A Low-cost Open-source 3D-printed High-resolution Soft Biomimetic Optical Tactile Sensor for use with Deep Learning

Nathan F. Lepora, Yijiong Lin, Ben Money-Coomes, John Lloyd

***Abstract*—Deep learning combined with high-resolution tactile sensing could lead to highly capable dexterous robots. However, the specialised equipment and expertise is major barrier to research. The DIGIT tactile sensor offers a low-cost open-source entry to tactile dexterity using GelSight-type sensors. Here we provide greater diversity of tactile hardware by customizing the DIGIT to have a 3D-printed sensing surface based on the TacTip family of soft bioimmetic tactile sensors. In keeping with the low-cost aims, we introduce a desktop robot arm system to mount the sensors as end effectors. We use tactile servo control with a deep learning model for pose prediction to compare the DIGIT, TacTip and DIGIT-TacTip for edge- and surface-following over 3D-shapes. All optical tactile sensors performed similarly at pose prediction, but their constructions led to differing performances at tactile servo control, offering guidance for researchers selecting or innovating tactile sensor design. All hardware and software will be openly released, and we encourage other researchers in tactile robotics to also adopt a similarly open perspective.**

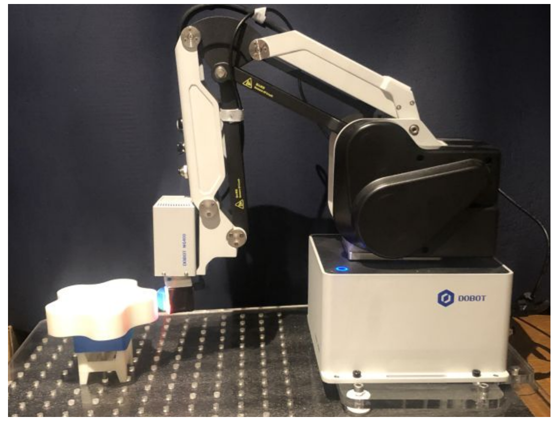

Figure 1: Tactile robotic system: DIGIT-TacTip on a desktop robot arm (Dobot MG400) performing tactile servo control.

I. INTRODUCTION

Advances in deep learning combined with innovation in high-resolution tactile sensing give a plausible route to robots with the dexterous capabilities of the human hand. Consider, for example, the revolution in computer vision where 1000s of researchers have ready access to deep learning infrastructure and vast amounts of openly-shared visual data [1]. In contrast, research on applying deep learning to robot dexterity requires access to advanced robot manipulators such as industrial arms integrated with specialist tactile sensing hardware and proprietary software for robot control. This need for specialised equipment and expertise presents a major barrier for entry into the development of deep learning for tactile robotics. Consequently, progress is slow and narrow in scope from just a few research laboratories.

Researchers in Meta AI have developed the DIGIT as a low-cost high-resolution tactile sensor [2]. They have open-sourced the sensor design and in partnership with the company GelSight commercially manufacture the sensor for sale [3]. To lower the barrier of entry to using machine learning (ML) with tactile sensors like the DIGIT, an accompanying library of ML models and functionality for touch sensing has also been released, called PyTouch [4] alongside a simulation environment (TACTO) for high-resolution vision-based tactile sensors [5]. The overall concept is to provide a complete ecosystem for teaching robots to perceive, understand and interact through touch [6].

In our view, these developments will be strengthened by providing a greater diversity of tactile sensing hardware and ML models. To this end, here we customize the DIGIT to have a sensing surface based on the TacTip family of soft biomimetic optical tactile sensors [7], [8]. We also adapt recent progress in using deep learning for posed-based tactile servo control developed with the TacTip to both the DIGIT and DIGIT-TacTip. As part of this contribution, we introduce a low-cost desktop robot system for testing the performance of the servo control with these tactile sensors. By open-sourcing all hardware and software components, we aim to enable other labs to more easily enter this field of research with access to multiple types of optical tactile sensor and a variety of perception and control methods that complement those offered by the DIGIT/PyTouch ecosystem.

The main contributions of this work are in summary:
1) We show how the DIGIT can be customized to replace the (molded) GelSight sensing surface with a 3D-printed soft biomimetic skin based on the TacTip family of sensors [7], [8]). For the first time, this enables direct comparison of these sensors with the same hardware and software infrastructure.
2) In keeping with the aims of a low-cost system, we introduce a desktop robot system (Fig. 1) for mounting the DIGIT and TacTip sensors to ease tactile data collection and sensor comparison. The complete software system comprises the robot API, optical tactile data capture software and ML models.
3) We apply recent developments in pose-based tactile servo control [9], [10] to test this tactile robot system, by learning to slide over the edges and surfaces of unknown 3D objects while maintaining safe, delicate contact. This raises several challenges, including how to apply methods developed with industrial robots to a lower-capability desktop robots, how to use and compare distinct optical tactile sensors with the same hardware/software infrastructure, and how to conduct the research in a manner amenable to open sourcing.

NL and JL were supported by a Leadership Award from the Leverhulme Trust on ‘A biomimetic forebrain for robot touch’ (RL-2016-39).

All authors are with the Department of Engineering Mathematics and Bristol Robotics Laboratory, University of Bristol, Bristol, U.K.

Corresponding author: n.lepora@bristol.ac.uk

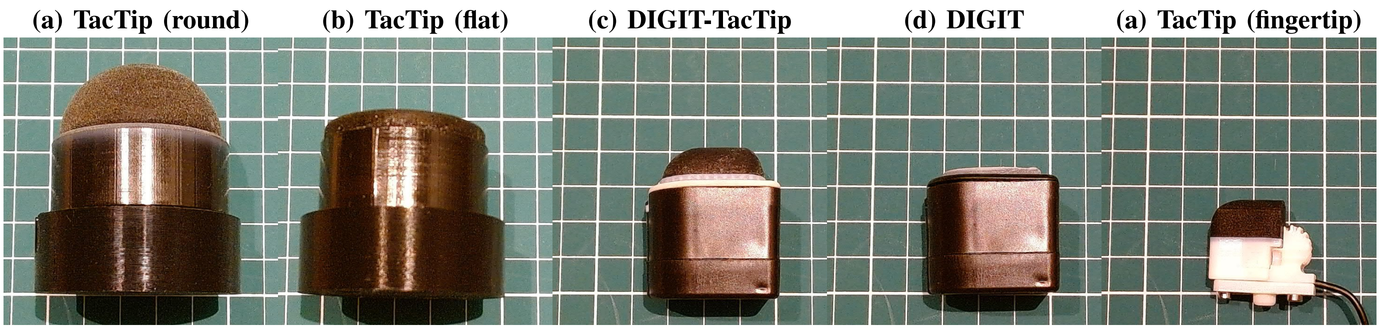

Figure 2: Comparative form factors of (a) TacTip (round tip), (b) TacTip (flat tip), (c) DIGIT-TacTip (curved tip); (d) DIGIT (flat GelSight skin) and (e) fingertip-sized TacTip [11]. The background grid spacing is 10 mm.

II. Background and Related Work

A benefit and constraint of the DIGIT-TACTO-PyTouch ecosystem is the focus on one type of high-resolution optical tactile sensor: the GelSight [12], [13]. The GelSight images indentation of an elastomeric 'skin' from the surface shading on a reflective coating illuminated by multiple internal light sources. This design concept has diversified into various reflection-based optical tactile sensors [14], [15] including the DIGIT [3]. A substantive body of work uses ML models with the GelSight, including the first studies of deep learning for optical tactile sensing [16].

The present article focuses on another type of high-resolution optical tactile sensor that instead captures images of inner markers [17], where valuable progress in tactile sensing has also been made particularly in the application of deep learning [8]. Some GelSight sensors also use markers printed on the reflective coating [13] to enable sensitivity to shear contact that is not apparent from imaging reflection, showing the complementary nature of these two artificial tactile sensing mechanisms. At present, there is rapid innovation in embedding markers within the tactile skin and surrounding material to transduce surface contact, e.g. [18]–[20].

The TacTip is unique within marker-based optical tactile sensors by using an array of internal pins with markers on the tips. The pins act as levers to amplify the marker motion from surface indentation and shear [8]. This design is biomimetic because human skin is structured around analogous dermal papillae whose motion is signalled by nearby mechanoreceptors. Recent experiments have confirmed for the first time in any artificial tactile sensor that signals derived from the TacTip markers closely resembles neural activity from primary SA-I and RA-I tactile afferents [21]. Further, the raw tactile images from the TacTip are well-suited for processing by convolutional neural networks, leading to a range of applications including tactile servo control [10], [22] from pose models [9], object pushing manipulation [23], in-hand manipulation [24] and sim-to-real deep reinforcement for tactile pushing, rolling and servoing [25]. A review of these capabilities was published recently [8].

All tactile sensors have their pros and cons. The GelSight and TacTip have a common reliance on imaging an internally-illuminated skin, enabling the present DIGIT to DIGIT-TacTip customization. However, there are differences in their elasticity, robustness, friction and sensitivity to contact features that may make their operation in practise rather different. Our work here aims to bring together knowledge across the field to make it possible to trade-off aspects of these distinct tactile sensors to encourage progress towards tactile-enabled robot dexterity.

III. Methods

A. *DIGIT-TacTip design and fabrication*

The design of the DIGIT optical tactile sensor is based on [2]: (i) being sufficiently compact to fit as an array of end effectors/fingertips on multi-fingered robot hands or arms; (ii) having a sensing surface (gel) that is robust and easily interchanged; and (iii) easing the fabrication process by using off-the-shelf components and a snap-fit assembly. The design is open-sourced [3] and the external housing can be fabricated on a standard 3d-printer or made in bulk with automated manufacturing.

In practise, the DIGIT has two distinct assemblies:
(**A1**) The **base unit** comprising the internal lighting, camera with PCB and housing (Fig. 3C-F same as [2, Fig. 2]D-G);
(**A2**) The **sensing surface** on its acrylic window and housing that snap fits onto the base. This sensing surface based on the GelSight family of sensors, comprising a painted elastomer, acrylic window and snap-fit holder ([2, Fig. 2]A-C). Several different elastomers were trialled, including markers to be sensitive to shear and a transparent surface [2, Fig. 4]. It was observed that other types of vision-based tactile sensor may also be compatible with this design, e.g. the TacTip.

Here we introduce a TacTip version of the sensing surface to customize the DIGIT into a TacTip optical tactile sensor. The differences from the DIGIT are:
(**D1**) The original plastic snap-fit holder is redesigned to house a compliant skin on the underside of which are 140 2 mm-papillae tipped by markers (Fig 4). This component is fabricated in one piece on a multi-material 3D-printer (Stratasys J826), using a rubber polymer (Agilus30, black) for the skin and papillae and acrylic resin (VeroWhite) for the holder and markers.
(**D2**) A 1 mm-thick acrylic window replaces the original 6 mm-thick window. The original window acted as a light guide so that indentations of the GelSight-type sensing surface are illuminated laterally to emphasise shading. However, the main function of the window for the TacTip is to contain a compliant gel (see D3 below). A thinner window is preferred for more

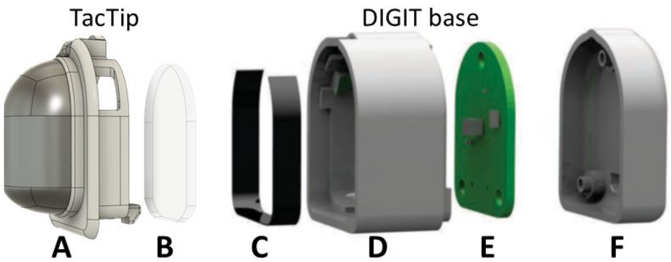

Figure 3: TacTip sensing surface integrated with DIGIT base. A) 3D-printed TacTip, B) acrylic window, C) lighting PCB, D) plastic housing, E) camera PCB, F) back housing.

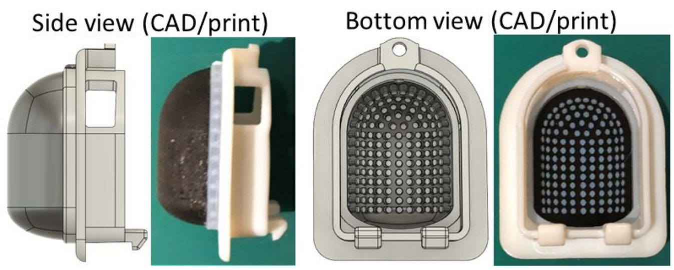

Figure 4: 3D-printable design and fabricated DIGIT-TacTip sensing surface with press-fit housing.

Table I. Comparision of DIGIT, DIGIT-TacTip and TacTip.

	DIGIT	**DIGIT-TacTip**	**TacTip**
size $l \times w \times h$ [mm]	36×26×33	36×26×39	48 dia.×55
weight [g]	20	20	50
sensing field [mm]	19×25	19×25	40 dia.
resolution [pix]	640×480	640×480	1920×1080
frame rate [per sec]	60	60	120
markers	-	140	331
cost	\$15 (\$300)	+ \$15 (£100)	£50 (£300)

direct marker illumination, to avoid spurious reflections and to save weight.
(**D3**) The enclosure between the skin and window is filled with a soft optically-clear gel as in other TacTip sensors [7], [8]. Here we used a silicone gel (Techsil, Shore A Hardness 15), which was injected through a small (1.5 mm-dia.) filling hole near the retaining screw on the front of the sensing surface, then plugged with a 3D-printed stopper.

The DIGIT-TacTip sensing surface is assembled the same way as other TacTip sensors (see the Soft Robotics Toolkit for a step-by-step guide). The assembly is fairly straightforward once all components have been fabricated. The use of multi-material 3D-printing makes it easy to customize the design, which has led to a wide range of TacTip form-factors and integrated robotic systems (Fig 2; see also [8, Fig. 4]). There is a competitive online marketplace for mail-ordering multi-material 3D-prints and for laser-cutting acrylic. Therefore, anyone should be able to obtain and assemble the parts for the DIGIT-TacTip from the open-sourced designs.

shape between the sensors. The DIGIT TacTip differs from the DIGIT sensor in that it has a

A comparison of the sensors (Table I) shows the main difference in shape between the sensors. The DIGIT-TacTip differs from the DIGIT sensor in that it has a thicker, curved sensing surface, which we will see later is far softer than the original elastomer. In comparison to the standard domed-TacTip (Fig. 2A), the DIGIT and DIGIT-TacTip are sufficently small and light to be compatible with some grippers (e.g. the Allegro hand shown in [2]). However, they are too bulky for anthropomorphic robot hands, where a custom TacTip (Fig. 2E) is currently the only integrated high-resolution optical tactile sensor.

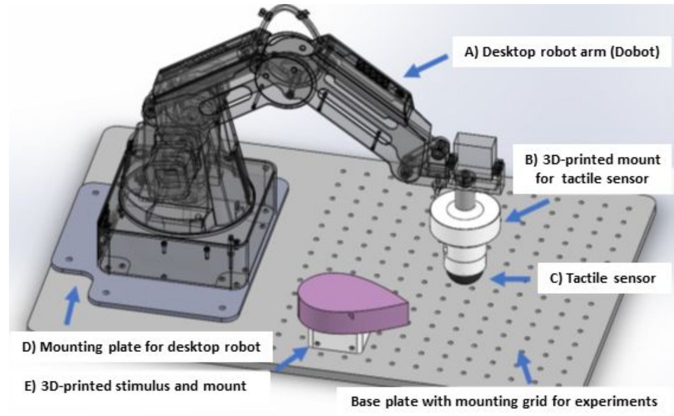

Figure 5: Test platform: A) desktop robot arm; B) 3D-printed mount for tactile sensor; C) tactile sensor (here a TacTip); D) mounting plate for robot arm; E) 3D-printed stimulus and mount; F) base plate with mounting grid.

B. *Desktop tactile robot and software infrastructure*

A major goal of tactile sensing research is to develop models for predicting and interpreting real-time interactions, so that a robot can be controlled to interact in a safe and robust manner with its physical environment. For optical tactile sensors, convolutional neural networks trained on thousands of tactile images offer unrivalled model performance while being insensitive to confounding contact variables, such as predicting hardness in the presence of unknown contact shape [16]. In particular, predicting contact pose in a manner that is insensitive to contact shear [9] enables robust and accurate tactile servo control to delicately contact and slide over complex objects [9], [10], [22] or manipulate objects by pushing [23].

The infrastructure required for such research has been:
(**I1**) Robot manipulators, such as ABB and Universal Robotics industrial robot arms. These are highly capable and accurate (e.g. ABB-IRB120 repeatability ± 0.01 mm), but are large, expensive items of equipment that must be installed and operated safely in a laboratory or industrial setting.
(**I2**) Python software libraries for capturing images, processing with deep learning models, and controlling the robots asynchronously in real-time. Different laboratories have various solutions. In BRL, we have developed libraries[1], VSP and CRI, for image capture and interfacing with proprietary robot control software/APIs, which are openly available.

Here we introduce a low-cost, safe alternative to large industrial robot arms with a test platform to ease the setup and repeatability of tactile experiments and data gathering (Fig. 5).

[1] So far, we have avoided using ROS because of difficulties with also using deep learning libraries such as TensorFlow in real-time.

This platform comprises:

(**P1**) Desktop robot arm, for which we use a Dobot MG400 4-axis arm designed for affordable automation. The base and control unit has footprint 190 mm×190 mm, payload 750 g, maximum reach 440 mm and repeatability ±0.05 mm. As we describe later, the accuracy of tactile models trained using this arm is similar to larger industrial robot arms. The main constraint is that only the (x, y, z)-position and rotation around the z-axis of the end effector are actuated.

(**P2**) Base plate with a mounting plate for the desktop robot and a grid of holes for mounting stimuli in precise locations relative to the robot. The base plate was laser cut from an acrylic sheet of size 600 mm×400 mm×10 mm, with 25 mm grid-spacing. The robot mounting plate was also laser cut from 10 mm-thick acrylic then screwed to the base plate (in practice, we also used spacers to tilt the robot so its coordinate frame was reasonably parallel to the base plate).

(**P3**) Normal and right-angle mounts for the DIGIT and TacTip sensors so they can be used as end effectors. These were 3D-printed from designs adapted from an end-flange supplied with the MG400. A choice of mounts allows the tactile sensing surface to be oriented in a horizontal or vertical plane, as the end effector can rotate only around a vertical axis.

(**P4**) Test stimuli with mounts to attach to the base plate. Here we use circular, square and circular-wave shapes of ∼100 mm diameter with 30 mm walls, 3D-printed in ABS. .

Another benefit of the Dobot MG400 desktop robot is that the API is open-source and written in python. We have released a version of our CRI robot interface libraries that integrates this API, which can be updated to include other functionality as the robot firmware is improved.

All designs for making the base plates, mounting plates, tactile sensor mounts and stimuli for the test robot will be openly released for others to reproduce and build upon.

C. Task: Tactile Servo Control on a Contour and Surface

In this paper, we use servo control around a contour and over a surface to test and compare the various tactile sensors with the desktop robot. Tactile servo control is analogous to visual servo control, with tactile data used instead of vision data in a feedback loop to control the robot motion. In pose-based tactile servo control, the pose error ${}^SE_R$ between the sensor pose ${}^FP_S$ and a reference pose ${}^FP_R$ (in a local object feature frame F) drives the feedback loop [10] (Fig. 6 top).

For high-resolution optical tactile sensors, the sensor pose ${}^FP_S$ in the object feature frame (here of an edge or surface) can be predicted using a suitably-trained 'PoseNet' convolutional neural network on a tactile image [9] (Fig. 6). For robust pose predictions while interacting with the object, it is necessary to train the model to be insensitive to contact shear motion by sliding against the object used for training as the sensor reaches its labelled pose [9], [10], [22].

Here we use two tactile servo control tasks adapted from the 3D-tasks reported in earlier work [10]. We perform these tasks using the desktop tactile robot with the DIGIT, DIGIT-TacTip and TacTip tactile sensors:

Task 1: Edge-following is around horizontal flat shapes (here

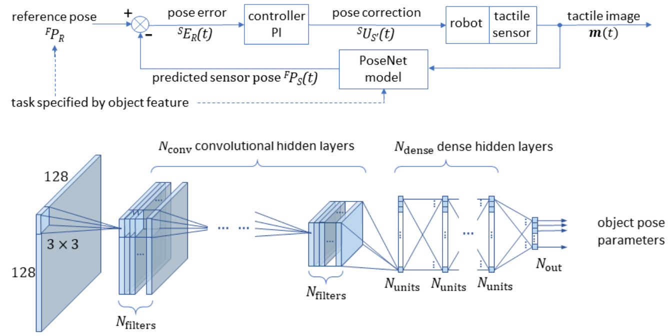

Figure 6: Pose-based tactile servo control loop with PoseNet convolutional neural network model from tactile images.

Table II. Tactile image data collection for sliding contacts: top: pose parameter ranges; bottom: slide ranges to pose. 5000 uniformly-random samples are collected per stimulus.

	pose parameter ranges			
stimulus	x-position	y-position	z-position	angle
edge	0 mm	[−5,+5] mm	[−1,+1] mm	[−45°,+45°]
surface	0 mm	[−5,−1] mm	0 mm	[−30°,+30°]

	slide parameter ranges			
stimulus	x-position	y-position	z-position	angle
edge	[−5,+5] mm	[−5,+5] mm	0 mm	[−5°,+5°]
surface	[−5,+5] mm	0 mm	0 mm	[−5°,+5°]

we use circle, square and circular-wave objects described in [10]). The PoseNet model is trained on a straight edge of the square block. During training, the sensor pose is varied in its perpendicular distance from the edge and across a range of orientations, using a horizontal sliding motion to move it into position (Table II). Unlabelled variations in contact depth (z) were introduced to train the model to be insensitive to sub-mm variations in object height due to imperfect levelling of the robot (which happen in practise).

Task 2: Surface-following is carried out around the walls of the shapes described above with the tactile sensor oriented so the sensing surface is vertical. The PoseNet model is trained on a straight vertical wall of the square block. The labelled pose is varied in distance, normal to the surface, and over a range of surface angles, following a 2D sliding motion tangential to the surface (Table II). A subtlety for servoing over surfaces, is that the tool centre point needs tool centre point (TCP) needs to be adjusted so that the z-axis of the end-effector frame is coincident with the tip of the sensor (implemented in the CRI library as it was not available in the Dobot API).

The PoseNet models are trained on 75% of 5000 random poses (uniformly distributed), with test accuracies reported on the remaining 25%. Network hyperparameters are from ref. [10, Table II] without further tuning, except the input layers were changed to correspond to 160×120 pixel subsampled tactile images for the DIGIT and DIGIT-TacTip and 128×128 for the TacTip, with the latter two binarized using adaptive thresholding. Networks were trained over 100 epochs (∼30 minutes on a standard PC with 6Gb GPU).

The tactile sensors are compared both by the model performance on the edge and surface test data and by the deviation of the controlled trajectories from the known object shapes.

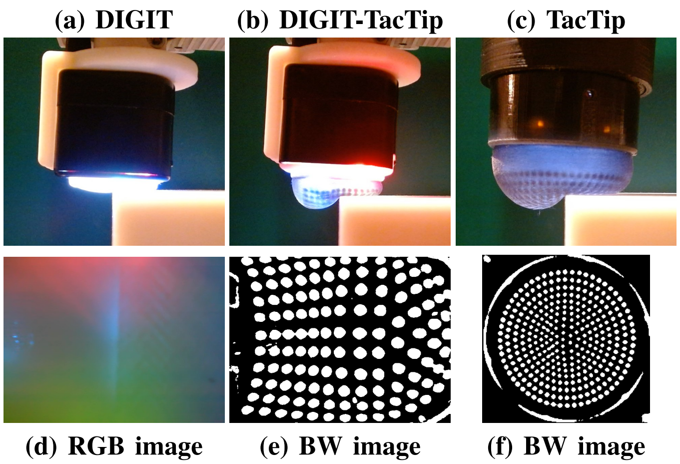

Figure 7: Top: views of the DIGIT, DigiTac and TacTip (round) pressing on an edge. Bottom: corresponding tactile iamges.

IV. RESULTS

A. Appraisal of DIGIT, DIGIT-TacTip and TacTip

For an initial qualitative comparison of the three optical tactile sensors, we pressed them against a 3D-printed straight edge and captured the tactile images (Fig. 7).

From the external appearance of the deformation, the DIGIT-TacTip and TacTip (Figs 7b,c) are much softer than the DIGIT (Fig. 7a), with a large compression of several millimeters over the contact region and a corresponding bulging of part of the sensing surface not in contact. In contrast, the DIGIT sensing surface is fairly stiff with about 1 mm deformation. The maximum compression of the TacTip is about 6-8 mm before damaged will occur and for the DIGIT about 1-2 mm.

Another difference is that the DIGIT sensing surface has higher friction than the DIGIT-TacTip and TacTip for similar contact forces. It is fairly easy to slide a DIGIT-TacTip or TacTip over 3D-printed surface with a slight texture, whereas the DIGIT tends to stick then slip.

From their tactile sensor images, the edge is clearly visible with the DIGIT as a shaded line located at the point of contact between the edge and sensor (Fig 7d). For the DIGIT-TacTip and DIGIT, one can infer where the edge is located by where the markers are more widely spaced (Fig 7e,f). Thus, it is more difficult to see edge location by eye; however, we will see later that the edge can be precisely localized by using a convolutional neural network on the entire tactile image.

The DIGIT is sensitive enough for the texture of the 3D-print to be just visible (Fig 7d, to right of edge). This information is absent from static touch with the DIGIT-TacTip and TacTip. In this respect, the DIGIT is superior to the human sense of touch: one cannot feel that the 3D-print is textured by statically holding a fingertip on the surface. (Instead, humans can feel fine texture by dynamically sliding a fingertip across the surface.)

B. Sensor Comparison using Edge Following

Next, we compare the tactile sensors on predicting edge position and angle under sliding contacts, then use this pose

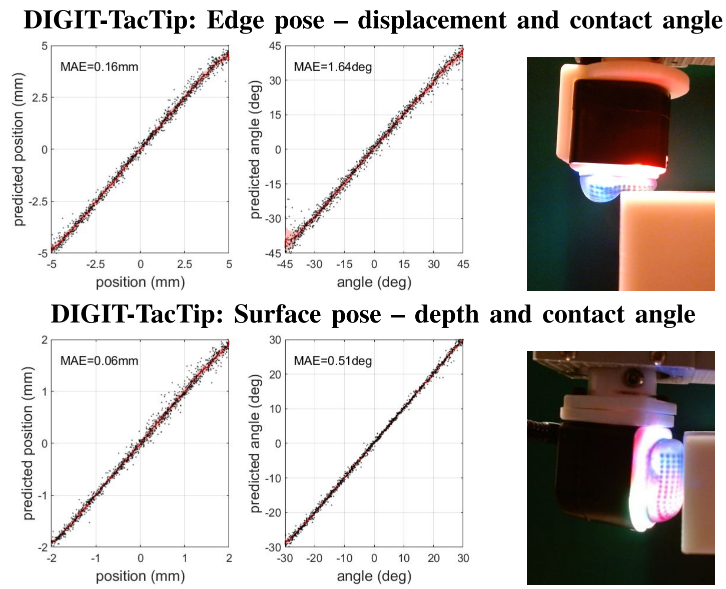

Figure 8: Pose prediction with the DigiTac. Top: edge displacement and angle. Bottom: surface depth and angle. Predictions are under random unknown sliding contacts (Table II).

Table III. Accuracy (MAE) of pose estimation for the DIGIT, DIGIT-TacTip and TacTip on straight edge and flat surface. Predictions are under random sliding contacts (Table II).

sensor	stimulus	position y MAE / range	angle MAE / range
DIGIT (Dobot MG400)	edge	0.19 mm / 10 mm	1.83° / 90°
	surface	NA	NA
DIGIT-TacTip (Dobot MG400)	edge	0.16 mm / 10 mm	1.64° / 90°
	surface	0.06 mm / 4 mm	0.51° / 60°
TacTip (Dobot MG400)	edge	0.16 mm / 10 mm	1.66° / 90°
	surface	0.11 mm / 4 mm	0.73° / 60°
TacTip (old) (ABB IRB120)	edge	0.23 mm / 10 mm	2.50° / 90°
	surface	0.12 mm / 4 mm	0.50° / 60°

model for tactile servo control around the edges of three test objects: a circular disk, square block and circular-wave.

For offline edge-pose prediction on the test data, both the DIGIT-TacTip and TacTip are similarly accurate with edge position to 0.16 mm and edge angle to $\sim$1.6° (Table III). These values are about 1.5% of the total ranges (10 mm and 90°), giving little scatter on plots of the predictions against ground truths (Fig. 8). It appears the smaller size of the DIGIT-TacTip and fewer markers (Table I) does not affect its capability for predicting edge pose. These results are better than when similar data was collected with an industrial (ABB) robot arm (Table III, bottom); however, that study used an older version of the TacTip with only 127 markers (rather than 331 here) which may be a factor in the lower accuracy [9], [10].

In comparison, the DIGIT gave similar accuracies for edge position (0.19 mm vs 0.16 mm) and angle (1.82° vs $\sim$1.6°) compared with the DIGIT-TacTip. To isolate the effects of sensor surface material and geometry from subsequent processing, we used the same neural network architectures and hyperparameters with binary tactile images for the DIGIT-TacTip and shaded images for the DIGIT. While these results could change with a different choices of neural networks, all accuracies are sub-mm and around 1-2 degrees, which

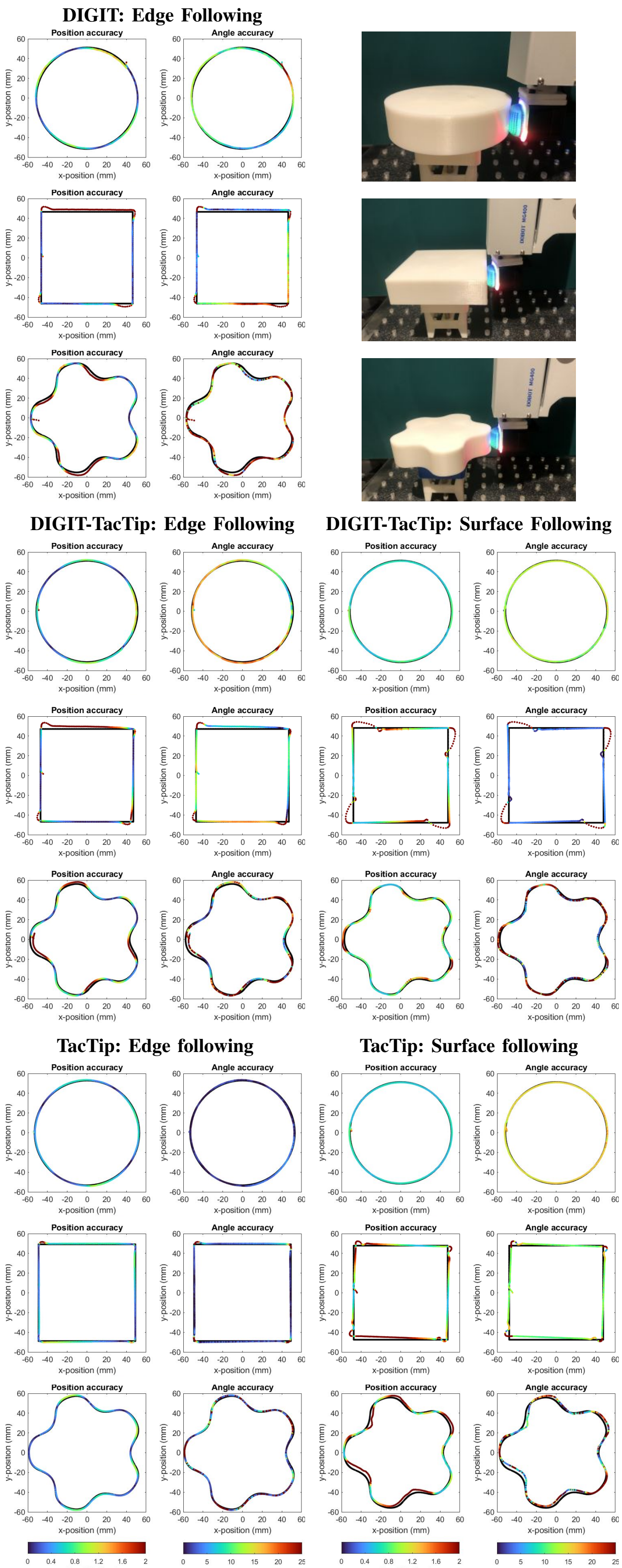

Figure 9: Edge and surface following with the DIGIT, DIGIT-TacTip and TacTip for the circular disk, square box and circular-wave shapes.

Table IV. Accuracy of edge and surface following for the DIGIT, DIGIT-TacTip and TacTip.

sensor	stimulus	shape	position MAE	angle MAE
DIGIT	edge	circle	0.6 mm	10.7°
	edge	square	0.9 mm	12.7°
	edge	circular-wave	1.2 mm	29.7°
DIGIT-TacTip	edge	circle	0.6 mm	15.1°
	edge	square	1.0 mm	15.0°
	edge	circular-wave	1.1 mm	26.2°
	surface	circle	0.7 mm	12.9°
	surface	square	1.5 mm	10.2°
	surface	circular-wave	1.0 mm	27.9°
TacTip	edge	circle	0.4 mm	1.6°
	edge	square	0.5 mm	4.6°
	edge	circular-wave	0.4 mm	19.6°
	surface	circle	0.6 mm	15.4°
	surface	square	1.5 mm	14.7°
	surface	circular-wave	1.6 mm	23.0°

are appropriate for the contour-following experiments reported below.

When applied to edge following on the three test shapes, the DIGIT, DIGIT-TacTip and TacTip all accurately traced around the shapes to sub-mm accuracy (Fig. 9, two left columns). For all three sensors and all three shapes, the mean absolute position errors were mainly sub-millimeter (Table IV, edge stimuli), with the most accurate being for the TacTip (0.4-0.5 mm) and the DIGIT and DIGIT-TacTip slightly less accurate (0.6-1.2 mm). In terms of tracing the shapes, the circular wave is most demanding, followed by the square (because of the corners) and the circle is the easiest. All position errors are larger than the test predictions ($\sim$0.15 mm), which was expected as the servo control task introduces factors such as the corners on the square and curves of the circular-wave that differ from the straight edges used in training.

The angle prediction performance showed more variability, and represents how accurately the sensor maintains normality to the edge during servoing (Fig. 9; Table IV). For just the circle and square, the TacTip was the most accurate ($\lesssim$5°) and the DIGIT and DIGIT-TacTip had similar angular errors of (10-15°). All sensors were inaccurate on the circular-wave (20-30°), which we attribute to the difficulty of contour following around the shape.

C. Sensor Comparison using Surface Following

Our other comparison of the tactile sensors is on predicting surface angle and contact depth under sliding, which is then used for tactile servo control to slide around the vertical walls of the three test objects.

For offline surface-pose prediction on the test data, both the DIGIT-TacTip and TacTip accurately predict surface pose, with the best predictions with the DIGIT-TacTip giving contact depth accurate to 0.06 mm and angle error to 0.5° (Table III). These correspond to 1.5% and $\sim$1% of the ranges (4 mm and 60°), giving little scatter on the prediction vs ground truth plots (Fig. 8). The accuracy in contact depth is similar to the repeatability (0.05 mm) of the dobot, which may be a limiting factor. These results are similar for angle and better for contact depth when using an industrial (ABB) robot arm and an older version of the TacTip (Table III, bottom).

For the DIGIT, we were not able to collect the same ranges of surface angle and contact depth data because of the flatter/stiffer sensing surface. Smaller ranges were considered, but we had concerns these would not lead to effective performance for surface following (and we damaged one sensor trying). Hence, we do not report surface results for the DIGIT.

When applied to surface following on the three test shapes, both the DIGIT-TacTip and TacTip had similar accuracy ranges of 0.6-1.5 mm, with the circle the most accurately traced at $\sim$0.5 mm error (Fig. 9, Table IV). Both sensors struggled to turn the corners of the square, and for the DIGIT-TacTip we needed to advance the angular set point to 5° for the task to complete. Like edge-following, the circular-wave was the most demanding shape to accurately trace. The angle errors were similar on both tactile sensors and are least for the circle and square (10°-15°) and largest on the circular-disk ($\sim 25^\circ$).

V. Discussion

In this paper, we introduced a new high-resolution optical tactile sensor that combines the base of low-cost DIGIT GelSight-type sensor with a 3D-printed soft biomimetic skin from the TacTip family of sensors. In keeping with the low-cost theme, we also introduced a low-cost desktop robot system to ease data collection for testing these tactile sensors and developing deep learning models. The DIGIT, DIGIT-TacTip and TacTip were compared on 2D-pose prediction of position and angle of a straight edge and flat surface under unknown shearing motion. We then implemented pose-based tactile servo control to delicately trace around the edges and vertical walls of several objects, to both demonstrate the capabilities of this tactile robot and compare sensor performance on real-time physical tactile control tasks.

Overall, all three optical tactile sensors performed well at pose prediction and pose-based tactile servo control, with pose-prediction accuracy of $\sim$0.1 mm and $\sim 1^\circ$, and servo control accuracy typically better than 1 mm. There was some biasing of contact angle during the servo control tasks, mainly for the DIGIT and DIGIT-TacTip sensors, but this did not affect the overall capability to follow edge and surface contours.

It turns out that the most significant differences between the sensors is their material properties and construction. The DIGIT sensing surface is flat and fairly inelastic compared to the soft curved sensing surface of the TacTip. GelSight-type sensors usually have flat sensing surfaces illuminated from the side with a molded elastomer, which are highly effective at imaging fine surface detail. In contrast, TacTip-type sensors come in various shapes and sizes (Fig. 2 and [8, Fig. 6]) with a flexible 3D-printed skin and compliance from a soft gel. For the servo control tasks considered here, a soft curved tactile sensor was more practical to fit into curved surface and have greater tolerance in safely contacting the object.

The robustness of the sensors also depends on their material properties and construction, which is important because touch involves contact with the potential for damage. Our tests were demanding because: (i) thousands of sliding contacts were needed to train the pose-prediction models; (ii) surface and edge following shears the sensor surface as it rubs against the object; (iii) surface following can also lead to collisions with the test object. During the tests, we broke one DIGIT-TacTip by ripping the skin where it joins the housing and one DIGIT by shearing off the elastomer from a collision.

To conclude, an aim of this work is to help open-up the field of high-resolution tactile sensing by providing more options to researchers to enter the field or innovate from existing knowledge. To this end, we will open-source the TacTip-DIGIT skin, components for the desktop tactile robot and software infrastructure including robot interface and libraries for the experiments. We will also release all data and models used in this paper. As a final comment, we encourage others in tactile robotics to adopt a similarly open perspective, and look forward to seeing versions of other optical tactile sensors combined with the DIGIT as we have done here.

Acknowledgements: We thank Mike Lambeta and Roberto Calandra for donating the DIGIT sensors.

References

[1] Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton. ImageNet Classification with Deep Convolutional Neural Networks. In *Advances in Neural Information Processing Systems*, volume 25. Curran Associates, Inc., 2012.

[2] Mike Lambeta, Po-Wei Chou, Stephen Tian, Brian Yang, Benjamin Maloon, Victoria Rose Most, Dave Stroud, Raymond Santos, Ahmad Byagowi, Gregg Kammerer, Dinesh Jayaraman, and Roberto Calandra. DIGIT: A Novel Design for a Low-Cost Compact High-Resolution Tactile Sensor With Application to In-Hand Manipulation. *IEEE Robotics and Automation Letters*, 5(3):3838–3845, July 2020.

[3] Roberto Calandra. DIGIT. http://www.digit.ml/.

[4] Mike Lambeta, Huazhe Xu, Jingwei Xu, Po-Wei Chou, Shaoxiong Wang, Trevor Darrell, and Roberto Calandra. PyTouch: A Machine Learning Library for Touch Processing. In *2021 IEEE International Conference on Robotics and Automation (ICRA)*, pages 13208–13214, May 2021.

[5] Shaoxiong Wang, Mike Maroje Lambeta, Po-Wei Chou, and Roberto Calandra. TACTO: A Fast, Flexible, and Open-source Simulator for High-resolution Vision-based Tactile Sensors. *IEEE Robotics and Automation Letters*, pages 1–1, 2022.

[6] Teaching robots to perceive, understand, and interact through touch. https://ai.facebook.com/blog/teaching-robots-to-perceive-understand-and-interact-through-touch/.

[7] B. Ward-Cherrier, N. Pestell, L. Cramphorn, B. Winstone, M. E. Giannaccini, J. Rossiter, and N. Lepora. The TacTip Family: Soft Optical Tactile Sensors with 3D-Printed Biomimetic Morphologies. *Soft Robotics*, 5(2):216–227, 2018.

[8] Nathan F. Lepora. Soft Biomimetic Optical Tactile Sensing With the TacTip: A Review. *IEEE Sensors Journal*, 21(19):21131–21143, October 2021.

[9] Nathan F. Lepora and John Lloyd. Optimal Deep Learning for Robot Touch: Training Accurate Pose Models of 3D Surfaces and Edges. *IEEE Robotics & Automation Magazine*, 27(2):66–77, June 2020.

[10] Nathan F. Lepora and John Lloyd. Pose-Based Tactile Servoing: Controlled Soft Touch Using Deep Learning. *IEEE Robotics & Automation Magazine*, 28(4):43–55, December 2021.

[11] Nathan F Lepora, Chris Ford, Andrew Stinchcombe, Alfred Brown, John Lloyd, Manuel G Catalano, Matteo Bianchi, and Benjamin Ward-Cherrier. Towards integrated tactile sensorimotor control in anthropomorphic soft robotic hands. In *2021 IEEE International Conference on Robotics and Automation (ICRA)*, pages 1622–1628. IEEE, 2021.

[12] M. K. Johnson and E. H. Adelson. Retrographic sensing for the measurement of surface texture and shape. In *IEEE Conference on Computer Vision and Pattern Recognition*, pages 1070–1077, 2009.

[13] Wenzhen Yuan, Siyuan Dong, and Adelson Adelson, Edward H. GelSight: High-Resolution Robot Tactile Sensors for Estimating Geometry and Force. *Sensors*, 17(12):2762, 2017.

[14] Daniel Fernandes Gomes, Zhonglin Lin, and Shan Luo. GelTip: A Finger-shaped Optical Tactile Sensor for Robotic Manipulation. In *2020 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pages 9903–9909, Las Vegas, NV, USA, October 2020. IEEE.

[15] Branden Romero, Filipe Veiga, and Edward Adelson. Soft, Round, High Resolution Tactile Fingertip Sensors for Dexterous Robotic Manipulation. In *2020 IEEE International Conference on Robotics and Automation (ICRA)*, pages 4796–4802, Paris, France, May 2020. IEEE.

[16] Wenzhen Yuan, Chenzhuo Zhu, Andrew Owens, Mandayam A Srinivasan, and Edward H Adelson. Shape-independent hardness estimation using deep learning and a gelsight tactile sensor. In *2017 IEEE International Conference on Robotics and Automation (ICRA)*, pages 951–958. IEEE, 2017.

[17] Kazuto Kamiyama, Kevin Vlack, Terukazu Mizota, Hiroyuki Kajimoto, K Kawakami, and Susumu Tachi. Vision-based sensor for real-time measuring of surface traction fields. *IEEE Computer Graphics and Applications*, 25(1):68–75, 2005.

[18] Xi Lin, Laurence Willemet, Alexandre Bailleul, and Michaël Wiertlewski. Curvature sensing with a spherical tactile sensor using the color-interference of a marker array. In *2020 IEEE International Conference on Robotics and Automation (ICRA)*, pages 603–609. IEEE, 2020.

[19] Carmelo Sferrazza and Raffaello D'Andrea. Design, motivation and evaluation of a full-resolution optical tactile sensor. *Sensors*, 19(4):928, 2019.

[20] Lunwei Zhang, Yue Wang, and Yao Jiang. Tac3d: A novel vision-based tactile sensor for measuring forces distribution and estimating friction coefficient distribution. *arXiv preprint arXiv:2202.06211*, 2022.

[21] Nicholas Pestell, Thom Griffith, and Nathan F Lepora. Artificial sa-i and ra-i afferentsfor tactile sensing of ridges and gratings. *Journal of the Royal Society Interface*, 2021.

[22] N. F. Lepora, A. Church, C. de Kerckhove, R. Hadsell, and J. Lloyd. From Pixels to Percepts: Highly Robust Edge Perception and Contour Following Using Deep Learning and an Optical Biomimetic Tactile Sensor. *IEEE Robotics and Automation Letters*, 4(2):2101–2107, 2019.

[23] John Lloyd and Nathan Lepora. Goal-Driven Robotic Pushing Using Tactile and Proprioceptive Feedback. *IEEE Transactions on Robotics*, pages 1–12, 2021.

[24] Efi Psomopoulou, Nicholas Pestell, Fotios Papadopoulos, John Lloyd, Zoe Doulgeri, and Nathan F Lepora. A robust controller for stable 3d pinching using tactile sensing. *IEEE Robotics and Automation Letters*, 6(4):8150–8157, 2021.

[25] Alex Church, John Lloyd, Raia Hadsell, and Nathan F. Lepora. Tactile Sim-to-Real Policy Transfer via Real-to-Sim Image Translation. In *Proceedings of the 5th Conference on Robot Learning*, pages 1645–1654. PMLR, January 2022.