# Haptic Identification of Remote Environment Properties

Robert D. Howe
Division of Engineering and Applied Sciences
Harvard University
Cambridge, MA 02138
howe@deas.harvard.edu

Thomas Debus and Pierre Dupont
Aerospace and Mechanical Engineering
Boston University
Boston, MA 02215
tdebus@bu.edu, pierre@bu.edu

## ABSTRACT

In teleoperation, automatic identification of remote environment properties such as object weight, size, and friction can assist the teleoperator in determining optimal manipulation strategies. Similarly, virtual training systems can be calibrated using such an automatic identification procedure. For those properties which can be described by parameterized constraint equations, this paper provides a method by which the active constraints can be determined during each portion of the remote manipulator's data stream. The parameterized properties can then be estimated from the appropriate data stream segments. The approach is validated for peg-in-hole insertion using a desktop teleoperator system.

**Keywords:** teleoperation, parameter identification, data segmentation, constraints.

## 1. INTRODUCTION

We are working to develop systems that can identify the properties of remote environments during teleoperation. These systems determine properties such as the size, weight, and friction of objects in the remote environment as they are manipulated. This information can improve the performance of teleoperated manipulation systems in many applications. For example, in remediation of toxic waste dumps, quantitative measurements of the size and weight of the containers can help to infer their contents and to determine optimal handling strategies (Griebenow 1994). Additional applications areas where the teleoperator is required to manipulate unfamiliar objects include undersea salvage, interplanetary exploration, and explosives defusing.

Automatic identification systems can also help to train new operators by creating and calibrating models of the environment for real-time simulators. In this scenario, the system extracts model of remote objects and their properties from sensor data acquired during actual telemanipulation. Training systems calibrated using actual feedback data would provide a realistic and safe practice environment for surgical applications, toxic waste remediation, and munitions loading. In contrast, the usual method to calibrate virtual models relies on subjective hand tuning of simplified physical models. Some work has recently appeared, however, on measuring environmental properties for creation of virtual environments (MacLean 1996, Miller and Colgate 1998).

In previous work, we proposed a framework for solution of the automatic property identification problem (Schulteis et al. 1996, Dupont, Schulteis, and Howe 1997, 1998). This framework is based on the fact that many properties can be identified only when the system is in a certain state. For example, the weight of an object can be measured only when it is freely supported by the robot, and measurement of an object's surface friction requires that another object slide over the object.

The framework thus reduces the automatic property identification problem to three subproblems: *task decomposition*, *data segmentation*, and *property estimation*. The goal of *task decomposition* is to divide the overall sequence of manipulation operations into a sequence of states defined by the interactions between the robot and objects in the remote environment. *Data segmentation* breaks the stream of data from various robot sensors into a segments that correspond to specific states. Subsequent *property estimation* finds the numerical values (or bounds on values) of the properties that can be determined in each state. Our previous papers presented algorithms for finding simple properties such as the weight and size of grasped objects, and the presence of motion constraints.

In this paper, we present a new procedure for finding the geometry of objects and surfaces in the remote environment. The method is based on the kinematics of constrained motion, where a grasped object slides, pivots, or rolls against surfaces in the environment. The concept is roughly analogous to a human probing with a stick in the dark, where neither the shape of the stick nor the shapes and locations of the environmental surfaces are known. From sensed motion and force patterns, the length of the stick and the shape of objects in the environment are discerned. In our approach, analysis of the constraint kinematics provides the general forms for the motion of the grasped object in each contact state. By comparing the observed motion of the grasped object with the motion predicted for each of the possible contact states, the active state may be inferred. Once the active state is known, the object parameters appropriate to that state may be estimated.

In the next section, the property identification framework of Dupont et al. (1997, 1998) is summarized. The subsequent section describes the segmentation and property estimation procedure developed for contact properties. We then present experimental implementation of the procedure on a laboratory teleoperation testbed consisting of two Phantom haptic interface robots. The geometric properties of a peg and hole are estimated during a planar insertion task. Finally, we discuss limitations of the approach and directions for future work.

## 2. PROPERTY ESTIMATION FRAMEWORK

From Schulteis et al. (1996) and Dupont et al. (1998), the identification problem can be formally defined:

> *Given a task description,* $\mathrm{T}$*, a sensor data stream,* $d(t)$*, and a set of properties to be determined,* $p$*, compute estimates of the states,* $\hat{x}(t)$*, and the properties,* $\hat{p}(t)$*, for* $t \in [0, t_{\text{final}}]$.

A *task description*, T, contains, at a minimum, a specification of the desired interactions between objects in the remote environment. Additional detail could indicate which objects the robot should handle and available grasp configurations. It could also include parameterized models of objects relating to, e.g., geometry and contact forces. *State,* $x(t)$, is defined by the manipulated object and a description of the set of active constraints between it and all other objects in the environment, including the remote manipulator. *Properties* estimated in the identification problem are those of the manipulated objects and of those objects with which they have contact. The latter class includes the remote manipulator. Examples of such properties are shape, size, weight, mass distribution, stiffness and friction.

### 2.1 Solution Procedure

The following decomposition of the identification will be used here:

1. Task decomposition - the process of resolving a task $\mathrm{T}$ into a minimal sequence of *subtasks*, $s_i$, described by contact states and their associated sets of properties, $\mathrm{T} = \{s_1 = (x_1, p_1), s_2 = (x_2, p_2), \ldots, s_q = (x_q, p_q)\}$ where $p_i$, $i = 1, \ldots, r$, are subsets of $p$. Note that an individual state and/or property may be associated with multiple subtasks.

2. Data segmentation - Given a task decomposition $\mathrm{T} = \{s_1, s_2, \ldots, s_q\}$ and the sensor data stream $d(t)$, find the time intervals corresponding to each subtask, $\{(t_{1,i}, t_{1,f}), (t_{2,i}, t_{2,f}), \ldots, (t_{q,i}, t_{q,f})\}$. To allow for sensor noise as well as unanticipated states, it is not required that $t_{j,f} = t_{j+1,i}$. Since there is uncertainty in determining the time intervals, the $j^{\text{th}}$ interval provides only estimates of the subtask and state, $\hat{s}_j$ and $\hat{x}_j$, respectively. Data segmentation may be performed either on or off line. If performed on line, the estimates can be expressed as functions of time.

3. Property estimation - Given the time intervals $\{(t_{1,i}, t_{1,f}), (t_{2,i}, t_{2,f}), \ldots, (t_{q,i}, t_{q,f})\}$ associated with each subtask, estimate the desired properties, $\hat{p}$.

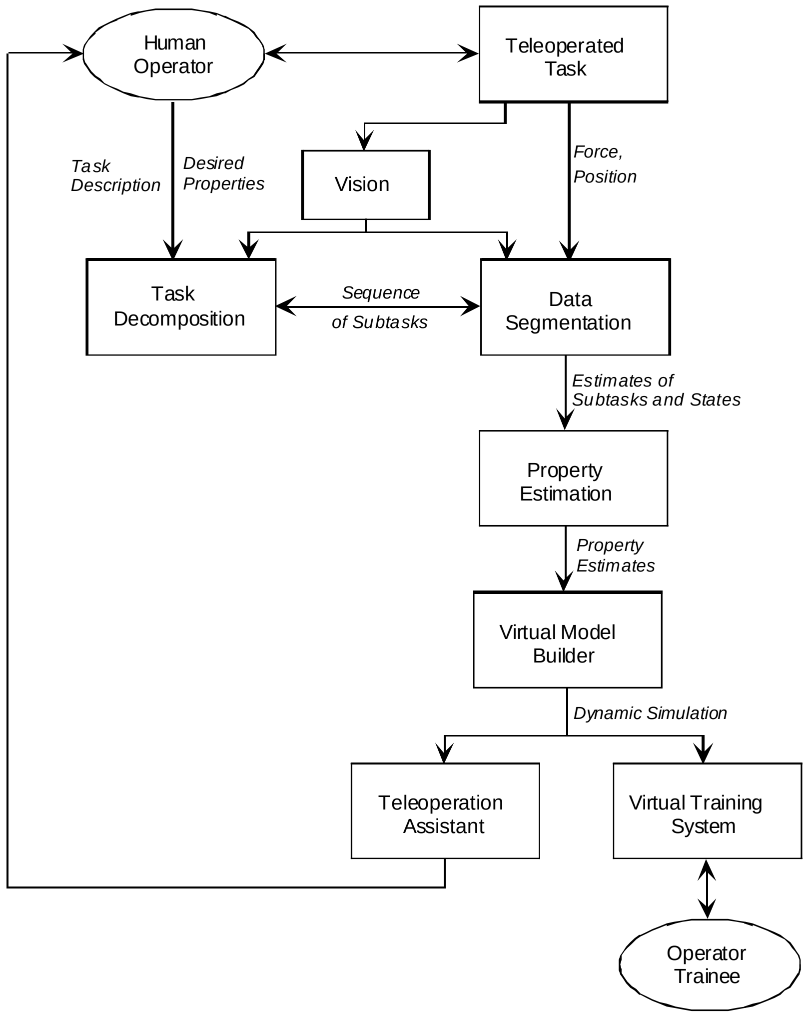


Figure 1. Automatic Identification Systems Components.

Figure 1 depicts the organization of the automatic environment identification system. As a normal teleoperated task is performed, the system collects such data as task descriptions and desired properties from the operator. The resulting forces and motions are received from sensors in the remote environment. Visual feedback, as well as interaction with the human operator and data segmentation module, may also be necessary to efficiently decompose the task into its constituent parts. Based on the deduced sequence of subtasks, the data segmentation module associates subtasks (and thus states) with time segments of the data stream. The desired properties are then estimated and used to build and calibrate a model of the remote environment. As shown, the model can then be used either to provide immediate assistance to the operator or as the basis of a training system.

## 2.2 Prior Work

This paper focuses on the subproblems of data segmentation and property estimation. Prior work on these topics has not addressed property identification. For example, Pook and Ballard (1993) employed data segmentation to understand the qualitative control characteristics of an example task performed on a teleoperated system. Kang and Ikeuchi (1993) were interested in assembly task programming and used segmented data from a grasp task for the purpose of understanding the grasp motions. Delson and West (1996) used human demonstration to program robots and in the process segmented the data into subtasks that facilitated the generation of a robot program. Hannaford and Lee (1991) used hidden Markov models to segment force data from a teleoperated task. Other approaches to segmentation of manipulation data includes qualitative reasoning with thresholding (McCarragher 1994a), neural networks for off-line segmentation (Fiorini 1992) and Petri nets (McCarragher 1994b).

Most work on property estimation assumes a parameterized model, e.g., a geometric or contact force model. A significant portion of this literature is devoted to robot parameter identification. For example, the identification of link inertial parameters has been studied by Khosla and Kanade (1985) and An et al. (1985). Others have investigated the identification of kinematic parameters (Driels 1993). In addition, a few authors have addressed identification of robot payload and environment properties. Methods for estimating payload inertia appear in the work of Atkeson et al. (1985) and Lin and Yae (1992). Lin and Yae also estimate certain parameters relating to constraints of the operating environment. Constraint existence and modeling are studied by Dupont et al. (1997), and constraint parameter identification by Bruyninckx (1995).

## 3. CONTACT CONSTRAINT SEGMENTATION AND ESTIMATION

The approach developed here uses the characteristics of constrained motion to simultaneously segment the data from the remote robot sensors and to estimate the parameters that describe the surface geometries. Constraint due to contact between objects produce characteristic patterns of motion. One simple example is a flat-sided object sliding over another, which results in straight line motion of the sliding object; another example is an object pivoting on its corner against a surface, which results in rotation of the object about the corner. If the robot is firmly gripping the object, we can use data from the robot's joint sensors and the kinematic model of the robot to resolve the grasped object's motion to the fixed coordinate frame at the base of the robot. In many cases the grasped object will be interacting with surfaces in the environment that remain immobile in the base frame. Thus the sensed motion of the robot gripper reveals the relative motion between the grasped object and the environmental surface.

One advantage of this approach is that it can be used to simultaneously solve the subproblems of parameter estimation and data segmentation in a combined way. From the given task decomposition, there are a finite set of contact states that may be active. By comparing the observed motion to the type of motion predicted for each state from the kinematic analysis, the active contact state can be inferred. Thus if precise straight line motion of the grasped object is observed, it may possible to infer that a flat-sided object is sliding over a flat surface. Once the contact state is determined, the appropriate parameters may be estimated; in this example, parameters might include the shape of the two objects and their coefficient of friction.

To look at estimation of geometry in a specific case, we will analyze a peg-in-hole assembly task. This task has well-defined interactions that are straightforward to analyze, and it is of considerable practical importance as a prototype for a wide range of assembly tasks. The goal is to observe the robot sensor data during the teleoperated insertion process, and infer the dimensions of the hole, i.e. the locations of the corners of the hole in the robot base frame.

### 3.1 Contact Constraints

During planar peg-in-hole insertion, four primary contact states can occur, as shown in Figure 2: (A) corner of hole against side of peg, (B) corner of peg against side of hole, (C) side-to-side contact of peg and hole, and (D) corner-to-corner contact of peg and hole. For our purposes, the two flat surfaces adjacent to the hole and the two flat surfaces within the hole are equivalent, as they both constrain a point on the peg to move in a straight line. By combining these primary contacts, the multiple contact states that are encountered as the peg is inserted can be created.

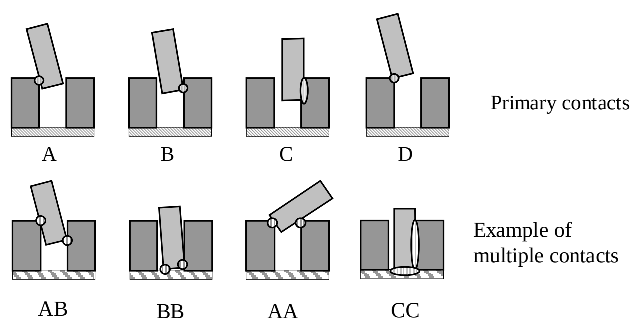


Figure 2. Primary and multiple contact states.

We begin by analyzing case (A) in Figure 2. As the peg moves into the hole in this contact state, it pivots and slides against the hole's corner. If we consider the side of the peg at one instant during this process (Figure 3), it can be described by the equation of a line

$$y = m_i\, x + b_i \qquad (1)$$

where *(x,y)* are the coordinates of the points along the peg side in base frame coordinates, and $m_i$ and $b_i$ are constants that vary as the peg slides and pivots into the hole. If we assume that we know the peg's dimensions and its configuration in the gripper, then we can find values for $m_i$ and $b_i$ at each instant in time by transforming the known gripper frame configuration to the base frame using the current robot joint configuration data and the robot's forward kinematics. At a later time in the insertion process, the line describing the peg side has different values for the constants $m_i$ and $b_i$. The pivot location remains constant, however, so there is a point $(x_p,y_p)$ that lies on the side of the peg throughout this contact state. We may estimate the hole corner coordinates by simultaneous solving two instantiations of equation (1), at two different instants in time, as the values of $m_i$ and $b_i$ may always be found from the sensor data. To improve the robustness of the measurement, it is of course useful to combine many sensor measurements. Analysis of the other contact states, both primary and multiple, follows the same approach.

### 3.2 Segmentation

The above approach assumes knowledge of the peg's contact state, but the technique can also be used to determine which contact is active. This is accomplished by calculating the geometric parameters for each of the possible constraint states at each instant in time. If a constraint is not active, the parameter estimate is unlikely to remain at a constant value for long. Figure 3 shows an example of this approach. If the peg is in two-point contact as shown in Figure 3(b), then the estimation algorithm will yield a constant value for the location of the hole corner that acts as a pivot, and a constant value for the location of the hole side on which the peg corner is sliding. If, however, the peg is in one-point contact as shown in Figure 3(a), then estimation algorithm will produce a constant value for the location of the hole corner that acts as a pivot, but the value for the location of the hole side on which the peg corner is sliding will vary continuously.

The overall segmentation and estimation algorithm is a generalization of these concepts. The system begins with the assumption that the peg is not in contact with surfaces in the environment. When contact is detected (using a force threshold), the systems starts to calculate the parameters for all contact states that can ensue from the no-contact state. Generation of this set of possible states and the transition rules between them is part of the task decomposition subproblem, which may require human intervention and is not addressed here. The system then monitors the variation in the estimated parameters as data is collected. Stability of a compatible set of parameters across a suitable time interval indicates which contact state is active. Those parameters are taken as valid estimates of the environmental parameters, and the other parameter estimates are ignored.

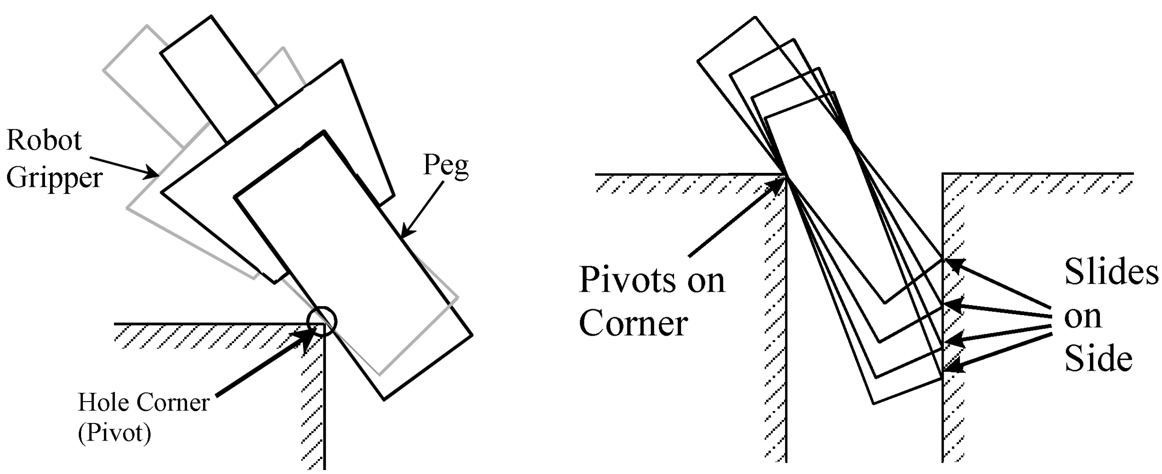


Figure 3. (a) Primary contact which allows pivoting and sliding of the peg about the hole corner. (b) Multiple contact which allows pivoting and sliding of the peg about the hole corner and straight-line sliding of the peg corner along the hole side.

## 4. EXPERIMENTAL EXAMPLE

A tabletop teleoperator system, composed of two Phantom haptic interface robots is used to perform the planar peg-in-hole insertion task. A sketch of the system is shown in Figure 4. Each device is a 3 degree of freedom manipulator. In order to accomplish the desired task, a gripper is added to the remote manipulator. The operator controls the master by manipulating a stylus attached through a passive spherical wrist. At each sample time, the forward kinematics are computed such that the position of the end effector with respect to the base frame is known. The workspace is a box of roughly 20 cm $\times$ 27 cm $\times$ 38 cm in size. Each device can exert a continuous tip force of 1.7 N, and a maximum force of 8.5 N can be achieved.

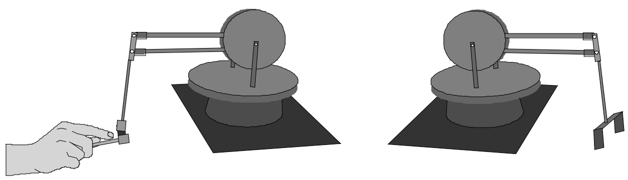

Figure 4. Two Phantom haptic interface devices used as a teleoperator system.

The controller uses a symmetric position-error based force reflection control scheme based on position and velocity error between the master and remote manipulators; see equation (2). The controller gains are adjusted experimentally to achieve stability and good force feedback fidelity. The controller output is taken as an estimate of the force acting on the robot’s tip. The control loop servo rate is approximately 10 kHz.

$$\begin{aligned} F_i^{remote} &= K_{pi}\left(X_i^{master} - X_i^{remote}\right) + K_{vi}\left(\dot{X}_i^{master} - \dot{X}_i^{remote}\right) \\ F_i^{master} &= -F_i^{remote},\ \ i = \{x, y, z\} \end{aligned} \tag{2}$$

Figure 5 depicts the anticipated progression of contacts during the insertion task. The operator first slides the peg toward the hole on the table surface. As the peg enters the hole, it first slides on one corner of the hole (contact state A). It then makes contact with both sides of the hole (contacts A and B) and maintains these contacts until the bottom of the hole is reached (contacts B and B’). Finally, it is placed flush with the right side of the hole (contacts C and C’) and released. As a means of verifying the automatic segmentation procedure, the operator presses a switch during the task at each change of contact state. Peg position, velocity and angle are recorded at a rate of 50 Hz.

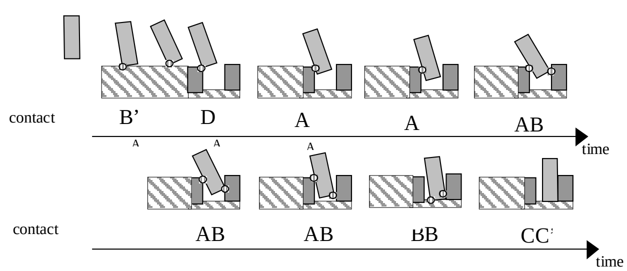


Figure 5. Sequence of subtasks resulting from task decomposition.

During data segmentation, position error between the master and remote manipulators is used to compute contact force. At the start of the task, vertical contact force is filtered to identify contact. The estimation algorithms for the states in Figure 5 were calculated, and the correlations of these across time are compared to find the state. Results of this process for one trial are shown in Figure 6. The actual and estimated peg and hole locations, illustrated at one second intervals, show good agreement.

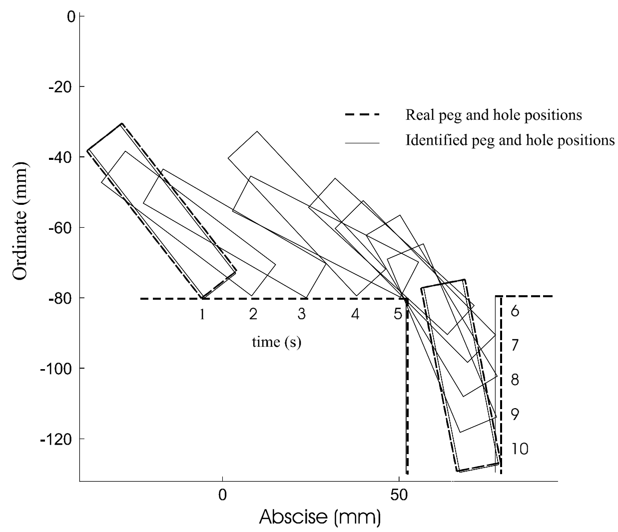


Figure 6. Actual and estimated peg and hole locations. The peg is depicted at one second intervals during the insertion task.

## 5. CONCLUSIONS

The preceding example demonstrates that machine interpretation of the remote environment data stream can produce effective quantitative estimates of pertinent parameters. The proposed approach to contact state identification was clearly on a par with that of the operator. With regard to property estimation, it is apparent that the level of accuracy far exceeds what could be achieved by the operator using visual and kinesthetic feedback.

Broad classes of environment identification problems require segmentation of data based on contact state. For those applications in which the contact states can be described by parameterized constraint equations, the proposed segmentation technique holds promise. Clearly, additional work is needed to extend the technique to more sophisticated physics-based contact models which incorporate velocity and force data. The limits of this approach must also be investigated. For example, the sensitivity of the estimation algorithms to the details of the trajectory are not clear; a skilled operator may not make contact with surfaces in the environmental often enough to permit accurate measurement of the surface geometry. Further analysis should yield insight to this aspect of the problem.

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