Parameter Estimation of a Class of Mechanical Systems Using Only Position Measurement

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***Abstract*— In this paper, we propose a method to estimate some physical parameters of a class of mechanical systems, considering that only position states are available. The class of systems is identified by imposing some conditions on the inertia matrix. The creation of a linear regression (LRE) equation is done, and the estimation of parameters is ensured using intervally excited (IE) regressors, as demonstrated in the newly released Least Squares+ Dynamic Regressor Extension and Mixing (LSD) estimator. A 2D SpiderCrane Mechanism is used to validate the proposed theory through simulations.**

I. Introduction

The ease of manipulation, usability, and dexterity of mechanical systems have made them a very useful component in industrial tasks such as assembly, welding, and material handling; and in industries such as logistics, agriculture, medical, and manufacturing. Euler-Lagrange formalism, where only potential and kinetic energies are needed, the control community has adopted them to study several important research phenomena. Examples include designing trajectory tracking controllers, robust controllers, and identifying and observing unmeasurable states, just to name a few.

Particularly, the design of trajectory tracking control for mechanical systems assuming that the physical parameters are unknown has been studied over the last three decades. This assumption is logical because it's difficult to accurately determine masses, inertia tensors, lengths, and other parameters. The first seminal work proposing adaptive control to ensure trajectory tracking for these systems was [2] and the parameters were estimated if a condition of persistent excitation was fulfilled. The adaptation law took off from [1], where for the first time, a linear regression equation for unknown parameters was designed for mechanical systems modeled with the Newton-Euler formalism. By using a modified least squares algorithm, estimates of these parameters were obtained. After [2], a large number of adaptive trajectory tracking controllers have been published up to this day. For example, works relevant regarding the high number of citations we have [7]– [10]. Recent research has revealed schemes that enhance performance using neural networks or iterative learning methods [11]– [14], but they depend on complicated adaptation laws to estimate unknown parameters and incur computational burden.

A survey on composite adaptation and learning techniques to improve parameter convergence in adaptive control for robot control applications is presented in [15]. Unfortunately, the majority of works mentioned previously have a complicated parameterization of the LRE, and parameter convergence is ensured by imposing the unfeasible persistent excitation (PE) condition. Moreover, the major drawback is that the regressor matrix is a function of the generalized coordinates position and velocity. In particular, the PE condition for regressor matrices has recently been relaxed by an Interval Excitation (IE) which is strictly weaker than PE [16], [17]. In contrast to the classical parameterization existing for parameter estimators and adaptive controllers of mechanical systems, which includes complicated signal and parameter relations introduced by the Coriolis and centrifugal forces matrix, in [18] the power balance equation was exploited to generate a novel LRE, which has considerably simpler analytic expressions and lower dimension; that is, it is a vector of dimension $1 \times s$, with s representing the number of unknown parameters. Hence, if the number of degrees of freedom increases (DoF), only the integer s increases. Thus, together with the high performance parameter estimator of [16], [17], an adaptive global tracking controller with verifiable performance improvement was designed. Also refer to [19] for two new adaptive tracking controllers, which use the result [18].

On the other hand, it is well known that the velocity in mechanical systems cannot be measured, so costly sensors are used to obtain the signal. Thus, velocity observers have been proposed along the last three decades. Based on the Immersion and Invariance theory, the first globally exponentially velocity observer

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design for n–DoF mechanical systems was proposed in [20]. Subsequently, it was employed in [21] to design the initial exponential feedback trajectory tracking globally in mechanical systems. However, these results assume that the parameters are known. It's normal to assume that dealing with the trajectory tracking task without measuring velocity and with unknown parameters is a difficult problem. In fact, very few works can be found in the literature on solving the problem of tracking output feedback trajectory for mechanical systems considering that the parameters are unavailable. As previously mentioned, the primary problem is that the classical regressor matrix for parameter estimation in mechanical systems is influenced by the velocity. Hence, in the few literature addressed this problem, discontinuous and high gain techniques have been used to avoid this issue. For example, in [22], trajectory tracking is ensured while the observer velocity errors converge asymptotically to zero and the error parameters remain bounded. The whole design relies on a discontinuous velocity observer and a discontinuous adaptation law. In [23], a discontinuous observer is proposed in conjunction with an adaptation law based on a projection operator introduced to ensure the boundedness of parameter estimators. However, the semi-global asymptotically stable tracking error, observation error, and parameter estimation error hold assuming that some signals dependent on the model parameters and its time derivative are bounded. The ultimate bounded property for tracking and observation errors was achieved in [24] by combining a simple implementable velocity observer with a discontinuous adaptive scheme. This scheme was validated experimentally and reported in [25].

Clearly, the main issue with the trajectory tracking problem is the fact that the regressor matrix used in the adaptation law is constructed with the velocity coordinate. Hence, to contribute to the parameter estimation problem, we identify a class of mechanical systems described by the Euler-Lagrange formalism in this note, so that we can design a LRE that is independent of the velocity signal. After that, using the recently developed least squares parameter estimator for non-linear regression with relaxed excitation condition, known as the LS+D estimator, we can estimate part of the physical parameters of the mechanical systems.

The rest of the paper has the following structure. In Section II is defined the main objective of the note. The main result appears in Section III. In Section IV we present some simulation results. Finally, in Section V we include some conclusion and future work.

Notation. I_n is the $n \times n$ identity matrix. $\mathbb{Z}_{>0}$ denotes the positive integer numbers. $\mathrm{col}(x_1, \cdots, x_n)$ denotes the column vector $x \in \mathbb{R}^n$. The vector $e_j \in \mathbb{R}^n$, with $j \in \{1, 2, \cdots, n\}$, is the j-th element of the unitary Euclidean n-dimensional basis. For a differentiable mapping $L : \mathbb{R}^n \to \mathbb{R}$ we define the gradient transpose operator $\nabla L(x) := \left(\frac{\partial L(x)}{\partial x}\right)^\top$.

II. Model systems and main objective

In this section, we characterize the class of systems to be addressed in the note.

A. *Euler Lagrange systems*

We consider (simple) Euler-Lagrange (EL) systems [4] with generalized coordinates $q(t) \in \mathbb{R}^{n_q}$ and Lagrangian function

$$\mathcal{L}(q, \dot{q}) = \mathcal{K}(q, \dot{q}) - U(q),$$

where $\mathcal{K} : \mathbb{R}^{n_q \times n_q} \to \mathbb{R}$ is the kinetic energy, which is of the form

$$\mathcal{K}(q, \dot{q}) = \frac{1}{2}\dot{q}^\top M(q)\dot{q},$$

with $M : \mathbb{R}^{n_q} \to \mathbb{R}^{n_q \times n_q}$, $M(q) > 0$, the generalized inertia matrix, and $U : \mathbb{R}^{n_q} \to \mathbb{R}$ the potential energy function. We assume that *some* of the coordinates are subject to external forces, that is, control signals $u(t) \in \mathbb{R}^m$.

Thus, the dynamic model of the EL system is given as

$$\frac{d}{dt}[\nabla_{\dot{q}}\mathcal{L}] - \nabla_q \mathcal{L} = G(q)u, \tag{1}$$

where $G : \mathbb{R}^{n_q} \to \mathbb{R}^{n_q \times m}$ with $m \leq n_q$ the input matrix and without loss of generality, we define the input matrix as

$$G = \begin{bmatrix} G_u(q) \\ G_a(q) \end{bmatrix}, \tag{2}$$

where $G_u : \mathbb{R}^{n_q} \to \mathbb{R}^{s \times m}$ and $G_a : \mathbb{R}^{n_q} \to \mathbb{R}^{m \times m}$ for $s := n_q - m$. We notice that the EL system dynamics (1) may be written in the alternative form

$$\begin{aligned} \frac{d}{dt}[M\dot{q}] + \nabla U &= \nabla_q \mathcal{K} + Gu \\ &= \frac{1}{2}\nabla_q(\dot{q}^\top M \dot{q}) + Gu \\ &= \frac{1}{2}\nabla_q^\top (M\dot{q})\dot{q} + Gu, \end{aligned} \tag{3}$$

that will be instrumental for the development of our main results.

B. Assumptions and main objective

First, to simplify the notation, we partition the generalised coordinates as $q = \text{col}(q_u, q_a)$, $\dot{q} = \text{col}(\dot{q}_u, \dot{q}_a)$ with $q_a, \dot{q}_a \in \mathbb{R}^m$ and $q_u, \dot{q}_u, \in \mathbb{R}^s$. In addition, we partition the inertia matrix as

$$M(q) = \begin{bmatrix} m_{uu}(q) & m_{au}^\top(q) \\ m_{au}(q) & m_{aa}(q) \end{bmatrix}, \tag{4}$$

where $m_{aa} : \mathbb{R}^{n_q} \to \mathbb{R}^{m\times m}$, $m_{au} : \mathbb{R}^{n_q} \to \mathbb{R}^{m\times s}$ and $m_{uu} : \mathbb{R}^{n_q} \to \mathbb{R}^{s\times s}$. The following assumptions identify the class of systems for which our parameter estimation is applicable.

Assumption 1: The inertia matrix depends only on the variables q_u, that is, $M(q) = M(q_u)$.

Assumption 2: The rows of $m_{au}(q_u)$ are gradient vector fields, that is,

$$(\nabla m_{au})^i = [(\nabla m_{au})^i]^\top, \ \forall i \in \bar{m}.$$

Equivalently, there exists a mapping $\mathcal{N} : \mathbb{R}^s \to \mathbb{R}^m$ such that

$$\dot{\mathcal{N}} = m_{au}(q_u)\dot{q}_u. \tag{5}$$

Assumption 3: The constant physical parameters in the sub-block matrices m_{au}, m_{aa} and the vector ∇_{q_a} are *unknown* with m_{aa} *constant*. The parameters of the sub-block m_{uu} and the vector $\nabla_{q_u} U$ are known.

Consequently, the mapping $\mathcal{N}$ verifying (5), the vector matrix $m_{aa}\dot{q}_a$ and the gravity vector $\nabla_{q_a} U$ can be rewritten as

$$\mathcal{N}(q_u) = \varphi_1^\top(q_u)\theta_1, \tag{6}$$
$$m_{aa}\dot{q}_a = \varphi_2^\top(t)\theta_2 \tag{7}$$
$$\nabla_{q_a} U = \varphi_3^\top(t)\theta_3 \tag{8}$$

with unknown constant vector parameters $\theta_1 \in \mathbb{R}^p$ with $m \le p$, $\theta_2 \in \mathbb{R}^r$, where $r = \sum_{j=1}^m j$ for $m \le r$ and $\theta_3 \in \mathbb{R}^h$ with $m \le h$; and known regressor matrices $\varphi_1 : \mathbb{R}^m \to \mathbb{R}^{p\times m}$, $\varphi_2(t) : \mathbb{R}^m \to \mathbb{R}^{r\times m}$ and $\varphi_3(t) : \mathbb{R}^m \to \mathbb{R}^{h\times s}$.

Fact 1: From partition of the matrix M given by (4) and Assumption 1 we have that for q_a, the following holds

$$\nabla_{q_a}(M\dot{q}) = 0_{n_q\times m}. \tag{9}$$

Main objective: Assuming that the generalized coordinates q can be measured and that *some* of the system parameters are known. Then, for a class of systems, we identify the remaining parameter systems using only signal q.

Remark 1: The class of systems verifying assumption 1 has been used to design PID-based controllers [27] and velocity observers [28]. Systems that fall under this category include the 2D SpiderCrane Mechanism, 3D overhead cranes, a spherical pendulum on a puck, an inverted pendulum on a cart, and Tora system, among others.

III. Main result

In this section we present the main result of the note.

A. Computation of the unknown parameters

Proposition 1: Consider the system (3) verifying Assumptions 1–3. Define the LTI filter

$$\mathcal{H}(\mathfrak{s}) = \frac{\lambda^2}{(\mathfrak{s}+\lambda)^2} \tag{10}$$

with $\lambda > 0$ and $\mathfrak{s} = \frac{d}{dt}$. Then, for the q_a–dynamic the following Linear Regression Equation (LRE) holds

$$\varphi^\top(q)\theta = y \tag{11}$$

where

$$\begin{aligned} \varphi(q) =& \mathcal{H}(\mathfrak{s}) \begin{bmatrix} \mathfrak{s}^2\varphi_1 \\ \mathfrak{s}^2\varphi_2 \\ \varphi_3 \end{bmatrix} \in \mathbb{R}^{v\times m}, \quad \theta = \begin{pmatrix} \theta_1 \\ \theta_2 \\ \theta_3 \end{pmatrix} \in \mathbb{R}^v, \\ y =& \mathcal{H}(\mathfrak{s})[G_a u] \in \mathbb{R}^m \end{aligned} \tag{12}$$

and $v = m + p + r$.

Proof: Under partition (4) and Assumption 1, we have that (3) can be written in the form

$$\frac{d}{dt}[m_{uu}\dot{q}_u + m_{au}^\top \dot{q}_a] = \frac{1}{2}\nabla_{q_u}(\dot{q}^\top M\dot{q}) - \nabla_{q_u}U + G_u u \tag{13}$$

$$\frac{d}{dt}[m_{au}\dot{q}_u + m_{aa}\dot{q}_a] = G_a u - \nabla_{q_a}U(q), \tag{14}$$

where to get the second equation we have used Fact. 1.

Invoking Assumption 2, the q_a–dynamics given by (14) take the form

$$\frac{d}{dt}[\dot{\mathcal{N}}(q_u) + m_{aa}\dot{q}_a] = G_a u - \nabla_{q_a}U(q), \tag{15}$$

or equivalently

$$\ddot{\mathcal{N}}(q_u) + m_{aa}\ddot{q}_a = G_a u - \nabla_{q_a}U(q). \tag{16}$$

Now, applying the filter (10) to both sides of (16) we obtain

$$\mathcal{H}(\mathfrak{s})\mathfrak{s}^2[\mathcal{N}(q_u) + m_{aa}q_a] = \mathcal{H}(\mathfrak{s})[G_a u - \nabla_{q_a}U(u)].$$

From Assumption 3, the expression can be written as

$$\mathcal{H}(\mathfrak{s})\mathfrak{s}^2[\varphi_1^\top\theta_1 + \varphi_2^\top\theta_2] = \mathcal{H}(\mathfrak{s})[G_a u] - \mathcal{H}(\mathfrak{s})[\varphi_3^\top\theta_3].$$

Rearranging the terms we obtain (11). This completes the proof. ■

B. Parameter estimation

To state the parameter estimation result—whose proof is given in [17]—we need to impose the following assumption.

Assumption 4: [Interval Excitation] The regressor $\varphi(t)$ is interval exciting (IE) [3, Definition 3.1]. That is, there exists constants $C_c > 0$ and $T_c > 0$ such that

$$\int_0^{T_c} \varphi(s)\varphi^\top(s)ds \geq C_c I_v.$$

Proposition 2: Consider the LRE (11) with $\varphi(t)$ verifying Assumption 4. Define the LSD estimator with forgetting factor as

$$\dot{\hat{\eta}} = \alpha P\varphi(y - \varphi^\top \hat{\eta}), \quad \hat{\eta}(0) =: \hat{\eta}_0 \in \mathbb{R}^v, \tag{17}$$
$$\dot{P} = -\alpha P\varphi\varphi^\top P + \beta P, \quad P(0) = p_0 I_v, \tag{18}$$
$$\dot{\hat{\theta}} = \gamma\Delta(\mathbb{Y} - \Delta\hat{\theta}), \quad \hat{\theta}(0) =: \hat{\theta}_0 \in \mathbb{R}^v, \tag{19}$$
$$\dot{f} = -\beta f, \quad f(0) = 1, \tag{20}$$

where

$$\beta = \beta_0\left(1 - \frac{1}{F}\|P\|\right), \tag{21}$$
$$\Delta = \det\{I_v - fp_0 P\}, \tag{22}$$
$$\mathbb{Y} = \mathrm{adj}\{I_v - fp_0 P\}[\hat{\eta} - fp_0 P\hat{\eta}_0], \tag{23}$$

which generate *scalar* LREs of the form

$$\mathbb{Y}_i = \Delta\theta_i \tag{24}$$

with tuning gains $\alpha > 0$, $\beta > 0$, $F \geq \frac{1}{p_0}$ and $\gamma > 0$. Then, for all initial state conditions and all $p_0 > 0$, $\hat{\eta}_0, \hat{\theta}_0 \in \mathbb{R}^v$, all signals remain bounded. Moreover, there exists $\Delta_{\min} > 0$ such that

$$\Delta(t) \geq \Delta_{\min}, \ \forall t \geq t_c, \tag{25}$$

hence, $\Delta(t)$ *is PE*. Thus, the estimation errors

$$\tilde{\theta}_i(t) := \hat{\theta}_i(t) - \theta_i$$

for $i = 0, 1, 2, .., v$ *exponentially* converge to zero.

IV. Simulations

In this section we conduct simulations to validate the estimator proposed using the 2D- SpiderCrane Mechanism. The system has three DoF, two actuated $q_a \in \mathbb{R}^2$ representing the crane position and one underactuated $q_u \in \mathbb{R}$ denoting the payload angle about the vertical. See Fig. 1. According to partition (4) the inertia matrix is described by $m_{uu} = mL_3^2$ and

$$m_{au}(q_u) = \begin{bmatrix} mL_3\sin(q_u) \\ mL_3\cos(q_u) \end{bmatrix}, \quad m_{aa} = (M+m)I_2.$$

The potential energy is $U = (M+m)gq_{a1} - mgL_3\cos(q_u)$ with g the gravity constant. The input matrix (2) has the form $G_u = [0\ 0] \in \mathbb{R}^{2\times 1}$, $G_a = I_2$ and the input controller is $u = \mathrm{col}(F_x,\ F_y)$. The definition of all constants may be found in [26].

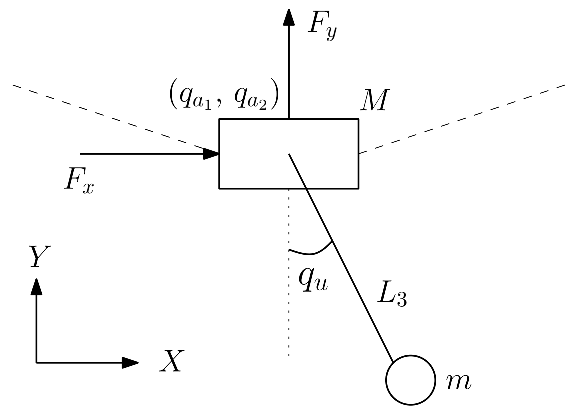

Fig. 1. 2D-Spider crane gantry cart

Clearly, Assumption 1 is verified. Moreover, Assumption 2 is validated with

$$\mathcal{N}(q_u) = mL_3\begin{bmatrix} -\cos(q_u) \\ \sin(q_u) \end{bmatrix}. \tag{26}$$

From the potential energy, m_{aa} and (26), Assumption 3 is verified with

$$\begin{aligned}\varphi_1 &= \begin{bmatrix} -\cos(q_u) & \sin(q_u) \end{bmatrix}, \\ \varphi_2 &= \begin{bmatrix} q_{a_1} & q_{a_2} \end{bmatrix}, \\ \varphi_3 &= \begin{bmatrix} g & 0 \end{bmatrix}\end{aligned} \tag{27}$$

and $\theta_1 = mL_3$, $\theta_2 = \theta_3 = (M+m)$. Hence, the LRE (11) is satisfied with

$$\varphi^\top = \mathcal{H}\begin{bmatrix} -\mathfrak{s}^2\cos(q_u) & \mathfrak{s}^2 q_{a_1} + g \\ \mathfrak{s}^2\sin(q_u) & \mathfrak{s}^2 q_{a_2} \end{bmatrix}, \quad \theta = \mathrm{col}(\theta_1, \theta_2) \tag{28}$$

and $y = \mathcal{H}[u]$.

To carry out the simulations, the parameters were chosen as $M = 0.5\ kg$, $m = 1\ kg$ and $L_3 = 0.9\ m$. Since the parameters and velocities are not available, the proposed input control was

$$u = \begin{bmatrix} g - k_{p1}(\exp(q_{a1} - \alpha_1) - 1) \\ -k_{p2}(\exp(q_{a2} - \alpha_2) - 1) \end{bmatrix} \tag{29}$$

with $k_{p_1} = 49$, $k_{p_2} = 19$, and $\alpha_1 = \alpha_2 = 0.5$. On the other hand, the LTI filter was implemented with $\alpha = 5.2$, which was set arbitrarily. The estimator parameters were chosen as $\alpha = 5.3$, $\gamma = 7.2$, $p_0 = 0.26$, $F = 23$ and $\beta_0 = 1.981$. Additionally, the initial state and initial estimator conditions were defined as $\dot{q}(0) = 0$, $q(0) = (0.01,\ 0.4,\ 0.5)$, $\hat{\eta}_0 = (1,\ 0.8)$ and $\hat{\theta}_0 = (-0.7,\ 0)$.

In Fig. 2 , we appreciate the transient behavior of the states living around a constant value, which is sufficient to ensure the interval excitation necessary in Assumption 4. The estimators in Fig. 3 display excellent behavior, with exponential convergence errors, which validates the proposed theory.

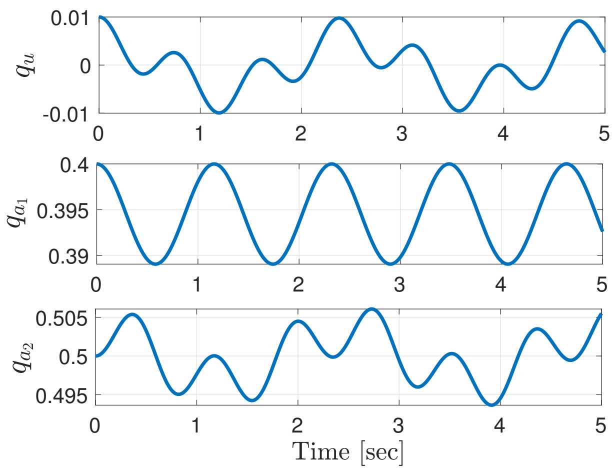

Fig. 2. Transient behavior of the states q

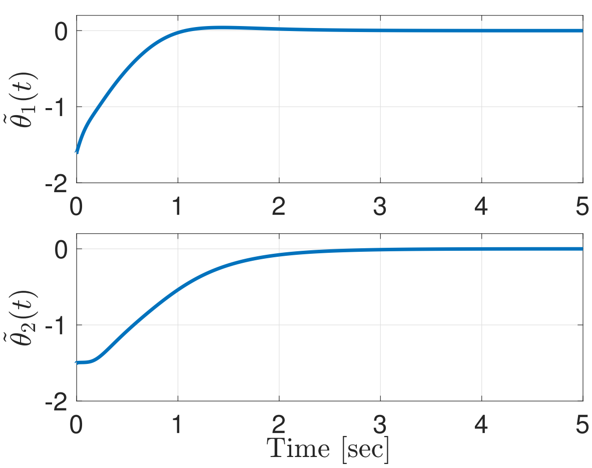

Fig. 3. Transient behavior of $\tilde{\theta}_1$ and $\tilde{\theta}_2$

In addition, the robustness of the proposed estimator is evaluated by adding the white noise shown in Fig. 4 to the measurable signals q_u. For this case, the same initial states, estimator initial conditions, control gains, and filter gains used in the previous case were considered. As observed in Fig. 5, the estimation errors of both estimators tend toward zero. Moreover, the first estimator appears to be less sensitive to noise.

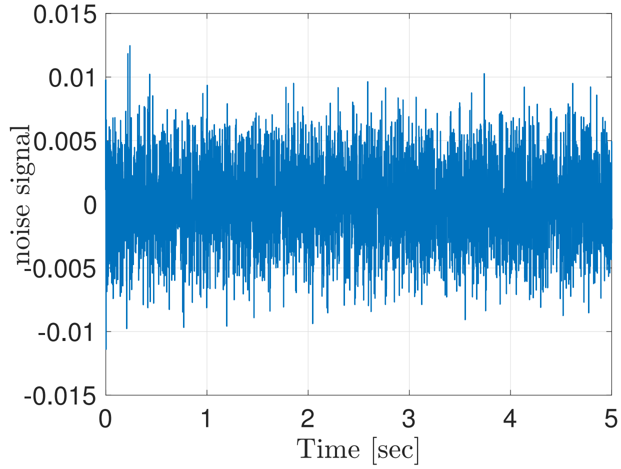

Fig. 4. Noise signal added to q_u

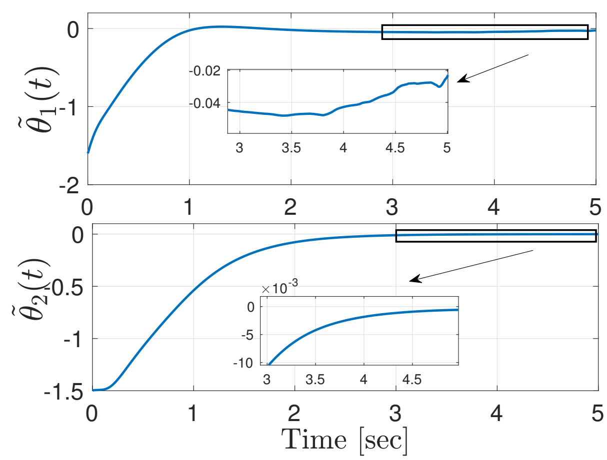

Fig. 5. Transient behavior of $\tilde{\theta}_1$ and $\tilde{\theta}_2$ with white noise added to q_u

V. Conclusions and Future work

A simple approach to estimate physical parameters for a class of Euler- Lagrange systems is provided by measuring the position coordinate. In order to perform estimation, we must impose some conditions on a sub block of the inertia matrix. Thus, a LRE is created that assumes an interval-excited regressor, and the parameters are estimated using the recently published advanced LSD estimator. As future work, we intend to replace the LSD estimator with a finite time convergence estimator in order to construct an adaptive velocity observer that only uses position state as information available.

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