
5	0.745	0.683	0.116

Table 3. The initial PID parameter for autotuning (Position control).

Dataset	K_P	K_I	K_D
1	609.452	431.277	387.719
2	107.360	511.833	362.728
3	151.294	643.179	500.736
4	488.165	261.922	162.625
5	246.271	686.575	426.023

Table 4. The PID parameter results from autotuning (Position control).

Algorithm	K_P	K_I	K_D
Adaptive SLP	5401.311	6100.090	1211.540
Traditional SLP	8747.044	10765.113	2118.267
NN	7064.423	5953.074	4281.641
GA	6204.271	3275.392	1832.823
PSO	5926.135	1301.306	1825.176
KIA [18]	6013.090	2687.432	2196.920

4.2. Simulation results

To determine the performance and robustness of the autotuning, the proposed method is compared to simulation results obtained using the traditional SLP, NN, GA, PSO and KIA [18] based on the TWIP. In the verification, 2 case studies are performed, i.e., a system without noise and one with noise. For the system without noise, the position reference (x) is 0.5 m, and the angle reference (θ) is 0°. The time of simulation is 1.5 seconds. The dataset of PID parameters for each algorithm is 5 data sets, and the number of iterations is 150. The initial values of each algorithm are same as equitable verification, which is shown in Tables 2 and 3. This paper generates the initial value by random because in practical, the optimal value corresponds the current characteristic of the system. That means in a dynamic system, the initial value for each changing condition of operation is unknown. In case of β as (7), it affects the response of the system. When it is less than 0.7, the transient response in term of Ts and Tr is improved. Otherwise, the Mp and Ess are reduced [15]. So, in this paper, it is set 0.75 which corresponds the learning rate adjusting. In the case of the system with noise, the position reference (x) is 1 m, and the angle reference for (θ) is 0°. The time of simulation is 5 seconds.

Table 5. The analysis of the transient response for position control.

Algorithm	$Mp(m)$	$Ess(m)$	$Ts(s)$	$Tr(s)$
Adaptive SLP	0.004	0.004	0.221	0.067
Traditional SLP	0.001	-0.001	0.309	0.082
NN	-0.043	0.036	0.390	0.082
GA	-0.024	0.017	0.629	0.122
PSO	-0.106	0.092	1.154	0.153
KIA [18]	-0.060	-0.029	0.253	0.069

Table 6. The PID parameter results from autotuning (Angular control).

Algorithm	K_P	K_I	K_D
Adaptive SLP	0.552	0.712	0.174
Traditional SLP	1.136	1.114	0.243
NN	1.569	0.597	0.292
GA	1.581	0.184	0.278
PSO	1.952	0.624	0.310
KIA [18]	0.784	0.834	0.172

Table 7. The analysis of the transient response for angular control.

Algorithm	$Mp(m)$	$Ess(m)$	$Ts(s)$	$Tr(s)$
Adaptive SLP	1.775	0.019	0.389	0.012
Traditional SLP	1.901	-0.043	0.526	0.010
NN	2.183	-0.049	0.487	0.010
GA	1.342	-0.087	1.198	0.025
PSO	1.153	-0.082	1.192	0.043
KIA [18]	2.193	-0.439	0.475	0.010

In Tables 4 and 5, the PID parameters for position and angular control are provided. They are tuned with 150 iterations based on the TWIP control system without noise. The data in Tables 6 and 7 and in Figs. 4 and 5 show that the proposed method performs better with respect to the rise time, the settling time and the steady-state error than the traditional SLP, NN, GA, PSO and KIA [18] algorithms for position and angular control. However, the proposed method has a larger maximum overshoot than the traditional SLP for position and angular control and NN, GA and PSO for angular control.

The noise that is added to the TWIP control system is shown in Fig. 8. In Figs. 6 and 7, a comparison of the system response of autotuning the PID parameter with noise for position and angular control is presented. To show the superiority performance of autotuning PID parameter, Tables 8 and 9 present the Mp and variation of response of the system when noise is added to the system.

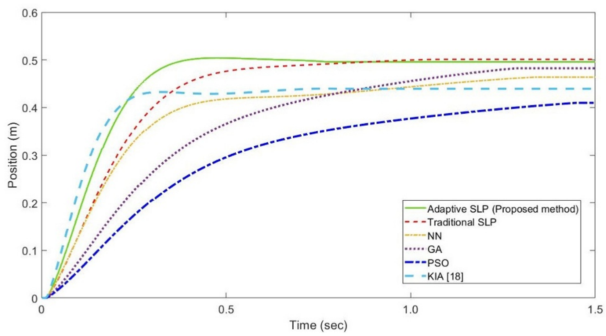

Fig. 4. The transient response for position control (system without noise).

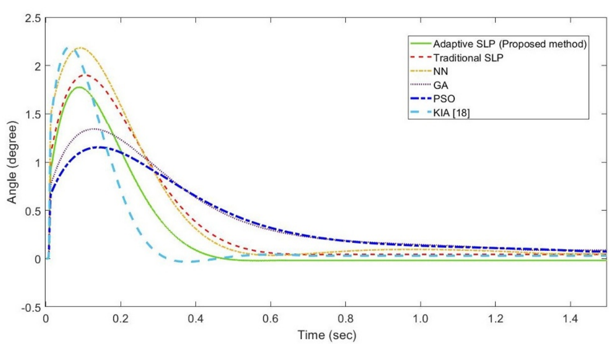

Fig. 5. The transient response for angular control (system without noise).

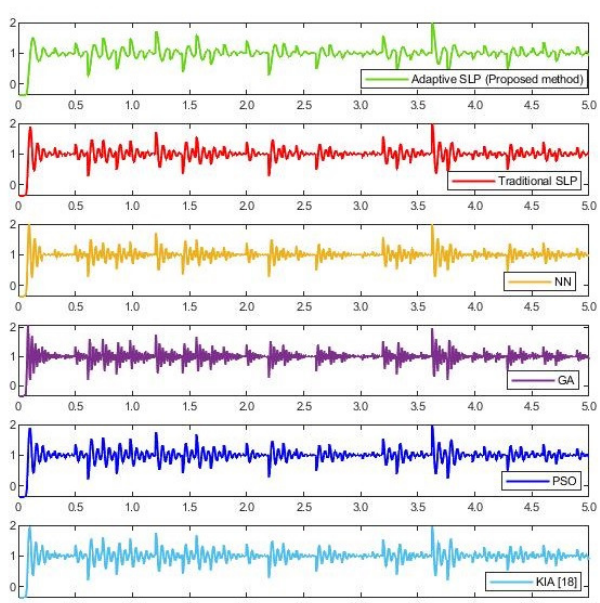

Fig. 6. The response of position control.

In Fig. 9, a comparison of the convergence of autotuning the PID parameter based on the TWIP without noise is shown. The proposed method provides a better minimization of the fitness function than the traditional SLP,

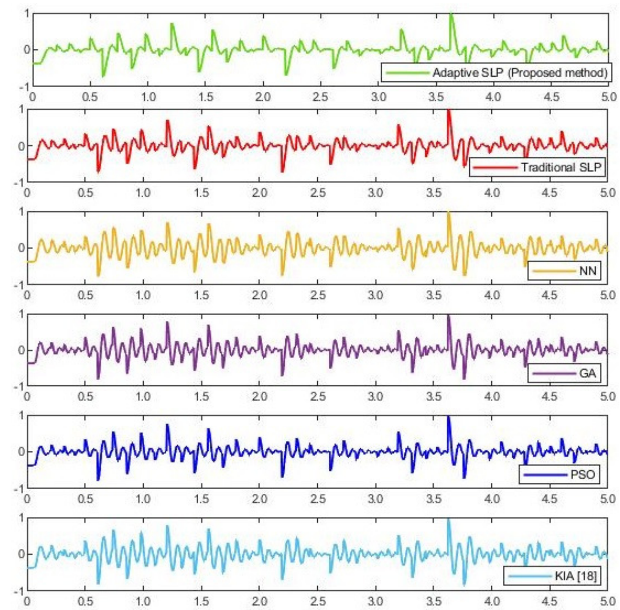

Fig. 7. The response of angular control.

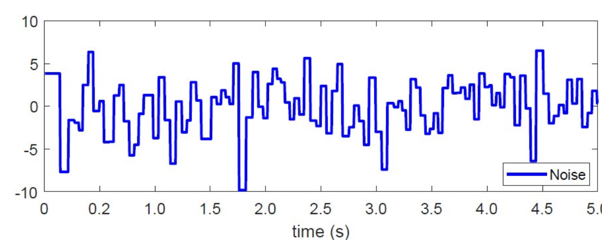

Fig. 8. The noise in the TWIP system .

Table 8. The system response analysis for position control (with noise).

Algorithm	Mp (m)	Standard deviation (SD)
Adaptive SLP	1.201	0.223
Traditional SLP	1.238	0.247
NN	1.204	0.239
GA	1.308	0.245
PSO	1.299	0.256
KIA [18]	1.311	0.257

Table 9. The system response analysis for angular control (with noise).

Algorithm	Mp (m)	Standard deviation (SD)
Adaptive SLP	1.220	0.170
Traditional SLP	1.226	0.187
NN	1.296	0.224
GA	1.316	0.201
PSO	1.278	0.181
KIA [18]	1.324	0.216

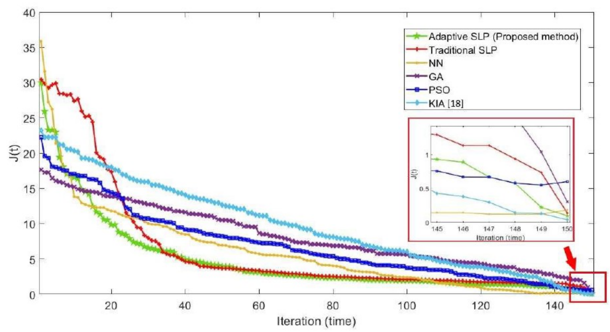

Fig. 9. Comparison of convergence curve.

NN, GA, PSO and KIA [18]; i.e., it obtains 0.096, while the traditional SLP obtains 0.137, NN obtains 0.184, GA obtains 0.304, PSO obtains 0.601 and KIA obtains 0.058 [18]. In the case of angular control, the proposed method also provides a better minimization of fitness function than the traditional SLP, NN, GA, PSO and KIA [18]; i.e., it obtains 0.966, while the traditional SLP obtains 1.043 , NN obtains 1.128, GA obtains 1.205, PSO obtains 1.118 and KIA obtains 0.972 [18].

From Figs. 6 and 7, the response of the proposed method oscillates less than the traditional SLP, GA, NN, PSO and KIA [18] for both position control and angular control. According to Mp and SD as shown in Table 8 and 9, the proposed method also provides the result less than the traditional SLP, GA, NN, PSO and KIA [18] for both position control and angular control.

Remark 2: Although the traditional SLP, NN, GA, PSO and KIA [18] are online tuning algorithms that are similar to the proposed method, they update the K_P, K_I and K_D based on randomness. Specifically, NN, GA, PSO and KIA [18] update using the prior initial values. In a system with high complexity, such as the example which is performed to verify the performance and robustness, the algorithms take time to find the optimal value. The proposed method updates based on the learning rate by considering the current transients, i.e., the error, the settling time, the rise time and the overshoot. Moreover, it protects the local minima by deleting the values that are used to teach the system by evaluation based on the leaning criteria. Hence, the proposed method can provide better performance and convergence than the traditional SLP, NN, GA, PSO and KIA [18] algorithms.

5. CONCLUSION

In this paper, an adaptive SLP algorithm is proposed to design optimal PID parameters. The algorithm proposes to improve the traditional SLP algorithm for a MIMO system based on the stable learning rate. Stability is guaranteed according to the Lyapunov stability theorem. The performance and robustness are verified with 2 case studies based on the two-wheel inverted pendulum system, i.e., the TWIP without noise and with noise. In the case without noise, the proposed method provides a better settling time, rise time and steady-state error than the traditional SLP, GA, NN, PSO and KIA [18] for position and angular control. The proposed method provides a larger overshoot than the traditional SLP, GA, NN, PSO and KIA [18] for position control and is better than GA and PSO for angular control because of the random learning rate. With respect to convergence, in case of position control, although the proposed method can provide the better minimization of the fitness function compared to the KIA [18]; however, since the adaptive SLP algorithm adjusts the PID parameter based on Ess, thus it may give the high Ess and Mp. However, the Ess and Mp is nearly the setpoint while other algorithms provide under the setpoint. For angular control, the proposed method can provide the better minimization of the fitness function compared to the traditional SLP, GA, NN, PSO and KIA [18]. Additionally, in case of system with noise, the proposed method can provide the response, SD and Mp better than the traditional SLP, GA, NN, PSO and KIA [18]. So, when the response based on overall of controlling system for both performance and convergence has been analyzed, one can conclude that the proposed theoretical approach claims the greater performance, robustness and convergence in optimal PID parameter autotuning design for practical applications with MIMO system. However, in this paper, the adaptive SLP algorithm is only shown to apply in the PID autotuning. Actually, this technique can be applied to observe system, predict the behavior of the system [39], also approximate response of system in discrete time [40].

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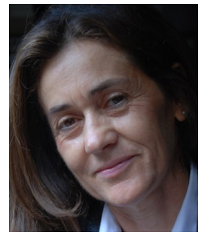
Jirapun Pongfai received her bachelor of engineering degree in computer engineering from Naresuan University (NU), Pitsanulok, Thailand, in 2015 and a master of engineering degree in electrical and information Engineering from King Mongkut's University of Technology Thonburi (KMUTT), Bangkok, Thailand, in 2017. Her research interests are intelligence control, optimal and predictive controller design and artifitial intelligence and embedded system design.



Chrissanthi Angeli received her master of science degree in intelligent systems from the University of Plymouth and a D.Phil. in intelligent fault detection techniques from the University of Sussex. Currently she is a professor at the Technological Education Institute of Piraeus. Her current research interests include real-time expert systems, web-based expert systems and artificial intelligence techniques for fault detection.

Peng Shi received his Ph.D. degree in electrical engineering from the University of Newcastle, Australia; a Ph.D. degree in mathematics from the University of South Australia. He was awarded a Doctor of Science degree from the University of Glamorgan, UK in 2006, and a Doctor of Engineering degree from the University of Adelaide in 2015. He is now a professor at the University of Adelaide, and Victoria University, Australia. He was a professor at the University of Glamorgan, UK; and a senior scientist in the Defence Science and Technology Organisation, Australia. His research interests include system and control theory, computational intelligence, and operational research. He has actively served in the editorial board of a number of journals, including Automatica, IEEE Transactions on Automatic Control; IEEE Transactions on Fuzzy Systems; IEEE Transactions on Cybernetics; IEEE Transactions on Circuits and Systems-I: Regular Papers; and IEEE Access. He is a Fellow of the Institution of Engineering and Technology, and the Institute of Mathematics and its Applications. He was the Chair of Control Aerospace and Electronic Systems Chapter, IEEE South Australia Section. Currently he serves as an IEEE Distinguished Lecturer, and a Member of Australian Research Council, College of Expert.

Xiaojie Su received his bachelor's degree from Jiamusi University, China, in 2008; a master's degree from Harbin Institute of Technology, China, in 2010 and a Ph.D. from Harbin Institute of Technology, China, in 2013. Currently, he is a professor at the College of Automation, Chongqing, China. His research interests are in fuzzy systems, optimal filtering, optimal controller design, and model reduction. He serves as an associate editoe for IEEE Access, Information Sciences, Signal Processing, IET Electronic Letter, Neurocomputing, Asia Journal of Control, and International Journal of Control, Automation, and System. Additionally, he is an associate editor for conference editorial board, IEEE Control System Society.

Wudhichai Assawinchaichote received his B.S. degree with honor in electrical engineering from Assumption University, Bangkok, Thailand, in 1994; an M.E. degree in electrical engineering from Pennsylvania State University (Main Campus), PA, USA, in 1997; and a Ph.D. degree in electrical engineering from the University of Auckland, New Zealand, in 2004. Currently, he is an Associate Professor at the department of Electronic and Telecommunication Engineering, King Mongkut's University of Technology Thonburi (KMUTT), Bangkok, Thailand. He has published a research monograph and more than 20 research papers in international refereed journals indexed by SCI/ESCI (Clarivate Analytics). His current research interests include fuzzy control, robust control, optimal control, system and control theory, computational intelligence, and PID controller design. He currently serves as an Associate Editor for a number of journals and also serve as a reviewer, including Automatica; IEEE Transactions on Industrial Electronics; IEEE Transactions on Fuzzy Systems; IEEE Transactions on Cybernetics; IEEE Transactions on Systems, Man and Cybernetics: Systems; Neural Computing and Applications; and IEEE Access.