NEURO - ADAPTIVE HYBRID POS I TION/FORCE CONTROL OF ROBOTIC MANIPULATORS

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ABSTRACT

This paper presents a neural network approach to the hybrid control of manipulators while interacting with the environment. The overall control strategy comprises a nominal model of the manipulator with separate neural network compensators along the force and motion controlled directions in the task co-ordinate frame. With the learning mechanism operating in the task space, modelling errors, dynamic friction and changes in environment stiffness are automatically compensated for, which result in highly desirable task oriented performance characteristics. Simulation results are provided using the PUMA 560 arm which demonstrates the applicability of the proposed method to the position/ force hybrid control of manipulators.

1. INTRODUCTION

Many of present day industrial robots are used for welding, spray painting and material handling tasks which only require the control of manipulator end effector position and velocity. In contrast to these, several applications, such as assembly and machining of parts, involve continuous contact between the end effector and the environment. In these applications the robot end effector applies forces on various objects in it's environment and moves along their surfaces. If all the parameters of the robot and it's environment are known and robot positioning is precise it might be possible to accomplish these tasks using motion control strategies only. However, in the presence of inevitable discrepancies in modelling the manipulator and the environment, large reaction forces at the point of contact between the end effector and the environment may be developed that might damage the manipulator and it's environment. In such situations controlling the interacting forces is a better option.

Conceptually, when a robot makes contact with a smooth and stiff surface, it is impossible to move the end effector into the surface or to exert a force tangent to the surface. In a properly defined task co-ordinate system the position controlled axes and the force controlled axes are orthogonal [9] thereby providing for independent control of position and force. Numerous position/ force control schemes have been devised based on Cartesian co-ordinates of the end point or of some external reference frame. Overview of these schemes may be found in [15] [16]. These position/ force control schemes may be categorised in terms of whether a dynamic model of the arm is included in the control structure [1] [7] or not [11] [12].

Adaptive force control techniques have been proposed to improve performance under parameter uncertainties [2] [3]. These approaches have been designed to maintain accurate motion and force control in the presence of structured uncertainties in the system model, however, their performance cannot be guaranteed in the presence of unstructured uncertainties. If differences occur in the actual system and the model structure, the robustness of the adaptive control schemes decreases [10]. Consequently, it may be desirable to utilise control techniques that learn from experience. Neural Networks offer one such alternative. Advances in artificial neural networks have provided the potential for new approaches to the control of systems with complex, unknown and non-linear dynamics. The advantages of using neural networks for control applications can be summarised as three-fold. First, they have a flexible structure to express non-linear systems which may provide for a robust controller. Second, because of their structure they have a flexible learning capability compared to adaptive control methods which stay within pre-defined set of parameters of a model. In addition parallel processing and fault tolerance are easily achieved.

Recently there has been considerable interest in the application of neural networks to hybrid position/ force control of manipulators [5], [13], [14]. These efforts aim at compensating the dynamics of the arm and the environment within a central neural controller. Single link or two link manipulators have been considered in the above approaches. As the number of links of the arm increases, the complexity and non-linearity of the underlying system increases tremendously, which has to be controlled by the central neural controller. The neural network controller may therefore require excessive amount of training data in order to yield a reasonable generalisation and thereby increasing the training period. Also, since inverse dynamics of manipulators can be computed efficiently to a fair degree of accuracy using, for example, the Newton

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Euler equations, it is reasonable to utilise the inverse dynamic model and assist it through neural networks to compensate for the uncertainties of manipulators. The use of a model also decouples the position and force control directions so that independent neural networks of relatively small sizes can be used for each degree of freedom, each of which has to learn lesser amount of data as compared to a central neural controller.

This paper presents a new de-centralised approach to adaptive hybrid control of robots using neural network compensators. The motion and force degrees of freedom are effectively decoupled through a nominal model of the robot. Each motion and force degree of freedom is then controlled separately by a neural network controller. The effectiveness of the scheme is demonstrated by simulation studies on the PUMA 560 interacting with a rough surface in the presence of uncertainties in the robot model and that of the environment.

2. DYNAMIC MODEL FORMULATION

The dynamic equation of a general n-link manipulator can be represented by

$$D(\theta)\ddot{\theta} + h(\theta,\dot{\theta}) + g(\theta) = u(t) \tag{1}$$

where $u(t)$ is an $n\times1$ applied torque vector for joint actuators, $\theta(t)$ is the $n\times1$ joint angular position vector, $\dot{\theta}(t)$ is the $n\times1$ joint angular velocity vector, $\ddot{\theta}(t)$ is the $n\times1$ joint angular acceleration vector, $g(\theta)$ is an $n\times1$ gravitational force vector, $h(\theta,\dot{\theta})$ is an $n\times1$ Coriolis and centrifugal force vector and $D(\theta)$ is an $n\times n$ acceleration-related inertia matrix. When the robot makes contact with the environment a reactive force at the end effector will be felt at each joint. The dynamic equation then becomes

$$D(\theta)\ddot{\theta} + h(\theta,\dot{\theta}) + g(\theta) = u(t) - J^{T}(\theta)R \tag{2}$$

where $J(\theta)$ is the $n\times n$ Jacobian matrix, T is the transpose operator and R the reaction force/ moment vector at the end effector. In this paper it is assumed that $J(\theta)$ is bounded away from singularities or equivalently that the arm is bounded away from the corresponding joint positions causing $J(\theta)$ to be singular. In order to perform hybrid control in Cartesian co-ordinates the dynamics can be derived in Cartesian co-ordinates as shown below.

Let x be an $n\times1$ vector representing a set of Cartesian states of the end effector in a reference frame R_0. The forward kinematic relationship between joint positions and end effector configuration can be written as

$$x = f(\theta) \tag{3}$$

and the corresponding velocity relation

$$\dot{x} = J(\theta)\dot{\theta} \tag{4}$$

Differentiating equation (4) with respect to time the joint acceleration can be obtained

$$\ddot{\theta} = J^{-1}(\theta)(\ddot{x} - \dot{J}(\theta,\dot{\theta})\dot{\theta}) \tag{5}$$

The applied torque vector u(t) in (2) can be replaced by an $n\times1$ fictitious force/ torque vector F using the relationship

$$u(t) = J^{T}(\theta)F \tag{6}$$

substituting (5), (6) in (2) we get

$$D_x(\theta)\ddot{x} + H_x(\theta,\dot{\theta}) + G_x(\theta) + R = F \tag{7}$$

where $D_x(\theta)$ the Cartesian mass matrix, $H_x(\theta,\dot{\theta})$ the vector of velocity terms in Cartesian space and $G_x(\theta)$ the vector of gravity terms in Cartesian space are given by

$$\begin{aligned} D_x(\theta) &= J^{-T}(\theta)D(\theta)J^{-1}(\theta) \\ H_x(\theta,\dot{\theta}) &= J^{-T}(\theta)(h(\theta,\dot{\theta}) - D(\theta)J^{-1}(\theta)\dot{J}(\theta,\dot{\theta})\dot{\theta}) \\ G_x(\theta) &= J^{-T}(\theta)g(\theta) \end{aligned} \tag{8}$$

If the manipulator is in contact with a surface at a point whose position is x_e in R_0 frame while the effector position is x(t) then the interaction can be modelled as a pure elastic restoring force/ torque given by

$$R = K_e(x(t) - x_e) \tag{9}$$

where K_e is the environment stiffness matrix. If the manipulator is moving along a rough surface in a direction perpendicular to the force controlled direction, frictional forces are developed tangent to the surface which have not been considered in (7). The magnitude of these forces depends upon the magnitude of reaction force R. In this paper the friction model used is given by

$$f_r = -(\mu R_i v + \zeta_{ran}) \tag{10}$$

where μ is the coefficient of friction, v is the unit vector in the direction of constrained velocity, R_i is the force applied on the surface and ζ_{ran} is a random signal due to surface irregularities. This friction force may be considered as an unknown disturbance which the position controller has to neutralise.

3. HYBRID CONTROL

Using [4] and knowing the estimates of $D_x(\theta)$, $H_x(\theta,\dot{\theta})$ and $G_x(\theta)$, equation (7) can be used to decouple the constrained system into n sub-systems along n degrees of freedom in Cartesian co-ordinates and modelling errors can then be compensated by independent controllers with one controller along each degree of

freedom. However, Cartesian space dynamic equation (7) is computationally very expensive which presents a major obstacle in its real time implementation. As an alternative to (7), it can be readily seen that the joint torque u(t) needed for the constrained motion and force control can be computed efficiently through Newton Euler equations using the formula

$$u(t) = D(\theta)\ddot{\theta}^* + h(\theta,\dot{\theta}) + g(\theta) + R^* \qquad (11)$$

where $\ddot{\theta}^*$ is the $n\times1$ acceleration command vector for motion control and R^* is the $n\times1$ command vector for force control, both in joint co-ordinates. In this paper equation (11) is used for hybrid position / force control and $\ddot{\theta}^*$ and R^* are generated utilising neural networks to maintain position and force tracking accuracy in the presence of modelling errors.

3.1 Motion control

To generate $\ddot{\theta}^*$, the motion command vector in joint space, first a pseudo-control vector is formed in Cartesian space utilising neural networks, which is then transformed into joint space using the Jacobian relation. For the p motion degrees of freedom $\ddot{\theta}^*$ is given below

$$\ddot{\theta}^* = J^{-1}\begin{bmatrix} NN^{(1)} + PD^{(1)} \\ \cdot \\ \cdot \\ NN^{(p)} + PD^{(p)} \end{bmatrix} \qquad (12)$$

$$= J^{-1}\begin{bmatrix} f_1(\theta,\dot{\theta},\ddot{x}_d^{(1)}) + \{K_p(x_d^{(1)} - x^{(1)}) + K_v(\dot{x}_d^{(1)} - \dot{x}^{(1)})\} \\ \cdot \\ \cdot \\ f_p(\theta,\dot{\theta},\ddot{x}_d^{(p)}) + \{K_p(x_d^{(p)} - x^{(p)}) + K_v(\dot{x}_d^{(p)} - \dot{x}^{(p)})\} \end{bmatrix}$$

where $NN^{(i)} = f_i(\theta,\dot{\theta},\ddot{x}_d^{(i)})$ is the non-linear compensating function of joint positions, joint velocities and desired Cartesian acceleration along the ith degree of motion freedom, implemented through neural networks. $PD^{(i)} = K_p(\cdot) + K_v(\cdot)$ is the output of the PD controller in Cartesian co-ordinates along the ith degree of motion freedom with K_p and K_v being positive gains. The PD controller output also acts as an error signal used for updating the weights of the corresponding neural network. Each of the p neural networks has 2n+1 inputs and one output. Equation (12) may be compared with (5) and re-written as

$$\ddot{\theta} = J^{-1}\begin{bmatrix} g_1(\theta,\dot{\theta},\ddot{x}^{(1)}) \\ \cdot \\ \cdot \\ g_p(\theta,\dot{\theta},\ddot{x}^{(p)}) \end{bmatrix} \qquad (13)$$

The job of neural network implementing $f_i(\cdot)$, apart from compensating for $g_i(\cdot)$, is to reduce motion tracking errors along the ith degree of motion freedom, while motion errors along the remaining n-p force control directions are ignored.

3.2 Force control

Similar to the motion control strategy, pseudo-control vectors are generated in Cartesian co-ordinates in the n-p force degrees of freedom which are then transformed into joint co-ordinates using Jacobian relations to form R^*. When contact is made with a hard surface having a large stiffness value, due to very high loop gains, the force error signal $f_e' = f_d - f$ has very high frequency components. Use of this signal as the error measure for updating the weights of neural networks in the force loop resulted in poor convergence. This force error signal was smoothed out to generate f_e, a suitable error measure for the neural networks in force loops. Smoothing was performed using an exponentially weighted recursive filter given by the following equation

$$f_e^{(k+1)} = \alpha \times f_e^{(k)} + (1-\alpha)\times(f_d^{(k+1)} - f^{(k+1)})$$
$$0 \le \alpha \le 1 \qquad (14)$$

The force command vector R^* is then given by

$$R^* = J^T\begin{bmatrix} NN^{(1)} + P^{(1)} \\ \cdot \\ \cdot \\ NN^{(n-p)} + P^{(n-p)} \end{bmatrix} \qquad (15)$$

$$R^* = J^T\begin{bmatrix} F_1(f_d^{(1)}, f^{(1)}) + K_f f_e^{(1)} \\ \cdot \\ \cdot \\ F_{(n-p)}(f_d^{(n-p)}, f^{(n-p)}) + K_f f_e^{(n-p)} \end{bmatrix}$$

which can be compared with (6). $NN^{(i)} = F_i(f_d^{(i)}, f^{(i)})$ is the non-linear function compensator implemented by the neural network along the ith degree of force freedom and $P^{(i)} = K_f(\cdot)$ is the proportional gain also used as an error signal for neural network weight update. Each neural network in the force loop has two inputs and one output. Force errors along the p motion controlled directions are ignored.

The control structure for an n link robot is shown in Figure 1 where EWRF is the exponentially weighted recursive filter and Γ represents the forward kinematic transformations. The scheme is computationally efficient and is amenable to parallel processing implementation within a computing architecture. The inverse dynamics part, being computationally the most involved part in the algorithm, can be computed using Newton Euler equations in time linear in the number of links on a single processor. Moreover, very efficient implementations of Newton Euler formulas have been

achieved on multiple general purpose processors [6], and pipelined dedicated hardwares have been proposed to further cut down the computation time [8]. The neural network part is inherently parallel and two levels of parallelism may be observed. A higher level of parallelism exists because of independent neural networks in the position and force loops while a lower level of parallelism that is inherent to the neural network structure also exists. In Figure 1 a damping velocity feedback loop with gain K has also been added which is absent in conventional dynamic hybrid control [1]. This loop was found to be important in establishing a stable contact when dealing with a stiff environment in the presence of modelling errors.

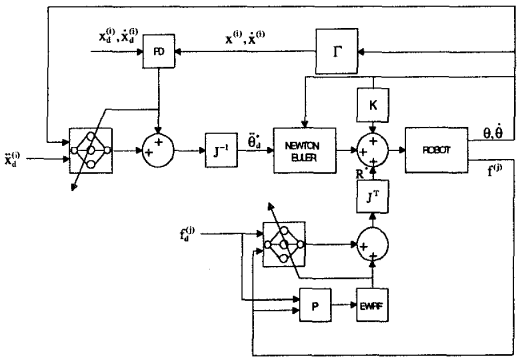

Figure 1. Hybrid control structure

4. SIMULATION APPLICATION

To demonstrate the effectiveness of the control scheme, the first 3 links of the PUMA 560 arm are used in the dynamic simulations. A schematic diagram of the system is shown in Figure 2, where a global reference frame R_0 is fixed to the base frame. The manipulator end point is moved in a circular trajectory along a surface parallel to the y-z plane of R_0 while applying a force in the direction of the x axis. A rigid robot is assumed, and modelling errors are introduced by changing the values of the robot inertia parameters by 25% from those used in the controller design. In addition using equation (10), frictional forces acting as disturbances for the motion control part are introduced tangent to the surface. There are two neural network compensators for the two motion degrees of freedom and one neural network in the single force loop. Every neural network has two hidden layers with sigmoidal activation function and a linear output neuron. The number of neurons in the first and second hidden layer being 20 and 10, respectively. Standard back-propagation [17] is employed for the learning process. The inputs to the neural network in the ith motion loop are the joint angles, their velocities and the desired acceleration in Cartesian co-ordinates for the ith degree of motion freedom. The inputs to the neural network in the jth force loop is the jth component of the sensed force vector after being suitably processed by a low pass filter and the desired force. Neural network weights were initialised to small random values. Simulation parameters are given in Table 1. Two values for the environment stiffness were used, 10^7 N/m for hard surfaces and 10^4 N/m for relatively soft surfaces. For the sake of comparison force control without neural network control is also shown.

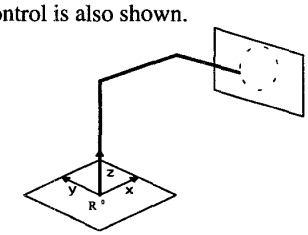

Figure 2. schematic diagram of 3 degree of freedom constrained system

During simulations it was observed that when significant modelling errors, in the form of inertia parameter errors and friction forces, were introduced then for a stiff surface a high value of damping velocity gain K was required to achieve an initial bump-less stable contact. However, if neural compensation was not used then because of the high damping gain the position response became very poor. In fact, the position response was improved if the gain K was reduced, but this then generated an unstable contact. Thus without neural compensation there had to be a compromise between position and force responses. By using neural networks in the position and force loops and a high value of damping gain, (K=400), both the objectives of accurate position and force control were achieved.

Figure 3 shows the desired and actual motion trajectories along the y-z plane for neuro-adaptive control with stiffness of the surface equal to 10^7 N/m. Very low tracking errors were observed throughout the course of the circular trajectory. Figure 4 shows the desired and actual force trajectories for the neuro-adaptive case with stiffness equal to 10^7 N/m. Figures 5 and 6 show the same trajectories when the surface stiffness was reduced to 10^4 N/m. Thus, figures 3 to 6 show that both motion and force tracking was good with a stable bump-less contact with the surface over a wide range of surface stiffness.

For comparison, force control without neural networks with surface stiffness of 10^7 N/m and K equal to 400 is shown in Figures 7 and 8. In Figure 7, it may be observed that the position response is poor owing to the high value of K, but without which, an unstable contact was observed as shown in Figure 9.

TABLE 1- Simulation Parameters.

K_p	500
K_v	50
K_f	0.1
μ	0.2
α	0.98
Inertia parameter error	25 %
Control cycle	200 Hz
Weight update rate	200 Hz

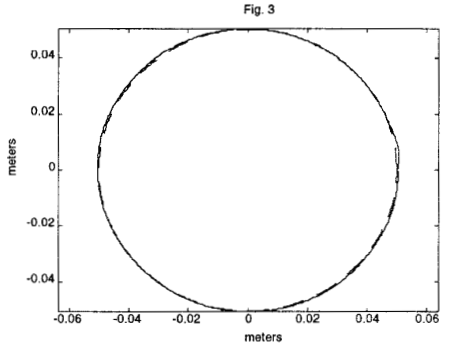

Figure 3. Desired and actual motion trajectory with Neural Compensation for stiffness 10^7 N/m.

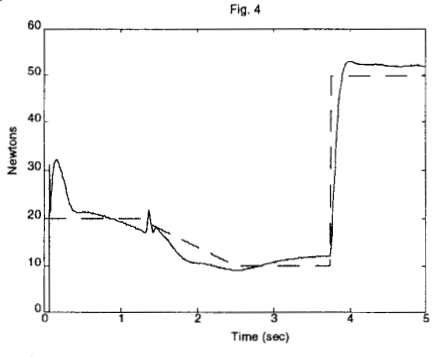

Figure 4. Desired and actual force trajectory with Neural Compensation for stiffness 10^7 N/m.

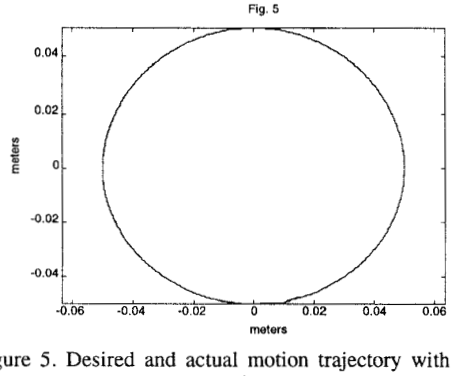

Figure 5. Desired and actual motion trajectory with Neural Compensation for stiffness 10^4 N/m

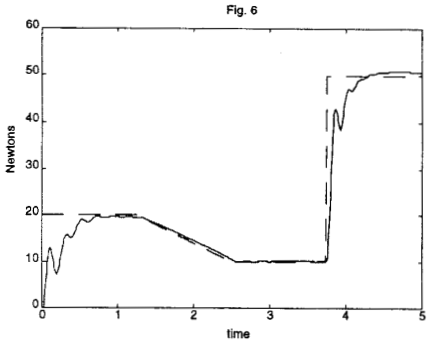

Figure 6. Desired and actual force trajectory with Neural Compensation for stiffness 10^4 N/m

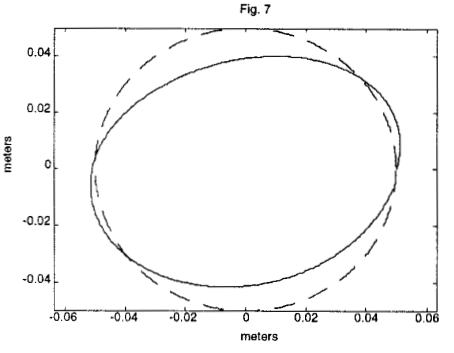

Figure 7. Desired and actual motion trajectory without Neural Compensation for stiffness 10^7 N/m.

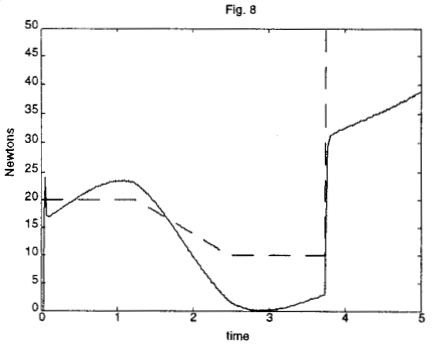

Figure 8. Desired and actual force trajectory without Neural Compensation for stiffness = 10^7 N/m and K = 400.

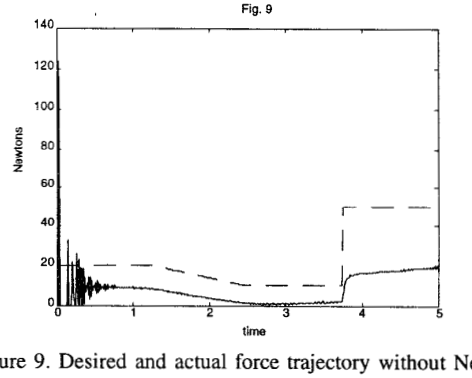

Figure 9. Desired and actual force trajectory without Neural Compensation for stiffness = 10^7 N/m and K = 40.

5. CONCLUSIONS

This paper presents an on-line neural network based scheme for hybrid position/ force control of manipulators. The scheme is based on the belief that neural networks perform best when they are not required to learn too much data, too fast. The use of a nominal dynamic model of the manipulator arm in conjunction with neural networks reduces the task required of neural networks to compensation of modelling uncertainties rather than generating the model itself. Because robot dynamics are highly non-linear and coupled, a central neural controller would require a large training set and long training periods, if it were to model the whole non-linear dynamics. This problem is particularly acute for robots having more than two degrees of freedom. By using a decentralised neural network compensation scheme along with a nominal model, smaller networks for each degree of motion/ force freedom can be used effectively. The role of neural networks in such a hybrid control scheme is a supportive one in that each neural network plays a small part in the overall control loop. Simulation studies, conducted on a realistic system, demonstrate accurate position and force tracking performance in the presence of uncertainties in the manipulator model and the environment. The scheme is computationally efficient and is well suited for parallel processing implementation within a computing architecture.

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