2007 IEEE International Conference on
Robotics and Automation
Roma, Italy, 10-14 April 2007

On–line parameter identification and adaptive control of rigid robots using base reaction forces/torques

Eftychios G. Christoforou
Washington University, Dept. of Electrical and Systems Engineering
One Brookings Drive, Campus Box 1127, St. Louis, MO 63130, USA
christoforou@ese.wustl.edu

***Abstract*— The reaction forces at the base of a robotic manipulator contain model parameter information which can be acquired and used towards improving manipulation performance. The on–line extraction of this parameter content and its use towards improving the performance of model–based trajectory tracking controllers is examined. A modified version of a previously proposed nonlinear adaptive control scheme for rigid robots is also considered and the above source of information is used to drive its parameters update law. Simulation studies based on the model of a multilink rigid robot are employed to demonstrate these approaches.**

***Index Terms*— Base reaction forces/torques, on–line parameter identification, adaptive control, composite adaptive control.**

I. INTRODUCTION

Model–based controllers are typically used in robotics for trajectory tracking applications. Dynamic models are required for this purpose, the accuracy of which also depends on the knowledge of the manipulator parameters. The model parameters are often poorly known and this fact may affect the stability or compromise the performance of the controllers. A typical example is the well–known *computed torque method* (CTM) [1], originally proposed by Luh et al. [2]. It consists of a model–based feedforward and a feedback part. The selection of the feedforward part renders the system linear in closed loop and allows the design of a feedback controller based on well–established linear techniques. If there is uncertainty due to unmodelled dynamics or parameter ignorance, the scheme fails to decouple and linearize the closed–loop system, resulting in deterioration of performance or even in instabilities. This is the “Achilles’s heel” of the method.

The present work focuses on dealing with uncertainty related to the inertial parameters of the links. The disassembling of the robot and the measurement of the inertial parameters of its components is in general not a feasible option. One alternative for the estimation of model parameters is solid modelling using computer aided design (CAD) packages, which is also difficult for robots with numerous components of irregular shapes, made of a variety of materials. Given the above difficulties various parameter identification techniques have been proposed. From a control perspective in order to deal with the parameter uncertainty problem, robust and adaptive control techniques have been developed. The former are characterized by the ability to maintain stability and good performance in the presence of parameter uncertainty, unmodelled dynamics and disturbances. The latter are endowed with parameter learning capabilities so that manipulation performance improves with time [3].

Three different sources of parameter information for robotic manipulators exist, which can be used to drive parameter identification algorithms or adaptive controllers:

1) Trajectory tracking errors of model–based controllers. Clearly, lack of parameter knowledge is reflected on the tracking performance.
2) Joint torques (or power input). Given a set of parameter estimates, the difference between the predicted and the measured torques (or power input) at the joints is a measure of parameter ignorance.
3) Base forces/torques. Having a set of parameter estimates, the difference between the predicted and actual forces/torques reflects the lack of parameter knowledge.

The first source of parameter information, i.e., tracking errors at the joint or task space of the manipulator, has typically been the driving force for the parameter update laws of various adaptive control schemes (e.g., [4], [5]). Extracting parameter information from joint torques has attracted less attention, due to practical difficulties typically associated with the measurement of joint torques. This measurement can be done through the torque constants of the actuators, whose knowledge is usually not very accurate and also changes with ageing. Another problem is that torque measurements provided by this method do not include the friction at the joints, which often plays a significant role in the dynamics. Parameter identification methods using joint torques were investigated by Atkeson et al. [6], Khosla [7], and Chan [8].

Identification of parameters using base forces/torques was mainly based on the off–line processing of motion data [9], [10], rather than on–line identification or adaptive control, which are examined in this work. Techniques relevant to base reaction forces/torques require the use of sensors external to the manipulator. Sensors for the measurement of forces and moments along all three cartesian axes are available commercially. Alternatively, force sensors can be developed using structures of suitable geometry on which strain–gauges can be attached at specific locations. The reaction forces/torques can then be derived from the set of strain measurements.

II. SYSTEM MODELLING

The dynamics of a rigid robot are represented by the following equation:

$$\boldsymbol{M}(\boldsymbol{\theta})\ddot{\boldsymbol{\theta}} + \boldsymbol{C}(\boldsymbol{\theta},\dot{\boldsymbol{\theta}})\dot{\boldsymbol{\theta}} + \boldsymbol{G}(\boldsymbol{\theta}) = \boldsymbol{\tau} \tag{1}$$

with $\boldsymbol{M}$ the mass matrix and $\boldsymbol{C}$ the matrix with the nonlinear terms. Matrix $\boldsymbol{G}$ is the vector with the gravitational torques and $\boldsymbol{\tau}$ the vector with the control torques. For the present study it will be assumed that various unmodelled effects like joint friction, backlash, joint and structural elasticity, and rotor inertias are insignificant. An important property of the system is that the model can be written as:

$$\boldsymbol{M}(\boldsymbol{\theta})\ddot{\boldsymbol{\theta}} + \boldsymbol{C}(\boldsymbol{\theta},\dot{\boldsymbol{\theta}})\dot{\boldsymbol{\theta}} + \boldsymbol{G}(\boldsymbol{\theta}) = \boldsymbol{Y}(\ddot{\boldsymbol{\theta}},\dot{\boldsymbol{\theta}},\boldsymbol{\theta})\boldsymbol{\alpha}, \tag{2}$$

where $\boldsymbol{Y}$ is called the *regressor matrix* and $\boldsymbol{\alpha}$ is the vector of suitably selected parameters [3].

When systems of interconnected bodies are considered not all the mass properties of the mechanism are required for a complete description of the dynamics, as a result of the kinematical constrains imposed on the relative motion of the members. In other words, some of the parameters have no effect on the kinetic or potential energy of the system. Moreover, in multilink robots some of the parameters are redundant in the sense that they appear in linear combinations with other parameters [6], [11], [12], [13]. Therefore, when constructing the regressor matrix the dynamics can be formulated on the basis of a minimal number of inertial properties which are called *base parameters*. This problem was treated analytically by Mayeda et al. [11] for the case of rigid manipulators with rotational joints having the adjacent joint axes either parallel or perpendicular to each other. Gautier and Khalil [12] presented a systematic way for the determination of the minimal set of inertial parameters of serial robots.

The reaction forces and torques along each one of the three cartesian axes at the base of the manipulator can be collected in a vector $\boldsymbol{F} = [F_x, F_y, F_z, T_x, T_y, T_z]^T$. An important property of the dynamics of the rigid robot is that this vector can be written as [9], [10]:

$$\boldsymbol{F} = \boldsymbol{W}(\ddot{\boldsymbol{\theta}},\dot{\boldsymbol{\theta}},\boldsymbol{\theta})\boldsymbol{\beta}, \tag{3}$$

with $\boldsymbol{\beta}$ a vector with suitably selected parameters. Moreover, the base parameters vector $\boldsymbol{\alpha}$ of Eq. (2) and $\boldsymbol{\beta}$ of Eq. (3) are related as follows: (1) Num. of elements in $\boldsymbol{\alpha} \leq$ Num. of elements in $\boldsymbol{\beta}$, (2) The values of the parameters in $\boldsymbol{\alpha}$ can be deduced from the values of the parameters in $\boldsymbol{\beta}$. A systematic procedure for the minimal parameterization of both Eqs. (2) and (3) was presented by Fisette et al. [13].

III. PREVIOUS WORK ON PARAMETER IDENTIFICATION USING BASE REACTION FORCES/TORQUES

The linear relationship described by Eq. (3) is well–suited for parameter identification purposes. It has been used by Raucent et al. [9] to experimentally determine the mass properties of a PUMA robot. The required base forces/torques were measured using a sensing platform and the joint motion using an external vision system. Processing of the recorded data yielded estimates for the model parameters. Validation tests were based on the identification of a known load which was attached to the robot.

Another relevant study is the experimental work of Liu et al. [10] (also involving a PUMA manipulator) where base force measurements and joint motion data were recorded during maneuvering. Off–line processing using the least–squares method yielded an estimated set of parameters. A verification test involved using the estimated parameters to predict the forces and torques at the base of the robot while in motion. In order to avoid the measurement of accelerations needed for the construction of $\boldsymbol{W}$, a filtered version of the linear relationship (Eq. (3)) was used instead [14], which does not include the accelerations.

The combination of base reaction forces/torques together with joint forces/torques measurements in order to improve the accuracy of the identification was proposed in [15]. Experimental results involved the off–line parameter identification followed by validation tests, which were based on the prediction of the actual joint and base reaction forces/torques.

The identification of parameters as required for gravity compensation purposes was examined by West et al. [16]. For this purpose, a manipulator was mounted on a six–DOF force/torque sensor, which was attached to a Stewart platform so that its orientation can be varied. The method involved the recording and processing of the static reactions due to gravity forces for different postures of the manipulator as well as for various orientations of the base.

Finally, base reaction forces can also provide information relevant to joint friction. In Morel et al. [17], a motion control method was developed and examined experimentally, which allows compensation for joint friction using base force/torque measurements. The method exploits the fact that the net torques applied to the system can be "seen" by the base forces.

IV. ON–LINE PARAMETER IDENTIFICATION USING BASE FORCES/TORQUES

Given a vector of estimates $\widehat{\boldsymbol{\beta}}(t)$ for the parameters in Eq. (3), the parameter estimation error is defined as:

$$\tilde{\boldsymbol{\beta}}(t) \triangleq \widehat{\boldsymbol{\beta}}(t) - \boldsymbol{\beta}. \tag{4}$$

The base forces prediction error can be expressed on the basis of Eq. (3):

$$\begin{aligned} \varepsilon(t) &= \widehat{\boldsymbol{F}}(t) - \boldsymbol{F}(t) \\ &= \boldsymbol{W}(\ddot{\boldsymbol{\theta}},\dot{\boldsymbol{\theta}},\boldsymbol{\theta})\widehat{\boldsymbol{\beta}} - \boldsymbol{W}(\ddot{\boldsymbol{\theta}},\dot{\boldsymbol{\theta}},\boldsymbol{\theta})\boldsymbol{\beta} \\ &= \boldsymbol{W}\tilde{\boldsymbol{\beta}}(t), \end{aligned} \tag{5}$$

with $\widehat{\boldsymbol{F}}(t)$ the estimated base forces and $\boldsymbol{F}(t)$ the measured ones. Obviously, perfect knowledge of the inertial parameters results to zero base forces prediction error.

A. Recursive identification and model–based trajectory tracking controllers

Given that $\dot{\widehat{\boldsymbol{\beta}}} = \dot{\tilde{\boldsymbol{\beta}}}$, the unknown parameters can be identified through the above error equation by the real–time or off–line integration of:

$$\dot{\widehat{\boldsymbol{\beta}}} = -\boldsymbol{\Gamma}^{-1}\boldsymbol{W}^T\varepsilon \tag{6}$$

with $\boldsymbol{\Gamma} = \boldsymbol{\Gamma}^T > \mathbf{O}$ the parameter updates gain. For the above least–squares estimator it is ensured that $\widehat{\boldsymbol{\beta}}$ is bounded and ε belongs to $\boldsymbol{L}_2$. This can be proved using the Lyapunov function $V = \frac{1}{2}\tilde{\boldsymbol{\beta}}^T\boldsymbol{\Gamma}\tilde{\boldsymbol{\beta}}$, the derivative of which is $\dot{V} = -\varepsilon^{\mathbf{T}}\varepsilon \leq \mathbf{0}$. The convergence of the parameter estimates to their actual values depends on *persistency of excitation* issues [3], loosely speaking on how "sufficiently exciting" the trajectories are.

Often some of the inertial parameters of the manipulator are known with adequate accuracy and only the rest need to be identified. In such case the vector $\boldsymbol{\beta}$ can be divided into a known parameters part, $\boldsymbol{\beta}_1$, and an unknown part, $\boldsymbol{\beta}_2$. The regressor matrix $\boldsymbol{W}$ in Eq. (3) can be partitioned consistently as:

$$\boldsymbol{\beta} = \begin{bmatrix} \boldsymbol{\beta}_1 \\ \boldsymbol{\beta}_2 \end{bmatrix}, \quad \boldsymbol{W} = \begin{bmatrix} \boldsymbol{W}_1 & \boldsymbol{W}_2 \end{bmatrix}. \tag{7}$$

The base forces and the prediction error can be written as:

$$\boldsymbol{F} = \boldsymbol{W}_1\boldsymbol{\beta}_1 + \boldsymbol{W}_2\boldsymbol{\beta}_2, \tag{8}$$

$$\begin{aligned} \varepsilon &= \left(\boldsymbol{W}_1\boldsymbol{\beta}_1 + \boldsymbol{W}_2\widehat{\boldsymbol{\beta}}_2\right) - (\boldsymbol{W}_1\boldsymbol{\beta}_1 + \boldsymbol{W}_2\boldsymbol{\beta}_2) \\ &= \boldsymbol{W}_2\tilde{\boldsymbol{\beta}}_2 \end{aligned} \tag{9}$$

and Eq. (6), which gives the parameter estimation law, changes to:

$$\dot{\widehat{\boldsymbol{\beta}}}_2 = -\boldsymbol{\Gamma}^{-1}\boldsymbol{W}_2^T\varepsilon \tag{10}$$

with the base forces prediction error $\varepsilon(t) = (\boldsymbol{W}_1\boldsymbol{\beta}_1 + \boldsymbol{W}_2\widehat{\boldsymbol{\beta}}_2) - \boldsymbol{F}(t)$.

The above estimator can supply a suitable model–based trajectory tracking controller with parameter estimates. As a representative of this class of model–based controllers it will be considered the following scheme:

$$\begin{aligned} \boldsymbol{\tau}(t) = \widehat{\boldsymbol{M}}(\boldsymbol{\theta})\ddot{\boldsymbol{\theta}}_d + \widehat{\boldsymbol{C}}(\boldsymbol{\theta},\dot{\boldsymbol{\theta}})\dot{\boldsymbol{\theta}}_d + \widehat{\boldsymbol{G}}(\boldsymbol{\theta}) - \\ \boldsymbol{K}_p(\boldsymbol{\theta} - \boldsymbol{\theta}_d) - \boldsymbol{K}_d(\dot{\boldsymbol{\theta}} - \dot{\boldsymbol{\theta}}_d) \end{aligned} \tag{11}$$

with $\boldsymbol{\theta}_d$ the desired trajectory, $\boldsymbol{K}_p$ and $\boldsymbol{K}_d$ the proportional and derivative gains respectively. Matrices $\widehat{\boldsymbol{M}}$ and $\widehat{\boldsymbol{C}}$ are the mass and nonlinear terms matrices, and $\widehat{\boldsymbol{G}}$ the vector with the gravitational torques evaluated using the parameter estimates provided by Eq. (10). The above control scheme is a modification of the CTM originally proposed by Paden and Panja [18]. It was named as "PD+" controller given that its structure consists of a PD feedback controller augmented by a nonlinear feedforward term. Proofs of global asymptotic stability exist and also an interpretation of the scheme on the basis of passivity theory is possible [19]. Given the passivity foundation of the scheme, better robustness characteristics are expected when compared to the CTM, the success of which relies on the exact linearization of the dynamics. In Christoforou and Damaren [20], the scheme was shown to maintain stability and reasonably good joint trajectory tracking performance when tested experimentally on a three–DOF flexible–link arm.

The implementation of the PD+ controller with parameter values supplied by the estimation law (Eq. (10)) in real–time will be considered here. This is effectively an adaptive control scheme and the tracking performance is expected to improve with time while better parameter estimates become available. However, given the lack of stability proofs for this control scheme one can only rely on the good robustness characteristics of the PD+ controller. Finally, it is worth mentioning that implementation of the CTM with parameters values provided in real–time by a simple least–squares estimation law based on Eq. (2) is an adaptive controller for which the stability proof can be found in Ciliz and Narendra [21].

V. ADAPTIVE CONTROL USING BASE FORCES/TORQUES

A. *Classification of adaptive controllers in robotics*

In the adaptive control literature, one of the classifications that have been proposed is on the basis of the signal that drives the parameter update, according to which adaptive techniques can be divided into three broad categories [22]. The first includes the schemes that extract parameter information from the tracking errors and they are called *direct*. The second category includes the schemes which are using a model of the plant and its parameters are updated so that the difference between the predicted and the actual input/output behavior is driven to zero, and they are called *indirect* (for the case of robotic manipulators see the second and third sources of parameter information mentioned in Section I). Finally, controllers that exploit both the tracking and prediction errors are called *composite* adaptive controllers.

A most important direct adaptive robotic controller was proposed by Slotine and Li [5], [23], and is a globally convergent passivity–based [19] control scheme. Due to its relevance to the present work it will be briefly described. The scheme belongs to the generation of adaptive controllers which exploit the linearity property of the manipulator dynamics expressed by Eq. (2). When some of the model parameters are known with adequate accuracy, only the rest need to be adaptively identified. In that case, the vector $\boldsymbol{\alpha}$ can be divided into a part with the known parameters, $\boldsymbol{\alpha}_1$, and a part with the unknown parameters, $\boldsymbol{\alpha}_2$. The regressor matrix $\boldsymbol{Y}$ can be partitioned consistently:

$$\boldsymbol{\alpha} = \begin{bmatrix} \boldsymbol{\alpha}_1 \\ \boldsymbol{\alpha}_2 \end{bmatrix}, \quad \boldsymbol{Y} = \begin{bmatrix} \boldsymbol{Y}_1 & \boldsymbol{Y}_2 \end{bmatrix}. \tag{12}$$

The control law takes the following form:

$$\begin{aligned} \boldsymbol{\tau} &= \widehat{\boldsymbol{M}}(\boldsymbol{\theta})\ddot{\boldsymbol{\theta}}_r + \widehat{\boldsymbol{C}}\dot{\boldsymbol{\theta}}_r + \widehat{\boldsymbol{G}}(\boldsymbol{\theta}) - \boldsymbol{K}_d\boldsymbol{s} \\ &= \boldsymbol{Y}_1\left(\ddot{\boldsymbol{\theta}}_r, \dot{\boldsymbol{\theta}}_r, \dot{\boldsymbol{\theta}}, \boldsymbol{\theta}\right)\boldsymbol{\alpha}_1 + \boldsymbol{Y}_2\left(\ddot{\boldsymbol{\theta}}_r, \dot{\boldsymbol{\theta}}_r, \dot{\boldsymbol{\theta}}, \boldsymbol{\theta}\right)\widehat{\boldsymbol{\alpha}}_2 - \boldsymbol{K}_d\boldsymbol{s} \end{aligned} \tag{13}$$

coupled with a parameter estimation law:

$$\dot{\widehat{\boldsymbol{\alpha}}}_2(t) = -\boldsymbol{P}\boldsymbol{Y}_2^T(\ddot{\boldsymbol{\theta}}_r, \dot{\boldsymbol{\theta}}_r, \dot{\boldsymbol{\theta}}, \boldsymbol{\theta})\boldsymbol{s}, \tag{14}$$

with $\boldsymbol{K}_d = \boldsymbol{K}_d^T > \mathbf{O}$ and $\boldsymbol{P} = \boldsymbol{P}^T > \mathbf{O}$ being the matrices with the feedback and adaptation gains respectively. For the feedback part of the controller a simple proportional term was selected and the following quantities were defined:

$$\begin{aligned} \dot{\boldsymbol{\theta}}_r &= \dot{\boldsymbol{\theta}}_d - \boldsymbol{\Lambda}\tilde{\boldsymbol{\theta}}, \\ \ddot{\boldsymbol{\theta}}_r &= \ddot{\boldsymbol{\theta}}_d - \boldsymbol{\Lambda}\dot{\tilde{\boldsymbol{\theta}}}, \\ \boldsymbol{s} &= \dot{\boldsymbol{\theta}} - \dot{\boldsymbol{\theta}}_r = \dot{\tilde{\boldsymbol{\theta}}} + \boldsymbol{\Lambda}\tilde{\boldsymbol{\theta}} \end{aligned} \tag{15}$$

where $\tilde{\boldsymbol{\theta}}(t) = \boldsymbol{\theta} - \boldsymbol{\theta}_d$ is the tracking error and $\boldsymbol{\Lambda} = \boldsymbol{\Lambda}^T > \mathbf{O}$ is a weighting matrix. The estimation law extracts parameter information from the tracking errors so that tracking performance improves with time.

B. Composite adaptive control driven by tracking errors and base forces prediction errors

In Slotine and Li [22], the adaptive control scheme summarized above was enhanced by incorporating a prediction error term to the adaptation law, yielding a composite adaptive controller. The additional term uses joint torques (or power input) prediction error. In order to avoid the need of acceleration measurements, a filtering technique was effectively employed [14]. The composite adaptive scheme was shown to exhibit faster parameter convergence when compared with the corresponding direct controller. The composite version of the scheme will be considered here, and it will be examined how it can be implemented using the joint trajectory tracking errors together with the base forces/torqes prediction error instead of the joint torques prediction error.

The partitioning of the sets of parameters $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ into a known and an unknown part as given by Eqs. (12) and (7) respectively, is also considered here. The dynamics of a rigid robot (Eq. (2)), and the base forces (Eq. (8)) can be written as:

$$\boldsymbol{M}(\boldsymbol{\theta})\ddot{\boldsymbol{\theta}} + \boldsymbol{C}(\boldsymbol{\theta},\dot{\boldsymbol{\theta}})\dot{\boldsymbol{\theta}} + \boldsymbol{G}(\boldsymbol{\theta}) = \boldsymbol{Y}_1(\ddot{\boldsymbol{\theta}},\dot{\boldsymbol{\theta}},\boldsymbol{\theta})\boldsymbol{\alpha}_1 + \boldsymbol{Y}_2(\ddot{\boldsymbol{\theta}},\dot{\boldsymbol{\theta}},\boldsymbol{\theta})\boldsymbol{\alpha}_2, \tag{16}$$

$$\boldsymbol{F} = \boldsymbol{W}_1\boldsymbol{\beta}_1 + \boldsymbol{W}_2\boldsymbol{\beta}_2 \tag{17}$$

with the sets of parameters $\boldsymbol{\alpha}_1$ and $\boldsymbol{\beta}_1$ known, and the $\boldsymbol{\alpha}_2$ and $\boldsymbol{\beta}_2$ unknown. Taking $\boldsymbol{\alpha}_2 \equiv \boldsymbol{\beta}_2$, the adaptive control scheme can be implemented as:

$$\boldsymbol{\tau} = \boldsymbol{Y}_1\left(\ddot{\boldsymbol{\theta}}_r,\dot{\boldsymbol{\theta}}_r,\dot{\boldsymbol{\theta}},\boldsymbol{\theta}\right)\boldsymbol{\alpha}_1 + \boldsymbol{Y}_2\left(\ddot{\boldsymbol{\theta}}_r,\dot{\boldsymbol{\theta}}_r,\dot{\boldsymbol{\theta}},\boldsymbol{\theta}\right)\widehat{\boldsymbol{\alpha}}_2 - \boldsymbol{K}_d\boldsymbol{s}, \tag{18}$$

$$\dot{\widehat{\boldsymbol{\alpha}}}_2 = \boldsymbol{P}(t)\left[\boldsymbol{Y}_2^T\boldsymbol{s} + \boldsymbol{W}_2^T\boldsymbol{R}(t)\varepsilon\right] \tag{19}$$

with the error quantities ε and $\boldsymbol{s}$ defined by Eqs. (9) and (15) respectively.

The composite adaptation law yields parameter information by effectively fusing information from two different sources: trajectory tracking errors and base forces prediction error. How much emphasis the adaptation process gives to each one of the two sources of information is determined by the uniformly positive definite matrix $\boldsymbol{R}(t)$. The values of the entries of this matrix should reflect the quality of the sensory information provided by each one of the two sources. Taking $\boldsymbol{R}(t) = \mathbf{O}$ the control scheme reduces to the original direct adaptive version [5] summarized in the previous paragraph.

The global asymptotic convergence of the above controller can be shown using the Lyapunov function $V = \frac{1}{2}(\boldsymbol{s}^T\boldsymbol{M}\boldsymbol{s} + \tilde{\boldsymbol{\alpha}}_2^T\boldsymbol{P}\tilde{\boldsymbol{\alpha}}_2)$. Differentiating this expression and using the skew–symmetry property of the matrix $(\dot{\boldsymbol{M}} - 2\boldsymbol{C})$ [3], the derivative of the Lyapunov function becomes: $\dot{V} = -\boldsymbol{s}^T\boldsymbol{K}_d\boldsymbol{s} - \tilde{\boldsymbol{\alpha}}_2^T\boldsymbol{W}_2^T\boldsymbol{W}_2\tilde{\boldsymbol{\alpha}}_2 = -\boldsymbol{s}^T\boldsymbol{K}_d\boldsymbol{s} - \varepsilon^{\mathbf{T}}\varepsilon \leq \mathbf{0}$. Using equivalent arguments as in [22] it follows that both the tracking as well as the prediction error will converge to zero, and the parameter estimation error remains bounded. Moreover, if the desired trajectory is persistently exciting the parameter estimates will converge to their actual values.

VI. Simulation studies

The model of a planar, three–DOF manipulator operating in the horizontal plane (i.e., gravity does not affect its motion dynamics) was used for the simulation studies, as shown in Figure 1. For simplicity, the gravity torques vector, $\boldsymbol{G}(\boldsymbol{\theta})$, in Eq. (1) was excluded from the simulation model, i.e., the resulting base reaction force F_z and the reaction torques T_x and T_y are zero. Measurements of the two reaction forces in the horizontal plane and the torque about the vertical axis, as well as availability of joint position, velocity and acceleration measurements is assumed.

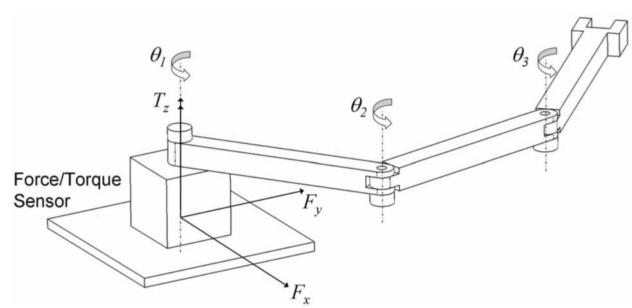

Fig. 1. Schematic representation of the arm.

Given that each link of the manipulator is restricted to move on the horizontal plane and only rotate about a vertical axis (links are further assumed to have symmetric cross section about the axis along their length), the parameterizations of Eqs. (2) and (3) involve: $\boldsymbol{\alpha} = [m_2,\ m_3,\ I_1,\ I_2,\ I_3,\ c_{x2},\ c_{x3}]^T$, and $\boldsymbol{\beta} = [m_2,\ m_3,\ I_1,\ I_2,\ I_3,\ c_{x1},\ c_{x2},\ c_{x3}]^T$, where m_i is the mass, c_{xi} is the first moment of inertia measured along the length and I_i is the second moment of inertia about the vertical coordinate axis of the i–th link. It should be pointed out that the set of elements in $\boldsymbol{\alpha}$ is a subset of the set of parameters in $\boldsymbol{\beta}$. However, the above vectors $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ do not correspond to minimal parameterizations of Eqs. (2) and (3). For a minimal parameterization the following parameter sets can be used [13]:

$$\boldsymbol{\alpha} = [\alpha_1,\ \alpha_2,\ \alpha_3,\ \alpha_4,\ \alpha_5]^T, \tag{20}$$

$$\boldsymbol{\beta} = [\alpha_1,\ \alpha_2,\ \alpha_3,\ \alpha_4,\ \alpha_5,\ \alpha_6]^T, \tag{21}$$

with $\alpha_1 = I_3$, $\alpha_2 = c_{x3}$, $\alpha_3 = I_2 + m_3 l_2^2$, $\alpha_4 = c_{x2} + m_3 l_2$, $\alpha_5 = I_1 + (m_2 + m_3)l_1^2$, and $\alpha_6 = c_{x1} + (m_2 + m_3)l_1$. For the simulation model all links ($i = 1, 2, 3$) were considered to be identical with length $l_i = 1$ m, $m_i = 1$ kg, $I_i = 0.333$ kg·m^2, and $c_{xi} = 0.5$ kg·m.

For all simulation studies the desired joint trajectory, $\boldsymbol{\theta}_d$, is such that all three DOF of the arm follow a quintic polynomial between an initial, $\boldsymbol{\theta}_i$, and a final position, $\boldsymbol{\theta}_f$:

$$\boldsymbol{\theta}_d(t) = \left[10\left(\frac{t}{t_f}\right)^3 - 15\left(\frac{t}{t_f}\right)^4 + 6\left(\frac{t}{t_f}\right)^5\right](\boldsymbol{\theta}_f - \boldsymbol{\theta}_i) + \boldsymbol{\theta}_i. \tag{22}$$

The initial joint configuration is taken to be $\boldsymbol{\theta}_i = [0, 0, 0]^T$ rad, the final one $\boldsymbol{\theta}_f = \left[\frac{\pi}{2}, \frac{\pi}{2}, \frac{\pi}{2}\right]^T$ rad and the duration of the motion $t_f = 3$ seconds. This maneuver is then reversed to bring the arm back to its initial position and the whole motion is repeated two times. The above quintic polynomial is characterized by smooth velocities and accelerations and has been useful in motion planning for manipulators.

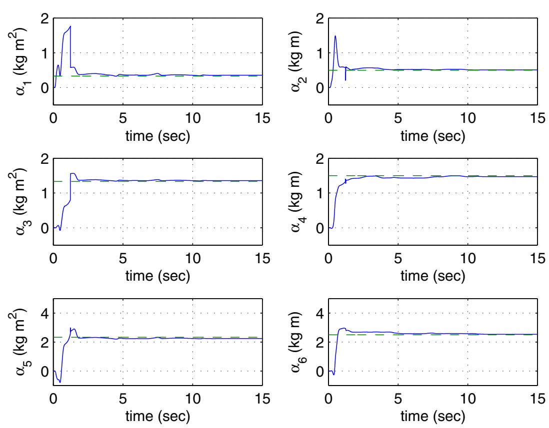

Fig. 2. Parameter identification scheme: Parameter updates (— — — actual values, —— estimated values).

A. PD+ *control coupled with real-time parameter estimation*

On–line parameter identification based on Eq. (6) was implemented while the manipulator was maneuvering. The motion of the manipulator was controlled under the PD+ scheme (Eq. (11)), the feedforward part of which was constantly updated with the current parameter estimates. The estimation algorithm was implemented based on vector $\boldsymbol{\beta}$ given by Eq. (21). The initial estimates of the updated parameters were all considered to be zero. For the identification gains a diagonal matrix was selected, $\boldsymbol{\Gamma}^{-1} = \text{diag}\{12, 3, 10, 3, 55, 15\}$, and the feedback gains were $\boldsymbol{K}_p = \text{diag}\{10, 10, 10\}$ N·m/rad and $\boldsymbol{K}_d = \text{diag}\{5, 5, 5\}$ N·m·s/rad. Moderate gains were selected for this example so that the effect of feedback does not mask the role of feedforward, due to which tracking performance is expected to improve with time. Fig. 2 shows the parameter updates (continuous line) provided by the identification algorithm and used for the calculation of the feedforward part of the controller. All updates converge to the actual values of the parameters (dashed line). Fig. 3 shows the tracking of the desired joint trajectories and the corresponding tracking errors. Clearly, tracking performance improves with time while better parameter information becomes available. The tracking errors approach zero and remain very close to it.

B. *Composite adaptive control*

For the implementation of the composite adaptive controller presented in Section V, the feedback gain matrix was selected as $\boldsymbol{K}_d = \text{diag}\{10, 10, 10\}$ N·m·s/rad. The weighting matrix was taken to be $\boldsymbol{\Lambda} = 5 \cdot \mathbf{1}$ s^{-1}. The adaptation was based on the parameters vector $\boldsymbol{\alpha}$ given by Eq. (20), and the adaptation gains matrix was selected to be diagonal, $\boldsymbol{P} = \text{diag}\{5, 5, 20, 5, 20\}$. The size of each entry was tuned manually. The weighting matrix in the adaptation law was taken as $\boldsymbol{R}(t) = \mathbf{1}$. It was assumed that no a priori information is available relevant to the set of adaptively updated parameters and their initial estimates were all set to zero.

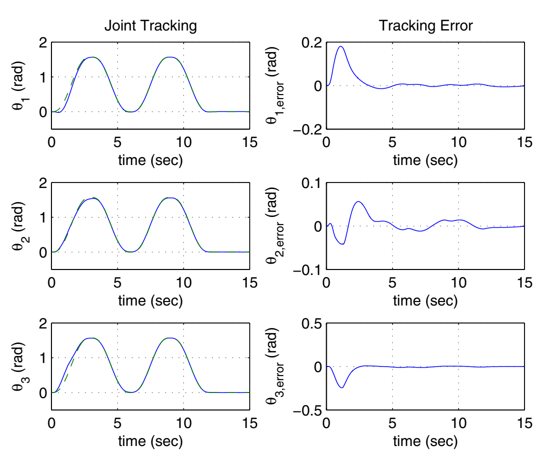

Fig. 3. PD+ controller with real–time update of inertial parameters: Joint tracking (— — — desired trajectory, —— actual motion) and tracking errors.

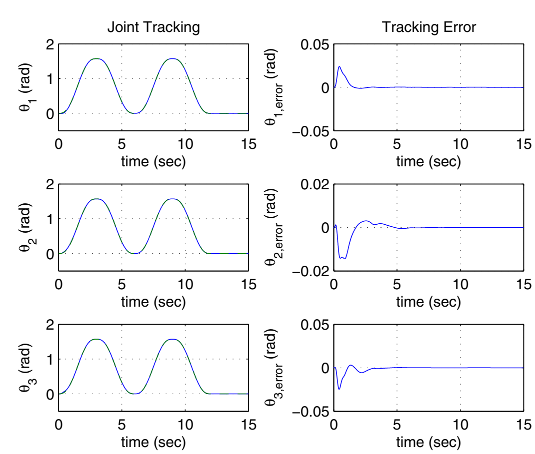

Fig. 4. Composite adaptive controller: Joint tracking (— — — desired trajectory, —— actual motion) and tracking errors.

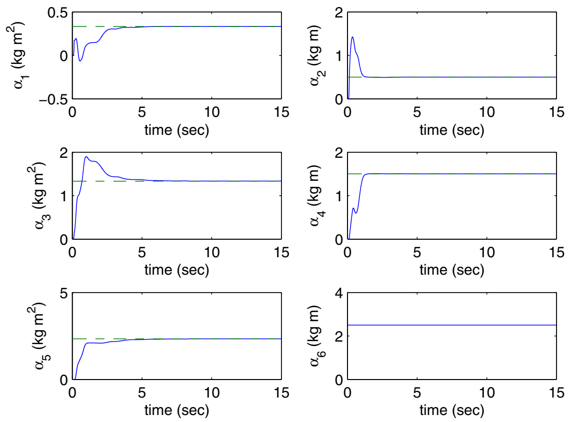

Fig. 5. Composite adaptive controller: Parameter updates (— — — actual values, —— estimated values).

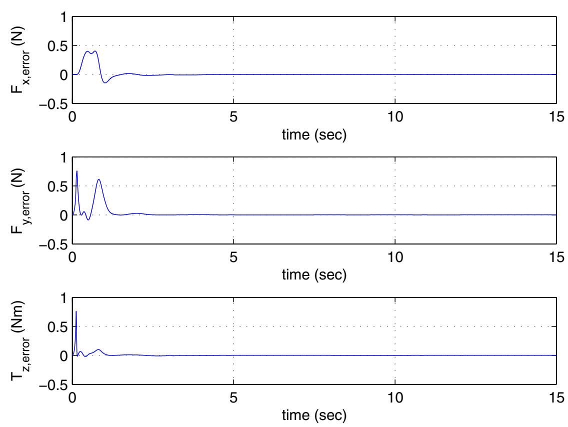

Fig. 6. Composite adaptive controller: Base forces/torques prediction errors.

The tracking of the desired trajectories and the corresponding tracking errors are shown in Fig. 4. The time histories of the updated parameters are shown in Fig. 5. All parameters estimates initially increase and converge to their nominal values. Clearly, the extraction of parameter information is reflected on the tracking performance which improves with time, while the tracking errors approaching zero. The base forces/torques prediction errors also converge to zero as can be seen in Fig. 6.

VII. Conclusions

One of the sources of inertial parameters information for rigid robots is the base reaction forces, which can be exploited for on–line parameter identification or drive a suitable adaptive control scheme. On–line parameter identification coupled with a model–based trajectory tracking controller (effectively an indirect adaptive control scheme) was shown to improve manipulation performance. It was also shown that a composite adaptive controller previously proposed for rigid robots can be modified in order to effectively extract parameter information both from tracking errors (direct source) and base forces prediction errors (indirect source).

References

[1] C. Canudas de Wit, B. Siciliano, and G. Bastin (Editors), "Theory of robot control," Springer–Verlag, London, 1996.
[2] J.Y.S. Luh, M.W. Walker and R.P.C. Paul, "Resolved–Acceleration Control of Mechanical Manipulators," IEEE Trans Automatic Control, vol. AC–25, no. 3, pp. 468–474, 1980.
[3] R. Ortega, and M. Spong, "Adaptive motion control of rigid robots: a tutorial," Automatica, vol. 25, no. 6, pp. 877–888, 1989.
[4] J.J. Craig, P. Hsu and S.S. Sastry, "Adaptive control of mechanical manipulators," Int J of Robotics Research, vol. 6, no. 2, pp. 172–184, 1987.
[5] J.–J.E. Slotine and W. Li, "On the adaptive control of robot manipulators," Int J of Robotics Research, vol. 6, no. 3, pp. 49–59, 1987.
[6] C.G. Atkeson, C.H. An and J.M. Hollerbach, "Estimation of inertial parameters of manipulator loads and links," Int J of Robotics Research, vol. 5, no. 3, pp. 101–119, 1986.
[7] P.K. Khosla, "Estimation of robot dynamics parameters: theory and application," Int Journal of Robotics and Automation, vol. 3, no. 1, pp. 35–41, 1988.
[8] S.P. Chan, "An efficient algorithm for identification of robot parameters including drive characteristics," J Intelligent and Robotic Systems, vol. 32, pp. 291–305, 2001.
[9] B. Raucent, G. Campion, G. Bastin, J.C. Samin and P. Y. Willems, "Identification of the barycentric parameters of robot manipulators from external measurements," Automatica, vol. 28, no. 5, pp. 1011–1016, 1992.
[10] G. Liu, K. Iagnemma, S. Dubowsky and G. Morel, "A base force/torque sensor approach to robot manipulator inertial parameter estimation," IEEE Int Conf Robot and Automat, Leuven, Belgium, May 16–20, pp. 3316–3321, 1998.
[11] H. Mayeda, K. Yoshida and K. Osuka, "Base parameters of manipulator dynamic models," IEEE Int Conf Robot and Automat, Philadelphia, Pennsylvania, April 24–29, vol. 3, pp. 1367–1372, 1988.
[12] M. Gautier and W. Khalil, "Direct calculation of minimum set of inertial parameters of serial robots," IEEE Trans Robot Automat, vol. 6, no. 3, pp. 368–373, 1990.
[13] P. Fisette, B. Raucent and J.C. Samin, "Minimal dynamic characterization of tree–like multibody systems," Nonlinear Dynamics, vol. 9, pp. 165–184, 1996.
[14] R.H. Middleton and G.C. Goodwin, "Adaptive computed torque control for rigid link manipulators," Systems & Control Letters, vol. 10, pp. 9–16, 1988.
[15] W. Verdonck, J. Swevers and J.–C. Samin, "Experimental robot identification: Advantages of combining internal and external measurements and of using periodic excitation," J Dynam Sys Measurement and Control, vol. 123, pp. 630–636, 2001.
[16] H. West, E. Papadopoulos, S. Dubowsky and H. Cheah, "A method for estimating the mass properties of a manipulator by measuring the reaction moments at its base," IEEE Int Conf Robot and Automat, Scottsdale, Arizona, May 14–19, pp. 1510–1516, 1989.
[17] G. Morel, K. Iagnemma and S. Dubowsky, "The precise control of manipulators with high joint–friction using base force/torque sensing," Automatica, vol. 36, no. 7, pp. 931–941, 2000.
[18] B. Paden and R. Panja, "Globally asymptotically stable 'PD+' controller for robot manipulators," Int J Contr, vol. 47, no. 6, pp. 1697–1712, 1988.
[19] R. Ortega, A. Loría, P.J. Nicklasson, and H. Sira–Ramírez, "Passivity–based control of Euler–Lagrange systems," Springer–Verlag, London, 1998.
[20] E. Christoforou and C.J. Damaren, "A passivity–based control case study of flexible–link manipulators," IEEE Int Conf Robot and Automat, Barcelona, Spain, Apr 18–22, pp. 1005–1010, 2005.
[21] K. Ciliz and K. S. Narendra, "Adaptive control of robotic manipulators using multible models and switching," Int J of Robotics Research, vol. 15, no. 6, pp. 592–610, 1996.
[22] J.–J.E. Slotine and W. Li, "Composite adaptive control of robot manipulators," Automatica, vol. 25, no. 4, pp. 509–519, 1989.
[23] J.–J.E. Slotine and W. Li, "Adaptive manipulator control: A case study," IEEE Trans Automatic Control, vol. 33, no. 11, pp. 995–1003, 1988.