Extremum Seeking-Based Indirect Adaptive Control for Nonlinear Systems with Time-varying Uncertainties

Xia, M.; Benosman, M.

TR2015-042 July 16, 2015

Abstract

We study in this paper the problem of adaptive trajectory tracking control for nonlinear systems affine in the control with time-varying parametric uncertainties. We propose to use a modular approach, in the sense that we first design a robust nonlinear state feedback which renders the closed loop input to state stable (ISS) between an estimation error of the uncertain parameters and an output tracking error. Next, we complement this robust ISS controller with a model-free extremum seeking (ES) algorithm to estimate the time-varying model uncertainties. The combination of the ISS feedback and the ES algorithm gives an indirect adaptive controller. We show the efficiency of this approach on a two-link robot manipulator example.

2015 European Control Conference (ECC)
Extremum Seeking-Based Indirect Adaptive Control for Nonlinear Systems with Time-varying Uncertainties

Meng Xia and Mouhacine Benosman

Abstract—We study in this paper the problem of adaptive trajectory tracking control for nonlinear systems affine in the control with time-varying parametric uncertainties. We propose to use a modular approach, in the sense that we first design a robust nonlinear state feedback which renders the closed loop input to state stable (ISS) between an estimation error of the uncertain parameters and an output tracking error. Next, we complement this robust ISS controller with a model-free extremum seeking (ES) algorithm to estimate the time-varying model uncertainties. The combination of the ISS feedback and the ES algorithm gives an indirect adaptive controller. We show the efficiency of this approach on a two-link robot manipulator example.

I. INTRODUCTION

Extremum Seeking (ES) method has often been used as a real-time optimization tool [1]. As opposed to the classical model-based control, extremum seeking does not need detailed modeling of the process. Since ES controllers do not depend on exact plant models and also can easily deal with multi-input systems, they have been used in many control applications, such as automotive brakes [2], electromagnetic actuators [3], [4] and stirred-tank bioreactors [5]. On the other hand, model-based Input-output feedback linearization has been proven to be powerful in the control design for trajectory tracking and stabilization of nonlinear systems [6].

One shortcoming of the feedback linearization approach is that it requires precise system modeling [6]. When there exist model uncertainties, a robust input-output linearization approach needs to be developed. For instance, high-gain observers [7] and linear robust controllers [8] have been proposed in combination with the feedback linearization techniques. Another approach to deal with model uncertainties is using adaptive control methods. Of particular interest to us is the modular approach to adaptive nonlinear control, e.g. [9].

In this approach, first the controller is designed by assuming all the parameters are known and then an identifier is used to guarantee certain boundedness of the estimation error. The identifier is independent of the designed controller and thus the approach is called ‘modular’. A modular approach has been proposed in [10] for adaptive neural control of pure-feedback nonlinear systems, where the input-to-state stability (ISS) modularity of the controller-estimator is achieved and the closed-loop stability is guaranteed by the small-gain theorem.

In this paper, we study a class of nonlinear systems which are input-output linearizable through static state feedback [11]. We assume that the uncertainties in the linearized model are additive as guaranteed by the ‘matching condition’ [12]. The control objective is to achieve asymptotic tracking of a desired trajectory. The robust controller for the uncertain nonlinear system can be designed according to the following guidelines. In the first step, we design a controller for the nominal model (i.e. when the uncertainties are assumed to be zero) so that the tracking error dynamics is asymptotically stable. In the second step, we use a Lyapunov reconstruction method [11] to show that the error dynamics are input-to-state stable (ISS) [13] where the estimation error in the parameters is the input to the system and the tracking error represents the system state. Finally, we use ES to guarantee that the error in the estimation of parameters are bounded and decreasing so that the the tracking error will be bounded and decreasing, as guaranteed by the ISS property. Learning-based adaptive control for nonlinear systems has been studied in [3], [4]. In these two papers, the problem of adaptive robust control of electromagnetic actuators was studied, where ES was used to tune the feedback gains of the nonlinear controller in [3] and ES was used to estimate the unknown model parameters in [4].

An extension to the general case of nonlinear systems was proposed in [15], [16]. We relax here the strong assumption, used in [15], [16], about the existence of an ISS feedback controller, and propose a constructive proof to design such an ISS feedback for the particular case of nonlinear systems affine in the control.

The rest of the paper is organized as follows. In Section II, we present notations, together with some fundamental definitions and results. In Section III, we provide our problem formulation. The nominal controller design is presented in Section IV. In Section V, three cases are considered for the uncertain system based on the structure of uncertainties term in the model and a robust controller is designed for each case such that ISS is guaranteed from the estimation errors input to the tracking errors state. The stability of the multi-parametric extremum seeking (MES) algorithm that is used for parameters estimation is provided in Section VI. Note that the proofs of our Theorems have been omitted due to space constraints, however, they will be reported in a future journal version of this work. Section VII is dedicated to an application example and the paper conclusion is given in Section VIII.
Throughout the paper, we use $\| \cdot \|$ to denote the Euclidean norm; i.e., for a vector $x \in \mathbb{R}^n$, we have $\|x\| \triangleq \|x\|_2 = \sqrt{x^T x}$, where $x^T$ denotes the transpose of the vector $x$. The 1-norm of $x \in \mathbb{R}^n$ is denoted by $\|x\|_1$. In this paper, when we refer to a matrix norm, we mean the Frobenius norm, which for a matrix $A \in \mathbb{R}^{m \times n}$, with elements $a_{ij}$, is defined as $\|A\| \triangleq \sqrt{\sum_{i=1}^{m} \sum_{j=1}^{n} |a_{ij}|^2}$. We use the following norm properties for the need of our proof: 1) for any $x \in \mathbb{R}^n$, $\|x\| \leq \|x\|_1$, 2) for any $x, y \in \mathbb{R}^n$, $\|x + y\| \leq \|x\| + \|y\|$, 3) for any $x, y \in \mathbb{R}^n$, $x^T y \leq \|x\|\|y\|$. Given $x \in \mathbb{R}^n$, the signum function is defined as $\text{sign}(x) \triangleq [\text{sign}(x_1), \text{sign}(x_2), \ldots, \text{sign}(x_m)]^T$, where $x_i$ denotes the $i$-th $(1 \leq i \leq m)$ element of $x$. We have $x^T \text{sign}(x) = \|x\|_1$. For an $n \times n$ matrix $P$, we denote by $P > 0$ if it is positive definite. Similarly, we denote by $P < 0$ if it is negative definite. We use $\text{diag}\{A_1, A_2, \ldots, A_n\}$ to denote a diagonal block matrix with $n$ blocks. For a matrix $B$, we denote $B(i,j)$ as the element that locates in the $i$-th row and $j$-th column of matrix $B$. We denote $I_n$ as the identity matrix or simply $I$ if the dimension is clear from the context. We use $f$ to denote the time derivative of $f$ and $f^{(r)}(t)$ for the $r$-th derivative of $f(t)$, i.e., $f^{(r)} \triangleq \frac{d^r f}{dt^r}$. We denote by $C^k$ functions that are $k$ times differentiable and by $C^{\infty}$ a smooth function. A continuous function $\alpha : [0, a) \rightarrow [0, \infty)$ is said to belong to class $K$ if it is strictly increasing and $\alpha(0) = 0$. It is said to belong to class $K_{\infty}$ if $a = \infty$ and $\alpha(r) \rightarrow \infty$ as $r \rightarrow \infty$ [11, pp. 144]. A continuous function $\beta : [0, a) \times [0, \infty) ightarrow [0, \infty)$ is said to belong to class $KL$ if, for a fixed $s$, the mapping $\beta(r, s)$ belongs to class $K$ with respect to $r$ and, for each fixed $r$, the mapping $\beta(r, s)$ is decreasing with respect to $s$ and $\beta(r, s) \rightarrow 0$ as $s \rightarrow \infty$ [11, pp. 144].

Consider the system
\begin{equation}
\dot{x} = f(t, x, u)
\end{equation}
where $f : [0, \infty) \times \mathbb{R}^n \times \mathbb{R}^m \rightarrow \mathbb{R}^n$ is piecewise continuous in $t$ and locally Lipschitz in $x$ and $u$, uniformly in $t$. The input $u(t)$ is piecewise continuous, bounded function of $t$ for all $t \geq 0$.

**Definition 1 ([11]):** The system (1) is said to be input-to-state stable (ISS) if there exist a class $KL$ function $\beta$ and a class $K$ function $\gamma$ such that for any initial state $x(t_0)$ and any bounded input $u(t)$, the solution $x(t)$ exists for all $t \geq t_0$ and satisfies
\[ \|x(t)\| \leq \beta(\|x(t_0)\|, t - t_0) + \gamma(\sup_{t_0 \leq \tau \leq t} \|u(\tau)\|). \]

**Theorem 1 ([11]):** Let $V : [0, \infty) \times \mathbb{R}^n \rightarrow \mathbb{R}$ be a continuously differentiable function such that
\[ \alpha_1(\|x\|) \leq V(t, x) \leq \alpha_2(\|x\|) \]
\[ \frac{\partial V}{\partial t} + \frac{\partial V}{\partial x} f(t, x, u) \leq -W(x), \quad \forall \|x\| \geq \rho(\|u\|) > 0 \]
for all $(t, x, u) \in [0, \infty) \times \mathbb{R}^n \times \mathbb{R}^m$, where $\alpha_1, \alpha_2$ are class $K_{\infty}$ functions, $\rho$ is a class $K$ function, and $W(x)$ is a continuous positive definite function on $\mathbb{R}^n$. Then, the system (1) is input-to-state stable (ISS).
where $\Delta b(t, \xi(t))$ is $C^1$ on $\tilde{X}$.

If we consider the nominal model (4) first, then we can define a virtual input vector $v(t)$ as

$$v(t) = b(\xi(t)) + A(\xi(t))u(t).$$

Combining (4) and (7), we can obtain the following input-output mapping

$$y^{(r)}(t) = v(t).$$

Based on the linear system (8), it is straightforward to apply a stabilizing controller for the nominal system (4) as

$$u_n = A^{-1}(\xi) [v_n(t, \xi) - b(\xi)],$$

where $v_n$ is a $m \times 1$ vector and the $i$-th $(1 \leq i \leq m)$ element $v_{ni}$ is given by

$$v_{ni} = y^{(r)}_{id}(r_i = 1 - K_{ri}^i y_i - y_{id}).$$

Denote the tracking error as $e(t) = y(t) - y_{id}(t)$, we obtain the following tracking error dynamics

$$e(t) + K_{ri}^i e_{i-1}(t) + \cdots + K_{ri}^i e(t) = 0,$$

where $i \in \{1, 2, \ldots, m\}$. By selecting the gains $K_{ri}^i$ where $i \in \{1, 2, \ldots, m\}$ and $j \in \{1, 2, \ldots, r_i\}$, we can obtain global asymptotic stability of the tracking errors $e_i(t)$. To formalize this condition, we make the following assumption.

**Assumption 5:** There exists a non-empty set $A$ where $K_{ri}^i \in A$ such that the polynomials in (11) are Hurwitz, where $i \in \{1, 2, \ldots, m\}$ and $j \in \{1, 2, \ldots, r_i\}$.

To this end, we define $z = [z^1, z^2, \ldots, z^m]^T$, where $z^i = [e_1, e_2, \ldots, e^{(r_i-1)}]$ and $i \in \{1, 2, \ldots, m\}$. Then, from (11), we can obtain

$$\dot{z} = \tilde{A}z,$$

where $\tilde{A} \in \mathbb{R}^{n \times n}$ is a diagonal block matrix given by

$$\tilde{A} = \text{diag}\{\tilde{A}_1, \tilde{A}_2, \ldots, \tilde{A}_m\},$$

and $\tilde{A}_i (1 \leq i \leq m)$ is a $r_i \times r_i$ matrix given by

$$\tilde{A}_i = \begin{bmatrix}
0 & 1 & 0 & \cdots & 0 \\
0 & 0 & 1 & \cdots & 0 \\
\vdots & & & & \vdots \\
-K_{r_i}^1 & -K_{r_i}^2 & \cdots & -K_{r_i}^{r_i} & 1
\end{bmatrix}.$$  

As discussed above, the gains $K_{ri}^i$ can be chosen so that the matrix $\tilde{A}$ is Hurwitz. Thus, there exists a positive definite matrix $P > 0$ such that (see e.g. [11])

$$\tilde{A}^T P + P \tilde{A} = -I.$$  

**V. ROBUST CONTROLLER DESIGN**

**A. Preliminary Analysis**

We now consider the uncertain model (3), i.e., when $\Delta f(t, x) \neq 0$. The corresponding linearized model is given by (6) where $\Delta b(t, \xi(t)) \neq 0$. The global asymptotic stability of the error dynamics (11) cannot be guaranteed anymore due to the additive uncertainty $\Delta b(t, \xi(t))$. We use Lyapunov reconstruction techniques to design a new controller so that the tracking error is guaranteed to be bounded. The new controller for the uncertain model (6) is defined as

$$u_f = u_n + u_r,$$

where the nominal controller $u_n$ is given by (9) and the robust controller $u_r$ will be given later on based on particular forms of the uncertainty $\Delta b(t, \xi(t))$. By using the controller (14), from (6) we obtain

$$\dot{y}(t) = b(\xi(t)) + A(\xi(t))u_f + \Delta b(t, \xi(t)) = b(\xi(t)) + A(\xi(t))u_n + A(\xi(t))u_r + \Delta b(t, \xi(t)) = v_n(t, \xi) + A(\xi(t))u_r + \Delta b(t, \xi(t)),$$

Further, the dynamics for $z$ is given by

$$\dot{z} = \tilde{A}z + \tilde{B}\delta,$$

where $\tilde{A}$ is defined in (12), $\delta$ is a $m \times 1$ vector given by

$$\delta = A(\xi(t))u_r + \Delta b(t, \xi(t)),$$

and the matrix $\tilde{B} \in \mathbb{R}^{n \times m}$ is given by

$$\tilde{B} = \begin{bmatrix}
\tilde{B}_1 \\
\tilde{B}_2 \\
\vdots \\
\tilde{B}_m
\end{bmatrix},$$

with $\tilde{B}_i (1 \leq i \leq m)$ given by a $r_i \times m$ matrix such that

$$\tilde{B}_i(l, q) = \begin{cases}
1 & \text{if } l = r_i \text{ and } q = i \\
0 & \text{otherwise}
\end{cases}$$

If we apply $V(z) = z^T P z$ as a Lyapunov function for the dynamics (16), where $P$ is the solution of the Lyapunov equation (13), then we obtain

$$\dot{V}(t) = \frac{\partial V}{\partial z} \dot{z} = z^T (\tilde{A}^T P + P \tilde{A}) z + 2z^T P \tilde{B} \delta = -\|z\|^2 + 2z^T P \tilde{B} \delta,$$

where $\delta$ defined by (17) depends on the robust controller $u_r$. Next, we will design the controller $u_r$ based on the particular forms of the uncertainties that appear in (6), i.e., $\Delta b(t, \xi(t))$. For notational convenience, the unknown parameter vector/matrix (which may be time-varying) is denoted by $\Delta(t)$ and the estimate for the unknowns is denoted by $\hat{\Delta}(t)$. Further, the estimation error vector/matrix is given by $e(\Delta) = \Delta(t) - \hat{\Delta}(t)$. The dimensions of $\Delta$ (and in turn, $\hat{\Delta}$ and $e(\Delta)$ will be clear from the context.
B. Case 1: State-Independent Uncertainties

We consider the case when $\Delta b(t, \xi(t))$ is simply $\Delta(t)$, where $\Delta(t) = [\Delta_1(t), \ldots, \Delta_m(t)]^T$. Assume that we can obtain the estimate (e.g. by ES) of the unknown parameters $\Delta(t)$, which may be time-varying and is denoted by $\hat{\Delta}(t)$, for $i=1,2,\ldots,m$. Let $\hat{\Delta}(t) = [\hat{\Delta}_1(t), \ldots, \hat{\Delta}_m(t)]^T$. We use the following robust controller

$$u_r = -A^{-1}(\xi)(B^TPz + \hat{\Delta}(t)). \quad (20)$$

The closed-loop error dynamics can be written as

$$\dot{z} = f(z, e_\Delta), \quad (21)$$

where $e_\Delta(t)$ is the input to the system, $z(t)$ represents the system state and $f$ is given by

$$f(z, e_\Delta) = (A - BB^TP)z + \tilde{B}e_\Delta.$$

**Theorem 2:** Consider the system (3), under Assumptions 1-5 and the assumption that $\Delta b(t, \xi(t)) = [\Delta_1(t), \ldots, \Delta_m(t)]^T$, with the feedback controller (14), where $u_n$ is given by (9) and $u_r$ is given by (20). Then, the closed-loop system (21) is ISS from the estimation errors input $e_\Delta(t) \in \mathbb{R}^m$ to the tracking errors state $z(t) \in \mathbb{R}^n$.

C. Case 2: State-Dependent Uncertainties

We consider the second case when $\|\Delta b(t, \xi(t))\|$ is upper bounded by a function of the state $\xi(t)$, i.e.

$$\|\Delta b(t, \xi(t))\| \leq \|\Delta(t)||L(\xi)||,$$  

where $\Delta(t) \in \mathbb{R}^{m \times m}$ and $L(\xi)$ is a known bounded function. Assume that we can obtain the estimate (e.g. by ES) for $\Delta(i,j)$, which may be time-varying and is denoted by $\hat{\Delta}(i,j)$, for $i,j=1,2,\ldots,m$. Let $\hat{\Delta}(t)$ be the matrix with the element $\hat{\Delta}(i,j)$. We use the following robust controller

$$u_r = -A^{-1}(\xi)B^TPz||L(\xi)||^2$$

$$-A^{-1}(\xi)||\hat{\Delta}(t)||L(\xi)||\text{sign}(B^TPz). \quad (23)$$

Similar to the previous case, the closed-loop error dynamics can be written in the form of

$$\dot{z} = f(t, z, e_\Delta), \quad (24)$$

where $e_\Delta(t)$ is the system input and $z(t)$ is the system state.

**Theorem 3:** Consider the system (3), under Assumptions 1-5 and the assumption that $\Delta b(t, \xi(t))$ satisfies (22), with the feedback controller (14), where $u_n$ is given by (9) and $u_r$ is given by (23). Then, the closed-loop system (24) is ISS from the estimation errors input $e_\Delta(t) \in \mathbb{R}^{m \times m}$ to the tracking errors state $z(t) \in \mathbb{R}^n$.

D. Case 3: Sum of a State-dependent Term and a Time-dependent Term

We consider the third case when $\Delta b(t, \xi(t))$ is composed of a state-dependent term and a time-dependent term, i.e.

$$\Delta b(t, \xi(t)) = \Delta(t)(Q(\xi) + \eta(t)), \quad (25)$$

where $\Delta(t) \in \mathbb{R}^{m \times m}$, $Q(\xi)$ is a known bounded function, the vector $\eta(t)$ is unknown but the upper bound for $||\eta(t)||$ is known to be $C_1$, i.e. $||\eta(t)|| \leq C_1$. Assume that we can obtain the estimate (e.g. by ES) for $\hat{\Delta}(i,j)$, which may be time-varying and is denoted by $\hat{\Delta}(i,j)$, for $i,j=1,2,\ldots,m$. Let $\hat{\Delta}(t)$ be the matrix with the element $\hat{\Delta}(i,j)$ that locates at the $i$-th row and $j$-th column. We use the following robust controller

$$u_r = -A^{-1}(\xi)[B^TPz||Q(\xi)||^2 + \hat{\Delta}(t) \times Q(\xi)] + \|\hat{\Delta}(t)||C_1\text{sign}(B^TPz) + B^TPzC_1^2]. \quad (26)$$

Similar to the previous two cases, the closed-loop error dynamics can be written in the following form

$$\dot{z} = F(t, z, e_\Delta), \quad (27)$$

where $e_\Delta(t)$ is the system input and $z(t)$ is the system state.

**Theorem 4:** Consider the system (3), under Assumptions 1-5 and the assumption that $\Delta b(t, \xi(t))$ satisfies (25), with the feedback controller (14), where $u_n$ is given by (9) and $u_r$ is given by (26). Then, the closed-loop system (27) is ISS from the estimation errors input $e_\Delta(t) \in \mathbb{R}^{m \times m}$ to the tracking errors state $z(t) \in \mathbb{R}^n$.

VI. MULTI-PARAMETRIC ES-BASED ADAPTATION

Let us now define the following cost function

$$J(\hat{\Delta}, t) = F(z(\hat{\Delta}), t) \quad (28)$$

where $F : \mathbb{R}^n \times \mathbb{R}^+ \rightarrow \mathbb{R}^+$, $F(0, t) = 0$, $F(z, t) > 0$ for $z \neq 0$. We need the following assumptions on $J$.

**Assumption 6:** The cost function $J$ has a local minimum at $\hat{\Delta}^*(t) = \Delta(t)$.

**Assumption 7:** $|\partial J(\hat{\Delta}, t)| < \rho_j$, for any $t \in \mathbb{R}^+$ and any $\hat{\Delta} \in \mathbb{R}^p$.

**Remark 1:** Assumption 6 simply states that the cost function $J$ has at least a local minimum at the true values of the uncertain parameters.

We can now present the following result for Case 1, i.e. the case that is studied in Section V-B.

**Lemma 1:** Consider the system (16) with the cost function (28), under Assumptions 6-7 and the assumption that $\Delta(t) = [\Delta_1(t), \ldots, \Delta_m(t)]^T$, with the feedback controller (14), where $u_n$ is given by (9) and $u_r$ is given by (20), and $\hat{\Delta}(t)$ is estimated through the MES algorithm

$$\hat{\Delta}_i = a_i \sqrt{w_i} \cos(\omega_i t) - k_i \sqrt{w_i} \sin(\omega_i t)J(\hat{\Delta}, t), \quad (29)$$

where $i \in \{1,2,\ldots,p\}$, $a_i > 0$, $k_i > 0$, $\omega_i \neq \omega_j$, and $\omega_i > \omega^*$, with $\omega^*$ large enough, ensures that the norm of the tracking error admits the following bound

$$||z(t)|| \leq \beta(||z(t_0)||, \gamma + \sup_{0 \leq \tau \leq t} ||e_\Delta(\tau)||)$$

where $\beta \in K\mathcal{L}$, $\gamma \in \mathbb{K}$ and $||e_\Delta||$ satisfies:

1) $(\frac{1}{\omega}, d)$-Uniform Stability: For every $c_2 \in (d, \infty)$, there exists $c_1 \in (0, \infty)$ and $\hat{\omega} > 0$ such that for all $t_0 \in \mathbb{R}$ and for all $e_\Delta(0) \in \mathbb{R}^m$ with $||e_\Delta(0)|| < c_1$ and for all $\omega > \hat{\omega}$,

$$||e_\Delta(t, e_\Delta(0))|| < c_2, \quad \forall t \in [t_0, \infty)$$
TABLE I
SYSTEM PARAMETERS FOR THE MANIPULATOR EXAMPLE.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$I_2$</td>
<td>$\frac{q}{10} [kg \cdot m^2]$</td>
</tr>
<tr>
<td>$m_1$</td>
<td>10 [kg]</td>
</tr>
<tr>
<td>$m_2$</td>
<td>5 [kg]</td>
</tr>
<tr>
<td>$I_1$</td>
<td>1 [m]</td>
</tr>
<tr>
<td>$I_2$</td>
<td>1 [m]</td>
</tr>
<tr>
<td>$\epsilon_{e1}$</td>
<td>0.5 [m]</td>
</tr>
<tr>
<td>$\epsilon_{e2}$</td>
<td>0.5 [m]</td>
</tr>
<tr>
<td>$I_1$</td>
<td>$\frac{q}{10} [kg \cdot m^2]$</td>
</tr>
<tr>
<td>$g$</td>
<td>9.8 [m/s$^2$]</td>
</tr>
</tbody>
</table>

2) $(t, \omega)$-Uniform Ultimate Boundedness: For every $c_1 \in (0, \infty)$, there exists $c_2 \in (d, \infty)$ and $\omega > 0$ such that for all $t_0 \in \mathbb{R}$ and for all $e(0) \in \mathbb{R}^m$ with $\|e(0)\| < c_1$ and for all $\omega > \omega$, 
\[ \|e(t, e(0))\| < c_2, \quad \forall t \in [t_0, \infty) \]

3) $(t, \omega)$-Global Uniform Attractivity: For all $c_1, c_2 \in (d, \infty)$ there exists $T \in [0, \infty)$ and $\omega > 0$ such that for all $t_0 \in \mathbb{R}$ and for all $e(0) \in \mathbb{R}^m$ with $\|e(0)\| < c_1$ and for all $\omega > \omega$, 
\[ \|e(t, e(0))\| < c_2, \quad \forall t \in [t_0 + T, \infty) \]

Similar bounds can be derived for the two remaining cases but are omitted here because of space constraints.

VII. MECHEATRONIC EXAMPLE

A. Two-link Manipulator

We consider here a two-link robot manipulator. The dynamics for the manipulator is given by (see e.g. [14])
\[ H(q)\ddot{q} + C(q, \dot{q})\dot{q} + G(q) = \tau, \]
(30)
where $q \triangleq [q_1, q_2]^T$ denotes the two joint angles and $\tau \triangleq [\tau_1, \tau_2]^T$ denotes the two joint torques. The matrix $H$ is assumed to be non-singular and is given by
\[ H \triangleq \begin{bmatrix} H_{11} & H_{12} \\ H_{21} & H_{22} \end{bmatrix}, \]
where
\[ H_{11} = m_1\ell_1^2 + I_1 + m_2(\ell_1^2 + \ell_2^2 + 2\ell_1\ell_2 \cos(q_2)) + I_2 \]
\[ H_{12} = m_2\ell_1\ell_2 \cos(q_2) + m_2\ell_2^2 + I_2 \]
\[ H_{21} = H_{12} \]
\[ H_{22} = m_2\ell_2^2 + I_2. \]
(31)
The matrix $C(q, \dot{q})$ is given by
\[ C(q, \dot{q}) \triangleq \begin{bmatrix} -h\dot{q}_2 & -h\dot{q}_1 - h\dot{q}_2 \\ h\dot{q}_1 & 0 \end{bmatrix}, \]
where $h = m_2\ell_1\ell_2 \sin(q_2)$. The vector $G = [G_1, G_2]^T$ is given by
\[ G_1 = m_1\ell_1g \cos(q_1) + m_2g(\ell_2 \cos(q_1 + q_2) + \ell_1 \cos(q_1)) \]
\[ G_2 = m_2\ell_2g \cos(q_1 + q_2). \]
(32)
In our simulations, we assume that the parameters take values according to [14], and summarized in Table I. The system dynamics (30) can be rewritten as
\[ \ddot{q} = H^{-1}(q)\tau - H^{-1}(q)\left[ C(q, \dot{q})\dot{q} + G(q) \right]. \]
(33)
Thus, the nominal controller is given by
\[ u_n = [C(q, \dot{q})\dot{q} + G(q)] + H(q) [\dot{q}_d - K_2(\dot{q} - \dot{q}_d) - K_1(q - q_d)], \]
(34)
where $q_d = [q_{1d}, q_{2d}]^T$, denotes the desired trajectory and the feedback gains $K_1 > 0, K_2 > 0$, are chosen such that the tracking error go to zero asymptotically. For simplicity, we use the feedback gains $K_1^j = 1 \text{ in (10)}$ for $i = 1, 2$ and $j = 1, 2$ in our simulations. The reference trajectory is given by the following function from the initial time $t_0 = 0$ to the final time $t_f$,
\[ q_{id}(t) = \frac{1}{1 + \exp(-t)}, \quad i = 1, 2 \]
Now we assume that the nonlinear model (30) is uncertain. In particular, we assume that there exist additive uncertainties in the model (33), i.e.
\[ \ddot{q} = H^{-1}(q)\tau - H^{-1}(q)\left[ C(q, \dot{q})\dot{q} + G(q) \right] + \Delta b(q, t). \]
(35)
We will illustrate our approach for the uncertain model (35). In the following, we consider the cost function
\[ J = Q_1 \int_0^{t_f} \|q - q_d\|^2 dt + Q_2 \int_0^{t_f} \|\dot{q} - \dot{q}_d\|^2 dt, \]
where $Q_1 > 0$ and $Q_2 > 0$ denote the weighting parameters.

B. MES Based Adaptation

Due to space limitation, we report hereafter only the case presented in Section V-B, when $\Delta b(q, t)$ is simply a time-varying vector $\Delta(t)$, where $\Delta(t) = [\Delta_1(t), \Delta_2(t)]^T$. However, we underline that we have successfully tested the remaining cases and that all the results will be reported in a longer journal version of this work.

Here the controller is designed according to Theorem 2 and the two unknowns $\Delta_1(t)$ and $\Delta_2(t)$ are identified by the MES (29) such that the cost function $J$ in (36) is minimized.

We simulate the system with
\[ \Delta_1(t) = 1 - 0.14 \sin(0.01t) \]
\[ \Delta_2(t) = 1 - 0.12 \cos(0.01t). \]
(37)
The estimate of these two parameters $\hat{\Delta}_i (i = 1, 2)$ are computed using a discrete version of (29), given by
\[ \hat{\Delta}_i(k + 1) = \hat{\Delta}_i(k) + \tilde{t}_f(\omega_i^k \sqrt{\omega_i^k} \sin(\omega_i^k t_f k) - \kappa_i \sqrt{\omega_i^k} \sin(\omega_i^k t_f k) J), \]
(38)
where $k = 0, 1, 2, \cdots$ denotes the iteration index and $\hat{\Delta}_i (i = 1, 2)$ start from zero initial conditions. The parameters used in the cost function (36) and the MES (38) are summarized in Table II. For more details about the tuning of the parameters in the MES, we refer the reader to [1]. However, we underline here that the frequencies $\omega_1$ and $\omega_2$ have been selected high enough to ensure efficient
with a model-free ES algorithm to obtain a learning-based adaptive controller. We have presented the stability proof of this controller and have shown a detailed application of this approach on a two-link robot manipulator example. Future works will deal with considering controllers under input constraints, using different ES algorithms with less restrictive tuning conditions, and comparing the obtained controllers to some available classical nonlinear adaptive controllers.

**REFERENCES**


