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Adaptive Control for Robots Manipulators with Velocity Observer.

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Abstract: This work presents a novel algorithm to trajectory tracking control of robot manipulators with uncertain parameters and without joint velocity measurements. To cover these lack of joint velocity measurements, a free-model observer is employed. To test the usefulness of this proposed adaptive control, a comparison is made with two other adaptive controls. It is presented simulation results together with an index performance on tracking and speed errors to show the best behavior.

Keywords: Adaptive control, observer, robot manipulator, tracking, robotics.

1. INTRODUCTION

The robot manipulators are a field of great interest and have been explored for the purpose of achieving the execution of tasks in a perfectly and precisely way through which the tracking errors decrease exponentially and requires little effort from the robot joint motors. Based on all the research carried out over the years, many problems have been solved, from modelling to control to achieving the objectives in an acceptable way.

Peisen et al. (1992) presents a simple adaptive learning control scheme for multi-joint robotic manipulators. Their control objective was to achieve accurate tracking to the desired motion trajectory by trails where joint position and velocity were available.

Some papers have worked with the trajectories tracking problem with absence of joint speed measurements even with the partial-knowledge of the robot dynamic model had been treated in conjunction. This is the case of Kaneko and Horowitz (1997), where through repeated learning trials achieves the objective of tracking. They only unknown the inertial parameters and use a velocity observer to estimate the manipulator joint velocities, which is formulated based on the desired input/output relation of the manipulator.

Also, in Villani et al. (1999) is presented an adaptive control with properties of exponentially stable that is derived starting from a passivity-based position control algorithm and achieves force tracking capabilities by using time-varying PID force feedback, for that task they use the adaptive control to compensate the stiffness coefficient, but count with the joint velocity measurements.

In Quan et al. (2007) an iterative adaptive controller is used assuming that the robots manipulators in the industry repeat a task continuously. They based their proposed scheme on a PD control and achieved convergence with an appropriate set of coefficients in the higher-order adaptive iterative control law to ensure it, worked with an unknown robot dynamic model but had joint velocity measurements available.

As we can see, there are a wide variety of controllers related to the tracking control of robots manipulators with parametric uncertainty, have joint velocity measurements available. Others works deal this problem with the lack of joint velocity measurements and the partial parameters uncertainty, since they are able to compensate the terms of gravity and friction by the partial knowledge of the robot dynamic model.

In Yoo and Ham (2000), it is proposed a robust adaptive control based on Lyapunov stability theory, they use a fuzzy compensator that needs too many fuzzy rules because uncertainties depend on all state variables. They do this because when the control algorithm is only based on the robot dynamic model, it is very difficult to achieve the desired control performance.

In this paper is proposed a solution for the issue of tracking control with parametric uncertainty and absence of joint velocity measurements using an adaptive control in conjunction with a joint velocity observer. With this novel algorithm, we ensure that tracking and observer errors were ultimated bounded. This is very important because it does not need any excitation conditions, but if the trajectory count with persistent excitation (PE), exponential stability is guaranteed.

This paper is organized as follows: Section 2 presents the robot manipulator model employed. Section 3 contains an explanation of the proposed control along with the adaptive schemes whose performance will be compared. In Section 4, the simulation results are shown with two index performance tables to support the importance of the algorithm developed. Finally, Section 5 lays out the conclusions and future work.

Fig. 1. Robot Arm A465 of *CSR Robotics*.

2. PRELIMINARIES

In this section, the dynamic model of the robot employed is presented, also some properties that robots with rotational joints preserve. The robot whose dynamical model was used can be seen in Figure 1.

2.1 Robot dynamic model

The robot model used in this work is the Robot Arm A465 of *CSR Robotics*. This system has 6 degree of freedom (*DOF*) but only the first three DOF are considered because the orientation of the end effector is not controlled. Furthermore, the dynamics motors was considered due to the actuators are DC motors.

Then, the robot dynamic model is

$$\boldsymbol{H}(\boldsymbol{q})\ddot{\boldsymbol{q}} + \boldsymbol{C}(\boldsymbol{q},\dot{\boldsymbol{q}})\dot{\boldsymbol{q}} + \boldsymbol{D}\dot{\boldsymbol{q}} + \boldsymbol{f}_{\mathrm{c}}(\dot{\boldsymbol{q}}) + \boldsymbol{g}(\boldsymbol{q}) = \boldsymbol{D}_{\mathrm{n}}^{-1}\boldsymbol{D}_{\mathrm{k}}\boldsymbol{v} \quad (1)$$

where $\boldsymbol{q} \in \Re^3$ is the vector of generalized joint coordinates, $\boldsymbol{H}(\boldsymbol{q}) \in \Re^{3\times3}$ is the symmetric positive inertia matrix, $\boldsymbol{C}(\boldsymbol{q},\dot{\boldsymbol{q}})\dot{\boldsymbol{q}} \in \Re^3$ is the vector of Coriolis and centrifugal torques, $\boldsymbol{D} \in \Re^{3\times3}$ is the positive semidefinite diagonal matrix that accounts with the joint viscous friction coefficients, $\boldsymbol{f}_{\mathrm{c}}(\dot{\boldsymbol{q}}) \in \Re^3$ is the vector of Coulomb friction terms, $\boldsymbol{g}(\boldsymbol{q}) \in \Re^3$ is the gravitational forces vector, $\boldsymbol{D}_{\mathrm{n}}$ and $\boldsymbol{D}_{\mathrm{k}} \in \Re^{3\times3}$ define the motor dynamics and $\boldsymbol{v} \in \Re^3$ is the input voltage vector.

The motor dynamics data are defined in $\boldsymbol{D}_{\mathrm{n}}$ and $\boldsymbol{D}_{\mathrm{k}} \in \Re^{3\times3}$, they are $\boldsymbol{D}_{\mathrm{n}}^{-1} = \text{block diag}\{r_1^2 \;\; r_2^2 \;\; r_3^2\}$ and $\boldsymbol{D}_{\mathrm{k}} = \text{block diag}\{\frac{K_{a1}}{R_{a1}r_1} \;\; \frac{K_{a2}}{R_{a2}r_2} \;\; \frac{K_{a3}}{R_{a3}r_3}\}$. Where r stands for the gear ratio, K_a is the torque constant and R_a the armature resistance, whose values are $r_i = 100$, $K_{ai} = 0.1424$ $[Nm/A]$ and $R_{ai} = 0.84$ $[\Omega]$ for $i = 1, 2, 3$.

The values of every matrix component is taken from Gudino-Lau and Arteaga (2005).

2.2 Robot properties

Before to present the properties from Arteaga-Pérez (1998), it must to establish that the largest (smallest) eigenvalue of a matrix is denoted by $\lambda_{max}(\cdot)$ $(\lambda_{min}(\cdot))$. Revolute joints are considered so the following properties can be established:

Property 2.1. It holds $\lambda_{\mathrm{h}}||\boldsymbol{x}||^2 \le \boldsymbol{x}^{\mathrm{T}}\boldsymbol{H}(\boldsymbol{q})\boldsymbol{x} \le \lambda_{\mathrm{H}}||\boldsymbol{x}||^2$ $\forall \boldsymbol{q}, \boldsymbol{x} \in \Re^n$, and $0 < \lambda_{\mathrm{h}} \le \lambda_{\mathrm{H}} < \infty$, with $\lambda_{\mathrm{h}} \triangleq \min_{\forall \boldsymbol{q} \in \Re^n} \lambda_{\min}(\boldsymbol{H}(\boldsymbol{q}))$, $\lambda_{\mathrm{H}} \triangleq \max_{\forall \boldsymbol{q} \in \Re^n} \lambda_{\min}(\boldsymbol{H}(\boldsymbol{q}))$.
△

Property 2.2. By using the Christoffel symbols (of the first kind) to compute $\boldsymbol{C}(\boldsymbol{q},\dot{\boldsymbol{q}})$, $\dot{\boldsymbol{H}}(\boldsymbol{q}) - 2\boldsymbol{C}(\boldsymbol{q},\dot{\boldsymbol{q}})$ is skew symmetric.

△

Property 2.3. With a proper definition of the robot model parameters, it holds

$$\boldsymbol{H}(\boldsymbol{q})\ddot{\boldsymbol{q}} + \boldsymbol{C}(\boldsymbol{q},\dot{\boldsymbol{q}})\dot{\boldsymbol{q}} + \boldsymbol{D}\dot{\boldsymbol{q}} + \boldsymbol{g}(\boldsymbol{q}) + \boldsymbol{f}_{\mathrm{c}}(\dot{\boldsymbol{q}}) = \boldsymbol{\tau} = \boldsymbol{Y}(\boldsymbol{q},\dot{\boldsymbol{q}},\ddot{\boldsymbol{q}})\boldsymbol{\theta}, \quad (2)$$

where $\boldsymbol{Y}(\boldsymbol{q},\dot{\boldsymbol{q}},\ddot{\boldsymbol{q}}) \in \Re^{n\times p}$ is the *regressor* and $\boldsymbol{\theta} \in \Re^p$ is a constant vector of parameters.

△

3. ADAPTIVE SCHEMES

A succinct description of the adaptive controllers used is presented in this section, also the proposed scheme with a brief explanation of their stability properties.

3.1 Adaptive Control Slotine and Li (1987)

The control scheme used of this work is

$$\boldsymbol{\tau} = -\boldsymbol{K}_{\mathrm{s}}\boldsymbol{s} + \boldsymbol{Y}(\boldsymbol{q},\dot{\boldsymbol{q}},\dot{\boldsymbol{q}}_{\mathrm{r}},\ddot{\boldsymbol{q}}_{\mathrm{r}})\hat{\boldsymbol{\theta}} \quad (3)$$

$$\dot{\hat{\boldsymbol{\theta}}} = \boldsymbol{\Gamma}_s\boldsymbol{Y}^{\mathrm{T}}(\boldsymbol{q},\dot{\boldsymbol{q}},\dot{\boldsymbol{q}}_{\mathrm{r}},\ddot{\boldsymbol{q}}_{\mathrm{r}})\boldsymbol{s}, \quad (4)$$

with the variable $\dot{\boldsymbol{q}}_{\mathrm{r}}$ and the sliding variable are defined as

$$\dot{\boldsymbol{q}}_{\mathrm{r}} = \dot{\boldsymbol{q}}_{\mathrm{d}} - \boldsymbol{\Lambda}_e\boldsymbol{e} \quad (5)$$

$$\boldsymbol{s} = \dot{\boldsymbol{q}} - \dot{\boldsymbol{q}}_{\mathrm{r}} \quad (6)$$

$$\boldsymbol{e} = \boldsymbol{q} - \boldsymbol{q}_{\mathrm{d}}, \quad (7)$$

where $\boldsymbol{e} \in \Re^n$ is the tracking error and $\boldsymbol{q}_{\mathrm{d}} \in \Re^n$ is the desired trajectory. As is well known, this scheme attains the tracking convergence to zero when $t \to \infty$, this means that the algorithm assures that the system in closed loop is global asymptotic stable (*GAS*). Also, if the persistent excitation is not met, just ensures that $\tilde{\boldsymbol{\theta}} < \infty$.

3.2 Adaptive Control Tang and Arteaga-Pérez (1994)

The adaptive control worked is

$$\boldsymbol{\tau} = \boldsymbol{K}_{\mathrm{s}}\boldsymbol{s} - \boldsymbol{Y}(\boldsymbol{q},\dot{\boldsymbol{q}},\boldsymbol{a},\dot{\boldsymbol{a}})\hat{\boldsymbol{\theta}} \quad (8)$$

$$\dot{\hat{\boldsymbol{\theta}}} = -\delta\boldsymbol{g} - \boldsymbol{\Gamma}_1\boldsymbol{Y}^{\mathrm{T}}(\boldsymbol{q},\dot{\boldsymbol{q}},\boldsymbol{a},\dot{\boldsymbol{a}})\boldsymbol{s}, \quad (9)$$

with

$$\begin{aligned}
\boldsymbol{a} &= \dot{\boldsymbol{q}}_{\rm d} - \boldsymbol{\Lambda}_{\rm q}\boldsymbol{e} \\
\dot{\boldsymbol{g}} &= -\lambda_{\rm g}\boldsymbol{g} - \delta\boldsymbol{Z}\boldsymbol{g} + \gamma_2\boldsymbol{Y}_f^{\rm T}(\boldsymbol{q},\dot{\boldsymbol{q}})\boldsymbol{\epsilon} \\
&\quad -\boldsymbol{\Gamma}_1\boldsymbol{Z}\boldsymbol{Y}^{\rm T}(\boldsymbol{q},\dot{\boldsymbol{q}},\boldsymbol{a},\dot{\boldsymbol{a}})\boldsymbol{s}, \qquad \boldsymbol{g}(0)=\boldsymbol{0} \\
\dot{\boldsymbol{Z}} &= -\lambda_{\rm g}\boldsymbol{Z} + \gamma_2\boldsymbol{Y}_f^{\rm T}(\boldsymbol{q},\dot{\boldsymbol{q}})\boldsymbol{Y}_f(\boldsymbol{q},\dot{\boldsymbol{q}}), \quad \boldsymbol{Z}(0)=\boldsymbol{O} \\
\boldsymbol{\epsilon} &= \boldsymbol{Y}_f(\boldsymbol{q},\dot{\boldsymbol{q}})\hat{\boldsymbol{\theta}} - \boldsymbol{\tau}_f,
\end{aligned}$$

where the sliding variable $\boldsymbol{s}$ is the same defined in (6), the tracking error $\boldsymbol{e}$ is (7) and

$$\boldsymbol{\tau}_f = W(s)\boldsymbol{\tau} \tag{10}$$

$$\boldsymbol{Y}_f = W(s)\boldsymbol{Y}(\boldsymbol{q},\dot{\boldsymbol{q}},\ddot{\boldsymbol{q}}) \tag{11}$$

$$W(s) = \frac{\lambda_f}{s+\lambda_f}, \tag{12}$$

where $W(s)$ is a kind of low pass filter.

This algorithm achieves exponential stability without persistent excitation (PE).

3.3 Proposed Scheme

The proposed algorithm is able to reach the tracking control without joint velocity measurements, its stability analysis is not treated here due to dearth of space.

This enhanced adaptive control works with a joint velocity observer that does not depend on the dynamic model of the system and assures ultimate bounded stability of the observer errors.

The proposed control scheme is

$$\boldsymbol{\tau} = -\boldsymbol{K}_{\rm v}\boldsymbol{s}_o + \boldsymbol{Y}_o\hat{\boldsymbol{\theta}}_o \tag{13}$$

$$\dot{\hat{\boldsymbol{\theta}}}_o = -\boldsymbol{\Gamma}\left(\beta\boldsymbol{w}(t) + \boldsymbol{Y}_o^{\rm T}\boldsymbol{s}_o + \boldsymbol{f}_{\rm b}\right), \tag{14}$$

where $\boldsymbol{\Gamma} \in \Re^{18\times18}$ is a positive definite matrix. The sliding variable is defined as

$$\boldsymbol{s}_o = \dot{\boldsymbol{q}}_o - \dot{\boldsymbol{q}}_{\rm r} \tag{15}$$

with

$$\begin{aligned}
\dot{\boldsymbol{q}}_{\rm r} &= \dot{\boldsymbol{q}}_{\rm d} - \boldsymbol{\Lambda}\boldsymbol{e} \\
\ddot{\boldsymbol{q}}_{\rm r} &= \ddot{\boldsymbol{q}}_{\rm d} - \boldsymbol{\Lambda}\left(\dot{\boldsymbol{q}}_o - \dot{\boldsymbol{q}}_{\rm d}\right) \\
\dot{\boldsymbol{q}}_o &= \dot{\hat{\boldsymbol{q}}} - \boldsymbol{\Lambda}_z\boldsymbol{z},
\end{aligned}$$

where $\boldsymbol{z} \in \Re^3$ is the observer error, $\boldsymbol{K}_{\rm v}, \boldsymbol{\Lambda}, \boldsymbol{\Lambda}_z \in \Re^{3\times3}$ are positive definite matrices and

$$\begin{aligned}
\boldsymbol{Y}_o\hat{\boldsymbol{\theta}}_o &= \hat{\boldsymbol{H}}(\boldsymbol{q})\ddot{\boldsymbol{q}}_{\rm r} + \hat{\boldsymbol{C}}(\boldsymbol{q},\dot{\boldsymbol{q}}_{\rm r})\dot{\boldsymbol{q}}_{\rm r} + \hat{\boldsymbol{D}}\dot{\boldsymbol{q}}_{\rm r} + \hat{\boldsymbol{g}}(\boldsymbol{q}) \\
&= \boldsymbol{Y}_o\left(\boldsymbol{q},\dot{\boldsymbol{q}}_{\rm r},\ddot{\boldsymbol{q}}_{\rm r}\right)\hat{\boldsymbol{\theta}}_o.
\end{aligned}$$

For the adaptive law (14)

$$\dot{\boldsymbol{w}} = -\lambda\boldsymbol{w} + \gamma\hat{\boldsymbol{Y}}_{\rm f}^{\rm T}\boldsymbol{\epsilon} + \boldsymbol{Z}\dot{\hat{\theta}}_o, \quad \boldsymbol{w}(0)=\boldsymbol{0} \tag{16}$$

$$\dot{\boldsymbol{Z}} = -\lambda\boldsymbol{Z} + \gamma\hat{\boldsymbol{Y}}_{\rm f}^{\rm T}\hat{\boldsymbol{Y}}_{\rm f}, \qquad \boldsymbol{Z}(0)=\boldsymbol{O} \tag{17}$$

$$\boldsymbol{\epsilon} = \hat{\boldsymbol{Y}}_{\rm f}\hat{\boldsymbol{\theta}}_o - \boldsymbol{Y}_{\rm f}\boldsymbol{\theta}, \tag{18}$$

with $\lambda, \gamma > 0$ and the regressors $\boldsymbol{Y}_{\rm f}(\boldsymbol{q},\dot{\boldsymbol{q}}), \hat{\boldsymbol{Y}}_{\rm f}(\boldsymbol{q},\dot{\boldsymbol{q}}_o) \in \Re^{3\times18}$ are established using Property 2.3 as

$$\begin{aligned}
\boldsymbol{Y}_{\rm f}(\boldsymbol{q},\dot{\boldsymbol{q}})\boldsymbol{\theta} &= W(s)\boldsymbol{Y}(\boldsymbol{q},\dot{\boldsymbol{q}},\ddot{\boldsymbol{q}})\boldsymbol{\theta} = \boldsymbol{\tau}_f \\
\hat{\boldsymbol{Y}}_{\rm f}(\boldsymbol{q},\dot{\boldsymbol{q}}_o) &= \boldsymbol{Y}_{\rm f}(\boldsymbol{q},\dot{\boldsymbol{q}}_o),
\end{aligned}$$

where $\lambda_{\rm f} > 0$ and $W(s)$ is stipulated in (12).

Besides, the term f_{bi} set in (14) is

$$f_{bi} = \text{sign}(\tilde{\theta}_i)\rho_i\delta_i|\beta w_i + \boldsymbol{y}_{ai}^{\rm T}\boldsymbol{s}_o| \tag{19}$$

with $\beta > 0$, $\rho_i > 1$ and δ_i is used for achieving boundedness of estimated parameters employing projections, this variable is computed as

$$\delta_i = \begin{cases} \dfrac{\theta_{2i}-\hat{\theta}_i}{\theta_{2i}-\theta_{1i}}, & \text{if } \theta_{1i} \le \hat{\theta}_i < \theta_{2i} \\ 0, & \text{if } \theta_{2i} \le \hat{\theta}_i \le \theta_{3i} \\ \dfrac{\hat{\theta}_i-\theta_{3i}}{\theta_{4i}-\theta_{3i}}, & \text{if } \theta_{3i} < \hat{\theta}_i < \theta_{4i}. \end{cases} \tag{20}$$

A simplified version of Arteaga-Pérez (2003) is treated and is assumed that for every element of parameters vector θ_i with $i = 1,...,18$, exist an upper and lower bound known so that $\theta_{{\rm m}i} \le \theta_i \le \theta_{{\rm M}i}$ holds. For that reason, θ_{ji} with $j = 1,...,4$ must to be set as $\theta_{1i} < \theta_{2i} \le \theta_{{\rm m}i} < \theta_{{\rm M}i} \le \theta_{3i} < \theta_{4i}$. Lower bounds can be considered zero and the upper bounds can be set large if necessary.

The deployed observer Arteaga-Pérez et al. (2017) is defined as

$$\dot{\boldsymbol{\xi}} = \boldsymbol{z} \tag{21}$$

$$\boldsymbol{\zeta} = \dot{\boldsymbol{q}}_{\rm d} - \boldsymbol{\Lambda}_{\rm x}\tilde{\boldsymbol{q}} + \boldsymbol{K}_{\rm d}\boldsymbol{\Lambda}_{\rm z}\boldsymbol{\xi} \tag{22}$$

$$\dot{\hat{\boldsymbol{q}}} = \boldsymbol{\zeta} + \boldsymbol{\Lambda}_{\rm z}\boldsymbol{z} + \boldsymbol{K}_{\rm d}\boldsymbol{z} \tag{23}$$

where $\boldsymbol{\Lambda}_{\rm x}, \boldsymbol{K}_{\rm d}, \boldsymbol{\Lambda}_{\rm z} \in \Re^{3\times3}$ are diagonal positive matrices.

4. SIMULATIONS RESULTS

Here, the real parameters vector and the values of controller gains for each control scheme are presented. Moreover, the resulting comparison is depict through graphics and performance index tables.

4.1 Parameters vector

The robot model employed for simulation can be found in Gudino-Lau and Arteaga (2005). For comparison purposes the elements of the parameter vector are:

$$\begin{aligned}
\theta_{o1} &= 0.0055\ [Kg\ m^2], & \theta_{o2} &= 0.008\ [Kg\ m^2], \\
\theta_{o3} &= 0.0024\ [Kg\ m^2], & \theta_{o4} &= 0.0118\ [Kg\ m^2], \\
\theta_{o5} &= 0.0041\ [Kg\ m^2], & \theta_{o6} &= 9\times10^{-4}\ [Kg\ m^2], \\
\theta_{o7} &= 7\times10^{-4}\ [Kg\ m^2], & \theta_{o8} &= 2.0007\ [Kg\ m^2], \\
\theta_{o9} &= 11.80\ [Kg\ m^2], & \theta_{o10} &= 2.80\ [Kg\ m^2], \\
\theta_{o11} &= 25.0\ [N\ m\ s], & \theta_{o12} &= 35.0\ [N\ m\ s], \\
\theta_{o13} &= 36.0\ [N\ m\ s], & \theta_{o14} &= 0.20\ [N\ m], \\
\theta_{o15} &= 2.50\ [N\ m], & \theta_{o16} &= 2.50\ [N\ m], \\
\theta_{o17} &= 22.0\ [N\ m], & \theta_{o18} &= 11.0\ [N\ m].
\end{aligned}$$

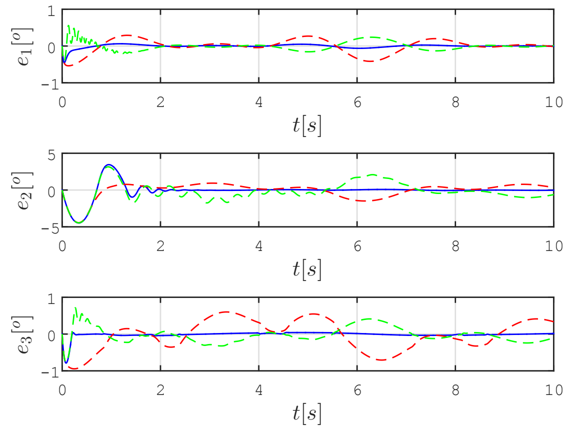

Fig. 2. Joint tracking errors. Proposed control-observer (--), adaptive control (Tang and Arteaga-Pérez) (- -), adaptive control (Slotine and Li) (- -).

4.2 Gains values

Proposed scheme. The gains for the developed control-observer have been chosen as: $\boldsymbol{K}_v = \text{block diag}\{40\ 80\ 75\}$, $\boldsymbol{\Lambda}_{\text{z}} = \text{block diag}\{100\ 50\ 110\}$, $\boldsymbol{\Lambda} = \text{block diag}\{60\ 80\ 70\}$, $\gamma = 0.1$, $\rho = 2.5$, $\beta = 5.5$, $\lambda = 125$, $\lambda_f = 70$ and $\boldsymbol{\Gamma} = \text{block diag}\{21 \times 10^{-6}, 17 \times 10^{-6}, 85 \times 10^{-7}, 0.0011, 0.001, 0.0012, 0.0017, 2.5, 0.7, 0.9, 47, 4.9, 25, 0.21, 0.089, 1.45, 50, 5.5\}$

For the adaptive scheme, the upper and lower bounds were chosen as

$$\theta_{1i} = -0.0001$$
$$\theta_{2i} = 0.0$$
$$\theta_{3i} = 10.0\ \theta_{\text{o}i}$$
$$\theta_{4i} = 10.1\ \theta_{\text{o}i}$$

using the idea that the minimum value $\theta_{mi} = \theta_{2i}$ that a parameter can reach is 0 and the maximum $\theta_{Mi} = \theta_{3i}$ can be 10 times the nominal value $\theta_{\text{o}i}$.

Adaptive control Slotine and Li (1987). The gains for adaptive control given in this paper were chosen such as: $\boldsymbol{K}_{\text{s}} = \text{block diag}\{95\ 115\ 110\}$, $\boldsymbol{\Lambda}_e = \text{block diag}\{10\ 6.5\ 8\}$ and $\boldsymbol{\Gamma}_s = \text{block diag}\{21 \times 10^{-6}, 17 \times 10^{-6}, 85 \times 10^{-7}, 0011, 0.001, 0.0012, 0.0017, 4.3, 0.7, 3, 47, 5.5, 42, 0.21, 0.69, 0.845, 40, 22.5\}$.

Adaptive control Tang and Arteaga-Pérez (1994). In order to fulfil all the conditions that this work indicates, the gains have been chosen as: $\boldsymbol{K}_{\text{s}} = \text{block diag}\{60\ 15\ 40\}$, $\boldsymbol{\Lambda}_{\text{q}} = \text{block diag}\{190\ 230\ 220\}$, $\delta = 0.1$, $\gamma_2 = 0.05$, $\lambda_{\text{g}} = 20$, $\lambda_f = 15$ and $\boldsymbol{\Gamma}_1 = \text{block diag}\{0.017, 0.017, 0.01, 0.017, 0.07, 0.002, 0.01, 0.08, 0.3, 0.17, 2.8, 0.12, 30.83, 0.0001, 0.09, 0.35, 12.75, 1.02\}$.

4.3 Results

The desired trajectories are given in articular coordinates, the objective is follow the variable signal

$$\boldsymbol{q}_{\text{d}} = \begin{bmatrix} 5\sin(t) + 5\sin(2t) + 2.5\sin(3t) \\ 15\sin(t) + 2.5\sin(3t) + 3\sin(2t) + 90 \\ 10\sin(t) + 2\sin(2t) + 3\sin(3t) - 90 \end{bmatrix} [^\circ]. \quad (24)$$

since the initial position $\boldsymbol{q}_{\text{o}} = [0\ 90\ \ -90]^{\text{T}}\ [^o]$.

With the aim of numerically comparing simulated algorithms, the performance index $\mathcal{I}(\cdot) = \sqrt{\frac{1}{k}\sum_0^{k-1} \|\cdot\|^2}$ has been employed with $k = 3000$, where k is the number of samples. The results of the performance comparison are stipulated in Table 1 and 2.

Figure 2 displays the joint errors that each controller algorithm exposed, the demeanour between them is very similar, so the Table 1 presents the performance index, in which it is shown that the adaptive control Slotine and Li has a worse result in compare with the other two. In addition, it is conspicuous that the proposed scheme presents a resembling value to the adaptive controller Tang and Arteaga-Pérez, despite the lack of joint velocity measurements.

Velocity joint errors are depict in Figure 3, where the behaviour of Slotine and Li is clearly inferior in comparison with the other two, because the settling time is the biggest and in the third joint converges to a bounded limit. Table 2 contains the index performance of the joint velocity errors and it confirms that the observer used in the proposed scheme to estimate joint velocities, performs very well.

Figure 4 shows the observer errors, where for the first joint z_1 stays upper bounded by $z_{1\text{max}} = 0.023\ [^\circ]$, the error for second articulation stays under $z_{2\text{max}} = 0.027\ [^\circ]$ and the last error remains under $z_{3\text{max}} = 0.019\ [^\circ]$.

Figures 5 - 7 exhibit the behaviour of the vector of estimated parameters. Just the algorithms of Tang and Arteaga-Pérez and the proposed make that the estimated signal converge at a constant value but only the proposed scheme attains a closer convergence to the real in some cases.

Finally, through the index performance tables can be noticed also that the control algorithm of Tang and Arteaga-Pérez delivers similar results to the proposed scheme, but the first one counts with the velocity measurements.

Table 1. Performance index of the joint space errors

Algorithm	$\mathcal{I}(e_1)$ $[^o]$	$\mathcal{I}(e_2)$ $[^o]$	$\mathcal{I}(e_3)$ $[^o]$
Proposed scheme	0.0004	0.0351	0.00004
Adaptive controller (Tang and Arteaga-Pérez)	0.0011	0.0334	0.0033
Adaptive controller (Slotine and Li)	0.0016	0.0180	0.0086

Table 2. Performance index of the joint velocity errors

Algorithm	$\mathcal{I}(\dot{e}_1)$ $[\frac{o}{s}]$	$\mathcal{I}(\dot{e}_2)$ $[\frac{o}{s}]$	$\mathcal{I}(\dot{e}_3)$ $[\frac{o}{s}]$
Proposed scheme	0.0037	0.3350	0.0023
Adaptive controller (Tang and Arteaga-Pérez)	0.0504	0.3228	0.0222
Adaptive controller (Slotine and Li)	0.0174	0.1501	0.0244

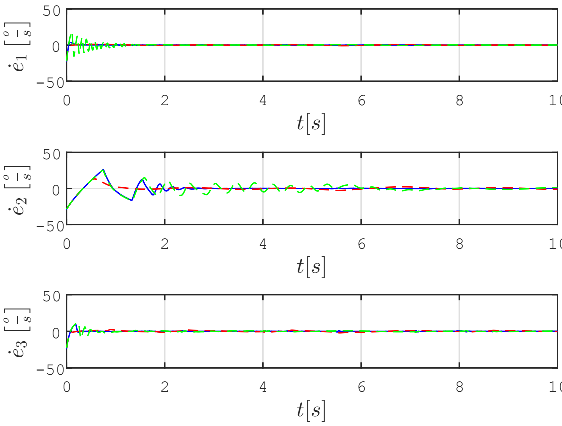

Fig. 3. Joint velocity errors. Proposed scheme (- -), adaptive control (Tang and Arteaga-Pérez) (- -), adaptive control (Slotine and Li) (- -).

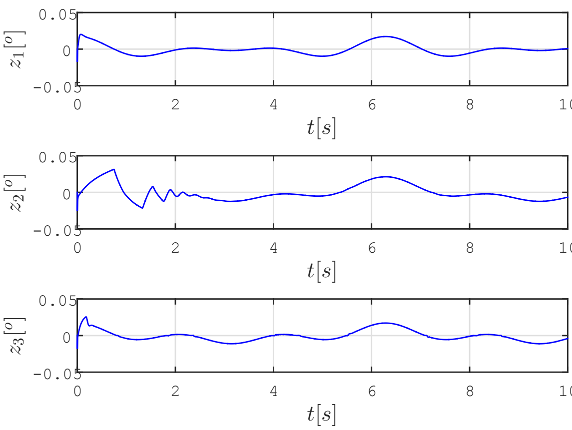

Fig. 4. Observation errors, (21)-(23).

Just as it is expected, the adaptive control of Slotine and Li presents the worst performance, although it has the known speed, this is because it does not have the variables that help in the adaptation part.

5. CONCLUSION

A novel scheme was proposed with an observer to provides the joint velocity measurements due to absence of sensors to bring that information. Also was presented a comparison with two adaptive controllers that have the joint velocity knowledge in order to demonstrate the best performance of the novel proposed scheme.

The objective had been accomplished with the proposed scheme and the convergence to the real parameters was reached in some cases, a situation that was not attained with the other two schemes.

To obtain a better reference for comparing the simulation results, the performance index had been calculated and, as was expected, the outcomes establish that the proposed scheme had an outstanding performance.

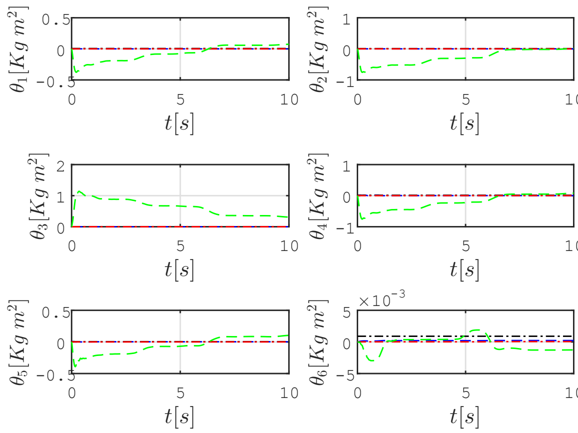

Fig. 5. Inertia parameters estimated with the adaptive law proposed (- -), adaptive control (Tang and Arteaga-Pérez) (- -), adaptive control (Slotine and Li) (-·-) and the real value of parameter (-·-).

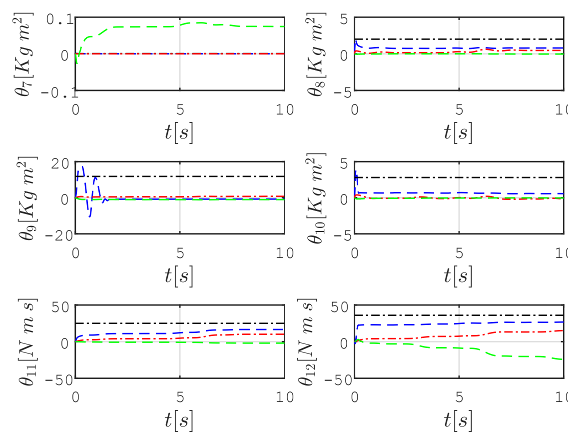

Fig. 6. Estimated parameters with the adaptive law proposed (- -), adaptive control (Tang and Arteaga-Pérez) (- -), adaptive control (Slotine and Li) (-·-) and the real value of parameter (-·-). Inertia parameters $\theta_7 - \theta_{10}$, viscous friction parameters $\theta_{11} - \theta_{12}$.

Finally, this scheme will be implemented in the real system and a similar comparison will be made with variable joint trajectories to demonstrate the advantages offered by the developed control.

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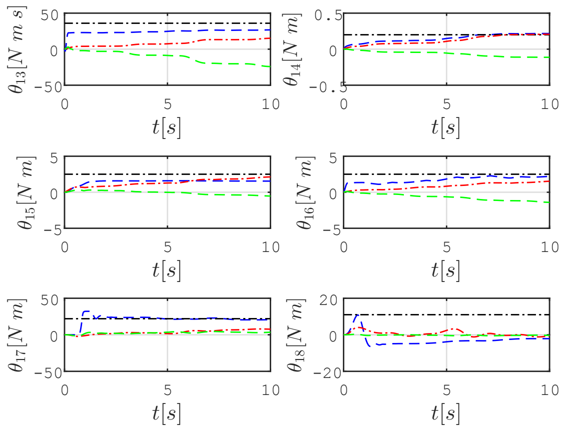

Fig. 7. Estimated parameters with the adaptive law proposed (- -), adaptive control (Tang and Arteaga-Pérez) (- -), adaptive control (Slotine and Li) (-·-) and the real value of parameter (-·-). Viscous friction parameter θ_{13}, dry friction parameters $\theta_{14} - \theta_{16}$, gravity parameters $\theta_{17} - \theta_{18}$.

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