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Haptic Perception With an Articulated, Sensate Robot Hand

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Abstract

In this paper we present a series of haptic exploratory procedures, or EPs, implemented for a multi-fingered, articulated, sensate robot hand. These EPs are designed to extract specific tactile and kinesthetic information from an object via their purposive invocation by an intelligent robotic system. Taken together, they form an active robotic touch perception system to be used both in extracting information about the environment for internal representation and in acquiring grasps for manipulation.

The haptic system presented utilizes an integrated robotic system consisting of a PUMA 560 robot arm, a JPL/Stanford robot hand, with joint torque sensing in the fingers, a wrist force/torque sensor, and a 256 element, spatially-resolved fingertip tactile array. We describe the EPs implemented for this system and provide experimental results which illustrate how they function and how the information which they extract may be used. In addition to the sensate hand and arm, the robot also contains structured-lighting vision and a Prolog-based reasoning system capable of grasp generation and object categorization. We present a set of simple tasks which show how both grasping and recognition may be enhanced by the addition of active touch perception.

1 Introduction

1.1 Motivation

We motivate this work with two basic assumptions. First, a useful robot must manipulate its environment. There are exceptions to this statement, of course – a space-faring robotic probe doing planetary imaging is an example – but for the most part, robots are intended to carry out tasks which involve grasping and manipulation of a variety of objects, either autonomously or in conjunction with a human coordinator. Second, because the world is dynamic and uncertain, the robot must interface with its environment via sensing. We define perception as the intelligent utilization of this sensed data. Perception allows the robot to compensate for the uncertainties and changes in its environment, to build meaningful internal representations, and to make decisions about the objects in its world which may be useful in completing its designated tasks.

Most of the work in robotic perception to date has been in computer vision. Research in this area ranges from low-level edge detection to high-level object recognition. Such work is primarily concerned with segmenting multiple object scenes, determining the location of an object, and extracting information about an object's form and structure. Research in robotic manipulation has largely concentrated on design and control of mechanical hands and on (primarily) analytical studies of the positioning and forces required to generate stable grasps.

Let us make two observations: First, while vision is an undeniably important perceptual capability, it is often inadequate. Under the best of circumstances, it provides only partial information – we cannot visually perceive an entire object in a single sensing step. In addition, objects are often occluded by other objects, or even by the hand and arm in the case of a manipulation task. And finally, many of the environments where robots will prove most useful provide extremely poor visibility, creating conditions under which vision systems will not function optimally. Second, invoking our first basic assumption, the reason for the robot to be in these environments is to carry out useful tasks. Since the tasks involve manipulation, the robot will be equipped with one or more end-effectors. If the tasks are sufficiently complex and variable, one of these end-effectors might well be a multi-fingered, articulated hand. By augmenting this end-effector with sensors and developing a haptic perceptual system which utilizes this sensate hand, we create a complimentary perceptual system which may be used either alone, or in conjunction with vision, to allow the robot to explore and model its environment. The additional information provided may also be used during manipulation to acquire and maintain grasps by allowing the robot to sense local object properties and error conditions such as object slippage.

1.2 Related Work

There have been many projects involving the design of tactile sensors. Raibert [25], Siegel [28] and Fearing [10], Begej [4], and Tise [34] present spatially-resolved tactile sensors for normal force measurement based upon resistance, capacitance, optical, and piezoresistance transduction techniques, respectively. Novak [22] presents a spatially-resolved capacitance sensor for normal and shear force measurement, while Brock [7] presents a force/torque fingertip sensor. Despite this body of previous work, however, few sensors have been developed which have left the lab and found their way into use as tools for those interested in utilizing such devices for further research. The reasons for this include lack of robustness, repeatability and design of supporting electronics and interfaces.

Despite this dearth of devices, several researchers have addressed the issue of how to utilize tactile sensing in a robotic system. The largest effort has been in the use of a single tactile sensor for data extraction. A representative sampling of such work follows: Grimson [11] and Ellis [8] obtain position and surface normal data, which is then used to determine where to next move the sensor. The final goal is the recognition of objects modeled as polyhedra. Bajcsy [3] explores the usefulness of the data obtained from spatially-resolved tactile arrays in both planar and curved geometries. Hillis [12] uses pattern recognition techniques to analyze tactile array images of objects smaller than the sensor pad, while Overton [23] and Shen [27], among others, use static tactile array images to extract information about objects larger than the sensor. Allen [1] presents an active touch system utilizing a tactile array with curved geometry. Positional information is obtained by moving the sensor along a surface. The points obtained are used to build a parametric surface description which is used for model-based recognition. Stansfield [32] takes a different approach, presenting the design of an active robotic touch system based upon theories of human haptic perception. A series of exploratory procedures are described which utilize a combination force/torque - tactile array sensor mounted on a robot arm. These EPs are used to haptically explore an unknown object for categorization.

A few researchers have done work in object recognition using tactile sensors mounted on twofingered, parallel-jaw grippers. Briot [6] uses tactile arrays mounted on a gripper to identify elementary shapes for objects smaller than the sensor pad. Luo [20] uses a pair of tactile array sensors mounted on a gripper, along with two-dimensional vision, to recognize objects using the moment invariants of object silhouettes. Koutsou [17] extends the work of Stansfield [32] by adding EPs to extract information about the weight and gross size of an object using a pair of force/torque - tactile array sensors mounted on a gripper. The gripper allows the robot to span and lift the object.

Parallel-jaw grippers have limited use for perception, however, due to their lack of dexterity. The next logical step is to explore the use of multi-fingered, dextrous hands for touch sensing. To date, most research in sensate hands has involved the use of torque sensing in the joints or force and torque sensing at the fingertips to produce and maintain stable grasps. Among the researchers contributing to this area are Salisbury [26], Fearing [9], Brock [7], and Bicchi [5]. The use of a sensate hand for perception has received far less attention. Kinoshita [14] and Stojilkovic [33] present early research in the use of a multi-fingered hand for pattern recognition. Allen [2] uses a dextrous, multi-fingered hand for model-based object recognition. Contact points are obtained from the object by having the hand grasp it from several different pre-specified positions. A superquadric is then fit to the data and is used to match the object against a database of known objects. The integration of a fingertip tactile array sensor into the system is also briefly discussed.

1.3 Synopsis

The research presented in this paper extends the work of Stansfield [32] to a multi-fingered, dextrous, sensate robot hand. We have used theories of human haptic perception as a guide in designing a robotic touch perception system. Our goal is flexibility. It is obvious that the human hand is not only a useful general-purpose manipulator, but also that it is a valuable perceptual system. Studies have shown, for example, that the haptic system is capable of fast and accurate object recognition [15]. Robotics researchers, however, usually address perception and manipulation as two separate problems, thereby missing the important link between the two. It is our goal to explore the interactions of manipulation with haptic perception. In this first stage of our work, we do not address the problem of utilizing touch data to maintain grasps, but rather look at how the sensate hand may be used as an exploratory and perceptual device. However, we do not ignore the link between manipulation and perception even at this stage. The haptic exploratory procedures which we present make ample use of our robotic grasp generator to both shape the hand for exploration and to acquire the objects to be explored. Uses for the haptic information acquired during this exploration include choosing initial values for parameters such as grasp force and adjusting the initial hand position and posture before manipulation begins.

The remainder of this paper is structured as follows. Section 2 briefly discusses the theories of human haptic perception which we have adopted and the model of robotic touch perception which we have designed based upon them. Section 3 presents the haptic EPs which we have implemented and provides experimental results for each. Section 4 presents a few simple tasks which demonstrate how augmenting a robot hand with a haptic perception system might be useful.

2 Haptic Perception: A Model

2.1 Theories of Human Haptic Perception

Psychological studies of human haptics by Klatzky and Lederman [18, 16] point out the link between desired knowledge about an object's properties and the hand motions executed to acquire that knowledge. Central to their studies is the idea that the haptic system is active and purposive. It is made up of two subsystems: the motor subsystem and the sensory subsystem, with the sensory subsystem piggy-backed onto the motor subsystem. Hence, unlike visual perception, it is not only the processing of the sensory data which is important, but also the way in which the motor system is used to extract that data.

Through a series of experiments, they have compiled a set of exploratory procedures, or EPs, directly linked to the extraction of specific haptic object properties. Each EP is a stereotypical movement pattern which has certain characteristics which are either invariant or highly typical. That is not to say, however, that an EP need correspond to a particular end-effector, hand posture, fixed pressure, etc. An example is the "pressure" EP used to extract hardness information. This EP involves the application of shear and normal forces to an object. These forces may be applied either by pushing on the object with a single finger, or by squeezing the object between the fingers and the palm (or in any number of other ways.) It is the application of pressure which is the invariant. Figure 1 presents a list of the EPs which Lederman and Klatzky propose for the human

Figure 1: EPs and the properties they extract.

Exploratory Procedure	Haptic Properties Extracted
lateral motion	texture
pressure	hardness
static contact	temperature
enclosure	global shape, volume
contour following	exact shape, volume
unsupported holding	weight
part motion test	part motion
function test	specific function

hand, along with the haptic properties which each extracts.

2.2 Design of a Robot Haptic System

We have based the design of our robotic haptic system upon this theory of stereotypical exploratory movements used to extract a fixed lexicon of haptic properties. These EPs (that is, the motor and sensory processing modules which comprise them) must, of course, fit into some larger computational model of perception. We have addressed this issue in [32]. In that work, we propose a structure for the perceptual system which consists of a hierarchy of problem-solving modules each of which is domain-specific and informationally-encapsulated. Processing within this system proceeds via the assignment of a set of intermediate levels of representation of the sensed world, beginning with low-level primitives and ending with an abstract, symbolic representation to be used by the cognitive system. This model is not unlike that proposed for the visual system by Marr [21]. Our current work with the sensate hand remains true to this model: the EPs comprise the lowest levels of this hierarchy, extracting information about the world and making it available to upper levels for further processing. Thus the EPs themselves may be thought of as a collection of tools available for purposive, knowledge-driven invocation by higher-level modules. The order of invocation for EPs within the human system is addressed in [19]. We discuss the incorporation of these ideas into our robotic system in Section 4.

2.3 Implementation: the Robotic System

In this subsection, we briefly present the integrated robotic system upon which this work is implemented. Section 3 discusses the implementation of specific EPs. The robot haptic system consists of the following.

- A 6 degree-of-freedom PUMA 560 robot arm.
- A wrist sensor which measures three force and three moment vectors about a central set of axes.
- A JPL/Stanford robot hand. This articulated hand has three fingers, with three joints per finger, for a total of nine degrees-of-freedom. The hand provides joint positions and torques, as well as Cartesian positions for the fingertips.
- A 16 X 16 element tactile array sensor based upon piezoresistive transduction [13, 29]. This sensor responds with scalar outputs to applied pressure.

The wrist sensor is mounted on the wrist of the robot arm. The hand is then mounted on this sensor. The tactile array is mounted on the tip of one finger of the hand. We will discuss the configuration of the tactile array sensor in Section 3.

In addition to the haptics hardware, the robotic system also contains structured-lighting vision and Prolog-based expert systems capable of object categorization and grasp generation. This integrated system provides an excellent testbed for our theories. Not only does it allow us to demonstrate how the work presented in this paper fits into an overall structure for robotic manipulation, but also how it enhances the performance of other, non-haptic, components as well. The examples presented in Section 4 utilize all components of our robotic system to make this point.

3 Active Exploratory Procedures for a Sensate Hand

In this section we present the haptic exploratory procedures which we have implemented for the system described in Section 2. The EPs are organized according to the specific haptic property which they are designed to extract. In most cases, an EP utilizes information from more than one of the touch sensors. In addition, for several of the properties, we have implemented multiple

EPs for extracting that property. The choice of which to invoke may depend upon such factors as previously extracted information about the object being explored and the sequence of invocation for the set of EPs which constitute the entire exploration. For example, the hardness of an object which fits into the hand might be obtained by squeezing, however the hardness of a support surface is better determined by pushing on it with a single finger.

3.1 Cutaneous Properties

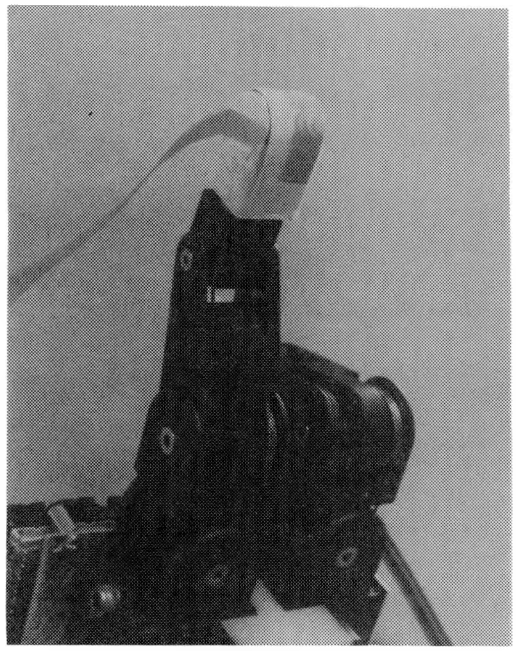
Cutaneous properties are obtained from the tactile array sensor mounted on the fingertip. The sensor contains a 16 X 16 array in a sensing area of dimension 10 mm X 25 mm. The sensor is designed to be wrapped "Bandaid-like" around a cylindrical fingertip. We found this to be a less than ideal configuration for exploration, however. Instead, we have designed a new fingertip for the sensor which consists of a planar portion, which we refer to as the pad and a curved portion, which we refer to as the tip. The tactile array is mounted length-wise as shown in Figure 2. The planar pad gives us a larger, less ambiguous contact surface for extracting tactile images. The curved tip is actually at the top of the fingertip, allowing us to use the sensor for probe-like movements of the finger. We also throw away half of the data, giving us a 16 X 8 array which better corresponds to the dimensions of the sensing surface. Rows 0-5 constitute the tip of the finger. Rows 6-15 constitute the pad.

Cutaneous Contact By classifying the tactile image obtained on the fingertip during a contact, we may get some idea of the local properties of the underlying object. These properties may then be used to make further decisions during exploration. We currently classify a cutaneous, or tactile, contact as one of four types:

- Extended contacts cover some large percentage of the sensor surface. They are usually created by blunt objects larger than the sensor pad. Figure 3a shows an extended contact created by pushing the flat end of a ruler against the pad[1].
- Multiple contacts are distinct regions of contact within a single tactile image. We will return to this property when we discuss texture. Figure 3b shows multiple contacts created by

[1]The horizontal white line in the tactile images separates the planar pad portion from the curved tip portion of the fingertip.

Figure 2: Fingertip for tactile array sensor.

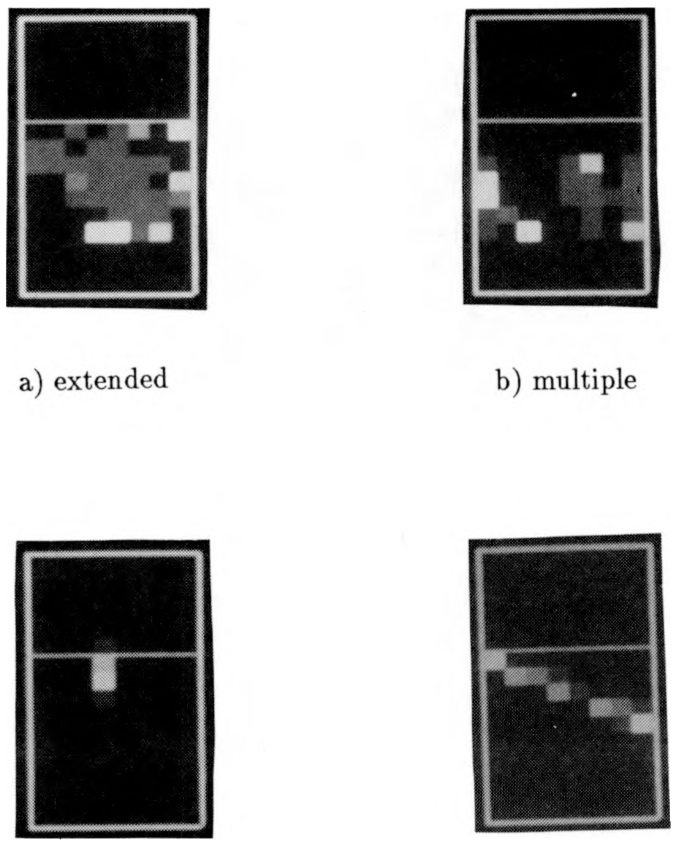


pushing a twisted-pair cable against the sensor pad.

- Small contacts cover only a small percentage of the sensor surface. They are usually created by an object smaller than the fingertip, or by some part of a larger object which is smaller than the fingertip. Figure 3c shows a small contact created by the tip of a screwdriver.
- Edge contacts are highly elongated and are usually created by contacting the edge of a large object. Figure 3d shows the contact obtained for the edge of a ruler pressed diagonally across the pad.

Surface Texture Because the array sensor is highly sensitive, it has a tendency to saturate easily; therefore, we use it primarily as a binary device (contact/no-contact for each site.) For the same reason, it is difficult to get meaningful statistics for the greyscale values when trying to determine whether or not a given contact indicates a textured surface. Fortunately, because of the density and tight spacing (approximately 1.37 mm between active sites) of the array, we can often determine surface texture from the number of contacts contained in a single image. A static contact EP which produces an image containing a single extended contact indicates a smooth surface, while

Figure 3: Tactile contacts on fingertip pad.



a) extended

b) multiple

c) small

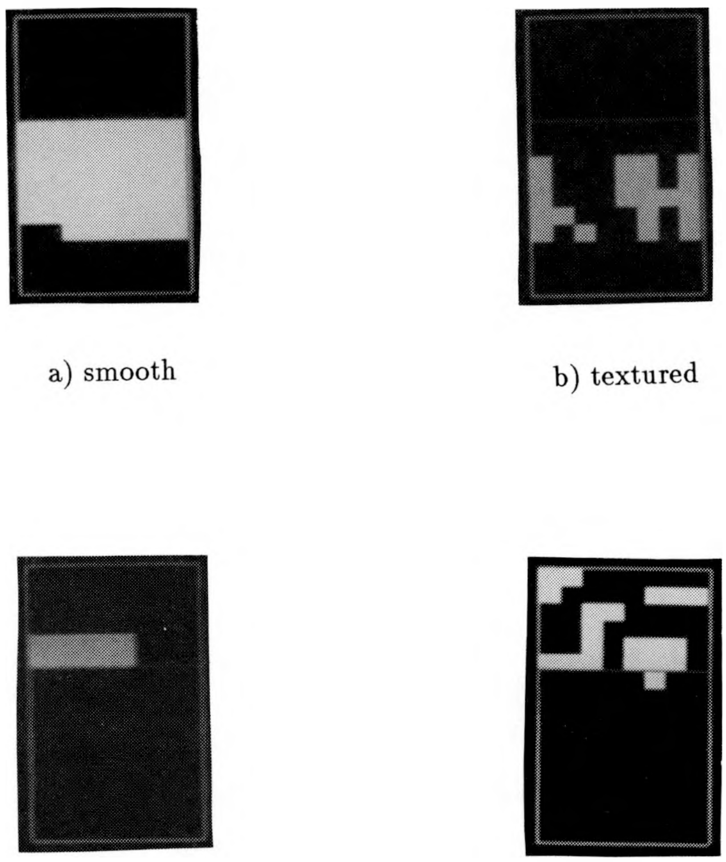
d) edge

a static contact EP which produces an image having distinct multiple contacts indicates a rough or textured surface. To determine this, a binary image is created via thresholding and the regions contained in this image are then determined. Figure 4 shows the results of this process for both the pad and the tip portions of the array. Figure 4a shows the processed regions for the extended contact created by the flat side of a ruler. Figure 4b shows the multiple regions obtained from the twisted-pair cable. Figure 4c shows an extended contact on the tip of the sensor (the curved portion is here pressed against a flat metal surface.) Figure 4d shows multiple contact regions for a surface of coarse sand.

3.2 Contour Following

The contour following EP is broken down into two steps: edge acquisition and edge following. The cutaneous information obtained at the fingertip is used primarily, although the hand posture is also utilized, particularly during error recovery. Figure 5 shows the hand during edge following. Essentially, the robot uses the positions of its fingers to determine if the object is within its grasp. If so, the hand is moved along the surface until an edge contact is sensed. The edge following EP is then invoked. This EP determines the orientation and extent of the current edge contact from the tactile image. It then opens the hand and moves the arm based upon this information in order to properly place the hand and finger for the next sensing step. The hand is then closed and the next tactile image of the edge is obtained. If the robot determines that it has lost either the object or the edge, it reinvokes the edge acquisition EP. Figure 6 shows the results of running the contour following EP on one edge of a styrofoam block: The top of the block was first sparsely imaged visually to obtain positioning and exploration delimiters for the hand. The horizontal grey lines in the image show this visual data. The hand is then moved to approximately the position of the block and the contour following EP is invoked. The white dots in Figure 6 indicate the position of the center of the tactile contact during edge following. Only a small portion of the block was explored due mostly to the fact that the length of the block is less than twice the width of the hand, and the sensor covers a relatively small portion of one finger of this hand.

Figure 4: Textured and non-textured surfaces determined by tactile contact.



a) smooth

b) textured

c) smooth

d) textured

Figure 5: Hand and arm configuration for following the edge of the block.

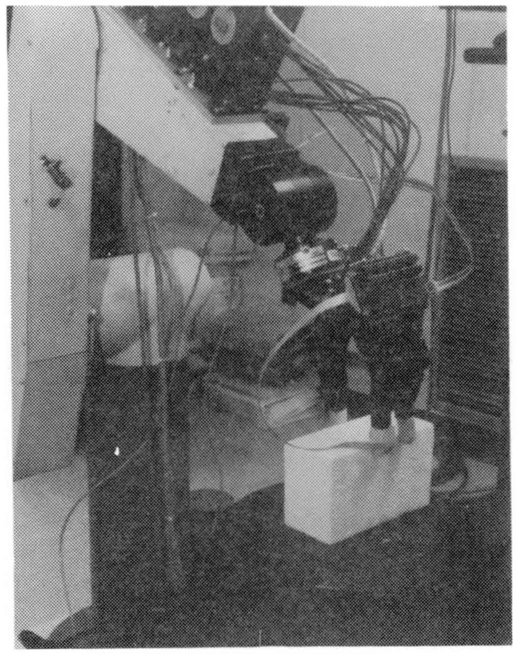


Figure 6: Results of contour following for the block.

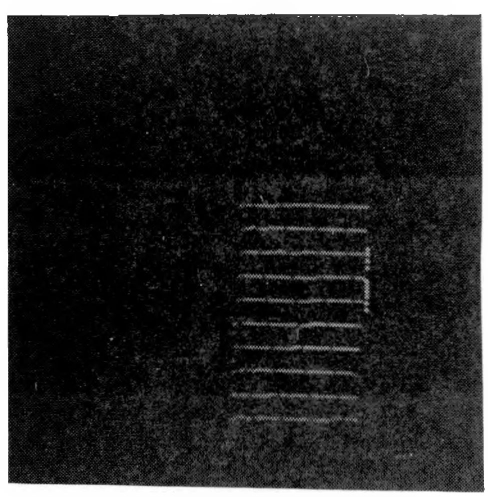
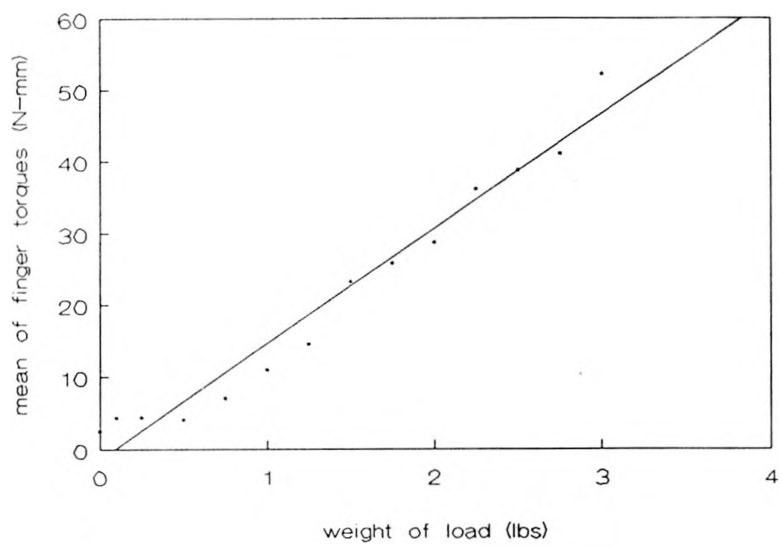


Figure 7: Mean of finger joint torques vs. weight.



3.3 Weight

The weight EP is implemented as unsupported holding: an object is grasped and lifted. A measure of the weight of the object may then be obtained via two independent means. Both the change in the magnitude of the forces at the wrist and the change in the torques at the joints of the fingers provide a good indication of the weight of an object: In both cases, the relationship is linear. Figure 7 shows a graph of the mean of the changes in the nine joint torques for known weights. Thresholds chosen from these graphs may be used to assign objects into qualitative categories such as "light" or "heavy" which may then be used for such diverse tasks as object categorization or determining the state (full or empty) of a grasped container.

3.4 Local Surface Shape

Local surface shape is obtained from the kinesthetic information contained in the finger joint positions after an object has been grasped multiple times. The EP involves local exploration of the surface by the hand: the hand is put into a known posture and moved to the object. The grasp is then closed. The grasp is opened, the fingers spread, and the grasp closed again. Finally, the

Figure 8: Surface shape classification by local exploration.

Object	Surface Shape Classification
right planar polyhedron	planar
right planar tube	planar
inclined plane (45 degrees)	planar
cylinder (42 mm radius)	singly curved
cylinder (50 mm radius)	singly curved
cylindrical tube (95 mm radius)	singly curved
hemispheroid (47 mm radius)	doubly curved
hemispheroid (108 mm radius)	doubly curved
ellipsoid	doubly curved

hand is returned to its initial posture and the arm is used to transport the hand vertically before the grasp is once again closed. From the joint positions of the fingers during these three grasps, the robot is able to categorize a surface as either planar or singly or doubly curved. Figure 8 shows the results obtained by the surface shape EP for a variety of objects. While haptic surface shape categorization is relatively simple, such information may prove useful in poor visibility situations when the shape of the surface is important for either grasping or recognition.

3.5 Spatial Extent

Spatial extent may be obtained almost immediately from the kinesthetic information contained in the positions of the finger joints and tips during grasping. The object may be grasped once to provide rough extent in one or two dimensions by either holding it at the fingertips or enclosing it in a wrap-type grasp. More complete and accurate information on extent and volume may be obtained through multiple grasps of the object. Figure 9 shows the results of two experiments in which the robot obtained the relative width of a series of cylinders of varying radii via an enclosing grasp. After the robot was presented with the series of cylinders in arbitrary order, it was directed to sort them by decreasing size. Figure 10 shows the robot holding a cylinder in this type of enclosing grasp. Figure 11 shows the results of two experiments in which the robot held the cylinders lengthwise in a fingertip grasp. Objects are again sorted by decreasing size in the measured dimension. By executing these two grasps consecutively for each object, one could determine a fair estimate of

Figure 9: Extent from enclosing grasp.

Cylinders (order of presentation)	Robot's Odering (decreasing size)	Cylinders (order of presentation)	Robot's Odering (decreasing size)
G (58 mm radius)	G (58 mm radius)	F (48 mm radius)	G (58 mm radius)
F (48 mm radius)	F (48 mm radius)	C (33 mm radius)	F (48 mm radius)
E (43 mm radius)	E (43 mm radius)	A (17 mm radius)	E (43 mm radius)
D (40 mm radius)	D (40 mm radius)	G (58 mm radius)	D (40 mm radius)
C (33 mm radius)	C (33 mm radius)	D (40 mm radius)	C (33 mm radius)
B (25 mm radius)	B (25 mm radius)	B (25 mm radius)	B (25 mm radius)
A (17 mm radius)	A (17 mm radius)	E (43 mm radius)	A (17 mm radius)

the overall extent or volume for each cylinder.

Determining the rough spatial extent of an object is a quick way of pruning hypotheses during object recognition. Such a skill might also prove useful as a verification mechanism. For example, if the different tools which the robot uses were designed with different sized handles, then the robot could verify that it had the proper tool during the grasp required in order to use that tool.

3.6 Hardness

Hardness, or stiffness, is obtained via the pressure EP. We have implemented this EP in three different ways: two involve grasping the object and squeezing it, the third involves using one finger as a probe to push against the surface. The robot may use the first two to determine the hardness of objects which fit into its grasp. The third allows the robot to categorize large objects, such as the support surface upon which other objects rest.

Hardness Via Squeezing Figures 12 and 13 show the results obtained for the pressure EP, implemented as squeezing, for enclosing and fingertip grasps respectively. In this case, the change in the joint positions of the fingers is used to determine hardness: the robot closes its grasp around an object using a specified joint torque threshold. The grasp is then further closed using double that threshold. Very hard objects will prevent the fingers from moving at all during this operation. Soft objects will deform, allowing the fingers to move easily. The larger the change in hand posture, the softer the object.

Figure 10: Enclosing grasp for extent determination.

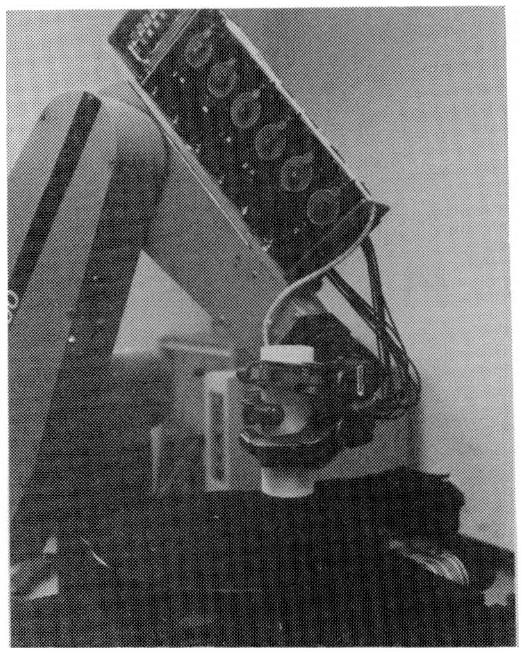


Figure 11: Extent from fingertip grasp.

Cylinders (order of presentation)	Robot's Odering (decreasing size)	Cylinders (order of presentation)	Robot's Odering (decreasing size)
A (140 mm length)	A (140 mm length)	F (1 mm length)	A (140 mm length)
B (115 mm length)	B (115 mm length)	E (25 mm length)	B (115 mm length)
C (95 mm length)	C (95 mm length)	D (45 mm length)	C (95 mm length)
D (45 mm length)	D (45 mm length)	C (95 mm length)	D (45 mm length)
E (25 mm length)	E (25 mm length)	B (115 mm length)	E (25 mm length)
F (1 mm length)	F (1 mm length)	A (140 mm length)	F (1 mm length)

Figure 12: Hardness by squeezing (enclosing grasp).

Contents of tube (order of presentation)	Robot's Odering (increasing hardness)	Contents of tube (order of presentation)	Robot's Odering (increasing hardness)
empty	empty	light sponge	empty
tissue paper	tissue paper	empty	light sponge
light sponge	light sponge	metal cylinder	tissue paper
dense foam rubber	dense foam rubber	tissue paper	dense foam rubber
metal cylinder	metal cylinder	dense foam rubber	metal cylinder

In the set of experiments performed, the robot was presented with a series of paper cylinders all of the same size, but containing materials of differing hardness. Of all of the properties we extract with the haptic system, hardness is perhaps the most subjective. In experiments using both grasp types, we noted that the robot sometimes produced a hardness ordering which ranked the tissue-paper-filled cylinder as softer than the light sponge cylinder and at other times produced an ordering which ranked it as harder. Since the physical characterization of materials is a complex procedure (see for example, chapter 2 of [24]) which is additionally impossible to apply to full objects, we opted for a less formal approach to exploring the nature of this ambiguity. In an informal set of experiments, we gave the same set of objects used by the robot to several human subjects. We found that about half of them ranked the tissue-paper as harder, half the light sponge as harder. Based on these observations, we speculate that one possible explanation for the phenomenon is that we allowed neither the robot nor our human subjects the choice of saying that two cylinders were equally hard. The humans made an arbitrary choice based upon their individual perceptions. The robot, operating within the limits of its precision, simply generated a ranking based on meaningless digits. This result shows how important it is for perception to take a step beyond the application of physical laws to observed data to the qualitative labeling of a quantity in order to give it meaning.

Hardness Via Pushing Our third implementation of the pressure EP uses a single finger to push against a surface. This probe posture is shown in Figure 14. In this case, the position is controlled and the finger torques are used to determine hardness: the hand is positioned so that the probe-finger will push against the surface. Transportation of the hand is via the arm with

Figure 13: Hardness by squeezing (fingertip grasp).

Contents of tube (order of presentation)	Robot's Odering (increasing hardness)	Contents of tube (order of presentation)	Robot's Odering (increasing hardness)
empty tissue paper light sponge dense foam rubber metal cylinder	empty tissue paper light sponge dense foam rubber metal cylinder	tissue paper dense foam rubber empty metal cylinder light sponge	empty light sponge tissue paper dense foam rubber metal cylinder

the move guarded using the finger joint torques. The finger is moved against the surface until a specified torque threshold is seen on any of the finger joints. The arm then moves 5 mm more, so that the finger is further pushed against the surface. The mean of the change in the joint torques for the probe finger indicates the hardness of the surface. A hard surface will not deform, creating large torques as the finger presses into it. A soft, deformable surface will create smaller torques on the finger joints. Figure 15 shows the results of using the probe posture to determine hardness for a series of surfaces. In this case, the robot makes a binary decision, assigning each surface the label of "hard" or "soft" depending on the value of the measured changes in joint torque. (For the purpose of this illustrative example, we have hardwired the threshold based upon multiple experiments. The robot could easily learn these thresholds through training sessions.)

3.7 Elasticity/Plasticity

Determining the elasticity or plasticity of a surface or object is a natural extension of determining its hardness. An elastic surface is one which regains its previous shape after deformation. A plastic surface will remain deformed after the applied pressure is removed. By our definition, only a deformable, or soft, surface may be elastic/plastic. The EP for this property involves applying and then removing pressure in a known way. The sensory inputs are the joint torques and the cutaneous information from the tactile array. The robot invokes the pressure EP in the same way as for hardness using the probe configuration. In this case, however, it moves against the surface until a threshold on the size of the cutaneous contact is exceeded. It next presses against the surface with a 5 mm movement of the arm and then backs away from the surface with a 4 mm movement

Figure 14: Probe posture used for extracting hardness.

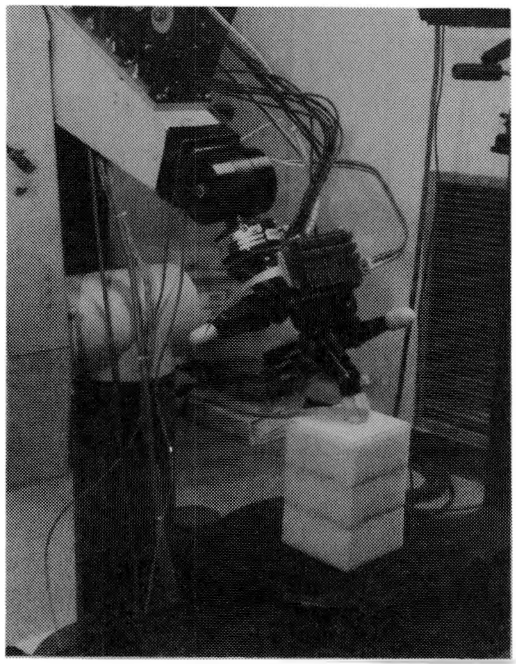


Figure 15: Hardness by pushing against surface.

Surface Material	Del_jtorque	Hard/Soft
wood	123.88	hard
metal	104.47	hard
plastic	73.85	hard
styrofoam	65.06	hard
sand	32.67	soft
sponge	24.85	soft
tissue paper	15.88	soft
salt	15.76	soft
dough	11.75	soft
cotton balls	4.92	soft

Figure 16: Surface deformation by probing.

Surface Material	Elastic/plastic
cotton balls	elastic
tissue paper	elastic
sponge	elastic
dough	plastic
sand	plastic
salt	plastic

of the arm. If there is still contact on tactile array, then the surface has recovered its shape as the pressure against it is released and the surface is labeled as elastic. If there is no cutaneous contact as the finger moves away, then the surface has retained its deformation and it is labeled plastic. Figure 16 shows the results of applying this EP to a series of different materials.

3.8 Surface Solidity

Our final haptic property is surface solidity. The EP again involves moving the finger against the surface using the probe configuration: the pressure EP is invoked to ensure that the finger is pressed firmly against the surface. The robot then attempts to move its fingertip laterally against the surface by changing the angular position of the most distal joint in a known way (in this case by 30 degrees.) This movement is guarded using the joint torques. If the surface is non-solid, the robot will be able to move its finger through the surface material to attain the new posture. If the surface is solid, then the finger will not be able to achieve the new posture, but will simply press against the surface until the joint torque threshold is reached[2]. Figure 17 shows the results of invoking this EP for a series of surface materials. The robot currently makes a binary classification of materials as either solid or non-solid.

[2]Solid but deformable materials, such as sponge, will allow some lateral motion.

Figure 17: Solidity by moving laterally against surface.

Surface Material	Del_ja3	Solid/Non-solid
metal	3 deg	solid
styrofoam	4 deg	solid
tissue paper	9 deg	solid
sponge	12 deg	solid
sand	30 deg	non-solid
salt	30 deg	non-solid
dough	30 deg	non-solid
cotton balls	30 deg	non-solid

4 Demonstrating the Usefulness of Haptic Perception

In this section we present three tasks which illustrate ways in which haptic perception may be used to enhance the performance of a robotic system. While the tasks presented are relatively simple, and are meant only to be illustrative, they do utilize the haptic system as part of an integrated robotic system. As such, they demonstrate that our model for haptic perception fits into a larger structure for robotic manipulation and multi-sensory perception. These larger, more complex examples also allow us to explore the sequence of invocation of EPs when several are to be utilized for a single task.

Obviously, the desired information about the object being explored will determine which EPs will be invoked. For example, in our first task, haptic EPs are used to augment visual information in order to prune the set of hypotheses for the object of interest. In this case, the EPs are invoked individually, as they are needed.

When the task is haptic object recognition, as in our second example, then the robot must invoke a sequence of EPs before attempting to identify the object. In this case, we must look more closely at the order in which these EPs are executed. Important factors are speed and efficiency of execution. By grouping EPs according to their compatibility, we can create hybrid movements which combine similar EPs and hence do not require radical changes in the posture or position of the hand and arm between consecutive executions. Additionally, it makes sense to try to combine exploratory procedures with the hand shaping and wrist orientation required for grasping. The pressure EP for the probe posture, combined with the EPs for elasticity and solidity, is an example of the former. The pressure EP for squeezing, implemented for several hand postures, is an example of the latter.

In our object categorization task, we combine the hand posture for surface shape determination with the EPs for hardness and weight: the hand is properly configured and moved to the object. The pressure EP is applied, and the object hefted, in a hybrid movement which extracts both hardness and weight. This combination grasp, squeeze, and heft is a very economical way of extracting multiple properties. The more time-consuming and specialized exploration required for surface shape determination is then executed without reshaping the hand or further moving the arm. We must, of course, be careful that the EPs which we combine do not interfere with each other: the pressure applied to the object must be discontinued (by opening the hand) before the surface shape EP is initiated, since the shape of a soft surface may be changed by the pressure EP. Likewise, a determination of overall extent is combined with the multiple grasps and object reorientations required for determining the shapes of the multiple surfaces of an object. This reduces, by at least three, the number of grasps required to fully explore the object.

Finally, our third example illustrates the use of haptic properties for a task other than object categorization. The information is extracted on an "as-needed" basis and is used to make decisions required for the successful completion of a multiple component task.

4.1 Multi-Sensory Integration for Object Categorization

In this example, the task is object categorization of geometrically simple shapes made of different materials. The object database consists of a set of generic models for blocks, cylinders, and spheres made of metal, styrofoam, and sponge, for a total of nine objects. The object being sensed is a polyhedral styrofoam block.

The robot uses its visual perception system to build a symbolic description of the object. The object representation paradigm and reasoning mechanism are described in [30]. For the purposes of this example, we need only point out that the result of the visual perception is a set of frames containing aspects for the object as shown in Figure 18 for the styrofoam block. Figure 19 shows the results of matching for this object. With the purely spatial and geometric information provided by vision, the robot is able to distinguish between the different geometric shapes and correctly

Figure 18: Results of visual processing for styrofoam block.

```
object frame                      component frame
dimension: 3                      component: body (255)
components: [body]                enclosing volume: [119,93,112]
enclosing volume: [119,93,112]

surface frame           surface frame
component: body (255)   component: body (255)
view is top             view is front
shape is planar         shape is planar

surface frame           surface frame
component: body (255)   component: body (255)
view is back            view is left
shape is planar         shape is planar

surface frame
component: body (255)
view is right
shape is planar
```

identify the object as a block, but it is unable to distinguish between blocks of different materials.

If we now allow the robot to further explore the object haptically (in this case via the invocation of weight and hardness EPs) and then integrate this information into the symbolic representation of the object, the robot is able to correctly identify the styrofoam block. Figure 20 shows the results of matching when only the weight slot is filled for the object, and when both the weight and hardness slots are filled.

4.2 Haptic Object Categorization

In this example, the task is haptic object categorization. The haptic system is used exclusively to extract the properties required to fill in the slots of the object's frames for matching. In general, for haptic exploration, the object is placed into the subject's hands. Both hands are then used not only for executing EPs, but also for supporting and reorienting the object during exploration. Obviously, the robot has only one hand and arm and is therefore incapable of this kind of behavior. We mimic it by having the robot request reorientation of the object when needed. Exploration proceeds in the following way: the hand is moved to the object and a grasp posture is affected. The grasp is closed, and the robot executes the hybrid pressure/hefting movement to obtain hardness and

Figure 19: Identifying the styrofoam block with visual information only.

```
/* styrofoam block: vision only */

  what_is_object(obj).

Object hypothesis is: metal_block
matched faces are:  top   bottom left  right front back
                    side1 side2  side5 side6 side3 side4

Object hypothesis is: styrofoam_block
matched faces are:  top   bottom left  right front back
                    side1 side2  side5 side6 side3 side4

Object hypothesis is: sponge_block
matched faces are:  top   bottom left  right front back
                    side1 side2  side5 side6 side3 side4
```

Figure 20: Identifying the styrofoam block with vision and haptics.

```
/* styrofoam block with weight characteristic.
          value is ''light''  */

   what_is_object(obj).

Object hypothesis is: styrofoam_block
matched faces are:  top   bottom left  right front back
                    side1 side2  side5 side6 side3 side4

Object hypothesis is: sponge_block
matched faces are:  top   bottom left  right front back
                    side1 side2  side5 side6 side3 side4

/* styrofoam block with weight  and hardness characteristics.
          values are ''light'' and ''hard'' */

   what_is_object(obj).

Object hypothesis is: styrofoam_block
matched faces are:  top   bottom left  right front back
                    side1 side2  side5 side6 side3 side4
```

Figure 21: Results of haptic exploration and match for sponge block.

```
object is light
object is soft

back:  surface is planar
right: surface is planar
front: surface is planar
left:  surface is planar
top:   surface is planar

bounding volume is [100.59, 100.92, 94.59]

object dimension is 3D

Object hypothesis is: sponge_block
matched faces are:  top   bottom left  right front back
                    side1 side2  side5 side6 side3 side4
```

weight properties. Simultaneously, one-dimensional extent is obtained. The robot then executes a series of grasps of the object, invoking the surface shape EP for each of the five aspects required by the object representation. As it grasps the object in different orientations, the robot also extracts further extent measurements, giving it a global extent or volume for the object at the conclusion of the exploration. Figures 21 and 22 show the results of this exploration, along with the results of matching, for a sponge block and a sponge cylinder, respectively. The database is the same as that used for the previous vision/haptics recognition task.

4.3 A Multi-Component Task Utilizing Haptics

In this example, we show how haptic information may be used during task execution to allow the robot to acquire grasps and to make decisions about the objects in its environment, particularly under conditions of poor visibility. The task is to clear the support surface of unknown objects, sorting them into different trays based upon weight, and to then categorize the support surface and place an appropriate marker. The only information which the robot is given is the position and rough extent of the objects to be cleared. Thus it knows where, and roughly how big, objects are, but it has no other information about them. Figure 23 shows the set-up for this task. The scene consists of a polygonal box filled with paper clips, and a mangled, empty cylindrical can. These

Figure 22: Results of haptic exploration and match for sponge cylinder.

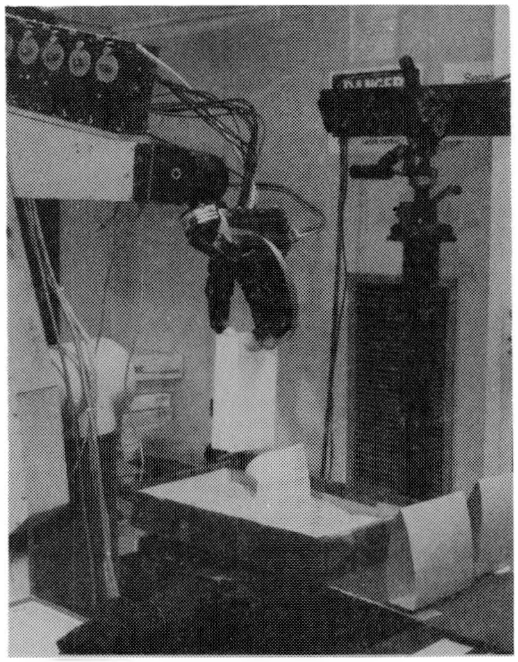
```
object is light
object is soft

back:  surface is singly curved
right: surface is singly curved
front: surface is singly curved
left:  surface is singly curved
top:   surface is planar

bounding volume is [117.34, 120.48, 95.69]

object dimension is 3D

Object hypothesis is: sponge_cylinder
matched faces are:  top   bottom left  right front back
                    side1 side2  side5 side6 side3 side4
```

objects are sitting on a support surface of coarse sand. Figure 24 shows a script of the execution of this "clearing" task.

The first thing the robot must do is to grasp, lift, and place each object. It utilizes a model for grasping described in [31]. In this model, the shape of an object is used to determine which of a set of grasps will be most stable for that object. For example, a fingertip *grip* grasp produces a stable, highly dextrous grasp for the edges of a planar, polygonal object, while an enclosing *wrap* grasp is more stable (though less dextrous) for a curved object. Ideally, shape information is provided by the visual system. However, in a poor visibility situation such as we are simulating here, the robot may obtain this information using haptics. Thus, for each object in turn, the robot executes the surface shape EP and based upon this determination, invokes and executes the most appropriate grasp. The robot then lifts the object, simultaneously invoking the hefting EP which determines weight. If the object is heavy, as in the case of the full box, it is placed in tray 1; if light, as in the case of the empty can, it is placed in tray 2. Note that even without adequate vision, the robot generates appropriate grasps for the regularly-shaped box and the irregularly-shaped can. It then properly sorts the objects based upon the non-visual weight information.

Once all objects have been cleared, the robot categorizes the support surface as either solid or non-solid. Again, this is a determination which would be difficult, if not impossible, to make visually. The robot accomplishes this component of the task by executing the pressure EP to

Figure 23: Experimental set-up for the clearing task.



determine if the support surface is hard or soft. If the surface is hard, then it is also solid by default. If the surface is soft, then the solidity EP using lateral motion is executed to make the final judgement. In this case, the support surface, which is sand, is both soft and non-solid.

5 Summary

Two skills which will enhance the usefulness of a robot are perception and flexible manipulation. The former allows the robot to maintain and update internal models of its environment via sensing and hence to respond to uncertainties and changes in the dynamic world as they are encountered. The latter allows the robot to carry out tasks for which the tools and components need not be rigidly specified. Haptics is the science of understanding the nature of the information which comes from the sensate hand and how it is utilized. As such it provides the link between perception and manipulation. It seems logical, then, that research into robot haptics should help bring us closer to our goal of building useful robots.

In this paper we have presented a series of haptic exploratory procedures implemented for a dextrous, sensate robot hand. These EPs are designed to extract specific tactile and kinesthetic

Figure 24: Script of execution of the clearing task.

```
determine surface shape for first object
surface is planar locally
grasp choice is grip grasp of object top edge
hefting object for weight determination
object is heavy
placing first object in tray 1

determine surface shape for second object
surface is doubly curved locally
grasp choice is wrap grasp of object
hefting object for weight determination
object is light
placing second object in tray 2

categorizing support surface:
surface is soft
surface is non-solid
placing maker 1
```

information from an object via their purposive invocation. Taken together, they form an active robotic touch system. This system may be used by an intelligent, autonomous robot to extract information about the world and to acquire grasps during manipulation. It may also be used to enhance a tele-operated robot by increasing the capabilities of the remote device and thus eliminating many of the problems associated with sensory feedback to the human operator. For example, in current tele-operated grasping, the operator must place the hand properly, and, if he is given force feedback at all, must somehow interpret and respond to the created forces (often with time delays) before he either loses or crushes the object. Imagine, for instance, attempting to lift the lid off of a delicate cardboard box in this way. On the other hand, if the robot itself is able to handle the manipulation details, then all the operator need do is approximately place the hand and give a high-level command. As an example, we have implemented the lid lifting task with no sensory feedback to the operator. The hand is placed over the object. The edge acquisition EP is then invoked to more precisely place the fingers on the lid. This operation includes the interpretation of force and tactile data at the device level. Once the edge, and hence the lid, is acquired, the lid may be lifted by a simple movement of the arm. We have also implemented this task for solely autonomous execution, by having the robot acquire the object via its visual system, rather than having the operator place the hand. The same set of haptic EPs is invoked in both cases.

The work presented in this paper has concentrated on hand motions and sensory processing for knowledge-driven haptic exploration. The next phase of our research will explore the use of haptic information as part of a data-driven, reactive mechanism for grasp maintenance during manipulation.

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