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Brief paper

Adaptive inverse dynamics control of robots with uncertain kinematics and dynamics ☆

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ABSTRACT

It has been about two decades since the first globally convergent adaptive tracking controller was derived for robots with dynamic uncertainties. However, not until recently has the problem of concurrent adaptation to both the kinematic and dynamic uncertainties found its solution. This adaptive controller belongs to passivity-based control. Though passivity-based controllers have many attractive properties, in general, they are not able to guarantee the uniform performance of the robot over the entire workspace. Even in the ideal case of perfect knowledge of the manipulator parameters, the closed-loop system remains nonlinear and coupled. Thus the closed-loop tracking performance is difficult to quantify, while the inverse dynamics controllers can overcome these deficiencies. Therefore, in this work, we will develop a new adaptive Jacobian tracking controller based on the inverse manipulator dynamics. Using the Lyapunov approach, we have proved that the end-effector motion tracking errors converge asymptotically to zero. Simulation results are presented to show the performance of the proposed controller.

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1. Introduction

Human beings do not have an exact knowledge of the real world, but are still able to act and execute various tasks in it. It is the eyes of the humans that play a significant role in these tasks. With the help of our eyes, we obtain the target location in both the eye coordinates and the hand coordinates (Buneo, Jarvis, Batista, & Andersen, 2002). Also, with the aid of our eyes, we are able to pick up various objects with unknown kinematic and dynamic properties, and to manipulate them skillfully to complete a task. And we can grip a tool at different grasping points and orientations, and use it without any difficulty. In all cases, people seem to extend their self-perception to include the unknown tool as part of their body, and can learn experiences and adapt to the uncertainties from previous experiences (Sekiyama, Miyauchi, Imaruoka, Egusa, & Tashiro, 2000). The longer we use a tool, the more skillfully we can manipulate it. The way by which people manipulate an unknown object conveniently and dexterously suggests that we do not need an accurate knowledge of the kinematics and dynamics of our arms and the object. The capability of sensing and responding to changes without an exact knowledge of sensorimotor transformation (Pouget & Snyder, 2000) gives humans the high degree of flexibility in coping with unforeseen changes in the real world.

The manipulator kinematics and dynamics are highly nonlinear. In cases where the robot model is accurately calibrated, model-based controllers (Craig, 2005; Hollerbach, 1980; Luh, Walker, & Paul, 1980a,b) can give good performance. But when a robot picks up tools of different lengths, unknown gripping points and orientations, the kinematics and dynamics of the robot change and are difficult to derive exactly. Therefore, the assumption of an accurate knowledge of the manipulator model significantly degrades the robot's adaptability to changes and uncertainties from the robot and the environment. Although calibrations and identification approaches (Gatla, Lumia, Wood, & Starr, 2007; Jiang, Ishida, & Sunawada, 2006; Renders, Rossignol, Becquet, & Hanus, 1991) may be helpful in deriving the kinematic and dynamic parameters of the manipulator with sufficient accuracy, it seems not flexible to do calibration or parameter identification for every object that the robot picks up, before manipulating it. It is also impossible for the robot to grasp the tool at the same gripping point and orientation, even if the same tool is used again. Thus, the development of robot controllers that can cope flexibly with uncertainties in both kinematics and dynamics represents an important step towards dexterous robot manipulation.

Many adaptive controllers have been proposed to deal with dynamic uncertainties. In general, these controllers can be classified into three classes based on the differences in control

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objectives and the driving signals of the parameter adaptation. In the first category, the adaptation driving signals are the tracking errors (Craig, Hsu, & Sastry, 1987; Slotine & Li, 1987, 1988; Spong & Ortega, 1990). Their objective is to reduce the tracking errors. In Craig et al. (1987) and Spong and Ortega (1990), they proposed adaptive inverse dynamics controllers and the control objective, which is achievable in the ideal case of perfect knowledge of the dynamic parameters, is to obtain a closed-loop system which is linear and decoupled and can guarantee good transient performance. But the results in Craig et al. (1987) require the measurement of the joint acceleration and the existence of the inverse of the estimated inertia matrix. Therefore Spong and Ortega (1990) proposed an alternative adaptive inverse dynamics controller to avoid using the estimated inertia matrix. Slotine and Li (1987, 1988) attacked this problem from a fundamentally new perspective. Fully exploiting the structural characteristics of the manipulator dynamics, they devised a relatively simple adaptive controller using a sliding variable. This controller does not need the measurement of joint acceleration or the uniform invertibility of the estimated inertia matrix. In the second category, the parameter adaptation is driven by prediction errors (Middleton & Goodwin, 1988). Prediction error based adaptive control is very similar to the conventional self-tuning control. The prediction error based controller proposed in Middleton and Goodwin (1988) utilizes the prediction errors of the filtered torque to generate the adaptation law. And it is composed of a modified computed torque controller and a modified least-square estimator. The asymptotic stability of the closed-loop system is derived based on input-output stability analysis. The third category is called composite adaptive control (Slotine & Li, 1989), where the parameter adaptation is driven by both tracking errors and prediction errors. It is shown that composite adaptive controller yields faster parameter convergence and better tracking accuracy, and thus enjoys enhanced robustness to unmodeled dynamics. However, in all of the above adaptive control schemes, the kinematics is assumed to be known exactly.

Recently, a number of approximate Jacobian controllers (Cheah, Kawamura, & Arimoto, 1999; Cheah, Hirano, Kawamura, & Arimoto, 2003; Dixon, 2007; Yazarel & Cheah, 2002) have been presented to cope with the uncertain robot kinematics and dynamics. The proposed controllers do not require the exact knowledge of the kinematics and Jacobian matrix. Nevertheless, the results in Cheah et al. (1999), Cheah et al. (2003), Dixon (2007) and Yazarel and Cheah (2002) are focusing on set-point control or point-to-point control of robot manipulators. Thus, Cheah, Liu, and Slotine (2006) proposed an adaptive Jacobian tracking controller to realize the end-effector trajectory tracking. Based on Lyapunov stability analysis, it is shown that the robot end-effector tracking errors converge asymptotically.

The controller proposed in Cheah et al. (2006) belongs to passivity based control, which adopted approximate transpose Jacobian feedback to accomplish the end-point tracking of the manipulator. Transpose Jacobian controller conserves passivity of the system. However, as stated by Craig (2005), the performance of the transpose Jacobian controller is not good over the entire workspace of the robot. In other words, we cannot choose fixed gains that will result in fixed closed-loop poles. The dynamic response of such controllers will vary with the arm configuration. In addition, even in the ideal case of exact knowledge of the robot parameters, passivity based controllers still lead to nonlinear and coupled error dynamics. Thus, the performance of the system is difficult to quantify. Unlike passivity based controllers, inverse dynamics controllers (Craig et al., 1987; Middleton & Goodwin, 1988; Spong & Ortega, 1990), in the ideal case of perfect knowledge of the manipulator parameters, yield linear and decoupled error dynamics, whose tracking performance is very convenient to quantify. Unfortunately, there is still no adaptive inverse dynamics controller that is able to cope with kinematic uncertainties. Thus, in this work, we will derive a new adaptive inverse dynamics controller for robots with unknown properties in both kinematics and dynamics.

2. Robot kinematics and dynamics

The generalized end-effector position $\mathbf{x} \in \Re^n$ can be expressed as

$$\mathbf{x} = \mathbf{h}(\mathbf{q}) \tag{1}$$

where $\mathbf{h}(\cdot) \in \Re^n \to \Re^n$ is generally a nonlinear transformation describing the relation between joint space and task space, $\mathbf{q} \in \Re^n$ is the joint angle vector. The end-effector velocity $\dot{\mathbf{x}}$ is related to the joint-space velocity $\dot{\mathbf{q}}$ through the so-called Jacobian and can be expressed linearly in a set of kinematic parameters $\mathbf{a}_k = (a_{k1}, a_{k2}, \ldots, a_{ki})^{\mathrm{T}}$,

$$\dot{\mathbf{x}} = \mathbf{J}(\mathbf{q})\,\dot{\mathbf{q}} = \mathbf{Y}_k(\mathbf{q}, \dot{\mathbf{q}})\,\mathbf{a}_k \tag{2}$$

where $\mathbf{J}(\mathbf{q}) \in \Re^{n\times n}$ is the Jacobian matrix mapping from joint space to task space, and $\mathbf{Y}_k(\mathbf{q}, \dot{\mathbf{q}})$ is a regressor matrix. To avoid measuring task-space velocity, we can filter the task-space velocity using a low-pass filter,

$$\dot{\mathbf{y}} + \lambda\mathbf{y} = \lambda\dot{\mathbf{x}} \tag{3}$$

where $\lambda > 0$ and $\mathbf{y}$ is the filtered output of the task-space velocity with zero initial value (i.e., $\mathbf{y}(0) = 0$). Then, we have

$$\mathbf{y} = \lambda/(\lambda + p)\,\dot{\mathbf{x}} = \mathbf{W}_k(t)\,\mathbf{a}_k \tag{4}$$

where $\mathbf{W}_k(t) = \lambda/(\lambda + p)\,\mathbf{Y}_k(\mathbf{q}, \dot{\mathbf{q}})$, p is the Laplace variable and the initial value of $\mathbf{W}_k$ is $\mathbf{W}_k(0) = 0$.

The equations of motion of the manipulator are (Slotine & Li, 1991),

$$\mathbf{M}(\mathbf{q})\,\ddot{\mathbf{q}} + \mathbf{C}(\mathbf{q}, \dot{\mathbf{q}})\,\dot{\mathbf{q}} + \mathbf{g}(\mathbf{q}) = \boldsymbol{\tau} \tag{5}$$

where $\mathbf{M}(\mathbf{q}) \in \Re^{n\times n}$ is the inertia matrix, $\mathbf{C}(\mathbf{q}, \dot{\mathbf{q}})\dot{\mathbf{q}} \in \Re^n$ is the centripetal and Coriolis force, $\mathbf{g}(\mathbf{q}) \in \Re^n$ is the gravitational force, and $\boldsymbol{\tau} \in \Re^n$ is the exerted joint torque.

Even if the equations of motion of the robot (i.e. Eq. (5)) are complex and highly nonlinear, there are still some basic properties in Eq. (5) that are convenient for controller design. These properties are as follows.

Property 1. *The inertia matrix* $\mathbf{M}(\mathbf{q})$ *is uniformly positive definite, and there exist positive constants* α_1, α_2 *such that,*

$$\alpha_1\mathbf{I} \le \mathbf{M}(\mathbf{q}) \le \alpha_2\mathbf{I}. \tag{6}$$

Property 2. *The manipulator dynamics (5) is linear in a set of physical parameters* $\mathbf{a}_d = (a_{d1}, a_{d2}, \ldots, a_{dp})^{\mathrm{T}}$,

$$\mathbf{M}(\mathbf{q})\,\ddot{\mathbf{q}} + \mathbf{C}(\mathbf{q}, \dot{\mathbf{q}})\,\dot{\mathbf{q}} + \mathbf{g}(\mathbf{q}) = \mathbf{Y}(\mathbf{q}, \dot{\mathbf{q}}, \ddot{\mathbf{q}})\,\mathbf{a}_d \tag{7}$$

where $\mathbf{Y}(\mathbf{q}, \dot{\mathbf{q}}, \ddot{\mathbf{q}}) \in \Re^{n\times p}$ *is usually called the dynamic regressor matrix.*

3. Inverse dynamics control of robots in task space

In this section, we will concentrate on the inverse dynamics control of robots in task space. The robot is required to track a given desired task-space trajectory $\mathbf{x}_d$. And we assume that $\mathbf{x}_d$, $\dot{\mathbf{x}}_d$ and $\ddot{\mathbf{x}}_d$ are all bounded. Then the control objective is to drive the motion tracking errors to zero.

3.1. Known parameter case

The basic idea of the well-known inverse dynamics control is to seek a nonlinear feedback control law to cancel exactly all of the nonlinear terms in Eq. (5), so that, in the ideal case, the closed-loop system is linear and decoupled.

For trajectory tracking in task space, resolved acceleration control (Luh et al., 1980b) can be adopted,

$$\tau = \mathbf{M}(\mathbf{q})\left[\mathbf{J}^{-1}(\mathbf{q})\left(\ddot{\mathbf{x}}_d - \mathbf{K}_v\Delta\dot{\mathbf{x}} - \mathbf{K}_P\Delta\mathbf{x} - \dot{\mathbf{J}}(\mathbf{q})\dot{\mathbf{q}}\right)\right] + \mathbf{C}(\mathbf{q},\dot{\mathbf{q}})\dot{\mathbf{q}} + \mathbf{g}(\mathbf{q}) \tag{8}$$

where $\Delta\mathbf{x} = \mathbf{x} - \mathbf{x}_d$ is the end-effector position tracking error, $\Delta\dot{\mathbf{x}} = \dot{\mathbf{x}} - \dot{\mathbf{x}}_d$ is the end-effector velocity tracking error, $\mathbf{K}_v$, $\mathbf{K}_P$ are positive definite diagonal matrices, and $\dot{\mathbf{J}}(\mathbf{q})$ is the time derivative of the matrix $\mathbf{J}(\mathbf{q})$.

Substituting the control law (8) into the robot dynamics (5), we have

$$\mathbf{M}(\mathbf{q})\mathbf{J}^{-1}(\mathbf{q})\left(\Delta\ddot{\mathbf{x}} + \mathbf{K}_v\Delta\dot{\mathbf{x}} + \mathbf{K}_P\Delta\mathbf{x}\right) = 0. \tag{9}$$

If $\mathbf{J}(\mathbf{q})$ is non-singular, Eq. (9) will lead to a linear error dynamic equation

$$\Delta\ddot{\mathbf{x}} + \mathbf{K}_v\Delta\dot{\mathbf{x}} + \mathbf{K}_P\Delta\mathbf{x} = 0. \tag{10}$$

Since $\mathbf{K}_v$, $\mathbf{K}_P$ are positive definite diagonal matrices, then the closed-loop system is linear, decoupled and exponentially stable. Stability for this controller is thus obvious.

3.2. Adaptive case

When the robot parameters are unknown, we cannot use the control law (8). Replacing the unknown parameters in Eq. (8) with their estimates, we get the following inverse dynamics control law,

$$\tau = \hat{\mathbf{M}}(\mathbf{q})\left[\hat{\mathbf{J}}^{-1}(\mathbf{q})\left(\ddot{\mathbf{x}}_d - \mathbf{K}_v\Delta\dot{\hat{\mathbf{x}}} - \mathbf{K}_P\Delta\mathbf{x} - \dot{\hat{\mathbf{J}}}\dot{\mathbf{q}}\right)\right] + \hat{\mathbf{C}}(\mathbf{q},\dot{\mathbf{q}})\dot{\mathbf{q}} + \hat{\mathbf{g}}(\mathbf{q}) \tag{11}$$

where $\hat{\mathbf{J}}(\mathbf{q})$ is the estimate of the Jacobian matrix $\mathbf{J}(\mathbf{q})$, $\dot{\hat{\mathbf{J}}}$ is the time derivative of $\hat{\mathbf{J}}$, and $\hat{\mathbf{a}}_k$ is the estimate of the kinematic parameter $\mathbf{a}_k$, which will be updated by the adaptation law to be given later, $\Delta\dot{\hat{\mathbf{x}}} = \dot{\hat{\mathbf{x}}} - \dot{\mathbf{x}}_d$, and $\dot{\hat{\mathbf{x}}} = \hat{\mathbf{J}}(\mathbf{q})\dot{\mathbf{q}}$ is the estimated end-effector velocity. Substituting the control law (11) into Eq. (5), we have

$$\begin{aligned}\mathbf{M}(\mathbf{q})\ddot{\mathbf{q}} + \mathbf{C}(\mathbf{q},\dot{\mathbf{q}})\dot{\mathbf{q}} + \mathbf{g}(\mathbf{q}) &= \hat{\mathbf{M}}(\mathbf{q})\left[\hat{\mathbf{J}}^{-1}(\mathbf{q})\left(\ddot{\mathbf{x}}_d - \mathbf{K}_v\Delta\dot{\hat{\mathbf{x}}} - \mathbf{K}_P\Delta\mathbf{x} - \dot{\hat{\mathbf{J}}}(\mathbf{q})\dot{\mathbf{q}}\right)\right] \\ &\quad + \hat{\mathbf{C}}(\mathbf{q},\dot{\mathbf{q}})\dot{\mathbf{q}} + \hat{\mathbf{g}}(\mathbf{q}).\end{aligned} \tag{12}$$

Eq. (12) is rewritten as

$$\hat{\mathbf{M}}\left[\ddot{\mathbf{q}} - \hat{\mathbf{J}}^{-1}\left(\ddot{\mathbf{x}}_d - \mathbf{K}_v\Delta\dot{\hat{\mathbf{x}}} - \mathbf{K}_P\Delta\mathbf{x} - \dot{\hat{\mathbf{J}}}(\mathbf{q})\dot{\mathbf{q}}\right)\right] = \mathbf{Y}(\mathbf{q},\dot{\mathbf{q}},\ddot{\mathbf{q}})\Delta\mathbf{a}_d \tag{13}$$

where $\Delta\mathbf{a}_d = \hat{\mathbf{a}}_d - \mathbf{a}_d$ is the dynamic parameter estimation error.

The estimation of the robot end-effector velocity is

$$\dot{\hat{\mathbf{x}}} = \hat{\mathbf{J}}(\mathbf{q})\dot{\mathbf{q}}. \tag{14}$$

Differentiating equation (14) with respect to time, we get

$$\ddot{\hat{\mathbf{x}}} = \hat{\mathbf{J}}(\mathbf{q})\ddot{\mathbf{q}} + \dot{\hat{\mathbf{J}}}(\mathbf{q})\dot{\mathbf{q}} \tag{15}$$

where $\ddot{\hat{\mathbf{x}}}$ is the time derivative of $\dot{\hat{\mathbf{x}}}$. Substituting Eq. (15) into Eq. (13), we have,

$$\hat{\mathbf{M}}\hat{\mathbf{J}}^{-1}\left(\Delta\ddot{\hat{\mathbf{x}}} + \mathbf{K}_v\Delta\dot{\hat{\mathbf{x}}} + \mathbf{K}_P\Delta\mathbf{x}\right) = \mathbf{Y}(\mathbf{q},\dot{\mathbf{q}},\ddot{\mathbf{q}})\Delta\mathbf{a}_d \tag{16}$$

where $\Delta\ddot{\hat{\mathbf{x}}} = \ddot{\hat{\mathbf{x}}} - \ddot{\mathbf{x}}_d$. Eq. (16) can be further expressed as,

$$\Delta\ddot{\hat{\mathbf{x}}} + \mathbf{K}_v\Delta\dot{\hat{\mathbf{x}}} + \mathbf{K}_P\Delta\mathbf{x} = \hat{\mathbf{J}}\hat{\mathbf{M}}^{-1}\mathbf{Y}(\mathbf{q},\dot{\mathbf{q}},\ddot{\mathbf{q}})\Delta\mathbf{a}_d = \mathbf{\Phi}\Delta\mathbf{a}_d \tag{17}$$

where $\mathbf{\Phi} = \hat{\mathbf{J}}\hat{\mathbf{M}}^{-1}\mathbf{Y}(\mathbf{q},\dot{\mathbf{q}},\ddot{\mathbf{q}})$.

Assuming that $\ddot{\mathbf{q}}$ is measurable, $\hat{\mathbf{M}}^{-1}$ and $\hat{\mathbf{J}}^{-1}$ are bounded, we have the following theorem.

Theorem 1. *Choose the parameter updating laws as*

$$\dot{\hat{\mathbf{a}}}_d = -\mathbf{\Gamma}_d\mathbf{\Phi}^{\mathrm{T}}\left(\Delta\dot{\hat{\mathbf{x}}} + \alpha\Delta\mathbf{x}\right) \tag{18}$$

$$\dot{\hat{\mathbf{a}}}_k = \mathbf{\Gamma}_k\left[\mathbf{Y}_k^{\mathrm{T}}(\mathbf{K}_P + \alpha\mathbf{K}_v)\Delta\mathbf{x} + \alpha\mathbf{Y}_k^{\mathrm{T}}\Delta\dot{\hat{\mathbf{x}}} - \mathbf{W}_k^{\mathrm{T}}\mathbf{R}_k\left(\mathbf{W}_k\hat{\mathbf{a}}_k - \mathbf{y}\right)\right] \tag{19}$$

where $\alpha > 0$ is a positive design constant and is chosen such that $\mathbf{K}_v - \alpha\mathbf{I} \geq \beta\mathbf{I}$, and $\beta > 0$ is a positive constant, $\mathbf{R}_k$ is a positive definite symmetric matrix. Then, the control law (11) for the robot system (5) leads to convergence of the end-effector motion tracking errors. That is, $\Delta\mathbf{x} \to 0$ and $\Delta\dot{\mathbf{x}} \to 0$ as $t \to \infty$.

Proof. Let us consider the Lyapunov function candidate

$$\begin{aligned}V &= \frac{1}{2}\left(\Delta\dot{\hat{\mathbf{x}}} + \alpha\Delta\mathbf{x}\right)^{\mathrm{T}}\left(\Delta\dot{\hat{\mathbf{x}}} + \alpha\Delta\mathbf{x}\right) + \frac{1}{2}\Delta\mathbf{x}^{\mathrm{T}}(\mathbf{K}_P + \alpha\mathbf{K}_v \\ &\quad - \alpha^2\mathbf{I})\Delta\mathbf{x} + \frac{1}{2}\Delta\mathbf{a}_d^{\mathrm{T}}\mathbf{\Gamma}_d^{-1}\Delta\mathbf{a}_d + \frac{1}{2}\Delta\mathbf{a}_k^{\mathrm{T}}\mathbf{\Gamma}_k^{-1}\Delta\mathbf{a}_k\end{aligned} \tag{20}$$

where $\Delta\mathbf{a}_k = \hat{\mathbf{a}}_k - \mathbf{a}_k$ is the kinematic parameter estimation error.

Differentiating V with respect to time along trajectories of Eq. (17), we get

$$\begin{aligned}\dot{V} &= \left(\Delta\dot{\hat{\mathbf{x}}} + \alpha\Delta\mathbf{x}\right)^{\mathrm{T}}\left(-\mathbf{K}_v\Delta\dot{\hat{\mathbf{x}}} - \mathbf{K}_P\Delta\mathbf{x} + \mathbf{\Phi}\Delta\mathbf{a}_d + \alpha\Delta\dot{\mathbf{x}}\right) \\ &\quad + \Delta\dot{\mathbf{x}}^{\mathrm{T}}\left(\mathbf{K}_P + \alpha\mathbf{K}_v - \alpha^2\mathbf{I}\right)\Delta\mathbf{x} + \Delta\mathbf{a}_d^{\mathrm{T}}\mathbf{\Gamma}_d^{-1}\dot{\hat{\mathbf{a}}}_d + \Delta\mathbf{a}_k^{\mathrm{T}}\mathbf{\Gamma}_k^{-1}\dot{\hat{\mathbf{a}}}_k \\ &= \left(\Delta\dot{\hat{\mathbf{x}}} + \alpha\Delta\mathbf{x}\right)^{\mathrm{T}}\left(-(\mathbf{K}_v - \alpha\mathbf{I})\Delta\dot{\hat{\mathbf{x}}} - \mathbf{K}_P\Delta\mathbf{x} + \mathbf{\Phi}\Delta\mathbf{a}_d - \alpha\mathbf{Y}_k\Delta\mathbf{a}_k\right) \\ &\quad + \Delta\dot{\mathbf{x}}^{\mathrm{T}}\left(\mathbf{K}_P + \alpha\mathbf{K}_v - \alpha^2\mathbf{I}\right)\Delta\mathbf{x} + \Delta\mathbf{a}_d^{\mathrm{T}}\mathbf{\Gamma}_d^{-1}\dot{\hat{\mathbf{a}}}_d + \Delta\mathbf{a}_k^{\mathrm{T}}\mathbf{\Gamma}_k^{-1}\dot{\hat{\mathbf{a}}}_k.\end{aligned} \tag{21}$$

Eq. (21) can be reformulated as

$$\begin{aligned}\dot{V} &= -\Delta\dot{\hat{\mathbf{x}}}^{\mathrm{T}}(\mathbf{K}_v - \alpha\mathbf{I})\Delta\dot{\hat{\mathbf{x}}} - \alpha\Delta\mathbf{x}^{\mathrm{T}}\mathbf{K}_P\Delta\mathbf{x} \\ &\quad - \Delta\dot{\hat{\mathbf{x}}}^{\mathrm{T}}\left(\mathbf{K}_P + \alpha\mathbf{K}_v - \alpha^2\mathbf{I}\right)\Delta\mathbf{x} - \alpha\left(\Delta\dot{\hat{\mathbf{x}}} + \alpha\Delta\mathbf{x}\right)^{\mathrm{T}}\mathbf{Y}_k\Delta\mathbf{a}_k \\ &\quad + \left(\Delta\dot{\hat{\mathbf{x}}} + \alpha\Delta\mathbf{x}\right)^{\mathrm{T}}\mathbf{\Phi}\Delta\mathbf{a}_d + \Delta\dot{\mathbf{x}}^{\mathrm{T}}\left(\mathbf{K}_P + \alpha\mathbf{K}_v - \alpha^2\mathbf{I}\right)\Delta\mathbf{x} \\ &\quad + \Delta\mathbf{a}_d^{\mathrm{T}}\mathbf{\Gamma}_d^{-1}\dot{\hat{\mathbf{a}}}_d + \Delta\mathbf{a}_k^{\mathrm{T}}\mathbf{\Gamma}_k^{-1}\dot{\hat{\mathbf{a}}}_k \\ &= -\Delta\dot{\hat{\mathbf{x}}}^{\mathrm{T}}(\mathbf{K}_v - \alpha\mathbf{I})\Delta\dot{\hat{\mathbf{x}}} - \alpha\Delta\mathbf{x}^{\mathrm{T}}\mathbf{K}_P\Delta\mathbf{x} \\ &\quad - \Delta\mathbf{a}_k^{\mathrm{T}}\mathbf{Y}_k^{\mathrm{T}}\left[(\mathbf{K}_P + \alpha\mathbf{K}_v)\Delta\mathbf{x} + \alpha\Delta\dot{\hat{\mathbf{x}}}\right] \\ &\quad + \left(\Delta\dot{\hat{\mathbf{x}}} + \alpha\Delta\mathbf{x}\right)^{\mathrm{T}}\mathbf{\Phi}\Delta\mathbf{a}_d + \Delta\mathbf{a}_d^{\mathrm{T}}\mathbf{\Gamma}_d^{-1}\dot{\hat{\mathbf{a}}}_d + \Delta\mathbf{a}_k^{\mathrm{T}}\mathbf{\Gamma}_k^{-1}\dot{\hat{\mathbf{a}}}_k.\end{aligned} \tag{22}$$

Substituting the parameter updating laws (18) and (19) into Eq. (22), we have

$$\dot{V} \leq -\beta\Delta\dot{\hat{\mathbf{x}}}^{\mathrm{T}}\Delta\dot{\hat{\mathbf{x}}} - \alpha\Delta\mathbf{x}^{\mathrm{T}}\mathbf{K}_P\Delta\mathbf{x} - \Delta\mathbf{a}_k^{\mathrm{T}}\mathbf{W}_k^{\mathrm{T}}\mathbf{R}_k\mathbf{W}_k\Delta\mathbf{a}_k \leq 0. \tag{23}$$

This implies that $\Delta\mathbf{x}, \Delta\dot{\hat{\mathbf{x}}} \in \mathbf{L}_2 \cap \mathbf{L}_\infty$, $\mathbf{W}_k\Delta\mathbf{a}_k \in \mathbf{L}_2$, $\Delta\mathbf{a}_d$ and $\Delta\mathbf{a}_k$ are both bounded. $\Delta\dot{\hat{\mathbf{x}}} \in \mathbf{L}_\infty$ implies that $\dot{\hat{\mathbf{x}}} \in \mathbf{L}_\infty$. From Eq. (14), we have $\dot{\mathbf{q}} \in \mathbf{L}_\infty$, which leads to the fact that $\dot{\mathbf{x}} \in \mathbf{L}_\infty$, and thus $\mathbf{y} \in \mathbf{L}_\infty$. Using Eq. (19), we get $\dot{\hat{\mathbf{a}}}_k \in \mathbf{L}_\infty$ since $\mathbf{Y}_k$ and $\mathbf{W}_k$ are both bounded. From Eq. (11), we know that $\tau \in \mathbf{L}_\infty$. Based on the robot dynamics (5), we obtain that $\ddot{\mathbf{q}} \in \mathbf{L}_\infty$, and therefore $\ddot{\mathbf{x}} \in \mathbf{L}_\infty$ is also implied.

From the previous results, we have

$$\begin{aligned}&\Delta\dot{\mathbf{x}} \in \mathbf{L}_\infty, \qquad \Delta\ddot{\hat{\mathbf{x}}} = \ddot{\hat{\mathbf{x}}} - \ddot{\mathbf{x}}_d = \hat{\mathbf{J}}\ddot{\mathbf{q}} + \dot{\hat{\mathbf{J}}}\dot{\mathbf{q}} - \ddot{\mathbf{x}}_d \in \mathbf{L}_\infty, \\ &\frac{\mathrm{d}}{\mathrm{d}t}(\mathbf{W}_k\Delta\mathbf{a}_k) = \dot{\mathbf{W}}_k\Delta\mathbf{a}_k + \mathbf{W}_k\dot{\hat{\mathbf{a}}}_k \in \mathbf{L}_\infty.\end{aligned} \tag{24}$$

As a result, $\Delta\mathbf{x} \to 0$, $\Delta\dot{\hat{\mathbf{x}}} = \dot{\hat{\mathbf{x}}} - \dot{\mathbf{x}}_d \to 0$, and $\mathbf{W}_k\Delta\mathbf{a}_k \to 0$ as $t \to \infty$. Since $\Delta\ddot{\mathbf{x}} \in \mathbf{L}_\infty$ is implied by $\ddot{\mathbf{x}} \in \mathbf{L}_\infty$, $\Delta\dot{\mathbf{x}}$ is uniformly continuous. Using Barbalat Lemma (Slotine & Li, 1991), we obtain that $\Delta\dot{\mathbf{x}} \to 0$ as $t \to \infty$. This completes the proof of Theorem 1. △

Remark 1. It seems that there is a little difference between Eq. (17) and the ideal linear error dynamics (10), i.e., the left side of Eq. (17) is not a linear system's expression, which is caused by the uncertain kinematics. However, if task-space velocity is measurable, we can consider the control law

$$\tau = \hat{\mathbf{M}}(\mathbf{q})\left[\hat{\mathbf{J}}^{-1}(\mathbf{q})\left(\ddot{\mathbf{x}}_d - \mathbf{K}_v\Delta\dot{\mathbf{x}} - \mathbf{K}_P\Delta\mathbf{x} - \hat{\dot{\mathbf{J}}}(\mathbf{q})\dot{\mathbf{q}}\right)\right] + \hat{\mathbf{C}}(\mathbf{q},\dot{\mathbf{q}})\dot{\mathbf{q}} + \hat{\mathbf{g}}(\mathbf{q}) \tag{25}$$

where $\hat{\dot{\mathbf{J}}}(\mathbf{q})$ is the estimate of the matrix $\dot{\mathbf{J}}(\mathbf{q})$.

Substituting Eq. (25) into Eq. (5), we obtain the closed-loop dynamics

$$\Delta\ddot{\mathbf{x}} + \mathbf{K}_v\Delta\dot{\mathbf{x}} + \mathbf{K}_P\Delta\mathbf{x} = \mathbf{\Phi}\Delta\mathbf{a}_d - \bar{\mathbf{Y}}_k\Delta\mathbf{a}_k \tag{26}$$

where $\bar{\mathbf{Y}}_k$ is defined as

$$\ddot{\mathbf{x}} = \mathbf{J}(\mathbf{q})\ddot{\mathbf{q}} + \dot{\mathbf{J}}(\mathbf{q})\dot{\mathbf{q}} = \bar{\mathbf{Y}}_k(\mathbf{q},\dot{\mathbf{q}},\ddot{\mathbf{q}})\mathbf{a}_k. \tag{27}$$

We may write the system (26) in state space as

$$\dot{\boldsymbol{\xi}} = \mathbf{A}\boldsymbol{\xi} + \mathbf{B}\left(\mathbf{\Phi}\Delta\mathbf{a}_d - \bar{\mathbf{Y}}_k\Delta\mathbf{a}_k\right) \tag{28}$$

where

$$\mathbf{A} = \begin{bmatrix} \mathbf{0} & \mathbf{I} \\ -\mathbf{K}_P & -\mathbf{K}_v \end{bmatrix}, \qquad \mathbf{B} = \begin{bmatrix} \mathbf{0} \\ \mathbf{I} \end{bmatrix} \quad \text{and} \quad \boldsymbol{\xi} = \begin{bmatrix} \Delta\mathbf{x} \\ \Delta\dot{\mathbf{x}} \end{bmatrix}.$$

The parameters adaptation laws are determined as

$$\dot{\hat{\mathbf{a}}}_d = -\mathbf{\Gamma}_d\mathbf{\Phi}^{\mathrm{T}}\mathbf{B}^{\mathrm{T}}\mathbf{P}\boldsymbol{\xi} \tag{29}$$

$$\dot{\hat{\mathbf{a}}}_k = \mathbf{\Gamma}_k\left(\bar{\mathbf{Y}}_k^{\mathrm{T}}\mathbf{B}^{\mathrm{T}}\mathbf{P}\boldsymbol{\xi} - \mathbf{Y}_k^{\mathrm{T}}\mathbf{R}_k\left(\mathbf{Y}_k\hat{\mathbf{a}}_k - \dot{\mathbf{x}}\right)\right) \tag{30}$$

where $\mathbf{R}_k$ is a positive definite symmetric matrix and $\mathbf{P}$ is the unique symmetric positive definite solution of the Lyapunov equation

$$\mathbf{A}^{\mathrm{T}}\mathbf{P} + \mathbf{P}\mathbf{A} = -\mathbf{Q} \tag{31}$$

for a given symmetric positive definite matrix $\mathbf{Q}$. And the stability issue of the controller (25), (29) and (30) is similar to that of the adaptive inverse dynamics controller in joint space proposed by Craig et al. (1987).

We can see that the adaptive inverse dynamics controller (25), (29) and (30) indeed linearizes the robot dynamics. Nevertheless, both the kinematic and dynamic parameter updating laws require the measurement of the joint acceleration, which means that this controller is more sensitive to the noise and less robust than the controller (11), (18) and (19). Also, measuring task-space velocity tends to introduce more noise.

3.3. *An improved adaptive controller*

The results obtained in the previous section suffer from the deficiency that $\hat{\mathbf{M}}$ should be guaranteed to be uniformly invertible during the parameter adaptation. Actually, it is very difficult to guarantee the invertibility of the estimated inertia matrix $\hat{\mathbf{M}}$. Evoked by the approach proposed in Spong and Ortega (1990) and Dawson and Lewis (1991), we propose the following improved control law

$$\tau = \hat{\mathbf{M}}_0(\mathbf{q})\mathbf{v} + \hat{\mathbf{C}}(\mathbf{q},\dot{\mathbf{q}})\dot{\mathbf{q}} + \hat{\mathbf{g}}(\mathbf{q}) + \delta \tag{32}$$

where

$$\mathbf{v} = \hat{\mathbf{J}}^{-1}(\ddot{\mathbf{x}}_d - \mathbf{K}_v\Delta\hat{\dot{\mathbf{x}}} - \mathbf{K}_P\Delta\mathbf{x} - \hat{\dot{\mathbf{J}}}(\mathbf{q})\dot{\mathbf{q}}), \qquad \hat{\mathbf{M}}_0 = \hat{\mathbf{M}}_0^{\mathrm{T}} > 0$$

is the priori estimate of $\mathbf{M}$, which is obtained by replacing $\mathbf{a}_d$ in $\mathbf{M}$ with $\hat{\mathbf{a}}_{d0}$, where $\hat{\mathbf{a}}_{d0}$ is the priori estimate of $\mathbf{a}_d$. δ is used to compensate for the errors $\Delta\mathbf{M} = \hat{\mathbf{M}}_0 - \mathbf{M}$. Also, we note that $\hat{\mathbf{M}}_0$ is not updated online, and hence the invertibility of $\hat{\mathbf{M}}_0$ is not a problem. Next, we will determine δ and the parameter adaptation laws.

Substituting Eq. (32) into Eq. (5), we get,

$$\hat{\mathbf{M}}_0\hat{\mathbf{J}}^{-1}\left(\Delta\hat{\ddot{\mathbf{x}}} + \mathbf{K}_v\Delta\hat{\dot{\mathbf{x}}} + \mathbf{K}_P\Delta\mathbf{x}\right) + \left(\hat{\mathbf{M}} - \hat{\mathbf{M}}_0\right)\ddot{\mathbf{q}} - \delta = \mathbf{Y}(\mathbf{q},\dot{\mathbf{q}},\ddot{\mathbf{q}})\Delta\mathbf{a}_d. \tag{33}$$

Choose δ as

$$\delta = \left(\hat{\mathbf{M}} - \hat{\mathbf{M}}_0\right)\ddot{\mathbf{q}}. \tag{34}$$

Then substituting Eq. (34) into Eq. (33), we obtain,

$$\Delta\hat{\ddot{\mathbf{x}}} + \mathbf{K}_v\hat{\dot{\mathbf{x}}} + \mathbf{K}_P\Delta\mathbf{x} = \mathbf{\Phi}_1\Delta\mathbf{a}_d \tag{35}$$

where $\mathbf{\Phi}_1 = \hat{\mathbf{J}}\hat{\mathbf{M}}_0^{-1}\mathbf{Y}(\mathbf{q},\dot{\mathbf{q}},\ddot{\mathbf{q}})$.

Now we are in a position to state the following theorem.

Theorem 2. *Choose the parameter adaptation laws as*

$$\dot{\hat{\mathbf{a}}}_d = -\mathbf{\Gamma}_d\mathbf{\Phi}_1^{\mathrm{T}}\left(\Delta\hat{\dot{\mathbf{x}}} + \alpha\Delta\mathbf{x}\right) \tag{36}$$

$$\dot{\hat{\mathbf{a}}}_k = \mathbf{\Gamma}_k\left[\mathbf{Y}_k^{\mathrm{T}}(\mathbf{K}_P + \alpha\mathbf{K}_v)\Delta\mathbf{x} + \alpha\mathbf{Y}_k^{\mathrm{T}}\Delta\hat{\dot{\mathbf{x}}} - \mathbf{W}_k^{\mathrm{T}}\mathbf{R}_k\left(\mathbf{W}_k\hat{\mathbf{a}}_k - \mathbf{y}\right)\right] \tag{37}$$

where $\alpha > 0$ is a positive design constant and is also chosen such that $\mathbf{K}_v - \alpha\mathbf{I} \geq \beta\mathbf{I}$, and $\beta > 0$ is a positive constant. If $\mathbf{M} + \hat{\mathbf{M}}_0 - \hat{\mathbf{M}}$ is uniformly invertible, then the control (32) for the robot system (5) leads to the convergence of the end-effector motion tracking errors. That is, $\Delta\mathbf{x} \to 0$ and $\Delta\dot{\mathbf{x}} \to 0$ as $t \to \infty$.

The proof of Theorem 2 shall be similar to that of Theorem 1.

Remark 2. The improved adaptive inverse dynamics controller (32) (34), (36) and (37) does not require the uniform invertibility of $\hat{\mathbf{M}}$ while the controller (11), (18) and (19) does. The improved controller requires only that both $\hat{\mathbf{M}}_0$ and $\mathbf{M} + \hat{\mathbf{M}}_0 - \hat{\mathbf{M}}$ are uniformly invertible. It seems that the invertibility of $\hat{\mathbf{M}}_0$ and $\mathbf{M} + \hat{\mathbf{M}}_0 - \hat{\mathbf{M}}$ is easier to fulfill than that of $\hat{\mathbf{M}}$. However, the improved controller consists of acceleration signals in both the control law and the dynamic parameter adaptations, while the original controller consists of acceleration signals only in the dynamic parameter adaptations.

4. Simulations

In this section, simulations of a 2-DOF manipulator are conducted to illustrate the performance of the proposed controller. Comparisons between the proposed controllers and the passivity based controller presented in Cheah et al. (2006) have also been done. In addition, we assume that the end-effector position can be obtained from a position sensor, such as vision systems, electromagnetic measurement systems, position sensitive detectors, or laser trackers.

The manipulator Jacobian matrix $\mathbf{J}(\mathbf{q})$ mapping from joint space to task space is given as,

$$\mathbf{J}(\mathbf{q}) = \begin{bmatrix} -l_1\sin(q_1) - l_2\sin(q_1+q_2) & -l_2\sin(q_1+q_2) \\ l_1\cos(q_1) + l_2\cos(q_1+q_2) & l_2\cos(q_1+q_2) \end{bmatrix} \tag{38}$$

where l_1 and l_2 are the lengths of the first and second links, respectively, and $\mathbf{q} = \begin{bmatrix} q_1 & q_2 \end{bmatrix}^{\mathrm{T}}$ is the joint angle vector of the robot.

Then the end-effector velocity $\dot{\mathbf{x}}$ can be expressed as the product of a kinematic regressor matrix $\mathbf{Y}_k(\mathbf{q},\dot{\mathbf{q}})$ and an unknown parameter vector $\mathbf{a}_k$ where

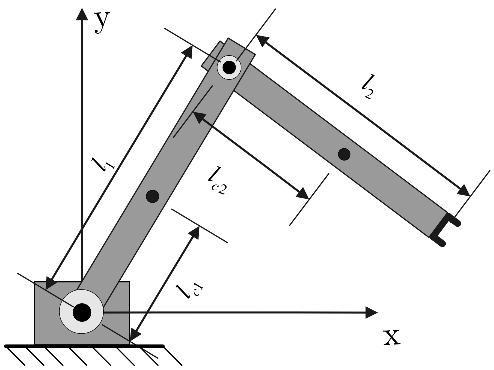

Fig. 1. A two-DOF manipulator.

Table 1
The manipulator parameters.

ith body	m_i (Kg)	I_i (Kg m^2)	l_i (m)	l_{ci} (m)
1	1.0	0.12	1.0	0.5
2	2.0	0.25	1.2	0.6

$$\mathbf{Y}_k(\mathbf{q},\dot{\mathbf{q}}) = \begin{bmatrix} -\sin(q_1)\dot{q}_1 & -\sin(q_1+q_2)(\dot{q}_1+\dot{q}_2) \\ \cos(q_1)\dot{q}_1 & \cos(q_1+q_2)(\dot{q}_1+\dot{q}_2) \end{bmatrix} \quad (39)$$

$$\mathbf{a}_k = \begin{bmatrix} l_1 & l_2 \end{bmatrix}^{\mathrm{T}}. \quad (40)$$

The physical manipulator parameters are given in the above table (Table 1). In Table 1, m_1 and m_2 are the masses of the two links and I_1 and I_2 are their moments of inertia. The parameters l_{c1} and l_{c2} describe the centers of the mass of the links as shown in Fig. 1.

For simplicity, the gravitational forces are assumed to be zero. The robot dynamic parameters $\mathbf{a}_d = \begin{bmatrix} a_1 & a_2 & a_3 \end{bmatrix}^{\mathrm{T}}$ are selected as $a_1 = I_1 + m_1 l_{c1}^2 + m_2 l_1^2 + I_2 + m_2 l_{c2}^2$, $a_2 = m_2 l_1 l_{c2}$, $a_3 = I_2 + m_2 l_{c2}^2$. The elements of the inertia matrix $\mathbf{M}(\mathbf{q})$ and the matrix $\mathbf{C}(\mathbf{q},\dot{\mathbf{q}})$ are $M_{11} = a_1 + 2a_2\cos(q_2)$, $M_{12} = M_{21} = a_3 + a_2\cos(q_2)$, $M_{22} = a_3$, $C_{11} = -a_2\sin(q_2)\dot{q}_2$, $C_{12} = -a_2\sin(q_2)(\dot{q}_1+\dot{q}_2)$, $C_{21} = a_2\sin(q_2)\dot{q}_1$, $C_{22} = 0$.

Then the dynamic regressor matrix $\mathbf{Y}(\mathbf{q},\dot{\mathbf{q}},\ddot{\mathbf{q}})$ can be obtained based on Eq. (7).

In simulations, the desired end-effector trajectory of the 2-DOF manipulator is a circle in task space,

$$\mathbf{x}_d(t) = \begin{bmatrix} 0.8 + 0.3\cos(\pi t) \\ 0.3\sin(\pi t) \end{bmatrix}. \quad (41)$$

The initial joint configuration of the robot is set as $\mathbf{q}(0) = \begin{bmatrix} \pi/3 & -2\pi/3 \end{bmatrix}^{\mathrm{T}}$ and the initial end-effector position is $\mathbf{x}(0) = \begin{bmatrix} 1.1 & -0.1732 \end{bmatrix}^{\mathrm{T}}$. Initial dynamic and kinematic parameter estimates are set as $\hat{\mathbf{a}}_d(0) = [4.0\ 0.5\ 0.5]^{\mathrm{T}}$ and $\hat{\mathbf{a}}_k(0) = [1.4\ 1.5]^{\mathrm{T}}$, respectively. The joint accelerations are derived by filtering the velocity signals (Spong & Vidyasagar, 1989), i.e., $\hat{\ddot{\mathbf{q}}} = p/(\lambda_a p + 1)\dot{\mathbf{q}}$ where $\lambda_a = 1/60$ is a very small positive number. The design parameters of the proposed controller are determined as $\mathbf{K}_v = 40\mathbf{I}$, $\mathbf{K}_P = 400\mathbf{I}$, $\alpha = 5.0$, $\boldsymbol{\Gamma}_d = \mathrm{diag}\{4.5, 1.5, 1.5\}$, $\boldsymbol{\Gamma}_k = 0.05\mathbf{I}$, $\mathbf{R}_k = 50.0\mathbf{I}$, $\lambda = 10$. Fig. 2 shows the end-effector tracking errors of the adaptive inverse dynamics controller. Figs. 3 and 4 illustrate the kinematic and dynamic parameter estimates. Fig. 5 demonstrates the tracking performance of the improved inverse dynamics controller (32), where $\hat{\mathbf{a}}_{d0}$ is determined as $\hat{\mathbf{a}}_{d0} = \hat{\mathbf{a}}_d(0)$.

In order to compare the performance of the proposed controller with the passivity based controller proposed by Cheah et al. (2006). Simulations of the Cheah et al. controller have also been conducted. This controller is also capable of avoiding the measurement of the task-space velocity, however at the expense of overparameterization of the robot dynamics (i.e., $\mathbf{a}_d \to \bar{\mathbf{a}}_d$, where the dimension of $\bar{\mathbf{a}}_d$ is much larger than that of $\mathbf{a}_d$). For simplicity, here, we assume that the task-space velocity is measurable, and thus the problem of overparameterization disappears. The design parameters of Cheah et al. controller are determined as $\mathbf{K}_v = 40\mathbf{I}$, $\mathbf{K}_P = 400\mathbf{I}$, $\boldsymbol{\Gamma}_d = \mathrm{diag}\{4.5, 1.5, 1.5\}$, $\boldsymbol{\Gamma}_k = 0.05\mathbf{I}$, $\alpha = 5.0$. Other initial conditions are the same as our adaptive controller. Simulation results of the passivity based controller are given in Fig. 6. From the simulations, we can see that the performance of the proposed controller in this paper is comparable to the Cheah et al. controller.

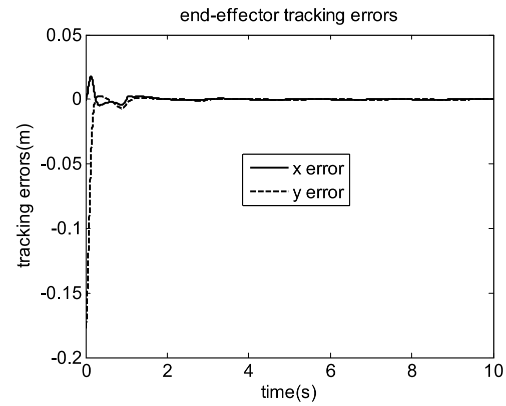

Fig. 2. End-effector tracking errors.

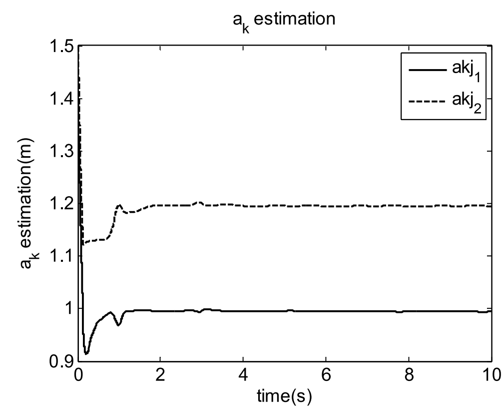

Fig. 3. Kinematic parameter estimates.

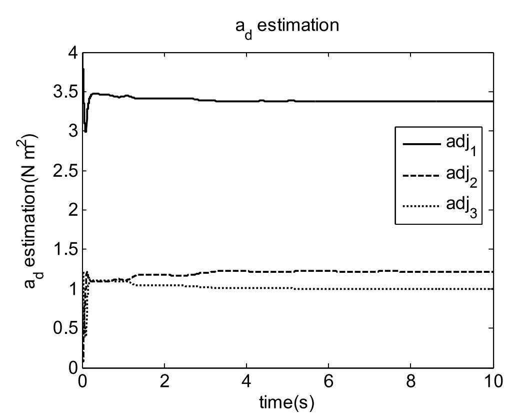

Fig. 4. Dynamic parameter estimates.

5. Conclusions

In this work, we have presented a new adaptive inverse dynamics controller to cope with the tracking problem for

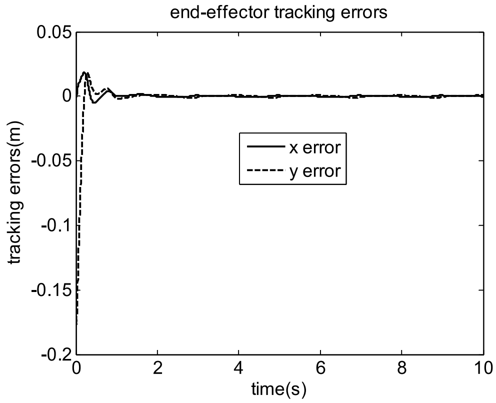

Fig. 5. End-effector tracking errors. (Improved inverse dynamics controller).

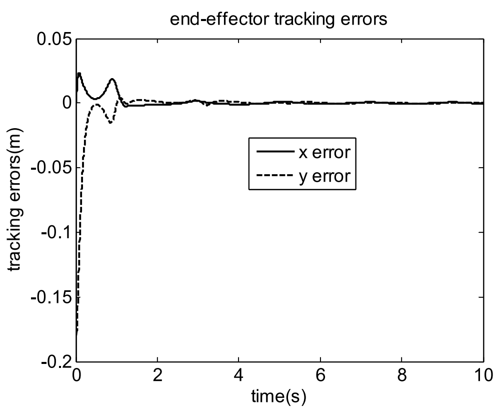

Fig. 6. End-effector tracking errors (Cheah et al. controller).

robots with uncertainties in both kinematics and dynamics. The concurrent adaptation to both the kinematic and dynamic uncertainties ensures the convergence of the end-effector tracking errors. It is shown that the closed-loop system is asymptotically stable based on Lyapunov stability analysis. Simulation results show that the performance of the proposed inverse dynamics controller is comparable to that of Cheah et al. controller. The main advantage of the proposed controller is that it yields linear error dynamics in the case of perfect knowledge of the robot parameters, while the dynamic response of passivity based controllers varies with the configuration of the manipulator.

Future work will be devoted to the experimental validation of the proposed controller.

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