N93-11959

FUZZY LOGIC CONTROL OF TELEROBOT MANIPULATORS

Ernest A. Franke and Ashok Nedungadi
Robotics and Automation Department
Southwest Research Institute
6220 Culebra Road
San Antonio, TX 78228-0510

ABSTRACT

Telerobot systems for advanced applications will require manipulators with redundant degrees-of-freedom that are capable of adapting manipulator configurations to avoid obstacles while achieving the user specified goal. Conventional methods for control of manipulators (based on solution of the inverse kinematics) cannot be easily extended to these situations. Fuzzy logic control offers a possible solution to these needs.

A current research program at Southwest Research Institute has developed a fuzzy logic controller for a redundant, 4 degree-of-freedom (DOF), planar manipulator. The manipulator end point trajectory can be specified by either a computer program (robot mode) or by manual input (teleoperator mode). The approach used expresses end-point error and the location of manipulator joints as fuzzy variables. Joint motions are determined by a fuzzy rule set without requiring solution of the inverse kinematics. Additional rules for sensor data, obstacle avoidance and preferred manipulator configuration, eg. "righty" or "lefty", are easily accommodated. The procedure used to generate the fuzzy rules can be extended to higher DOF systems.

INTRODUCTION

Telerobots, mechanical manipulators that are controlled by an operator from a remote location and are also capable of automatically performing programmed tasks, will become increasingly important in the future as more complex and demanding applications are attempted. Telerobot applications typically occur in locations where direct access by humans is restricted by the remoteness (undersea and space) or by the environment (nuclear or chemical waste sites). In contrast to industrial robotic applications, the workcell for these telerobot tasks is unstructured and the exact operations required are not known in advance. Operator guidance and control of the remote manipulator is necessary but at the same time there will be some operations that occur so often it is desirable to provide the capability for automated execution of specific task elements upon operator command. In many instances the operator will maneuver the telerobot manipulator into the desired position and then initiate a programmed task element such as scanning, cutting, turning or grasping.

Current and anticipated applications for telerobots will be difficult to accomplish with typical approaches to manipulator kinematics and control. One capability that will be important in future telerobotic designs is kinematic redundancy, or the use of additional degrees-of-freedom in the mechanical structure of manipulator. The great majority of robot and telerobot systems in use today are non-redundant so that they are constrained to reaching a specified end position in only one geometric orientation. Kinematic redundancy provides several advantages including:

- Obstacle avoidance - the manipulator can reach around objects in the workspace and still achieve the desired endpoint position.
- Fail functional - the manipulator can continue to operate in spite of the failure of a motor or gearbox although the advantages of kinematic redundancy may be lost.
- Configuration for tasks - different tasks such as pushing, pulling, turning, or grasping can be performed more efficiently with different manipulator configurations. Kinematic redundancy provides a means of selecting a desired configuration for a specific task.

In spite of the advantages, there are several reasons why kinematic redundancy is not in greater use. The use of additional joints increases both the cost and the complexity of manipulators. In addition, control of redundant systems requires selecting one configuration or path from a great number of possibilities instead of simply following the single path that is possible in the case of non-redundant systems. Approaches to the control of these systems have been based on optimization techniques and are not suited for real time use due to excessive computational requirements. [1]

In order to meet the requirements of future applications, an advanced telerobotic system should be capable of [2]:

- End point control - The manipulator should be able to position itself as required to reach an end point specified by the operator without requiring the operator to specify the alignment of each manipulator link.
- Obstacle avoidance - The manipulator should be able to sense obstacles in the workspace, store their locations, and select manipulator configurations to avoid obstacles without direct operator instructions.
- Sensor based control - Sensors should be included to monitor variations in the task

(process) being performed, variations between workpieces, variations in the workcell, and variations in the manipulator itself. Control of the telerobot should include provisions to automatically compensate for variations when possible or for allowing corrections to be made by the operator when necessary.

- The controller should have the capability for selecting manipulator configurations to enhance particular operations. This should include the ability to utilize joint angle combinations that provide the maximum force or torque to be exerted, configurations that minimize manipulator inertia during moves, and configurations that will be most convenient in making the transition to the next operation.

CONVENTIONAL MANIPULATOR CONTROL

Typical teleoperator manipulator control provides the operator with a direct control signal to each axis of the remote manipulator. In a master-slave arrangement, control signals from each axis of the local master unit are used to drive the corresponding axis of the remote (slave) manipulator. This requires that the two units have the same number of axis and correspond kinematically. The most common arrangements approximate the geometry of the human arm. The use of direct correspondence between master and slave axis control signals makes it difficult to accommodate redundant kinematics and does not allow the controller to implement sensor based operations or adaptive configuration control.

An alternative approach is to provide direct joint control of the remote manipulator by joysticks or other signal input devices. This eliminates the need for kinematic correspondence (since there is no master unit) but coordinated motions are more difficult to achieve. Joystick control of a remote unit requires an interface to inform the operator of the location and configuration of the manipulator, something that is best accomplished with graphic presentations. In addition, joystick control methods retain the one-to-one control signal to axis drive arrangement that does not allow implementation of adaptive motion or configuration control.

Conventional robot control systems are based on a mathematical model of manipulator kinematics. Measurement of axis variables allows calculation of the manipulator end-point location by solving the forward kinematic model of the manipulator. Motion control is accomplished by solving the inverse kinematic equations to determine the axis values needed to position the end-point at specified locations. This can be computationally difficult since the equations of motion are generally nonlinear and the inverse solution may not be unique for all points along a desired path. In order to cope with these difficulties, designers have resorted to linearizing the kinematic models, building relatively massive, slow robots, and avoiding redundant kinematic configurations. Conventional approaches to robot control make it very difficult to provide adaptive motion control such as modifying the path dynamically to adjust offset and orientation to a workpiece as might be needed to perform a surface inspection using an eddy current probe. Conventional approaches also are unable to cope with redundant kinematic geometries since the mathematical model of the system (including solution of the inverse kinematic equations) is too complex to permit real-time solutions.

MODEL-FREE APPROACHES TO ROBOT CONTROL

Even cursory consideration of biological motion control systems shows that the approach is completely different from that of conventional robot control. When we reach for an object, we determine the approximate error (distance from our hand to the object) and move in such a way as to reduce the error. We do not precompute the path or the elbow or shoulder angles that will be required to grasp the object. Our motions are directed toward the goal of continually reducing the distance between our hand and the object. This goal directed strategy makes it very natural to incorporate adaptive elements such as path changes to conform to a surface or to track a moving object. In fact, we are very successful at reaching and grasping both stationary and moving objects and apparently accomplish these feats without an accurate mathematical model of the kinematics involved.

Recent developments in neural networks and fuzzy logic have shown that non-biological systems can also perform feedback control without the use of an accurate model of the process or motion involved. This is accomplished by the use of neural networks or fuzzy associative memories that "estimate continuous functions from data without specifying mathematically how outputs depend on inputs" [3]. Control by neural networks and by fuzzy logic is similar in many ways. From the implementation standpoint, neural systems encode information in an unstructured form and typically are taught the function to be estimated by examination of a series of examples. In all but the simplest cases, when a neural network controller has been taught a particular function, the estimating function is distributed through the connections, summing nodes, and weights of the system. This makes it difficult to determine the effect that changes in the network will have on performance and also difficult to determine what changes should be made in the network to effect desired changes in performance. In many cases it is preferable to completely retrain the network to obtain modified performance rather than make incremental changes to the network structure or weights.

Fuzzy logic control systems encode knowledge in a much more structured way. Rather than being taught from examples, fuzzy logic systems are typically implemented by drawing on knowledge of system operation to construct the cause-and-effect relationship rules entries. Specific input-output relations are expressed as Fuzzy Associative Memory (FAM) elements and the relationship between specific performance measures and FAM rules can bê determined more easily than for neural network systems. This provides the designer with better understanding of the effect of changes in the rules and allows modification or extension of the rules to incorporate new performance requirements.

Although both neural network and fuzzy logic approaches can be used for manipulator control, the fuzzy logic approach was selected for the research reported here. The fuzzy logic approach allowed an initial control system to be derived from fundamental concepts without the need for extended training sets. It provided a better understanding of effect of changes in the controller structure and allowed beginning with examples of reduced dimensionality and generalizing the results to higher dimensions and kinematic redundancy. Finally, the fuzzy logic control approach includes the capability for adding additional rules to incorporate additional features such as sensor adaptive control, obstacle avoidance, and configuration modifications without requiring a new training set for these additions. [4]

The proposed fuzzy logic robot controller mimics intelligent human-like decision-making through a fuzzy rule base, which is essentially a collection of varying degrees of cause-and-effect relationships, such as: "If A is observed then perform control action B" or "If less of A is observed then perform less of control action B" or conversely "If more of A is observed then perform more of control action B". Since the fuzzy logic robot controller presented in this paper is based on linguistic rules, it does not require the derivation of the complex inverse kinematic equations.

The approach used to implement fuzzy logic control of a manipulator was to calculate the error between the actual manipulator end-point (given by solution of the forward kinematic equations) and the desired end-point specified by a trajectory generator. A set of FAM-rule matrices was derived for each manipulator axis to associate the controller inputs (the end-point error and joint positions) to the desired output (drive signals to the joint motor). The investigation began with simulations of controller performance for a two-axis planar robot and was then extended to three- and four-axis kinematically redundant planar robot simulations.

DEVELOPMENT OF THE RULE BASE

The procedure used for development of the fuzzy rule base is derived from the forward kinematic equation for a four DOF planar manipulator, shown in Figure 1.

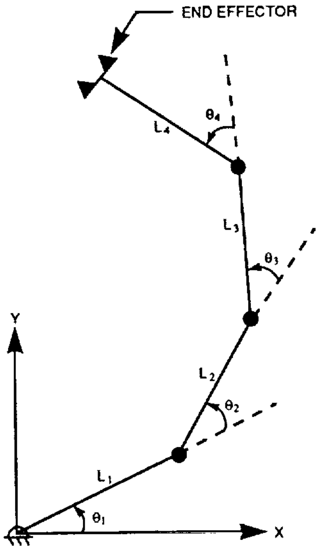


Figure 1. A Four DOF Planar Manipulator

Referring to Figure 1, the end point coordinates of the manipulator X_0 and Y_0 can be expressed as a function of the joint angles and link lengths L_1, L_2, L_3, and L_4.

$$\begin{aligned} X_0 &= L_1\cos(\theta_1)+L_2\cos(\theta_1+\theta_2)+L_3\cos(\theta_1+\theta_2+\theta_3)+ \\ &\quad L_4\cos(\theta_1+\theta_2+\theta_3+\theta_4) \\ Y_0 &= L_1\sin(\theta_1)+L_2\sin(\theta_1+\theta_2)+L_3\sin(\theta_1+\theta_2+\theta_3)+ \\ &\quad L_4\sin(\theta_1+\theta_2+\theta_3+\theta_4) \end{aligned} \tag{1}$$

Equation (1) describes the forward kinematic model for the four DOF planar robot of Figure 1. Taking the first variations of equation (1) from some nominal robot configuration θ_1, θ_2, θ_3, and θ_4 we have:

$$\begin{aligned} \delta x &= [\frac{\partial x}{\partial\theta_1}]\delta\theta_1+[\frac{\partial x}{\partial\theta_2}]\delta\theta_2+[\frac{\partial x}{\partial\theta_3}]\delta\theta_3+[\frac{\partial x}{\partial\theta_4}]\delta\theta_4 \\ \delta y &= [\frac{\partial y}{\partial\theta_1}]\delta\theta_1+[\frac{\partial y}{\partial\theta_2}]\delta\theta_2+[\frac{\partial y}{\partial\theta_3}]\delta\theta_3+[\frac{\partial y}{\partial\theta_4}]\delta\theta_4 \\ \delta x &= A_1\delta\theta_1+A_2\delta\theta_2+A_3\delta\theta_3+A_4\delta\theta_4 \\ \delta y &= B_1\delta\theta_1+B_2\delta\theta_2+B_3\delta\theta_3+B_4\delta\theta_4 \end{aligned} \tag{2}$$

where:

$A_1 = -[L_1 \sin(\theta_1) + L_2 \sin(\theta_1+\theta_2) + L_3 \sin(\theta_1+\theta_2+\theta_3) + L_4 \sin(\theta_1+\theta_2+\theta_3+\theta_4)]$

$A_2 = -[L_2 \sin(\theta_1+\theta_2) + L_3 \sin(\theta_1+\theta_2+\theta_3) + L_4 \sin(\theta_1+\theta_2+\theta_3+\theta_4)]$

$A_3 = -[L_3 \sin(\theta_1+\theta_2+\theta_3) + L_4 \sin(\theta_1+\theta_2+\theta_3+\theta_4)]$

$A_4 = -[L_4 \sin(\theta_1+\theta_2+\theta_3+\theta_4)]$

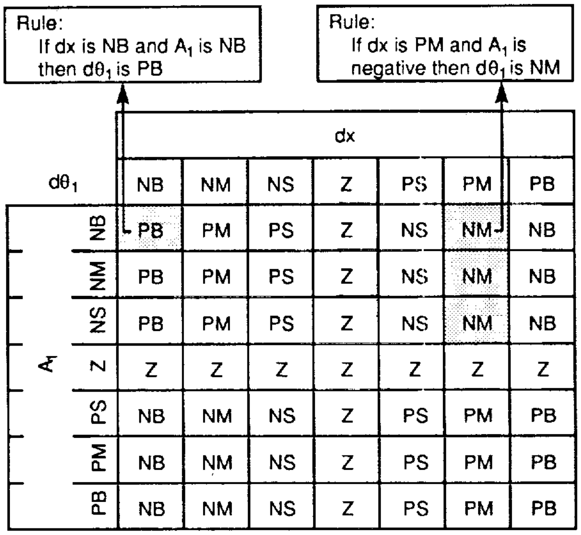
$B_1 = [L_1 \cos(\theta_1) + L_2 \cos(\theta_1+\theta_2) + L_3 \cos(\theta_1+\theta_2+\theta_3) + L_4 \cos(\theta_1+\theta_2+\theta_3+\theta_4)]$

$B_2 = [L_2 \cos(\theta_1+\theta_2) + L_3 \cos(\theta_1+\theta_2+\theta_3) + L_4 \cos(\theta_1+\theta_2+\theta_3+\theta_4)]$

$B_3 = [L_3 \cos(\theta_1+\theta_2+\theta_3) + L_4 \cos(\theta_1+\theta_2+\theta_3+\theta_4)]$

$B_4 = [L_4 \cos(\theta_1+\theta_2+\theta_3+\theta_4)]$

Since equation (2) represents the linearized kinematic model of the 4 DOF planar robot, the Principle of Superposition is valid when applied to the individual joint angle variations $\delta\theta_1$, $\delta\theta_2$, $\delta\theta_3$, and $\delta\theta_4$. Thus the combined contribution of $\delta\theta_1$, $\delta\theta_2$, $\delta\theta_3$, and $\delta\theta_4$ for a given δ_x and δ_y is equal to the individual contributions of $\delta\theta_1$, $\delta\theta_2$, $\delta\theta_3$, and $\delta\theta_4$. We assume that each of the four joint variations ($\delta\theta_1$, $\delta\theta_2$, $\delta\theta_3$, and $\delta\theta_4$), the desired move in the *x* and *y* directions and variables A_1, .. A_4 and B_1, .. B_4 of equation (2) are characterized by the following primary fuzzy sets: Large Positive (LP), Medium Positive (MP), Small Positive (SP), Small Negative (SN), Medium Negative (MN), and large Negative (LN). Inspecting equation (2) and applying the Superposition Principle, two Banks of Fuzzy Associative Memory rules (FAM) are proposed that together determine $\delta\theta_1$ for a given δ_x and δ_y. The rules relating required changes in θ_1 to desired end-point motion in the x-direction are shown in Figure 2. The rules for desired y-motion are the same except for use of the B_i coefficients rather than the A_i.



Rule:
If dx is NB and A_1 is NB
then $d\theta_1$ is PB

Rule:
If dx is PM and A_1 is
negative then $d\theta_1$ is NM

		dx						
$d\theta_1$		NB	NM	NS	Z	PS	PM	PB
A_1	NB	PB	PM	PS	Z	NS	NM	NB
	NM	PB	PM	PS	Z	NS	NM	NB
	NS	PB	PM	PS	Z	NS	NM	NB
	Z	Z	Z	Z	Z	Z	Z	Z
	PS	NB	NM	NS	Z	PS	PM	PB
	PM	NB	NM	NS	Z	PS	PM	PB
	PB	NB	NM	NS	Z	PS	PM	PB

Figure 2. FAM Bank for Joint 1 (δ_x term).

The fuzzy rules for the remaining joints (θ_2, θ_3, θ_4) are similar. The entries of each FAM bank were filled through graphical inspection. For example, if the commanded move in the *x* direction were MP and A_1 were to MN, then a MN $\delta\theta_1$ is required to achieve the requested move. In a similar fashion, each of the entries of the above FAM Bank (A) can be filled out. Each entry in the FAM bank represents a fuzzy associative memory rule or input-output transformation of the form:

IF (A_1 is MN) AND (δ_x is MP) THEN $\delta\theta_1$ is MN

Thus FAM bank A is comprised of 7 x 7 = 49 rules. Inspecting the symmetry of the FAM bank, the following compound rules can be formulated:

IF (A_1 is LN) OR (A_2 is MN) OR (A_3 is SN) AND (δ_x is SN)
THEN $\delta\theta_1$ is SP

This construct reduces the 49 rules per FAM bank to 14 rules per table. Furthermore the overlapping (25%) of the seven primary fuzzy sets that describe A_1, δ_x, and $\delta\theta_1$ are such that a state (A_1, δ_x) can belong simultaneously to a maximum of 2 fuzzy sets, therefore only a maximum of 4 rules per FAM bank will have a non-zero contribution.

CURRENT RESEARCH

The fuzzy logic control scheme described above has been simulated using a PC-AT computer and a Fuzzy-C Development System from Togai Infralogic. Kinematic models of several planar manipulators were used to investigate performance for two, three, and four DOF systems. The fuzzy rule sets were translated into C code and program modules were added to generate end-point path trajectories and provide graphic display of the robot motion. Straight line and circular path trajectories were generated and the motion of the simulated manipulators was analyzed.

The simulation showed that the manipulators with the fuzzy controller were able to follow the specified trajectories. For two and three DOF manipulators, the results were similar to conventional control systems. The more interesting results were obtained for the four DOF, redundant robot case. For very small path steps, the actual path followed differed from the specified trajectory by only small amounts. As the step size was increased, the following error increased. For large step sizes (and correspondingly large errors) the system became unstable and the simulated robot left the commanded trajectory and wandered about the work space. Since analysis shows that the computational requirements for fuzzy control are much less than for conventional approaches of control of redundant manipulators, it should be possible to maintain a high servo update rate so that the step size will be small even for large velocities.

Bench mark tests comparing the execution speed of the fuzzy logic controller with the classical controller revealed that the approach described in this work was 1.5 times faster than traditional methods which requires solution of the inverse kinematic equations. This increase in performance was achieved mainly because the FLC did not solve any inverse kinematic equations and all internal evaluations of the fuzzy rule base was performed by integer additions and multiplications. On the other hand, traditional methods require several matrix manipulations such as inversions and multiplications. The tradeoff for the increased speed of the developed FLC is greater trajectory tracking errors compared to classical controllers that explicitly solve the inverse kinematic equations. This is typical of a fuzzy rule base approach because a fuzzy rule base describes a patch in the state space rather than an exact single point. In several robotic applications, the reduced tracking ability may not necessarily be a drawback. There are numerous robot applications which do not require precise trajectory tracking, such as paint stripping, paint application, obstacle avoidance or applications that re^uire the robot to move a payload from one point to another.

A noteworthy aspect of the FLC controller is that the total number of rules required to control the robot arm is linearly dependent to the total number of degrees-of-freedom. This implies that the scheme is still implementable for robots with higher degrees of freedom.

On inspection of the proposed fuzzy rules, it is evident that the contribution of the individual joints is evaluated independent of the other axis. The individual contributions are then combined using the Principle of Superposition to result in some motion at the end point of the robot. This implies that the individual axis motion of the robot can be decoupled and therefore evaluated independently and simultaneously resulting in a very straightforward parallel implementation with a single dedicated fuzzy chip for each axis of motion.

The fuzzy controller has also been used to control a small four DOF planar manipulator at SwRI. This robot had been built for research in control of redundant systems and includes a flexible VME-based general purpose minicomputer motion controller [5]. Fuzzy control was implemented by transferring the C code from the simulator to the VME computer system and developing program modules for the interface to the servomotor controllers. Preliminary tests of straight line trajectories demonstrate that the fuzzy controller is operating satisfactorily on this system.

Plans for future work include additional tests and performance measurements using the planar research robot. Preliminary investigations have indicated that rules for obstacle avoidance can be expressed as fuzzy associative memories and combined with the motion control FAM's. This concept will be simulated and then tested on the planar research robot. Other plans include extension of the FLC approach to spatial robots and development of a hardware implementation of the fuzzy controller.

APPLICATIONS

The results of this research project have far-reaching implications for control of both robotic and telerobotic systems. The ability to perform end-point control of a manipulator without the need for solving the inverse kinematic equations can lead to considerable reductions in computational requirements for robot and telerobot controllers. In addition, it has been noted that there is no interaction between fuzzy rules governing the motion of the individual manipulator joints. This allows the evaluation of the control signals for each joint to be performed independently and simultaneously and leads to a very straightforward parallel implementation of microprocessors. Figure 3 illustrates one possible block diagram for a controller based on fuzzy logic. In the telerobotic mode, operator inputs (from joystick or hand controller) will be used to specify the desired end point motion. The trajectory generator performs smoothing and interpolation to calculate the specified position at discrete time intervals. Simultaneously, a second processor receives the measured joint angles and calculates the position of each joint using the forward kinematic solution. In the simplest configuration, the actual position and the difference between the actual and desired positions provide inputs to the FAM Axis Controller processors. These processors, one for each axis of the telerobot, compute the control signals for all axis drives simultaneously.

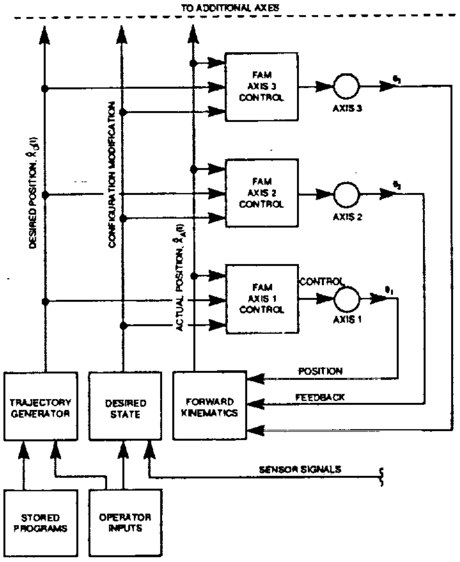


Figure 3. Block Diagram for a Telerobot Fuzzy Logic Controller.

The fuzzy logic controller can perform end point control of a redundant telerobot without requiring a kinematic correspondence between the master controller and the remote manipulator. This capability can be used in applications where redundancy is needed for fail-functional capability (operations on planetary space missions) or to provide maximum reach from a small ingress envelope (operations inside a nuclear waste storage vessel). In these cases the operator can use a simple hand controller to achieve the desired vector motions of the end point without having to be concerned about coordinated control of multiple manipulator joints.

An additional advantage of the fuzzy logic approach and the controller described above is that it provides a structure for adding additional fuzzy rules to provide sensor-adaptive control, obstacle avoidance and other enhancements. As shown in the block diagram this is accomplished by adding signals that describe the desired state of the system and using these to drive additional fuzzy rules in each axis controller. This is most advantageous when applied to redundant manipulators since the configuration and positions of joints can be changed without affecting the position of the end point. In some telerobot applications the operator's control console would include switches to specify preferred configurations:

- elbow to right
- elbow to left
- use "zig-zag" configuration (for maximum force or torque)
- "open bow" configuration (for obstacle avoidance)
- configuration that keeps links near the manipulator base (to minimize inertia during moves)

Signals from each of these switches would activate or disable sets of fuzzy rules at each axis controller. The results of these fuzzy rule evaluations would be combined with the results of the position error rules in order to generate a command signal for each joint that would move the end point nearer the desired position (primary goal) while attempting to maintain the specified manipulator configuration (secondary goal). These techniques would be most effective for transport and assembly operations such as space station or subsea activities.

Signals from sensory devices can be used as inputs to fuzzy rule sets in the same way as signals from the operator's console. This provides a convenient extension to obstacle avoidance and adaptive path motion control. Obstacles in the workspace could be detected by sensors mounted on the manipulator links or by sensors having a global view of the workspace. Each axis controller would include fuzzy rules to move the manipulator links away from nearby obstacles. The obstacle avoidance signals would be combined with motion control and configuration preference signals to define the complete control signal. Similar techniques could be used to sense and maintain standoff distance from a surface or position relative to a seam. A telerobot equipped with these sensors would be useful for surface inspection since the operator could concentrate on maneuvering the end effector over the required surface confident that the fuzzy controller would maintain the correct standoff distance and prevent collisions with obstacles. Other applications include task level programming and navigation for autonomous mobile robots.

CONCLUSIONS

A non-algorithmic, model free approach has been developed that relies on a fuzzy rule base to evaluate the required axis motion to result in user desired end-point motion of the robot. This scheme does not require solution of the complex non-linear inverse kinematic equations to arrive at joint set points. This is in sharp contrast with traditional robot controllers. The fuzzy rule based controller provides fast execution speed because the fuzzy rules perform simple integer additions and multiplications to evaluate the required axis motion. It can be shown that only a maximum of fifteen rules are required to evaluate individual joint axis motion and that a linear relationship exists between the number of rules and the degrees-of-freedom of the robot. This allows extension to higher DOF systems, including robots and telerobots with serial redundancy. Laboratory tests have demonstrated that FLC can be applied successfully to systems with kinematic redundancy and leads to implementation with far less computational requirements than conventional approaches. Finally, the FLC approach is very suitable for parallel processor implementation utilizing a dedicated fuzzy processor chip for each axis.

ACKNOWLEDGEMENTS

The authors gratefully acknowledge the support of the Internal Research and Development program of Southwest Research Institute.

REFERENCES

[1] "New Inverse Kinematic Algorithms for Redundant Robots," T. C. Hsia and Z. Y. Guo, Journal of Robotic Systems 8(1), pp. 117-132, 1991 .

[2] "Sensor Integrated Control fȯr Manipulators", E. Franke, V. Sturdivant, A. Nedungadi, proceedings of 1990 IEEE International Conference on Systems, Man, and Cybernetics, November, 1990.

[3] "Neural Network and Fuzzy Systems", B. Kosko, Prentiss Hall, Englewood Cliffs, June 1991.

[4] "Fuzzy Logic in Control Systems: Fuzzy Logic Controller - Part II, C. C. Lee, IEEE Transactions on Systems, Man and Cybernetics, Vol. 20, No. 2, March/April, 1990.

[5] "Investigation of Kinematically Redundant Serial Linkages", A. Nedungadi, Final Report for SwRI Internal Research Project 05-9508, 1989.