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SLIDING MODE TRACKING CONTROL USING DIFFERENTIAL EVOLUTION OPTIMIZATION ALGORITHM FOR A CLASS OF UNCERTAIN SYSTEMS WITH INPUT CONSTRAINTS

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Abstract. *This paper presents sliding mode tracking control for a class of uncertain high-order dynamic systems with input constraints and external time varying disturbances. The input signals of systems are nonlinear saturation involving unknown parameters. The sliding mode controller using differential evolution optimization algorithm is proposed for the unknown parameters estimation and the tracking controller is robust to the time varying external disturbances. The design of auxiliary subsystem in the sliding mode tracking systems realizes the compensation of the constrained input signals. The effectiveness of the proposed approach is verified by simulations and the results exhibit the high precision output tracking performances.*
Keywords: Tracking control, Differential evolution, Input constraints, Sliding mode, Uncertain systems

1. **Introduction.** Tracking control for the uncertain systems has attracted extensive attention in the research areas. One of the tracking control techniques is sliding mode control (SMC), which is applied frequently and has been regarded as one of the effective robust control methods for dynamic systems with model uncertainties. Due to the strong robust properties, SMC is applied to a wide range of industrial areas for trajectory tracking problems, including robotic manipulators system [1],vehicle systems [2,3], motor system [4,5], power system [6] and chaotic system [7].

To achieve optimized tracking target for the uncertain systems, intelligent optimal algorithms are introduced into the sliding mode tracking control. The tracking technique has been developed on the basis of optimization algorithm, such as genetic algorithm [8] and particle swarm algorithm [9,10]. SMC using the intelligent algorithms solves a class of tracking problems, when the structural information of dynamic systems is limited and the parameters are uncertain, but these methods are difficult to solve a class of uncertain systems, when the input signals are nonlinear constraint with uncertain parameters. The limitations have strong effect on the convergence properties and tracking performances.

Differential evolution (DE) algorithm based on global search algorithm has good convergence properties and search performance [11-13]. A comparative analysis of the performance of particle swarm optimization (PSO) algorithms, firefly algorithm (FA) and DE algorithms is shown in [14] and the results demonstrate DE is better than other optimization algorithm for parameters estimation. Due to the advantages, DE algorithm is used in a variety of industry areas to obtain faster convergence and accurate search properties, such as back-analysis of tunnel response [15], robust H-infinity control [16], robot path planning [17], permanent magnet synchronous motor control [18] and chaotic control [19].

DE optimization technique has features in faster convergence and precision estimation and it was applied for controlling unconstraint actuators mostly, which the input signals of the system are not constraint. Due to the existence of "imperfect" actuators, input constraints are frequently encountered in engineering applications, such as input saturation [20-22], input dead-zone [23-25] and input hysteresis [26]. To solve the constrained input problems, the research work related to the effectiveness of SMC for dynamic systems with input constraints has been demonstrated. For example, Zhang and Kurihara [27] designed SMC with input dead-zone. Zhou and Chen [28] proposed sliding mode control based on nonlinear disturbance observer to handle input saturation with system uncertainty, but the saturation input signals with the unknown parameters are still hard to be dealt with for tracking control.

This paper proposes sliding mode tracking control for the uncertain dynamic systems with input constraints, unknown parameters and external time varying disturbances. To deal with the unknown parameters incorporated into the constrained input signals, the sliding mode controller using DE algorithm is presented to estimate the unknown parameters with fast convergence and accurate estimation. The designed auxiliary subsystem provides compensation for the constrained input signals. The new system states which are produced from auxiliary subsystems eliminate the undesired effects caused by the nonlinear saturation constraints. The auxiliary subsystem in the feedback loop overcomes the saturation nonlinearity. The stability of the tracking system is analyzed and the tracking errors converge to the origin. Simulation verifies the effectiveness of the proposed sliding mode tracking control method.

The paper is organized as follows. In Section 2, a description of uncertain dynamic systems is given. In Section 3, sliding mode tracking control based on the differential evolution algorithm and auxiliary system is designed and demonstrated. The effectiveness of sliding mode tracking control synthesized differential evolution algorithm is verified in Section 4. The conclusions are shown in Section 5.

2. **Problem Formulation.** Consider a class of higher-order uncertain dynamic system as Equation (1)

$$\begin{aligned} \dot{x}_i(t) &= x_{i+1}(t) \\ \dot{x}_n(t) &= f(x,t) + bu(t) + d(t) \\ y(t) &= x_1(t),\ t \in [0,T] \end{aligned} \tag{1}$$

where x_i, $i = 1, 2, \ldots, n-1$ are the system state vectors, $u(t)$ and $y(t)$ are the control input signals and system output signals respectively, $f(x,t)$ is known linear function, and $b \neq 0$ is the unknown parameter. The time-varying disturbance variable $d(t)$ is bounded as $|d(t)| \leq D$ and D is positive constant. Considering the saturation input $u(t) = sat(v)$ is defined as shown in Figure 1, where v is referred to as the designed control law $v(t)$ with upper bound and lower bound, and $u_{\max} > 0$ is a known constant. To facilitate the tracking controller design, some assumptions are presented as follows.

Assumption 2.1. *The desired output trajectory $y_d(t)$ is differentiable with respect to time t and all of the higher-order derivatives are available.*

Aiming to track the desired trajectory in high precision, the sliding mode controller provides $u(t)$ for the uncertain dynamic systems with a prescribed accuracy parameter μ, which is sufficiently small, as follows

$$|y(t) - y_d(t)| \leq \mu$$

The constraint input signals are nonlinear saturation and involve unknown parameter. This means the sliding mode controller both needs to overcome the input constraints and estimate the unknown parameters.

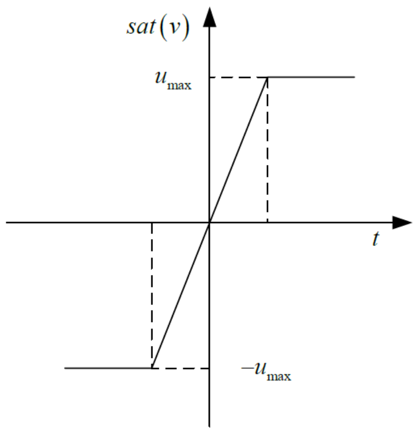


FIGURE 1. Input saturation constraints

3. **Sliding Mode Tracking Control with Input Constraints and Stability Analysis.** In this section, sliding mode tracking controller is designed for the uncertain dynamic system with input saturation, unknown parameters, and time varying disturbances. The tracking controller for the constraint input incorporating unknown parameter is designed to overcome uncertain nonlinear limitation; therefore, the auxiliary system and differential evolution (DE) algorithm are applied to the design of sliding mode tracking control system. The auxiliary system provides compensation for constraint input and the differential evolution (DE) algorithm is utilized to approach the unknown parameters.

3.1. **Derivation of sliding surface.** Sliding surface is given as Equation (2)

$$s(t) = c_1 e(t) + c_2 \dot{e}(t) + \cdots + c_n e^{(n-1)}(t) = \sum_{i=1}^{n} c_i e(t)^{(i-1)} \tag{2}$$

where the tracking system output errors $e(t) = y(t) - y_d(t)$ and parameters $c_1, c_2, \ldots, c_n$ are positive constants and Hurwitz. The tracking errors are also described as $e(t) = y(t) - y_d(t) = x_1(t) - y_d(t)$.

Equation (3) is obtained by the differential of both sides of Equation (2)

$$\dot{s}(t) = c_1 \dot{e}(t) + c_2 \ddot{e}(t) + \cdots + c_n e^{(n)}(t) = \sum_{i=1}^{n} c_i e(t)^{(i)} \tag{3}$$

Equation (3) is further expanded as Equation (4)

$$\begin{aligned} \dot{s}(t) &= c_1[x_2(t) - \dot{y}_d(t)] + c_2[x_3(t) - \ddot{y}_d(t)] + \cdots + c_n\left[f(x,t) + bu(t) + d(t) - y_d^{(n)}(t)\right] \\ &= \sum_{i=1}^{n-1} c_i x_{i+1} - \sum_{i=1}^{n} c_i y_d^{(i)} + c_n[f(x,t) + bu(t) + d(t)] \end{aligned} \tag{4}$$

The sliding variable dynamics is given as Equation (4). The condition, $s(t) = 0$, converges the system states to move within the sliding manifold.

3.2. **Differential evolution algorithm.** Differential evolution algorithms use a simple differential operator to create new candidate solutions and employ a one-to-one competition scheme to greedily select new candidates [29]. The key steps of differential evolution algorithm are mutation, crossover, and selection. The initial individuals satisfying constraints are generated by adding normally distributed random deviations as Equation (5)

$$x_{ij}(0) = rand_{ij}(0,1)\left(x_{ij}^U - x_{ij}^L\right) + x_{ij}^L \tag{5}$$

where $x_{ij}(t)$ $i, j = 1, 2, 3, \ldots, NP$ is each target vector, x_{ij}^U and x_{ij}^L are the upper and lower bounds of the jth component among total components respectively, and $rand_{ij}(0, 1)$ is a random decimal within $[0, 1]$. Differential evolution algorithms generate a mutate vector by adding the weighted difference of two vectors to the third vector as Equation (6)

$$h_{ij}(t+1) = x_{p_1 j}(t) + F\left(x_{p_2 j}(t) - x_{p_3 j}(t)\right) \tag{6}$$

The integer indexes randomly are selected as p_1, p_2, p_3 are mutually different and also chosen to be different from the running index i referred to the ith candidate in the population consisting of n candidates and t is denoted generation counter. The target vector, $x_{p_1 j}(t)$ in this case, is a random individual and $x_{p_2 j}(t)$, $x_{p_3 j}(t)$ are two randomly selected individuals in the current population. The scale factor $F > 0$ controls the amplification level of the differential variation. The trial vector is defined componentwise as a binomial crossover operator as Equation (7)

$$v_{ij}(t+1) = \begin{cases} h_{ij}(t+1), & randl_{ij} \leq CR \\ x_{ij}(t), & \text{otherwise} \end{cases} \tag{7}$$

where $randl_{ij}$ is a random number generated by using the uniform probability distribution in the range 0-1. The crossover constant $CR \in [0, 1]$ is to be determined by the user. If the trial vector is measured to be better by the fitness function, the trial vector will replace the target vector; otherwise, $x_i(t)$ is retained as Equation (8).

$$x_i(t+1) = \begin{cases} v_i(t+1), & f(v_i(t+1)) < f(x_i(t)) \\ x_i(t), & \text{otherwise} \end{cases} \tag{8}$$

Mutation, crossover, and selection will repeat until the update reaches to the maximum number of iteration G. The differential evolution optimization algorithm is depicted in Figure 2. To estimate the unknown parameter, the tracking system will be rewritten as Equation (9)

$$Y(t) = bu(t) \tag{9}$$

The optimization criterion J is designed as Equation (10)

$$J = \sum_{i=1}^{N} \frac{1}{2} \left(y_i - \hat{y}_i\right)^T \left(y_i - \hat{y}_i\right) \tag{10}$$

where N is the total number of test data, $y_i = Y(i)$, $i = 1, 2, \ldots, n-1$. The true parameters vector is b and $\hat{b}$ is the estimation parameters vector. Then we have $\lim_{J \to 0} \hat{b} = b$, when criterion J approaches to zero.

3.3. **The auxiliary system design of sliding mode control with input constraints.** The auxiliary system is given by Equation (11)

$$\begin{aligned} \dot{\lambda}_i(t) &= -m_i \lambda_i(t) + \lambda_{i+1}(t) \\ \dot{\lambda}_n(t) &= -m_n \lambda_n(t) + b\Delta u(t) \end{aligned} \tag{11}$$

where λ_i, $i = 1, 2, \ldots, n-1$ is auxiliary state vectors and $m_i > 0$, $i = 1, 2, \ldots, n-1$ and input constraint deviation is $\Delta u(t) = u(t) - v(t)$. Define

$$A = \begin{bmatrix} -m_1 & 1 & 0 & \ldots & 0 \\ 0 & -m_2 & 1 & \ldots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & \ldots & \ldots & -m_{n-1} & 1 \\ 0 & \ldots & \ldots & \ldots & -m_n \end{bmatrix}$$

where A is Hurwitz and $\Delta u(t)$ is bounded, $\lim_{t \to \infty} \lambda_i(t) = 0$ is obtained. In the uncertain dynamic systems, the constraint input and unknown parameter affect the sliding mode control stability. New states produced by the auxiliary system are added into the output

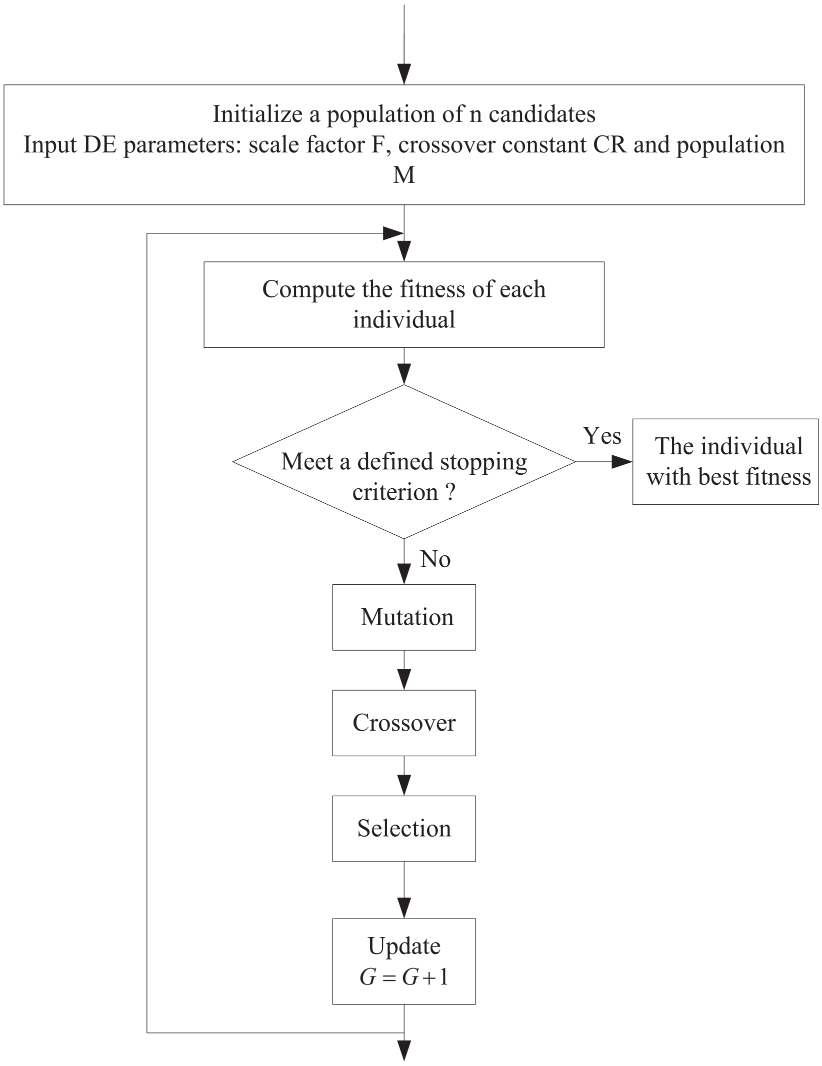


Figure 2. Differential evolution algorithm

tracking error, aroused by the error amplification method. The input signals with constraints are compensated by using the auxiliary system. The output error $e(t)$ is redefined as $e(t) = y(t) - y_d(t) - \lambda_1(t)$ and $e^{(n)}(t) = y^{(n)}(t) - y_d^{(n)}(t) - \lambda_1^{(n)}(t)$. Correspondingly, Equation (3) is redefined as Equation (12)

$$\dot{s}(t) = c_1\dot{e}(t) + c_2\ddot{e}(t) + \cdots + c_n e^{(n)}(t) = \sum_{i=1}^{n} c_i e(t)^{(i)} \tag{12}$$

The above equation can be further expanded as Equation (13)

$$\begin{aligned}\dot{s}(t) &= c_1\left[x_2(t) - \dot{y}_d(t) - \dot{\lambda}_1(t)\right] + c_2\left[x_3(t) - \ddot{y}_d(t) - \ddot{\lambda}_1(t)\right] + \cdots + c_n\Big[f(x,t) + bu(t) \\ &\quad + d(t) - y_d^{(n)}(t) - \lambda_1^{(n)}(t)\Big] \\ &= \sum_{i=1}^{n-1} c_i x_{i+1}(t) - \sum_{i=1}^{n} c_i y_d^{(i)}(t) - \sum_{i=1}^{n-1} c_i \lambda_1^{(i)}(t) + f(x,t) + bu(t) + d(t) - b\Delta u(t) \\ &\quad - \sum_{k=1}^{n} (-1)^{n+1-k}\left[\sum_{i_1+i_2+\cdots+i_k=n+1-k}\left(\prod_{j=1}^{k} m_j^{i_j}\right)\right]\lambda_k \\ &\qquad i_j = 0, 1, \ldots, n+1-k, \quad j = 1, 2, \ldots, k, \quad k = 1, 2, \ldots, n\end{aligned} \tag{13}$$

where $c_n = 1$, so the coefficients c_n will be omitted to simplify the equation presentation.

Theorem 3.1. *For system (1) with the input nonlinear saturation incorporate unknown parameters, the sliding mode controller using DE algorithm added auxiliary system is designed as*

$$v(t) = \frac{1}{\hat{b}}\left\{\begin{array}{l} -\sum_{i=1}^{n-1} c_i x_{i+1}(t) + \sum_{i=1}^{n} c_i y_d^{(i)}(t) + \sum_{i=1}^{n-1} c_i \lambda_1^{(i)}(t) - f(x,t) \\ +\sum_{k=1}^{n}(-1)^{n+1-k}\left[\sum_{i_1+i_2+\cdots+i_k=n+1-k}\left(\prod_{j=1}^{k} m_j^{i_j}\right)\right]\lambda_k - \eta\,\mathrm{sgn}(s) \end{array}\right\} = \frac{1}{\hat{b}}\mathrm{M}(t)$$

$$\begin{aligned} \mathrm{M}(t) = &-\sum_{i=1}^{n-1} c_i x_{i+1}(t) + \sum_{i=1}^{n} c_i y_d^{(i)}(t) + \sum_{i=1}^{n-1} c_i \lambda_1^{(i)}(t) - f(x,t) \\ &+\sum_{k=1}^{n}(-1)^{n+1-k}\left[\sum_{i_1+i_2+\cdots+i_k=n+1-k}\left(\prod_{j=1}^{k} m_j^{i_j}\right)\right]\lambda_k - \eta\,\mathrm{sgn}(s) \end{aligned} \tag{14}$$

and the design parameters are chosen as $\eta \geq D$. Then we have the results as follows

$$x_i(t) \to y_d^{(i-1)}(t),\ i = 1, 2. \quad t \to \infty$$

Proof: The stability of the tracking system is proved using Lyapunov analysis. Consider the Lyapunov function as Equation (15)

$$V = \frac{1}{2}s^2 \tag{15}$$

The derivative of Lyapunov function with respect to time t is given by Equation (16)

$$\begin{aligned} \dot{V} &= s\dot{s} \\ &= s\left\{\sum_{i=1}^{n-1} c_i x_{i+1}(t) - \sum_{i=1}^{n} c_i y_d^{(i)}(t) - \sum_{i=1}^{n-1} c_i \lambda_1^{(i)}(t) + f(x,t) + bu(t) + d(t) - b\Delta u(t) \right. \\ &\quad \left. -\sum_{k=1}^{n}(-1)^{n+1-k}\left[\sum_{i_1+i_2+\cdots+i_k=n+1-k}\left(\prod_{j=1}^{k} m_j^{i_j}\right)\right]\lambda_k\right\} \\ &= s\left\{\sum_{i=1}^{n-1} c_i x_{i+1}(t) - \sum_{i=1}^{n} c_i y_d^{(i)}(t) - \sum_{i=1}^{n-1} c_i \lambda_1^{(i)}(t) + f(x,t) + bv(t) + d(t) \right. \\ &\quad \left. -\sum_{k=1}^{n}(-1)^{n+1-k}\left[\sum_{i_1+i_2+\cdots+i_k=n+1-k}\left(\prod_{j=1}^{k} m_j^{i_j}\right)\right]\lambda_k\right\} \\ &= s\left\{\sum_{i=1}^{n-1} c_i x_{i+1}(t) - \sum_{i=1}^{n} c_i y_d^{(i)}(t) - \sum_{i=1}^{n-1} c_i \lambda_1^{(i)}(t) + f(x,t) + \frac{\hat{b} + b - \hat{b}}{\hat{b}}\mathrm{M}(t) + d(t) \right. \\ &\quad \left. -\sum_{k=1}^{n}(-1)^{n+1-k}\left[\sum_{i_1+i_2+\cdots+i_k=n+1-k}\left(\prod_{j=1}^{k} m_j^{i_j}\right)\right]\lambda_k\right\} \\ &\leq |s|\frac{\left|b - \hat{b}\right|}{\left|\hat{b}\right|}|\mathrm{M}(t)| + |s||d(t)| - \eta|s| \end{aligned} \tag{16}$$

when J is sufficiently small, we have

$$\lim_{J \to 0}\left|b - \hat{b}\right| = 0$$

Finally, $\dot{V} \le D|s| - \eta|s| \le 0$; therefore, the system is stable and the tracking errors converge to zero on the sliding manifold.

4. **Simulation.** To verify the tracking performances of the proposed algorithm, we consider a motor dynamic system with time-varying disturbances and the time-varying disturbances and actuators defections will exaggerate the input saturation nonlinearity. The input signals combined with unknown parameters will be constrained over the tracking period continuously. The complicated case is shown with the motor systems [30] as follows

$$\begin{aligned} \dot{x}_1(t) &= x_2(t) \\ \dot{x}_2(t) &= bu(t) + d(t) \end{aligned}$$

The input signal $u(t)$ is constrained with saturation parameter $|u_{\max}| = 0.43$ and the time-varying disturbance is $10\sin(t)$. SMC using DE algorithm estimates the unknown parameter b, and the process of dynamic optimization criterion J for uncertain parameter b is presented in Figure 3(a). In this simulation example, the scale factor is $F = 0.7$. Crossover probability is chosen to be $CR = 0.6$ and the size of the population is 50. The maximum number of iteration is 200 and the true value of estimation parameter is $b = 23$.

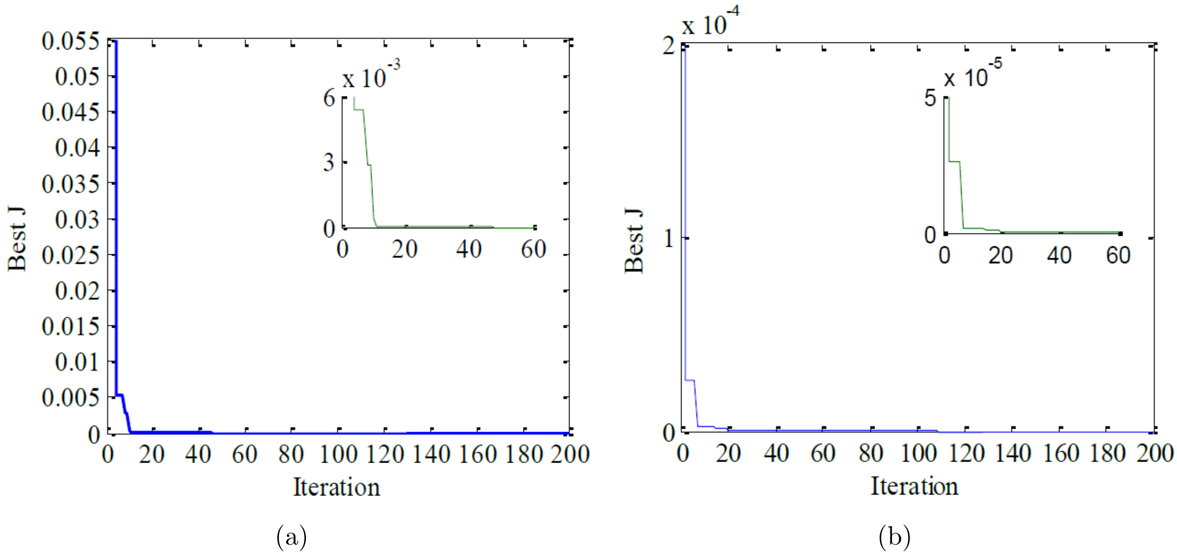
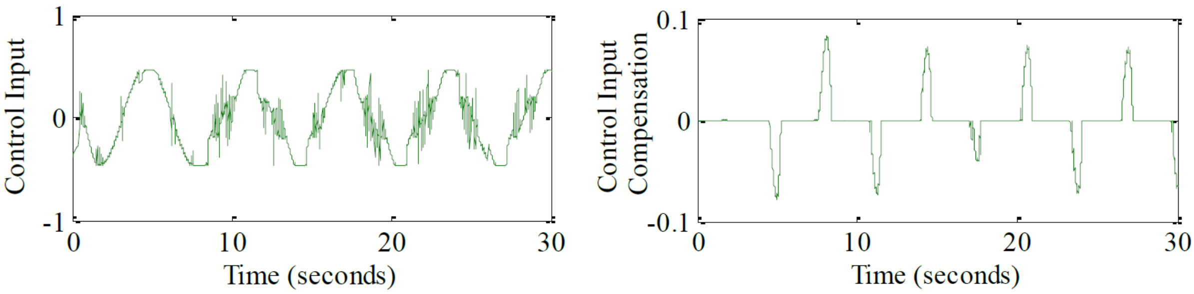


Figure 3. (a) Optimization criterion J in motor system using DE, (b) optimization criterion J in motor system using PSO

The estimation result in Figure 3(a) is $\hat{b} = 23$ and $J_i = 0$. The simulation shows the results of the tracking output performance using DE algorithm for uncertain dynamic systems with constraint input incorporating unknown parameters. Compared to the PSO algorithm shown in Figure 3(b), although the result is $\hat{b} = 23$ and $J_i = 0$, it is clear that DE algorithm has much faster convergence to the zero. Figure 4 displays the control input signals with saturation constraints and corresponding input compensation signals from the auxiliary system. Tracking of the system output angle signals and speed signals corresponding to the desired trajectory in motor system is demonstrated in Figure 5 and Figure 6. It shows that the system product output signals track the desired trajectory in high precision despite the input nonlinear saturation and time-varying disturbance. Although there exist nonlinear saturation constraints and time-varying disturbance, the desired trajectory tracking results show accurate tracking performance. The output tracking errors converge to origin in faster convergence, which verifies the proposed algorithm's effectiveness.



(a) (b)

FIGURE 4. (a) Control input in the motor system, (b) control input compensation in the motor system

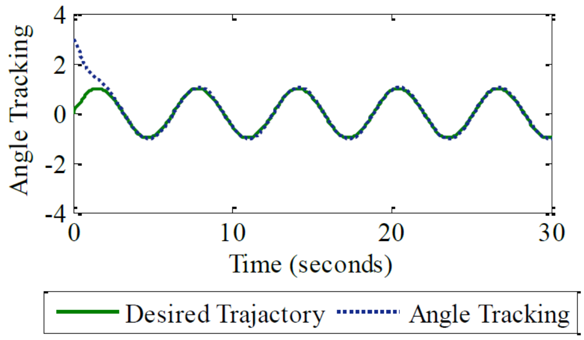


FIGURE 5. Angle of the motor system output tracking

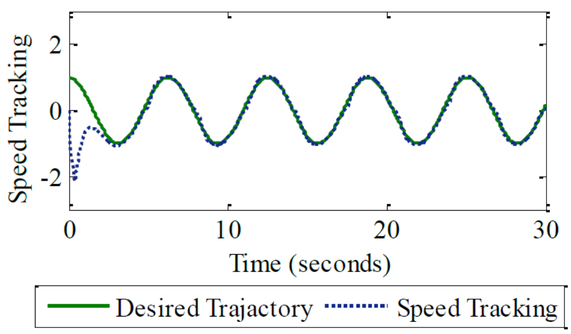
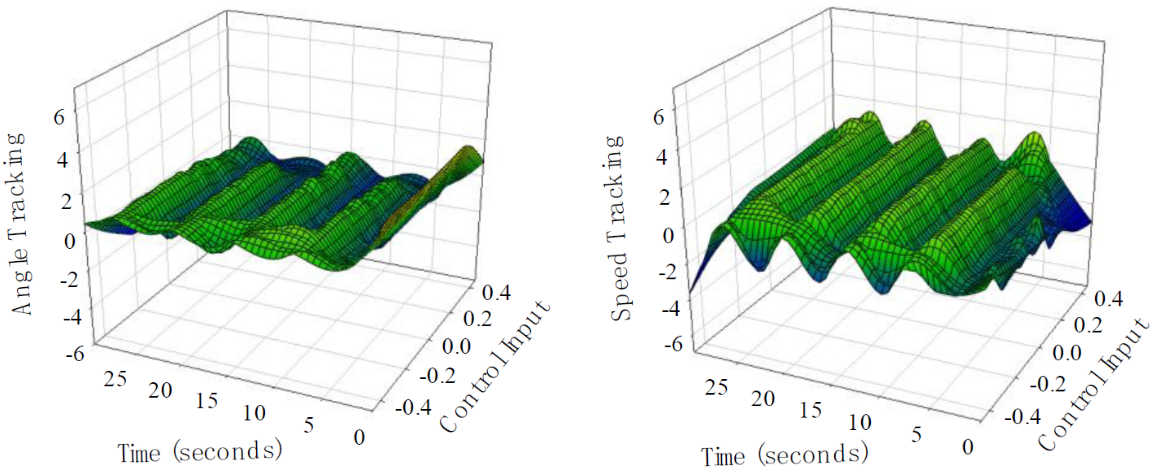


FIGURE 6. Speed of the motor system output tracking



(a) (b)

FIGURE 7. (a) Control input and angle tracking in the motor system, (b) control input and speed tracking in the motor system

The sliding mode controller using DE and auxiliary compensation provides a steady tracking in high precision. As shown in Figure 7, the surface created from constraint input signal and position and speed tracking signals is smooth without sharp oscillation, eliminating the chattering and disturbance effects. Although the control input signals are defected over the tracking period, the stable accurate tracking trajectory is obtained as shown in Figure 7.

5. **Conclusions.** In this paper, sliding mode tracking control method using differential evolution algorithm based on the auxiliary subsystems is proposed for a class of uncertain dynamic systems with input constraints combined with unknown parameters and external time varying disturbances. Differential evolution algorithm and an auxiliary subsystem are incorporated into the design of the sliding mode tracking controller, dealing with the nonlinear input constraints with unknown parameters. The unknown parameters estimation is accurate by the sliding mode tracking controller using DE algorithm. The saturation constraints of the input are compensated by the design of auxiliary subsystem in the tracking control system. The stability of the tracking system is proved and analyzed on the basis of Lyapunov approach. The simulation shows output tracking performance at high precision with fast convergence. For other input constraint in dead zone will be researched in the future.

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