Fifth IFSA World Congress (1993), 1203-1206

Positioning an Elastic Arm by Using Fuzzy Methods

Brian Feeny

Dept. of Mechanical Engineering, Michigan State University, East Lansing, MI 48824 U.S.A.

Abstract

Fuzzy techniques are applied to the positioning of an elastic beam. The advantage is that the system model is not needed. A simple fuzzy friction compensator is also used. The final position is achieved within 3/2 the period of the fundamental mode. A fuzzy set of rules is applied for large-angle positioning, with adaptations that reduce the effects of shock. In this case, the final position is achieved within two fundamental periods. There is typically some final error attributed to the dry friction.

Introduction

The control of flexible manipulators has received considerable attention recently. This is partly because this simply posed system challenges the theoretical aspects of traditional control methods. Another reason is more practical: as manipulators become smaller and lighter in the goal of increasing speed, they become more flexible.

Some general and theoretical aspects are discussed in [1-2]. Most authors have successfully used state-feedback control, such as the LQ method [3-5], although Laplace transform techniques [6] and inverse methods [7] have also been proposed.

The drawbacks are that the system must be accurately (and sometimes painstakingly) identified, and the the nonlinear features of cheap, commercially available motors are detrimental to performance. Traditional control strategies also introduce shocks, which reduce the quality of the result. Shaped-torque techniques have been developed to deal with this problem [5,8-9].

This paper investigates an alternative. A flexible beam is controlled by fuzzy methods. No system model is used. Only one elastic mode is controlled. Furthermore, cheap harmonic-drive motors are used. These motors have friction. A fuzzy method is used to compensate for friction. Since this uses no modeling, it is easy, but there is some tradeoff with precision.

The Experimental Robot

The experiment (Figure 1) consisted of a flexible, hardened steel beam, 0.72 m in length and 1 mm thick, clamped to a rigid hub. The radius of the mount was 1 cm. The hub was attached to a Modro Robot [10]. A harmonic-drive motor with a gear ratio of 100:1 applied torque to the hub. The angular deflection of the hub was sensed with an optical encoder. Strain gages sensed the bending of the beam. This signal was calibrated against the first bending mode to approximate the tip deflection.

A steel beam of 0.4 m length and 2 mm thickness was mounted to the above beam in effort to separate natural frequencies in the first and higher modes of vibration. At times, a 200 g payload was attached to the tip of the beam. With the payload, the beam exhibited a visible torsional effect during deflection.

For small vibrations in the clamped beam, the fundamental frequency was 0.97 Hz, and the second modal frequency was 10. Hz. With the payload, the fundamental frequency was 0.46 Hz.

The attached steel beam, the strain-gage sensor system, and the torsional effect, are examples of aspects which are difficult to model, adding to the temptation of avoiding the system-identification step by using a fuzzy controller. Additional modeling obstacles are the friction and play in the harmonic-drive motor.

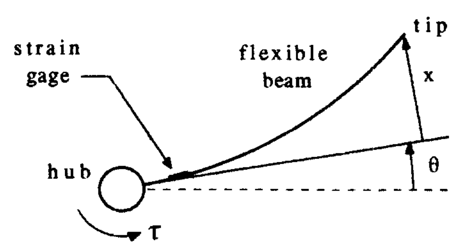


Figure 1. Schematic diagram of the experimental robot. θ represents the angle of the rigid hub, and x represents the relative tip displacement. τ is the torque applied to the hub.

Fuzzy Methods

Normally, fuzzy controllers take all of the measured outputs, convert them to fuzzy vectors, employ a rule table, and defuzzify to obtain the control signal [11]. In the case of the elastic beam, we measure four states: hub angle, angular velocity, relative strain, and strain rate. Four outputs lead to a fourth-order rule table, i.e. a table of dimension $n \times n \times n \times n$, given n membership functions for each signal. This is too large to visualize. Without visualization, it is difficult to use intuition.

To this end, we have constructed two second-order rule tables, one corresponding to hub angle and angular velocity, and the other relating to relative strain and strain rate. Each lower-order subset is operated upon in the usual fuzzy manner. The resulting two defuzzified outputs are weighted and summed, so that $u = k_x u_x + k_\theta u_\theta$, where u is the control signal, u_x and u_θ are the defuzzified signals associated with the relative displacement and angle, respectively.

For simplicity, the same form of membership functions is used for each variable, and also for the control signal. The form membership functions, shown in Figure 2, effectively introduces control parameters to the system. In this experiment, $b = 0.025$ m for the relative displacement signal, $b = 1.375$ m/s for the relative velocity signal, $b = 0.075$ rad for the hub-angle signal, and $b = 0.25$ rad/s for the angular-velocity signal. These values were taken based on envisioned ranges of the motion.

The two rule tables (Figure 3) are generated from intuition. The idea is that a positive torque on the hub

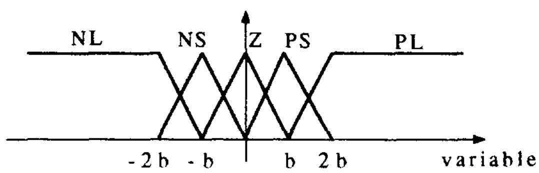


Figure 2. Membership functions for variables θ, $\dot{\theta}$, x, and $\dot{x}$. NL, NS, Z, PS, and PL stand for negative large, negative small, near zero, positive small, and positive large.

(a)

$\dot{\theta}$ \ θ	NL	NS	Z	PS	PL
PL	Z	NS	NL	NL	NL
PL	PS	Z	NS	NS	NL
Z	PL	PS	Z	NS	NL
NS	PL	PS	PS	Z	NS
NL	PL	PL	PL	PS	Z

(b)

$\dot{x}$ \ x	NL	NS	Z	PS	PL
PL	Z	PS	PL	PL	PL
PS	NS	Z	PS	PL	PL
Z	NL	NS	Z	PS	PS
NS	NL	NS	NS	Z	Z
NL	NL	NL	NL	NS	Z

Figure 3. The rule tables for (a) θ and $\dot{\theta}$, and (b) x and $\dot{x}$. The abbreviations NL, NS, Z, PS, and PL stand for negative large, negative small, near zero, positive small, and positive large, respectively. For example, if x is negative large, and x is positive small, then the table indicates a control signal that is negative small.

tends to increase the hub angle and angular velocity, while it tends to decrease the relative strain and strain rate. This is consistent with an optimal linear-feedback controller for a single-mode model of the system [4].

The defuzzification procedure was motivated by simplicity. The defuzzifying membership functions are specified by mass and centroid alone. The shapes of these functions are thus not unique. (The centroids and masses were derived from membership functions of the same shape as those used above.) In defuzzification, the weighted sum of these masses is performed. The weights are determined via the minimum operator [11]. The resulting controller is piecewise smooth with saturation, similar to a sliding-mode controller with a boundary layer [12].

The sampling time was 0.05 seconds.

Friction Compensation

In the experimental setup, friction is a dominating force. The beam tip is capable of oscillating with an amplitude of approximately 0.1 m without overcoming the static friction in the hub. Not only can friction limit the accuracy of the manipulator, it can also lead to limit cycles and other complicated behavior [13]. For these reasons, friction *must* be compensated.

Traditionally, friction is compensated in a variety of ways, ranging from rather sophisticated observer systems [14-16] to simply counteracting with a signum function [17]. As long as this signum function exceeds the actual friction force, precision can be obtained [18] (perhaps with chattering in the controller). Another alternative is to use stiff controllers (see Gorinevski [19]).

Since we are working with fuzzy systems, there is no sense in using observer systems that need system models. This controller employs a fuzzy friction compensator. The value of static friction μ_s is estimated roughly. Based on estimates of the angular velocity, a fuzzy vector is constructed which indicates whether the hub is probably slipping, or probably sticking. These membership functions are shown in Figure 4. The parameter $b = 0.005$ rad/s. If it is probably sticking, it is probably given enough extra force to overcome stiction. Defuzzification is performed as above, producing a friction compensation torque μ which is then added to the control signal. Thus, the net applied torque τ has the form $\tau = u + \mu$.

Such a fuzzy compensator is equivalent to a piecewise-linear approximation to a signum function. The width d of the transition from positive friction to negative friction introduces a parameter to the system. This parameter will affect the accuracy of the final position of the robot. However, this region of finite slope removes the chattering effect observed with signum compensators.

Results

The fuzzy controller is applied to the problem of positioning a beam, initially at rest, from a start postition to an end position, which is taken to be zero. An example of a small motion (on the order of tenths of meters) is shown in Figure 5 in terms of the absolute displacement of the tip, the control signal, and the friction compensation. The parameters were $k_x = 0.2$ and $k_\theta = 0.4$. The time at

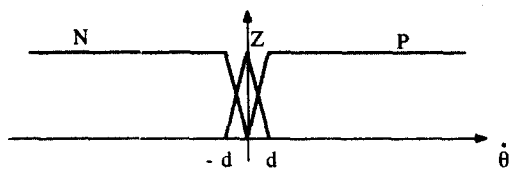


Figure 4. Stick-slip membership functions. P, N, and Z are for positive slip, negative slip, and zero velocity (possibly sticking). d = 0.005 rad/s.

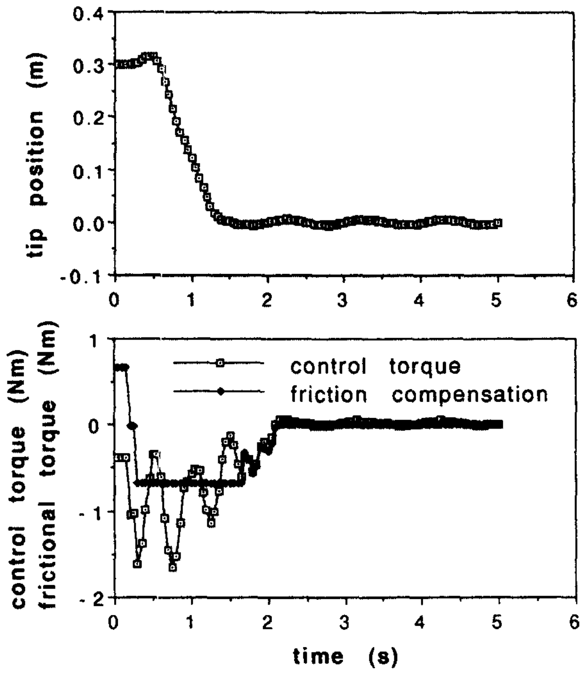


Figure 5. The upper graph plots the estimated motion of the beam tip. The lower graph shows the control signals μ and τ = μ + *u*.

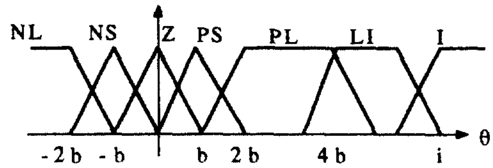
which the end position is achieved is approximately 3/2 the period of the first mode of the uncontrolled beam. (High-performance flexible robots might typically be in the range of 3/2 the period). Similar results were obtained with other parameter values, with different settling times and overshoots.

There is a residual oscillation visible at the end of the control step. It is likely that this is present because the friction compensation is done in approximation. This can also cause a final offset in position.

Note that the displacement is estimated from the strain based on the first mode of bending. Ignoring higher modes can cause instability.

The controller has also been applied to a robot with a payload. Results are similar if the values of k_x and k_θ are adjusted slightly. Note that, with a payload, unmodeled torsional effects are visible.

Finally, a modified set of memberships and rules (Figure 6) are applied to the robot for large motions (around $\pi/2$ in hub angle, or nearly a meter circumferentially).



θ̇ \ θ	NL	NS	Z	PS	PL	LI	I
PL	Z	NS	NL	NL	NL	NX	NX
PS	PS	Z	NS	NS	NL	NX	NX
Z	PL	PS	Z	NS	NL	NX	NL
NS	PL	PS	PS	Z	NS	NX	NX
NL	PL	PL	PL	PS	Z	NS	NL

Figure 6. Membership functions and rule table for large, positive initial angles. I and LI refer to "initial angle" and "large angles near the initial angle". NX calls for a negative, extra-large torque.

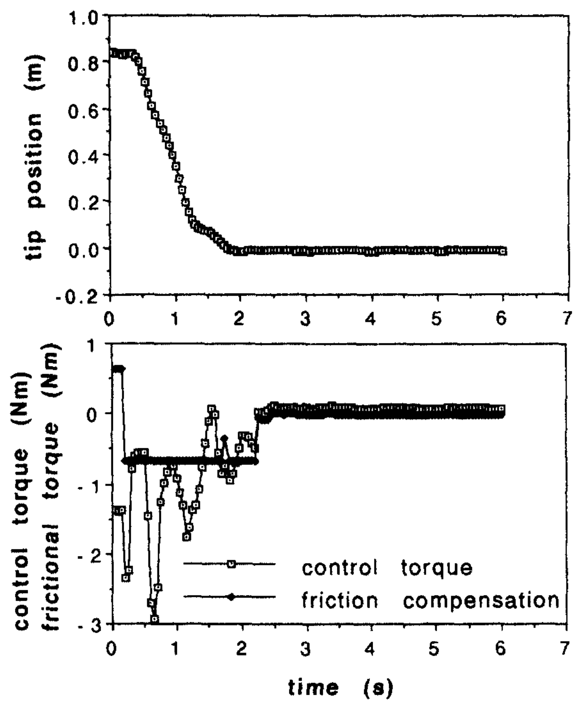


Figure 7. The upper graph shows the large-angle motion of the beam tip. The lower graph plots the control signals μ and τ = μ + *u*.

These modified rules include additional members of "very large angle" and "very large torque". Near the starting point, however, the applied torque is to be small. The goal here is to avoid large shocks and residual vibrations.

The controller operates reasonably for some initial positions. Since this controller adds nonlinearities, response varies with the initial conditions. Figure 7 shows an example of positioning for large angles. In this case, the tip reaches the target in approximately two fundamental periods of motion, with little residual vibration.

Conclusions

We have applied fuzzy control methods to an elastic arm. The object was to seek an easy way to steer elastic robots. The entire system identification step has thus been removed, and only the first mode of the robot has been considered for the intuitive control scheme. This might limit performance.

The implemented fuzzy friction compensator is equivalent to a piecewise-linear approximation to a signum function. Again, it required no system identification or observer construction. An estimate of the static friction is all that was used. Error in the friction compensation causes some final oscillation or offset.

The controller was in some sense a hybrid of proportional feedback and fuzzy control. Coupling the fuzzy controller to the friction compensator, the resulting robot motion would be adequate for low-precision tasks.

The parameters have been chosen based on intuition and simplicity. Some type of optimization strategy, such as in [20], might improve the results. Improvements would also accompany an upgrade in the friction compensation.

Controlling higher modes might bring improvements. Using modal sensors, the intuition would be similar to that of the first mode. For even-numbered modes, the intuition would be negative that of the first and other odd-numbered modes. The weights necessary for each modal control signal would have to be determined.

Acknowledgements

The work was funded and motivated by the ETH Institut für Robotik, under Professor G. Schweitzer. The experiment was set up with the help of R. Hüppi, E. Nielson, R. Kummer, and D. Kunzler, at the ETH. Helpful discussions also came from S. Vestli, D. Vischer, N. Tschichold-Gürman, and G. Caurin.

References

[1] Cetinkunt, S. and W.-L. Yu, Closed-loop behavior of a feedback-controlled flexible arm: a comparative study, *Int. J. Robotics Res.,* 10(3), 263-274, 1991.

[2] Chait, Y., M. Miklavcic, C. R. MacCluer, and C. J. Radcliffe, A natural modal expansion for the flexible robot arm problem via a self-adjoint formulation, *IEEE Trans. Robotics and Automation,* 6(5), 601-603, 1990.

[3] Cannon, R. H., and E. Schmitz, Initial experiments on the end-point control of a flexible one-link robot, *Int. J. Robotics Research,* 3(3), 62-75, 1984.

[4] Bhat, S. P., and D. K. Miu, Precise point-to-point positioning control of flexible structures, *J. Dynamic Syst., Meas. Contr.,* 112(4), 667-674, 1990.

[5] Meckl, P. H., and W. P. Seering, Experimental evalulation of shaped inputs to reduce vibration for a Cartesian robot, *J. Dynamic Syst., Meas. Contr.,* 112(2), 159-165, 1990.

[6] Bhat, S. P., and D. K. Miu, Solutions to point-to-point control problems using Laplace transform technique, *J. Dynamic Syst., Meas. Contr.,* 113(3), 425-432, 1991.

[7] Moulin, H., and E. Bayo, On the accuracy of end-point trajectory tracking for flexible arms by non-causal inverse dynamic solutions, *J. Dynamic Syst., Meas. Contr.,* 113(2), 320-323, 1991.

[8] Swigert, C. J., Shaped torque techniques, *J. Guidance Contr.,* 3(5), 460-467, 1980.

[9] Singer, N. C., and W. P. Seering, Preshaping command inputs to reduce system vibration, *J. of Dynamic Syst., Meas. Contr.,* 112, 76-82, 1990.

[10] Nielsen, E., and R. Hüppi, Modro: a modular concept for an application-adapted robotic system, *23rd Int. Symp. on Industr. Robots,* Barcelona, October 6-9, 1992.

[11] Geering, H. P., *Introduction to Fuzzy Control,* IMRT-Bericht Nr. 24, ETH Zürich, Switzerland, 1992.

[12] Palm, R., Sliding-mode fuzzy control, *IEEE International Conf. on Fuzzy Systems,* San Diego, March 8-12, 1992.

[13] Singh, S. K., *Modified PID control with Stiction: Periodic Orbits, Bifurcation and Chaos,* paper CAR-90-04, Dartmouth, NH, July 1990.

[14] Müller, P. C., Compensation of Coulomb friction in the position control of industrial robots, *Third German-Japanese Seminar on Nonlinear Problems in Dynamical Systems–Theory and Applications*, Stuttgart, Germany, 13.1-13.11, 1987.

[15] Caurin, Glauco, *Roboterachse mit Reibungsbeobachter,* Nachdiplomarbeit, ETH Zürich, Switzerland, 1990.

[16] Schäfer, U., and G. Brandenburg, Model reference position control of anelstic two-mass system with backlash and Coulomb friction using different types of observers, *Proc. of the Sixth Conf. on Power Electronics and Motions Control III,* Budapest, Hungary, October 1-3, 797-802, 1990.

[17] Kubo, T., G. Anwar, and M. Tomizuka, Application of nonlinear friction compensation to robot arm control, *Proc. of the IEEE Int. Conf. Robotics and Automation,* San Francisco, 722-727, 1986.

[18] Southward, S. C., Radcliffe, C., and C. R. MacCluer, Robust nonlinear stick-slip friction compensation, *ASME Winter Annual Meeting,* Paper 90-WA/DSC-8, Dallas, Texas, Novermber 25-30, 1990.

[19] Gorinevsky, D. M., A. V. Lensky, and E. I. Sabitov, Feedback control of one-link flexible manipulator with gear train, *J. Robotic Syst.,* 8(5), 1991.

[20] Sulzberger, S., N. N. Tschichold-Gürman, and S. J. Vestli, FUN: optimization of fuzzy-rule based systems using neural networks, *IEEE Int. Conf. on Neural Networks,* San Francisco, March 28, 1993.