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METHODOLOGIES AND APPLICATION

Combined PID and LQR controller using optimized fuzzy rules

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Abstract

In this paper, a combination of PID controller and linear quadratic regulator is proposed. A fuzzy switching module is applied to optimally fuse both controllers. A new adaptive version of charged system search algorithm optimizes the membership functions of the fuzzy module. By the time, the algorithm changes itself to find a proper solution faster. To show the efficiency of the designed intelligent controller, the results of a simulated unicycle robot under disturbances are presented.

Keywords Artificial intelligence · Adaptive charged system search · PID controller · Linear quadratic regulator · Fuzzy logic

1 Introduction

Nowadays controller design for nonlinear systems is an attractive topic for researchers. Most of systems are nonlinear, and because of this fact, there is a wide usage of different control systems. Robotic systems are examples of highly nonlinear systems. The unicycle robot is an interesting nonlinear system for controlling. Although it is a kind of inverted pendulum, it should be controlled in three angles (roll, pitch and yaw); therefore, it is a challenging problem in robotics. In order to control the unicycle robot, three motors are used to control each angle. Linear method for balance control of pitch direction was designed and used in 1987 (Schoonwinkel 1988).

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The researchers found that when people ride a unicycle, the trunk, the thigh and the shank would constitute two closed-loop structures. In previous researches, various types of controllers have been used to control the unicycle robot (Han et al. 2015; Taniguchi et al. 2014; Do 2013; Rizal et al. 2015). The LQR controller is one of the most common optimal control methods used to control many robotic systems (Guo et al. 2014; Hu et al. 2014).

On the other hand, the artificial intelligence is used in different ways to solve engineering problems (Asl et al. 2015; Nobarian et al. 2016). Evolutionary algorithms (Pourabdollah et al. 2017; Mohammadi Asl et al. 2017a), artificial neural networks and fuzzy systems are different kinds of artificial intelligence which have been used in engineering problems. For instance, a fuzzy logic has been applied on a hybrid fault-tolerant system in Shabbouei Hagh et al. (2017). The proposed method is a combination of robust control method and sliding mode controller. In another research, the neural network has been combined with sliding mode controller to control robotic arm (Mohammadi Asl et al. 2017b). The proposed controller has been developed to work based on the estimation of a the system, which is presented by Kalman filter. The filter has been optimized by evolutionary algorithm. The logic has been used to manage the control input. The fuzzy logic-based methods have important effect on solving engineering problems. The fuzzy logic systems have a big advantage, which is that they do not need the structure and mathematical equations of the systems and can be based on some linguistic definitions. Many researches have been done to develop the fuzzy logic (Arqub et al. 2016). For instance, the kernel algorithm has been

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employed to solve second-order fuzzy boundary problems (Arqub 2017). The performance of the presented method has been guaranteed by an efficient evolutionary algorithm. In another research, a new method has been developed to solve fuzzy Fredholm–Volterra integrodifferential equations (Arqub et al. 2017). The presented method has been designed based on kernel method. Evolutionary algorithms are usually used in controller design. As one of the strongest evolutionary algorithms, biogeography-based optimization (BBO) is used to control a five-bar robotic manipulator (Kankashvar et al. 2015). In other researches, different evolutionary algorithms are applied to control nonlinear and linear systems (Taher et al. 2014; Hashim et al. 2015). Fuzzy logic is usually used to design different types of controllers (Ren et al. 2014; Mao et al. 2014). Charged system search (CSS) is developed recently as a strong evolutionary algorithm. It is used to design different kinds of controllers (Precup et al. 2014b). Modified versions are introduced recently to further improve performance (Precup et al. 2014a).

In this paper, a combination of PID controller and LQR controller is introduced. A fuzzy logic-based switching system is applied to switch between the two controllers. Our contribution is the development of a new adaptive algorithm for tuning the membership functions of the fuzzy switching module. The algorithm called adaptive charged search system (ACSS). To show the efficiency of the proposed controller, it is applied to control a unicycle robot.

The rest of this paper is arranged in three sections. Methods, which have been used for designing the controller, are reviewed in Sect. 2. Section 3 gives information about the system and the results of the application of the proposed method on the system. Section 4 concludes the paper.

2 Methods and materials

In this section, methods, which are used for designing the proposed controller, are described and a brief review is given.

2.1 Proportional–integral–differential (PID) controller

One of the most important and practical controllers has been known as PID controller. The overall formula of this controller can be given as

$$u_{\mathrm{PID}}(t) = K_{\mathrm{P}} e(t) + K_{\mathrm{I}} \int_0^t e(\tau)\, d\tau + K_{\mathrm{D}} \frac{\mathrm{d}e(t)}{\mathrm{d}t} \tag{1}$$

where K_{P}, K_{I} and K_{D} are defined as proportional, integral and differential parts, respectively. The error between desired value and the true value of the system is given by e.

2.2 Linear quadratic regulator (LQR)

The stability guarantee and the systematic method to calculate the control input are the most significant advantages of the LQR controller that make it useful for many applications. The control input of this method is as

$$u_{\mathrm{LQR}}(t) = -Kx(t) \tag{2}$$

where K and x are the feedback control gain and the sates of the system, respectively. The control input is chosen in a way that minimizes the following equation

$$J = \int_0^{\infty} \left(x^T Q x + u^T R u\right) \mathrm{d}t \tag{3}$$

Table 1 The detail of benchmark functions (Mohammadi Asl et al. 2017a; Mirjalili et al. 2014)

Function	Formulation	D	Minimum
Beale	$f(x) = (1.5 - x_1 + x_1x_2)^2 + (2.25 - x_1 + x_1x_2)^2 + (2.625 - x_1 + x_1x_2)^2$	2	0
Bohachevsky 1	$f(x) = x_1^2 + 2x_2^2 - 0.3\cos(3\pi x_1) - 0.4\cos(4\pi x_2) + 0.7$	2	0
Bohachevsky 2	$f(x) = x_1^2 + 2x_2^2 - 0.3\cos(3\pi x_1)(4\pi x_2) + 0.3$	2	0
Bohachevsky 3	$f(x) = x_1^2 + 2x_2^2 - 0.3\cos(3\pi x_1 + 4\pi x_2) + 0.3$	2	0
Booth	$f(x) = (x_1 + 2x_2 - 7)^2 + (2x_1 + x_2 - 5)^2$	2	0
Achley	$f(x) = -20\exp\left(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{D} x_i^2}\right) - \exp\left(\frac{1}{n}\sum_{i=1}^{D}\cos(2\pi x_i)\right) + 20 + e$	30	0
Schwefel 2.22	$f(x) = \sum_{i=1}^{D}\lvert x_i\rvert + \Pi_{i=1}^{D}\lvert x_i\rvert$	30	0
Rosenbrock	$f(x) = \sum_{i=1}^{D-1} 100\left(x_{i+1} - x_i^2\right)^2 + (x_i - 1)^2$	30	0
Rastrigin	$f(x) = \sum_{i=1}^{D}\left(x_i^2 - 10\cos(2\pi x_i) + 10\right)$	30	0
Griewank	$f(x) = \frac{1}{4000}\left(\sum_{i=1}^{D}(x_i - 100)^2\right) - \left(\Pi_{i=1}^{D}\cos\left(\frac{x_i - 100}{\sqrt{i}}\right)\right) + 1$	30	0

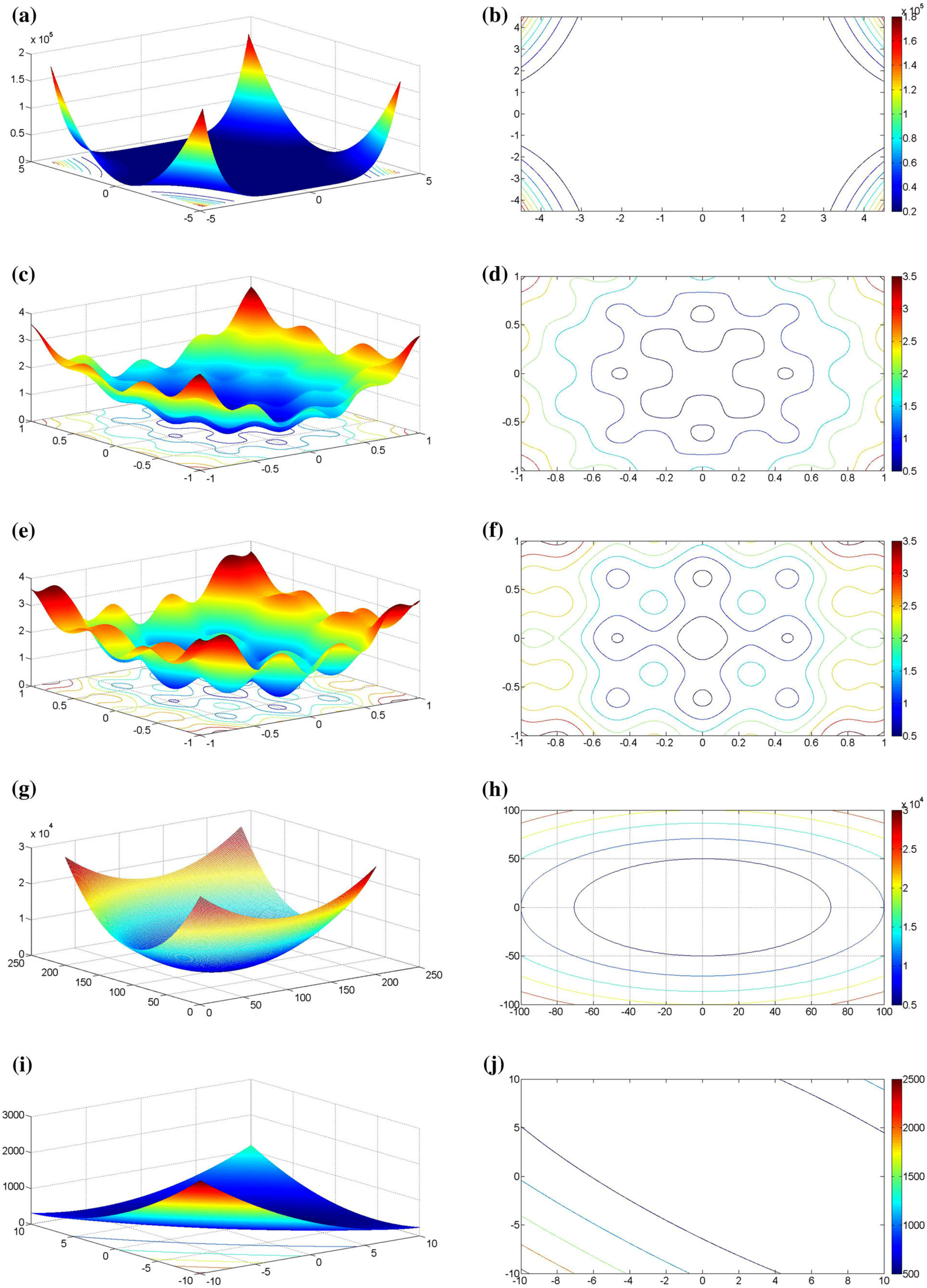

Fig. 1 The 3D and contour view of the function of: **a**, **b** Beale, **c**, **d** Bohachevsky 1, **e**, **f** Bohachevsky 2, **g**, **h** Bohachevsky 3 and **i**, **j** Booth

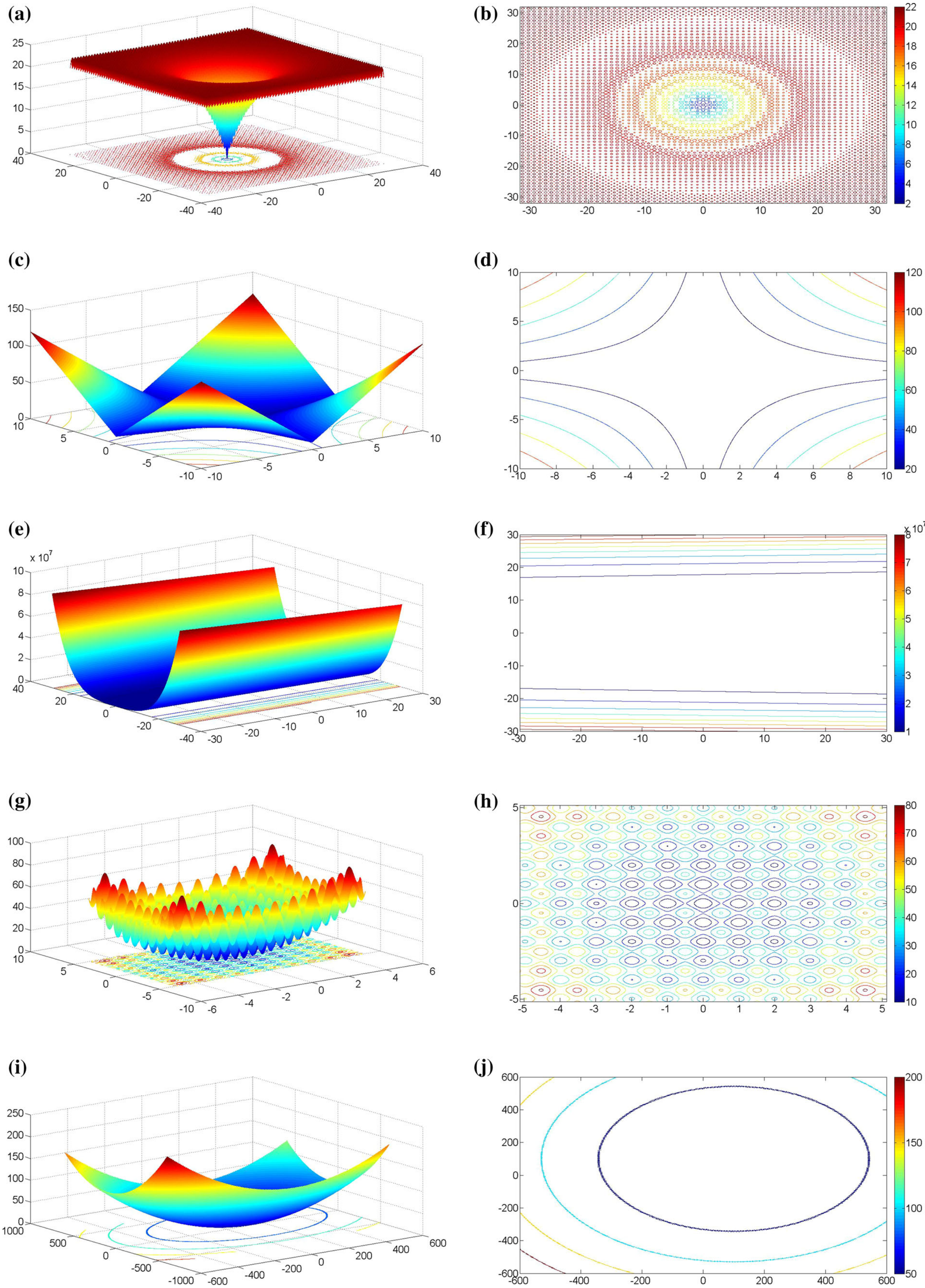

Fig. 2 The 3D and contour view of the function of: **a**, **b** Achley, **c**, **d** Schwefel 2.22, **e**, **f** Rosenbrock, **g**, **h** Rastrigin and **i**, **j** Griewank

Table 2 Comparative results of ACSS with GA, DE, PSO, and CSS

Function	GA	DE	PSO	CSS	ACSS
Beale	0	0	0	0	0
Bohachevsky 1	0	0	0	0	0
Bohachevsky 2	0.0527	0	0	0.0638	0
Bohachevsky 3	0	0	0	0	0
Booth	0	0	0	2.41E−05	0
Achley	0.0778	5.5E−06	0.0665		6.1E−03
Schwefel 2.22	0	0	0	0	0
Rosenbrock	2.1E−07	4.1E−09	4.8E−07	7.1E−08	1.1E−09
Rastrigin	8.7E−08	7.7E−08	1.3E−06	2.4E−07	7.9E−08
Griewank	0	7E−07	5.7E−07	0.0753	0

where the definite positive matrices Q and R show the matrices of the states and input of the system, respectively. Regarding this definitions, the control input is calculated as

$$K = R^{-1}B^T P \tag{4}$$

where B represents the input matrix of the system. Regarding Ricatti equation, the matrix P is computed

$$A^T P + PA + Q - \mathrm{PBR}^{-1}B^T P = 0 \tag{5}$$

where A is the state matrix (Bemporad et al. 2002).

2.3 Fuzzy switching module

A fuzzy module is applied to change between controllers regarding the system error and its derivative. The simplicity and the independence of the real system model are the features of this logic, which make it feasible to use in many systems. The output of this module can be shown as

$$\xi_i = t\left(\upsilon_{\epsilon_1}, \ldots, \mu_{\epsilon_l}\right), \quad i = 1, 2. \tag{6}$$

The fuzzification amount, output and error and its derivation are given by υ, ξ and ω, respectively. The t norm is given by $t(.)$. The overall model of the fuzzy logic is as follows

"if ω_1 *is* Θ_{11} and ω_2 *is* Θ_{21} and, $\ldots$, then ξ_1 *is* Δ_{11} and ξ_2 *is* Δ_{21}

$\vdots$

if ω_1 *is* Θ_{1k} and ω_2 *is* Θ_{2k} and, $\ldots$, then ξ_1 *is* Δ_{1k} and ξ_2 *is* Δ_{2k}"

The output of the fuzzy module will be used to calculate the amount of the control input as Shabbouei Hagh et al. (2017)

$$u = \xi_1.u_{\mathrm{PID}} + \xi_2.u_{\mathrm{LQR}} \tag{7}$$

Tuning of the membership functions is done using the proposed ACSS algorithm explained in Sect. 2.4.

2.4 Adaptive charged system search (ACSS)

The proposed adaptive charged system search (ACSS) is an adaptive version of the basic charged system search (CSS) algorithm. CSS is introduced by Kaveh and his colleague in 2010 for the first time (Kaveh and Talatahari 2010). Coulomb and Gauss and the Newton laws are the basic principles of developing this algorithm. Regarding these laws, the radius of each charged particle will be calculated as (Mohammadi Asl et al. 2017b)

$$q_i = \frac{\mathrm{fitness}_i - \mathrm{fitness}_{\mathrm{worst}}}{\mathrm{fitness}_{\mathrm{best}} - \mathrm{fitness}_{\mathrm{worst}}}, \qquad i = 1, 2, \ldots, N. \tag{8}$$

where the value of the fitness function and its best and worst value in each iteration are given by $\mathrm{fitness}_i$, $\mathrm{fitness}_{\mathrm{best}}$ and $\mathrm{fitness}_{\mathrm{worst}}$, respectively.

The overall procedure of this algorithm can be summarized as following steps:

Step 1: *Initialization*: The initial values of the charged particles are calculated as

$$\begin{aligned} \mathrm{CP}_i^{(o)} &= \mathrm{CP}_{i,m} + rand_i\left(X_{i.M} - \mathrm{CP}_{i,m}\right) \\ V_i^{(o)} &= 0, \qquad i = 1, 2, \ldots, N. \end{aligned} \tag{9}$$

where the minimum and the maximum of the search space are given by $\mathrm{CP}_{i,m}$ and $\mathrm{CP}_{i,M}$, respectively. The parameters, $\mathrm{CP}_i^{(o)}$, $V_i^{(o)}$ and i, show the initial values of the CPs and their speed and the number of ranges, respectively.

Step 2: *Force calculation*: the force between CPs is calculated as

$$r_{ij} = \frac{\left\|\mathrm{CP}_i - \mathrm{CP}_j\right\|}{\left\|\frac{(\mathrm{CP}_i + \mathrm{CP}_j)}{2} - \mathrm{CP}_{\mathrm{best}}\right\|} \tag{10}$$

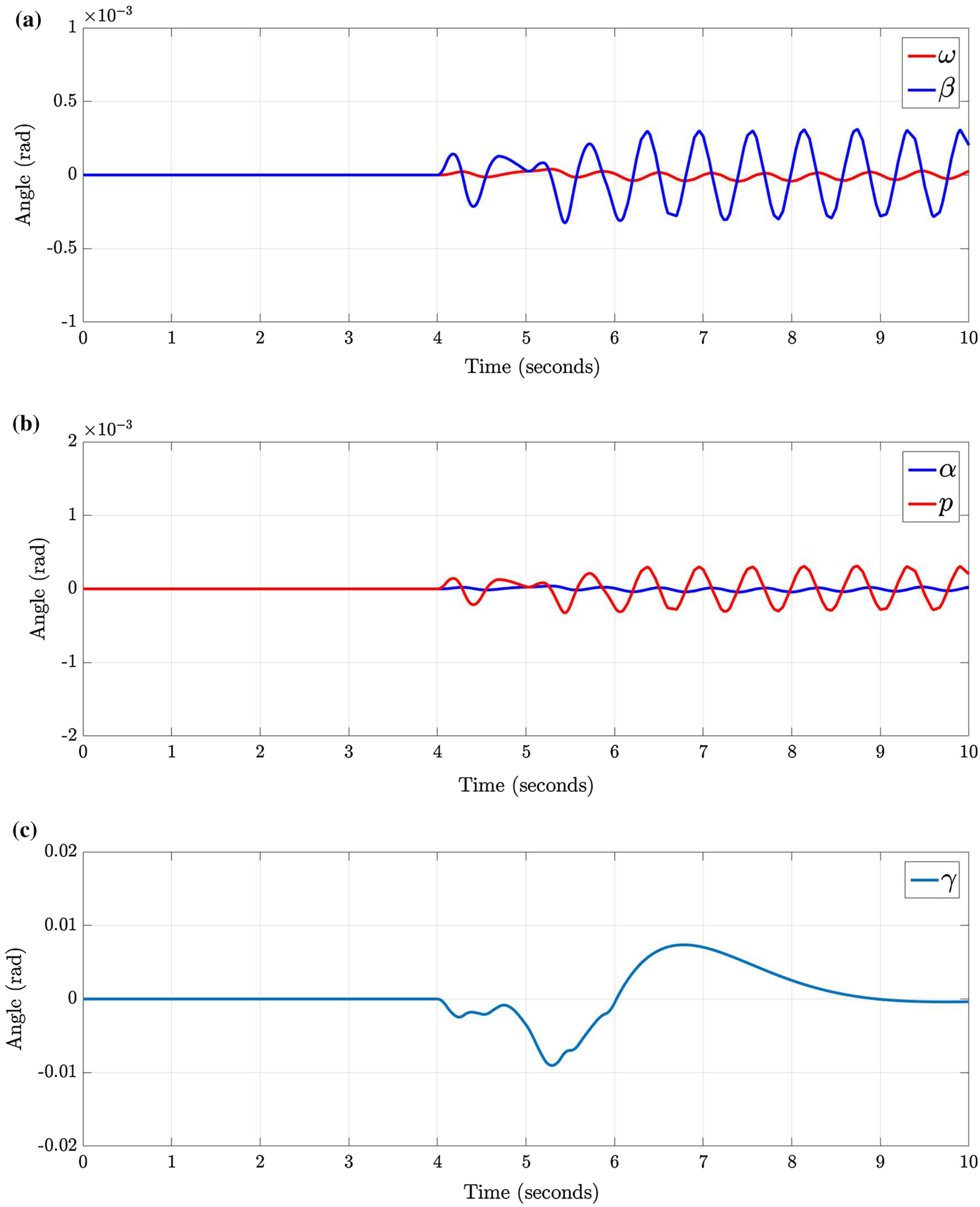

Fig. 3 The response of the subsystems using conventional PID controller. **a** The subsystem 1. **b** The subsystem 2. **c** The subsystem 3

where the indexes i and j show the place of the CPs in the search space. $\mathrm{CP}_{\mathrm{best}}$ is the cp with best fitness value.

Step 3: *Electrical force calculation*: In order to update the candidate CPs, it is necessary to calculate the electrical force for each CP as

$$F_j = q_j \sum_{i=1, i \neq j}^{N} \left[q_i c_{ij} \left(\frac{r_{ij} i_1}{a^3} + \frac{i_2}{r_{ij}^2} \right) (\mathrm{CP}_i - \mathrm{CP}_j) \right]$$

$$c_{ij} = \begin{cases} -1 & if \quad \text{finesst}_i < \text{fitness}_j \\ 1 & \text{otherwise} \end{cases} \tag{11}$$

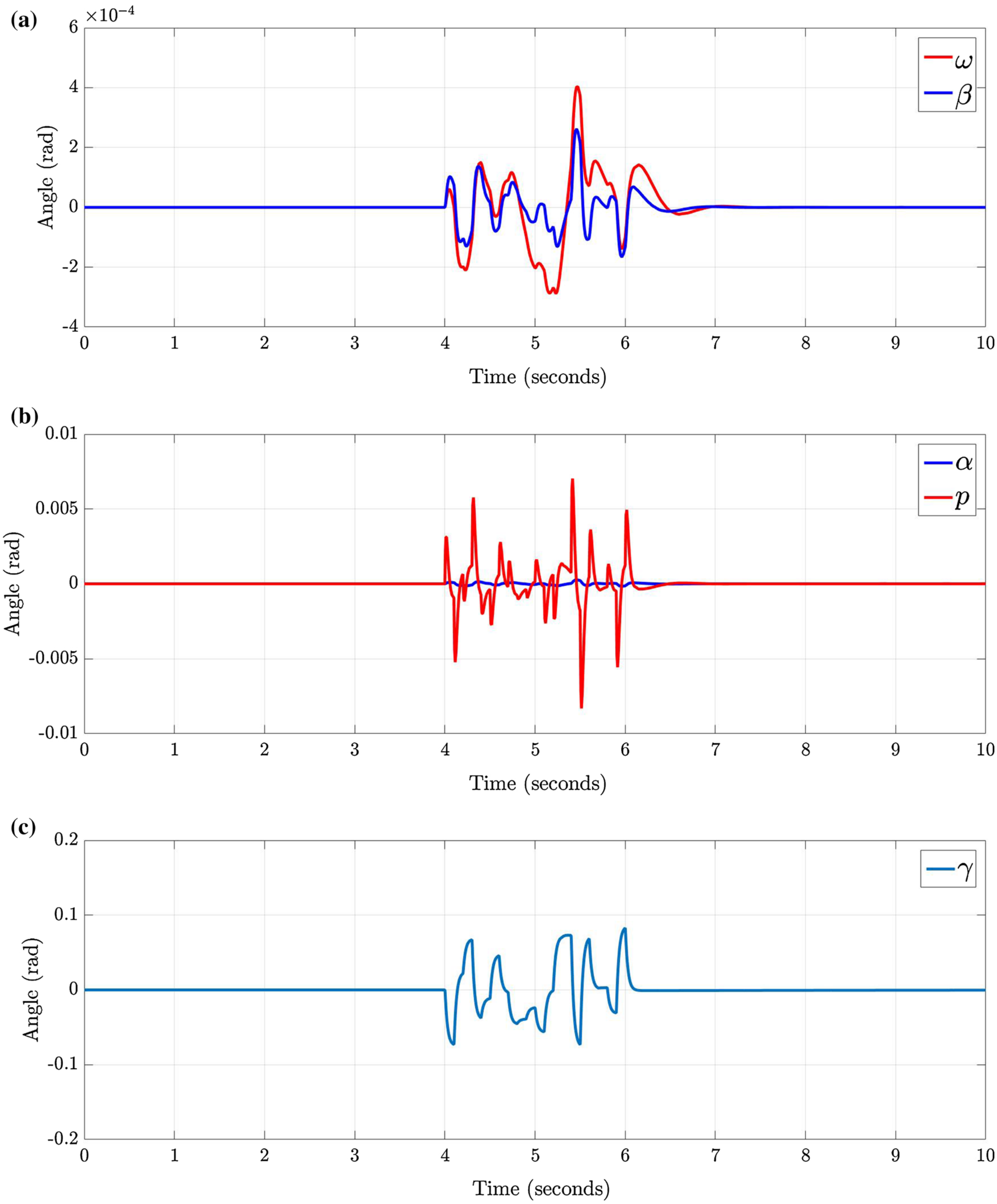

Fig. 4 The response of the subsystems using LQR controller. **a** The subsystem 1. **b** The subsystem 2. **c** The subsystem 3

Step 4: *Updating CPs*: The candidate CPs is updated as

$$X_j(k+1) = r_{j1}k_a.\frac{F_j}{m_j}.\Delta t^2 + r_{j2}k_v V_j(k)\,\Delta t + \mathrm{CP}_j(k)$$
$$V_j(k+1) = \frac{\mathrm{CP}_j(k+1) - \mathrm{CP}_j(k)}{\Delta t} \tag{12}$$

(Kaveh and Talatahari 2010; Mohammadi Asl et al. 2017b).

Step 5: *STOP criteria*: If the stop criteria are satisfied, return the best solution, otherwise go to step 2

The based algorithm does not consider the value of the candidate solutions fitness. In order to consider the value of the fitness, the following formula is presented to update the candidates

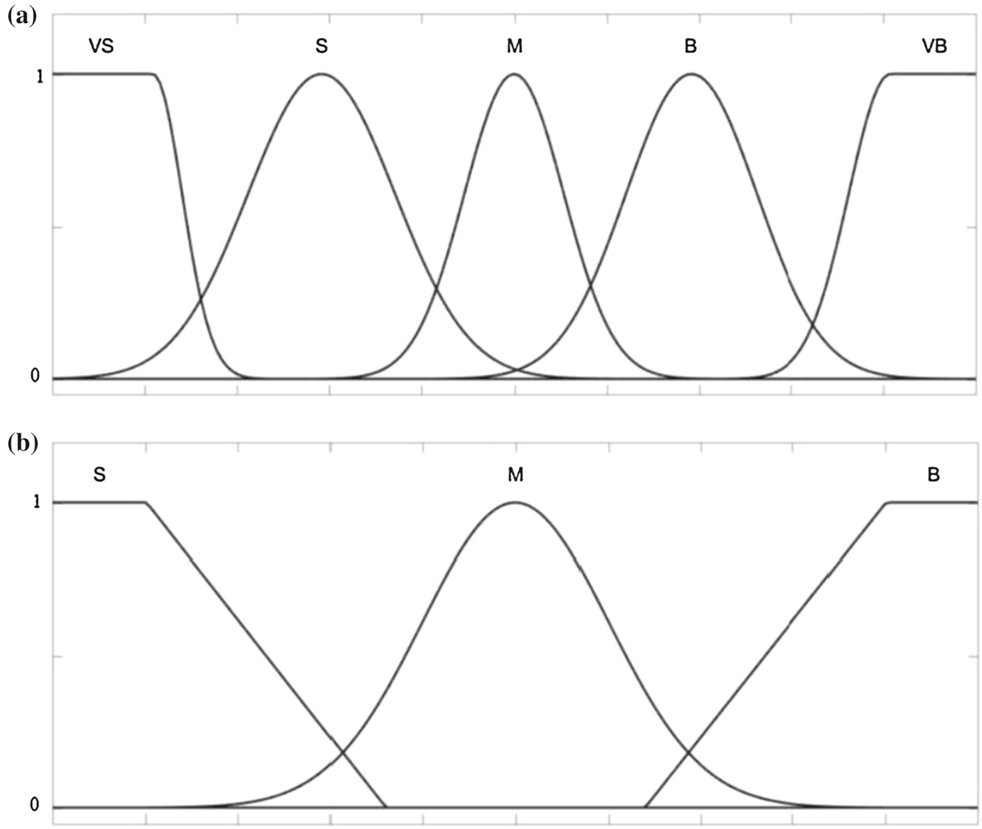

Fig. 5 The typical form of the membership functions of fuzzy logic switching system. **a** The membership functions of input. **b** The membership functions of output

Table 3 The parameters of adaptive charged system search

Parameter	Value
Population	20
Max iteration	10
Δt	1

Table 4 The fuzzy rules of switching system for PID controller

$e(t)$	$\dot{e}(t)$				
	VS	S	M	B	VB
VS	S	S	S	M	M
S	S	S	M	M	M
M	S	M	M	M	B
B	M	M	M	B	B
VB	M	M	B	B	B

$$V_j(k+1) = \left(\frac{\mathrm{CP}_j(k+1) - \mathrm{CP}_j(k)}{\Delta t}\right) \cdot \frac{1}{k} \tag{13}$$

Regarding this updating equation, the update of the velocity is based on the position of the candidate solution.

Table 5 The fuzzy rules of switching system for LQR controller

e(t)	$\dot{e}(t)$				
	VS	S	M	B	VB
VS	B	B	B	M	M
S	B	B	M	M	M
M	B	M	M	M	S
B	M	M	M	S	S
VB	M	M	S	S	S

2.4.1 ACSS validation

In order to calculate the proficiency of the proposed new algorithm, it is applied on different benchmark optimizing problems. The result of the proposed algorithm is compared with well-known conventional algorithm, including GA, PSO, DE and basic charged system search. The information of the benchmark functions is given in Table 1. Figures 1 and 2 show the benchmark functions. The figures give some useful information about the behavior of each function. To have a proper view of the behavior of the functions, they are figured from two perspective, 3D and counter view, which

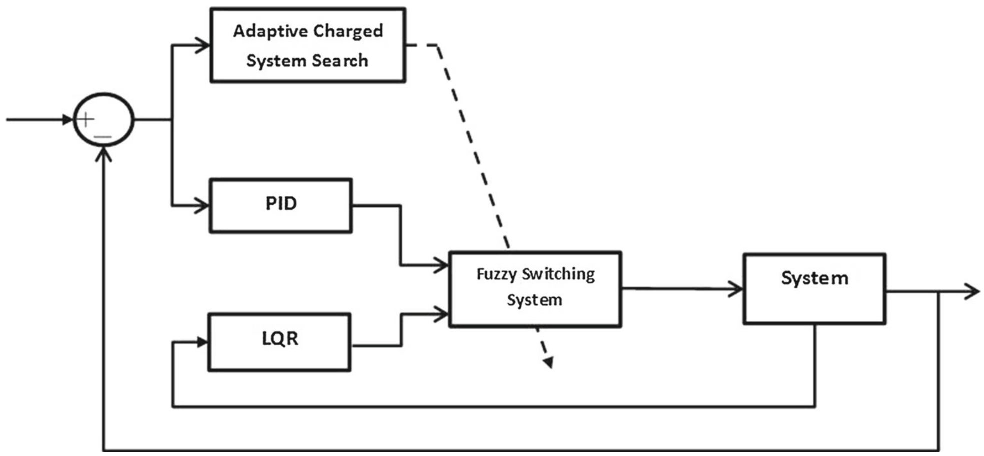

Fig. 6 The schematic of the proposed controlling system

can help to have a good idea about each function. The result of applying different methods on the functions is given in Table 2. The results for GA, DE and PSO are taken from Mohammadi Asl et al. (2017a).

3 Simulations

This section has two parts. First, a brief review of the unicycle robot will be presented, and then, the results of applying different controllers on the system will be given.

3.1 Unicycle robot

The unicycle robot as a high nonlinear practical system is an possible choice for applying different approaches on it. The system has five different and independent variables that will be tried to control by the proposed approach. The dynamical model of the system can be found in (Hu et al. 2014). In order to simplify the procedure of the control system, it is divided into three subsystems. In the following parts, the procedure of the control subsystems will be presented; then, the results will be given.

3.2 PID controller and LQR controller

In this section, PID controller and LQR controller design for the unicycle robot are reviewed.

A conventional PID is designed for each subsystem by using Ziegler–Nichols closed-loop test method. The PID parameters of the subsystems are as follows:
Subsystem 1:

$$K_{P_1} = 450, \quad K_{I_1} = 9, \quad K_{D_1} = 38 \tag{14}$$

Subsystem 2:

$$K_{P_2} = 21, \quad K_{I_2} = 0.4, \quad K_{D_2} = 12 \tag{15}$$

Subsystem 3:

$$K_{P_3} = 10, \quad K_{I_3} = 5, \quad K_{D_3} = 19 \tag{16}$$

The eigenvalues of all the closed-loop subsystems have negative real part, which guarantee stability of all the subsystems. The simulation results of applying the PID to the balancing control of the unicycle robot are presented in Fig. 3. The system is influenced by a disturbance at $t = 4\,s$. On the other hand, the LQR controller is designed for each subsystem, where the controller gains are as follows:
Subsystem 1:

$$\begin{aligned} &Q = diag\,[50, 50, 50, 50], \ R = [100], \\ &K_1 = [223.73 \quad 3.91 \quad -814.32 \quad -35.21] \end{aligned} \tag{17}$$

Subsystem 2:

$$\begin{aligned} &Q = diag\,[70, 70, 70, 70], \ R = [100], \\ &K_2 = [15.24 \quad -13.52 \quad 13.96 \quad 17.81] \end{aligned} \tag{18}$$

Subsystem 3:

$$Q = diag\,[50], \ R = [100], \ K_3 = [33.19 \quad 5.87] \tag{19}$$

where LQR controller guarantees the stability of the system and the controlled system can be supposed as a stable system. The simulation results of applying the LQR controller to the balancing control of the unicycle robot are presented in Fig. 4, where the system is influenced by a disturbance at $t = 4\,s$.

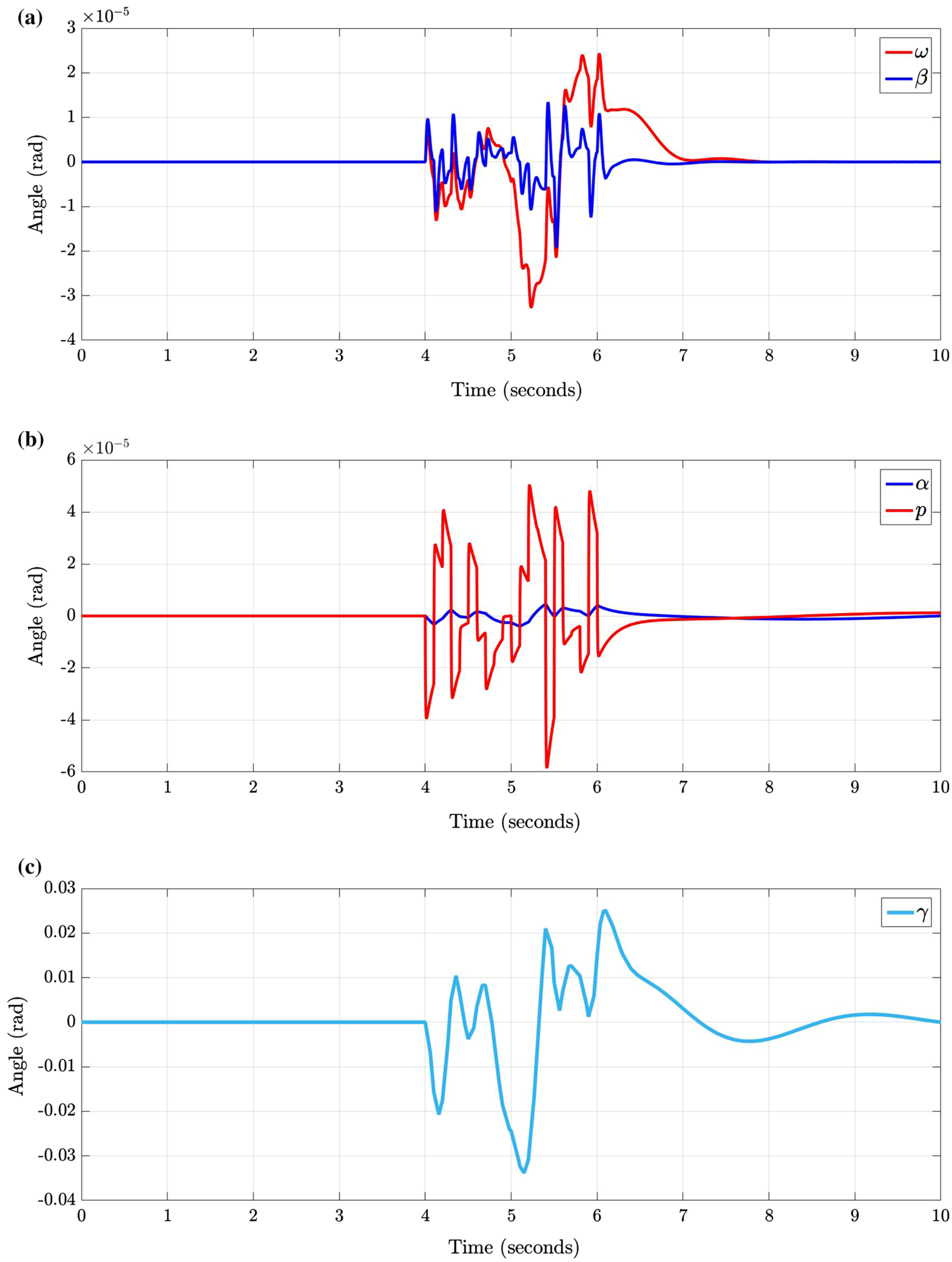

Fig. 7 The response of the subsystems using the proposed controller with a fuzzy logic-based switching system. **a** The subsystem 1. **b** The subsystem 2. **c** The subsystem 3

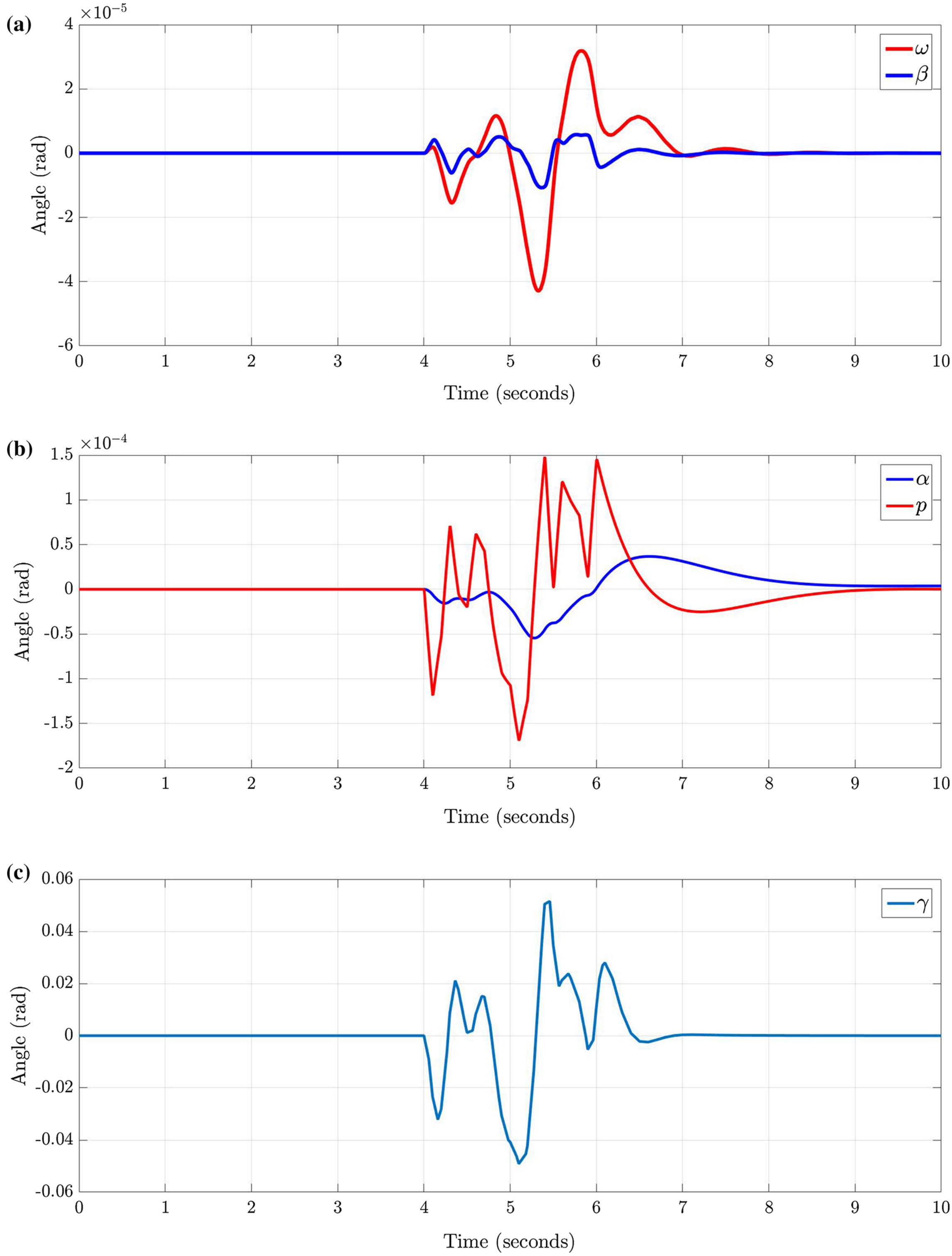

Fig. 8 The response of the subsystems using the basic charged system search algorithm. **a** The subsystem 1. **b** The subsystem 2. **c** The subsystem 3

Table 6 The values of mean square error

Method	Parameter				
	ω	β	α	p	γ
PID controller	1×10^{-4}	3.2×10^{-4}	3.4×10^{-4}	5×10^{-4}	0.083
LQR controller	4×10^{-4}	2.3×10^{-4}	2×10^{-4}	7.3×10^{-4}	0.084
Fuzzy switching-based controller (CSS)	4.2×10^{-5}	1.1×10^{-5}	1.7×10^{-4}	5.3×10^{-5}	0.031
Fuzzy switching-based controller (ACSS)	3.3×10^{-5}	1.8×10^{-5}	2.3×10^{-6}	5.8×10^{-5}	0.012

3.3 The proposed controller

In this section, the proposed controller, which is investigated by the combination of PID and LQR controller with a fuzzy-based switching system, is introduced and the results of applying this controller to the balancing control of the unicycle robot, which is under a disturbance, are shown. Each controller has its advantages. PID and LQR have different controller structures which result in different closed-loop system models and performance tunings. PID controller's error and overshoot are smaller than LQR controller, and its implementation is easier than LQR. On the other hand, LQR controller's rise time and settling time are smaller than PID controller. There are differences between results of PID and LQR controllers, and the difference is because of the different methods of calculating feedback gain matrix. In order to decrease the error, a complex controller is designed. The controller is designed in a way that when system's error is small, LQR controller is applied, and when the error is big, PID controller is chosen. The proposed controller has advantages of both LQR and PID controllers. On the other hand, in order to avoid on-off switching, a fuzzy logic-based switching system is applied to change between control signals. By using system's error and its derivative, the proposed fuzzy switching system gives two factors. They are used for calculating the controlling signal as a combination of the output signals of PID and LQR controllers. The values of center of the membership functions are tuned by the algorithm. These values are important and have significant role in the final value of the control input. Suppose the centers are not arranged in a proper way, so the fuzzy logics output will have wrong values so the control input will not have proper control input; therefore, it is possible to have unstable system. In another condition, the inefficient values of the centers can cause to have slow speed in reaching the proper position. The model of switching system can be expressed as follows:

$$u = \xi_1 . u_{\mathrm{PID}} + \xi_2 . u_{\mathrm{LQR}} \tag{20}$$

where ξ_1 and ξ_2 are the switching factors of controllers, which are calculated by fuzzy switching system. The typical form of membership functions for fuzzy systems is shown in Fig. 5. The center of these membership functions is tuned by the proposed adaptive charged system search algorithm (ACSS) in a way to minimize the following fitness function:

$$\text{Fitness} = \int_0^t e^2(\tau)\,\tau \tag{21}$$

where $e(t)$ is the tracking error. Table 3 introduces the parameters of ACSS, which are used in simulation. The fuzzy rules of switching system are introduced in Tables 4 and 5 . The schematic of the proposed controlling system is shown in Fig. 6. The simulation results of applying the proposed controller are shown in Fig. 7. It is seen that the proposed controller can control the balance of the system better than PID and LQR controllers. In order to show the efficiency of the proposed algorithm applied for tuning the fuzzy switching system, the results of using the basic CSS algorithm are shown in Fig. 8. Both algorithms, CSS and ACSS, are used at the same conditions, and the results show that ACSS can tune the parameters of fuzzy system better than CSS (Table 6).

4 Conclusion

In this paper, a combination of PID controller and linear quadratic regulator (LQR) is introduced. A fuzzy logic-based switching system is applied to switch between the controllers. PID controller's errors and overshoot are smaller than LQR controller. On the other hand, LQR controller's rise time and setting time are smaller than the ones from PID controller. In order to use the advantages of both controllers, the combination of PID and LQR controller with a fuzzy switching system is investigated. To show the efficiency of the proposed controller, it is applied to unstable unicycle robot balance control under disturbances. The results prove that the proposed controller can maintain the stability of the system precisely.

Compliance with ethical standards

Conflict of interest All authors declare that they have no conflict of interest.

Human participants or animals rights statement This article does not contain any studies with human participants or animals performed by any of the authors.

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