

Dolan, J.M., Friedman, M.B., and Nagurka, M.L., "A Testbed for Measurement of Human Arm Impedance Parameters," Proceedings of the IEEE International Conference on Systems Engineering, Pittsburgh, PA, August 9-11, 1990, pp. 123-126.

A TESTBED FOR MEASUREMENT OF HUMAN ARM IMPEDANCE PARAMETERS

J.M. Dolan, M.B. Friedman*, and M.L. Nagurka

Department of Mechanical Engineering and *The Robotics Institute
Carnegie Mellon University, Pittsburgh, Pennsylvania 15213

ABSTRACT

This paper describes the development of an experimental testbed for investigation of human arm impedance. A two-degree-of-freedom SCARA-configuration robotic arm with an endpoint force sensor has been developed for measuring parameters such as postural viscosity and dynamic stiffness and viscosity. The measurement device is to be used in disturbance tests that will determine the degree and nature of impedance tuning during the accomplishment of various tasks. The experimental results may have applications both to prosthetics, where artificial limbs should mimic natural limbs as closely as possible, and to robotics, where the choice of parameters for impedance control is a current topic of research.

INTRODUCTION

Research in human motor control has led to a wide variety of viewpoints concerning the strategy used by the central nervous system (CNS) in controlling limb movements. Researchers have suggested control of muscle variables such as force, length, velocity, stiffness, and viscosity, although many have recognized the difficulty of positing a single strategy in light of the vast complexity of the human nervous system and the great variety of tasks of which it is capable [12].

Several researchers have proposed the control of mechanical impedance as a primary means of human motor control [1,5,11]. In a mechanical system, impedance is a description of the relationship between forces and displacements and forces and displacement rates. Stiffness, viscosity, and inertia are three basic components of impedance, relating force to position, velocity, and acceleration, respectively. An advantage of impedance control as a framework for motion control lies in its ability to unify position and force control, which it views as the limiting cases of zero and infinite impedance, respectively [7].

Theories and experiments regarding human limb impedance control have progressed historically from

consideration of single muscles to the investigation of multi-jointed limbs. Feldman [1] showed that the stiffness of an individual muscle about an invariable equilibrium length increases with neural activity. In order for different postures to be achieved, the equilibrium angle of a limb about a given joint axis must be variable. Hogan [5] went beyond consideration of single muscles to propose a simplified joint model in which coactivation of antagonist muscles allows variation of the joint's equilibrium angle as well as its stiffness about that angle. Extending this idea to more than one joint, he then showed that the stiffness tensor of the endpoint of the human arm should be tunable based on degrees of freedom provided by a combination of singly and doubly joint-connected antagonist muscle pairs at the shoulder and elbow.

In order to investigate the way in which the CNS controls stiffness to achieve posture, Mussa-Ivaldi *et al.* [10] displaced the human arm's endpoint from a series of equilibrium points in a plane and measured the corresponding restoring forces before the onset of any voluntary reaction. They concluded that the stiffness characteristic of the arm endpoint is spring-like, meaning that the stiffness for small displacements about an equilibrium position is symmetrical. They characterized the arm endpoint stiffness at various positions of several human subjects using ellipses representing contours of equal potential energy. The orientation with respect to a frame fixed in the body and the shape, or aspect ratio, of these ellipses was seen to remain relatively constant among subjects, whereas their sizes varied.

The postural stiffness investigated in [10] is the static case, in the sense that the person attempts to maintain the arm stationary rather than move it from one point to another. In the dynamic case, the idea that the CNS can vary the equilibrium position of a joint suggests the *equilibrium trajectory hypothesis*, which states that multi-joint arm movements are achieved by gradually shifting the commanded endpoint equilibrium positions and allowing muscle visco-elastic forces to propel the arm along the trajectory [6]. Flash tested this hypothesis by investigating the trajectories of reaching

motions [3]. A simple dynamic model of the human arm was used, and the elbow and shoulder joint positions and their derivatives were measured during a movement, resulting in the joint torques necessary to drive the arm. These torques were equated to a function of the instantaneous difference between the actual and equilibrium joint positions, and the joint velocities. The unknowns in this function were the (dynamic) joint stiffness and viscosity tensors, and the joint equilibrium positions. Because no experimental data on dynamic stiffness and viscosity were available, in order to solve for the joint equilibrium positions Flash assumed that postural viscosity scales with postural stiffness, which had been measured in [10], and that dynamic impedance (stiffness, viscosity and inertia) scales with postural impedance. Flash concluded that the equilibrium trajectory hypothesis is plausible, because the calculated joint equilibria lay along nearly straight lines connecting the initial and target points.

PROBLEM STATEMENT & ANALYTIC APPROACH

There are three basic ways in which the work to date in characterizing human arm impedance control may be extended. First, dynamic, rather than static, or postural, impedance can be measured. Thus far, based on certain assumptions, measurements of postural stiffness have been used to infer postural viscosity and dynamic stiffness and viscosity. Actual measurements of postural viscosity and dynamic impedance can be made. Secondly, variations in impedance can be investigated not simply for the case in which the arm is unimpeded, but also under different loadings, or impedances. Finally, the first and second steps can be repeated for different tasks and conditions, and variations in impedance across tasks can be investigated.

This study concerns itself with measurement of the gross mechanical properties of the endpoint of the intact human arm. It is possible to monitor myoelectric signals in an effort to determine the nature of human muscle and limb control at a more microscopic level, and many such studies have been made [4,9]. Although these studies provide valuable information about local control mechanisms, it is difficult to assess their importance with respect to the mechanical characteristics of the arm endpoint without exhaustive knowledge of the interconnections and overall structure of the human arm "control system." Because in many tasks the goal of the arm's neural activity appears to be control of the arm endpoint, it is justifiable to consider the degree and nature of the modulation of the endpoint's mechanical properties as a direct indicator of the nature of that control.

Many tasks performed by the human arm endpoint, such as moving from one point to another in pick-and-place operations, or maintaining a force normal to a surface as in driving a screw, are conveniently described in Cartesian space. This fact suggests the possibility that the CNS plans endpoint impedance in Cartesian space. Individual joint impedances are difficult to measure directly, although, if desired, they can be estimated from a dynamic model of the human arm coupled

with measurements of the endpoint Cartesian impedance to which they give rise. For these reasons, it is appropriate to measure human arm endpoint impedance in Cartesian space.

Because the human arm works in three-dimensional space, its endpoint has a three-dimensional impedance. In multi-dimensional space, impedances are represented by tensors, rather than by scalars as in the one-dimensional case [5]. The transition from one to two dimensions captures the essence of this qualitative change, and therefore, in the study reported in [10] and in this work, it has not been deemed necessary to incur the additional experimental complexity needed to extend impedance measurement to three dimensions.

A common method of identification of dynamic system parameters is the application of an input test signal and measurement of the resulting output. The input and output may then be correlated by any of a number of standard methods, yielding a description of the system dynamics [8]. This approach is most commonly used in the identification of open-loop systems, because it is difficult to isolate a given plant within a closed-loop system of unknown structure. Thus, for example, it is difficult to determine a model of the passive human arm by observing its closed-loop behavior, as it is actuated by neural control signals. Because it is the arm endpoint's closed-loop behavior which is of interest in our case, this does not present a problem. However, because the CNS is adaptive, input signals should be as unobtrusive as possible in order not to artificially change the level of adaptation.

The multi-dimensional Cartesian continuous-time identification problem involves determination of the relationship

$$F = f(X, \dot{X}, \ddot{X}) \quad (1)$$

where F and X are multi-dimensional vectors representing the arm endpoint input force perturbations and output displacements, respectively, and f is a vector of undetermined functions. If f is continuous and differentiable, linearization of equation (1) for small displacements yields

$$F = M\ddot{X} + B\dot{X} + KX \quad (2)$$

where M , B , and K are the localized inertia, viscosity, and stiffness tensors about a given point. In order to carry out the identification, it is necessary to use a device which can permit or impose a wide range of motions throughout a prescribed workspace while measuring desired input and output quantities. One such device is a robot manipulator. Mussa-Ivaldi *et al.* [10] determined the postural stiffness tensors at various points in a horizontal plane by using a two-degree-of-freedom motor-controlled planar manipulator to (i) displace the human arm from a series of equilibrium positions, and (ii) measure the final motor positions and torques. The Cartesian positions and forces were then calculated from the well-known kinematic relationships

$$X = L(\theta) \quad (3)$$

$$F = J^{-T}(\theta)\tau \quad (4)$$

where θ denotes the vector of joint angular displacements, L represents the manipulator forward kinematic transformation, and J is the manipulator Jacobian. The Cartesian stiffness tensor was then calculated according to:

$$F = KX \quad (5)$$

In order to determine the viscous and inertial components of impedance, endpoint force and position trajectories are required. Measurement of joint angles followed by a forward kinematic transformation yields the position trajectory, as before. However, the interpolation of time-varying endpoint Cartesian forces from joint motor torques is insufficiently accurate, because the forces exerted by the human arm are mediated through the manipulator, whose dynamic model is difficult to know exactly. The dynamic equation for the endpoint force in this case is

$$F = J^{-T}(\theta)[M(\theta)\ddot{\theta} + C(\theta, \dot{\theta}) - \tau] \quad (6)$$

where $M(\theta)$ is the manipulator inertia tensor, $C(\theta, \dot{\theta})$ represents the manipulator Coriolis and centripetal forces, and τ represents the actuator torques. This calculation is further complicated by the need for accurate values for the derivatives of θ and the potential noisiness of the digital control signal τ . Direct sensing of endpoint Cartesian force obviates these problems.

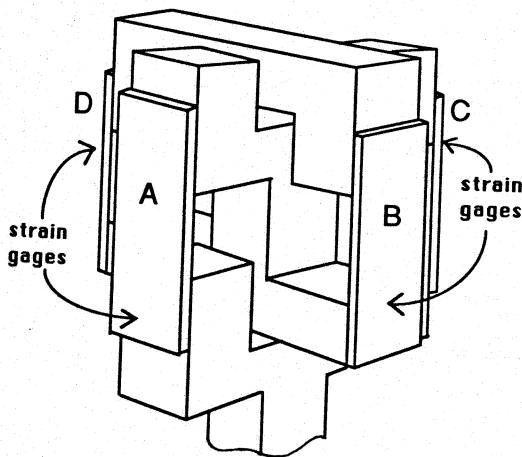


Figure 1a. Force Sensor (Internal).

Because data-gathering, as well as control of the manipulator, is most convenient in the digital domain, the initial identification is based on discrete values of the inputs and outputs. Application of the least-squares, maximum-likelihood or other method to a two-input, two-output system results in a discrete-domain 2×2 transfer function matrix $H(z)$ [8]. An estimate of the corresponding analog transfer function matrix $H(s)$ can be found by an extension to the multidimensional case of a technique described by Feliu [2]. The resulting parameters can be interpreted in terms of the stiffness, damping, and inertia tensors given in equation (2). Mussa-Ivaldi *et al.* [10] suggest representing a two-dimensional stiffness tensor by an ellipse characterized by size, shape or aspect ratio, and orientation. This representation is concise and visually appealing, and can be extended to representation of the inertial and viscous components of impedance.

TESTBED DESCRIPTION

We have designed and built a two-degree-of-freedom, SCARA-configuration, direct-drive robotic arm. The arm is kinematically anthropomorphic, with upper arm and forearm link lengths of 0.30 and 0.35 m, respectively. It is relatively lightweight, with link moments of inertia about their axes of rotation of approximately 0.15 N-m/rad/s^2 . Joint Coulomb friction is on the order of 0.05 N-m .

Each joint is driven by a PMI U12M4H DC servo motor. Each motor is controlled by an IBM PC AT by sending a digital voltage command to a DAC, feeding the resulting voltage into a PMI VXA voltage-to-current amplifier, and

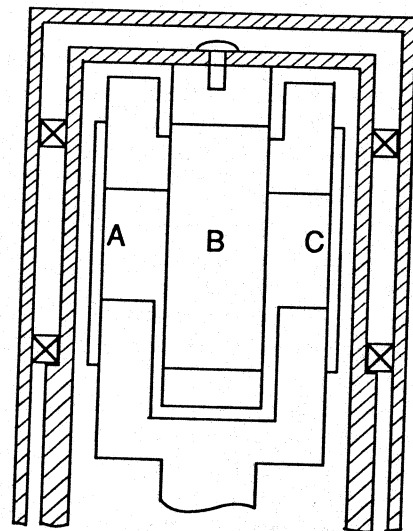


Figure 1b. Handle and Force Sensor.

applying the resulting current to the motor. Position information is acquired from an 8000-count encoder on each joint, giving a spatial resolution of about 0.25 mm for full extension of the arm. Software has been developed to exercise Cartesian or joint-based control, with the option to neglect or to account for dynamic coupling effects.

The endpoint two-axis force sensor, shown schematically in Figure 1, was designed for compactness and fits within a comfortably graspable 54 mm diameter handle. Each axis is formed by one pair of strain gages in a parallelogram linkage in order to limit errors introduced by off-center loading. Decoupling is achieved by transmitting all handle forces to one of these linkages, which senses forces along its loading axis and transmits forces orthogonal to its loading axis to the second linkage for sensing. Torque loadings are minimized by allowing the handle to rotate on bearings, permitting free rotation of the human wrist during experiments. Each axis can sense forces of up to 44.5 N (10 lb), with a resolution of 0.011 N (0.002 lb). The standard deviation of the sensor noise is 0.005 N (0.001 lb). Deviation from linearity is smaller than one percent. Hysteresis effects and repeatability are to within ± 0.011 N (0.002 lb).

SUMMARY

Human beings are adept at a wide variety of tasks, ranging from the maintenance of posture to the fine manipulation of tools in the face of environmental contact forces. To achieve these tasks, the CNS exercises complex and versatile control of the body's limbs. Investigators have sought to characterize aspects of this control in various ways. Some have taken a "low-level" approach, measuring the mechanical and myoelectric characteristics of individual muscle preparations, for example, or tracing the neural feedback of intact muscles in various situations. Others have focused on the gross mechanical properties of human limbs. Based on evidence from both of these lines of research, several researchers have theorized that in many tasks the CNS uses impedance control to move the limbs. Impedance has at least three familiar and physically intelligible components: stiffness, viscosity, and inertia.

In testing the impedance control hypothesis, the static (postural) stiffness of the human arm endpoint in various configurations has already been measured. These data have then been used to estimate viscosity characteristics and to investigate the use of impedance control as the arm traverses straight-line trajectories. The current work seeks to extend this by measuring postural viscosity and dynamic stiffness and viscosity under a variety of task conditions. It is hoped that lessons learned from human control of impedance in the face of deterministic as well as nondeterministic disturbance loading can be transferred to the control of robots and prosthetics. We are currently beginning the data collection phase of the study, and plan to report findings in a future communication.

REFERENCES

1. Feldman, A.G., *Change in the Length of the Muscle as a Consequence of a Shift in Equilibrium in the Muscle-Load System*, Biophysics (1974), 19, pp. 544-548.
2. Feliu, V., *A Transformation Algorithm for Estimating System Laplace Transform from Sampled Data.*, IEEE Transactions on Systems, Man, and Cybernetics (Jan./Feb. 1986), Vol. SMC-16, No. 1, 168-173.
3. Flash, T., *The Control of Hand Equilibrium Trajectories in Multi-Joint Arm Movements*, Biological Cybernetics (1987), 57, pp. 257-274.
4. Ghez, C. and Gordon, J., *Trajectory Control in Targeted Force Impulses.*, Experimental Brain Research (1987), 67, pp. 225-240.
5. Hogan, N., *Mechanical Impedance Control in Assistive Devices and Manipulators*, Proceedings of the Joint Automatic Control Conference, San Francisco, Aug. 13-15, 1980.
6. Hogan, N., *The Mechanics of Multi-Joint Posture and Movement*, Biological Cybernetics (1985), 52, pp. 315-331.
7. Hogan, N., *Impedance Control: An Approach to Manipulation: Part I - Theory*, ASME J. Dynamic Systems, Measurement, and Control (Mar. 1985), pp. 1-7.
8. Hsia, T.C., System Identification, Lexington, MA, D.C. Heath and Co. (1977).
9. Karst, G.M., and Hasan, Z., *Antagonist Muscle Activity During Human Forearm Movements Under Varying Kinematic and Loading Conditions*, Experimental Brain Research (1987), 67, pp. 391-401.
10. Mussa-Ivaldi, F.A., Hogan, N., and Bizzi, E., *Neural, Mechanical, and Geometric Factors Subserving Arm Posture in Humans*, Journal of Neuroscience (Oct. 1985), vol. 5, no. 10, pp. 2732-2743.
11. Nichols, T.R. and Houk, J.C., *The Improvement in Linearity and the Regulation of Stiffness that Results from the Actions of the Stretch Reflex*, Journal of Neurophysiology (1976), 39, pp. 119-142.
12. Stein, R.B., *What Muscle Variable(s) Does the Nervous System Control in Limb Movements?*, The Behavioral and Brain Sciences (1982), 5, pp. 535-577.