INTEGRATING FUZZY ADAPTIVE AND FUZZY ROBUST FORCE/POSITION CONTROL OF ROBOT MANIPULATORS

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Abstract: In this paper is proposed a control structure integrating fuzzy adaptive and fuzzy robust position and force control, in an explicit position based force control strategy, to compensate for modeling uncertainties of the manipulator and environment. The fuzzy robust controller is a position controller in the inner control loop, to compensate for uncertainties in the robot manipulator model. The control surfaces in the boundary layers are designed, so that the region near the origin of the state space can be reached faster. The fuzzy adaptive controller in the outer loop adjusts the manipulator tip position to compensate for uncertainties in the environment (stiffness and geometric location) with the purpose of reducing the error force. It uses a fuzzy inverse model and a learning mechanism to adapt the membership functions of the fuzzy logic controller. To show the performance on tracking force/position trajectories and to validate the proposed control structure scheme, simulations results are presented with a three degree of freedom manipulator.

Keywords: Robotics, fuzzy adaptive control, force control, fuzzy robust control.

1. INTRODUCTION

The classical force control strategies like impedance control (Hogan 1985), hybrid impedance control (Anderson and Spong 1988), parallel force/position control (Chiaverini *et al.* 1998), are not suffice to bring robots executing tasks with interaction with the environment, like grinding, deburring and polishing. This is due to variable payloads, torque disturbances, parameter variations, unmodeled dynamics and uncertainties in the environment parameters. Robust control (Liu and Goldenberg 1991), classical adaptive control (Colbaugh *et al.* 1993), neural network compensation (Jung and Hsia 1995) and fuzzy adaptive control (Hsu and Fu 1996) has been a solution proposed to deal some of those problems. Even so a great research activity in force control has been registered in the last decade, however, only a few of these results has been implemented in industrial robots. Therefore, more sophisticated control structures are required to cope with overall uncertainties in the force control problem. In (Marques and Sá da Costa 1999) it was proposed a Fuzzy Sliding mode Controller, "FSMC", in the realm of implicit force control, to compensate for uncertainties in the manipulator dynamic model. In another work, (Marques *et al.* 1997), it was proposed a position based explicit Fuzzy Adaptive Controller, "FAC", to compensate for uncertainties in the environment parameters. Both of these control strategies reveled a good performance in compensation of uncertainties they were designed to. In this paper it is proposed an integration of these two control strategies, in order to compensate for the overall uncertainties in the force control problem. So, this paper is organized as follows: Section 2 presents a brief description of the manipulator dynamics in the constraint coordinate frame and the environment model. Section 3 presents the overall control structure, with a brief description of the two control approach. Simulation results are presented in Section 4, and finally in Section 5 conclusions are drawn.

2. THE ROBOT DYNAMICS AND ENVIRONMENT

Consider the equation of a manipulator in constrained environment:

$$\boldsymbol{H}(\boldsymbol{q})\ddot{\boldsymbol{q}} + \boldsymbol{h}(\boldsymbol{q}, \dot{\boldsymbol{q}}) = \boldsymbol{\tau} - \boldsymbol{J}^T \boldsymbol{f}_e \tag{1}$$

The vectors $\boldsymbol{q}$, $\boldsymbol{\tau}$ and $\boldsymbol{f}_e \in \Re^n$ $(n \times 1)$ represent the internal coordinates, the torque at the joints, and the force exerted by the manipulator against the environment, respectively. The term $\boldsymbol{h}$ is composed by: $\boldsymbol{h}(\boldsymbol{q}, \dot{\boldsymbol{q}}) = \boldsymbol{C}(\boldsymbol{q}, \dot{\boldsymbol{q}})\dot{\boldsymbol{q}} + \boldsymbol{g}(\boldsymbol{q}) + \boldsymbol{d}(\dot{\boldsymbol{q}})$, $\boldsymbol{H}$ and $\boldsymbol{C}$ are the matrices of inertia and Coriolis, respectively, $\boldsymbol{g}$ and $\boldsymbol{d}$ are the vectors of torques due to the gravity and friction, respectively and $\boldsymbol{J}$ is the Jacobian matrix. Generally, a task frame attached to the constrained surface is selected, when the robot manipulator tip moves in a force control task, so as to easily describe position trajectories and desired force profile $\boldsymbol{f}_d$. The internal coordinates $\boldsymbol{q}$, $\dot{\boldsymbol{q}}$ and $\ddot{\boldsymbol{q}}$ must be transformed in external ones $\boldsymbol{x}$, $\dot{\boldsymbol{x}}$ and $\ddot{\boldsymbol{x}}$, by means of the direct kinematics, where $\boldsymbol{x}$ is the position of the tip manipulator in the task frame coordinates. Regarding the external forces, let decompose the force vector $\boldsymbol{f}_e$, given by the force sensor in all of it components and already transformed in the task frame: a normal component f_n in the perpendicular direction to the surface environment and a tangential component f_t, in the velocity tip manipulator direction. On the other hand, let assume the friction coefficient μ between the manipulator tip and the environment is well known. In this way, it is possible to know exactly the perpendicular direction $\widehat{\boldsymbol{n}}$ to the environment surface, implicitly given by the force sensor. So, without lost of generality, considering only three elements in position and force, the force $\boldsymbol{f}_e$ and position $\boldsymbol{x}$, defined in its components as: $\boldsymbol{f}_e = [f_n, f_t, 0]^T$ and $\boldsymbol{x} = [x_1, x_2, x_3]^T$ respectively. In this way, the force control is done along the first component and the position control is done on the other last two components. In what concerns to the environment characteristics, several models are proposed, based on elementary mechanic components (spring, dump and mass), with one or two degree of freedom (Epping and Seering 1987). In this article, the environment is modeling like a spring element with stiffness coefficient k_e.

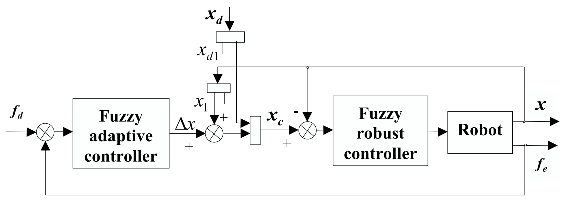


Fig. 1. Schema of the overall control structure.

3. THE OVERALL CONTROL STRUCTURE

A schema of the global control structure is represented in the Fig. 1. This control structure is a position based explicit force control. In the inner position controller is the FSMC to compensate for uncertainties in the dynamic model of the manipulator. The FAC adjusts the position of the tip manipulator x_1 in the perpendicular direction to the surface environment, based in the error force.

3.1 *The Fuzzy sliding mode controller*

The fuzzy robust controller here proposed, is a counterpart of the Sliding Mode Controller with Boundary Layer, SMCw/BL which is the so called Fuzzy Sliding Mode Controller, FSMC.

The Sliding Mode Control, SMC requires a control law such that, for a second order system, the state vector $(e,\ \dot{e})^T$; $e = x - x_d$, remains in the first order sliding line $s = \dot{e} + \lambda e = 0$. The introduction of a Boundary Layer BL, near the sliding line $s = 0$ smoothes out the dynamics of the control input, avoids the chattering phenomena, and ensures the system states remain within the BL. Inside this BL, the linear transfer characteristics states a null control signal along with it, and an increasing in the absolute value of the control signal as the states are far away from the switching line. This behavior is similar to a fuzzy system with a diagonal form. So, changing the output of the control signal given by the linear transfer characteristic of the sliding mode controller inside the BL, now given by a fuzzy system, we have the so called FSMC. We take back to the advantages of the FSMC. Lets first consider a vector cartesian acceleration control $\boldsymbol{u_x}$, based on a decentralized concept for each degree of freedom:

$$\boldsymbol{u_x} = \boldsymbol{G}\left(\ddot{\boldsymbol{x}}_d - \Lambda\dot{\boldsymbol{e}} - \boldsymbol{K}\boldsymbol{u}_{fz}\right), \tag{2}$$

where $\boldsymbol{G}$ e $\boldsymbol{K}$ are diagonal matrices based on the bounds of the unknowns and uncertainties, determined by the sliding condition of the sliding lines vector $\boldsymbol{s} = \boldsymbol{0}$ to be a domain of attraction, Λ is a diagonal matrix with frequency values λ_i, $\ddot{\boldsymbol{x}}_d$ is the desired acceleration, $\dot{\boldsymbol{e}} = \dot{\boldsymbol{x}} - \dot{\boldsymbol{x}}_d$ and $\boldsymbol{u_{fz}} = [u_{fz_1}\ u_{fz_2} \cdots\ u_{fz_n}]^T$ is the output vector of each fuzzy system. The difference between the SMCw/BL and the FSMC, lies on the term $\boldsymbol{u_{fz}}$ (Palm *et al.* 1997), so that, in the former that control term $\boldsymbol{u}_c$ is given by:

$$\boldsymbol{u}_c = sat\left(\boldsymbol{\Phi}^{-1}\boldsymbol{s}\right), \tag{3}$$

where the matrix $\boldsymbol{\Phi}$ is of diagonal form, with elements ϕ_i. The torque control $\boldsymbol{\tau}$ is obtained with the dynamic inverse control law:

$$\boldsymbol{\tau} = \boldsymbol{H}(\boldsymbol{q})\boldsymbol{u}_q + \boldsymbol{h}\left(\boldsymbol{q}, \dot{\boldsymbol{q}}\right), \tag{4}$$

where the joint acceleration $\boldsymbol{u}_q$ is achieved from the cartesian acceleration $\boldsymbol{u}_x$, by means of the Jacobian $\boldsymbol{J}$:

$$\boldsymbol{u}_q = \boldsymbol{J}^{-1}\left(\boldsymbol{u}_x - \dot{\boldsymbol{J}}\dot{\boldsymbol{q}}\right) \tag{5}$$

Lets concentrate on the fuzzy term $\boldsymbol{u_{fz}}$. The purpose of the FSMC is working inside the boundary layer, in such away that, the states in it, are faster attracted to the switching line components of $\boldsymbol{s} = \dot{\boldsymbol{e}} + \Lambda\boldsymbol{e}$, with $\boldsymbol{e} = [e_1\, e_2\, \cdots\, e_n]^T$ and $\dot{\boldsymbol{e}} = [\dot{e}_1\, \dot{e}_2\, \cdots\, \dot{e}_n]^T$, than in the simple SMCw/BL. Lets consider the normalized phase plane such that $\boldsymbol{s_N} = \dot{\boldsymbol{e}}_N + \boldsymbol{\Lambda}_N\boldsymbol{e}_N$, with $\boldsymbol{e}_N = [e_{N_1}\, e_{N_2}\, \cdots\, e_{N_n}]^T$, $\dot{\boldsymbol{e}}_N = [\dot{e}_{N_1}\, \dot{e}_{N_2}\, \cdots\, \dot{e}_{N_n}]^T$ with $\boldsymbol{e}_N = \boldsymbol{G}_e\boldsymbol{e}$ and $\dot{\boldsymbol{e}}_N = \boldsymbol{G}_{\dot{e}}\dot{\boldsymbol{e}}$, where $\boldsymbol{G}_e$ and $\boldsymbol{G}_{\dot{e}}$ are diagonal matrices with the scaling factors. Chosen $\boldsymbol{G}_e$ and $\boldsymbol{G}_{\dot{e}}$, the normalized slopes given in $\boldsymbol{\Lambda}_N$ with diagonal elements λ_{N_i}, are given by:

$$\boldsymbol{\Lambda}_N = \boldsymbol{G}_e^{-1}\boldsymbol{G}_{\dot{e}}\boldsymbol{\Lambda} \tag{6}$$

Also, the boundary layer $\boldsymbol{\Phi}$ is normalized in $\boldsymbol{\Phi}_N$ and given by:

$$\boldsymbol{\Phi}_N = \boldsymbol{G}_{\dot{e}}^{-1}\boldsymbol{\Phi} \tag{7}$$

In this away, the normalized phase plane $(e_{N_i}, \dot{e}_{N_i})$, each component can be represented in the Fig 2. In the SMCw/BL, the control u increases monotonically with the distance $|s|$, independently of the distance d_i in Fig 2 measured along of a parallel direction to the switching line. So, the errors along this parallel direction are interpreted in the same way. So, introducing an additional degree of freedom, distance d_i in Fig 2, the region near the state space can be reached faster. This is one concept of the FSMC given by (Palm *et al.* 1997). Regarding the two following rules:

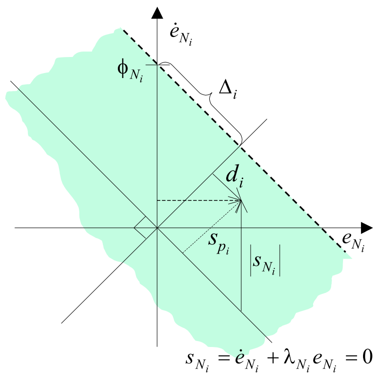


Fig. 2. Normalized phase plane.

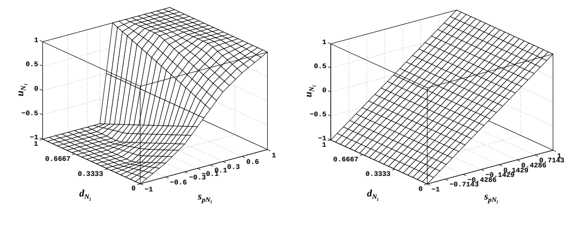
$$R1 : \boldsymbol{IF}\ |s_p|\ \text{increase}\ \boldsymbol{THEN}\ |u|\ \text{increase}$$
$$R2 : \boldsymbol{IF}\ d\ \text{increase}\ \boldsymbol{THEN}\ |u|\ \text{increase} \tag{8}$$

a rule base given at Table 1 can be designed to reflect this behavior. The suffix L, M and H

Table 1. Rule base s_p-d

$\mathbf{d/s_p}$	NH	NM	NL	ZN	ZP	PL	PM	PH
H	PH	PH	PH	PH	NH	NH	NH	NH
M	PH	PH	PH	PM	NM	NH	NH	NH
L	PH	PH	PM	PL	NL	NM	NH	NH
Z	PH	PM	PL	ZP	ZN	NL	NM	NH

stands for Low Medium and High respectively, the prefix N and P stands for Negative and Positive respectively, and Z for near Zero. The control surface generated by the fuzzy system of the FSMC, with a Takagi Sugeno system, a fuzzy partition in the antecedents and singleton values at the consequents, is represented in the Fig. 3a. In contrast, in the SMCw/BL, as that distance d_i is not considered, an equivalent flat control surface is generated, Fig. 3b. So it can be stated that SMCw/BL, is a particular case of the FSMC. In



(a) Control surface of the FSMC. *(b) Control surface of the SMCw/BL.*

Fig. 3. Control surfaces.

this way, each fuzzy system of the FSMC has two inputs: the distances s_{p_i} and d_i, and one output u_{fz_i}. The maximum value to s_{p_i} is achieved by:

$$s_{p_{i_{max}}} = \frac{\phi_{N_i}}{\sqrt{1 + \lambda_{N_i}^2}} \tag{9}$$

By the other hand, the maximum value allowed to d_i is the product of the parameter Δ_i, Fig. 3a, by a factor β_i. Being Δ_i given by:

$$\Delta_i = \frac{\lambda_{N_i}\phi_{N_i}}{\sqrt{1+\lambda_{N_i}^2}}, \qquad (10)$$

it can be defined the diagonal matrices $\boldsymbol{G}_{sp}$ and $\boldsymbol{G}_d$ which elements are: $\frac{\sqrt{1+\lambda_{N_i}^2}}{G_{\dot{e}_i}\phi_i}$ and $\frac{\sqrt{1+\lambda_{N_i}^2}}{\beta_i\lambda_{N_i}G_{\dot{e}_i}\phi_i}$ respectively, such that the normalized values s_{p_N} and d_N are:

$$\boldsymbol{s}_{pN} = \boldsymbol{G}_{sp}\ \boldsymbol{s}_p; \qquad \boldsymbol{d}_N = \boldsymbol{G}_d\ \boldsymbol{d} \qquad (11)$$

The output u_{fz_i} is in the interval $[-1,\ 1]$, such that the maximum absolute value of the term $K_i \times u_{fz_i}$ be K_i.

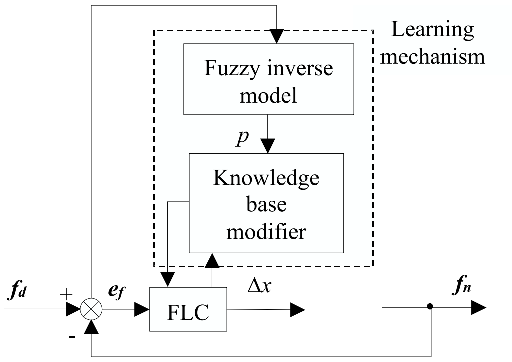


Fig. 4. Control schema of the FAC.

3.2 *The Fuzzy adaptive controller*

The FAC is a fuzzy adaptive controller, based on the Fuzzy Model Reference Learning Controller (Layne and Passino 1996). The FAC is mainly based on the Fuzzy Logic Controller FLC, and the learning mechanism. The FLC is adapted in the membership functions of its consequents by the learning mechanism. The inputs of the FLC are the error force $e_f(kT) = f_d(kT) - f_n(kT)$ and its finite difference $\Delta_{e_f}(kT) = e_f(kT) - e_f(kT-T)$ or by the trapezoidal area of the error force $\delta e_f(kT) = \frac{e_f(kT)+e_f(kT-T)}{2}T$. The learning mechanism is composed by the fuzzy inverse model and the knowledge-base modifier. The fuzzy inverse model attempts to characterize in an approximate away the representation of the inverse dynamics of the environment and so, it is called the fuzzy inverse model. The fuzzy inverse model, accordingly (Layne and Passino 1996), maps the error in the output variables and possibly other parameters such as the functions of the error and the process operating conditions, to the necessary changes in the input process. Here, the fuzzy inverse model is designed how to adjust the position tip manipulator, in the perpendicular direction to the environment surface, to compel the force $f_n(kT)$ exerted on it, to be as close as possible to $f_d(kT)$. The knowledge base modifier performs the function of modifying the fuzzy controller so that better performance is achieved. Based on the necessary changes given by the output of fuzzy inverse model $p(kT)$, the knowledge base modifier changes the membership functions of the FLC consequents, only for those whose activation level δ_{ij} are > 0 at the instant $(kT-T)$. All others remain unchanged. This can be formulated as:

$$\begin{aligned} C_{ij}(kT) &= C_{ij}(kT-T) + p(kT) \\ &\quad if \quad \delta_{ij}(kT-T) > 0; \end{aligned} \qquad (12)$$

and

$$\begin{aligned} C_{ij}(kT) &= C_{ij}(kT-T) \\ &\quad if \quad \delta_{ij}(kT-T) = 0 \end{aligned} \qquad (13)$$

It is shown in (Layne and Passino 1996), the FAC output that would have been desired, is expressed by:

$$\Delta x^*(kT-T) = \Delta x(kT-T) + p(kT) \qquad (14)$$

In the inner position controller - the FSMC - follows the commanded positions, velocities given by the planner in the positions controlled direction. In the force controlled direction those commanded position and velocity are given by the FAC. So, in this last controlled direction, representing the position and velocity as a two component vector $\boldsymbol{x}_c = [x_c\ \dot{x}_c]^T$, the element x_c is given by:

$$x_c = x + u_{FAC}, \qquad (15)$$

where x is the tip position manipulator and u_{FAC} is the output of the FAC. To determine the sliding variable along this direction, the vector $[e_x\ \dot{e}_x]^T$ is given by:

$$[e_x\ \dot{e}_x]^T = \boldsymbol{x} - \boldsymbol{x}_c = -[u_{FAC}\ \dot{u}_{FAC}]^T \qquad (16)$$

4. SIMULATION RESULTS

The overall control structure described in Section 3 is now applied, by simulation, to the first three links of the PUMA 560 robot, tracking a trajectory in and against the plane located at $x_e = 0.3m$ as shown in Figure 5. The simulation environment incorporates the model of the robot, as in (Corke 1996), including the non-linear arm dynamics and joint friction, providing the basis for a realistic evaluation of the controller performance. The control scheme applied to the dynamic model of the robot used in the study, was implemented in the MATLAB/SIMULINK environment, using the Runge-Kutta fourth order integration method. The control laws applied to the manipulator model where implemented with a sampling frequency of 1 kHz. The dynamic inverse control law of the manipulator only considered the main diagonal of the inertial matrix and the gravitational terms:

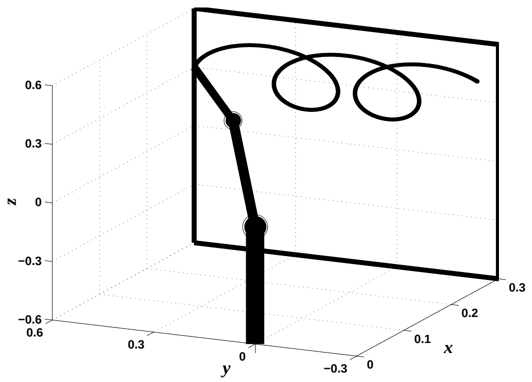
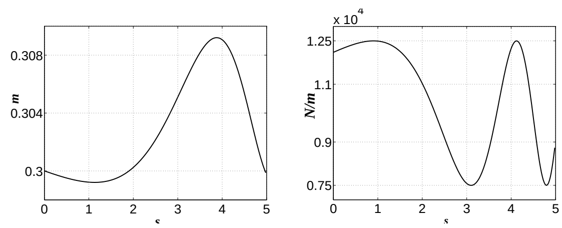


Fig. 5. trajectory of the 3-DOF manipulator

$$\begin{bmatrix} \tau_1 \\ \tau_2 \\ \tau_3 \end{bmatrix} = \begin{bmatrix} \widehat{H}_{1,1} & 0 & 0 \\ 0 & \widehat{H}_{2,2} & 0 \\ 0 & 0 & \widehat{H}_{3,3} \end{bmatrix} + \begin{bmatrix} g_1 \\ g_2 \\ g_3 \end{bmatrix} \quad (17)$$

For robustness studies, the inertial parameters, like link masses and moments of inertia are disturbed from its nominal value in a percentage between 10% and 30%. The desired force profile is presented in Fig. 4 and the environment assumes an irregularity along the x axis as in Fig. 7a and its stiffness coefficient varies accordingly Fig. 7b.

Fig. 6. Force profile.



(a) *Environment position* (b) *Environment stiffness*

Fig. 7. Real environment characteristics.

Table 2. Rule base of the fuzzy inverse model.

$\widetilde{e}_f \setminus \widetilde{\Delta e}_f$	NH	NM	NL	Z	PL	PM	PH
PH	Z	Z	PL	PL	PM	PH	PH
PM	NL	Z	PL	PL	PM	PM	PH
PL	NM	NL	Z	PL	PL	PH	PH
Z	NH	NM	NL	Z	PL	PM	PH
NL	NH	NM	NL	NL	Z	PL	PM
NM	NH	NM	NM	NL	NL	Z	PL
NH	NH	NH	NM	NL	NL	Z	Z

It is assumed that the manipulator is already in contact with the surface and the end-effector always maintains contact with the environment during the task execution. The values for the three parameters λ_i was chosen to be $\lambda_i = 50s^{-1}$; $i = 1, 2, 3$ assuming that the unmodeled frequencies are around $200s^{-1}$. The parameters of the matrices $\boldsymbol{G}$ and $\boldsymbol{K}$ given in (2) were assumed as: $\boldsymbol{G} = diag(G_1, G_2, G_3) = diag(0.485, 0.439, 0.389)$ and $\boldsymbol{K} = diag(K_1, K_2, K_3) = diag(20, 20, 25)$. The boundary layer thickness for the three subsystems was setting as $\boldsymbol{\Phi} = diag(\phi_1, \phi_2, \phi_3) = diag(0.06, 0.025, 0.1)$ for the three orthogonal directions. The scaling factors of the FSMC fuzzy systems are, $\boldsymbol{G}_e = diag(200, 200, 200)$ and $\boldsymbol{G}_{\dot{e}} = diag(4, 4, 4)$.

Table 3. Rule base of the FLC.

$\widetilde{e}_f \setminus \widetilde{\Delta e}_f$	N	Z	P
P	C_{11}	C_{12}	C_{13}
Z	C_{21}	C_{22}	C_{23}
N	C_{31}	C_{32}	C_{33}

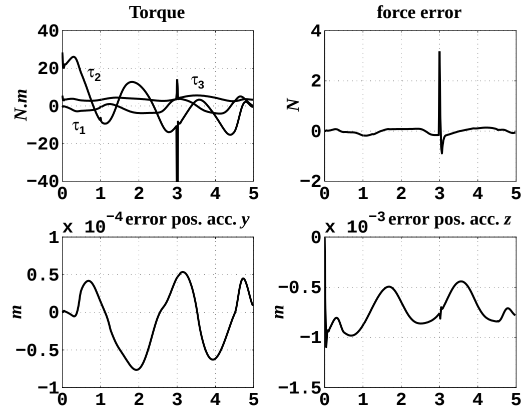


Fig. 8. Simulation results. Torque and errors

The rule base of the fuzzy inverse model is presented on Table 2 and the rule base of the FLC has nine rules, accordingly to Table 3. The centers C_{ij} are those adapted by the learning mechanism. It was assumed the inputs of the fuzzy inverse model and the FLC are the same: the force error e_f and its difference Δe_f. The scaling factors to the fuzzy inverse model are [8 6; .002] and [8 8; .001] for the FLC. All the fuzzy systems are Takagi Sugeno type, with a fuzzy partition at the antecedents, trapezoidal shape and singletons C_{ij} at the consequents. The simulation results can be observed in Figs 8, 9 and 10. In Fig 8 the torques and the errors in position and force are presented, where no chattering symptoms, even in the presence of uncertainties in both environment and manipulator model. In Fig 9 the results under the SMCw/BL and under the FSMC can be bring face to face. It shows the faster attraction of the states to the origin, when under the FSMC. Finally, the action of the FAC in the perpendicular direction of the environment surface, direction x, adapting the membership functions of the FLC consequents shows a very efective compensation for uncertainties in the environment.

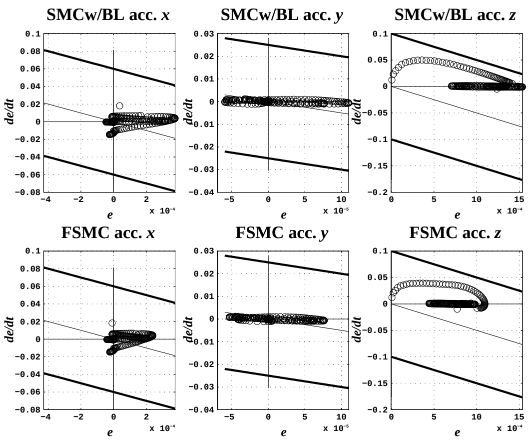


Fig. 9. The error in the phase plane under SMC with BL and FSMC.

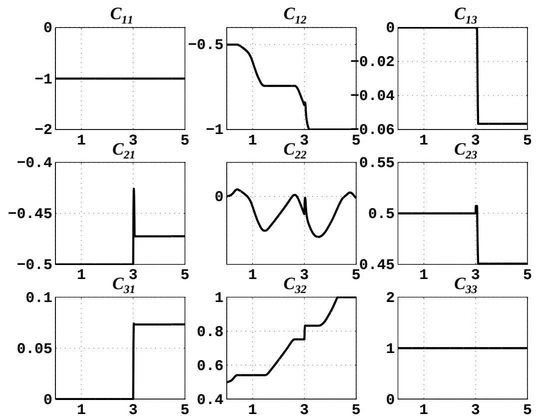


Fig. 10. The adaptation of the consequents of the FLC membership functions.

5. CONCLUSIONS

In this article, an integration of the fuzzy adaptive and fuzzy robust force/position control structure to compensate for overall uncertainties was presented. This control structure is an explicit position based force control. The position is adjusted by the fuzzy adaptive controller in the perpendicular direction to surface environment, to compensate for uncertainties in the environment. In the inner position controller a fuzzy sliding mode control compensates for uncertainties in the dynamic model of the manipulator. The states in the phase plane are attracted to the origin, introducing an additional degree of freedom, resulting an improvement in performance and chattering free. The interaction between the two controllers is effective and the overall uncertainties accordingly the perpendicular direction to the surface environment are both compensated. This control structure also behaves with a good performance in the presence of non rigid materials and considering noise in the force signal, even thought the results were not presented here, by the sake of brevity. An implementation on this control structure is undergoing on a robot PUMA 560.

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