HIERARCHICAL MODAL CONTROL OF A NOVEL MANIPULATOR

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Abstract: This paper focuses on the development and implementation of an intelligent hierarchical controller for the vibration control of a deployable manipulator. The emphasis is on the use of knowledge-based tuning of the low-level controller so as to improve the performance of the system. To this end, first a fuzzy inference system (FIS) is developed. The FIS is then combined with a conventional modal controller to construct a hierarchical control system. Specifically, a knowledge-based fuzzy system is used to tune the parameters of the modal controller. The effectiveness of the hierarchical control system is investigated through numerical simulation studies. Examples are considered where the system experiences vibrations due to initial disturbance at the flexible revolute joint or due to maneuvers of a deployable manipulator. The results show that the knowledge-based hierarchical control system is quite effective in suppressing vibrations induced due to the above mentioned disturbances. Results suggest that performance of the modal controller could be significantly improved through knowledge-based tuning.

1 INTRODUCTION

Among the fundamental developments in the modern control theory are the two sets of analytical results that underlie the linear quadratic regulator (LQR) and eigenstructure assignment regulator (EAR). Design and implementation of practical control of flexible structures have been accomplished using both the design techniques (Junkins, 1993). In the LQR approach, the central feature is the minimization of a quadratic performance index, subject to a linearized system model. However, a major drawback of the LQR is that it has no direct control of the system eigenstructure, which determines not only the level of stability but also the specific nature of the response to a control input (e.g., a step function). The LQR method does not involve the assignment of the system eigenstructure in a specified manner. Consequently, it is desirable to employ a control strategy that has the capability to modify the system eigenstructure appropriately to meet specified requirements. Such a control approach would prove more effective if the capability of the parameter tuning is available as well. To this end, a modal control strategy is introduced here. An intelligent control system, which combines a modal controller and a fuzzy tuning structure, is developed to 'intelligently' assign the system eigenstructure so as to obtain better performance of the controller in terms of response speed, overshoot, and steady state offset. Simulation studies have been carried out using this intelligent control system to suppress vibrations of a ground-based deployable manipulator. The approach may be conveniently applied to a space-based manipulator as well.

2 CONTROL SYSTEM DEVELOPMENT

2.1 Eigenvalue Assignment

A linear system may be expressed in the state-space form as

$$\dot{\boldsymbol{x}}_L = \boldsymbol{A}\boldsymbol{x}_L + \boldsymbol{B}\boldsymbol{u}_L , \qquad (1)$$

where the time-dependent state vector $\boldsymbol{x}_L$ contains generalized coordinates and their first time derivatives of the system. The square matrix $\boldsymbol{A}$ is composed of the matrices of mass, damping and stiffness. The term $\boldsymbol{B}\,\boldsymbol{u}_L(t)$ represents the effect of a control action, with $\boldsymbol{u}_L(t)$ and $\boldsymbol{B}$ being the control force (torque) vector and actuator placement matrix,

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respectively. As is normally the case in such studies, all states are assumed to be available thus making the system observable. By introducing state feedback, the control input $\boldsymbol{u}_L$ can be written as

$$\boldsymbol{u}_L = -\boldsymbol{K}\boldsymbol{x}_L \,. \tag{2}$$

Thus one obtains a closed loop system

$$\dot{\boldsymbol{x}}_L = (\boldsymbol{A} - \boldsymbol{B}\boldsymbol{K})\boldsymbol{x}_L \,. \tag{3}$$

In Equation (3), matrix $\boldsymbol{A}-\boldsymbol{B}\boldsymbol{K}$ decides the modal parameters of the closed loop system, such as the modal frequencies, damping ratios and mode shapes. A relation exists, between the modal parameters of the system and the eigen-parameters of matrix ***A-BK***, as eigen-parameters decide the controlled behavior of the closed loop system (Nishitani,1998), Equation (3). To obtain the relation explicitly, it is useful to define some notations. Assuming ***A-BK*** to be a matrix of real-numbers, the eigenvalues and eigenvectors of ***A-BK*** appear as conjugate pairs. Let λ_{2i-1} and λ_{2i} be the *i*th pair of eigenvalues, and $\boldsymbol{z}_{2i-1}$ and $\boldsymbol{z}_{2i}$ be the corresponding *i*th pair of eigenvectors. Also let ω_i, ζ_i and $\boldsymbol{n}_i$ denote, respectively, the modal frequency, damping ratio and mode shape of the *i*th mode. Then we have:

$$\lambda_{2i-1} = -\zeta_i\omega_i + \mathrm{j}\omega_i\sqrt{1-\zeta_i^2} \;;$$

$$\lambda_{2i} = -\zeta_i\omega_i - \mathrm{j}\omega_i\sqrt{1-\zeta_i^2} \;;$$

and

$$\boldsymbol{z}_{2i-1} = \begin{Bmatrix} \lambda_{2i-1}\boldsymbol{n}_i \\ \boldsymbol{n}_i \end{Bmatrix}; \qquad \boldsymbol{z}_{2i} = \begin{Bmatrix} \lambda_{2i}\boldsymbol{n}_i \\ \boldsymbol{n}_i \end{Bmatrix}\;; \qquad \text{for } i = 1 \text{ to } n\,, \tag{4}$$

where j = $\sqrt{-1}$, and n is the number of degrees of freedom of the system.

Equation (4) gives a one-to-one mapping between the system modal parameters and the eigen-parameters of matrix ***A-BK***. Therefore, if the modal parameters ω_i, ζ_i and $\boldsymbol{n}_i$ are specified in the domain, one can calculate the corresponding eigenvalues and eigenvectors for the closed loop system using Equation (4). Moreover, according to Equation (3), if one can modify and assign the eigenstructure at desired values by selecting proper feedback matrix ***K***, the modal property of the system can be modified accordingly. This is the essence of the modal control procedure. It is also the reason why modal control is also called eigenvalue assignment control.

2.2 Hierarchical Structure

The control system developed for the deployable manipulator system has a three-level structure. This hierarchical form combines the advantages of a crisp controller, i.e. a modal controller, with those of a soft, knowledge-based, supervisory controller. The overall structure can be developed into three main layers (de Silva, 1995).

Bottom Layer

The bottom layer deals with information coming from sensors attached to the system. This type of information is characterized by a large amount of high resolution data points produced and collected at high frequency. The crisp controller used is a state feedback regulator with feedback gain matrix determined using the eigenstructure assignment approach. The control algorithm can be described as:

$$\begin{aligned} \dot{\boldsymbol{x}} &= \boldsymbol{A}\boldsymbol{x} + \boldsymbol{B}\boldsymbol{u} \;; \\ \boldsymbol{u} &= -\boldsymbol{K}\boldsymbol{x} \;; \end{aligned} \tag{5}$$

where $\boldsymbol{u}$ is the control action and $\boldsymbol{K}$ the feedback matrix.

Intermediate Layer

The data processing for monitoring and evaluation of the system performance occurs in the intermediate layer. Here high-resolution, crisp data from sensors are filtered to allow representation of the current state of the manipulator. This servo-expert layer acts as an interface between the crisp controller, which regulates the servomotors at the bottom layer, and the knowledge-based controller at the top layer. The intermediate layer handles such tasks as performance specification, response processing, and computation of performance indices. This stage involves, for example, averaging or filtering of the data points, and computation of the rise time, overshoot, and steady state offset.

Top Layer

The knowledge base and the inference engine in the uppermost layer are used to make decisions that achieve the overall control objective, particularly by improving the performance of low-level direct control. This layer can serve such functions as monitoring the performance of the overall system, assessment of the quality of operation, tuning of the low-level controllers, and general supervisory control. In this layer, there is a high degree of information fuzziness and a relatively low control bandwidth. Figure 1 presents the hierarchical structure of the three-level control system.

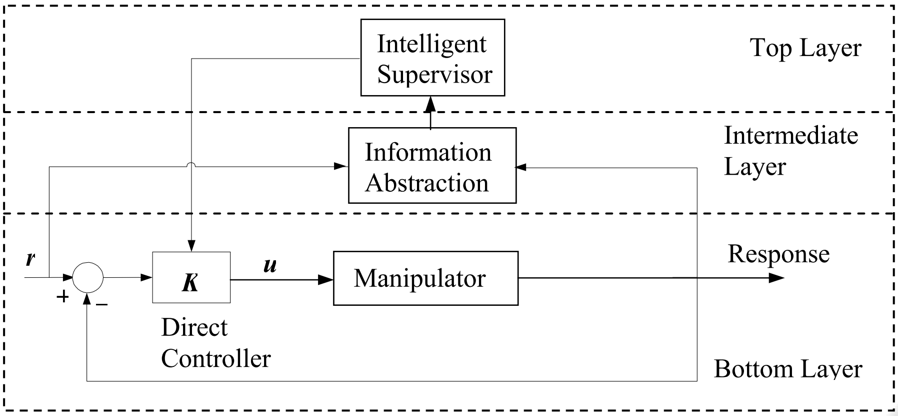

Figure 1: Schematic representation of the three-level controller.

2.3 Performance Specification, Evaluation, and Classification

The desired performance of the system is specified in terms of the following time domain parameters:

- Rise time (RST_d);
- Overshoot, if underdamped (OVS_d);
- Offset at steady state (OFS_d).

These three parameters are used to present the desired performance of the system. The rise-time is chosen as the time it takes for the response to reach 95% of the desired steady-state response. The overshoot is calculated at the first peak of the response. The steady-state offset is computed by taking the difference between the average of the last third of the response and the desired response.

The corresponding time domain parameters are obtained from the response of the actual system, with the subscript r referring to the real system response as: RST_r, OVS_r, and OFS_r. Once evaluated, the parameters of the real system are compared with the desired ones to get the index of deviation. For each performance attribute, an index of deviation is calculated using the following equation,

$$\textit{Index of deviation of } i^{th} \textit{ attribute} = 1 - \frac{i^{th} \textit{desired attribute}}{i^{th} \textit{actual attribute}} \tag{6}$$

The index is defined in such a way that the value of 1 corresponds to the worst-case performance, while zero means the actual performance of the system, for that particular attribute, exactly meets the specification. The indices are calculated according to:

$$RST_i = 1 - \frac{RST_d}{RST_r} = ERR(1)\,; \tag{7}$$

$$OVS_i = 1 - \frac{OVS_d}{OVS_r} = ERR(2)\,; \tag{8}$$

$$OFS_i = 1 - \frac{OFS_d}{OFS_r} = ERR(3)\,. \tag{9}$$

These indices represent the performance of the system and hence should correspond to the context of the rulebase of system tuning. The index of deviation is therefore fuzzified into membership values according to the five selected primary fuzzy states: Highly Unsatisfactory (*HIUN*), Needs Improvement (*NDIM*), Acceptable (*ACCP*), In Specification (*INSP*) and Over Specification (*OVSP*). In order to obtain a discrete set of performance indices *K(i)*, threshold values *TH*(*i*) are defined for each index of deviation over the interval $-\infty$ to 1, as given in Table 1.

Table 1: Mapping from the index of deviation to a discrete performance index

Discrete Performance Index *K(i)*	Index of Deviation
5	$ERR(i) < 0$
4	$0 < ERR(i) \le TH(1)$
3	$TH(1) \le ERR(i) \le TH(2)$
2	$TH(2) \le ERR(i) \le TH(3)$
1	$TH(3) \le ERR(i) \le 1$

The performance indices obtained in this manner are the input to a Fuzzy Inference System (FIS) which tunes the modal frequencies and damping ratios of the closed-loop system. The output from FIS is the tuning action that is used to update modal frequencies and modal damping ratios of the closed-loop system. Therefore, closed-loop poles can be modified correspondingly.

2.4 Fuzzy Tuner Layer

At the highest level of the hierarchical structure, there is a knowledge base for tuning a crisp controller. This knowledge may originate from human experts or some form of archives, and is expressed as linguistic rules containing fuzzy terms. For each status (context) of the system, a conceptual abstraction is computed, and the expert knowledge is transformed into a mathematical form by the use of the fuzzy set theory and fuzzy logic operations. A Fuzzy Inference System (FIS) has been built using the Matlab Toolbox to this end. To construct the system, one must first assign a membership function to each of the performance indices and tuning parameters. Then the knowledge base should be created. Taking performance indices as the input, Fuzzy Inference System carries out such tasks as fuzzification of the performance indices, operations of the fuzzy set, and defuzzifying of the tuning actions. The output of the FIS is a crisp tuning action corresponding to numerical context values of the system condition.

The tuned parameters are chosen to be the modal frequencies and modal damping ratios. As mentioned before, eigenstructure of the closed loop system plays a key role in determining the system performance. Required performance can be achieved by properly assigning the system eigenstructure. There are relationships between system eigenstructure and system modal parameters (Equation 4). They provide a way to modify the eigenstructure by tuning modal frequencies and modal damping ratios. These modal parameters are physically meaningful and hence chosen as the tuned parameters.

If ω_i and ζ_i represent the ith modal frequency and damping ratio, respectively, the relationship between modal parameters and system eigenstructure is given by Equation (4). At each tuning step, the values of ω_i and ζ_i are updated according to the tuning actions obtained from the Fuzzy Inference System (FIS). Once updated, the new values of parameters ω_i and ζ_i are used to determine the new desired eigrnstructure of the system. Relations used for updating ω_{ni} and ζ_i are:

$$\begin{aligned} \omega_i^{new} &= \omega_i^{old} + \Delta\omega_i / \omega_{isen}; \\ \zeta_i^{new} &= \zeta_i^{old} + \Delta\zeta_i / \zeta_{isen}; \end{aligned} \tag{10}$$

where the subscript 'new' denotes the updated value and 'old' refers to the previous value. The incremental action taken by the fuzzy controller is denoted by $\Delta\omega_i$ and $\Delta\zeta_i$. Parameters ω_{isen} and ζ_{isen} are introduced to adjust sensitivity of tuning, when needed.

2.5 Construction of Fuzzy Inference System

The expert tuning knowledge for a modal controller may utilize heuristics such as those given in Table 2. One may define the primary fuzzy sets for the performance indices for each context variable (i.e., *RST, OVS,* and *OFS*) as given in Table 3. Fuzzy tuning variables are defined as follows:

$DFREQ_i$ = Change in the ith modal frequency;
$DDAMP_i$ = Change in the ith modal damping ratio.

Each tuning variable may be expressed with fuzzy sets and representative numerical values that are listed in Table 4. The rulebase for control parameter tuning is given in Figure 2.

Table 2: Heuristics of modal control tuning.

Context	Actions for Performance Improvement: Modal Frequency ω_{ni}	Modal Damping Ratio ζ_i
Rise Time (*RST*)	Increase	Decrease
Overshoot (*OVS*)	------	Increase
Offset (*OFS*)	Increase	Decrease

Table 3: Fuzzy labels of performance indices

Perform. Index	Context Fuzzy Set	
	Notation	Fuzzy Value
1	*HIUN*	Highly Unsatisfactory
2	*NDIM*	Needs Improvement
3	*ACCP*	Acceptable
4	*INSP*	In Specification
5	*OVSP*	Over-Specification

Triangular membership functions for the performance attributes *RST, OVS, OFS* and for the fuzzy tuning actions $DFREQ_i$, $DDAMP_i$ are given in Figure 3 and Figure 4, respectively. Each fuzzy action or condition quantity has a representative

If *RST* is *HIUN*, then $DFREQ_i$ is *PL*, $DDAMP_i$ is *NM*,
or If *RST* is *NDIM*, then $DFREQ_i$ is *PM*, $DDAMP_i$ is *NS*,
or If *RST* is *ACCP*, then $DFREQ_i$ is *PM*, $DDAMP_i$ is *ZR*,
or If *RST* is *INSP*, then $DFREQ_i$ is *ZR*, $DDAMP_i$ is *ZR*,
or If *RST* is *OVSP*, then $DFREQ_i$ is *NS*, $DDAMP_i$ is *ZR*,
or If *OVS* is *HUIN*, then $DFREQ_i$ is *NM*, $DDAMP_i$ is *PL*,
or If *OVS* is *NDIM*, then $DFREQ_i$ is *NS*, $DDAMP_i$ is *PM*,
or If *OVS* is *ACCP*, then $DFREQ_i$ is *ZR*, $DDAMP_i$ is *PS*,
or If *OVS* is *INSP*, then $DFREQ_i$ is *ZR*, $DDAMP_i$ is *ZR*,
or If *OVS* is *OVSP*, then $DFREQ_i$ is *PS*, $DDAMP_i$ is *NS*,
or If *OFS* is *HIUN*, then $DFREQ_i$ is *PM*, $DDAMP_i$ is *NS*,
or If *OFS* is *NDIM*, then $DFREQ_i$ is *PS*, $DDAMP_i$ is *NS*,
or If *OFS* is *ACCP*, then $DFREQ_i$ is *ZR*, $DDAMP_i$ is *NS*,
or If *OFS* is *INSP*, then $DFREQ_i$ is *ZR*, $DDAMP_i$ is *ZR*,
or If *OFS* is *OVSP*, then $DFREQ_i$ is *NS*, $DDAMP_i$ is *ZR*,

Figure 2: Rulebase for the control parameter tuning.

value, which is assigned a membership grade equal to unity. The decreasing membership grade around that representative value introduces a degree of fuzziness.

Table 4: Tuning fuzzy sets and representative numerical values

Tuning Fuzzy Set		Integer Value
Notation	Fuzzy Value	
PL	Positive Large	3
PM	Positive Moderate	2
PS	Positive Small	1
ZR	Zero	0
NS	Negative Small	-1
NM	Negative Moderate	-2
NL	Negative Large	-3

3 GROUND-BASED SIMULATION

3.1 Modeling of a Ground-Based Manipulator System

The ground-based manipulator system considered for fuzzy tuning modal control is shown in Figure 5. The system consists of a single module manipulator carrying a point-mass payload held by the end effector. The module has two rigid links. The first link undergoes slewing motion through a flexible revolute joint. The other link can be deployed and retrieved by the rigid prismatic joint. The motion of the manipulator is confined to the horizontal plane, i.e. the gravity effects are not present.

The revolute joint is considered flexible. It is modeled by a linear torsional spring, with stiffness K, that connects the rotor of the servomotor to the slewing link. The angular motion of the rotor with respect to stator is denoted by α. The angular deformation of the torsional spring is given by β. Thus $\theta = \alpha + \beta$ is the total angular displacement of the slewing link.

3.2 Control System and Simulation Results

As mentioned before, the hierarchical structure used combines the advantages of a crisp modal controller with those of a soft, knowledge-based, supervisory controller. The three layers of the structure implement such tasks as collection of information coming from sensors, data processing and information abstraction, as well as general supervisory control.

This hierarchical control system is used to suppress the vibrations of the manipulator system described in Figure 5. The effectiveness of the control system is assessed by studying suppression of vibrations caused by different disturbances. In the first two cases, the initial disturbances at the flexible joint of the manipulator are considered. The length of the module may be specified at a fixed value through the Lagrange multiplier. Therefore, the subsystem considered for control simulation has two

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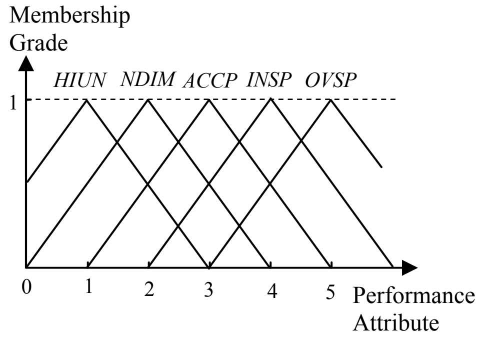


Figure 3: Membership functions for the fuzzy performance attributes

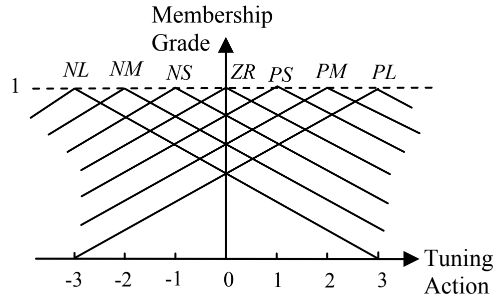


Figure 4: Membership functions for the fuzzy tuning actions

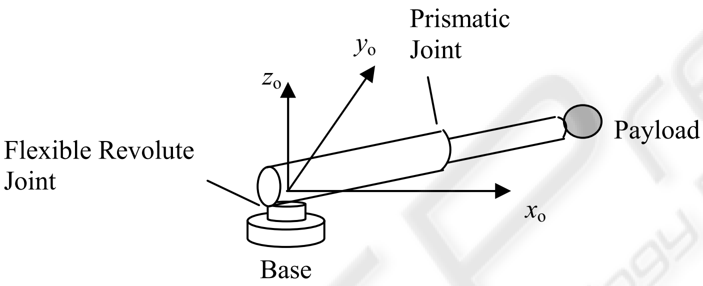


Figure 5: Configuration of the single-module manipulator with revolute and prismatic joints

degrees of freedom, with $\alpha, \beta, \dot{\alpha}, \dot{\beta}$ as the system state variables. The parameters for the first simulation case are given in Figure 6.

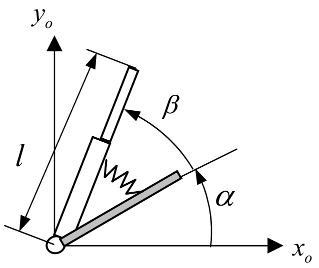
The initial feedback control gain is determined using the Linear Quadratic Regulator (LQR). Based on this, tuning action takes place. The tuning process involves analysis of the response to an initial disturbance listed in Figure 7, with respect to the performance requirements of rise time, overshoot, and steady-state error. The feedback gain matrix is updated by the supervisory controller accordingly.

Figure 7(a) shows the system response when controlled using the LQR strategy. The initial displacement (= 2°) of the torsional spring at the revolute joint results in vibrations at α and β. The suppression of the vibrations can be observed due to the application of the LQR controller. As can be seen, the convergence speed is slow in this case, and significant vibration remains after 10 seconds. Figure 7(b) shows the results after fuzzy tuning is applied. It can be observed that the convergence speed is much faster compared to that in the LQR controlled case. Within 4 seconds, the vibrations in each degree of freedom are eliminated. Further more, the peak amplitudes of the vibrations are significantly reduced.

In the above case, the response of a ground-based deployable manipulator, experiencing vibrations due to the initial disturbance at the revolute joint, was studied. To further evaluate the effectiveness of the hierarchical control system, a case of simultaneous 30° slew and 0.5 m deployment in 10 seconds was considered. Now the slew motion at the revolute joint and deployment at the prismatic joint are controlled using the nonlinear Feedback Linearization Technique (FLT). The desired profiles are described as

$$\boldsymbol{q}_s(\tau) = \frac{\Delta \boldsymbol{q}_s}{\Delta \tau}\left\{\tau - \frac{\Delta \tau}{2\pi}\sin\left(\frac{2\pi}{\Delta \tau}\tau\right)\right\}, \tag{11}$$

where $\boldsymbol{q}_S$ is the specified set of coordinates (α, l); $\Delta \boldsymbol{q}_S$ is its desired variation ($\Delta\alpha, \Delta l$); τ is the time; and $\Delta\tau$ is the time required for the maneuver.



Specified Coordinates

l = 1.5 m
(i.e., length is held fixed.)

Initial Conditions

$\alpha(0) = 0$, $\beta(0) = 2^\circ$;
$\dot{\alpha}(0) = \dot{\beta}(0) = 0.$

System Parameters

Slewing link:
l_1 = 1.0 m
m_1 = 2.0 kg
Deployable link:
l_2 = 1.0 m
m_2 = 2.0 kg
Payload:
m_p = 3.0 kg
Joint stiffness:
K = 80 Nm/rad
Rotor inertia:
J = 2 kg- m^2

Figure 6: Parameters for the ground-based simulation.

As can be expected, the large scale motions at both revolute and prismatic joints would result in vibration at the revolute joint, and this would persist if damping is not present in the system. This suggests a need for active control to suppress the maneuver-induced vibration. To that end, two control approaches are considered: the LQR and Tuned Modal Control. They are applied after the FLT- regulated maneuver is completed. Figure 8 (a) shows the system response when controlled by the combined FLT/LQR procedure. The rigid degrees of freedom are regulated very well within the first 10 seconds by the FLT. After that, the LQR is applied to suppress the maneuver-induced vibrations at the flexible revolute joint. It is apparent that the LQR is effective but its convergence speed is slow. Figure 8 (b) shows the system response when the combination of the FLT and Tuned Modal Control is employed. To obtain faster convergence speed, tuning action is carried out based on the LQR feedback gain matrix. It can be seen from Figure 8 (b) that, after a few tuning steps, much faster convergence speed is achieved. The vibrations at the flexible revolute joint are quickly eliminated right after completion of the maneuver, without any oscillations. Therefore, the developed knowledge-based tuning system is quite effective in improving the controller performance in presence of maneuvers. It should be pointed out that, by changing weight matrix of the LQR, a faster response than that shown in Figure 8 (a) may be achievable. However it is still significant to evaluate the effectiveness of the 'intelligent' tuning system in improving the controller performance.

4 CONCLUDING REMARKS

In this paper, a knowledge-based hierarchical control system was developed for the vibration control of a manipulator system. For this purpose, first a fuzzy inference system (FIS) was established. The FIS was then combined with a crisp modal controller to construct a hierarchical control system.

The effectiveness of the hierarchical control system was investigated through two simulation cases. In the first case, the system was experiencing vibration due to an initial disturbance at the revolute joint. The second case considered a system going through a simultaneous slew and deployment maneuver. The results showed that the knowledge-based tuning system developed here was quite effective. It was found that the performance of a modal controller for a manipulator could be significantly improved through knowledge-based tuning. On this basis one might conclude that additional tuning of the controller parameters could significantly improve the performance of a modal controller in general.

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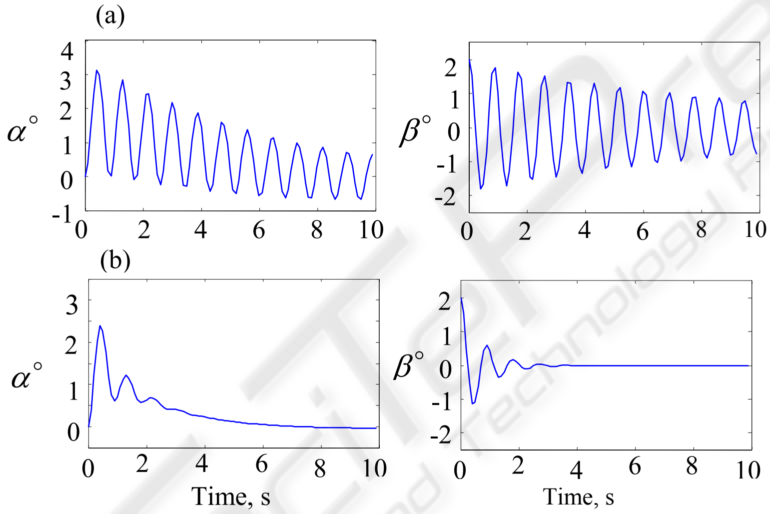

Figure 7: System response to an initial displacement at the revolute joint: (a) controlled by LQR; (b) controlled by hierarchical controller.

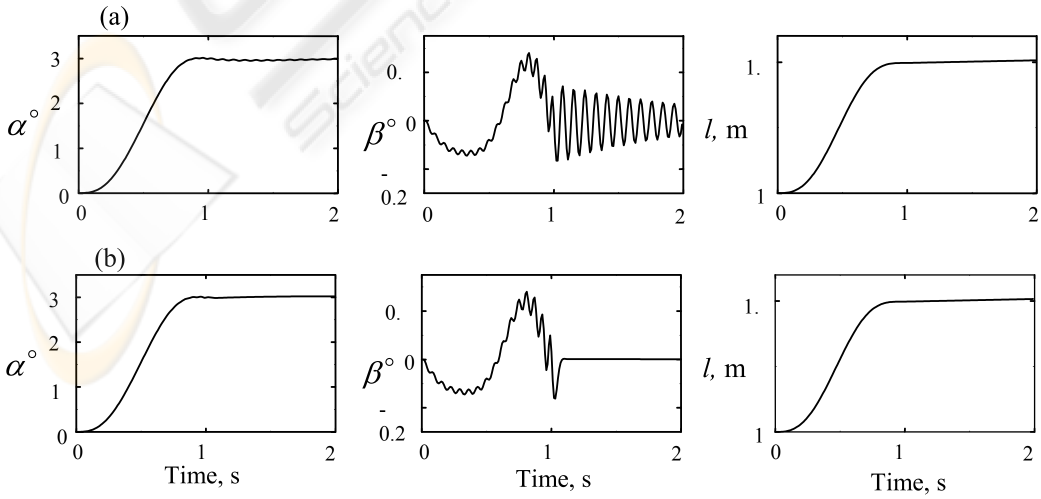

Figure 8: System response while going through a maneuver:
(a) controlled by the FLT/LQR;
(b) controlled by the FLT/Tuned Modal Control.