Examining Tactile Feature Extraction for Shape Reconstruction in Robotic Grippers

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***Abstract*— Different robotic setups provide tactile feedback about the objects they interact with in different manners. This makes it difficult to transfer the information gained from haptic exploration to different setups and to humans as well. We introduce "touch primitives", a set of object features for haptic shape representation which aim to reconstruct the shape of objects independent from the robot morphology. We investigate how precisely the primitives can be extracted from household objects by a commonly used gripper, on a set of objects that vary in size, shape and stiffness.**

I. INTRODUCTION

There are numerous different grippers and end-effectors available for robotic arms both commercially and for research purposes. Further, each gripper may be fitted with sensors for tactile and proprioceptive feedback. There are also a variety of different tactile sensors available which can be integrated with grippers. We can classify the most commonly used tactile sensors into two classes based on their working principle—first, optical sensors like Gelsight [1], DIGIT [2] and TacTip [3] which use vision processing from a camera embedded behind the sensor's surface membrane to extract information from object interations. Second, transductive sensors that convert mechanical changes to electric signals for feedback, like the SynTouch BioTAC [4], SINGLEX [5], Contactile [6] and uSkin [7]. The transductive sensors can further be split into sub-types based on how the mechanical interaction is converted to electrical signals. Some grippers like the BarrettHand [8] and Shadow Hand [9] may also come readily integrated with their own in-house tactile sensors.

For example, the GelSight sensor will give feedback in the form of an image of its membrane, which is not interpretable by other sensors. The BioTac sensor will provide feedback as a time series of measured reactive force at each fingertip, while the RG6 gripper will report back the force at its actuator. The feedback from the iCub hand will comprise of a series of values for each of its 104 tactile sensing units—12 on each finger and 44 in the palm. With the large variety of gripper and tactile sensing options available, data collection to build larger datasets of tactile robot-object interaction and manipulation faces some challenges. It is highly dependent on the robotic setup, since each morphological combination of {robotic arm, gripper, tactile sensor} will have different data structures for how interaction feedback is reported and stored. Compiling data from different setups for morphology-independent learning and exploration requires the development of processing methods for each setup individually. These factors also hinder the development of multimodal sensing datasets [10]–[13], even though such datasets exist from independent works, since it is difficult to compile and compare them because of the varying nature of tactile feedback data.

This work proposes "touch primitives", a set of morphology-independent features for haptic shape representation. The representation is based on how three-dimensional shapes are constructed in computer aided design methods [14]—simple features that may be extracted using any gripper and tactile sensor combination. We examine how precisely these primitives can be distinguished from each other using a commonly used gripper, the BarrettHand, and a set of five objects of varying size and stiffness. Since it is possible to extract the same features for many different robotic setups, they could also act as a common interpretation of object shape information between the different setups.

II. LITERATURE REVIEW

The first attempt to formalize a set of tactile primitives for object recognition was provided by Stansfield [15], who listed ten primitives that could describe not only the geometry but the physical properties of objects as well. Although research on physical property estimation for objects is scarce, a lot of work has been presented towards haptic geometric estimation and representation. Object recognition using feature detection was done by Liu et al. [16], where the features were represented via convolution with a sparse kernel space for categorization. More attempts for object recognition on specific robotic setups are presented in [17], [18].

Towards object reconstruction, Luo et al. [19] introduced iCLAP, an iterative touch exploration method to recreate objects accurately that decided exploration based on possible feature completion. Pezzementi et al. [20] used feature recognition from tactile arrays mounted on a gripper to formulate an exploration plan to reconstruct the shapes of objects. Rustler et al. [21] accomplish shape reconstruction by using a tactile "poking" action to detect contact with objects and subsequently filling the Cartesian space. The tactile exploration is paired with vision to generate object models with an Implicit Geometric Regularization Network (IGR) [22]. Very good accuracy was achieved for shape

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reconstruction within five to ten touches when visual data was also provided. Other works include edge following with the iCub robot [23] and a simulator for shape reconstruction [24].

III. TOUCH PRIMITIVES

A fundamental way to describe the shapes of objects is to break them down into vertices, edges and surfaces [14]. Although rudimentary, these four primitives shown in Figure 1 are the foundation to defining three-dimensional shapes.

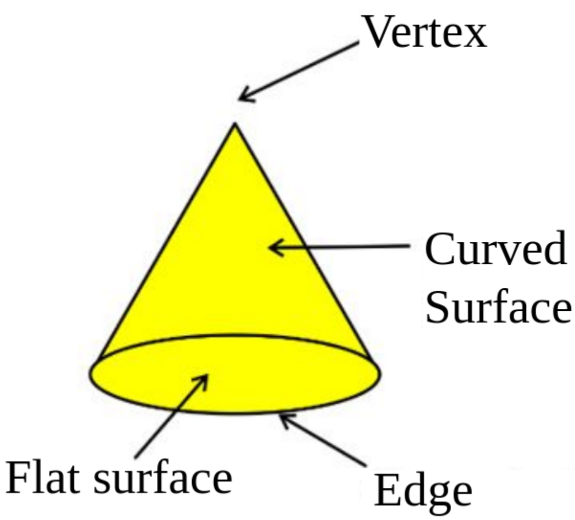

Fig. 1: Possible touch primitives on a target object.

This simplistic method does not take into account detailed features like surface texture or the roughness of materials, but by recognizing these features humans are able to achieve successful object recognition rapidly. We propose the identification of these same features by grippers as "touch primitives". Each exploration of the object can give multiple touch primitives depending on the number of fingers in the gripper and number of regions fitted with tactile arrays, and with sufficient sampling we are able to collect enough primitives to create a volumetric boundary for the object. The possible types of primitives are: vertex, edge, flat surface, and curved surface. As long as a gripper/sensor combination is able to detect these features, they should be able to record data in the suggested morphology-independent format below. An object exploration O is described as a set of primitives P, where each primitive is described by:

$$P = \{\vec{x}, i, \vec{d}_i\} \tag{1}$$

where $\vec{x}$ is the position and orientation of the finger or tactile array that detected the primitive, i is the type of primitive, holding values 1 to 4 for "vertex", "edge", "flat_surface" and "curved_surface" respectively. The primitive descriptor $\vec{d}_i$ helps us orient the primitive in 3D space with respect to $\vec{x}$. For the "vertex" primitive, it is the same as $\vec{x}$. For "edge" primitives, it is the slope of the detected edge on the surface of the tactile array. For the surface primitives, it is the normal to the tactile array at the point of maximum force.

IV. EVALUATION OF TOUCH PRIMITIVE EXTRACTION

To evaluate how precisely the suggested primitives can be extracted from objects, we test a simple feature extraction algorithm on the BarrettHand, a three fingered anthropomorphic hand with 24 tactile sensing units each on each finger and the palm. The arrangement of the sensing units allows us to recognize which primitives have been detected on each appendage using simple processing on the tactile image.

The classification of raw tactile data into primitive categories (independent for each finger and palm) is done via a simple pattern recognition algorithm described in Algorithm 1.

Algorithm 1 Algorithm to Categorize Touch Primitives

Obtain: $RawDataFromTaxels, \vec{x}$
Reshape: $RawDataFromTaxels$ to 3x8 grids for fingers and 7x4 grid for palm
for $Component \in Appendage$ **do**
  if $Num\_Excited\_Taxels <= 3$ **then**
    $Primitive \leftarrow Vertex$
    $\vec{d} \leftarrow \vec{x}$
  else
    $(Slope, Int, Coeff) \leftarrow Regress(Excited\_Taxels)$
    if $Coeff > Threshold$ **then**
      $Primitive \leftarrow Edge$
      $\vec{d} \leftarrow \vec{y}(Slope, Int)$ ▷ $\vec{y}$ is the orientation of the edge.
    else if $DetCurvedSurface(Excited\_Taxels)$ **then**
      $Primitive \leftarrow Curved\_Surface$
      $\vec{d} \leftarrow \vec{n}(Excited\_Taxels)$ ▷ $\vec{n}$ is the normal to the surface.
    else
      $Primitive \leftarrow Flat\_Surface$
      $\vec{d} \leftarrow \vec{n}(Excited\_Taxels)$
    end if
  end if
end for

We experiment on a small collection of objects shown in Figure 2a. These objects are collected to provide sufficient number of examples for each of the four primitives among rigid (spam can and marble brick) and deformable (white cube, red ball, mustard bottle) objects, and for two size scales—10 cm scale (mustard bottle) and 1 cm scale (all other objects). Objects smaller or larger than these scales are considered to be outside the group of target objects. For each object we task the BarrettHand with detecting a primitive a fixed number of times. Four different scenarios are examined, shown in Figure 2b. Experiments (1) and (2) differentiate between the finger and palm arrays in precision, while experiments (3) and (4) vary the grasp configuration.

Based on these experiments and the results shown in Figure 3, we are able to draw a few conclusions. First, vertices or edges can be precisely distinguished from the other primitives. The confusion is highest between flat surfaces

(a) (b)

Fig. 2: (a) Test object set. (b) Different test scenarios.

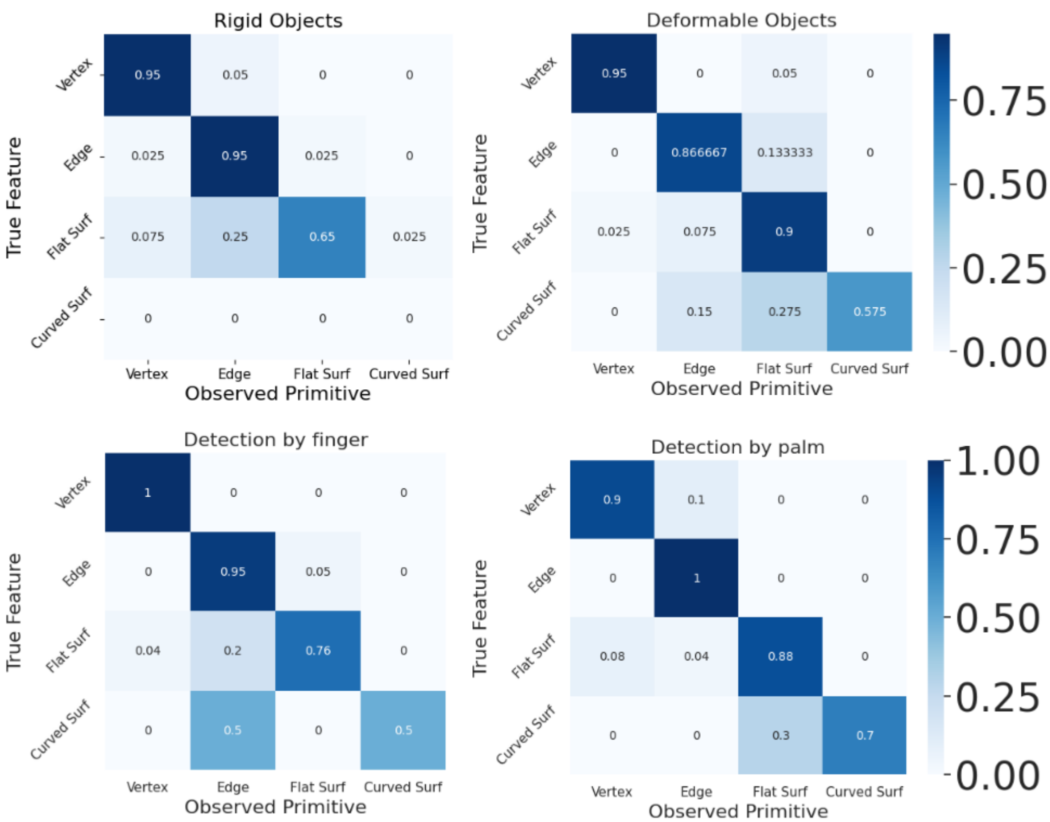

Fig. 3: Primitive Recognition results.

and curved surfaces, which can be attributed to the noise in tactile measurements. The finger components of the gripper have a physically smaller surface area and smaller tactile sensors. This leads to more confusion between edge and surface primitives as well when compared to the performance of the tactile array on the palm of the BarrettHand. Rigid objects have sharper features, which helps in improving the recognition performance.

This concept of using touch primitives for object representation opens up many avenues for future research as well. First, how these primitives can be used to recreate and recognize object shapes with accuracy. Further, how different grippers can extract the same primitives. Integrating grippers with various tactile sensors provides them with such capabilities, however, we can also investigate whether the same primitives can be recognized by the grippers as a result of sequential exploration without rich tactile feedback. Maye et al. [25] describe how sensorimotor contingency theory can be used to infer context and information from a robot based on its state and action exploration sequence. This theory may allow grippers without tactile sensing capabilities to extract touch primitives from target objects as well. Next, once the extraction of geometric touch primitives is accomplished, there will also be the possibility to integrate physical properties into the same description vector with stiffness and friction maps as seen in [26]. Finally, if the proposed method of representing objects is accurate and useful in transferring object information between robotic setups, generating grasp proposals using touch primitives as inputs can be explored.

As a smaller goal, preliminary work is restricted to shape recognition of target objects from a pool of already-known object models stored in memory. Building on this, complete shape reconstruction of objects will be attempted, which is a more complex exploration activity and more susceptible to environment and computational noise. Next, the independence of these primitives from the robot morphology will be examined with a knowledge transfer and grasping experiment between different robotic setups.

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