Method to find dynamic parameters of a system using Neuro-Fuzzy techniques and its application to a pantograph-based leg of a robot AMRU5

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Abstract

This paper proposes a method to find dynamic parameters of a system using Neuro-Fuzzy techniques. We have been focusing mainly on the identification of the elements of the inertia matrix rather than on the rest of the parameters (centrifugal and Coriolis vectors, frictions and gravitational forces) which will be considered as a whole. In many model-based and adaptive control strategies, the precise or estimated knowledge of these parameters is required. In order to determine these parameters, we first begin by building an input/output mapping using ANFIS [1] architecture based on input/output data pairs collected from an experiment or a simulation. The input data is the motion of the joints and the output their actuation. Then we use principles based on the properties of equation which described the dynamic model of robots in order to derive the dynamic parameters. Simulations on the systems where the mathematical dynamic model are well-known demonstrate that the proposed method is quite effective.

1 Introduction

There are different approaches to estimate the dynamic parameters of systems (robots). One solution is to dismantle the system and determine experimentally the mass, position of the center of mass, the moments and the products of inertia of the links. This method is very complex and time consuming. Next to that, we do not have information about the friction. Another approach is to estimate these parameters from

[1] Adaptive Neuro-Fuzzy Inference Systems

CAD[2]-models. With this approach, we encounter the same problem as previous. The approach that has been much applied is the identification using the measurements of motion and actuation data. In the past, this problem has been well-studied [9, 10, 11]. Various techniques based on MLE [3], Levenberg-Marquardt method, LSE [4], Kalman observers, pseudo-inverses ... have been developed. Since the dynamic behaviors of systems may be complicated due to varying environmental changes, the identification of their parameters using techniques mentioned above could be difficult. Soft-computing approaches such as Neuro-Fuzzy techniques are the alternative for solving such complex problems. In this paper, a method to find dynamic parameters using Neuro-Fuzzy techniques is proposed. The paper is organized as follows: in Section 2, some properties for robot dynamics used in the proposed method are enumerated. In section 3, the general principle of the method is presented. In section 4, we apply this method in the identification of the parameters of a two link planar arm and on a pantograph-based leg of a robot AMRU5. Section 5 concludes the paper.

2 Generalized model and some properties for robot dynamics

The dynamic model of robots with n degrees of freedom are formulated in general as follow:

$$\tau = A(\theta)\ddot{\theta} + C(\theta,\dot{\theta})\dot{\theta} + F(\theta,\dot{\theta}) + G(\theta) - J_F^T(\theta)F_{RF} \tag{1}$$

where:

$\tau = [\tau_1, \tau_2 \cdots \tau_{n-1}, \tau_n]^T$	is the vector of forces/torques
$\theta = [\theta_1, \theta_2 \cdots \theta_{n-1}, \theta_n]^T$	is the vector of the position coordinates
$A(\theta)$	is the inertia matrix
$C(\theta,\dot{\theta})$	the centrifugal and Coriolis vectors
$F(\theta,\dot{\theta})$	are frictions forces acting on the joints
$G(\theta)$	the vector of the gravitational forces/torques
$J_F^T(\theta)$	is a matrix $3 \times m$ which is the transpose of a Jacobian matrix
F_{RF}	is the $m \times 1$ vector of the reaction forces that the ground exerts on the robot feet. (F_{RF} is null during the transfer phase)

Equation 1 can be written in a compact way as follow:

$$\tau = A(\theta)\ddot{\theta} + H(\theta,\dot{\theta}) \tag{2}$$

with $H(\theta,\dot{\theta})$ being defined as a whole without distinguishing the differences among the different terms. $H(\theta,\dot{\theta})$ contains centrifugal, Coriolis, gravitational forces, viscous friction, coulomb friction and reaction forces terms. Some properties, used in this paper, of the robotic dynamics with n degrees of freedom are:

- **Inertia Matrix** $A(\theta)$
    1. It is symmetric, i.e. $A(\theta) = A^T(\theta)$

[2]Computer-Aided Design
[3]Maximum Likelihood Parameter Estimation
[4]Linear Least Squares Estimation

2. It is positive definite and bounded below and above, i.e. $\exists 0 < \alpha \leq \beta < \infty$, such that

$$\alpha I_n \leq A(\theta) \leq \beta I_n \ \forall \theta \in \Re^n \tag{3}$$

   where I_n is the $n \times n$ identity matrix.

3. Its inverse $A^{-1}(\theta)$ exists, and is also positive definite and bounded:

$$\frac{1}{\beta} I_n \leq A^{-1}(\theta) \leq \frac{1}{\alpha} I_n \tag{4}$$

- **Centrifugal and Coriolis Forces** $C(\theta, \dot{\theta})$
  1. It is bilinear in $\dot{\theta}$
  2. It may be written in several factorizations, such as

$$\begin{aligned} C(\theta,\dot{\theta})\dot{\theta} &= C_0(\theta,\dot{\theta}) = C_1(\theta)C_2[\dot{\theta}\dot{\theta}] \\ &= C_3(\theta)[\dot{\theta}\dot{\theta}] + C_4(\theta)[\dot{\theta}^2] \end{aligned} \tag{5}$$

     where $[\dot{\theta}\dot{\theta}] = [\dot{\theta}_1\dot{\theta}_2 \ \ \dot{\theta}_1\dot{\theta}_3 \cdots \dot{\theta}_{n-1}\dot{\theta}_n]^T$ and $[\dot{\theta}^2] = [\dot{\theta}_1^2 \ \ \dot{\theta}_1^2 \cdots \dot{\theta}_n^2]^T$
  3. Given two n-dimensional vectors x and y, we have $C(\theta, x)y = C(\theta, y)x$
- **Friction** $F(\theta, \dot{\theta})$: Friction terms are complex and are described only approximately by a deterministic model [1, 2, 3]. The friction is present between any pair of surfaces having relative motion. Despite its complexity, one of the most important characteristics is that it is energy dissipative, i.e. $\dot{\theta}^T F(\theta, \dot{\theta}) \leq 0$..
- **Gravitational force** $G(q)$
  1. It can be derived from the gravitational potential energy function $\mathcal{P}(\theta)$, i.e. $G(\theta) = \frac{\partial \mathcal{P}}{\partial \theta}$
  2. It is also bounded, i.e.

$$\|G(\theta)\| \leq \gamma(\theta)$$

     where γ is a scalar function. For revolute joints, the bound is a constant independent of θ whereas for prismatic joints, the bound may depend on θ.

3 Principle to find dynamic parameters using Neuro-Fuzzy techniques

Experimentally on the real system (robot) or on its simulator, we collect from sensors (encoder, tachogenerator, potentiometer,...) following data sets

$$\{\theta_1(k), \theta_2(k), \cdots, \theta_{n-1}, \theta_n, \tau_1(k), \tau_2(k), \cdots, \tau_{n-1}(k), \tau_n(k)\} \tag{6}$$

To collect these data, the trajectories should be well chosen. They will determine the accuracy of the dynamic parameters found. Much work has been done on this subject [13]. From these data, we constitute $\dot{\theta}_j(k)$ and $\ddot{\theta}_j(k)$ ($j = 1$ to n).
If data sets are collected from a simulator and have no noise, we can estimate the speed and the acceleration of the joints as follow:

$$\dot{\hat{\theta}}_j(k) = \frac{\theta_j(k+1) - \theta_j(k-1)}{2T} \tag{7}$$

$$\tilde{\ddot{\theta}}_j(k) = \frac{\theta_j(k+1) - 2\theta_j(k) + \theta_j(k-1)}{T^2} \tag{8}$$

where T is a sampling time.

In reality, collected data have noises and we cannot use the differentiators as above because they are excessively sensitive to even small errors (they behave as high pass-filter). To solve this problem we accept the assumption that the speeds and the accelerations of the joints change little during five consecutive observations. This assumption is practically valid because with actual microcontroller, the time of sampling is less than 1 ms. We also assume that these observations are near on a parabola of second order. Knowing $\theta_j(k-2),\ \theta_j(k-1),\ \theta_j(k),\ \theta_j(k+1),\ \theta_j(k+2)$ at respectively time $(k-2)T,\ (k-1)T,\ kT,\ (k+1)T,\ (k+2)T$; we would like to find a, b and c such that the errors of these observations data to the parabola $\theta_j = ax^2 + bx + c$ are minimal in the sense of least square. Solving this problem, we have:

$$a = \frac{2\theta_j(k-2) - \theta_j(k-1) - 2\theta_j(k) - \theta_j(k+1) + 2\theta_j(k+2)}{14T^2} \tag{9}$$

$$b = \frac{(20k+14)\theta_j(k-2) - (10k-7)\theta_j(k-1) - 20k\theta_j(k) - (10k+7)\theta_j(k+1) + (20k-14)\theta_j(k+2)}{-70T} \tag{10}$$

As $\dot{\theta}_j(k) = 2akT + b$, we obtain by calculation

$$\tilde{\dot{\theta}}_j(k) = \frac{2\theta_j(k-2) + \theta_j(k-1) - \theta_j(k+1) - 2\theta_j(k+2)}{-10T} \tag{11}$$

We can apply the same procedure to have the acceleration. Doing that, we obtain:

$$\begin{aligned} \tilde{\ddot{\theta}}_j &= \frac{2\dot{\theta}_j(k-2)+\dot{\theta}_j(k-1)-\dot{\theta}_j(k+1)-2\dot{\theta}_j(k+2)}{-10T} \\ &= \frac{4\theta_j(k-4)+4\theta_j(k-3)+\theta_j(k-2)-4\theta_j(k-1)-10\theta_j(k)-4\theta_j(k+1)+\theta_j(k+2)+4\theta_j(k+3)+4\theta_j(k+4)}{100T^2} \end{aligned} \tag{12}$$

Now with the extended collected data (which include the speeds and the accelerations of the joints), we can use these sets for mapping

$$\theta_1(k), \theta_2(k), \cdots, \theta_n, \dot{\theta}_1(k), \dot{\theta}_2(k), \cdots, \dot{\theta}_n, \ddot{\theta}_1(k), \ddot{\theta}_2(k), \cdots, \ddot{\theta}_n$$

to $\tau_j(k)$ (where $j = 1$ to n) in parallel identification model as shown in Figure 1.

ANFIS [5] architecture is used for that. It has been proved that Mamdani controllers as well as Sugeno controllers are universal approximators [4, 5]. ANFIS is one of the first fused Neuro-Fuzzy proposed by Jang [6]. It implements a Sugeno FIS [6]. It has five layers as shown on Figure 2 for 2 input and 3 membership functions.

The first layer has adaptive nodes and it is used for the fuzzification of the input variables. The output of this layer will depend on the selected membership function which can be a triangular, a gaussian, a trapezoidal, a bell-shaped etc. Those parameters which specify a membership function will be called *premise parameters*. The output of the second layer is the product of all incoming signals and represents the firing strength of a rule. The product (it is more appropriate) has been chosen but it can be any T-norm operator that performs fuzzy AND. The third layer normalizes the

[5] Adaptive Neuro-Fuzzy Inference Systems
[6] Fuzzy Inference System

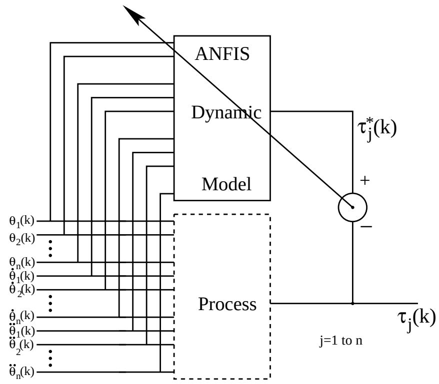

Figure 1: Offline ANFIS parallel identification model

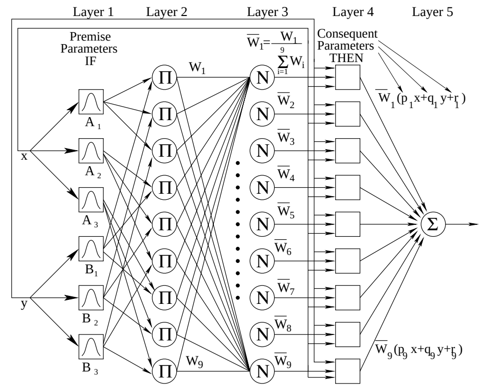

Figure 2: ANFIS architecture

rule strengths. The ith node is calculated as the ratio of the strength of the ith rule to the sum of all firing strengths. The fourth layer has also adaptive nodes. The output of this layer for one node will be the product between the normalized firing strength with a function. This function has parameters called *consequent parameters*. The fifth layer is the output. It computes the overall input as the summation of all incoming signals.

A step in the learning procedure (called hybrid learning) has got two parts [6]:

1. The premise parameters are fixed and the input patterns are propagated up to fourth level of the layer. With the values of this level and the output patterns, optimal consequent parameters are calculated using an iterative least mean square procedure. The least mean square can be used because the output is a linear function of the consequent parameters.

2. The patterns are propagated again with now, consequent parameters fixed. In this part the backpropagation algorithm is used to modify the premise parameters.

After obtaining n Anfis architectures (which express the mapping between data from the motion of the joints and the data of the torque of one joint), we carry out $n+1$ experiments on them. We maintain the same position and speed of the joints but we change $n+1$ times the accelerations. We have

$$\tau_{ij} = \sum_{k=1}^{n} A_{ik}\ddot{\theta}_{kj} + H_i(\theta, \dot{\theta}) \tag{13}$$

where τ_{ij} and $\ddot{\theta}_{ij}$ are respectively the values of the torques and the accelerations on the joint i obtained at the j^{th} experiment. From the properties of the robotic dynamics, the inertia matrix is only dependent of the position (angular or linear position) i.e. by changing only the acceleration, the value of A_{ik} will not change and $H_i(\theta, \dot{\theta})$ will remain the same. Subtracting relations (13) obtained on the same joint but at different experimentations, we have:

$$\tau_{i1} - \tau_{i(j+1)} = \sum_{k=1}^{n} (\ddot{\theta}_{k1} - \ddot{\theta}_{k(j+1)})A_{ik} \tag{14}$$

or

$$\Delta\tau_i = \Delta\ddot{\theta}\ A_i \tag{15}$$

where

$$\Delta\tau_i = \begin{pmatrix} \tau_{i1}-\tau_{i2} \\ \tau_{i1}-\tau_{i3} \\ \vdots \\ \tau_{i1}-\tau_{in} \\ \tau_{i1}-\tau_{i(n+1)} \end{pmatrix}, \Delta\ddot{\theta} = \begin{pmatrix} \ddot{\theta}_{11}-\ddot{\theta}_{12} & \ddot{\theta}_{21}-\ddot{\theta}_{22} & \cdots & \ddot{\theta}_{n1}-\ddot{\theta}_{n2} \\ \ddot{\theta}_{11}-\ddot{\theta}_{13} & \ddot{\theta}_{21}-\ddot{\theta}_{23} & \cdots & \ddot{\theta}_{n1}-\ddot{\theta}_{n3} \\ \vdots & \vdots & \ddots & \vdots \\ \ddot{\theta}_{11}-\ddot{\theta}_{1n} & \ddot{\theta}_{21}-\ddot{\theta}_{2n} & \cdots & \ddot{\theta}_{n1}-\ddot{\theta}_{nn} \\ \ddot{\theta}_{11}-\ddot{\theta}_{1(n+1)} & \ddot{\theta}_{21}-\ddot{\theta}_{2(n+1)} & \cdots & \ddot{\theta}_{n1}-\ddot{\theta}_{n(n+1)} \end{pmatrix},$$

and $A_i = \left[\begin{array}{cccccc} A_{i1} & A_{i2} & \cdots & A_{i(n-1)} & A_{in} \end{array}\right]^T$.

We can then calculate A_i if $\Delta\ddot{\theta}$ is invertible as follow:

$$A_i = \Delta\ddot{\theta}^{-1}\Delta\tau_i \tag{16}$$

And finally we deduced $H_i(\theta,\dot{\theta})$ from equation (13). We can use the property which stipulates that the inertia matrix is symmetric to check the validity of the values of its elements obtained on different joints and experiments (is A_{ij} equal to A_{ji}?).

4 Application of the method

4.1 Identification of the dynamic model and parameters estimation of a two link planar arm

To illustrate the method quoted above, we have applied it to a two link planar arm shown in Figure 3.

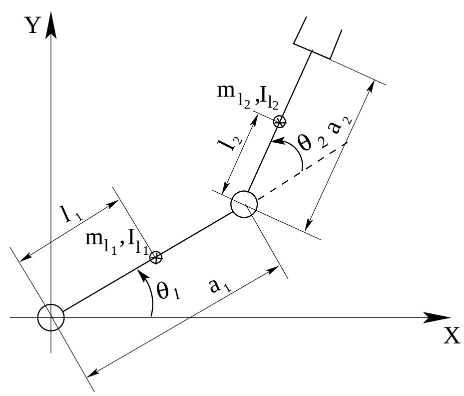

Figure 3: Two link planar arm

The parameters of its dynamic model are well-known. They will enable us to establish comparisons with those obtained by means of the Neuro-Fuzzy model. By neglecting the friction torques and the tip contact forces, the model of the two link planar arm is as follows:

$$\begin{aligned} \tau_1 &= A_{11}\ddot{\theta}_1 + A_{12}\ddot{\theta}_2 + H_1 \\ \tau_2 &= A_{12}\ddot{\theta}_1 + A_{22}\ddot{\theta}_2 + H_2 \end{aligned} \tag{17}$$

where

$$\begin{aligned} A_{11} &= I_{l_1} + m_{l_1}l_1^2 + k_{r1}^2 I_{m_1} + I_{l_2} + m_{l_2}(a_1^2 + l_2^2 + 2a_1 l_2\cos(\theta_2)) + I_{m_2} + m_{m_2}a_1^2 \\ A_{12} &= I_{l_2} + m_{l_2}(l_2^2 + a_1 l_2\cos(\theta_2)) + k_{r_2}I_{m_2} \\ H_1 &= -2m_{l_2}a_1 l_2\sin\theta_2\dot{\theta}_1\dot{\theta}_2 - m_{l_2}l_2\sin\theta_2\dot{\theta}_2^2 + (m_{l_1}l_1 + m_{m_2}a_1 + m_{l_2}a_1)g\cos\theta_1 \\ H_2 &= m_{l_2}a_1 l_2\sin\theta_2\dot{\theta}_1^2 + m_{l_2}l_2 g\cos(\theta_1+\theta_2) \end{aligned}$$

θ_2	$\tilde{A}_{11}$	A_{11}	$\tilde{A}_{12}(1)$	$\tilde{A}_{12}(2)$	A_{12}	$\tilde{A}_{22}$	A_{22}
0.1	249.8	249.76	48.408	48.303	48.375	122.53	122.5
0.2	249.03	249.01	48.022	47.98	48.002	122.52	122.5
0.3	247.78	247.78	47.39	47.38	47.383	122.51	122.5
0.4	246.05	246.06	46.525	46.524	46.527	122.5	122.5
0.5	243.88	243.89	45.435	45.432	45.44	122.49	122.5
0.6	241.27	241.28	44.131	44.122	44.133	122.48	122.5
0.7	238.26	238.25	42.622	42.61	42.621	122.47	122.5
0.8	234.85	234.85	40.916	40.91	40.918	122.46	122.5
0.9	231.06	231.09	39.022	39.048	39.04	122.45	122.5

Table 1: Estimation of the dynamic parameters of a two link planar arm

l_1, l_2 are the distances of the centres of mass of the two links from the respective joint axes;
m_{l_1}, m_{l_2} are the masses of the two links;
m_{m_1}, m_{m_1} are the masses of the rotors of the two joints motors;
I_{m_1}, I_{m_2} are the moments of inertia with respect to the axes of the two joints;
k_{r1}, k_{r2} are the reduction ratio of the gears;
and I_{l_1}, I_{l_2} are the moments of inertia relative to the centres of mass of the two links, respectively.
In order to have numerical values, we use the following data:

$$a_1 = a_2 = 1\text{m} \;\; l_1 = l_2 = 0.5\text{m} \;\; m_{l_1} = m_{l_2} = 50\text{kg} \;\; I_{l_1} = I_{l_2} = 10\text{kg.m}^2$$
$$k_{r1} = k_{r2} = 100 \;\; m_{m_1} = m_{m_2} = 5\text{kg} \;\; I_{m_1} = I_{m_2} = 0.01\text{kg.m}^2$$

From equation 17, we have collected data sets

$$\{\theta_1(k), \dot{\theta}_1(k), \ddot{\theta}_1(k), \theta_2(k), \dot{\theta}_2(k), \ddot{\theta}_2(k), \tau_1(k)\}$$
$$\text{and } \{\theta_1(k), \dot{\theta}_1(k), \ddot{\theta}_1(k), \theta_2(k), \dot{\theta}_2(k), \ddot{\theta}_2(k), \tau_2(k)\}$$

with $\theta_1(k)$ and $\theta_2(k)$ in the range of 0 to $\frac{\pi}{3}$ and k going from 1 to 4096 (the range and the number of data were taken to reduce the offline learning calculation time). We have made trials to determine the appropriate number of membership functions and the type of FIS by considering the final RMSE [7]. We find from different trials that 2 triangular membership functions (N and P) by input and a first-order Sugeno FIS give a small error.

After nearly 409600 iterations for each data sets, we have obtained a RMSE of about 0.0879 for τ_1 and 0.0862 for τ_2.

From the ANFIS models of the two link planar arm obtained, we have solved the equations 15 to estimate its dynamic parameters. Some results are shown in Table 1 (we have chosen for illustration the variation of θ_2 because the matrix A is only dependent on θ_2).

4.2 Identification of the dynamic model and parameters estimation of a AMRU5 leg

The pantograph mechanism has been used in many legged robots project (PV II, TITAN III, TITAN IV, RIMHO, ...). Opposed to other mechanisms, the pantograph

[7] Root Mean Square Error

mechanism exhibits the most potentiality for the following reasons [7, 8]:

- An exact-straight-line foot trajectory can be obtained by actuating only one linear actuator. A high energy efficiency is to be expected.
- The leg geometry can be made more compact by adjusting the magnification ratio.
- The input motions can be mechanically decoupled. The simplest approach to the foot trajectory control can be used.
- The closed-loop gives a good rigidity of the leg

As disadvantage of this mechanism: linear actuating systems are more difficult to design and to protect if normal electric motors are used. Also when using model-based controller, it is not easy to find the parameters of the leg due to the closed-loop. The first problem leads often to the choice of a 2D pantograph mechanism to make the design more compact. In this case, the GDA [8] is not perfect. A 2D pantograph (Figure 4) has been used on the robots MECANT, BOADICEA and the robot AMRU5 (Figure 5) that we have designed.

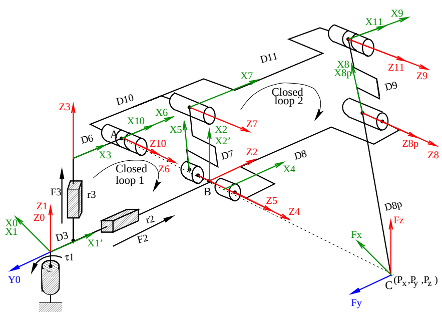

Figure 4: 2D Pantograph Mechanism

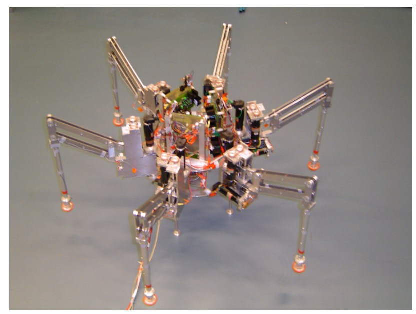

Figure 5: Hexagonal Robot AMRU5

The second problem has been solved using the method explained above. The pantograph mechanism has 2 closed loops and it is not an easy task to derive the dynamic model and the parameters of such mechanism using classical method (Newton-Euler formalism). that is why we have preferred to use Soft-Computing methodology to identify those parameters. Those parameters have been used in the control strategy of the robot. ANFIS has been proved to have the best performance in comparison to others methods (FNN [9], RBFNN [10], RKNN [11], ...) [12].

Due to the pantograph mechanism, the actuators responsible of the translation movement $r3$ will only be used to support the body of the robot against gravity forces and in transfer phase. The actuators that generate the translation movement $r2$ and the rotation θ are used in the tracking of the trajectory when the legs are in the stance phase. As we have a decoupling of $r3$ from $r2$ and θ_1, equation 2 can be split in two parts as follows:

$$\begin{pmatrix} \tau_1 \\ \tau_2 \end{pmatrix} = \begin{pmatrix} A_{11} & A_{12} \\ A_{12} & A_{22} \end{pmatrix} \begin{pmatrix} \ddot{\theta}_1 \\ \ddot{\theta}_2 \end{pmatrix} + \begin{pmatrix} H_1(\theta_1, \theta_2, \dot{\theta}_1, \dot{\theta}_2) \\ H_2(\theta_1, \theta_2, \dot{\theta}_1, \dot{\theta}_2) \end{pmatrix} \quad (18)$$

[8] Gravitational Decoupled Actuation

[9] Feedforward Neural Networks Architecture

[10] Radial Basis Function Neural Networks

[11] Runge-Kutta Neural Networks

$$\tau_3 = A_3\ddot{\theta}_3 + H_3(\theta_3, \dot{\theta}_3) \tag{19}$$

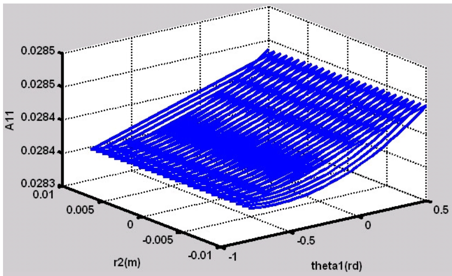

Figure 6: Element A_{11} of the inertia matrix

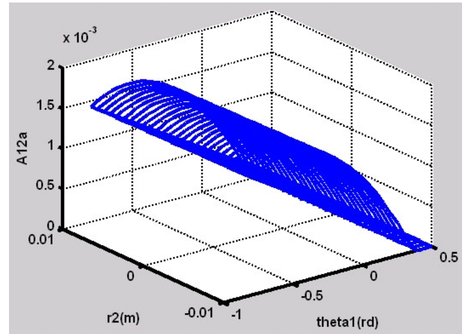

Figure 7: Element $(A_{12})_1$ of the inertia matrix (first method)

We will only consider the system of equation (18) in this paper. The first step to find the dynamic parameters of the AMRU5 leg was the design of an initial FLC [12]. With this initial FLC, the leg has been moved randomly and we have collected data sets necessary to train the ANFIS in the purpose of having the dynamic model of the two considered joints. After having use those data in the training of ANFIS architectures, we have obtained a RMSE of about 0.52 for the joint 1 and of about 6.01 for the joint 2. The results of the elements of the inertia matrix obtained are shown on Figures 6, 7, 8 and 9.

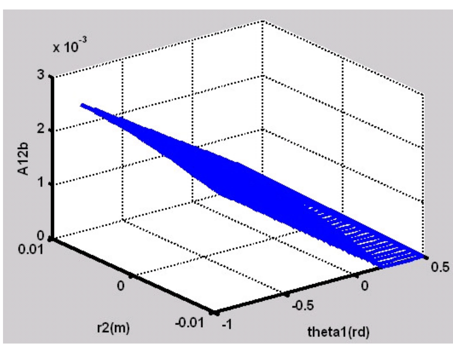

Figure 8: Element $(A_{12})_2$ of the inertia matrix (second method)

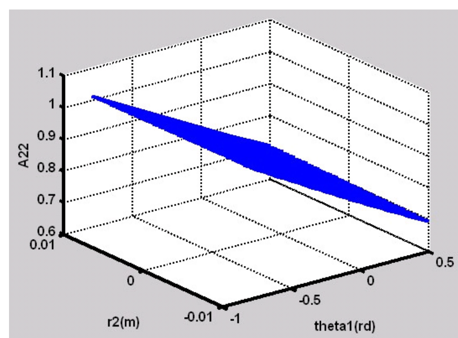

Figure 9: Element A_{22} of the inertia matrix

5 Conclusion

In this paper, we showed the principle to identify the dynamic parameters of a system using Soft-Computing methodology. We first begin by collecting motion and actuation data from well-selected trajectories of the joints. The assumption saying that the variations of the speeds and the accelerations of the joints during 5 consecutive observations are small allow us to derive the speeds and the accelerations of the joints from the measured positions (which include generally noises). This assumption is practically

[12] Fuzzy Logic Controller

acceptable in several parts of the selected trajectories. Then we use ANFIS architectures in the mapping of motion data of the joints to actuation data of one joint. Finally to identify the elements of the inertia matrix, we apply on the ANFIS architectures obtained, the principle that the elements of the inertia matrix are only dependent of the position of the joints . This method has been tested on a two link planar manipulator because we have a mathematical model of it. The comparison between the outputs of the method and the mathematical model show the validity of it. We have then used this method to identify the dynamic parameters of a pantograph-based leg of a robot AMRU5. The use of the parameters obtained in a model-based adaptive controller developed on a simulator of the leg, has shown the efficiency of this method.

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