A New Hamiltonian-Based Indentification Scheme for Robot Manipulators

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Abstract: - This paper addresses on the estimating dynamic parameters of robot manipulators. A new identification scheme is proposed. It is based on Hamiltonian dynamic model. An experimental evaluation is presented of three identification schemes such as: Energy and filtered power models vs proposed scheme on a direct drive robot pendulum.
Key-Words: - Prediction error, Least-Squares Algorithm, Regressor identification model

1 Introduction

Parameter identification techniques are particularly attractive to determine the dynamic parameter of robot manipulators. The usefulness of the dynamic parameters arise in implementation of advanced model-based controllers such as PD+ and Computed torque [1].

There are several identification schemes used in Robotics. Dynamics and Filtered Dynamics models. We also can mention to Energy and Potency models [2] [3] [4]. These models are based on recognition that combinations of dynamic parameters appear linearly in all the models. This property allows the estimation of dynamical parameters by standard least-squares techniques [3] [5].

The dynamic model suffers of a practical drawback; the joint acceleration is needed in the regressor; therefore the filtered dynamic model was proposed [6]. Additional to this drawback, also it yields a vector prediction error . On the other hand, the energy regression model proposed in [4] does not require the joint acceleration and it yields a scalar predicition. However, the energy model involves the integral of the power which produces in zero frequency a infinity gain. The filtered power regression model overcomes this drawback for including a low-pass filter.

In this paper we introduce a new Based–Hamiltonian regression model which produces a scalar prediction...

The contribution of this paper is to show that new Hamilton regressor scheme and its performance, as well as to present a experimental evaluation of three identification schemes on a robot-pendulum. We have used a identification scheme based on recursive least squares. The estimated parameters obtained from Hamiltonian regressor scheme were validated with simulated response using the direct-drive robot-pendulum model incorporating the identified parameters.

2 Robot Dynamics

The dynamics of a serial n-link rigid robot can be written as [7] [8]:

$$M(\boldsymbol{q})\ddot{\boldsymbol{q}} + C(\boldsymbol{q}, \dot{\boldsymbol{q}})\dot{\boldsymbol{q}} + \boldsymbol{g}(\boldsymbol{q}) + \boldsymbol{f}(\dot{\boldsymbol{q}}, \boldsymbol{\tau}) = \boldsymbol{\tau} \qquad (1)$$

where $\boldsymbol{q}$ is the $n \times 1$ vector of joint displacements; $\dot{\boldsymbol{q}}$ is the $n \times 1$ vector of joint velocities; $\boldsymbol{\tau}$ is the $n \times 1$

vector of input torques; $M(\boldsymbol{q})$ is the $n \times n$ symmetric positive definite manipulator inertia matrix, $C(\boldsymbol{q}, \dot{\boldsymbol{q}})$ is the $n \times n$ matrix of centripetal and Coriolis torques; $\boldsymbol{g}(\boldsymbol{q})$ is the $n \times 1$ vector of gravitational torques obtained as the gradient of the robot potential energy due to gravity and $\boldsymbol{f}(\dot{\boldsymbol{q}}, \boldsymbol{\tau})$ is the $n \times 1$ vector for the friction torques. The vector $\boldsymbol{f}(\dot{\boldsymbol{q}}, \boldsymbol{\tau})$ is decentralized in the sense that $\boldsymbol{f}(\dot{\boldsymbol{q}}, \boldsymbol{\tau})$ depends only on $\dot{q}_i$ and $\boldsymbol{\tau}_i$; that is,

$$\boldsymbol{f}(\dot{\boldsymbol{q}}, \boldsymbol{\tau}) = \begin{bmatrix} f_1(\dot{q}_1, \boldsymbol{\tau}_1) \\ f_2(\dot{q}_2, \boldsymbol{\tau}_2) \\ \vdots \\ f_n(\dot{q}_n, \boldsymbol{\tau}_n) \end{bmatrix}.$$

The friction torques $\boldsymbol{f}(\dot{\boldsymbol{q}}, \boldsymbol{\tau})$ are assumed to be dissipate energy at all non-zero velocities, and therefore, their entries are bounded within the first and third quadrants. This feature allows to consider the common Coulomb and viscous friction models. At zero velocities, only static friction is present satisfying

$$f_i(\mathbf{0}, \boldsymbol{\tau}_i) = \boldsymbol{\tau}_i - g_i(\boldsymbol{q})$$

for $-\bar{\mathrm{f}}_i \leq \boldsymbol{\tau}_i - g_i(\boldsymbol{q}) \leq \bar{\mathrm{f}}_i$, with $\bar{\mathrm{f}}_i$ being the limit on the static friction torques for joint i [9] [10].

It is assumed that the robot links are joined together with revolute joints. Although the equation of motion (1) is complex, it has several fundamental properties which can be exploited to facilitate control system design. For the new controller, the following important property is used:

Property 1: Linearity in the parameters of the robot dynamic.

Since the model (1), could be relationated with the applied torques at each joint with the regressor matrix and the parameter unknown vector it take us to the dynamic regression model [2][4]:

$$\mathbf{Y}(\mathbf{fq}, \dot{\boldsymbol{q}}, \ddot{\boldsymbol{q}})\boldsymbol{\theta} = \boldsymbol{\tau} \tag{2}$$

where $\mathbf{Y}(\mathbf{fq}, \dot{\boldsymbol{q}}, \ddot{\boldsymbol{q}})$ is a $n \times m$ matrix and $\boldsymbol{\theta}$is a m x 1 vector stand the dynamic parameters.

Property 2: Linearity in the parameters of the robot total energy.

The total energy $\mathcal{E}(\boldsymbol{q}, \dot{\boldsymbol{q}})$ of robot manipulators is given by the sum of kinetic energy $\mathcal{K}(\boldsymbol{q}, \dot{\boldsymbol{q}})$ plus potential energy $\mathcal{U}(\boldsymbol{q})$:

$$\mathcal{E}(\boldsymbol{q}, \dot{\boldsymbol{q}}) = \mathcal{K}(\boldsymbol{q}, \dot{\boldsymbol{q}}) + \mathcal{U}(\boldsymbol{q})$$

where $\dot{\boldsymbol{q}}$ stands the vector of position joints and $\dot{\boldsymbol{q}}$ is the vector of velocity joints.

The kinetic and potential energy can be written as a linear function of the dynamic parameters [4]:

$$\begin{aligned} \mathcal{K}(\boldsymbol{q}, \dot{\boldsymbol{q}}) &= \boldsymbol{\phi}_k(\boldsymbol{q}, \dot{\boldsymbol{q}})^T \boldsymbol{\theta}_k && (3) \\ \mathcal{U}(\boldsymbol{q}) &= \boldsymbol{\phi}_u(\boldsymbol{q})^T \boldsymbol{\theta}_u && (4) \end{aligned}$$

where $\boldsymbol{\phi}_k$ and $\boldsymbol{\phi}_u$ are $p_1 \times 1$ and $p_2 \times 1$ vector functions, $\boldsymbol{\theta}_k$ and $\boldsymbol{\theta}_u$ stand for $p_1 \times 1$ and $p_2 \times 1$ vectors which contain the dynamic parameters of the robot such as masses, moments of inertia and centers of gravity.

The total energy can be written as a linear regression in the following form:

$$\mathcal{E}(\boldsymbol{q}, \dot{\boldsymbol{q}}) = \boldsymbol{\phi}_{\mathcal{E}}(\boldsymbol{q}, \dot{\boldsymbol{q}})^T \boldsymbol{\theta}_{\mathcal{E}}$$

where

$$\begin{aligned} \boldsymbol{\phi}_{\mathcal{E}} &= [\boldsymbol{\phi}_k(\boldsymbol{q}, \dot{\boldsymbol{q}}) \quad \boldsymbol{\phi}_u(\boldsymbol{q})] && (5) \\ \boldsymbol{\theta}_{\mathcal{E}} &= [\boldsymbol{\theta}_k \quad \boldsymbol{\theta}_u]. && (6) \end{aligned}$$

The Coulomb and viscous friction can be presented as a linear regressor in the following equation:

$$\boldsymbol{f}(\dot{\boldsymbol{q}}) = \boldsymbol{\phi}_{\mathcal{F}}(\dot{\boldsymbol{q}})^T \boldsymbol{\theta}_{\mathcal{F}}$$

where $\boldsymbol{\phi}_{\mathcal{F}}$ is an $n \times 2n$ matrix function and $\boldsymbol{\theta}_{\mathcal{F}}$ stands $2n \times 1$ vector, which contains Coulomb and viscous friction coefficients.

3 Least-Squares Algorithm

The least-squares method is a basic technique for parameter identification. This method is particularly simple if the system model has the property of being linear in the parameters. It is well known that recursive least-squares is given by:

$$\begin{aligned} \boldsymbol{\theta}(k) &= \boldsymbol{\theta}(k-1) + \frac{P(k-1)\boldsymbol{\psi}(k)e(k)}{1 + \boldsymbol{\psi}(k)^T P(k-1)\boldsymbol{\psi}(k)} \\ P(k) &= P(k-1) - \frac{P(k-1)\boldsymbol{\psi}(k)\boldsymbol{\psi}(k)^T P(k-1)}{1 + \boldsymbol{\psi}(k)^T P(k-1)\boldsymbol{\psi}(k)} \end{aligned}$$

where $\boldsymbol{\psi}(k)$ is the $p \times 1$ regressor vector of known functions, and $\boldsymbol{\theta}(k)$ is the $p \times 1$ vector of unknown parameters. This model is indexed by variable k, which denotes the sampling time. $P(k) \in \mathbb{R}^{n\times n}$ is the covariance matrix; and $e(k)$ is the prediction error defined as:

$$e(k) = y(k) - \boldsymbol{\psi}(k)^T \boldsymbol{\theta}(k-1)$$

$y(k)$ is the robot response.

4 Identification Schemes

In this section, we present the identification schemes such as: supplied energy and filtered power regresion models. As well as the new regressor scheme based on Hamiltonian-dynamics.

The prediction error for the supplied energy regression model is defined as [4]:

$$\begin{aligned} e(k) &= \int_0^{kh} \boldsymbol{\tau}(\boldsymbol{\sigma})^T \dot{\boldsymbol{q}} d\boldsymbol{\sigma} - [\boldsymbol{\phi}_{\mathcal{E}}(\boldsymbol{q}, \boldsymbol{q})(k) \qquad (7) \\ & \int_0^{kh} \dot{\boldsymbol{q}}(\boldsymbol{\sigma})^T \boldsymbol{\phi}_{\mathcal{F}}(\dot{\boldsymbol{q}}) d\boldsymbol{\sigma} \Big] \boldsymbol{\theta}(k-1) \end{aligned}$$

The prediction error for the filtered power regression model is defined as [2]:

$$\begin{aligned} e(k) &= \frac{\boldsymbol{\lambda}}{\boldsymbol{\lambda}+s}(\boldsymbol{\tau}^T \dot{\boldsymbol{q}}(k)) \qquad (8) \\ & - \left[\frac{\boldsymbol{\lambda}}{\boldsymbol{\lambda}+s}(\boldsymbol{\psi}_{\mathcal{E}}(\boldsymbol{q}, \dot{\boldsymbol{q}})^T(k) \quad \frac{\boldsymbol{\lambda}}{\boldsymbol{\lambda}+s}(\dot{\boldsymbol{q}}^T \boldsymbol{\psi}_{\mathcal{F}}(\dot{\boldsymbol{q}})) \right] \boldsymbol{\theta}(k-1) \end{aligned}$$

The prediction error for the Hamiltonian-based regressor model is given by next equation:

$$e(k) = \boldsymbol{\tau} - \left[\dot{\boldsymbol{p}} + \frac{\partial \boldsymbol{p}^T M(\boldsymbol{q})^{-1} \boldsymbol{p}}{\partial \boldsymbol{q}} + \boldsymbol{g}(\boldsymbol{q}) + \boldsymbol{f}(\boldsymbol{p}) \right] \qquad (9)$$

The Dynamic model is well kown [6] [1] [2] and for this reason we dont written.

5 Experimental Set-Up

An experimental system for research of robot control algorithms has been designed and built at The Universidad Autnoma de Puebla, Mxico; it is a direct–drive robot pendulum (see Figure 1). The experimental robot consists of a link made of 6061 aluminum actuated by brushless direct drive servo actuator from Parker Compumotor to drive the joint without gear reduction. Advantages of this type of direct-drive actuator includes freedom from backslash and significantly lower joint friction compared with actuators composed by gear drives. The motor used in the experimental robot are listed in Table 1.

Table 1: Servo actuators of the experimental pendulum.

Link	Model	Torque [Nm]	p/rev
Pendulum	DM1015B	15	1,024,000

The servo is operated in torque mode, so the motors act as a torque source and they accept an analog voltage as a reference of torque signal. Position information is obtained from incremental encoder located on the motor. The standard backwards difference algorithm applied to the joint position measurements was used to generate the velocity signals. The manipulator workspace is a circle with a radius of 0.45 m.

Besides position sensors and motor drivers, the robot also includes a motion control board manufactured by Precision MicroDynamic Inc., which is used to obtain the joint positions. The control algorithm runs on a Pentium–II (333 Mhz) host computer.

Figure 1: Experimental robot.

6 Experimental Results

To support our theoretical developments, this Section presents an experimental comparison of different models for parameter identification on a pendulum robot. For all the case the algorithm were developed with the the $\mathbf{P(0)} = \mathbf{diag(10E6)}$ covariance matrix meanwhile $\boldsymbol{\theta}(0) = 0$ at their initial values. The persistent excitation was the same for each model in their amplituds and with the following structure $\boldsymbol{\tau} = 3sin(12.07 + ran_1) + 3sin(2.25 + ran_2)$ where ran_i are random values. The filter applied to the signals in the regressors was 31.83 Hz, it let work with the low frequencies and reject high frequencies and noise. These frequency was obtained from the biggest frequency component at the velocity. The Hamiltonian models proposed need the inverse inertial matrix in order to obtain the momentums , these situation came from their definition (8) for the experiment we considered the inertial found at the Dynamic Models.

The figures 2, 3, depicts the evolution in time for the Dynamic and Filtered Dynamic Models where we can see the convergence. Both models differ very few, the filtered is more smooth than the dynamic.

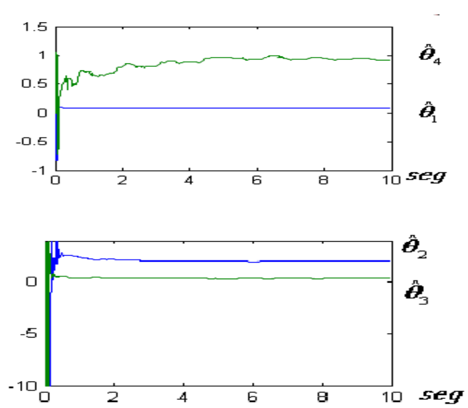

Figure 2: Dynamic Model

The parameter obtained from each model are show in the table 2, the value for $\boldsymbol{\theta}_3$ belongs to the viscous friction has the greater difference 6.5% meanwhile the others stand with less than 0.8%.

The figure 4 depicts the performance of the regressor for the energy model and their values are in the Tabla 2. Owing to the different concept of the

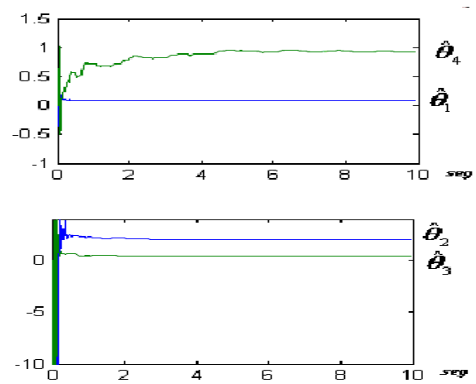

Figure 3: Filter Dynamic Model.

regressor the graphics are different but the parameter $\boldsymbol{\theta}_1$ $\boldsymbol{\theta}_2$ are closer to the dynamic model with a variation between 4% meanwhile the others $\boldsymbol{\theta}_3$ $\boldsymbol{\theta}_4$ are $\pm$ 21% and this is a considerable value.

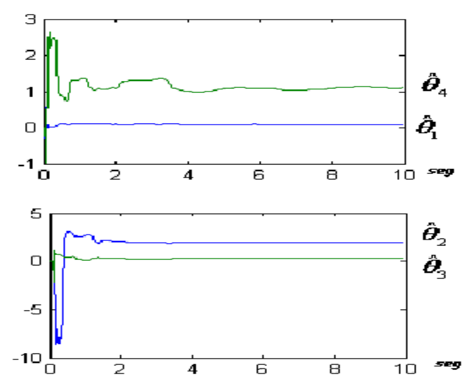

Figure 4: Energy Model.

The figure 5 depicts the evolution in time for Filtered power model, their values are in the Table 2. The estimate parameter $\boldsymbol{\theta}$ are in the range obtained until now, at these case the parameter obtained are closer to the energy model. However the performance at the convergence is better than the other methods.

At the figure 6 depicts the changes in estimate parameters trough the time for the first regressor proposed, the Hamiltonian model, we observed a bigger transitory than the previous models, it is longer but we can observer the parameter convergence.

The estimate parameter $\boldsymbol{\theta}$ obtained from the

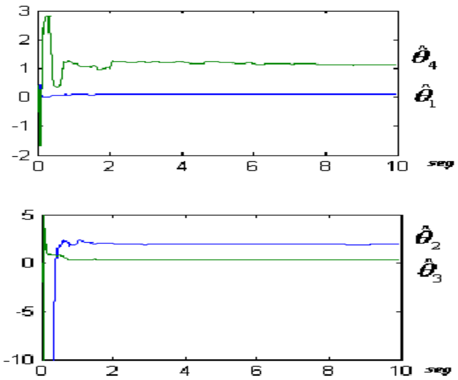

Figure 5: Filtered Power Model.

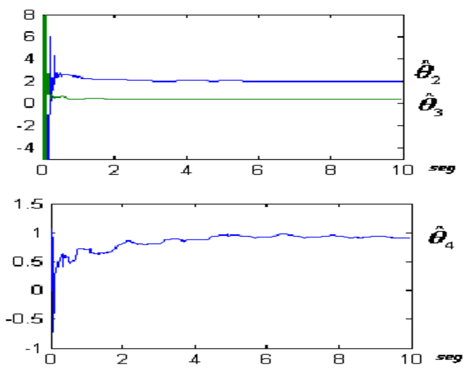

Figure 6: Hamiltonian Model.

Hamiltonian regressor are in the table 2, the inertia is obtained form the first one, the other parameter are practically the same that were obtained at the dynamic model.

The figure 7 show the estimate parameter performance for the Filtered Hamiltonian regressor, the graphic is practically the same that the least one. However the values are in the table 2 and they are practically the same that filtered dynamic modelo.

These two new regressor had been work with the momentum and their graphics for the estimate parameter are practically the same that the Dynamic an Filtered dynamic models respectily.

The $\boldsymbol{\theta}$ vector for us pendulum is defined by $\boldsymbol{\theta} = [I, mgl_c, b, f_c]^T$ where I stand the inertia, m is the total mass , b is the viscous friction and f_c is the coulomb friction. The values obtained for each model are resumed in the table 2.

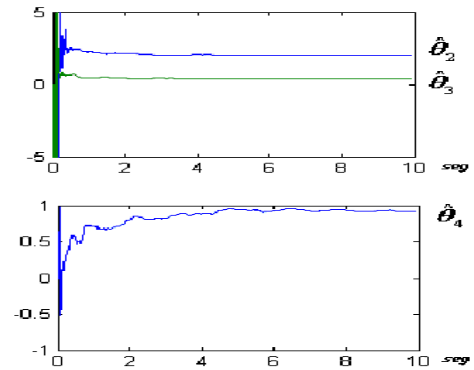

Figure 7: Filtered Hamiltonian Model.

Table 2: Experimental results for a pendulum.

Method	$\boldsymbol{\theta}_1$	$\boldsymbol{\theta}_2$	$\boldsymbol{\theta}_3$	$\boldsymbol{\theta}_4$
Dynamic	0.0895	2.0100	0.3638	0.9163
Filtered Dyn	0.0903	2.0171	0.3874	0.9229
Energy	0.0937	1.9496	0.3291	1.1109
Filtered Pw	0.0911	1.9335	0.3299	1.1201
Hamiltonian		2.0100	0.3638	0.9163
Filtered Ham.		2.0171	0.3874	0.9229

At this point we had obtained the global parameter for us system and we can test it and our models. We applied a signal to the system in open loop, for the simulation with the data report in table 2 we observed the position simulated will follow to the experimental. The figure 8 show the case for using the parameter obtained with the Hamiltonian model, it‘s very important to say that all the models simulated had a good performance,they are similar to this graphic.

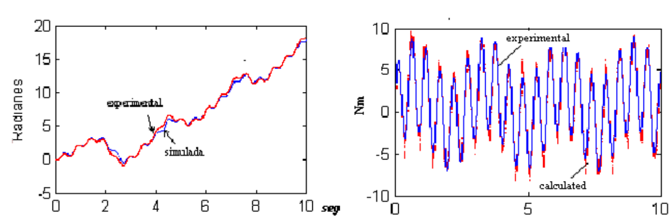

Figure 8: A)Following trayectory B)Torque applied

According to (1), where we employed the values from table II through the different techniques identification, we can obtain the torque applied therefore we can compare these one with the measure torque and we can observe that they are very similar with the same shape. The calculate torque present some peak, they are possible originated for errors introduced by the encoders, measure instruments, that generate this noise. The figure 8 show this situation for Hamiltonian Model and it is similar for the other models. In the same way the velocity obtained from a simulation is closer to the experimental for all models with a little deviations for the same reason that the torque. Let us applied the norm $\mathcal{L}_2$ [12], which is defined as (10) to the calculated and experimental torque so we can obtained a reference for the performance of each model. The results are depicted in figure 9.

$$\mathcal{L}_2 = \sqrt{\frac{1}{t-t_0}\int_{t_o}^{t} \boldsymbol{x}^T \boldsymbol{x} dt} \tag{10}$$

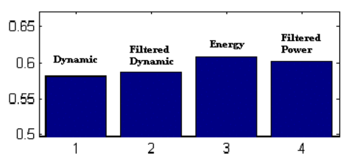

Figure 9: Norma $\mathcal{L}_2$ for all models.

7 Conclusions

The electronics an computation are advancing every day, with better equip and instrument to improve the different techniques for parameter identification according to specific requirement. All the models present here converge, the results from simulation have a good matching with the experimental ones and the $\boldsymbol{\theta}_4$ parameter, it stand the viscous friction, had a stranger performance. The two new regressor proposed presented a good performance with the same results obtained trough the Dynamics model. The norm L2 shows that the best performance is the dynamic model and the Hamiltonian.

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