

非一致目标跟踪的混合自适应迭代学习控制

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摘要: 针对一类含有时变和时不变参数的高阶非线性系统, 结合Backstepping方法, 提出了一种新的自适应迭代学习控制方法, 该方法由微分-差分型自适应率和学习控制率组成, 保证对非一致目标的跟踪误差平方在一个有限区间上的积分渐近收敛于零, 克服了传统的迭代学习控制(ILC)对目标轨线限制, 可以跟踪非一致目标轨线. 通过构造复合能量函数, 给出了闭环系统收敛的一个充分条件, 仿真结果说明了该方法的有效性和可行性.

关键词: 自适应迭代学习控制; Backstepping; 非一致目标跟踪; 混合型的参数非线性系统; 复合能量函数

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Hybrid adaptive iterative learning control of non-uniform trajectory tracking

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Abstract: A novel adaptive iterative learning control approach is proposed for a class of hybrid parametric nonlinear systems by means of Backstepping method. The approach consists of a differential-deference type updating law and a learning control law for handling the non-uniform trajectory tracking problem. It avoids the restrictions on the tracking trajectory in the traditional ILC. A sufficient condition for tracking error to converge to zero in the mean-square sense on the finite interval is also given by constructing a novel composite energy function. A simulation example shows the feasibility and effectiveness of the approach.

Key words: adaptive iterative learning control; Backstepping; non-uniform trajectory tracking; hybrid parametric nonlinear systems; composite energy function

1 引言(Introduction)

迭代学习控制是一种能有效地处理重复跟踪控制问题或周期性干扰抑制问题的新型控制方法^[1~4], 在现有的文献中, 要求目标轨迹在所有的迭代中是不变的, 对于复杂目标轨线(如沿迭代域可变目标轨线)现有的方法均无法解决. 非一致目标轨线可看作系统的某种不确定时变参数, 因此研究不确定性时变参数化系统的迭代学习控制成为关键问题. 文献[5]提出了D型, PD型和PID型学习算法, 解决了跟踪轨线在迭代域上慢时变的情况, 而文献[6]提出了新的迭代学习方法, 其控制律是由反馈项和学习项组成, 引进了Lyapunov函数, 对于一阶混合参数不确定性系统解决非一致目标跟踪控制问题.

众所周知, 自适应控制可以有效地处理系统含有常值参数的不确定性^[10], 对含有时变参数的不确定性系统, 实施自适应控制还是一个公开的难题^[11].

文献[7]利用Lyapunov理论给出了一种自适应迭代学习控制方法, 该方法只适合对某类相似可变轨迹的跟踪, 文献[8]基于神经网络对未知非线性系统提出了自适应迭代学习控制策略, 允许系统的结构有大的变化, 而对轨迹变化要求较强. 文献[12]对不确定机械手系统给出了一种无需初始状态重置的自适应重复学习控制算法, 对时变干扰和时不变线性参数化动态系统, 分别设计离散饱和型和微分型自适应率, 利用Lyapunov稳定性定理证明了机械手位移和角速度都精确跟踪上目标轨线, 但该方法假设目标轨线首尾值是相同的. 文献[13]针对状态难以直接测量的一类不确定非线性系统, 当任意两次迭代的目標軌迹完全不同时, 基于状态观测器进行相应的迭代学习控制设计, 可实现在给定区间上对变轨迹的跟踪误差渐近收敛至零.

本文研究高阶非线性时变不确定系统的非一致

目标跟踪问题, 提出了微分-差分型参数自适应律, 利用Backstepping方法^[9], 设计出一种混合自适应迭代学习控制, 使得跟踪误差在 L_T^2 意义下收敛于零. 该方法对于目标变化没有特殊限制, 适用于目标较大变化的情况. 通过构造新的复合能量函数, 对收敛性进行了严密的分析, 数值仿真说明了所提方法的可行性和有效性.

2 问题描述(Problem descriptions)

考虑下列高阶严格反馈非线性混合参数不确定性系统

$$\begin{cases} \dot{x} = Ax + b[\theta_1^T(t)\varphi(x) + u(t)] + [\theta_2^T F(x)]^T, \\ y = x_1, \end{cases} \quad (1)$$

其中: $x = [x_1, \dots, x_n]^T \in \mathbb{R}^n$ 是系统状态, $u \in \mathbb{R}$ 是系统的控制输入, y 表示系统的输出, $x(t_0) = x_0$, $\theta_1(t) \in \mathbb{R}^p$ 是未知连续时变参数向量, $\theta_2 \in \mathbb{R}^q$ 是未知时不变参数,

$$F(x) = [f_1(x_1), f_2(x_1, x_2), \dots, f_n(x)], \varphi(x) \in \mathbb{R}^p,$$

$f_1(x_1), f_2(x_1, x_2), \dots, f_n(x_1, x_2, \dots, x_n)$ 均为 q 维已知的光滑函数, 且 $\varphi(0) = 0$, $f_i(0) = 0$, $i = 1, \dots, n$, $y_r(t)$ 表示参考系统的输出,

$$A = \begin{bmatrix} 0 & & \\ & I_{n-1} & \\ \vdots & & \\ 0 & \dots & 0 \end{bmatrix}, b = [0, 0, \dots, 1]^T.$$

系统(1)满足下列假设:

假设 A1 $\varphi(x)$ 关于 x 是全局李普希茨连续, 即 $\forall x^1, x^2 \in \mathbb{R}^n$, 有 $\|\varphi(x^1) - \varphi(x^2)\| \leq l \|x^1 - x^2\|$, l 是未知李普希茨常数.

假设 A2 在第 j 次迭代中目标轨线为 $y_{r,j}(t)$, $y_{r,j}(t)$ 和它的一阶到 n 阶导数均在 L_T^2 -范数意义下是有界的, 即 $\int_0^T (y_{r,j}^{(k)}(\tau))^2 d\tau < \infty, k = 0, 1, \dots, n$, 并且 $y_{r,j}(0) = y_j(0)$.

注 1 满足假设 A1, A2 的系统(1)常见于机械臂系统、倒立摆系统等^[12], 对这样含混合参数的系统可变目标的迭代学习控制问题目前还没有有效的处理方法.

注 2 假设 A1 和 $\theta_1(t)$ 是连续向量函数, 确保了系统方程(1)的解存在唯一且连续, 假设 A2 是为了保证系统的所有信号均在 $L_{N \times [0, T]}^2$ -范数意义下是有界而提出的. $L_{N \times [0, T]}^2$ -范数定义为 $\|x\|_{L_{N \times [0, T]}^2} = \sup_{k \in N} \int_0^T \|x_k(t)\|^2 dt$.

控制目标是确定控制输入序列 u_j , 在区间 $[0, T]$ 上, 使得跟踪误差 $e_j = y_j - y_{r,j}$ 在 L_T^2 -范数意义下收敛到零, 并保证闭环系统的所有信号是有界的.

3 自适应迭代学习控制的设计(Adaptive iterative learning control design)

在下文中, 记

$$\bar{x}_{i,j} = (x_{1,j}, x_{2,j}, \dots, x_{i,j})^T,$$

$$\bar{y}_{r,j}^{(i)} = (y_{r,j}, \dot{y}_{r,j}, \dots, y_{r,j}^{(i)})^T,$$

$$f_{i,j} = f_i(\bar{x}_{i,j}), \alpha_{i,j} = \alpha_{i,j}(\cdot), w_{i,j} = w_{i,j}(\cdot),$$

$$\tau_{i,j} = \tau_{i,j}(\cdot), \hat{\theta}_{k,j} = \theta_k - \hat{\theta}_{k,j}(\cdot), i = 1, 2, \dots, n,$$

$\hat{\theta}_{k,j}(t)$ 是 $\theta_k (k=1, 2)$ 的第 j 次估计量. 利用Backstepping方法^[9], 在第 j 次迭代过程的控制器设计如下:

Step 1 令

$$z_{1,j} = x_{1,j} - y_{r,j},$$

$$z_{2,j} = x_{2,j} - \alpha_{1,j}(x_{1,j}, \hat{\theta}_{2,j}, y_{r,j}) - y_{r,j}^{(1)},$$

则有

$$\dot{z}_{1,j} = z_{2,j} + \alpha_{1,j} + \theta_2^T f_{1,j}.$$

选择第1个稳定化函数为

$$\alpha_{1,j} = -c_1 z_{1,j} - w_{1,j}^T \hat{\theta}_{2,j},$$

其中 $w_{1,j} = f_{1,j}$, 则有

$$\dot{z}_{1,j} = z_{2,j} - c_1 z_{1,j} + \tilde{\theta}_2^T w_{1,j}. \quad (2)$$

Step 2 令

$$z_{3,j} = x_{3,j} - \alpha_{2,j}(\bar{x}_{2,j}, \hat{\theta}_{2,j}, \bar{y}_{r,j}^{(1)}) - y_{r,j}^{(2)},$$

代入(1)则有

$$\begin{aligned} \dot{z}_{2,j} = & z_{3,j} + \alpha_{2,j} + \theta_2^T w_{2,j} - \frac{\partial \alpha_{1,j}}{\partial x_{1,j}} x_{2,j} - \\ & \frac{\partial \alpha_{1,j}}{\partial y_{r,j}} \dot{y}_{r,j} - \frac{\partial \alpha_{1,j}}{\partial \hat{\theta}_2} \dot{\hat{\theta}}_2, \end{aligned}$$

其中 $w_{2,j} = f_{2,j} - \frac{\partial \alpha_{1,j}}{\partial x_{1,j}} f_{1,j}$.

选择第2个稳定化函数为

$$\begin{aligned} \alpha_{2,j} = & -z_{1,j} - c_2 z_{2,j} - w_{2,j}^T \hat{\theta}_{2,j} + \frac{\partial \alpha_{1,j}}{\partial x_{1,j}} x_{2,j} + \\ & \frac{\partial \alpha_{1,j}}{\partial y_{r,j}} y_{r,j}^{(1)} + \frac{\partial \alpha_{1,j}}{\partial \hat{\theta}_{2,j}} \Gamma \tau_{2,j}, \end{aligned}$$

其中 $\tau_{2,j} = w_{1,j} z_{1,j} + w_{2,j} z_{2,j}$, $\Gamma = \Gamma^T > 0$, 则有

$$\begin{aligned} \dot{z}_{2,j} = & -z_{1,j} + z_{3,j} - c_2 z_{2,j} + \tilde{\theta}_2^T w_{2,j} + \\ & \frac{\partial \alpha_{1,j}}{\partial \hat{\theta}_2} (\Gamma \tau_{2,j} - \dot{\hat{\theta}}_2). \end{aligned} \quad (3)$$

Step i 令

$$\begin{aligned} z_{i+1,j} = & x_{i+1,j} - \alpha_{i,j}(\bar{x}_{i,j}, \hat{\theta}_{2,j}, \bar{y}_{r,j}^{(i-1)}) - y_{r,j}^{(i)}, \\ & i = 3, \dots, n-1, \end{aligned}$$

代入(1)可得

$$\dot{z}_{i,j} = z_{i+1,j} + \alpha_{i,j} + \theta_2^T w_{i,j} - y_{r,j}^{(i)} - \sum_{k=1}^{i-1} \left(\frac{\partial \alpha_{i-1,j}}{\partial x_{k,j}} x_{k+1,j} + \frac{\partial \alpha_{i-1,j}}{\partial y_{r,j}^{(k-1)}} y_{r,j}^{(k)} \right) - \frac{\partial \alpha_{i-1,j}}{\partial \hat{\theta}_2} \dot{\hat{\theta}}_2,$$

其中 $w_{i,j} = f_{i,j} - \sum_{k=1}^{i-1} \frac{\partial \alpha_{i-1,j}}{\partial x_{k,j}} f_{k,j}$. 选择第 i 个稳定化函数为

$$\begin{aligned} \alpha_{i,j} = & -z_{i-1,j} - c_i z_{i,j} - w_{i,j}^T \hat{\theta}_{2,j} + \\ & \sum_{k=1}^{i-1} \left(\frac{\partial \alpha_{i-1,j}}{\partial x_{k,j}} x_{k+1,j} + \frac{\partial \alpha_{i-1,j}}{\partial y_{r,j}^{(k-1)}} y_{r,j}^{(k)} \right) + \\ & \frac{\partial \alpha_{i-1,j}}{\partial \hat{\theta}_{2,j}} \Gamma \tau_{i,j} + \sum_{k=2}^{i-1} \frac{\partial \alpha_{k-1,j}}{\partial \hat{\theta}_{2,j}} \Gamma w_{i,j} z_{k,j}, \quad (4) \end{aligned}$$

其中 $\tau_{i,j} = \tau_{i-1,j} + w_{i,j} z_{i,j}$, 则有

$$\begin{aligned} \dot{z}_{i,j} = & -z_{i-1,j} + z_{i+1,j} - c_i z_{i,j} + \tilde{\theta}_{2,j}^T w_{i,j} - \\ & \sum_{k=2}^{i-1} \frac{\partial \alpha_{k-1,j}}{\partial \hat{\theta}_{2,j}} \Gamma w_{i,j} z_{k,j} + \frac{\partial \alpha_{i-1,j}}{\partial \hat{\theta}_{2,j}} (\Gamma \tau_{i,j} - \dot{\hat{\theta}}_{2,j}). \end{aligned} \quad (5)$$

Step n 由(1)及第 n 个坐标变换得

$$\begin{aligned} \dot{z}_{n,j} = & u_j + \theta_1^T(t) \varphi(x_j) + \theta_2^T w_{n,j} - \frac{\partial \alpha_{n-1,j}}{\partial \hat{\theta}_{2,j}} \dot{\hat{\theta}}_{2,j} - \\ & \sum_{k=1}^{n-1} \left(\frac{\partial \alpha_{n-1,j}}{\partial x_{k,j}} x_{k+1,j} - y_{r,j}^{(n)} + \frac{\partial \alpha_{n-1,j}}{\partial y_{r,j}^{(k-1)}} y_{r,j}^{(k)} \right), \end{aligned} \quad (6)$$

其中 $w_{n,j} = f_{n,j} - \sum_{k=1}^{n-1} \frac{\partial \alpha_{n-1,j}}{\partial x_{k,j}} f_{k,j}$.

在第 j 次迭代中, 设计新的迭代学习控制律为:

$$u_j = \alpha_{n,j}(x_j, \hat{\theta}_{2,j}, \bar{y}_{r,j}^{(n-1)}) + y_{r,j}^{(n)} - \hat{\theta}_{1,j}^T(t) \varphi_j(x), \quad (7)$$

其中:

$$\begin{aligned} \alpha_{n,j} = & -z_{n-1,j} - c_n z_{n,j} - w_{n,j}^T \hat{\theta}_{2,j} + \\ & \sum_{k=1}^{n-1} \left(\frac{\partial \alpha_{n-1,j}}{\partial x_{k,j}} x_{k+1,j} + \frac{\partial \alpha_{n-1,j}}{\partial y_{r,j}^{(k-1)}} y_{r,j}^{(k)} \right) + \\ & \frac{\partial \alpha_{n-1,j}}{\partial \hat{\theta}_{2,j}} \Gamma \tau_{n,j} + \sum_{k=1}^{n-1} \frac{\partial \alpha_{k-1,j}}{\partial \hat{\theta}_{2,j}} \Gamma w_{n,j} z_{k,j}, \\ \tau_{n,j} = & \tau_{n-1,j} + w_{n,j} z_{n,j}. \end{aligned}$$

常参数自适应律为:

$$\begin{cases} \dot{\hat{\theta}}_{2,j}(t) = \Gamma W_j z_j = \Gamma \tau_{n,j}, \\ \hat{\theta}_{2,j}(0) = \hat{\theta}_{2,j-1}(T), \hat{\theta}_{2,0}(0) = 0, \end{cases} \quad (8)$$

其中:

$$\begin{aligned} W_j = & [w_{1,j}, \dots, w_{n,j}], \\ z_j = & [z_{1,j}, z_{2,j}, \dots, z_{n,j}]^T. \end{aligned}$$

将式(7)(8)代入式(6)得

$$\begin{aligned} \dot{z}_{n,j} = & -z_{n-1,j} + z_{n+1,j} - c_n z_{n,j} + \tilde{\theta}_{2,j}^T w_{n,j} - \\ & \sum_{k=2}^{n-1} \frac{\partial \alpha_{k-1,j}}{\partial \hat{\theta}_{2,j}} \Gamma w_{n,j} z_{k,j}. \end{aligned} \quad (9)$$

由式(2)(3)(5)和(9)得, 第 j 次迭代闭环误差方程为:

$$\begin{aligned} \dot{z}_j = & A_{z,j}(z_j, \hat{\theta}_{2,j}, t) z_j + W_j^T(z_j, \hat{\theta}_{2,j}, t) \tilde{\theta}_{2,j} + \\ & b \tilde{\theta}_{1,j}^T(t) \varphi_j(x), \end{aligned} \quad (10)$$

其中:

$$\begin{aligned} A_{z,j} = & \begin{bmatrix} -c_1 & 1 & 0 & \cdots & 0 \\ -1 & -c_2 & 1 + \sigma_{23,j} & \cdots & \sigma_{2n,j} \\ 0 & -1 - \sigma_{23,j} & -c_3 & \cdots & \sigma_{3n,j} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & -\sigma_{2n,j} & -1 - \sigma_{n-1,n,j} & \cdots & -c_n \end{bmatrix}, \\ \sigma_{ik,j} = & -\frac{\partial \alpha_{i-1,j}}{\partial \hat{\theta}_{2,j}} \Gamma w_{k,j}. \end{aligned}$$

设计时变参数自适应律为:

$$\begin{cases} \dot{\hat{\theta}}_{1,j}(t) = \hat{\theta}_{1,j-1}(t) + q_1 \varphi_j(x) z_{n,j}(t), t \in [0, T], \\ \hat{\theta}_{1,-1}(t) = 0, t \in [0, T] \end{cases} \quad (11)$$

其中 $q_1 > 0$ 为设计参数.

假设 A3 在第 j 次迭代中 z 坐标初值为零, 即 $z_j(0) = 0$.

4 收敛性分析(Convergence analysis)

定理 1 由系统方程(1)和迭代学习控制律(7)以及参数校正律(8)和(11)组成的闭环系统具有如下特性:

1) 当迭代次数趋于无穷时在区间 $[0, T]$ 上跟踪误差, $e_j(t)$ 在 L_T^2 -范数意义下收敛于零, 即

$$\lim_{j \rightarrow \infty} \int_0^T e_j^2(\tau) d\tau = 0.$$

2) 闭环系统所有信号均在 $L_{N \times [0, T]}^2$ -范数意义下有界.

证 1) 定义复合能量函数为

$$\begin{aligned} E_j(t) = & \frac{1}{2} z_j^T(t) z_j(t) + \frac{1}{2q_1} \int_0^t \tilde{\theta}_{1,j}^T(\tau) \tilde{\theta}_{1,j}(\tau) d\tau + \\ & \frac{1}{2} \tilde{\theta}_{2,j}^T(t) \Gamma^{-1} \tilde{\theta}_{2,j}(t), \end{aligned} \quad (12)$$

$$\Delta E_j(t) = E_j(t) - E_{j-1}(t) =$$

$$\frac{1}{2} z_j^T(t) z_j(t) - \frac{1}{2} z_{j-1}^T(t) z_{j-1}(t) +$$

$$\frac{1}{2} [\tilde{\theta}_{2,j}^T(t) \Gamma^{-1} \tilde{\theta}_{2,j}(t) - \tilde{\theta}_{2,j-1}^T(t) \Gamma^{-1} \tilde{\theta}_{2,j-1}(t)] +$$

$$\frac{1}{2q_1} \int_0^t (\tilde{\theta}_{1,j}^T(\tau) \tilde{\theta}_{1,j}(\tau) - \tilde{\theta}_{1,j-1}^T(\tau) \tilde{\theta}_{1,j-1}(\tau)) d\tau. \quad (13)$$

由式(8)(10)(11)和假设A3, 类似于文[6]的推导, 可得

$$\begin{aligned} \Delta E_j(t) = & -\frac{1}{2}z_{j-1}^T(t)z_{j-1}(t) - \\ & \int_0^t \left(\sum_{i=1}^n c_i z_{i,j}^2 + \frac{1}{2}q_1 \varphi_j^T(x) \varphi_j(x) z_{n,j}^2(\tau) \right) d\tau + \\ & \frac{1}{2} \tilde{\theta}_{2,j}^T(0) \Gamma^{-1} \tilde{\theta}_{2,j}(0) - \frac{1}{2} \tilde{\theta}_{2,j-1}^T(t) \Gamma^{-1} \tilde{\theta}_{2,j-1}(t), \quad (14) \end{aligned}$$

则当 $t = T$ 时, 由式(14)有

$$\begin{aligned} \Delta E_j(T) = & -\frac{1}{2}z_{j-1}^T(T)z_{j-1}(T) - \int_0^T \sum_{i=1}^n c_i z_{i,j}^2 d\tau - \\ & \frac{1}{2} \int_0^T q_1 \|\varphi_j(x(\tau))\|^2 z_{n,j}^2(\tau) d\tau \leq \\ & - \int_0^T \sum_{i=1}^n c_i z_{i,j}^2 d\tau \leq - \int_0^T c_1 z_{1,j}^2 d\tau. \quad (15) \end{aligned}$$

由式(13)得

$$E_j(T) = E_0(T) + \sum_{l=1}^j \Delta E_l(T). \quad (16)$$

由式(15)可知, 只要 $E_0(T)$ 是有限的, 就能保证 $E_j(T)$ 的有限性. 以下证明 $E_0(t)$ 的有限性. 当 $j = 0$ 时, 对式(12)两端求导得

$$\begin{aligned} \dot{E}_0(t) = & - \sum_{i=1}^n c_i z_{i,0}^2 - \frac{q_1}{2} \varphi_0^2(x) z_{n,0}^2(t) + \frac{1}{2q_1} \theta_1^T(t) \theta_1(t) \leq \\ & \frac{1}{2q_1} \theta_1^T(t) \theta_1(t). \quad (17) \end{aligned}$$

因为 $\theta_1(t)$ 在 $[0, T]$ 上是连续的, 所以 $\theta_1(t)$ 在 $[0, T]$ 上有界, 由式(17)得, 存在一个常数

$$M = \max_{t \in [0, T]} \left(\frac{1}{2q_1} \theta_1^T(t) \theta_1(t) \right) < \infty,$$

使得 $\dot{E}_0(t) \leq M$.

由式(12)(17)得到

$$\begin{aligned} E_0(t) \leq & |E_0(0)| + \left| \int_0^t \dot{E}_0(\tau) d\tau \right| \leq \\ & \frac{1}{2} \tilde{\theta}_2^T(0) \Gamma^{-1} \tilde{\theta}_2(0) + MT < \infty, \quad (18) \end{aligned}$$

因此 $E_0(t), \forall t \in [0, T]$ 是有限的, $E_0(T)$ 有界, 从而由式(16)可知 $\lim_{j \rightarrow +\infty} E_j(T)$ 存在, 且有

$$E_j(T) \leq E_0(T) - \sum_{l=1}^j \int_0^T c_1 z_{1,l}^2 d\tau. \quad (19)$$

由式(19)可知 $\lim_{j \rightarrow \infty} \sum_{l=1}^j \int_0^T c_1 z_{1,l}^2 d\tau$ 存在.

因而

$$\lim_{j \rightarrow \infty} \int_0^T z_{1,j}^2 d\tau = 0,$$

所以 $z_{1,j}(t)$ 在 L_T^2 -范数意义下收敛于零.

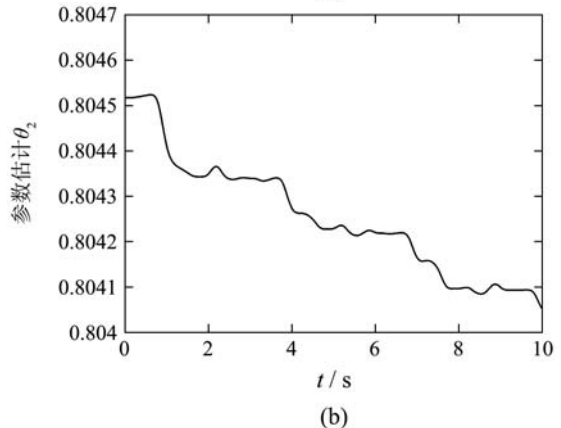
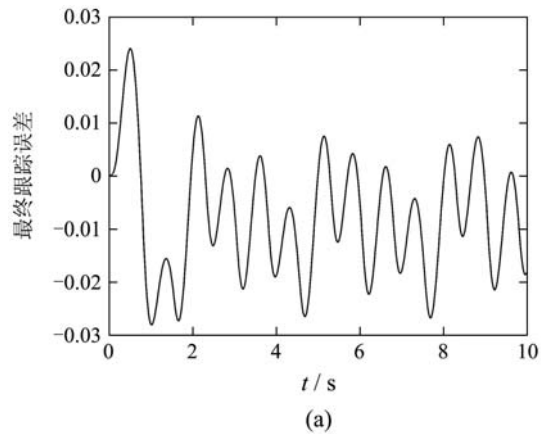
2) 以下证明所有信号的有界性, 前面已证明了 $E_j(T)$ 的有界性, 由 $E_j(t)$ 的定义(12)及 $E_j(T)$ 的有界性, 类似于文[6], 可知, $E_j(t) (\forall j \in Z_+)$ 是有界的, 从而保证了闭环系统的所有信号都在 $L_{N \times [0, T]}^2$ -范数下有界.

5 数值仿真(Numerical simulation)

考虑如下二阶混合参数化严格反馈非线性系统

$$\dot{x}_1 = x_2 + \theta_2 x_1^2, \dot{x}_2 = u + \theta_1(t) e^{x_1},$$

其中: θ_2 是未知常值参数, $\theta_1(t)$ 是未知时变参数, 在仿真中, 选择参考轨迹 $y_{r,j} = k_j \sin(2t)$, $T = 6$ s, $\theta_1(t) = |2 \sin(\frac{4}{3}\pi t)|$, $\theta_2 = 1$, $c_1 = 5$, $c_2 = 1$, $q_1 = 0.1$, $q_2 = 0.2$, $\hat{\theta}_2(0)$ 取为随机数. 利用本文设计的微分-差分自适应控制律, 对于变化的目标轨线情况, 选择 k_j 在 $[-0.5, 0.5]$ 内随机取值, 得到仿真结果如图1所示, 图1(a)给出了最终的跟踪误差曲线, 图1(b)和图1(c)分别给出了最终的时不变和时变参数估计曲线, 图1(d)给出了每次迭代的误差 L_T^2 -范数的变化曲线. 由图1结果表明本文所提方法对于非一致目标的迭代学习控制是可行和有效的.



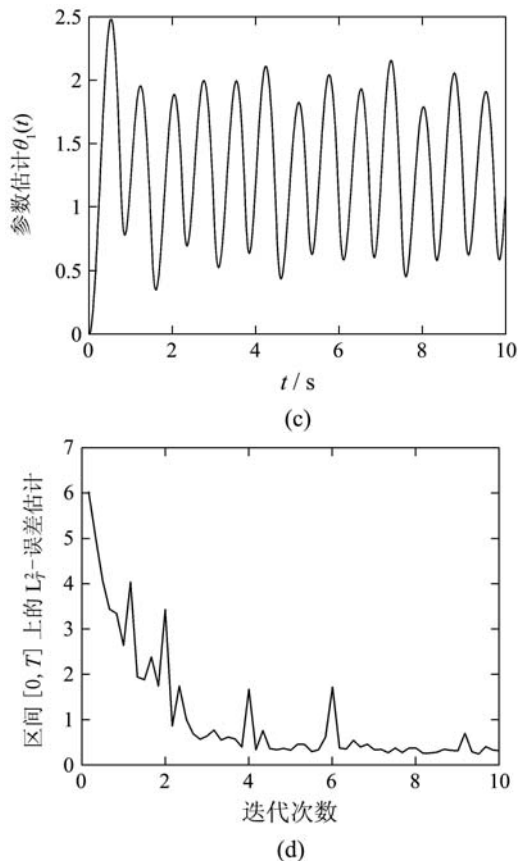


图1 非一致目标跟踪的系统曲线

Fig. 1 System curves of non-uniform trajectories tracking

6 结论(Conclusions)

针对一类混合型参数化高阶非线性系统, 利用Backstepping方法, 引进参数的微分-差分自适应律, 提出一种新的自适应迭代学习控制算法, 该算法对非一致目标实现了在 L_T^2 -范数意义下的精确跟踪. 通过构造复合能量函数, 证明了闭环系统的稳定性和算法的收敛性.

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