Feature-Based Tactile Object Recognition

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Abstract—Tactile sensing offers powerful capabilities for robotic perception. Through the use of array-force sensors, precisely located surface information about objects in the workspace is available wherever the robot arm may reach. In order to use this information to identify objects and their placement, interpretation processes should employ proprioceptive information and should use tactile image features which reflect object characteristics. A technique is described for the generation of constraints on object identity and placement such that information from multiple sensor contacts may cooperate towards interpretation.

Index Terms—Object recognition, robotics, tactile perception.

I. Introduction

Most existing robotic systems are only capable of operating within a completely understood layout of the workspace. For situations which vary from the prototype environment, the robot must be reprogrammed. The limitations imposed by this inability to adapt to the environment are well documented as arguments for the development of robotic perception [1].

Research in computational vision holds the promise of eventually providing the capability for robots to represent their environment sufficiently well to be able to react to variations in the workspace. However, because of the limitations of real-time operation, and because visual processing techniques are often designed in modules for the examination of isolated image aspects, progress in generalized robotic vision has been limited. In particular, some of the more effective methods, such as the use of structured light, impose tight constraints on the workspace layout.

Recently, interest has grown in the examination of the role of tactile information in robotic perception. There are two main reasons for believing that tactile perception will play an important part in robotics of the future. First, the data obtained through contact sensing do not underconstrain the scene interpretation as is the case for visual information, and therefore it may be more simply processed to yield knowledge of the environment. Second, the robot must contact and manipulate objects, and so tactile perception systems may utilize the robot's inherent capabilities.

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It is also clear that tactile perception offers information about the scene which is not available to visual sensors. This includes characteristics of surfaces which are visually occluded, purely tactile properties such as surface roughness and temperature, surface compliance, and physical resistance of objects. Also, the details of gripper placement and adequacy of force application are not available through visual sensing.

Further encouragements to pursue robotic tactile perception are found in the abilities of humans to identify objects on the basis of tactile information alone. For example, Klatsky, Lederman, and Metzger [2] have shown a 97 percent identification rate for common objects.

The most sophisticated forms of tactile sensors consist of a compliant surface capable of measuring force in an array of locations across the sensor. While the density and precision of the force measurements may vary, the result is a regularly tesselated force image across an area ranging up to about a square inch. There are several reviews of this technology available [3], [4].

Tactile perception is limited in the sense that it is always confined to very small areas of a scene, and relative to vision the time to relocate the sensor is very large. These disadvantages are somewhat offset by the precise spatial information about surface organization that is available to the tactile system, and by the flexibility of arbitrary orientation of the sensor. Any system which is to make full utility of these advantages in the tactile mode must provide for the extensive use of proprioceptive feedback, and must constrain the scene interpretation maximally for each piece of tactile data. Such a system should operate with clearly defined tactile image primitives which have counterparts in the imaged scene. In addition, the system must leave open the possibility of integration with other sensed information, in particular vision.

This paper describes a technique for the recognition of objects and their placement in the workspace using structured image features extracted from tactile force-sensed images, along with proprioceptive information about the location of surface contacts. Tactile features are translated into constraints on object identity and placement. These constraints are used to maintain small sets of consistent interpretations through the use of modified network consistency algorithms.

II. Using Proprioception in Object Recognition

Early approaches to the utilization of force sensed images treated the data as if obtained through visual sensors, making the assumption that entire objects could be imaged, and employed the image interpretation techniques of computational vision [5]. There are two drawbacks to this approach. First, the objects in the robotic environment will usually be large in relation to the sensor contact areas, and only small portions will be imaged. Second, this approach does not exploit the proprioceptive information known to play a significant role in human tactile sensing.

While human tactile-based object recognition is known to be quite accurate, it is also known to depend on kinesthetic feedback. Experiments which compare active with passive tactile capabilities show a marked decline in recognition ability when objects are simply pressed against the skin [6]. As the size of the object to be detected increases beyond fingertip size, the importance on kinesthetic feedback increases [7].

Other studies in human tactile recognition have demonstrated the importance of the perceived orientation of the area receiving stimulation [8]. Oldfield and Phillips [9] have also shown that identical patterns of cutaneous stimulation can yield different perception of object identity depending on the spatial orientation of the skin surface.

A realistic approach to robotic tactile perception is to rely on the constraints imposed on object identity and placement which are given by the information about where in space sensor contact takes place. Computational perception systems have been devised which employ contact position information. Bajcsy and Goldberg [10] used a cylindrical finger with point contact sensors to scan for the presence of objects. Once contact is made, a positional feedback system engages in the task of circumscribing the object. The joint positional information at each contact point is used to develop a cross-sectional model of the object, which is then matched against a database of objects to accomplish recognition.

Gaston and Lozano-Perez [11] use object models to build interpretation trees which represent each possible surface for each of the sensor contacts. The sensor information consists of the contact location and the surface normal at the contact point. By considering pairs of contacts, constraints are available on the matching surface pairs. These constraints are used to prune the interpretation trees and thereby yield the object configuration consistent with the sensor data.

While these two systems represent major advances in the use of tactile information, each is limited in the use of proprioception in that individual sensor contacts are not capable of exerting constraints on object identity and placement. Also, in each of these systems, only point contact sensing is assumed, and thus the full capabilities of tactile sensor technology are not exploited.

III. Tactile Features

The emergence of array force sensing technology has provided the capability to measure the detailed structure of the point of contact between the sensor and the object surface. Given that the surfaces of objects that the robot will contact will be much larger than the sensor's surface, we must find an alternative to the use of processing techniques which require images of the entire object.

There are several factors which combine to determine the actual "forcel" values of a tactile image:

1) The underlying shape of the contacted surfaces.
2) The textural properties of the surfaces.
3) The conditions of application of the sensor.
4) The compliance and response characteristics of the sensor.

While initial steps have been taken to formulate methods through which these separate factors might be recovered from images [12], the exact nature of such recovery algorithms remains an unsolved problem in tactile sensing.

Rather than attempting to use tactile images to recover structure explicitly, recently proposals have been made for the use of tactile images in the construction of a small set of "tactile features" which represent major image characteristics, and at the same time are useful in determining object identity and placement [13]–[15]. There has not been complete agreement as to which features might be the most useful to compute from tactile images. Bajcsy and Hager [13] have proposed hardness, surface normal, and surface curvature as the underlying characteristics of a "tactile primal sketch." Browse and Lederman [15], [16] have proposed surface roughness, surface curvature, and oriented edges as primary features in an attempt to maintain some consistency with proposed primitives of the human tactile system [17].

If a set of tactile features can be defined whose values are adequate to permit the interpretation of aspects of the robotic workspace layout, then it may be possible to compute those features locally, on the sensor, and thereby reduce the volume of information which must be passed forward to interpretation processes.

IV. A System for Tactile Object Recognition

The remainder of this paper describes a method for tactile robotic perception which employs a set of tactile features extracted from an array force sensor contact. The nature of the features found, along with the joint positional information giving the location of contact, provides constraints on object identity and positioning. By integrating across several tactile features, the system quickly arrives at a correct scene interpretation.

The system simulates the availability of tactile features along with sensor positions, and uses this information in the detection of object identity and placement. Initially, an object is selected from a set of models and arbitrarily "placed" on the table-top. Next, several simulated sensor contacts are chosen, and made available as tactile features with proprioceptive information about the placement of the sensor. Fig. 1 shows the set of objects from which an initial configuration is selected, such as in Fig. 2. Each model is a uniform cross-section object whose sides may be either planar or curved, and each model has associated with it a "home" placement, usually at the origin of the

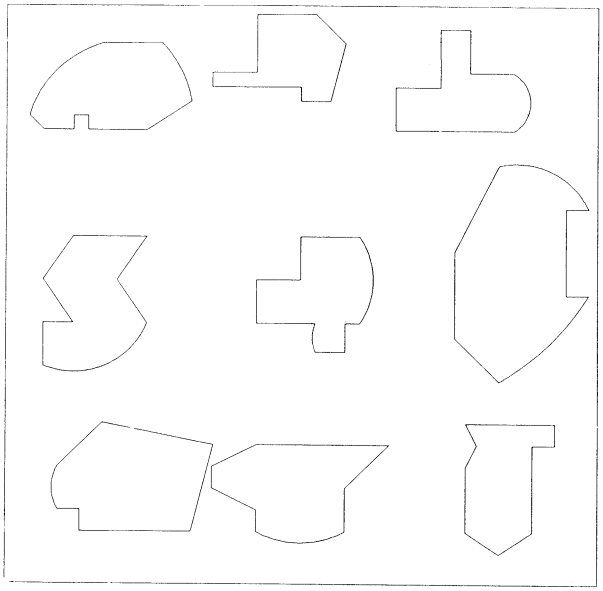

Fig. 1. The set of objects which are known to the system.

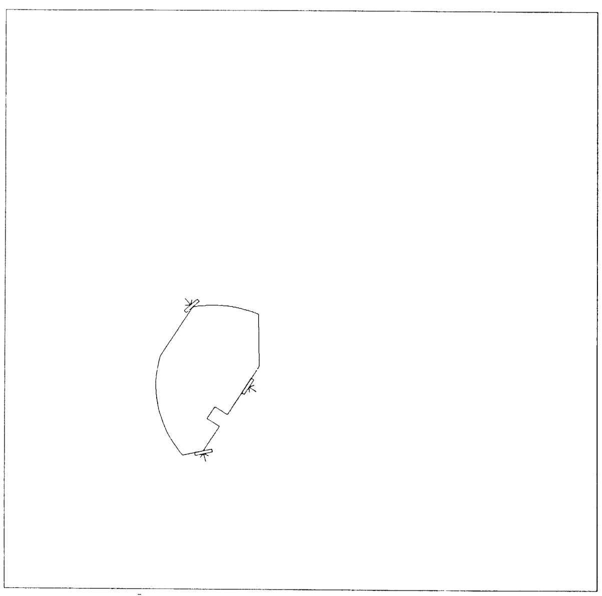

Fig. 2. An example of a starting configuration of object and sensor contacts from which the system performs interpretations.

2	71	32	0	0	0	0	0	0	0	0	0	0	0	0	0
3	114	80	4	0	0	0	0	0	0	0	0	0	0	0	0
7	38	47	40	11	0	0	0	0	0	0	0	0	0	0	0
4	34	55	80	56	55	32	0	0	0	0	0	0	0	0	0
2	100	127	192	136	84	61	32	0	0	0	0	0	0	0	0
1	200	119	212	151	144	107	160	72	8	0	0	0	0	0	0
3	60	63	87	127	224	91	96	95	160	32	0	0	0	0	0
1	31	43	79	143	200	143	176	123	159	160	64	0	0	0	0
2	53	63	111	224	200	128	79	111	133	128	119	160	8	0	0
3	44	63	98	111	144	128	87	112	111	170	146	143	160	16	0
0	0	15	36	32	8	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Fig. 3. A raw tactile image obtained from contact with the edge of a planar object.

0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0
0	1	0	0	0	0	1	1	1	1	1	1	1	1	1	0
0	0	1	1	1	1	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Fig. 4. Results of detecting edges in the tactile image of Fig. 3. The points indicated with a 1 are on the boundary.

tabletop coordinate system, from which any placement of that object may be referenced. The objects, and as well the sensor pad, are placed with three degrees of freedom on the table-top; one rotational, and two translational.

Recognition is defined to include object identity and the transformation necessary to take the object from its "home" position into the location at which it is detected. The four-tuple which the system determines for recognition is (i_o, ϕ_o, x_o, y_o) where the four values are the identity, rotation, and x and y translations of the object.

A. Recognition Features

The task of defining a useful set of tactile features involves determining tactile image structures which may be unambiguously computed and which have immediate correspondences to important aspects of the objects. The tactile features employed are a subset of the features for which extraction routines have been developed using a Barry Wright Corporation Sensoflex System. This device returns a 16 × 16 grid of force measurements across about one square inch of the compliant sensor. Fig. 3 shows an example of an initial tactile image obtained by pressing the sensor pad against a planar object with part of the pad overhanging. The integer values represent the force sensed at each of the 256 locations. Fig. 4 indicates the locations which were classified as belonging to the surface boundary, and Table I provides the symbolic information derived to represent the edges in this image.

The complete set of features is described elsewhere [17] but for the purposes of this recognition system, only a

TABLE I
THE SYMBOLIC INFORMATION FOR THE EDGES DETECTED IN THE TACTILE IMAGE SHOWN IN FIG. 3. THE INFORMATION INCLUDES ENDPOINTS, CURVATURE (0 INDICATES STRAIGHT), AND ORIENTATION OF THE EDGE

edge	start		end		curvature	orientation
	row	column	row	column		
1	9	1	9	14	0.00	180
2	8	13	1	3	0.00	304

TABLE II
TACTILE FEATURES AVAILABLE TO THE RECOGNITION SYSTEM

Features Available		
Name	Properties	number of possible property values
surfaces	estimate of radius of curvature of surface	5
edges	contact side estimate of radius of curvature of surface	2 5
corners	none	

TABLE III
CATEGORIZATION OF SURFACES WITH DIFFERENT RADII OF CURVATURE (r)

Categorization of Curvatures	
curve type	conditions on radius of curvature
0	$r > 2.0$
1	$2.2 \geq r \geq 0.75$
2	$0.9 \geq r \geq 0.5$
3	$0.6 \geq r \geq 0.3$
4	$0.35 \geq r \geq 0$

subset of the features are necessary because of the assumption of uniform cross-sectioned objects. The features shown in Table II are assumed available. Given the restricted nature of the object models and the tabletop environment, this set of features is sufficient to permit significant constraints on the placement and identity of objects.

As indicated in Table II, the basic features "surface" and "edge" carry with them a categorization of the radius of curvature of the object surface contacted. In addition, an edge may arise from the contacted surface being on the left or right side of the sensor. These properties are used in constructing an extended feature set in which 16 features are defined by the unique values of their properties.

Before the system begins its interpretation process, a representation is developed in which each extended feature has associated with it a list of all the objects' surfaces that could possibly give rise to the feature. For example, only surfaces of length greater than or equal to the sensor pad width may give rise to a flat "surface feature" without an edge present. Also, concave corners will not produce "corner features" because of the planar surface of the sensor.

The categorization of curvatures for surfaces reflects the resolving capabilities of the feature extraction program. Some surfaces will have curvatures which could be detected as belonging to either of two categories. In this case, more than one extended feature of the same basic type may list that surface as a potential scene-domain counterpart. Table III lists the categorization of surface curvature used.

B. Object Consistency

For each tactile feature F_i which is made available to the interpretation process there is a *candidates list* $C_i = \{(o_1, s_1), \cdots (o_n, s_n)\}$ where (o_j, s_j) is the jth object-surface candidate. If more than one feature is present, then a form of *object consistency* may be immediately imposed. The constraining condition is

$$(o_j, s_j) \in C_i \rightarrow (\forall F_k)((\exists s_m)(o_j, s_m) \in C_k)$$

Enforcing this consistency ensures the elimination of all object models which do not have a possible interpretation for every one of the available features. The use of this constraint requires the assumption that only one object is sensed at a time.

C. Surface Transformation Constraints

The basic idea behind the operation of the system is that each tactile feature that becomes available carries with it constraints on the possible object interpretations. For a single feature, there will be as many such possibilities as there are surfaces that can give rise to the feature, but for each such surface contact possibility there will be quite severe constraints on the placement of the object on the tabletop. In the case of several features, there is usually only one object placement which will meet the constraints imposed by all the features.

For each tactile feature, a five-tuple of information is given: $(i_p, s_p, \phi_p, x_p, y_p)$ where i_p is the feature type, s_p is the width of the sensor contact area, and (ϕ_p, x_p, y_p) is the transformation that takes the sensor pad to the contact position.

For each surface known to the system, the information shown in Table IV is retained for the object is in its "home" position (see Fig. 5).

The next step in the interpretation process is to extend each of the object-surface possibilities to include the constraints which the possibility imposes on the placement of that object on the tabletop. These constraints are generated using 1) the properties of the feature (as described above), 2) properties of the surface under consideration, and 3) templates for the construction of the constraints which are associated with the feature types. Table V describes the constraints associated with each of the major feature types.

Each of the feature types offers different constraints on the surface contact possibilities. The most constraining feature is an *edge* feature which results in the determination of the three values of the transformation necessary to take the object to the location where the feature is found [see Fig. 6(a)]. All other features leave the object transformation incompletely specified. For example, a *corner* feature locates an object vertex, but leaves the orientation about the vertex unspecified in a range dependent on the angle formed at the vertex, as shown in Fig. 6(b). The rotational freedom is not centered on the tabletop origin, so the resulting range of orientations provides a means of computing the x and y transformation components for any specific orientation.

TABLE IV
INFORMATION RETAINED FOR SURFACES KNOWN TO THE SYSTEM

(ρ_1, θ_1)	the polar coordinates of end-point 1
(ρ_2, θ_2)	the polar coordinates of end-point 2
(α_i, α_e)	entrance and exit angles to the surface
c_s	the curvature of the surface
ρ_s	the length of the surface
ϕ_s	the orientation of the surface

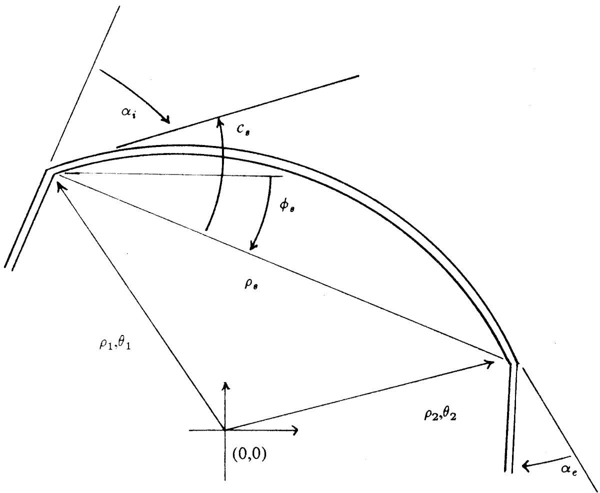

Fig. 5. Information retained for surfaces.

TABLE V
CONSTRAINT TEMPLATES FOR TACTILE FEATURES

Constraints Associated with Tactile Features
contact with a planar surface $\phi_o = \phi_p - \phi_s$ $x_p - \rho_1 \cos(\phi_o + \theta_1) - s_p \cos\phi_p \leq x_o \leq x_p - \rho_2 \cos(\phi_o + \theta_2) + s_p \cos\phi_p$ $y_o = y_p - \rho_2 \sin(\theta_2 + \phi_o) - (\tan\phi_p)(x_o + \rho_2 \cos(\theta_2 + \phi_o) - x_p)$
an edge (with surface to the left) $\phi_o = c_s + \phi_p - \phi_s$ $x_o = x_p - \rho_2 \cos(\theta_2 + c_s + \phi_p - \phi_s)$ $y_o = y_p - \rho_2 \sin(\theta_2 + c_s + \phi_p - \phi_s)$
an edge (with surface to the right) $\phi_o = \phi_p - \phi_s - c_s$ $x_o = x_p - \rho_1 \cos(\theta_1 + \phi_p - \phi_s - c_s)$ $y_o = y_p - \rho_1 \sin(\theta_1 + \phi_p - \phi_s - c_s)$
contact with curved surface $\phi_p - \phi_s - c_s \leq \phi_o \leq \phi_p - \phi_s + c_s$ $x_o = x_p - x_{arc}(\rho_1, \theta_1 + \phi_o, \rho_2, \theta_2 + \phi_o, c_s, (\phi_o - \phi_p - \phi_s))$ $y_o = y_p - y_{arc}(\rho_1, \theta_1 + \phi_o, \rho_2, \theta_2 + \phi_o, c_s, (\phi_o - \phi_p - \phi_s))$ where x_{arc} and y_{arc} are functions which return the x and y coordinates respectively of a point a given distance along an arc.
corner contact $\phi_p + \theta_{min} - \phi_s - c_s - \alpha_i \leq \phi_o \leq \phi_p - \theta_{min} - \phi_s - c_s$ $x_o = x_p - \rho_1 \cos(\theta_1 + \phi_o)$ $y_o = y_p - \rho_1 \sin(\theta_1 + \phi_o)$ where θ_{min} is the smallest contact angle which will produce a corner feature.

As shown in Fig. 6(c), contact with a planar surface without an edge present yields complete constraint on the rotational component, but leaves the possibility of the object being found anywhere along a line. Contact with a curved surface is slightly more complicated, but still only allows a limited range within one degree of freedom, as shown in Fig. 6(d).

For each tactile feature F_i, the members of the *candidates list* C_i are extended to include these surface transformation constraints, which we denote as

$$C_i = \{(o_1, s_1, \tau_1), \cdots (o_n, s_n, \tau_n)\}$$

where (o_j, s_j, τ_j) is the jth object-surface candidate, with τ_j being the transformational constraints. Taking into account the transformational constraints, the constraining relation among surface candidates is extended to

$$(o_j, s_j, \tau_j) \in C_i \rightarrow (\forall F_k)\big((\exists s_m)((o_j, s_m, \tau_m) \in C_k) \wedge (\tau_j \cap \tau_m = \varnothing)\big).$$

The intersection of the two transformation constraints $\tau_j \cap \tau_m$ is defined to be the values of the transformation parameters for the object which satisfies both constraint sets. This consistency requirement specifies that object-surface candidates are retained only if all other features retain some candidate which specifies a compatible transformation of the object under consideration. This condition forms the fundamental constraining relation for the operation of a network consistency algorithm adapted from Mackworth's [18] formulation. In this formulation the nodes are the available features, with an initial set of labels given by the feature's candidate list. This algorithm ensures that as each object-surface candidate is pruned due to inconsistency, that all other candidates which rely on it will be reconsidered.

In the implemented version of the tactile recognition system, these transformational constraints are represented as a list of values of the three parameters. Compatibility is then determined by measuring the actual difference between parameter values and comparing this difference to a threshold which indicates if the values are close enough to be considered the same.

While this may appear as a somewhat "brute-force" approach to implementing the constraints, there are two advantages. First, those feature interpretations which are found to be consistent may have their lists of transformation values reduced to exclude incompatible values. This is effectively an enforcement of the constraining relation on each of the transformation values in the list, rather than on the entire range of transformation possibilities. A second advantage is that the precision with which interpretation is required may be reflected in terms of the spacings used in generating the transformation values, and in the size of the permissible discrepancy between values.

V. AN EXAMPLE

In order to illustrate the operation of the tactile object recognition system, consider the initial configuration of three features available from three separate sensor contacts as shown in Fig. 2. As indicated in the first three lines of Table VI, any of the three features (F4, F5, and F6) offers between 49 and 61 different interpretations when considered separately. The *corner* feature and the flush-contact *surface* feature each allow slight variation in one degree of freedom. The interpretations which include the correct one[1] for each of these features are shown in Fig. 7. The *edge* feature has 49 possible interpretations, but each one has no variation permitted.

After the constraints of the *corner* and *surface* feature are considered together, there are only six remaining

[1]Fig. 6(a)–(c) depicts other interpretations for these same three features.

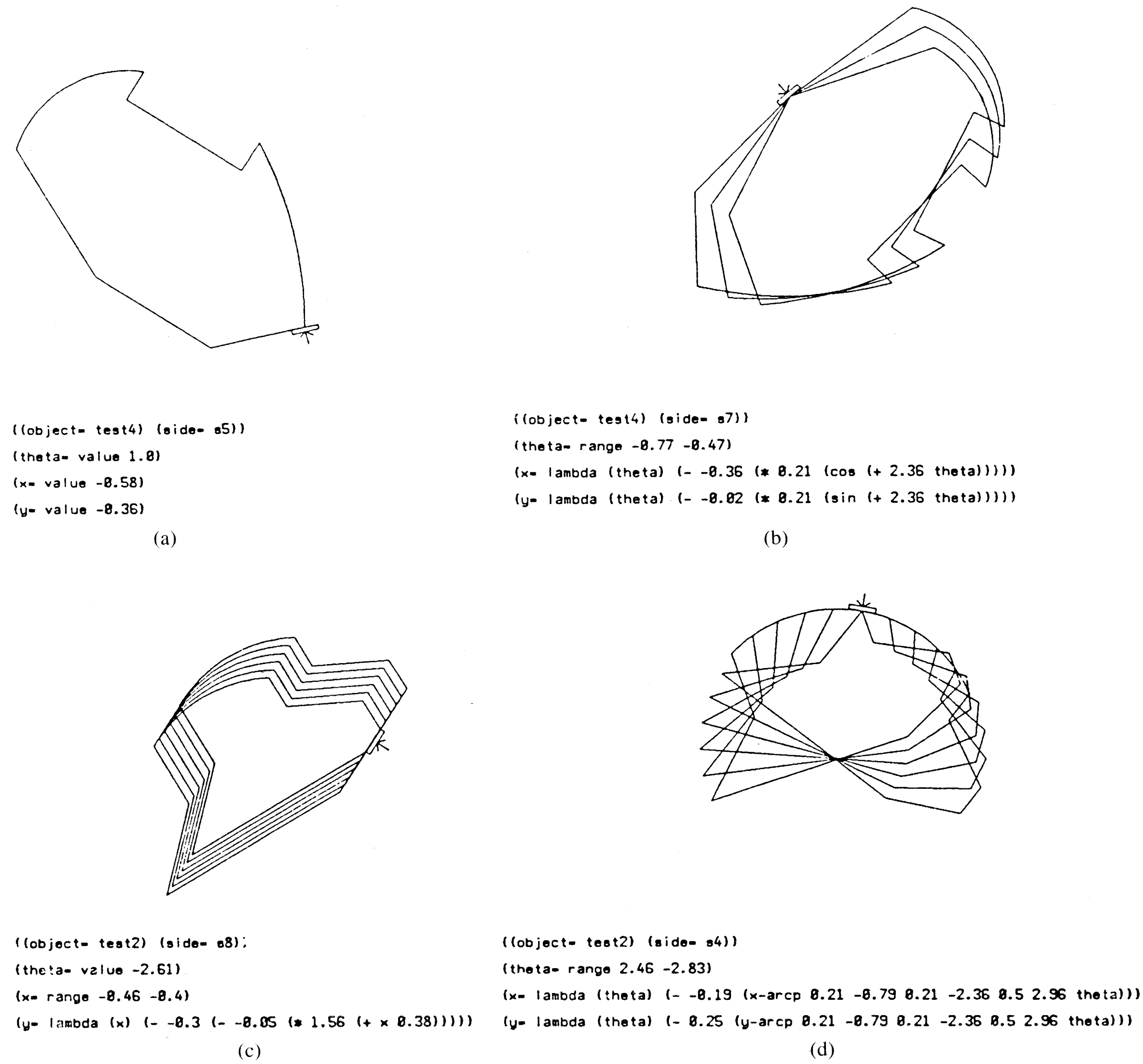

Fig. 6. The transformational constraints for (a) an edge feature, (b) a corner feature, (c) a planar surface, and (d) a curve surface. The range of possible values is demonstrated by plotting the object in several different positions.

TABLE VI
INTERPRETATION POSSIBILITIES FOR THREE TACTILE FEATURES CONSIDERED SEPARATELY, AND WHEN CONSIDERED TOGETHER

features	type	θ_p	x_p	y_p	interpretations
F00004	flush-0	4.14	-0.18	-0.33	61
F00005	corner	0.72	-0.36	-0.02	59
F00006	rightedge-0	3.36	-0.32	-0.52	49
F00004 & F00005	flush-0 corner	4.14 0.72	-0.18 -0.36	-0.33 -0.02	6
F00004 & F00005 & F00006	flush-0 corner rightedge-0	4.14 0.72 3.36	-0.18 -0.36 -0.32	-0.33 -0.02 -0.52	1

interpretations, each with very little or no variation of placement permitted. Fig. 8 shows three examples of these remaining possibilities. Consideration of the third, *edge* feature reduces the interpretation set down to a single object in a fixed position which corresponds to the starting configuration, as shown in Fig. 8(d). For the set of objects shown in Fig. 1, the results of this example are typical. Usually only two or three tactile features are sufficient to correctly identify and position the object.

VI. CONCLUSIONS AND FUTURE ISSUES

This paper has summarized an approach to tactile-based object recognition. The techniques rely on the availability of detailed array force-sensed images, which are processed to extract a small set of tactile features, supplemented with additional information about properties of the features. The set of objects being considered for recognition is preprocessed to determine which of their surfaces and corners may give rise to members of the set of tactile features. Thus an initial *object consistency* phase will eliminate consideration of any object which may not give rise to the features found. Each obtained tactile feature also carries with it proprioceptive information about the location and orientation of the sensor at the time of contact. This information, along with positional constraint templates associated with each feature type, is used to derive *surface transformation constraints* which specify the positioning of each possible object in the workspace that

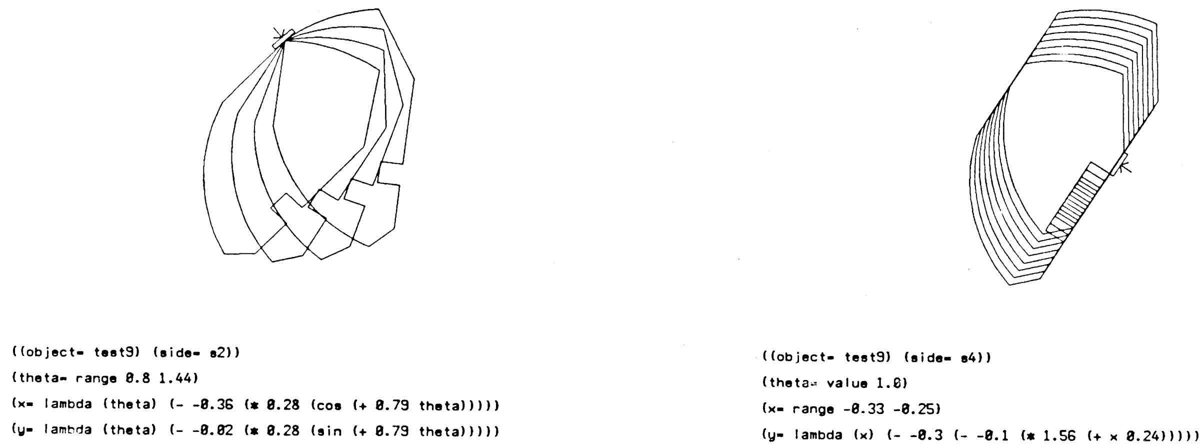

Fig. 7. Examples of interpretation possibilities for two of the features shown in Fig. 2.

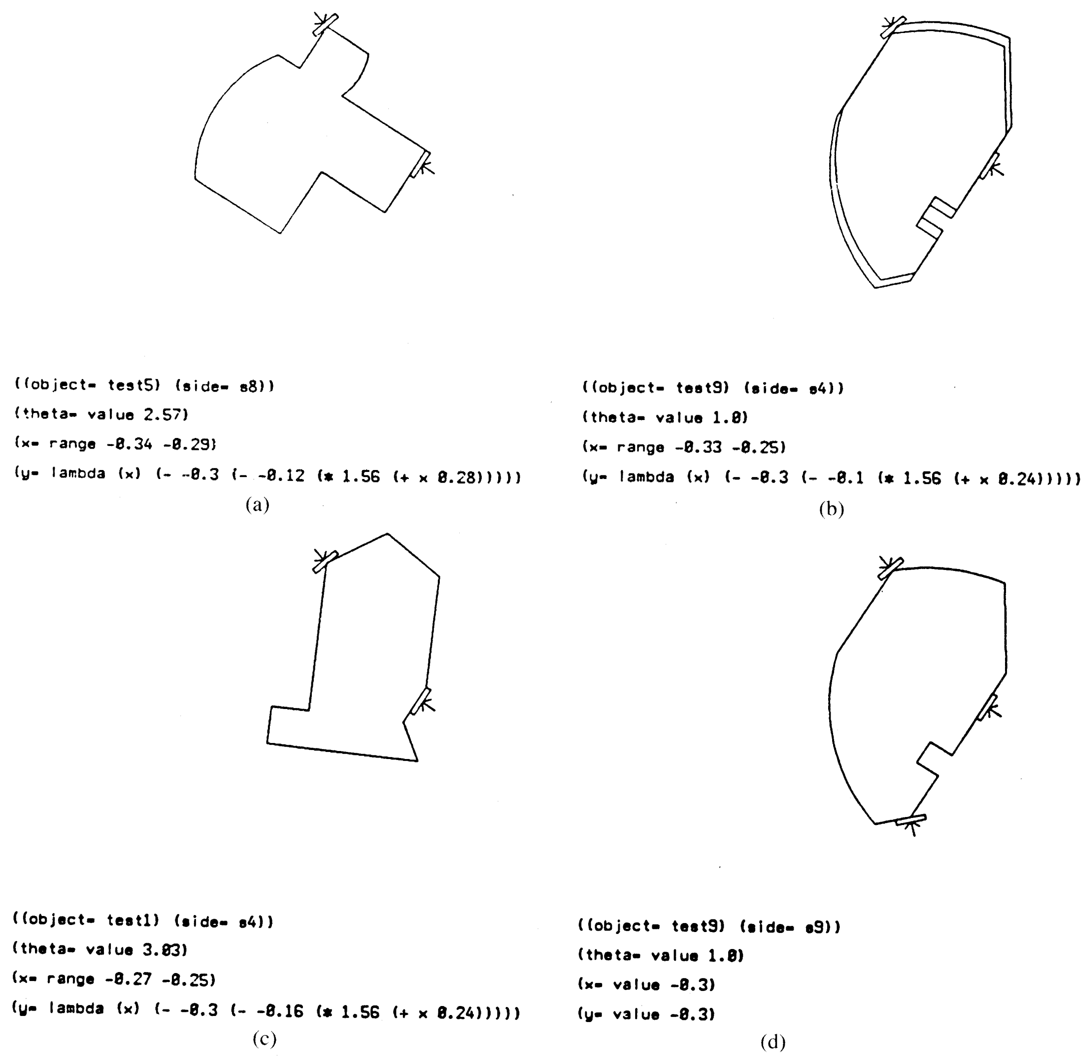

Fig. 8. Interpretations remaining after the constraints of multiple features have been considered together. (a)–(c) Three of the interpretation possibilities for two features. (d) The remaining correct solution after all three features are considered.

would be consistent with the tactile contacts. For several tactile contacts, the test set of nine objects often yields only one, correct, interpretation.

One advantage of this approach is that the constraints developed from each separate tactile feature may operate independently. No explicit consideration needs to be made of the relative positions of the sensors. Also, the system can operate with sparse information. In fact, usually only two contacts are sufficient to identify an object and its position from the test set of nine objects. When information from several features is used to constrain the interpretation, the system is indifferent to whether the features are obtained from the same tactile image, or from separate images. Whether the features are derived simultaneously from several different sensors, or from sequential application of the same sensor also makes no difference to the operation of the system.

This independence of the feature source has also been extended to include visual information. A version of the system has been devised which visually extracts straight line segments, and generates constraints on object identity and placement in the same form as the tactile constraints, thereby providing a mechanism for the integration across the senses for recognition purposes [19].

The system as described here makes a number of simplifying assumptions about the nature of the sensing situation.

1) Only one object is contacted.
2) The object is not movable or deformable.
3) The object has a uniform cross-section.
4) Object placement is defined with three degrees of freedom.

There are extensions necessary to lift each of these assumptions.

It will also be important to incorporate other tactile-based techniques such as the maintenance of a model of open space as proposed by Gaston and Lozano-Perez [11]. Of immediate concern is an extension which permits the system to draw conclusions about locations which are most likely to offer useful constraining features [20]. An examination of the three remaining possibilities in Fig. 8 indicates that some locations would be better than others for subsequent feature extraction. Of course these perceptual demands would have to be integrated with the planning of task accomplishment within the robotic application.

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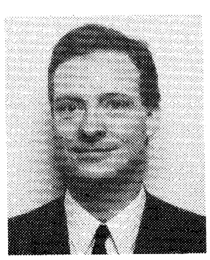

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