Tactile Mapping and Localization from High-Resolution Tactile Imprints

Maria Bauza, Oleguer Canal and Alberto Rodriguez
Mechanical Engineering Department — Massachusetts Institute of Technology
<bauza, oleguer, albertor>@mit.edu

I. Introduction

The correlation between hand dexterity and the spatial-and-pressure resolution of its tactile sensors has been of interest for a long time [1]. In the 19th century, Weber explored spatial acuity with the "two-point touch threshold", i.e., the shortest distance that can be perceived as two separate pressure points. Later, Max von Frey studied the sensitivity to different levels of applied pressure [2]. It comes with no surprise that the regions with finer spatial sensor resolution, and those that are more sensitive to pressure, are the tips of our fingers and the tip of our tongue, both known for their dexterity.

This work builds from a recent interest in image-based tactile sensors such as GelSlim [3] or GelSight [4] which, by virtue of using a soft gel skin and a camera as transducer, achieve very high spatial acuity and pressure sensitivity, yielding highly discriminative tactile signals.

In this work we show that we can combine tactile imprints with robot kinematics to build a tactile map of an object for localization. To do so, we present 3 contributions:

1. Local shape estimation: we use *tactile imprints* to estimate the shape of the contact patch using CNNs.
2. Global tactile mapping: we fuse the tactile imprints and the kinematics (gripper pose and opening) of multiple grasps of a fixed object to reconstruct its global *tactile shape*. This includes the object geometric shape as well as a discrete representation of its tactile imprints.
3. Object tactile localization: Figure 1 illustrates how we combine tactile imprints with an estimation of the shape of the contact patch to identify and localize a grasped object. Our ICP-based algorithm uses tactile imprints for coarse data association, and contact shape for fine refinement.

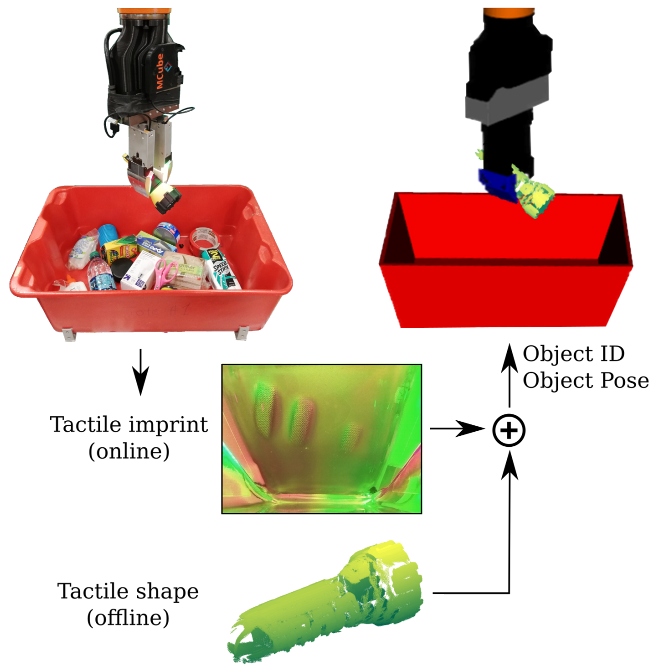

Fig. 1. **Tactile mapping and localization.** This work addresses the problem of in-hand object identification and localization using tactile sensing. Given a new tactile imprint from the tactile sensor in the robot's finger, we use the precomputed (offline) tactile map of an object to identify and find its location inside the grasp.

II. Local shape estimation

We recover the local shape of an object from a tactile imprint. The local shape is given as a heightmap and aims to represent the local geometry of an object at contact. In Fig. 2, we use a data-driven approach to build a map between tactile imprints and local shapes.

Given that tactile images and heightmaps are 2D arrays, we leverage standard CNNs. The basic architecture of the CNN we use is a sequential model of 10 convolutional layers with 64 filters each and a 3-by-3 sized kernel. To improve the robustness to illumination changes, we augment the data including random variations in the 3 channels of the tactile images. We also account for translations by adding two extra channels to the input with the x and y position of each pixel. A more in detail explanation of the data collection and training process can be found in the project's website [5]. When evaluating the model, the average reconstruction accuracy reaches 0.1mm on the test data with only 500 datapoints and 0.060±0.016mm with 2000.

III. Global Tactile And Shape Mapping

We combine a set of tactile imprints from an object to recover its tactile shape. This method for shape recovery relies on the accuracy of the robot kinematics and the gripper, and the precision of the heightmaps described in Sec.II.

Each tactile imprint of the tactile map can be converted in a point cloud in the world frame. For that, we first map the tactile imprint into a heightmap as explained before, and use an accurate calibration of the intrinsic parameters of the sensor's camera to convert this heightmap into a point cloud in the sensor's frame. Then we localize the point cloud in the world's frame by assuming a rigid and calibrated transformation between sensor, gripper and robot

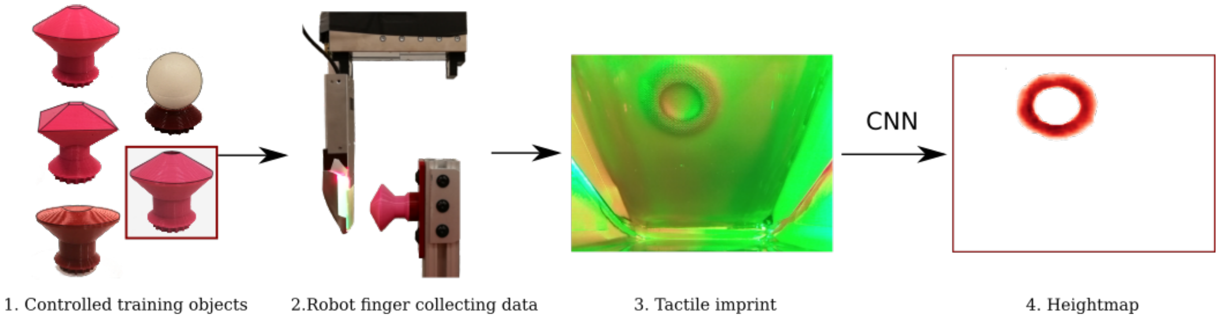

Fig. 2. **Local shape estimation.** To estimate the shape of an object at contact, we built a system that automatically collects data and maps tactile imprints to heightmaps of the local shape. From left to right: a) objects used for training, b) robot collecting data by frontally touching random locations of an object, 3) tactile image recorded during the touch, and 4) heightmap of the object's shape at contact obtained using a trained CNN.

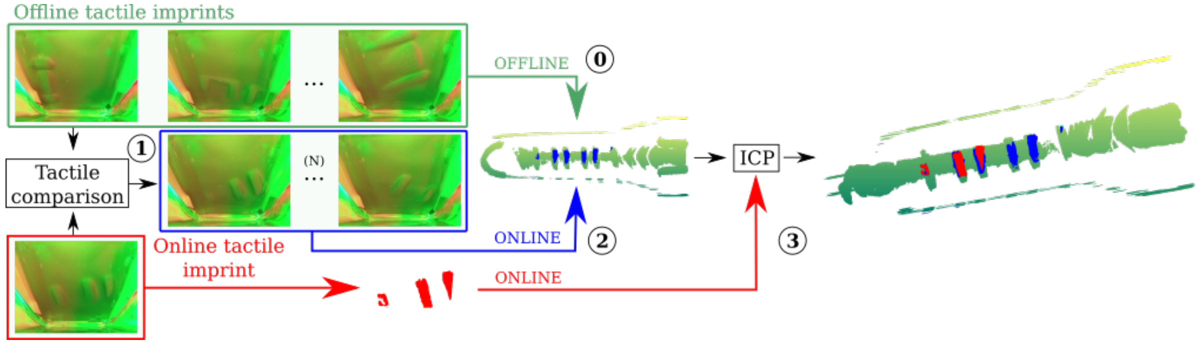

Fig. 3. **Tactile localization.** Given a new tactile imprint, we find its location in an offline computed tactile map (0) by following the steps: (1) find the N touches from the map that are more similar to the new one, (2) create an auxiliary point cloud with these N touches that is a subset of the global one, and (3) use ICP to stitch the local point cloud from the new tactile imprint to the auxiliary one to locate its pose in the global shape.

arm. Finally, we build a tactile map of an object by stitch all its point clouds obtained into a single one.

IV. Tactile Localization

Given the tactile map of an object, our goal is to effectively use it for robotic manipulation. To show this, we examine and evaluate how to localize the object based on correspondences between the tactile shape and local tactile imprints.

The proposed approach is described in Figure 3. We first recover the local shape in the sensor's frame as a point cloud using its tactile imprint as in Section II. Then we stitch this local point cloud to the global tactile shape of the object and infer how the resulting point cloud is located w.r.t to the tactile sensor. Finally, given the robot kinematics we estimate the actual pose of the object in the world frame.

V. In-hand identification and localization

Given a set of tactile shapes from explored objects and a new tactile imprint, our goal is to recover both the identity of the object and its location in-hand. We identify it by comparing the new tactile imprint to the ones used to create the global maps of each object, and assigning the identity from the most similar tactile imprint. Once identified, we stitch the new tactile imprint to its global shape as in Section IV and obtain its pose w.r.t. to the tactile sensor.

Figure 4 shows 3 examples of grasped objects and their tactile imprints. Our approach correctly identifies each object and estimates its location in-hand. The solution is fast enough to provide real time estimations of the pose as the only steps are: one CNN pass, a similarity comparison in a feature vector space and ICP with small point clouds.

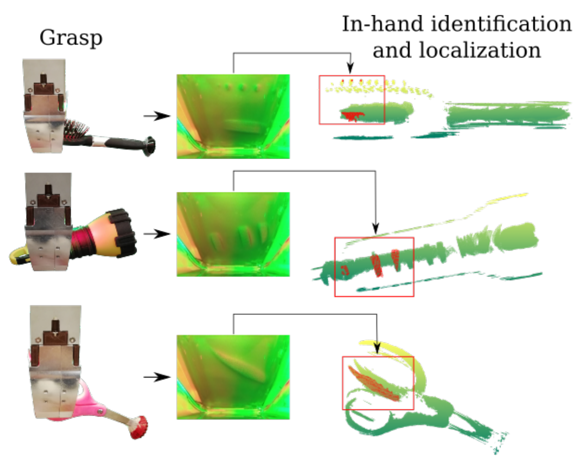

Fig. 4. **Object identification and localization.** From each random grasp and tactile imprint, our approach identifies correctly the object and accurately estimates its position in-hand.

References

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