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ADAPTIVE FUZZY SLIDING MODE MOTION CONTROL OF ROBOT MANIPULATOR

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Abstract: This paper describes development and implementation of a decentralized continuous sliding mode motion controller for the robot manipulators. Adaptive fuzzy logic systems (FLSs), one for each robot axis, are employed to approximate almost a whole system dynamics. The structural properties of the robot dynamics are used for division of the each FLS to three simpler subsystems. This reduces the FLS's complexity, emphasizes their transparency and enables systematized inclusion of the linguistic knowledge. The validity of the controller scheme was tested by experiments on a three-degree of freedom direct drive robot. *Copyright © 2002 IFAC*

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1. INTRODUCTION

Performance of many motion control systems is limited by variations of system parameters and disturbances such as payload changes. This specially applies for direct drive robots with their highly nonlinear dynamics and model uncertainties. The control approaches that can be used for control of such mechanisms range from classical adaptive and robust control to the new methods that usually combine good properties of the classical control schemes with fuzzy, genetic and neural network based approaches. Sliding mode control (SMC) is often favored basic control approach, especially because the insensitivity property toward the parametric uncertainties and the external disturbances (Utkin, 1981). However discontinuous control typical for this control leads to chattering, a high frequency oscillations in a velocity. To solve this problem the modification of SMC with a continuous approximation of discontinuous control law was proposed. Here the nonlinearity is approximated by high gain feedback in the boundary layer (Slotine, 1991). This eliminates chattering to some extent, but also the invariance properties associated with ideal sliding mode are lost. In the sequel research the continuous SMC law was proposed, (Šabanović et al., 1997; Jezernik, et al., 1994). However these schemes require dynamic model of a system or the disturbance estimation schemes. Also the FLSs or adaptive FLS have been used a lot in the model free robot control. The survey of their usage in the frame of sliding mode control is given by (Kaynak et al., 2001). Very often the approximation capabilities of a FLS are used for compensating the unknown dynamics. For example in (Yoo and Ham, 2000) FLS is used to compensate an influence of the friction and payload variation. Tsai (Tsai et al., 2000) uses FLS for compensating the whole dynamics and directly calculating the control. In (Hwang and Kuo, 2001) authors again use FLS to model uncertainties, which are not comprehended in the model derived with the Lagrange's dynamic principle. Weakness of the most of the listed schemes is that they employ a large number of rules for compensating only a small part of dynamics, which result in non-transparent 'neural network' like FLSs. Additionally they are mostly tested only by the simulations.

We are putting the emphasis in this work on the development of the disturbance estimator for the

robot mechanism, which is able to estimate whole dynamics and it is not too complex and computationally costly. In the application case study the motion control tasks were performed on a three-degree of freedom direct drive robot. A good tracking accuracy together with the robustness property demonstrated by the varying payload, confirms the usefulness of the proposed controller.
This paper is organized as follows. In Section 2 some sliding mode control preliminaries are given. In Section 3 a sliding mode control for robot is developed. An adaptive FLS for disturbance estimation is proposed in the section 4. A structure of FLS and adaptation laws are described. The stability is proved via the Lyapunov theorem. Section 5 presents division of FLSs into three subsystems. Section 6 describes the control plant, linguistic knowledge and its incorporation in the FLSs. In Section 7 the validity of the proposed controller is verified by the experiments. Conclusions are drawn in the Section 8.

2. CONTINUOUS SLIDING MODE CONTROL

Consider a system with uncertainities and external disturbances:

$$\dot{x}(t) = f(x) + \Delta f(x,\theta) + [B(x) + \Delta B(x,\theta)] \cdot u(t) + + d(x,\theta,t) \quad (1)$$

$x(t) \in \Re^n$ is the state vector, $u(t) \in \Re^m$ is the control vector, $f(x), \Delta f(x,\theta) \in \Re^n$, $B(x), \Delta B(x,\theta) \in \Re^{nxm}$. $\Delta f(x,\theta)$ and $\Delta B(x,\theta)$ represent the system uncertainties, θ is an unknown parameter vector. $d(x,\theta,t)$ includes unmodelled dynamics and external disturbances. When the matching condition is fulfilled as follows: $\Delta f(x,\theta) = B(x)\Delta\tilde{f}(x,\theta)$, $\Delta B(x,\theta) = B(x)\Delta\tilde{B}(x,\theta)$, $d(x,\theta,t) = B(x)\tilde{d}(x,\theta,t)$, then system (1) can be written as (2). $w(x,u,\theta,t)$ represents total plant uncertainties.

$$\dot{x}(t) = f(x) + B(x)u(t) + B(x)w(x,u,\theta,t) \quad (2)$$

First step in a sliding mode control design is to chose a set of sliding manifolds (3), so that system in the sliding mode has desired asymptoticaly stable dynamics.

$$\sigma(x) = [\sigma_1(x), \sigma_2(x), .. \sigma_m(x)]^T . \quad (3)$$

In the sliding mode (4) must be satisfied.

$$\sigma(x) = 0, \quad \dot{\sigma}(x) = 0 . \quad (4)$$

Next the control has to be determined. Mostly an equivalent control method is used. Equivalent control consist of the two parts:

$$u_{eq} = u_{dyn} + u_w \quad (5)$$

where u_{dyn} represents nominal control and u_w disturbance compensation part. Let the switching function be a linear function of the states. Then the nominal control for system (2) is (6). It can be derived by considering condition for sliding regime ($\dot{\sigma}(x) = [\partial\sigma/\partial x]\dot{x} = 0$).

$$u_{dyn} = -\left(\frac{\partial\sigma}{\partial x}B\right)^{-1} \frac{\partial\sigma}{\partial x} f(x) \quad (6)$$

In classical sliding mode control an additional switching part Δu is added to the control. The control now has a form (7). Switching part is needed to assure convergence of the system states to sliding manifolds in finite time.

$$u = u_{eq} + \Delta u \quad (7)$$

Δu can be calculated from global reaching condition $\dot{V}(\sigma(x)) < 0$, according to chosen Lyapunov function and its derivative. Constant convergence of system states to sliding surfaces is assured by (8).

$$V(\sigma(x)) = \sigma(x)^T \sigma(x)/2, \ \dot{V}(\sigma(x)) = -\sigma(x)^T K sig(\sigma(x)) \quad (8)$$

For this case the control (7) is:

$$u = -\left(\frac{\partial\sigma}{\partial x}B\right)^{-1} \left[\frac{\partial\sigma}{\partial x} f(x) + K sig(\sigma(x))\right] + u_w . \quad (9)$$

Systems with applied control (9) are also called variable structure systems. Disturbance part $u_w = w(x,u,\theta,t)$ is unknown and it is mostly compensated by setting parameters of $K \in \Re^{mxm}$ (positive definite diagonal matrix) to large values. Hovewer large values also increase chattering.

Other possibility is a continuous sliding mode control design. Here the derivative of the Lyapunov function (10) is continuous and corresponding control is (11).

$$V(\sigma(x)) = \sigma(x)^T \sigma(x)/2, \ \dot{V}(\sigma(x)) = -\sigma(x)^T D\sigma(x) \quad (10)$$

$$u = -\left(\frac{\partial\sigma}{\partial x}B\right)^{-1} \left[\frac{\partial\sigma}{\partial x} f(x) + D\sigma(x)\right] + u_w . \quad (11)$$

$D \in \Re^{mxm}$ is a positive definite diagonal matrix. Control (11) is continuous and does not cause chattering. But only using a disturbance estimation algorithm can compensate the disturbances. The system states reach prescribed sliding manifolds when the estimation is perfect. However in practice the disturbances can only be estimated to some arbitrary accuracy. So a term quasi-sliding mode control is adopted for this schemes (Šabanović, 1993). A quasi-sliding mode motion is any motion of system (1) in the ε-vicinity of manifolds (3) on which the sliding mode motion exists with the control (11).

3. DECOUPLED CONTINUOUS SLIDING MODE ROBOT CONTROL DESIGN

Dynamics of *k*-th robot axis for a direct drive robot with *m*-degrees of freedom is:

$$\tau_k = J_{kk}(\boldsymbol{q})\ddot{q}_k + \sum_{j=1, j\neq k}^{m} J_{kj}(\boldsymbol{q})\ddot{q}_j + \sum_{j=1}^{m}\sum_{l=1}^{m} C_{kjl}(\boldsymbol{q})\dot{q}_j\dot{q}_l + \\ + G_k(\boldsymbol{q}) + \tau_{t,k}(\boldsymbol{q},\dot{\boldsymbol{q}}) + \tau_{d,k} \quad (12)$$

where τ_k is motor torque of k-th axis, $J(\boldsymbol{q}) \in \Re^{mxm}$ is inertia matrix, $C(\boldsymbol{q}), G(\boldsymbol{q}) \in \Re^m$ are vectors of Coriollis and gravitation torques, $\tau_{t,k}(\boldsymbol{q},\dot{\boldsymbol{q}})$ and $\tau_{d,k}$ are friction torque and external disturbances for this axis. $\boldsymbol{q}$, $\dot{\boldsymbol{q}}$ and $\ddot{\boldsymbol{q}}$ are position, velocity and acceleration vectors.

Let us define a tracking problem as a problem of determining the torques τ_k, so that tracking error limits to zero $\lim_{t\to\infty} \boldsymbol{e_k} = 0$, $\boldsymbol{e_k} = [q_k^d - q_k, \dot{q}_k^d - \dot{q}_k]$. Superscript *d* stands for a reference trajectory.

To include tracking requirements, the sliding manifolds have to be chosen as a function of acceleration, velocity and position errors:

$$\sigma_k = (\ddot{q}_k^d - \ddot{q}_k^c) + K_{v,k}(\dot{q}_k^d - \dot{q}_k) + K_{p,k}(q_k^d - q_k), \quad (13)$$

where $K_{p,k}$ and $K_{v,k}$ are positional and velocity gains and determine the dynamics of the system in the sliding mode. The matching condition for robot is always fulfilled, so according to (2), dynamics (12) can be rewritten as:

$$\tau_k = J_{kk}(\boldsymbol{q})\ddot{q}_k + w_k(\boldsymbol{q},\dot{\boldsymbol{q}},\ddot{\boldsymbol{q}}). \quad (14)$$

Decentralized control was chosen as a basic control approach. If the coupling terms are neglected in (14) and actual inertia is replaced by an average one, then the system is described by:

$$\tau_k = \bar{J}_{kk}\ddot{q}_k + w_k(q_k, \dot{q}_k, \ddot{q}_k). \quad (15)$$

To derive the control we replace the actual uncertainitis by estimated one (16) and unavailable actual acceleration with calculated acceleration, derived from the condition for sliding mode (17).

$$w_k(\boldsymbol{q},\dot{\boldsymbol{q}},\ddot{\boldsymbol{q}}) \to w_k(q_k, \dot{q}_k, \ddot{q}_k) \quad (16)$$

$$\sigma(e,\dot{e}) = 0 \to \ddot{q}_k^c = \ddot{q}_k^d + K_{v,k}(\dot{q}_k^d - \dot{q}_k) + K_{p,k}(q_k^d - q_k). \quad (17)$$

Finally the control is:

$$\tau_k = \bar{J}_{kk}\ddot{q}_k^c + \hat{w}_k(q_k, \dot{q}_k, \ddot{q}_k). \quad (18)$$

Hovewer replacing the actual uncertainities by estimated one leads to system error equation (19).

$$\ddot{e}_k + K_{v,k}\dot{e}_k + K_{p,k}e = \bar{J}_{kk}^{-1}[\hat{w}_k(q_k, \dot{q}_k, \ddot{q}_k) - w(q_k, \dot{q}_k, \ddot{q}_k)] \quad (19)$$

The importance of a good disturbance estimation for achieving a good approximation of sliding mode motion is clearly stated by this equation.

Some disturbance estimation schemes from literature (Jezernik and Curk, 1993) were tested on laboratory direct drive robot, but failed to provide a good tracking accuracy especially for high-speed movements (Rojko and Jezernik, 1999). In the design of more suitable estimator for direct drive robot was our task beside good estimation also acceptable computational requirements, so that estimator can be implemented on the most controllers' hardware.

4. ADAPTIVE FUZZY ROBOT DISTURBANCE ESTIMATOR

FLSs are universal approximators, so they are able to approximate any real continuous function on compact set with prescribed accuracy (Wang 1994). This and the possibility to include the linguistic knowledge were our reasons to choose FLS for disturbance estimation. For decentralized control approach one FLS disturbance estimator has to be used for each robot axis. All FLSs have the same structure, so the subscript *k*, indicating *k*-th robot axis will be dropped in this section.

Fuzzy rule base of all FLS consist of IF-THEN rules R^l in the following classical form:

R^l: if $x^1 = X^{1,l}$ and $x^2 = X^{2,l}$ and .. and $x_k^i = X_k^{i,l}$ and ..and $x^n = X^{n,l}$ then $\hat{w} = W^l$ (20)

Superscript l refers to the l-th rule $l=1..M,$ and superscript i refers to the number of input variables in FLS, $i=1..m.$ x^n are input linguistic variables. For each axis a vector of input variables is defined as $\boldsymbol{x} = [q, \dot{q}, \ddot{q}^d]$. $X^{n,l}$ are fuzzy sets in input universe of discourse. $\hat{w}$ are output linguistic variables (robot axis disturbance torques) and W^l are singleton fuzzy sets in the output universe of discourse.

For FLS we chose singleton fuzzifier, product-operation rule of fuzzy implication and center of average deffuzifier. Bell function form was chosen for input membership functions $X^{n,l}$. Output membership functions are singletons.

The output of the resulting FLS can be calculated as:

$$\hat{w} = \frac{\sum_{l=1}^{M} \bar{y}^l \prod_{i=1}^{n} \left(1 \Big/ \left(1 + \left| \frac{x^i - \bar{x}^{i,l}}{\sigma^{i,l}} \right|^{2 \cdot b^{i,l}} \right) \right)}{\sum_{l=1}^{M} \prod_{i=1}^{n} \left(1 \Big/ \left(1 + \left| \frac{x^i - \bar{x}^{i,l}}{\sigma^{i,l}} \right|^{2 \cdot b^{i,l}} \right) \right)}. \quad (21)$$

$\bar{x}^{i,l}$ are centers of input membership functions, $\sigma^{i,l}$ determine the width of the bell function and $b^{i,l}$ its slope. At $\bar{y}^l$ the output membership functions achieve their maximum value.

All parameters of the FLS, $\bar{x}^{i,l}, \bar{y}^l$ and $\sigma^{i,l}$, can be chosen as adjustable. However that would require use of time consuming adjusting techniques such as back-propagation. So we decided to adjust only the centers of output membership functions $\bar{y}_k^l$'s while parameters concerning input membership functions remain fixed. The output of the FLS is linear in the parameters $\bar{y}^l$, so a gradient adaptation algorithm can be used. If we collect the adaptive parameters in the parameter vector $\hat{\boldsymbol{\theta}} = [\bar{y}^1, .., \bar{y}^M]^T$ and remaining part of (21) in the vector $\xi(\boldsymbol{x}) = [\xi^1(\boldsymbol{x}), .., \xi^l(\boldsymbol{x}), .., \xi^M(\boldsymbol{x})]^T$ it is possible to rewrite (21) in the parameter vector-regressor form:

$$\hat{w} = \sum_{l=1}^{M} \bar{y}^l \cdot \xi^l(\boldsymbol{x}) = \hat{\boldsymbol{\theta}}^T \cdot \xi(\boldsymbol{x}) \quad (22)$$

Let us define parameter vector error:

$$\boldsymbol{\Phi} = \hat{\boldsymbol{\theta}} - \boldsymbol{\theta} \quad (23)$$

and rewrite the error equation (19) as:

$$\dot{\boldsymbol{e}} = \boldsymbol{\Lambda}\boldsymbol{e} + \bar{J}^{-1}\boldsymbol{v} \cdot \boldsymbol{\Phi}^{\boldsymbol{T}} \cdot \xi(\boldsymbol{x}) . \quad (24)$$

Here are $\boldsymbol{v}$ =$[0,1]^T$ and $\Lambda = \begin{bmatrix} 0 & 1 \\ -K_p & -K_v \end{bmatrix}$. The gradient adaptive law was implemented:

$$\dot{\hat{\boldsymbol{\theta}}} = -\alpha \cdot fe \cdot \boldsymbol{\xi}(\boldsymbol{x}), \quad fe = \boldsymbol{e}^{\boldsymbol{T}} \cdot \boldsymbol{A} \cdot \boldsymbol{v} . \quad (25)$$

$\boldsymbol{A} = \begin{bmatrix} a_2 & a_1 \\ a_1 & a_2 \end{bmatrix}$ is a positive, symmetric matrix, which fulfils (26) for some positive definite matrix $\boldsymbol{Q}$.

$$\boldsymbol{\Lambda}^T \boldsymbol{A} + \boldsymbol{A}\boldsymbol{\Lambda} = -\boldsymbol{Q} . \quad (26)$$

The stability can be proven by Lyapunov function:

$$V = \frac{1}{2}\left(\boldsymbol{e}^T \cdot \boldsymbol{A} \cdot \boldsymbol{e} + \frac{\bar{J}^{-1}}{\alpha} \cdot \boldsymbol{\Phi}^T \cdot \boldsymbol{\Phi}\right) . \quad (27)$$

Its derivative is:

$$\dot{V} = \frac{1}{2}\left(\dot{\boldsymbol{e}}^T \boldsymbol{A}\boldsymbol{e} + \boldsymbol{e}^T \boldsymbol{A}\dot{\boldsymbol{e}} + \frac{\bar{J}^{-1}}{\alpha}\dot{\boldsymbol{\Phi}}^T \boldsymbol{\Phi} + \frac{\bar{J}^{-1}}{\alpha}\boldsymbol{\Phi}^T \dot{\boldsymbol{\Phi}}\right) \quad (28)$$

By including (24) and (26) in (28) we get:

$$\dot{V} = -\frac{1}{2}\boldsymbol{e}^T \boldsymbol{Q}\boldsymbol{e} + \bar{J}^{-1}\boldsymbol{e}^T \boldsymbol{A}\boldsymbol{v}\boldsymbol{\Phi}^{\boldsymbol{T}}\xi(\boldsymbol{x}) + \frac{\bar{J}^{-1}}{\alpha}\boldsymbol{\Phi}^T \dot{\boldsymbol{\Phi}} . \quad (29)$$

Next we use suppose $\dot{\boldsymbol{\Phi}} = \dot{\hat{\theta}}$, which is equivalent to consideration, that optimal parameter vector is constant. Finally we use (25) in (29) and calculate the derivative of the Lyapunov function (30). It is negative semi-definite and therefore equilibrium point $\boldsymbol{e}$=0 is stable.

$$\dot{V} = -\frac{1}{2}\boldsymbol{e}^T \boldsymbol{Q}\boldsymbol{e} < 0 \quad (30)$$

5. FUZZY LOGIC SUBSYSTEMS

The complexity of FLS for disturbance estimation with three inputs can be too high for practical implementation (in the literature this problem is often named *course of dimensionality)*. Even if we use only three membership functions for each input variable it is possible to write 27 complete rules, or even 63 rules if we consider rules without all inputs. This presents too heavy computational burden to the most controllers' hardware, especially because one FLS for each of the robot axis is required in our control scheme.

To simplify FLS and reduce the number of rules we divided FLSs into three fuzzy logic subsystems (FLSB). They have the structure as described in the previous section and the same algorithm for adaptation, but different inputs.

The first FLSB inputs are position and desired acceleration, $\boldsymbol{x_k} = [q_k, \ddot{q}_k^d]$. It is used for estimation of discrepancy between nominal inertia and the actual inertia:

$$\hat{w}_{1.FLS,k} = \left(J_{kk}(q_k) - \bar{J}_{kk}\right) \cdot \ddot{q}_k^d . \quad (31)$$

The second FLSB inputs are position and velocity, $\boldsymbol{x_k} = [q_k, \dot{q}_k]$. It is used for estimation of gravitation, Coriollis, centrifugal and viscous friction effects:

$$\hat{w}_{2.FLS,k} = C_k(q_k, \dot{q}_k,) + G_k(q_k) + F_{bk}(\dot{q}_k) . \quad (32)$$

The third FLSB is used for the estimation of varying payload effect or eventual residue of dynamics that should be approximated by first two FLSB. Its inputs are position, velocity and acceleration, $\boldsymbol{x_k} = [q_k, \dot{q}_k, \ddot{q}_k^d]$.

Because of this division the number of rules and inputs in each rule are reduced without negatively influencing the performance.

6. INCLUSION OF LINGUISTIC KNOWLEDGE

Our control plant is a three-degree of freedom Puma like configuration direct drive robot, Fig. 1. The robot is equipped with AC-motors that provide maximal torques of 220 Nm, 160 Nm and 60 Nm. These torques are physical constraints that limit maximal magnitude of adjustable FLS's parameters.

Available linguistic information about the system and its behavior in certain regions were used in the design of the initial FLSs. The knowledge concerning lower and upper bounds of state variables was used to choose the number, widths and distribution of the input membership functions. The initial values of the parameter vector $\hat{\theta}_k$ were chosen considering linguistic information as described in continuation.

First axis is not influenced by gravitation and only minor presence of Coriollis and centrifugal effect is noticeable for the most movements. Accordingly, the initial values of adjustable parameters of second FLSB were set to zero. Maximal torque is needed in the acceleration and breaking period, so the initial values of adjustable parameters of first FLSB were set to positive and negative values according to acceleration sign. Load changes and other influences cannot be predicted, so the values of adjustable parameters of third FLSB were set to small random numbers.

On the second axis the effect of gravitation strongly prevails over other dynamic effects. The torque needed for gravitation compensation is well known. The initial values of adjustable parameters of the second FLSB were set according to this knowledge. Adjustable parameters of first FLSB were set to zero and adjustable parameters of the third FLS to small random numbers.

The third robot's axis is balanced, so there is no need to compensate gravitation. However experience shows that control of this robot's axis is very problematic due to high friction influence, so we set initial adjustable parameters of rules of the second FLSB to small positive and negative numbers considering the velocity sign. Initial adjustable parameters for the third FLSB were set to small random numbers and adjustable parameters of the first FLSB to zero.

7. EXPERIMENTAL RESULTS

A sampling time of the control system has been set to 2ms. 15 rules have been used in FLS on second and third axes, three for first and second FLSB, and nine in third FLSB. In the control of first axis nine fuzzy rules have been used, three for each FLSB. Position gains have been chosen as $K_{p,k}$=[1000, 2400, 1200] and parameters of diagonal inertia matrix as $\bar{\boldsymbol{J}}$=diag([3.5, 2.5, 0.13]) kgm. Three membership functions have been used for each of the three inputs of FLS. Membership functions of all fuzzy sets have the bell form and are equally distributed in state space. Their positions and widths are shown in Fig. 2. and are the same for all three axes. The initial positions of output fuzzy function have been set according to the linguistic knowledge, as described in the previous section. Used learning parameters values $a_{1,k=1}=220$, $a_{2,k=1}=1.5$, $a_{1,k=2}=250$, $a_{2,k=2}=5$ and $a_{1,k=3}=35$ $a_{2,k=3}=1$ fulfill the condition (26). Small values of $a_{i=2,k=1,2,3}$ minimize the effect of noise in the measured velocity signals. Learning rates have been set to $\alpha_{k=1,2,3}=0.2$.

Experimental results are presented for two cases. In the first experiment a reference trajectory was an average point-to-point movement; the same for all three axes. Reference trajectory is presented in Fig. 3. The maximal robot tip velocity was 0.54 m/s. The robot tip's position error with a peak error of 2.6 mm is shown in Fig. 4. The positioning error falls to zero after 4s. Fig. 5. shows both by FLS estimated and nominal torques of all robots' axes for this movement.

The next experiment was a test of varying payload when performing the slow point-to-point movement. Movement is same for all three axes, with speed of 0.04 rad/s and the end position of all axis 0.8 rad. The motion started with payload of 5kg, which was released and again attached three times. First two changes happen between movement, the last one when the robot was in the end position. When the payload change occurs a peak in position error was observed, but after a short transient period it falls to normal value, Figure 6. Note that the oscillations observed in the signal are because of noisy actual signals and low speed of the robot, where Stribect effect already takes place. The peak position errors are increasing in every load change, because load torque also increases with the movement. This also shows that the FLS has no generalization property, which was expected because of small number of rules. This test additionally confirms the robustness property of the controller.

8. CONCLUSION

In this paper development and implementation of a robust tracking control for a robot motion control has been presented. Decentralized sliding mode controller employs a fuzzy disturbance estimation algorithm. Fuzzy rules are formed as for example:

IF *position of the i-th robot axis=positive* AND *velocity of the i-th robot axis=positive* AND *acceleration of i-th robot axis=zero* THEN *disturbance torque of i-th robot axis=T.*

Initial values of adaptive parameters have been set with the available linguistic knowledge. To cope with highly non-linear dynamics of the robot manipulator and incomplete linguistic knowledge, an on-line adjustment of some FLS's parameters has been used. If no linguistic knowledge is available this controller still remains a robust sliding mode nonlinear adaptive controller, with analytically using the fuzzy logic technique.

Experimental results, with three degree of freedom direct drive robot as a control object, show accurate tracking of the commanded trajectory even in the presence of the abrupt changes of dynamics caused by varying payload. Although the direct drive robot has been used as a control object, the proposed controller can be also used in the motion control of a class of second order nonlinear motion control systems.

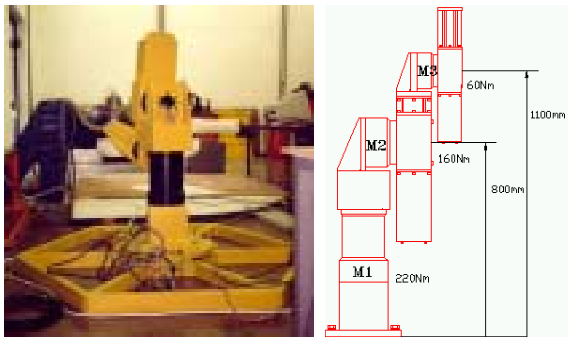

Fig.1. Direct drive robot

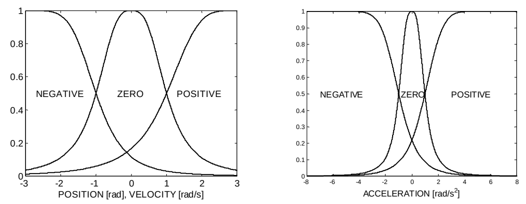

Fig. 2. Membership functions of input variables

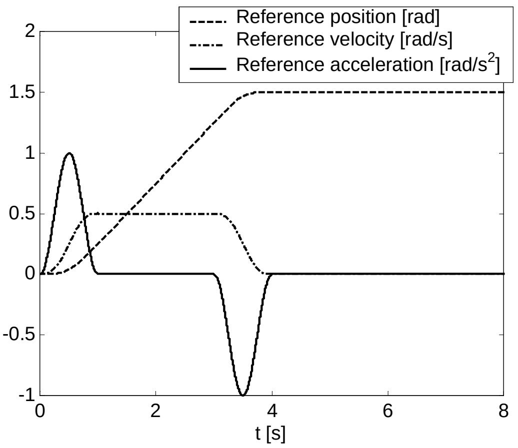

Fig. 3. Reference trajectory in joint coordinates

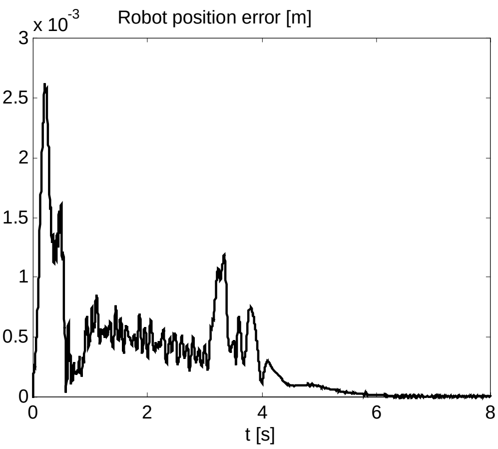

Fig. 4. Robot tip's position error

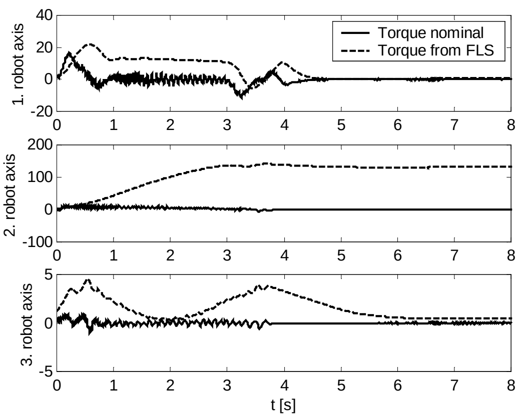

Fig. 5. Applied nominal and fuzzy disturbance torques for each robot joint

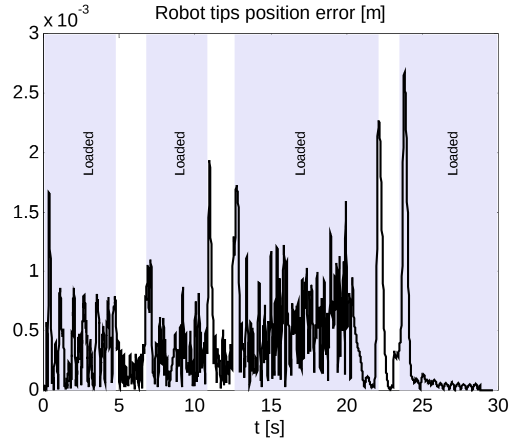

Fig 6. Robot tip's position error: test of varying payload between robot motion

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