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Control of Flexible-link Manipulators Using Neural Networks

With 55 Figures

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To Sarah and Sahar (HAT)
To Roshni (RVP)
To Kamyar, Arianne, and Anahita (KK)

Preface

The problem of modeling and control of flexible–link manipulators has received much attention since the 1980's. There are a number of potential advantages stemming from the use of light–weight flexible–link manipulators, such as faster operation, lower energy consumption, and higher load–carrying capacity for the amount of energy expended. However, structural flexibility causes many difficulties in modeling the manipulator dynamics and guaranteeing stable and efficient motion of the manipulator end–effector. Control difficulties are mainly due to the non-colocated nature of the sensor and actuator positions, which results in non–minimum phase behavior, i.e., unstable zero dynamics. Further complications arise because of the highly nonlinear nature of the system and the difficulty involved in accurately modeling various friction and backlash terms. Control strategies that ignore these problems generally fail to provide satisfactory closed–loop performance.

A number of conventional linear as well as nonlinear techniques have been developed in recent years to address the problem of controlling flexible-link manipulators. However, the highly nonlinear nature of the manipulator dynamics and the inherent uncertainty associated with obtaining accurate dynamic models of flexible-link manipulators make reliable practical control of such manipulators difficult. In recent years, a number of intelligent control techniques, especially those based on artificial neural networks have been proposed for problems where the system dynamics are difficult to model or prone to uncertainties. A flexible-link manipulator is an example of such a system, and its control involving various neural network–based control strategies is the subject of this monograph. More specifically, the monograph presents experimental evaluation of the performance of neural network–based controllers for tip position tracking of flexible-link manipulators. The controllers are designed by utilizing the output redefinition approach to overcome the problem caused by the non–minimum phase characteristic of the flexible–link system. Four different neural network schemes are proposed. The first two schemes are developed by using a modified version of the "feedback–error–learning" approach to learn the inverse dynamics of the flexible-link manipulator. The neural networks are trained and employed as online controllers. Both schemes require *only* a linear model of the system for defining the new outputs and for designing conventional PD–type controllers. This assumption is relaxed in the third and fourth schemes. In the third scheme, the controller is designed based on tracking the hub position while controlling the elastic deflection at the tip. In the fourth scheme which employs two neural networks, the first network (referred to as the output neural network) is responsible for specifying an appropriate output for ensuring minimum phase behavior of the system. The second neural network is responsible for implementing an inverse dynamics controller. Both networks are trained online. Finally, the four proposed neural network controllers are implemented on a single flexible–link experimental test–bed. To improve the transient as well as steady-state response of the system, the two schemes are modified by adding a joint PD controller to the neural network controller. Experimental results show that this modification results in significant improvement in the system response and increases the dynamic range of the neural network controller and the robustness of the system to changes in the desired trajectory. Experimental and simulation results are presented to illustrate the advantages and improved performance of the proposed tip position tracking controllers over the conventional PD–type controllers in the presence of unmodeled dynamics such as hub friction and stiction and payload variations.

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A	Link cross–sectional area
E	Young's modulus
e	Position error
$\dot{e}$	Velocity error
$\ddot{e}$	Acceleration error
F_1	Viscous damping at the hub
F_2	Damping matrix due to the internal viscous friction
f_c	Coulomb friction
H	Inverse of the inertia matrix
I	Area moment of inertia of the link
I_h	Hub inertia
J	Objective function of the neural network
J_0	Link inertia relative to the hub
J_l	Payload inertia
K	Stiffness matrix
K_p	Proportional gain of the PD controller
K_v	Velocity gain of the PD controller
l_i	Length of the *ith* link
M	Bending moment
$M(\theta, \delta)$	Inertia matrix
M_l	Payload mass
S	Shear force
u	Input torque
u_c	Output of the conventional controller
u_n	Output of the neural network controller
$W_i(x,t)$	Deflection of a point x along the *ith* link
$W_i(l_i,t)$	Tip deflection of the *ith* link

$\mathbf{w}$	Matrix of the weights of the neural network
y_{ai}	Redefined output for the *ith* link
y_r	Reference position trajectory
$\dot{y}_r$	Reference velocity trajectory
$\ddot{y}_r$	Reference acceleration trajectory
$y_r^{(r)}$	*rth* derivative of y_r
y_{ri}	Reflected tip position of the *ith* link
y_{ti}	Net tip position of the *ith* link
α_i	A scale factor corresponding to a specific point on the *ith* link
α_i^*	Critical value of α_i
α_{i0}	The value of α_i^* for zero payload mass
δ_{ij}	*jth* flexible mode of the *ith* link
η	Learning rate
θ_i	Joint position of the *ith* link
$\dot{\theta}_i$	Joint velocity of the *ith* link
$\ddot{\theta}_i$	Joint acceleration of the *ith* link
ρ	Uniform density of the link
τ_i	Input torque for the *ith* link
ϕ_{ij}	*jth* eigenfunction of the *ith* link
ω_{ij}	*jth* natural frequency of the *ith* link