Tactile identification of objects using Bayesian exploration

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Abstract—In order to endow robots with human-like tactile sensory abilities, they must be provided with tactile sensors and intelligent algorithms to select and control useful exploratory movements and interpret data from all available sensors. Current robotic systems do not possess such sensors or algorithms. In this study we integrate multimodal tactile sensing (force, vibration and temperature) from the BioTac® with a Shadow Dexterous Hand and program the robot to make exploratory movements similar to those humans make when identifying objects by their compliance, texture, and thermal properties. Signal processing strategies were developed to provide measures of these perceptual properties. When identifying an object, exploratory movements are intelligently selected using a process we have previously developed called Bayesian exploration [1], whereby exploratory movements that provide the most disambiguation between likely candidates of objects are automatically selected. The exploration algorithm was augmented with reinforcement learning whereby its internal representations of objects evolved according to its cumulative experience with them. This allowed the algorithm to compensate for drift in the performance of the anthropomorphic robot hand and the ambient conditions of testing, improving accuracy while reducing the number of exploratory movements required to identify an object. The robot correctly identified 10 different objects on 99 out of 100 presentations.

I. INTRODUCTION

Touch, by necessity, is an interactive sense. In order to determine an object’s tactile properties, exploratory movements must be made. Experimental psychologists have identified six general types of movements that humans make when tactually exploring objects: pressure to determine compliance, lateral sliding movements to determine surface texture, static contact to determine thermal properties, enclosure to determine global shape and volume, hefting to determine weight, and contour following to determine exact shape [2]. When performing these movements, humans are able to sense both proprioceptive information (position and forces applied to the joints and muscles) and cutaneous information (forces, vibrations and temperatures sensed in the skin) [3]. These sensory capabilities combined with the dexterity to produce these movements are essential for humans to identify objects by touch, and will be required by robots seeking the same abilities.

Previous studies used tactile information as a supplement or replacement to visual information to identify objects by their geometry. Allen et al. added simple contact sensing to confirm when the fingers contacted object surfaces identified from 3D vision [4], [5]. Browse et al. used a 16x16 array of tactile pixels to identify and track edges and other geometric features [6]. Schneider et al. used a 6x14 array of tactile pixels to identify objects using a bag-of-features classification technique [7]. In contrast, this study explores object identification without consideration of visual appearance using cutaneous information from a multimodal tactile sensor to extract tactile properties. Much prior art has focused on texture discrimination with tactile sensors [8]-[10]. This work extends our previous work in texture discrimination [1] to a more complex and anthropomorphic robotic system capable of performing the additional exploratory movements for compliance and thermal discrimination.

II. METHODS

A. Robotic System

1) Robotic Hand

The BioTac multimodal tactile sensors (SynTouch, Los Angeles, CA) were integrated both mechanically and electrically onto the robotic fingertips of the Shadow Dexterous Hand (Shadow Robot Company, London, UK). The five-fingered robotic hand has 20 active degrees of freedom, similar to the human hand. The BioTac is equivalent in size to the distal and middle phalanx of the human fingertip fused at a functional angle of 20° flexion, so the under-actuated distal joint of the Shadow finger is removed when the BioTac kit is installed. The robot was programmed to make limited exploratory movements exclusively by flexion-extension and abduction-adduction of the base of the index finger (equivalent to 2DOF

Figure 1 - Shadow Dexterous Hand with a BioTac exploring a copper puck.
metacarpal-phalangeal joint of the human hand). All other joints in the hand and wrist were deactivated and/or fixed to stabilize the system. The robot has four types of built-in joint controllers available: torque, velocity, position, and mixed position-velocity control. The control software in the PC operates under Robot Operating System (ROS) developed by Willow Garage.

2) The BioTac: Multimodal Tactile Sensor

The BioTac is a biomimetic tactile sensor designed to provide both robustness and sensitivity in multimodal tactile sensing. The space between its elastic skin and rigid core is filled with an incompressible liquid, giving it compliance similar to human finger pads. No transducers or electrical components are contained in the skin, making the design robust to grit, moisture, or other damage that typically plague tactile sensors. The BioTac consists of three complimentary sensory modalities:

- **Contact forces** distort the elastic skin and underlying conductive liquid, changing the impedances of 19 electrodes (labeled E1-E19) distributed over the surface of the rigid core [11], [12]; 50 samples/s per electrode.
- **Vibrations** in the skin propagate through the fluid and are detected by the pressure sensor [13], [14]; 2000 samples/s
- **Temperature and heat flow** are transduced by a thermistor near the surface of the rigid core [15]; 50 samples/s.

![Figure 2 - Cross-sectional schematic of the BioTac.](image)

The BioTac sensors are sampled and digitized internally and transmitted via SPI protocol to the microprocessor in the Shadow Hand, which integrates it with motor data for onward transmission via EtherCAT to the control PC running ROS.

B. Exploratory Movements

<table>
<thead>
<tr>
<th>Exploratory Movement</th>
<th>Control Variable</th>
<th>Feedback Variable</th>
<th>Sensory Information</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pressure</td>
<td>Fingertip Position</td>
<td>Fingertip Force</td>
<td><strong>Contact forces</strong></td>
</tr>
<tr>
<td>Lateral Sliding</td>
<td>Fingertip Velocity &amp; Force</td>
<td>Fingertip Velocity &amp; Force</td>
<td>Vibration</td>
</tr>
<tr>
<td>Static Contact</td>
<td>Fingertip Position</td>
<td>Local Deformation</td>
<td>Temperature and Heat Flow</td>
</tr>
<tr>
<td>Enclosure</td>
<td>Hand Joint Torques</td>
<td>Hand Joint Torques</td>
<td>Heat Flow</td>
</tr>
<tr>
<td>Hefting</td>
<td>Arm Joint Position</td>
<td>Arm Joint Positions</td>
<td>Heat Flow</td>
</tr>
<tr>
<td>Contour Following</td>
<td>Fingertip Position</td>
<td>Local Contact</td>
<td>Heat Flow</td>
</tr>
</tbody>
</table>

![Table 1 – Proposed control and feedback variables with sensory information to perform exploratory movements (italics: cutaneous information).](image)

Proposed control and feedback variables for reproducing the six exploratory movements and sensory abilities described above are listed in Table 1. Only three of these exploratory procedures require only cutaneous tactile information; they are the focus of this study (colored boxes).

1) Compliance:

Compliance can be described as the relationship between the deformation of an object and the force applied to it. In principle all of this information could be obtained from proprioceptive information in humans or its equivalent in a robot [16]; however, it has been demonstrated that humans are poor at discriminating material hardness when their fingertips are anesthetized, indicating the importance of cutaneous information [17]. The present study uses an approach developed in [18] that uses constant force and measures the deformation of the skin on the BioTac. The translational motion of the fingertip is smaller when pressing on harder materials (Figure 3 bottom). The conductive liquid under the skin at the point of contact is displaced laterally, resulting in an increased conductance to electrodes located adjacent to the region of contact (Figure 3 top, blue trace). For this study we used electrode E18 to measure compliance as confirmed in a previous study with the BioTac [18]. When pressed against softer materials, the surface of the material deforms, cupping a larger portion of the fingertip and reducing this lateral bulging of the skin (Figure 3 top, red trace) We measured compliance from the ratio of the change in conductance from lateral electrodes to the displacement distance under constant loading forces:

\[
\text{Compliance} = \log \left( \frac{A_{\text{Joint angle}}}{A_{\text{E18}}} \right)
\]

This exploratory movement consisted of applying constant force (approximately 1.47N) using the torque controllers of the fingertip and holding it for 4s to reach a steady state. The actual force at the fingertip tends to fluctuate because of the non-linear friction in the joints and tendons that route through the hand. For highly compliant objects, once the surface of the object has deformed sufficiently to push directly over the lateral electrode, further increases in applied force prevent bulging from fluid displacement because the fluid is displaced even further laterally. Empirically, the computation in Eq. 1 tended to produce more consistent estimates of compliance in the face of this uncertain force and motion.

![Figure 3 - Samples of signals used collected from a compliance exploratory movements.](image)
2) Texture

The ability to sense microvibrations in the skin enables humans to discriminate different textures when sliding their fingertips over the surfaces of objects [19], [20]. The BioTac has the ability to sense these vibrations with a sensitivity that exceeds human performance [14]. The skin of the BioTac also contains a fingerprint-like pattern that enhances these vibrations [21]. A previous study using the vibrations measured by the BioTac when sliding over textured surfaces indicated that the BioTac was able to discriminate among 117 different textured surfaces with 95.4% accuracy, outperforming even human subjects on difficult pairs of textures [1].

To conduct a sliding exploratory movement, contact force is set first using a torque controller before sliding velocity is controlled using the mixed position and velocity controller. Data are recorded during the middle 1.4 cm of the sliding motion to eliminate contributions of starting and stopping transients as the controller reaches a constant velocity. In this study, we analyzed only the “roughness” measure of texture as described in [1] (as opposed to “traction”, and “fineness” also used in that study). The vibration signal was filtered to the same bandwidth as the biological Pacinian corpuscles (20-500Hz). As shown in [1], vibrations induced by a rougher surface produce higher signal power, which was estimated from signal variance:

\[ Texture = \log_{10}(\text{var}(P_{AC,\text{filtered}})) \]  

3) Thermal Conductivity:

Thermal cues provide powerful signals to identify objects made from different materials. Studies have shown that when active exploratory movements are prohibited (yet contact is maintained with the object), humans have better performance in identifying objects with distinctive thermal properties (such as aluminum vs. wood) than objects with similar thermal properties (such as glass, rubber and polycarbonate) [3]. This discrimination is made possible by the thermal gradient between body temperature and room temperature and the fingertip’s ability to detect small changes in temperature as heat flows from the fingertip into a contacted object. Similar to the biological mechanisms, heaters inside the BioTac warm the device when powered on. A thermistor behind one of the electrodes near the tip detects temperature changes when objects are pressed against the tip. Objects that are more thermally conductive have been observed to produce a larger thermal gradient that can be detected in the dynamic temperature of the BioTac [15].

When first powered up, the BioTac is allowed 15-20 minutes to reach its steady state temperature (~31°C, ~10°C above ambient). To produce the thermal exploratory movement, the BioTac is pressed into an object with a force of approximately 2.59 N to allow the skin to come in contact with the core and the thermistor. This contact is maintained for 15 seconds to allow for heat flow. We use the analog derivative of temperature \( T_{AC} \) to estimate the thermal conductivity of the object (Figure 4). The initial peak in temperature change tends to be consistent for all objects because it arises from the change in temperature as the cooler surface of the skin is brought closer to the thermistor [15]. The distinguishing features begin after about 6s of contact; the classification algorithm used the value at 15s, which was found empirically to yield the best discrimination.

All training and validation trials were performed in a room with ambient temperature that varied throughout the day. The constant-power heating of the BioTac produced a resting temperature that was a fixed increase over ambient temperature, allowing consistent heat-flow measurements.

\[ \text{Thermal} = \Delta T_{Tac} \]  

Figure 4 - AC temperature for four different materials with unique thermal properties. The change between starting values and values 15 seconds later are larger for objects such as copper with larger thermal conductivity.

C. Bayesian Exploration Algorithm

The process of Bayesian exploration first described in [1] was used in this study. The derivation and justification of these approaches are summarized below, but covered in greater detail in the above reference.

1) Bayesian inference for discriminating objects

Consider an object from a set of objects \( O \). When producing an exploratory movement \( M_m \), an observable measurement \( X \) can be recorded. The probability that a particular object \( O_i \) caused this observation can be found using Bayesian inference from the following equation:

\[ P(O_i | X, M_m) = \frac{P(X | O_i, M_m) P(O_i)}{\sum P(X | O_j, M_m) P(O_j)} \]  

Following the assumption that errors in measurement are normally distributed, the probability density function can be defined according to a mean (μ) and standard deviation (σ) of these measurements and can be expressed as:

\[ P(X | O_i, M_m) = \frac{1}{\sqrt{2\pi \sigma_i^2}} e^{-\frac{(x-\mu_i)^2}{2\sigma_i^2}} \]  

Equations (4) and (5) can be used to update the posterior probability of an object \( O_i \) given observation \( X \) from a normally distributed set of expected observations.

2) Selection of optimal exploratory movements

We propose that humans use a carefully selected sequence of movements when exploring objects [22]. Active selection of movements requires prior experiences to determine which movements would gain the most information. Other studies to intelligently guide movement selection have included using bag-of-features [7] or selecting movements to reduce Shannon entropy [23]. In contrast with these approaches, we use a process whereby movements that produce the most distinction among candidate objects is selected [1]. This evolving strategy predicts the confusion probability between pairs of objects, defined by the amount
of overlap between their two probability density functions. A matrix describing the confusion probabilities for pairs of textures for a particular movement can be calculated by:

$$ C_{ij,m} = \int p(x | O_i, M_m) p(x | O_j, M_m) \, dx $$

(6)

For a given movement $M_m$, observation $X$, and pair of objects $i$ and $j$, a low value of confusion ($C_{ij,m}$) would indicate no confusion after performing $M_m$ while a high value would indicate $M_m$ as an undesirable movement for discriminating these two objects. For normally distributed populations, this reduces to:

$$ C_{ij,m} = \frac{(\mu_i - \mu_j)^2}{\sqrt{\sigma^2_{i,m} \sigma^2_{j,m}}} $$

(7)

The total amount of predicted uncertainty ($U_m$) remained after performing movement $M_m$ given the coefficient $C_{ij,m}$ can be determined as a summation of all possible object combinations weighted by their priors:

$$ U_m = \sum_i \left( \frac{\sum_j C_{ij,m} P(O_j)}{\sum_j C_{ij,m} P(O_j)} \right) P(O_i) $$

(8)

The movement that provides the lowest perceived uncertainty is the optimal movement to make. This approach offers many advantages as a scalable system by actively selecting only the movements that have anticipated benefit and ignoring tests that have low utility.

D. Training and Validation

1) Test Objects

A total of 10 objects were selected to train and validate the system for discriminating objects by touch (Figure 5). These objects were selected due to their differences between one another on at least one of the perceptual dimensions explored in this study.

<table>
<thead>
<tr>
<th>Properties</th>
<th>acrylic</th>
<th>brick</th>
</tr>
</thead>
<tbody>
<tr>
<td>Compliance</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Texture Roughness</td>
<td>-</td>
<td>+</td>
</tr>
<tr>
<td>Thermal Conductivity</td>
<td>0</td>
<td>+</td>
</tr>
<tr>
<td>copper</td>
<td>-</td>
<td>+</td>
</tr>
<tr>
<td>damp sponge</td>
<td>+</td>
<td>-</td>
</tr>
<tr>
<td>feather</td>
<td>+</td>
<td>-</td>
</tr>
<tr>
<td>soft foam</td>
<td>+</td>
<td>-</td>
</tr>
<tr>
<td>plush toy</td>
<td>+</td>
<td>-</td>
</tr>
<tr>
<td>silicone</td>
<td>+</td>
<td>-</td>
</tr>
<tr>
<td>foam</td>
<td>+</td>
<td>-</td>
</tr>
<tr>
<td>wood</td>
<td>+</td>
<td>-</td>
</tr>
</tbody>
</table>

Figure 5 - Ten objects used in the discrimination task. Perceptual properties as described subjectively by human subjects are indicated in the panel to the left of each object (++, very high; +, high; 0, neutral; -, low).

2) Data Collection and Training

For training, each of the 10 objects was placed under the index finger of the robot. Shims were added underneath the objects to ensure the upper surfaces of all objects were at the same height so that the contact angle of the fingertip would be approximately equal (in an unconstrained robot, this function would be achieved by a combination of vision and arm movement). In the training process, the program would perform five trials of each of the three exploratory movements on each object to gain experience. The object would be shifted manually between trials to ensure the training data were robust to variations in the contact location of the object. Tactile data were collected and processed in real-time using the above equations and stored to text files that would serve as the system’s memory.

3) Validation

When identifying an object, signals measured previously from each object are used to compute confusion probability matrices for each movement as described above. The system initially sets the priors to equal probability for each object (10%) and the optimal movement is selected using Bayesian exploration. After performing the movement, the probability of each object is updated and the next movement is calculated. The process is repeated until a single object has a probability of greater than 98%.

![Flowchart describing the exploration process.](Image)

It was observed that when using training data from previous days, small changes in the robot or the environment resulted in shifts in measured properties, indicating that using older training measurements was not sufficiently robust in this system. Such drift could result in longer convergence times and even the failure of the discrimination altogether. To fix this, we added a small set of reinforcement learning trials prior to unknown object exploration altogether. During five initial explorations, the classifier would be corrected by a supervisor if an incorrect classification was made; only the movements that were selected by the Bayesian exploration algorithm (rather than one of each movement) were added to the system’s memory.
For final system validation, the program performed 10 trials of object identification on each of 10 objects without adding new data to the system memory. The robot performed the object identifications in real time, and results of the final object classification and the number and types of movements conducted were saved to file.

III. RESULTS

Figure 7 - Object properties for the 10 objects. Point clusters represent five training trials (circles) and reinforcement training data (stars)

Results of the training and reinforcement data (Figure 7) indicate that measured properties correlated well with perceptual properties (Figure 5). Acrylic, brick, copper, and wood (object 1-3, and 10) have a similar low compliance as rigid objects while all other objects had higher compliance that was easier to discriminate. Texture tests classified brick, damp sponge, foam, and wood (objects 2, 4, 6, and 10) to be rough objects because they have relatively high variance in filtered vibration signal while acrylic, copper, feather, plush toy, silicone, and soft foam (object 1, 3, 5, 7, 8, 9) were classified as having smooth surface; their individual textures were hardly distinguishable from each other. For thermal tests, all objects except for the feather, foam, plush toy, and soft foam (object 5, 6, 7, and 9), which are all heat insulators, had distinguishable thermal properties. Copper has the greatest thermal conductivity and produced that largest heat flux among the 10 objects, although the scatter was fairly large. The confusion probability matrices for each of these tests are shown in Figure 8.

The result of validation trials shows that with 10 trials of object identification on each object, the algorithm only failed once, yielding a 99% of success rate. In the one failure the damp sponge was identified as a feather due to their similar compliance (Figure 9).

IV. DISCUSSION

A. Exploratory movements

In all cases, the measured properties of the exploratory movements corresponded with the perceptual properties experienced by human observers. Summaries of optimal movements for different pairings of objects are provided in Figure 8. In general, compliance was found to be the most useful exploratory test due its reproducibility and the distinguishing characteristics of this particular set of objects. The thermal test proved to be the second most-useful movement, particularly in the cases of rigid objects that were difficult to distinguish based on compliance. For a different set of objects, these relative utilities might well change.

Contrary to previous findings, the texture movement was far less effective in discriminating objects. In [1] precision robotic equipment was used to control the force of the BioTac when sliding over the texture, as well as the speed of
sliding. The motors used in that study were very low noise, permitting high-fidelity measurements to be recorded. In contrast, the robot used in this study was far from ideal. Controlling either force or velocity was particularly difficult, and the motors of the robotic finger produced large amounts of vibration noise that was picked up by the BioTac. This agrees with conclusions derived in the discussion of [1] that the better-than-human motors used in the texture exploration contributed to the better-than-human performance. In this study, we see the performance substantially degraded by the limitations of this robotic system. As indicated in Figure 8, however, the texture exploratory movement is optimal for distinguishing certain pairs of objects, particularly rigid objects that share similar thermal properties, such as wood and acrylic.

B. Reinforcement learning:

The use of reinforcement learning improved performance when identifying objects. This was seen in both the accuracy of classification as well as the reduced number of movements required to converge on the correct object (Figure 10). When collecting training data on one day, property measurements would appear to be tightly clustered, indicating optimal conditions for discrimination, but not reflective of the actual distributions that could be measured at another time. Presumably, small changes in the environment, the sensors or the robot cause these drifts. Allowing the system to evolve its understanding of objects over time by adding new measurements to its memory provided a more accurate population of expected object properties that take into account the true variability. While property measurements become more diffuse (and thus likely to be confused with other objects), the resulting information is far more accurate and useful to the system. Contrary to intuition, while more diffuse clustering of object properties does, in fact, increase the amount of inter-object confusion, the algorithm is ultimately more accurate because it is not using an erroneous expectation of high discriminability for a particular exploratory movement that may actually be ambiguous (Figure 10). If some of these changes represent steady drift rather than noise, the learning algorithm could be further improved by incorporating “forgetting” of older data points.

V. ACKNOWLEDGEMENT

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REFERENCES