# Shear-invariant Sliding Contact Perception with a Soft Tactile Sensor

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*Abstract*— Manipulation tasks often require robots to be continuously in contact with an object. Therefore tactile perception systems need to handle continuous contact data. Shear deformation causes the tactile sensor to output path-dependent readings in contrast to discrete contact readings. As such, in some continuous-contact tasks, sliding can be regarded as a disturbance over the sensor signal. Here we present a shearinvariant perception method based on principal component analysis (PCA) which outputs the required information about the environment despite sliding motion. A compliant tactile sensor (the TacTip) is used to investigate continuous tactile contact. First, we evaluate the method offline using test data collected whilst the sensor slides over an edge. Then, the method is used within a contour-following task applied to 6 objects with varying curvatures; all contours are successfully traced. The method demonstrates generalisation capabilities and could underlie a more sophisticated controller for challenging manipulation or exploration tasks in unstructured environments.

# I. INTRODUCTION

Continuous contact sensing is crucial for robot manipulation or tactile exploration as these activities usually require the robot to be in continuous contact with objects. Furthermore, it is frequently desirable to use compliant touch sensors, which make the perception more challenging due to motion dependency caused by their sensitivity to shear [1]. Shear deforms the sensor [\(Fig. 1\)](#page-0-0) depending on the sliding direction, thus making sensor readings history dependent.

The novelty of this work is to verify the hypothesis that features found in independent tactile readings (taps) can also be extracted from data perturbed by sliding motion. Sliding motion causes the sensor skin to deform, and so sensor readings would depend on both the tactile features of the object and the shear direction. Thus, while discrete tap data is similar for the same tactile features, with sliding motion those features can produce completely different readings. This paper finds a link between discrete tactile data (taps) and movement dependent data by showing that a linear transform can extract features of interest despite the sliding.

For validation, we apply a simple perception method trained on discrete contact data (taps) to continuous contact data collected offline and to continuous contact data for contour-following whilst sliding. The perception method uses principal component analysis (PCA) to extract features from tactile data which are then mapped to the sensor pose using

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Fig. 1: (a) The experimental setup showing four 3D-printed objects, a natural object (a tape measure) and a laser-cut spiral used for contour-following. The TacTip is the end effector of a 6 axis ABB robot (IRB120). (b) Close-up of the TacTip sensor. (c) The image captured by the TacTip at no contact.

nonlinear regression. We also exploit PCA to visualise the output of a soft biomimetic tactile sensor (the TacTip [2], [3], shown in [Fig. 1\)](#page-0-0) and show that the data are strongly influenced by the sliding direction of the sensor. This shear-invariant perception method extends previous tactile exploration studies [4], [5] that used tapping movements (independent tactile data) by demonstrating reliable sliding contact tactile exploration (contour-following) of various objects [\(Fig. 1a](#page-0-0)) despite being trained using discrete contacts on a straight edge.

## II. RESULTS

We present the online results for a tactile exploration task, specifically contour-following where the sensor continuously slides along the edge of various shapes.

We use four 3D-printed shapes, an acrylic laser-cut spiral shape, and a tape measure [\(Fig. 1a](#page-0-0)) for this task. The shapes were chosen to test the limits of the method. The rectangle has zero curvature and corners. The two circles have different constant curvatures. The flower-like shape has both negative and positive curvatures. The tape measure is a natural object and has different curvature values and a corner. Finally, the spiral shape has negative and positive curvatures, contains corners and has closely spaced features.

Our approach successfully traced all contours [\(Fig. 2\)](#page-1-0) by using the perception algorithm which consist of a PCA dimension reduction step and nonlinear regression along with a simple control policy. The RMS orientation errors are similar for all shapes with an average value of 12.2◦ which agrees

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Fig. 2: (a) The trajectory (blue trace) performed by the robot when following the contour of a: (a) rectangle, (b) large circle, (c) small circle and (d) flower-like shape. The grey lines show the normal to the object edge as perceived by the sensor.

with the errors obtained for the 270° sliding direction. The perception algorithm handles corners [\(Fig. 2a](#page-1-0)) by gradually perceiving a varying angle which changes smoothly over the corner. This was not a trained behaviour but emerged from the algorithm. The algorithm thus generalises to different curvatures.

The algorithm generalises from discrete contact tactile data collected on a zero curvature edge to data recorded whilst performing sliding motion over edges having varying curvature properties. The perception is not influenced by changes in curvature magnitude as shown by the two circles (Figs. [2b](#page-1-0), c) or by whether the curvature is positive or negative as demonstrated by the flower-like shape [\(Fig. 2d](#page-1-0)). The perceived lateral position errors do not impact the success of the contour-following as shown by the smooth shape-preserving trajectories achieved.

# III. DISCUSSION

The paper has demonstrated that a PCA-based perception algorithm can infer edge features invariant of the sliding motion. We achieved successful continuous contour-following of a wide range of shapes, thus showing that the simple features found by PCA with a suitable discrete contact training set are robust to sliding and to changes in curvature.

The PCA part of the algorithm also helps to visualise the sliding data which builds upon the tactile visualisation presented by Aquilina et al. [6]. Here we show that visualisation of the multi-directional data reveals continuous tactile data is history dependent on the sliding direction. However, PCA can also encode the sliding vector in each sensor frame, which may be useful in experiments where sliding is a quantity of interest.

Additionally, due to the simple features extracted using PCA, the algorithm was able to generalise to various flat objects of an unknown shape despite being trained only on a portion of a straight edge. This is related to the work by Luo et al. [7] where a specific data descriptor yields rotation and translation invariance. However, the most common approach is to obtain invariance by training on samples which have different properties such as the shapeinvariant method presented by Yuan et al. [8]. This would have been equivalent to using a sliding contact training set in this work. However, in practice it may not be possible

to train for every event the system could encounter; instead we view it desirable to have a robust system that produces reasonable results on a wide range of scenarios.

We expect the proposed method to apply to more challenging tasks due to its generalisation capabilities. Such a method could be combined with more complicated controllers using predictive or adaptive control to complete demanding manipulation or exploration tasks in unstructured environments.

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