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Environment Reconstruction and Force/Position Cycling Control of Robots in Interactive Tasks:

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Abstract

This paper explores the control of force and position by a robot interacting with its environment. In executing these "interactive" tasks, current robot control strategies generally (i) assume that environment parameters are known and (ii) sacrifice accuracy in force and/or position to achieve compliant behavior. Knowledge of the environment properties makes more robust and functional controllers possible. Here, a strategy for determining actual environment properties from force and position data acquired during execution of a task is proposed. In addition to acquiring the necessary data for environment parameter identification, the need to satisfy both force and position task constraints as a robot interacts with a compliant environment leads to a strategy of "cycling control". Cycling control offers a more flexible approach for carrying out interactive tasks by satisfying specified constraints, as well as determining "on-line" an appropriate control strategy to apply, such as force, position, or compliant control.

1. Introduction

In the investigation of robotic grasping and manipulation, there is significant interest in the execution of compliant or force control tasks [Hogan 87, Mason 81, Paul 87, Whitney 85]. These tasks can be identified as "interactive tasks", defined as tasks where the manipulator comes in contact with the environment and affects some change, such as an object grasp or reorientation, an assembly, or a material-removal operation. These tasks are fundamentally different from non-interactive tasks such as pick-and-place operations or spray painting, where the interaction forces are negligible and the robot can be controlled solely via position control. Using a position control scheme in an interactive task usually results in the generation of large forces in response to any "unexpected" robot/environment contact. These large forces are caused by the combination of high position feedback gains used to decrease position errors and high system (robot plus environment) stiffness. Such forces are undesirable and lead to poor task execution, with possible damage to the robot and/or part [Kazerooni 87, Paul 87]. In contrast, the use of force control alone in an interactive task results in instability when all system components have high stiffness. The instability is a result of high effective feedback gain associated with the high system stiffness [An 87, Eppinger 86, Hogan 87]. The significant differences in system response between pure force control and pure position control are well documented [An 87, Eppinger 86]. An analysis is developed in Appendix I which considers these differences, and emphasizes points of particular interest in this paper. The successful completion of an interactive task, such as grasping and manipulating an object, grinding, or turning a crank, requires use of an interactive or compliant control strategy, with regulation of both position and force [Mason 81, Raibert 81].

Humans performing interactive tasks seem to successfully monitor and control both force and position without the generation of destructive forces or instability in the face of misalignments, unexpected deviations, or stiff environments [Kazerooni 87, Cutkosky 86]. For example, in operating a hand grinder, one must control both the force exerted normal to the workpiece (for process considerations) and the position of the grinder normal to the workpiece (to maintain the proper geometry). Failing to satisfy either constraint results in unsatisfactory execution of the task. These concurrent force and position demands are especially evident in grinding a "soft" surface, where considerable deflection may occur normal to the surface.

The amazing feat of humans (and perhaps animals in general) is the ability to control both force and position in the same direction over what *appears to be* the same time interval. For example, in grinding, humans appear to adjust both the grinder's position and the applied force in the same (normal) direction at the same time. The ability to accomplish what appears to be simultaneous force/position control is in direct violation of the basic principle of causality in physical systems [Shearer 67, Hogan 85]. The principle states that physical systems are causal in nature, ie., there is a relationship between inputs and outputs specified by the system in terms of a constitutive equation. For instance, in the case of a pure mechanical spring, force, F, and displacement, x, are related by the functional relation $F = function(x)$, as shown in Figure 1. If the spring is linear, the constitutive equation is $F = Kx$, where K is the spring stiffness constant. The values F and x may not be specified independently. In general, the constitutive equation defines a system impedance or admittance, which for a mechanical system may have stiffness, damping, and inertial components. For an admittance, forces are inputs, and displacements are outputs; for an impedance, displacements are inputs, and forces are outputs.

A robot pushing against some environment stiffness can be modeled by a force source pushing against a mechanical spring, as shown in Figure 1. Despite the causality principle, there are many tasks for which it is necessary and/or advantageous to simultaneously control both force and position in a single direction (although this cannot actually occur). In manufacturing, tasks such as grinding, assembly, and fixturing all involve constraints on force and position in a single direction, and these types of tasks cannot be accomplished successfully with position or force

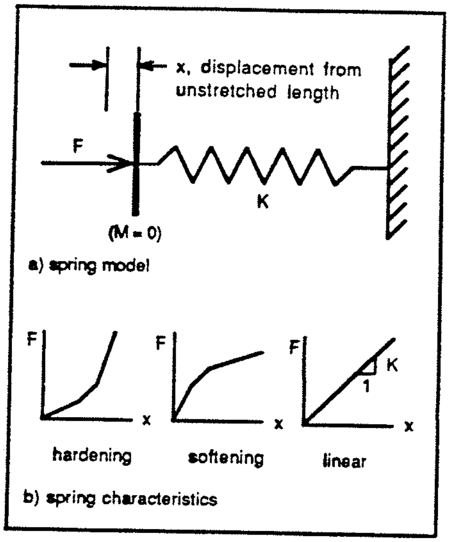


Figure 1: Force/Position Characteristics of a Pure Mechanical Spring.

control alone. Compliant control strategies also have difficulty with these tasks, since they either totally decouple force and position [Raibert 81], or obtain compliant behavior at the expense of accuracy in force and/or position [Hogan 87, Hogan 85]. Of primary interest are interactive tasks where the environment is not infinitely stiff, and where there are significant concurrent force and displacement constraints associated with the task. In these situations, a control strategy capable of accomplishing a compliant, interactive task while monitoring and/or controlling both force and position would be of considerable use. Such a strategy should require neither the total decoupling of force and position, nor the unnecessary sacrifice of accuracy in position or force.

2. Background

Several control methods are currently used for interactive tasks. In the method of **impedance control** [Hogan 85], it is assumed that the impedance of a dynamic system (e.g., a robot) executing a task is controllable. For instance, if the system is a pure, linear spring, it is assumed possible to adjust the spring constant *K*, the impedance, to achieve a desired force and displacement. More generally, it is assumed that the impedance of a robot (the controlled system) may be specified in order to achieve compliant behavior when contacting the environment. Using impedance control, it is possible to cause the robot to exhibit desired stiffness, damping, and inertial properties.

One drawback of impedance control is the possibility of instability which may result, for example, if the environment and the controlled system have comparable frequency response characteristics [Paul 87, Eppinger 86]. Examples of impedance control usually assume a stiff environment, with the controlled impedance designed to have a low stiffness in order to achieve compliant behavior. If the assumption is incorrect, instability could result.

Hybrid control [Raibert 81] assumes that any particular direction in a task will be either force or position controlled. In a task with multiple degrees of freedom, the force and position controlled directions must be orthogonal, which satisfies the causality principle, as the force and position directions are thus independent and decoupled. The central concept is that the task requirements determine which directions are force controlled and which are position controlled. For example, in grinding, force control can be employed in the coordinate direction normal to the surface (to maintain contact), whereas position control can be used for the two coordinate directions tangent to the normal (to achieve the correct surface geometry). This example may be thought of in another way. In the normal direction, the environment is stiff and determines the position, and so the controller determines the force. In the tangential directions, the environment is compliant and determines the force, and so the controller determines the position.

One drawback of hybrid control is that no provision is made for directions which are not totally stiff or compliant; that is, directions for which the choice of force or position control is not obvious. These may be thought of as directions of moderate stiffness, where both force and displacement values may vary significantly, and neither is totally obvious from the task specification. For example, in grinding a "soft" surface, the environment no longer totally determines the normal position, so a pure force control in that direction is not truly appropriate.

Additionally, hybrid control requires that a model of the environment is available. As a result of poor modeling or high system stiffness, it is possible for instability to result in either the force or position control mode. If instability occurs it can propagate to all controlled axes, since every controlled axis command signal has both force and position components. This is due to the fact that the force and position controlled directions are orthogonal in task space, but not necessarily in joint space.

Other approaches for executing interactive tasks include damping or **accommodation control** [Whitney 85]. These types of methods generally sacrifice position and/or force control accuracy to achieve compliant behavior.

There are also approaches that combine features of some of the methods described above. One example is **hybrid impedance control** [Anderson 87], which is a combination of the impedance and hybrid control methods. Generally, these types of methods extend the abilities of, but do not avoid the problems present in, the individual methods. For example, hybrid impedance control requires that an *a priori* environment model be available, can encounter possible stability problems, and does not overcome the imposed tradeoff between force and position in the individual hybrid and impedance control methods.

Techniques such as **adaptive control** and **optimal control** are also of interest [Goodwin 84, Lewis 86, Narendra 80]. In adaptive control, the control scheme dynamically changes its parameters in response to an undesirable system response. Adaptive control has promise for solving some of the problems of implementing force/position controllers without requiring a complete model of the environment. To date, most adaptive control applications in robotics have dealt with determining the dynamic equation parameters of a robot in pure position tasks [Dubowsky 79, Seraji 87].

There are, however, some recent efforts that discuss [Slotine 87] and apply [Fukuda 86, Fukuda 87] adaptive techniques to force control (interactive) tasks. The applied adaptive schemes show significant performance improvements in comparison to constant feedback gain strategies. However, the adaptive schemes still implicitly depend on environment information in order to ensure stability. In these schemes, the system behavior is modified by varying the feedback gain(s), and there are limits on how much the feedback gain may be varied without driving the system unstable.

In optimal control, the goal is to design a controller which realizes some functional optimum, such as minimum energy or minimum time in the execution of a task. Optimal control schemes may offer a way to account for force and position constraints in a task. For example, the function to be minimized might be the inverse of the distance from a constraint. However, the use of optimal control in interactive tasks appears to be limited, since prespecifying a function to be optimized also implies some knowledge of the environment characteristics.

2.1. Scope

In the review of current methods, there have been two recurring themes. One theme has been the need for knowledge of environment information, without which stability and overall performance cannot be ensured for any of the control methods. Most schemes assume (either implicitly or explicitly) that a model of the environment is available *a priori*. The second theme has been that non-trivial tasks exist where not only is compliance necessary, but also force and position needs must be met. Existing schemes do not adequately address this problem.

In this paper, it is proposed to use sensed force and position information to construct an environment characteristic that can then be used to improve the control performance. It is shown that actual environment parameters can be determined during the execution of a task. In addition, this paper investigates the problem of accounting for force and position constraints in compliant, interactive tasks. An approach is proposed that uses different control modes along the same axis, but *not at the same time*, and also adjusts the system response to satisfy specified constraints. This approach is consistent with the causality principle, and, through the constraint specification, allows significant generality. The strategy is designed to cycle between different control modes (such as pure force control, pure position control, or impedance control); hence it is called "cycling control". Cycling control identifies the most suitable control scheme for a given task on the basis of observed system response and environment information derived from gathered data.

3. Methodology

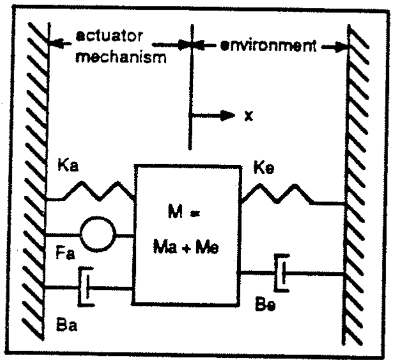


Figure 2: Actuator/Environment Model

Consider the one degree-of-freedom system model shown in Figure 2, which represents an actuator pushing against an environment. The actuator has effective stiffness K_a, damping B_a, and mass M_a, with force being supplied by an ideal source F_a. The environment has effective stiffness K_e, damping B_e, and mass M_e. In this model, there is no explicit provision for the loss of contact between the actuator and the environment, or for factors such as force sensor stiffness, damping or inertia. Henceforth, the combination of actuator and environment is referred to as "the system". For this second order system, the natural frequency ω_n and damping ratio ξ are:

$$\omega_n = \sqrt{\frac{K_a+K_e}{M}} \qquad \xi = \frac{B_a+B_e}{2\sqrt{(K_a+K_e)M}} \tag{1}$$

The actuator/environment displacement is represented by the variable x. It is assumed that the displacement, velocity, and acceleration $(x, \frac{dx}{dt}, \frac{d^2x}{dt^2})$ are available. It is also assumed that a force sensor gives the exact value F_{env}, which is the force applied to the environment.

3.1. Environment Reconstruction

This section describes a method for determining environment parameters, such as the impedance of a grasped object, from sampled force and kinematic data. It is assumed that the environment, as described in Figure 2, obeys the relation

$$F_{env} = K_e x + B_e \frac{dx}{dt} + M_e \frac{d^2x}{dt^2} \tag{2}$$

at any instant in time. The problem is to determine the parameter values K_e, B_e, M_e, which may be time-varying, but are assumed constant over a small time interval. An environment characteristic may be constructed by combining each set of discrete parameter values and the corresponding kinematic data samples. The three parameter values are solved for simultaneously using a least-squares algorithm [Hsia 77], as follows.

Consider a variable y_i ("the output") that is linearly related to a set of variables a_j ("the variables"). A set of unknown "parameters" p_j defines the linear relationship between the output and the variables. Assume that a linear system of m equations is formed from m samples of the output and the variables at different times. The ith equation has n unknown parameters p_j, one known output y_i, and n unknown coefficients $a_j(i)$. It is desired to solve the system for the n parameters. The ith equation of the linear system is stated as:

$$y_i = a_1(i)p_1 + a_2(i)p_2 + a_3(i)p_3 + \cdots + a_n(i)p_n \tag{3}$$
$$1 \le i \le m, \; 1 \le j \le n$$

The system of equations can be written in matrix form as

$$\mathbf{y} = \mathbf{A}\mathbf{p} \tag{4}$$

The vector **y** is an m element column vector of the outputs y_i, **A** is an $m \times n$ matrix of the variables, with the $(i,j)th$ element being $a_j(i)$, and **p** is an n element column vector of the unknown constant system parameters p_j. If $m > n$, the system is overconstrained, and has an estimated parameter solution **p'** which minimizes the total squared error. The minimum squared error solution **p'** is given by the matrix equation

$$\mathbf{p}' = (\mathbf{A}^T\mathbf{A})^{-1}\mathbf{A}^T\mathbf{y} \tag{5}$$

derived in [Hsia 77].

An extension of the basic least-squares reconstruction technique allows a continuous update of the parameter vector estimate as single, new data vectors are acquired, and eliminates the need for repetitive matrix inversions. It also makes the method appropriate for systems with time-varying parameters. The method is iteratively based, and depends on the definition of an error function which weights recent errors more heavily than earlier ones. The error function $J(q)$ at the qth sampling step is defined as

$$J(q) = \sum_{i=1}^{q} \lambda^{q-i} \varepsilon^2(i) \qquad 0 < \lambda \le 1 \tag{6}$$

where λ is a weighting factor that weights recent errors relative to earlier data, $\varepsilon(i)$ is the error at the ith step, and i is a time index.

At the $(i+1)th$ time step, it is assumed that the system obeys a relation of the form

$$y(i+1) = a_1(i+1)p_1(i+1) + \cdots + a_n(i+1)p_n(i+1) \tag{7}$$

which is functionally identical to Equation 3. It is assumed that values of $y(i+1), a_1(i+1), \ldots, a_n(i+1)$ are available. The determination of an estimate for the parameters $p_j(i)$ is desired, as before.

Using the error function (Equation 6), the values of $y(i+1), a_j(i+1)$, and the basic formulation of the least squares method (Equation 5), an iterative method for parameter estimation may be derived as in [Hsia 77]. A new estimate **p'**$(i+1)$ is generated by sequentially applying the following set of equations, which use the estimate **p'**(i), and the matrix **B**(i) from the previous (ith) estimate, as well data from the new $((i+1)th)$ step.

$$\gamma(i+1) = \frac{1}{1 + \mathbf{a}^T(i+1)\mathbf{B}(i)\mathbf{a}(i+1)} \tag{8}$$

$$\mathbf{B}(i+1) = \frac{1}{\lambda}[\mathbf{B}(i) - \gamma(i+1)\mathbf{B}(i)\mathbf{a}(i+1)\mathbf{a}^T(i+1)\mathbf{B}(i)] \tag{9}$$

$$\mathbf{p}'(i+1) = \mathbf{p}'(i) + \gamma(i+1)\mathbf{B}(i)\mathbf{a}(i+1)[y(i+1) - \mathbf{a}^T(i+1)\mathbf{p}'(i)] \tag{10}$$

In these equations, **B** is an $n \times n$ matrix, equal to the quantity $(\mathbf{A}^T\mathbf{A})^{-1}$ from the basic method, and **a** and $\mathbf{a}^T$ are n element column and row vectors, respectively, of the acquired variables $a_j(i+1)$. The calculated scalar $\gamma(i+1)$ is defined for convenience, λ is the scalar weighting factor, and $y(i+1)$ is the scalar value of the sampled system output. The value **p'** is a column vector of system parameter estimates, identical to **p'** in the basic least squares method. This method requires no inversions to compute **p'**$(i+1)$ and utilizes all data points up to the present time, not just a limited sample set. If the weighting factor $\lambda = 1$, the method reduces to a simpler version of the same method, the only difference being that it assumes constant-valued parameters. If $\lambda < 1$, the method weights recently acquired data more strongly in its parameter estimate; this allows some time variation in the parameter values. However, making λ small also increases the method's sensitivity to noise.

The method requires initial estimates for $\mathbf{p}'(i)$ and $\mathbf{B}(i)$, which may be obtained by solving the first m equations with the basic least squares method of Equation 5. This yields estimates for $\mathbf{p}'(0)$ and $\mathbf{B}(0)$. Subsequently, the iterative method can be applied.

Thus, the method for reconstructing the environment parameters uses the system model of Figure 2 and the iterative least squares method. The system equation is Equation 2 with K_e, B_e, M_e representing the system parameters, F_{env} being the measured system force output and $x, \frac{dx}{dt}, \frac{d^2x}{dt^2}$ being the measured variables. The necessary samples of $F_{env}, x, \frac{dx}{dt}, \frac{d^2x}{dt^2}$ are obtained at uniformly spaced time steps, and the iterative reconstruction algorithm is applied.

In order to gather data for the reconstruction, a control algorithm must be applied to the system formed by the actuator and the unknown environment. It is very difficult to ensure a stable, appropriate response with no knowledge of the environment. To solve this problem, an actuator input designed to yield slowly varying changes in the measured variables while monitoring the system response is applied. The input F_a is specified as a ramp function with saturation, as in Figure 4. The ramp slope is primarily determined by a limit on how fast the $x, \frac{dx}{dt}, \frac{d^2x}{dt^2}$ variables may change to ensure a valid determination of the parameters. The saturation value of F_a is determined by actuator and environment limitations (such as maximum applied force, or maximum displacement), and regulated by a constraint specification scheme (this idea will be discussed later). The scheme monitors the values of applied force F_a, position x, and velocity $\frac{dx}{dt}$ and if any value approaches a prespecified constraint, appropriate action is taken (saturation of the input F_a in the case of an F_a or x violation, and modification of ramp slope in the case of a $\frac{dx}{dt}$ violation). The point where the ramping function saturates is designated as the "break-off" point.

This strategy is essentially a careful probing of the unknown object or environment, as shown in the example of Figure 3. The probing strategy is used to both ensure the slow variation of the parameters throughout the sampling process and to provide a reliable source of input data. The goal of this strategy is to increase the likelihood of a correct identification of the environment parameters, particularly stiffness. In addition, some "quick" information about the environment is available through the conditions existing at the break-off point. Quantitatively, the ratio of the force and position values at the break-off point gives a rough measure of the environment stiffness. Qualitatively, for a "soft" environment, the position constraint will be violated first, and for a "stiff" environment, the force constraint will be violated first. The application of the least-squares algorithm then gives a more refined estimate of the stiffness, damping, and inertial (mass) parameters.

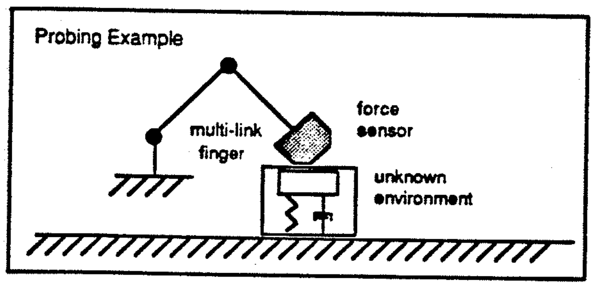


Figure 3: Example Application of Probing Algorithm

A probing and reconstruction of a relatively soft environment with a linear characteristic in stiffness, damping, and inertia (mass) was simulated. The environment values, $K_e = 250\frac{N}{m}, B_e = 1.0\frac{Nsec}{m}$, and $M_e = 0.0kg$, were unknown to the probing and reconstruction algorithms. In this case, the force constraint was set at $10N$ maximum, the position constraint was set at $50mm$ maximum, and the velocity constraint was set at $0.01\frac{m}{sec}$ maximum. The constraint values were chosen to roughly correspond to the abilities of a human or robot finger pushing on an object. A time step of 0.05 *sec* was used for the simulation.

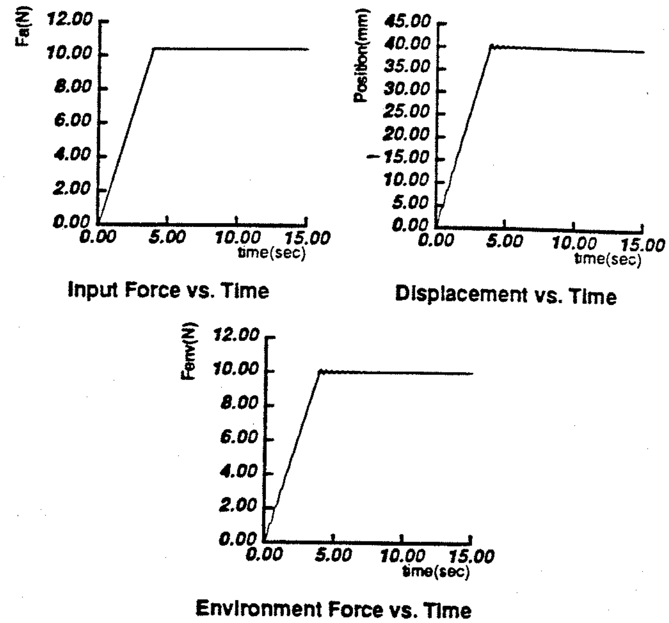


Figure 4: Probing Process (Soft Environment, $K_e = 250$ N/m)

Figure 4 shows the results of the probing simulation. The actuator presses slowly and steadily harder, until either the force or position constraint is nearly violated. In this case, the force constraint is violated first by a slight margin. This yields a qualitative evaluation of the system as "relatively stiff", implying that the environment is stiff *relative to the abilities of the system*, which is in practice a useful way to specify the environment stiffness. The numerical value of the stiffness means little unless some measure of the actuator's abilities is available as well.

At the break-off point, the input force F_a is held constant, and the system settles to a steady-state response. A coarse estimate of system stiffness is obtained from the ratio of force and position at the break off point, i.e., $\frac{10.0N}{0.041m} = 244\frac{N}{m}$. This coarse estimate closely matches the true value of $250\frac{N}{m}$.

The iterative reconstruction algorithm was then applied to the soft environment data gathered by the probing algorithm. In this reconstruction, the weighting factor was $\lambda = 1.0$, which assumes no time variation of the environment parameters. The results are shown in Figure 5.

The iterative method converges to nearly the exact values of the parameters, because it utilizes *all* of the input data available at the time of each estimate. The method is suitable for application in real time, since sampling and reevaluation of the parameter values occur within a reasonably small time step, allowing several estimates per second.

The same probing and reconstruction algorithm was also applied to a stiffer environment with a non-zero mass, i.e., $K_e = 2500\frac{N}{m}$ and $M_e = 1.0kg$. The environment damping was the same as before ($B_e = 1.0\frac{Nsec}{m}$), as were all other model parameters and constraint specifications. The results of the probing process were essentially the same as in the initial simulation, and are not displayed here.

The reconstruction method determines the parameter values accurately, although the estimates for damping and mass show more variation than before. In general, the estimates for the damping and inertial parameters become poorer, but the stiffness estimate remains relatively very accurate, as the environment stiffness is increased. In this case, this is primarily due to the higher stiffness dominating the environment relation of Equation 2, causing $\frac{dx}{dt}$ and $\frac{d^2x}{dt^2}$ to remain small.

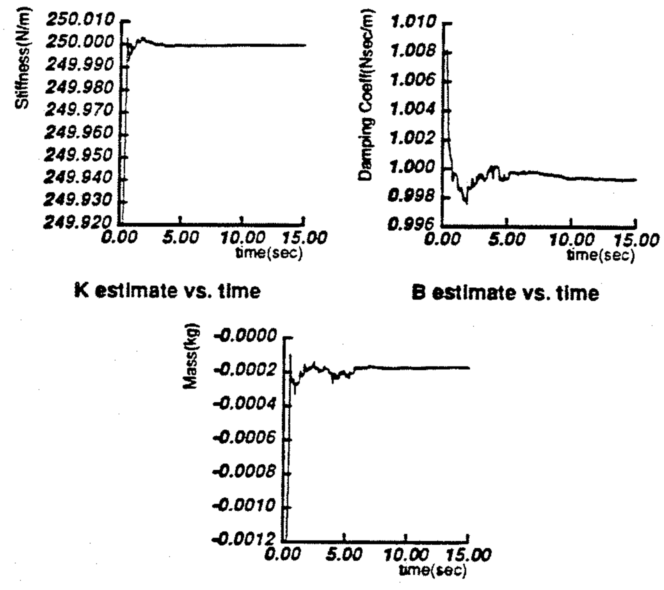


Figure 5: Reconstruction with Iterative Algorithm (Soft Environment, K_e = 250 N/m)

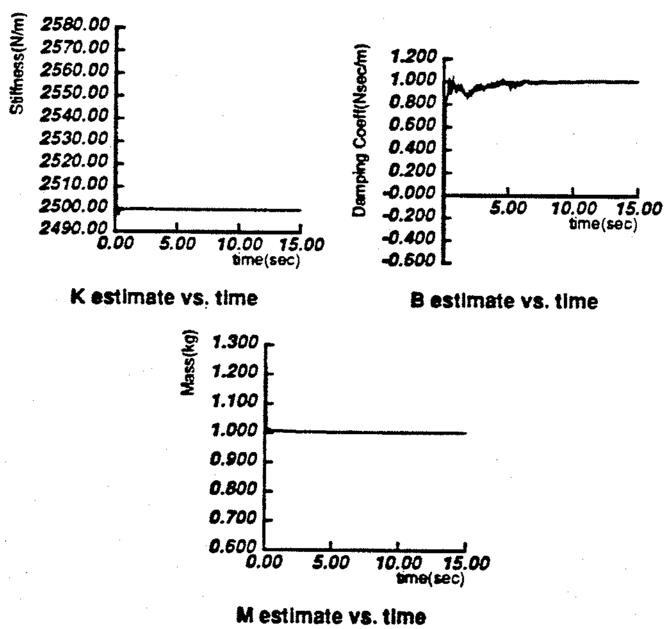


Figure 6: Reconstruction with Iterative Algorithm (Stiff Environment, K_e = 2500 N/m, M_e = 1.0 kg.)

The basic ability to extract unknown parameters from an environment has been demonstrated. This information is very useful in helping to design suitable control strategies for tasks involving interaction with the environment.

3.2. Cycling Control

As discussed earlier, it is necessary to consider both force and position in some important compliant tasks. To meet this need, a strategy of switching between different control modes while obeying specified constraints in the execution of a task is considered. Through "cycling control", the most appropriate control for a system can be determined.

A flowchart describing a basic cycling control strategy using force and position control loops is shown in Figure 7. The strategy monitors specified constraints on force and position, as represented by the inner flowchart loops. It may be desirable to either seek or avoid a certain constraint, depending on the task needs; the sense of the constraint is part of its specification. If there are violations (or near violations) of the constraints, the strategy attempts to correct by either changing the setpoint corresponding to the mode where the violation occurred, or disabling that mode. If there are no constraint violations, the system applies either force or position control. The controller may increment the force or position setpoint according to task requirements. The task is considered to be "finished" when the time exceeds some preset final time limit. There may also be some other task-specific notion of when the task is finished, such as the "break-point" of the probing algorithm, or a constraint being satisfied (e.g., a desired force level being achieved in a pushing task).

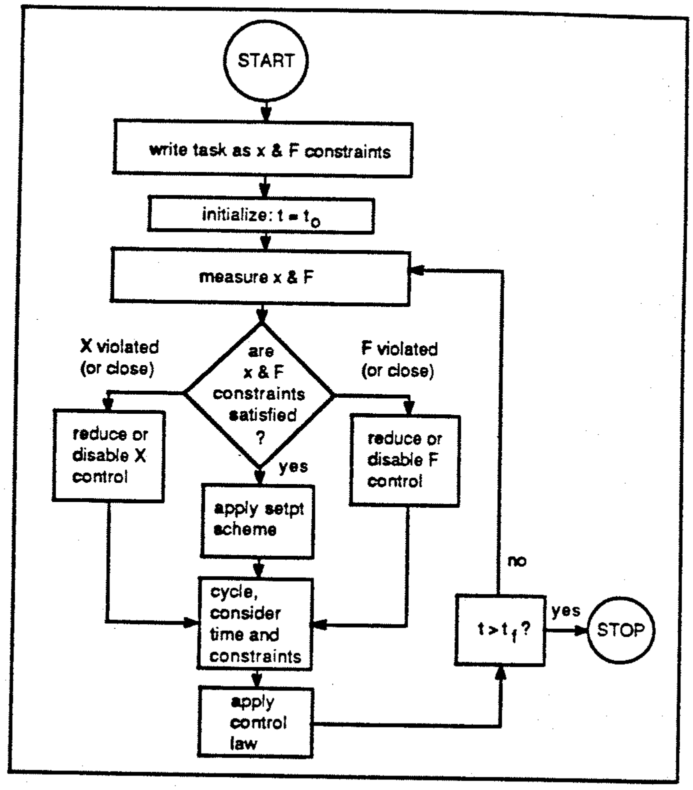


Figure 7: Flowchart of Basic Cycling Control Strategy.

As an example, consider a task which has maximum force and position constraints, shown as the dotted lines at F_c and X_c, respectively, in Figure 8. In general, the force and position constraints are dictated by the task, and can include requirements other than maximum values (e.g., actual trajectories). The displacement and force are both initially zero, and the control *attempts* to reach both the specified goal force F_g and goal position X_g within a final time constraint t_f. However, arbitrary force and position goals may not be reached simultaneously, in accordance with the causality principle. In this example, the force and position approach their respective constraints, and appropriate action is taken to avoid violating those constraints. The maximum distance from a constraint needed to trigger a response, called the radius of influence, is determined by task needs. The radius of influence of a constraint may be thought of as a safety factor; that is, if the constraint must be unconditionally avoided, the radius will be larger, and if the constraint is not as rigorous, the radius may be smaller. Setting the constraint radius of influence is part of the constraint specification. The response to crossing the radius of influence of a constraint may be a modification in setpoint, or a disabling of the mode in which the violation occurred. This implies that unstable responses will be detected and terminated.

Task constraints need not be limited to force and displacement. For example, in the probing algorithm presented in the reconstruction section, there was a constraint on system velocity as well as constraints on force

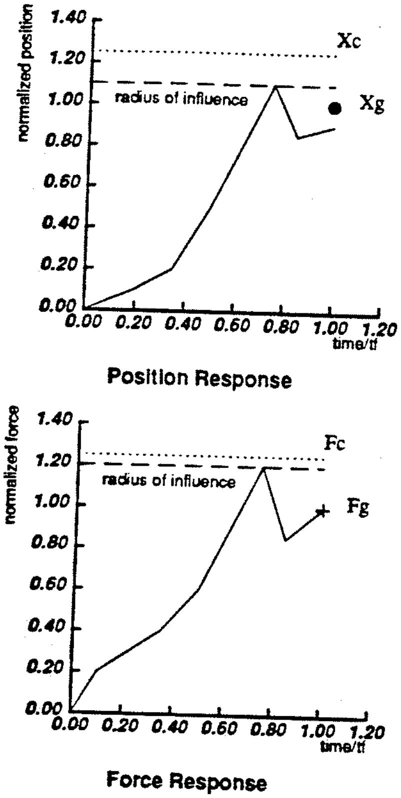


Figure 8: Illustration of Cycling Control Response

and position.

Consider the task of pinning down an object of unknown stiffness with one finger, as in Figure 3. Cycling control allows the determination of the object's properties, primarily stiffness in this case, as well as indicating a preferred control method from among those applied. Whether the object is compliant or stiff does not affect the functionality of the cycling control scheme, which conforms, through the constraint specification scheme, to the characteristics of the object. A standard adaptive or compliant control scheme must either assume some object stiffness (explicitly or implicitly), or sacrifice force and position accuracy in exchange for compliance. The cycling strategy allows the control algorithm to remain unprejudiced and to determine the control needs of the task in a reasonably general fashion.

In order to further investigate cycling control, a one degree-of-freedom, linear, time-invariant mechanical system was simulated. The full system (actuator plus environment) model is shown in Figure 9, along with a block diagram of the cycling control scheme. It is assumed that switching between force and position modes occurs instantaneously. The actuating (input) force is specified by either the proportional force (gain K_f) or position controller (gain K_p). An ideal force source supplies the actuating force F_a. In the simulation, the strategy of cycling at some fixed rate between the two modes in the absence of other factors, such as constraint violations, was adopted.

An example task was constructed, with environment and actuator properties set as follows: $K_a = 10.0\frac{N}{m}$, $B_a = 0.25\frac{Nsec}{m}$, $M_a = 1.0kg$, $K_e = 2500.0\frac{N}{m}$, $B_e = 1.0\frac{Nsec}{m}$, $M_e = 1.0kg$. The environment parameters were unknown to the control schemes. The task constraints were specified as maximum values of $X_c = 50mm$ and $F_c = 10N$, with no other constraints present. The parameters were chosen to represent a moderately stiff and weakly damped system, and they give an uncontrolled system natural frequency $\omega_n = 35.43\frac{rad}{sec}$ and damping ratio $\xi = 0.00882$. The proportional position and force controller gains were set as $K_p = 1.0\frac{N}{m}$ and $K_f = 1.0$ (unitless), respectively. Analyses (in Appendix I) of the steady state values show $X_{ss} = \frac{1}{2511}X_{ref}$ and $F_{ss} = \frac{2500}{5010}F_{ref}$, indicating a large steady-state error

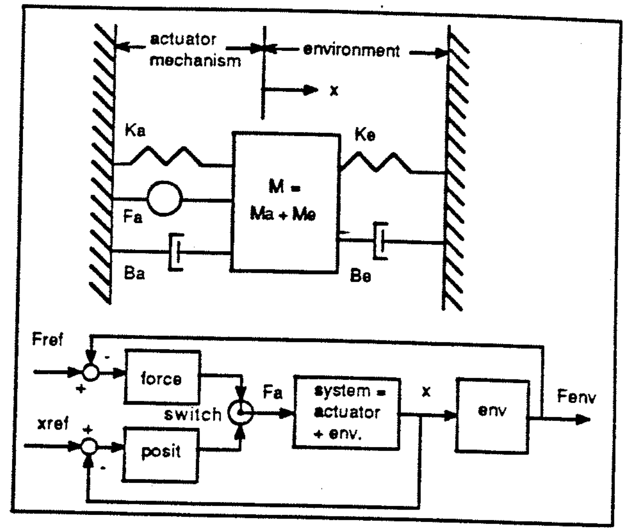


Figure 9: a) Model Used in Simulation and b) Control System Model.

in both modes. In this simulation, the force and position setpoints were held constant as $0.9F_c$ and $0.9X_c$, respectively. The cycling time for this example was fixed at 2.0 *sec.*, which is roughly five times the period of the uncontrolled system (which is ≈ 0.39 *sec*). Analyses showed that the position controlled system poles were at $s_{1,2} = -0.31 \pm 35.4i$, and the force controlled system poles were at $s_{1,2} = -0.56 \pm 50.0i$. These values represent highly oscillatory systems, as shown in the characteristics of Figure 10. The oscillatory, low damping system was chosen as a "worst case" upon which to apply the cycling scheme.

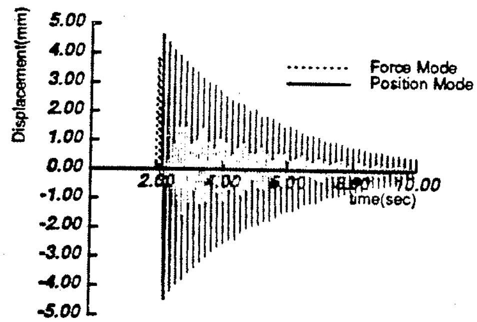
In the initial two-second cycling step, the cycling control strategy is in position control, with a large offset error resulting; the reference position is 45 *mm*, and the position response is extremely close to zero. At the end of the first cycling step (i.e., after 2.0 *sec.*), the cycling controller switches to the alternate force control scheme. Due to the relatively high environment stiffness, the force controller is highly oscillatory, and the force constraint is quickly violated, at which time the cycling controller switches back to the position mode, and stays there. The position controlled system also exhibits highly oscillatory behavior, but decays to a very small steady-state value, while satisfying all constraints. The cycling control avoids the undesirable force control mode, and determines, based on properties of the previously unknown environment that it evaluated, that the "best" controller would be the position controller.

The negative values of both position and force in this example imply that an unconnected actuator and environment would lose and regain contact, causing "chatter". This example was designed to demonstrate the basic features of the cycling control concept, the point being that it is possible to specify constraints that will cause avoidance of the chattering-type behavior. In addition, the cycling strategy may more generally switch between many different control modes, including impedance, force, position and adaptive control.

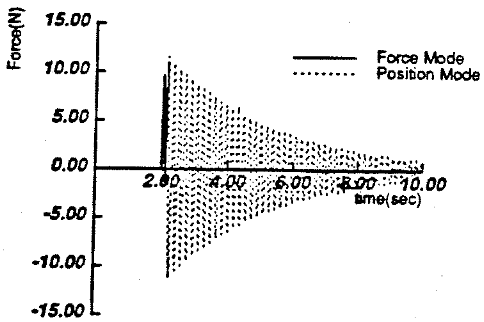
4. Summary and Directions of Future Work

In this paper, an identification method for determining unknown environment parameters has been demonstrated, along with a cycling control strategy which allows the application of different control algorithms to a system. A general and powerful constraint specification scheme is utilized to ensure stability and specify necessary operating characteristics in terms of desired response. The reconstruction scheme can identify a wide range of cases of stiffness, damping, and inertial (mass) parameter values. The cycling control scheme can detect and terminate inappropriate control modes, and can determine the most appropriate mode to be applied to control an actuator/environment system.

In the simulation studies, a force sensor reading was constructed from unknown environment parameters and available system state information. These force readings were assumed to be noise-free. In



System Displacement vs. Time



Environment Force vs. Time

Figure 10: Simulation Results for Force/Position Cycling

practice, sensor readings are always contaminated with noise; dealing with noisy sensors in the environment reconstruction and cycling control strategies will be the subject of future research.

In the environment reconstruction method, the environment parameters were assumed to be constant. In practice, these parameters may vary with time. The method as presented can accommodate time-varying parameters, and the exploration of the subject will be the subject of further research.

The reconstruction method was observed to become less accurate in determining damping and inertial parameters as the unknown environment stiffness increased. The investigation of this effect, and of alternate data gathering schemes, will be the subject of future work. In addition, the dependence of the reconstruction method on the data sampling frequency and the character of the acquired data will be investigated.

Additional future work will involve applying the reconstruction method to multi-degree of freedom systems, where stiffness, damping and inertial characteristics must be determined in several coordinate directions. Obtaining this information would allow, for example, the on-line determination of the force and position directions of hybrid control, with stiff directions being force controlled, and compliant directions being position controlled.

In the area of cycling control, future work will involve the determination of cycling times and rates, and their effect on system response, as opposed to the nominal values utilized in the current work. The reality of finite switching times, and its effect on system stability, will be explored.

Finally, these strategies will be implemented in hardware that has been built as part of previous development work in the area of robot hands and fingers [Wright 87]. The implementation will serve as "proof of concept", and expose the strengths and limitations of these ideas.

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Appendix I

Transfer Functions and Control Response of Force and Position Controlled Systems

The transfer function between position and applied force for the actuator/environment system of Figure 9 is found to be:

$$\frac{X}{F_a}=\frac{\frac{1}{M}}{s^2+\frac{B_a+B_e}{M}s+\frac{K_a+K_e}{M}} \quad (1)$$

The environment is assumed to obey the relation $F_{env}=K_e x+B_e\frac{dx}{dt}+M_e\frac{d^2x}{dt^2}$. In this analysis, it is assumed that $M_e=0.0$. A non-zero M_e will only scale the results, and not change the conclusions of the analysis. The transfer function of the environment block is:

$$\frac{F_{env}}{X}=K_e+sB_e \quad (2)$$

The proportional force and position controllers result in constant gain factors K_p and K_f for position and force, respectively. The relations for position and force mode are:

$$F_a=K_p(X_{ref}-X) \qquad F_a=K_f(F_{ref}-F_{env}) \quad (3)$$

For each of the implementation modes (force or position), a system closed loop transfer function is formed. Considering the system in position and force modes, respectively:

$$\frac{X}{X_{ref}}=\frac{\frac{K_p}{M}}{s^2+c_1 s+(c_2+\frac{K_p}{M})} \quad (4)$$

$$\frac{F_{env}}{F_{ref}}=\frac{\frac{K_f}{M}(K_e+sB_e)}{s^2+(c_1+\frac{K_fB_e}{M})s+(c_2+\frac{K_fK_e}{M})} \quad (5)$$

where $c_1=\frac{B_a+B_e}{M}$ and $c_2=\frac{K_a+K_e}{M}$. These transfer functions are used to determine information about the system such as the steady-state response, stability, natural frequency, and damping ratio.

The final value theorem is applied to each of the system transfer functions and it is found that the steady-state values of position and environment force (X_{ss},F_{ss}) and the steady-state errors (X_{err},F_{err}) are, in position mode:

$$X_{ss}=\frac{K_p}{K_a+K_e+K_p}X_{ref} \text{ so that } X_{err}=X_{ref}(1.0-\frac{K_p}{K_a+K_e+K_p}) \quad (6)$$

and, in force mode:

$$F_{ss}=\frac{K_fK_e}{K_a+K_e+K_fK_e}F_{ref} \text{ so that} \quad (7)$$

$$F_{err}=F_{ref}(1.0-\frac{K_fK_e}{K_a+K_e+K_fK_e})$$

In general, the steady-state values for force and position are different. It is seen that in position mode, the force resulting from the steady-state of position is $F_{e\ implied}=K_eX_{ss}$, and that in force mode, the position resulting from the steady-state value of force is $X_{implied}=\frac{F_{ss}}{K_e}$. In general the steady-state values of force and position are different for the different control modes. For example, in position mode, the system approaches the values of force and displacement $F_{e\ implied}$ and X_{ss}, as defined, and after switching to force mode, it approaches force and displacement F_{ss} and $X_{implied}$. If the approached values of force and displacement are different in force and position control modes, an oscillation at the switching frequency will occur, implying that switching should be minimized.

A final point of interest is the effect of K_e on the system response in force and position modes. The roots of the system characteristic equation (from the transfer functions of Equations 4, 5) in either force or position mode are:

$$s_1,s_2=\frac{-d_1\pm\sqrt{d_1^2-4d_2}}{2} \quad (8)$$

where d_1 and d_2 are defined for the position mode as:

$$d_1=\frac{B_a+B_e}{M} \qquad d_2=\frac{K_a+K_e+K_p}{M} \quad (9)$$

and for the force mode as:

$$d_1=\frac{B_a+B_e+K_fB_e}{M} \qquad d_2=\frac{K_a+K_e+K_fK_e}{M} \quad (10)$$

It can be seen that, in the absence of other parameter changes, the environment stiffness K_e, when increased, makes the system response more strongly oscillatory by increasing d_2, no matter what the control mode. The magnitude of this effect is greater in the force mode. If the environment stiffness is very large, the oscillations will be significant enough to cause unstable behavior. This will occur only in the force control mode, since the steady-state value of displacement with a large environment stiffness will be very small in position control (Equation 6). The analysis shows that the high environment stiffness has exactly the same destabilizing effect as a high feedback gain K_p or K_f