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Environment Estimation for Enhanced Impedance Control

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Abstract

Impedance control is a popular method of controlling the dynamic response a robot has to external forces. The advantage of such a control paradigm is the ability to manipulate in unconstrained, as well as constrained, environments. Unlike hybrid control methods that attempt to control forces and motions in orthogonal directions, impedance control consists of a single control scheme that accommodates both unconstrained and constrained maneuvers. One problem associated with such a control scheme is the selection of the robot's target impedance. This paper will illustrate, through analysis and experimentation, the shortcoming of improper target impedance selection. A new approach to adapting the target impedance, based upon an on-line estimate of the environment impedance, is proposed and demonstrated.

1. Introduction

New applications for robotic systems are demanding sophisticated control schemes that can facilitate a wide range of tasks. Many applications in industrial settings require only motion control of robotic systems. However, robotic applications such as nuclear waste remediation, robotic assisted surgery, and extraterrestrial exploration require a sophistication beyond simple motion control techniques.

Manipulation can be classified into two distinct classes; unconstrained and constrained tasks. During unconstrained maneuvers, a robot is free to move instantaneously in any direction. Motion control techniques are well suited for this class of tasks. Constrained tasks directly conflict with this form of control. Kinematic or dynamic constraints limit the motion of a robot[1]. Force becomes the state that is controlled along constrained degrees of freedom. Hybrid control techniques combine motion and force control. Motion control is provided along unconstrained degrees of freedom while force control is used along the directions that are constrained[2]. One limitation of this technique is the required knowledge of the location of the surface that produces the constraint.

In 1985, Hogan proposed a method of controlling the impedance of a manipulator[3]. An impedance controlled robot compensates for its own natural dynamics and provides a desired disturbance response to externally applied forces. This disturbance response is the desired impedance of the manipulator. One popular impedance model is a multiple degree of freedom, second order system. As such, the control designer can specify the effective mass, damping, and stiffness of the robot. The control design problem simplifies to specifying the robot's desired natural frequency and damping ratio.

During constrained manipulation, the dynamics of the robot coupled to its environment must be considered for proper control design. As such, a method of estimating the impedance of the environment is proposed. In addition, this identification technique is extended to a learning paradigm used to adapt the target impedance to variations in the environment impedance.

2. Control Design

Impedance control is used for the investigation of environment dynamics in this paper. The controller is based upon the computed torque method[4]. A robot's dynamic equations of motion can be expressed in the popular form

$$D(q)\ddot{q} + C(q,\dot{q})\dot{q} + g(q) = \tau + J^t(q)F \qquad (1)$$

where q is the nx1 generalized displacement and D(q), C(q,q), and g(q) are the inertia and coupling tensors and gravity load[5]. In addition, τ is the actuator torque and $J^t(q)F$ is the external force mapped to the generalize coordinates. A properly designed impedance controller will force the robot to behave as if it were a desired impedance

$$M_t\ddot{x} + B_t\dot{x} + K_t(x-\dot{x}) = F \qquad (2)$$

To produce such a controller, the transformation of the tip acceleration between the inertial coordinate system and its generalized coordinate systems is used.

$$\ddot{x} = J(q)\ddot{q} + \dot{J}(q)\dot{q} \qquad (3)$$

The acceleration, due to external forces and the target impedance is now expressed in the generalized coordinate system.

$$\ddot{q} = J^{-1}(q)M_t[F - B_t\dot{x} - K_t(x-x_0)] - J^{-1}(q)\dot{J}(q)\dot{q} \quad (4)$$

This acceleration term is directly substituted into the dynamic equations of motion and used to compute the torque required to compensate for the robot's natural dynamics and produce the dynamic response to forces described in Equation 2.

$$\tau = D(q)\left\{J^{-1}(q)M_t[F - B_t\dot{x} - K_t(x-x_0)] - J^{-1}(q)\dot{J}(q)\dot{q}\right\} + C(q,\dot{q})\dot{q} + g(q) - J^t(q)F \quad (5)$$

The vector x_0 provides the means for following a trajectory. When the robot has no contact force, the controller is similar to a PD controller described in an inertial coordinate system. The selection of the target mass, M_t, damping, B_t, and stiffness, K_t, control the response the robot has to external forces as well as tracking error.

The robot used for this study is illustrated in Figure 1. It consists of 2 degrees of freedom with two brushless DC servo motors providing actuation. Feedback signals include incremental encoders and tachometers on the actuators and a two DOF force transducer at the tip of the robot. The computation of the control signal is based on a TI TMS320C25 DSP located on a board on a PC expansion bus. The control loop is currently running at 1000 Hz.

3. Environment Influence

One advantage of impedance control over other popular robot control techniques is the ability to transform from unconstrained to constrained manipulation. An interesting problem to address is the selection of the target impedance. A general approach would consist of first specifying a simple second order dynamic system that the robot should emulate. This can be generalized as a target stiffness, damping and mass. The selection of these parameters control the natural frequency and damping ratio of the robot when a external force is applied.

$$\omega_n = \sqrt{\frac{K_t}{M_t}} \qquad \zeta = \frac{B_t}{2\sqrt{K_t M_t}} \quad (6)$$

The controller design simplifies to selecting the desired natural frequency and damping ratio of the robot. Problems arise when the robot is coupled to unstructured and unmodelled environment.

Consider the system illustrated in Figure 2. The spring-mass-dashpot represents an impedance controlled manipulator. The target impedance is based upon the desired natural frequency and damping discussed above. When the robot interacts with the environment, the external force has an order that is based upon the environment's impedance, modelled here as a spring, K_e. This provides the robot with a dynamic response that is different than the original design specifications.

$$\omega_n = \sqrt{\frac{K_t + K_e}{M_t}} \quad (7)$$

This increase in natural frequency directly effects the damping ratio of the coupled robot and environment.

$$\zeta = \frac{B_t}{2M_t\omega_n} \quad (8)$$

This effect is evident when attempting to control a robot during collision with a hard surface. Figure 5 illustrates the response of an impedance controlled robot colliding with a stiff wall. The target impedance model for the controller is critically damped, but the system vibrates when moving along the vertical wall. Figure 7 illustrates the response of the system if the controller is designed with the stiffness of the wall included in the target impedance. The target damping of the compensated robot controller is defined as

$$B_t = 2\zeta\sqrt{\frac{K_t + K_e}{M_t}} \quad (9)$$

It is evident that the performance of an impedance controlled manipulator increases if the desired impedance includes some modelling of the environment. The focus of this research is the design of a method of identifying the impedance of the environment in real-time.

4. MIMO Recursive Identification

The previous analysis illustrates how knowledge of the environment that a robot interacts with can improve the performance of the system. This section describes a method of modelling and identifying the impedance of an arbitrary environment.

If a MIMO linear system contains m inputs and p outputs, the system can be expressed by the linear transformation

$$y[k] = \phi^t[k]\,\theta \quad (10)$$

where the output vector, y[k], regression vector, ϕ[k], and parameter tensors, θ, are defined by the following.

$$\{y[k]\} = \{y_1[k]\,y_2[k]\cdots y_p[k]\} \quad (11)$$

$$\phi^t[k] = \{x_1[k]\cdots x_1[k-N]\,x_2[k]\cdots x_m[k-N]\,y_1[k-1]\cdots y_p[k-N]\}$$

$$\theta = \begin{bmatrix} \theta_{11} & \theta_{21} & \cdot & \theta_{pl} \\ \theta_{12} & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \\ \theta_{1N(m+p)} & \cdot & \cdot & \theta_{pN(m+p)} \end{bmatrix}$$

To completely solve the parameter tensor θ, N(m+p) equations are required.

$$Y = \begin{Bmatrix} y[k] \\ y[k-1] \\ \cdot \\ \cdot \\ y[k-N(m+p)] \end{Bmatrix} \qquad \Phi^t = \begin{Bmatrix} \phi^t[k] \\ \phi^t[k-1] \\ \cdot \\ \cdot \\ \phi^t[k-N(m+p)] \end{Bmatrix} \tag{12}$$

The linear model can be simplified by the tensor notation

$$Y = \Phi^t \theta \tag{13}$$

This leads to the solution of the general least squares problem. A performance index is defined that is equal to the square of the error between the modelled output and the actual output.

$$J(\theta) = \sum_{k=n}^{k=N+n} \left[y[k] - \phi^t[k]\theta\right]^t \Lambda \left[y[k] - \phi^t[k]\theta\right] \tag{14}$$

Minimizing this relationship with respect to the parameter tensor, θ, provides the batch solution

$$\theta = \left[\Phi \Phi^t\right]^{-1} \Phi Y \tag{15}$$

The matrix inversion lemma is utilized to avoid the complication of solving the matrix inversion in Equation 15. The solution to the linear system is then computed by a recursive algorithm. In addition, the weight, λ, provides a method of increasing the sensitivity of the estimation to changes in the environment. The solution to the linear regression then consists of the following:

$$L[k] = \frac{P[k-1]\phi[k]}{\left[\lambda + \phi[k]^t P[k-1]\phi[k]\right]} \tag{16}$$

$$\theta[k] = \theta[k-1] + L[k]\left\{Y[k] - \phi[k]^t\theta[k-1]\right\}$$

$$P[k] = \left(\frac{1}{\lambda}\right)\left[P[k-1] - \frac{P[k-1]\phi[k]\phi[k]^t P[k-1]}{\lambda + \phi[k]^t P[k-1]\phi[k]}\right]$$

At each sample period, the output vector y[k] and the regression vector ϕ[k] are updated. The weight λ controls the sensitivity of the algorithm to changes in the system. If λ is unity, the system collapses to the normal least squares solution. If λ is less than one, the model parameters can adapt to changes in the system[6]. The recursive solution provides a method of estimating the time and state variations of the robot's environment.

5. Environment Estimation

The objective of the identification process proposed in this paper is to estimate the location and dynamic characteristics of any constraints in a robot's workspace. To begin, the workspace is quantized into discrete components, each element representing a position of the robot's end effector. Figure 3 illustrates the platform used in this experiment. The array used to represent the robot's workspace is 100 x 100 elements. Each element of the array corresponds to one square centimeter of the robot's workspace. At each sample period of the controller, the tip force and position are recorded. This data is used in an identification algorithm, detailed shortly. Once the parameters associated with the environment are computed, they are stored in the corresponding x,y element in the array. These new parameter values are scaled and averaged with previous estimates of the environment at the corresponding tip position. Consider the stiffness tensor

$$\underline{K}(x,y)[k] = w\,K(x,y)[k] + (1-w)\,\underline{K}(x,y)[k-1] \tag{17}$$

The weight, w, provides sensitivity to current data. The tensor K(x,y)[k] is the current estimate of stiffness based upon most recent information. $\underline{K}$(x,y)[k-1] is the previous estimate of the stiffness at the current x,y position. The objective of the identification process is to construct a position dependent model of the robot's environment. This information may be used to adapt the impedance control to variations in the robot's environment.

A simple model representing the environment the robot may contact is

$$F = M\ddot{x} + K(x - x_0) \tag{18}$$

This model is specified in the robot's inertial coordinate system. The vectors F and x are n x 1. The inertia and stiffness tensors are n x n. The vector x_0 models the constraint surface in the robot's workspace. A method of estimating the parametric coefficients of the environment is desired. For this study, only 2 degrees of freedom are considered. To simplify the estimation process, first assume that the location of the constraint surface is locally stationary. This enables the above model to be defined as

$$\begin{Bmatrix} \delta F_x \\ \delta F_y \end{Bmatrix} = \begin{bmatrix} M_{xx} & M_{xy} \\ M_{yx} & M_{yy} \end{bmatrix} \begin{Bmatrix} \delta\ddot{x} \\ \delta\ddot{y} \end{Bmatrix} + \begin{bmatrix} K_{xx} & K_{xy} \\ K_{yx} & K_{yy} \end{bmatrix} \begin{Bmatrix} \delta x \\ \delta y \end{Bmatrix} \tag{19}$$

where δ represents a difference with respect to time. The above model is easily adapted to an MIMO recursive least squares estimation algorithm discussed earlier. Using the bilinear transformation, the continuous linear model is discretized to provide a model for linear estimation.

$$\{\delta F\} = \left[M\left(\frac{2}{T}\right)^2 \left(\frac{1-z^{-1}}{1+z^{-1}}\right)^2 + K\right]\{\delta x\} \tag{20}$$

$$\delta F = \begin{Bmatrix} (F_x[k] - F_x[k-1]) \\ (F_y[k] - F_y[k-1]) \end{Bmatrix} \qquad \delta x = \begin{Bmatrix} (x[k] - x[k-1]) \\ (y[k] - y[k-1]) \end{Bmatrix}$$

with M and K representing 2x2 tensors containing parameters associated with the environment stiffness and inertia. Expanding the above transformation,

$$\delta F[k]+2\delta F[k-1]+\delta F[k-2]=\left[M\left(\frac{2}{T}\right)^2+K\right](\delta x[k]+\delta x[k-2]) \\ +2\left[K-M\left(\frac{2}{T}\right)^2\right]\delta x[k-1] \tag{21}$$

This is expressed in a more general form

$$\delta F[k]+2\delta F[k-1]+\delta F[k-2]=[A]\;(\delta x[k]+\delta x[k-2]) \\ +\;2[B]\,\delta x[k-1] \tag{22}$$

The output vector of the MIMO RLS algorithm described earlier is defined as

$$Y^t = \delta F[k] + 2\delta F[k-1] + \delta F[k-2] \tag{23}$$

Likewise, the regression vector is

$$\phi[k] = \begin{Bmatrix} x[k] - x[k-1] + x[k-2] - x[k-3] \\ y[k] - y[k-1] + y[k-2] - y[k-3] \\ x[k-1] - x[k-2] \\ y[k-1] - y[k-2] \end{Bmatrix} \tag{24}$$

The WRLS algorithm is used to recursively solve for the 2x4 parameter tensor θ. This tensor can be manipulated to estimate the stiffness and inertia of the environment.

$$\theta = [A\,|\,B] \tag{25}$$

$$K = \frac{1}{4}\,[2A + B],\quad M = \frac{1}{4}\left(\frac{T}{2}\right)^2(2A - B)$$

These tensors are stored in the array element that corresponds to the robot's current location. As the robot manipulates its environment, the position dependent model of the robot's environment is established.

6. Experimental Results

The first set of experiments attempted to illustrate the methodology and accuracy of the identification algorithm. The target impedance of the robot was set at a target mass of 5 kg, target stiffness of 900 N/m and target damping of 100 kg/s. This provides the robot with a commanded natural frequency of 13.5 rad/s and a damping ratio of 0.75. The robot was commanded to follow a circular trajectory of radius 0.125m and centered at x=0.6096m and y=0.4596m. The robot traced the circle at a rate of one revolution in eight seconds. An unactuated roller at the tip of the robot provides rolling contact during manipulation of constraint surfaces.

A barrier, a 0.019m x 0.14m vertical wood beam, was located 0.825m from the base of the robot. This represents a simple constraint surface in the robot's workspace. The force and motion response of the robot during one run of the experiment is illustrated in Figures 5 and 6. When the robot is in contact with the wall, undesirable oscillations are generated. The stiffness of the beam, illustrated in Figure 4, is approximately 5000N/m at the point of contact. The analysis discussed earlier indicates that the natural frequency of the robot coupled to the environment should be approximately 35 rad/s. The experimentally measured frequency of oscillation during contact is 31.5 rad/s. The damping ratio of the combined system during contact is reduced to 0.32. The low damping is reflected in the vibration that initially increases to a potentially damaging level when in contact with the barrier. Figures 7 and 8 illustrates the performance of the robot when the target impedance is modified to include the environment stiffness. For this experiment, the target mass is increased to 10 kg and target damping to 200 kg/s while the target stiffness remains unchanged during the task.

During each repetition of the circle, the forces and displacements of the robot's tip were recorded and used in an attempt to identify the stiffness of the barrier. A 100 x 100 grid was used to represent the robot's workspace. Each element of the grid includes the stiffness parameters K_{xx}, K_{xy}, K_{yx}, and K_{yy}. Figures 9 through 12 illustrate the results. It is evident that an object with high stiffness in the K_{xx} element of the stiffness tensor is located approximately 82 cm from the robot's base. The remaining terms in the stiffness tensor are negligible. The identified stiffness, K_{xx}, also increases in magnitude as the position in the y direction decreases. This corresponds with static analysis of beam stiffness, illustrated in Figure 4. This indicates that the estimation algorithm produces a good approximation of the stiffness tensor and can be used for adaptation of the impedance control scheme. Some error is likely produced by the truncation of the model of the environment. The current system only models the environment as a mass and spring. The beam used for these experiments has more than one mode of vibration. Increased accuracy could possibly be obtained by attempting to identify these higher order terms, in addition to damping.

7. Conclusions

This research is addressing the problems associated with controlling a robot when it is manipulating an arbitrary and uncertain environment. This investigation illustrates the feasibility of identification of arbitrary environment impedance. A new approach to modelling and representing a robot's environment is introduced. In addition, this information is used to modify the control structure of a manipulator so as to provide stable response to transitions in environment resistance. Current work is focusing on the modelling and estimation of a robot's workspace. This investigation illustrates the need for such information during execution of tasks that require both unconstrained and constrained manipulation. Future work will focus on adapting the target impedance controller during the execution such task. In addition, this research will focus on extending the environment estimation to remote manipulation and semi-autonomous teleoperation.

8. Acknowledgements

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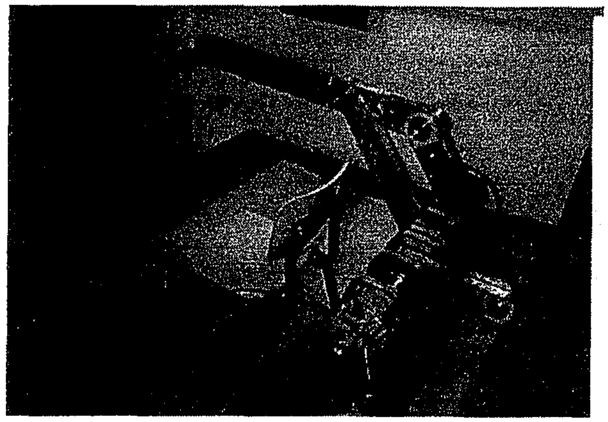

Figure 1: HURBIRT

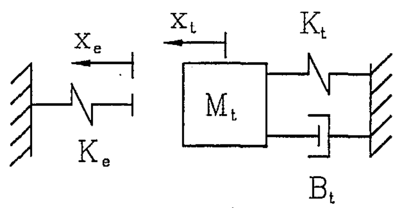

Figure 2: Robot and Environment

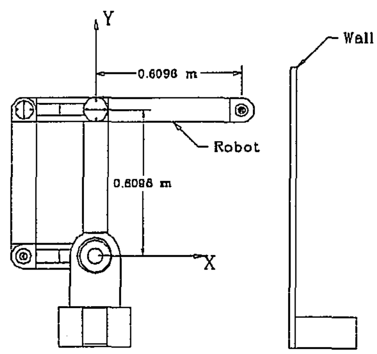

Figure 3: Experiment Testbed

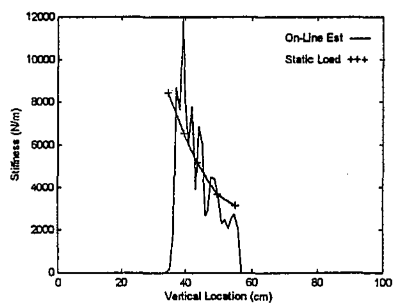

Figure 4: Wall Stiffness

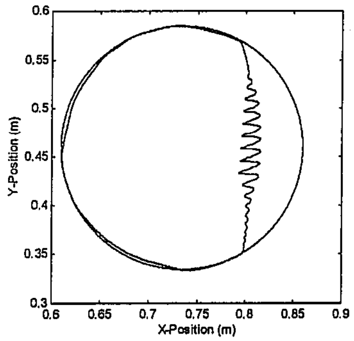

Figure 5: Circle Trajectory w/Wall

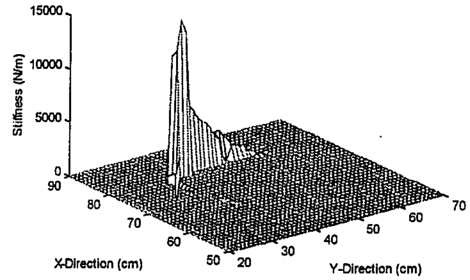

Figure 9: Stiffness Kxx

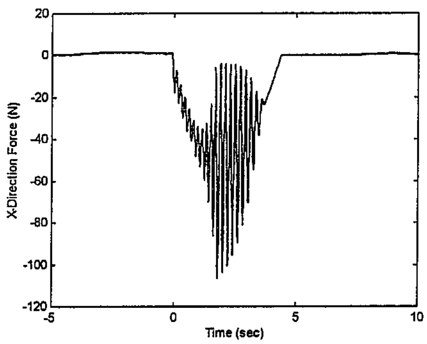

Figure 6: Force Profile

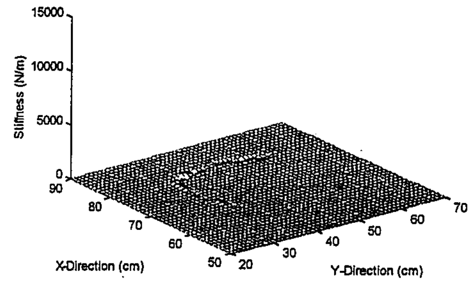

Figure 10: Stiffness Kyy

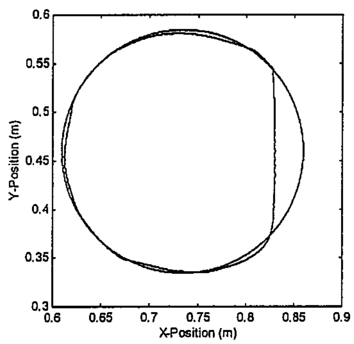

Figure 7: Compensated Response

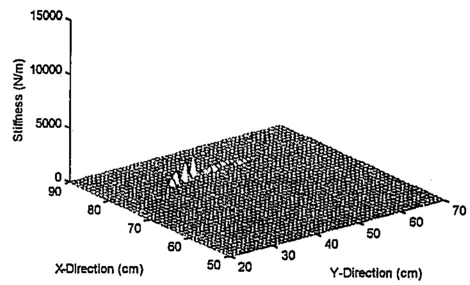

Figure 11: Stiffness Kxy

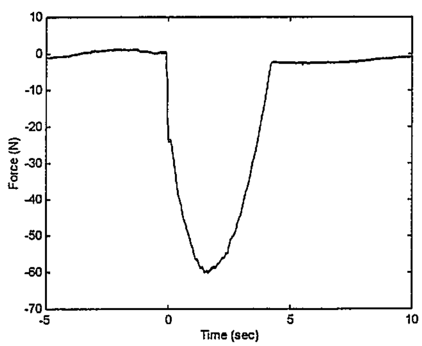

Figure 8: Compensated Force Profile

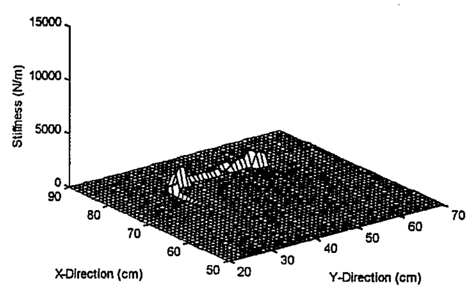

Figure 12: Stiffness Kyx