A Low-Cost Tactile Fingertip Design for Dexterous Robotic Hands

Zhuowei Xu, Zilin Si, Kevin Zhang, Moonyoung Lee, Shashwat Singh, Oliver Kroemer, and Zeynep Temel

***Abstract*—Touch sensing is a key modality that humans rely on to perform dexterous manipulation tasks in complex environments. However, most robotic hand systems lack tactile sensors due to their high cost, integration challenges, and limited reliability and robustness. In this work, we present a low-cost, bio-inspired tactile fingertip design for robotic hands. The proposed design utilizes strain gauges and a contact microphone to capture static and dynamic contact information. In addition, the design features a fingernail that enhances the manipulation of small objects and serves as a vibration-sensitive medium to improve dynamic contact detection. The fingertip is compact with a minimal sensor footprint and can be easily customized to be mounted on various robotic hands. Through sensor characterization, we demonstrate the system's high repeatability within a range of 0–5 N detection on 2D planar forces, as well as its ability to reliably distinguish between different materials. This fingertip design offers a simple yet effective solution for tactile sensing in robotic hands, enabling fine and dexterous manipulation.**

***Index Terms*—Tactile Sensing, Dexterous Manipulation, Bio-Inspired Robot Design**

I. Introduction

The human hand exhibits exceptional manipulation capabilities [1], which are attributed not only to its anatomical structure, but also to its rich tactile sensing [2]. Studies in individuals with tactile sensory loss have shown that, although vision remains functional, the absence of tactile feedback leads to significant impairments in motor accuracy and speed, particularly in hand-related tasks [3]. In the domain of robotics, although robotic hands have been widely developed with demonstrated capabilities of dexterous manipulation, many robotic hand systems lack tactile sensing capabilities and rely solely on visual input to close the control loop [4]. Visual information can offer a rich environmental context that can be used by the robot to reason and infer high-level plans [5]. However, vision is typically downscaled to lower resolutions for real-time inference and must deal with occlusions and large changes in camera position during manipulation. This can interfere with inferring nuanced interaction dynamics such as contact forces, slippage, and subtle deformations during manipulation. The use of tactile sensors addresses these limitations by providing detailed and rich contact feedback.

Although there is a variety of tactile sensor development in the literature, it can be challenging to integrate these tactile sensors into robotic hands. Piezoelectric, piezoresistive and magnetic sensors [6], [7], [8], [9], [10], [11], [12], [13] have shown high sensitivity in a compact form factor that is beneficial for use with robotic hands; however, they are difficult to manufacture and can only detect single types of contact. On the other hand, off-the-shelf sensors such as optical sensors [14], [15] have been widely applied in robotic systems given their high-dimensional readings, but these sensors are often large in size, expensive to process the data, and require frequent skin maintenance, which makes them ill-suited for multi-finger settings. Instead, inspired by human hands, we present a fingertip design for robotic hands with multimodal tactile sensing abilities. We embed strain gauges and a contact microphone into a simple fingertip structure. These sensors are low-cost, easy to use and have small footprints that allow for a compact fingertip design. Strain gauges can sense static forces, while contact microphones can pick up vibrations and infer dynamic contacts. The combination of these two types of sensors enables multimodal tactile sensing ability to handle complex contact scenarios induced inherently from dexterous manipulation.

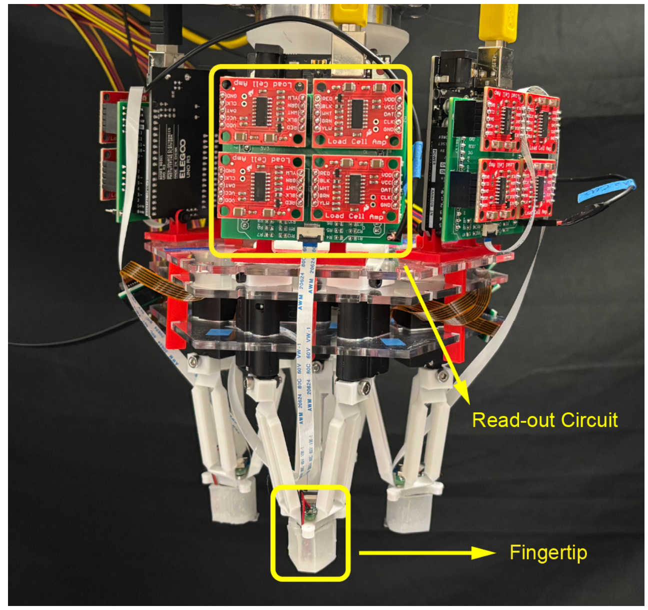

Fig. 1. We equip a DeltaHand [16] with our proposed tactile fingertips: Each fingertip integrates strain gauges and a contact microphone to enable multimodal tactile perception of both static forces and dynamic interactions. A flat flexible cable (FFC) transmits combined signals from the fingertip's sensors to an external read-out circuit for sensor reading amplification and data acquisition.

Therefore, we introduce a novel fingertip design as a simple yet effective solution to equip robotic hands with tactile sensing capabilities (Fig. 1). Inspired by the mechanical and sensory functionalities of the human hand, our design

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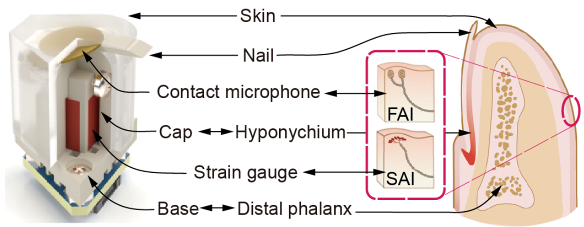

Fig. 2. Bio-inspired design of the fingertip: Structurally, the rigid fingernail corresponds to the keratin layer of the human fingernail, while the soft gel mimics the compliance of human skin, the cap mimics the hyponychium, and the base represents the distal phalanx. In terms of sensing functionality, the strain gauges emulate the role of slow adapting (SAI) mechanoreceptors, responsible for detecting sustained pressure, while the contact microphone replicates the function of fast adapting (FAI) mechanoreceptors, which are sensitive to dynamic tactile events such as vibrations and slip.

incorporates strain gauges and a contact microphone to achieve multimodal perception of both static force and dynamic interactions. The fingertip is compact (1.9cm$\times$1.9cm$\times$2.7cm), highly repeatable, and cost-effective (under \$100), while exhibiting structural and perceptual characteristics analogous to the human fingertip. Our contributions are summarized as follows:

- We design a compact, bio-inspired fingertip for improved manipulation of both rigid and deformable objects and a rigid fingernail that enhances vibration signal transmission to the contact microphone.
- We implement a multimodal sensing system by combining strain gauges and a contact microphone, enabling simultaneous detection of static forces and dynamic contact events.
- We validate the system performance through extensive characterization and demonstrate its reliability, data interpretability, and applicability to texture classification and dexterous manipulation tasks.

II. Methodology

We design a novel fingertip for robotic hands that is inspired by the human fingertip (Fig. 2). The design integrates functional structure (including rigid fingernail and soft skin) with sensors for multimodal contact perception into a single compact structure.

A. Fingertip design

As shown in Fig. 3, the fingertip structure consists of 1) a triangular base, 2) a compliant square prism, 3) a rigid cap with a rigid fingernail, and 4) a soft skin layer from bottom to top, inside to outside. The triangular base and the square prism are printed together with multimaterial on Raise 3D E2. The base is printed with soft TPU, while the prism is printed with a rigid PLA core. The rigid core can reduce the hysterisis induced by the soft material while having enough flexibility for strain gauge sensors. The soft skin layer is made of silicone rubber and molded over the cap.

The triangular base is used to mount the PCB for sensor data acquisition and as a structural interface to mount it on the robotic finger. The square prism is used to attach the strain gauge sensors. The cap is used to attach the contact microphone and transmit the vibration from the external contact on the fingernail to the contact microphone. The fingernail extends 1 mm beyond the skin surface to catch the edges of the objects. Finally, the soft skin layer provides more compliance and friction to increase the stability of the grip.

The overall structure maintains a compact form factor and can be adapted to the robotic hand fingers. It can be easily manufactured and reproduced in batches at low cost.

B. Strain gauge sensor

We use strain gauge sensors to sense 2-DoF normal forces applied on the surface of the fingertip. During the manufacturing of the fingertip, four strain gauges are affixed to the lateral surfaces of the square prism before putting the cap on it. An M2 screw rigidly secures the cap to the top of the square prism with a 1 mm gap on all sides, which allows the prism to bend freely under external contact forces. This deformation induces strain in the affixed sensors, which is further transduced into electrical signals. To account for the 3D geometry of the fingertip and the varying contact heights, we use four strain gauges rather than two to improve the estimation accuracy of the force direction.

C. Contact microphone sensor

We use a contact microphone sensor to detect dynamic contact events such as sliding. The sensor is rigidly attached to the top of the cap and is close to the fingernail. When the fingernail is in contact with an object and under lateral motions, the vibration generated from the motion is transmitted through the rigid material of the cap, captured by the sensor, and then transduced to electrical signals and used for frequency domain analysis.

D. Read-out circuit

A tiny custom PCB is designed to match the fingertip's footprint, interface with the sensors for data read-out, and is mounted beneath the structure using M2 screws. This PCB board takes signal inputs from both the strain gauges and the contact microphone and outputs them through a unified output port. The combined signal is then transmitted through a flat flexible cable (FFC), for a clean and reliable cable routing.

The FFC cable is then connected to another custom PCB (Fig. 1) for sensor reading amplification and analog-to-digital conversion. The signals from the contact microphone are amplified with a pre-amp. A Wheatstone bridge of standard configuration is used to read the resistance change of strain gauges and convert them into measurable differential voltage. The differential output of the bridge is then fed into an HX711 module for signal amplification and analog-to-digital conversion. The resulting digital signal is then transmitted to a PC via an Arduino and USB interface.

E. Fingertip fabrication

The fingertip fabrication procedure can be seen in Fig. 3 (a).

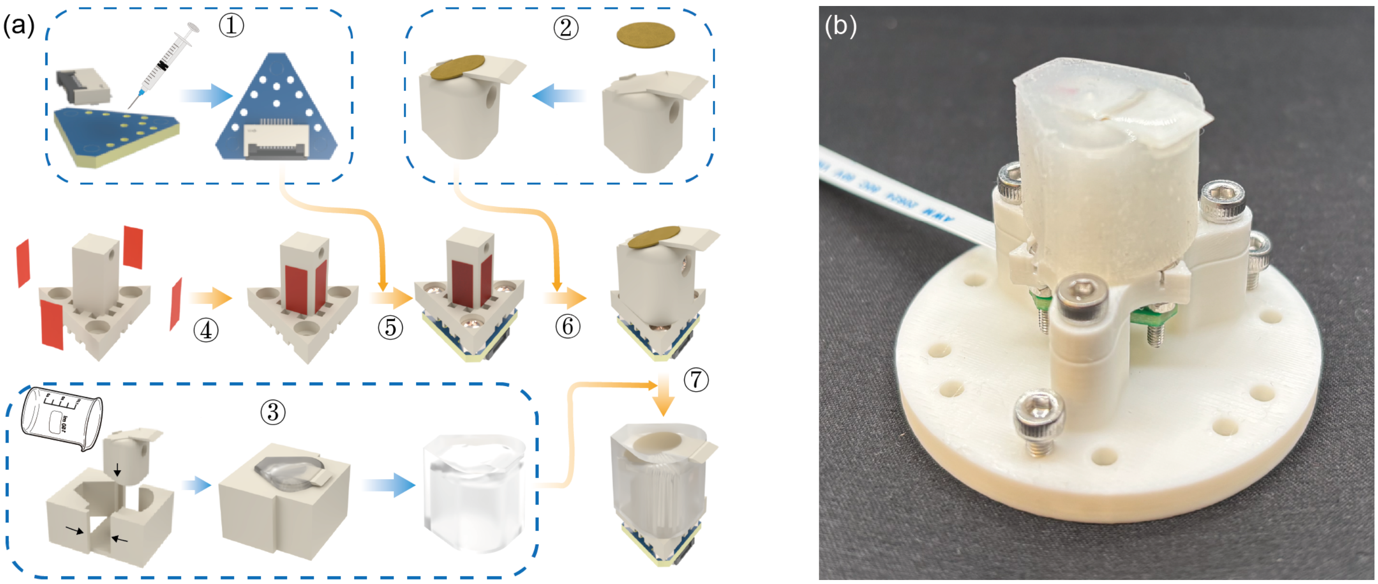

Fig. 3. The fabrication procedure, assembly, and final prototype of the fingertip. (a) Fingertip fabrication: ① Soldering the connector and the pcb; ② attaching the contact microphone on the top of the 3D printed cap using super glue; ③ making a soft skin for the cap using 3D printed mold and soft silicone (Mold Star 20T); ④ attaching four strain gauges on each side of sensor base; ⑤ mounting the pcb onto base by M2 screws and soldering the cable of contact microphone and strain gauges to the pcb; ⑥ Assembling the cap and the base by a M2 acrew; ⑦ placing the soft skin over the cap. (b) Final assembled fingertip prototype

We fabricate the fingertip by 3D printing a PLA-TPU hybrid base using a Raise3D printer and printing the cap and nail with PLA on a Bambu Lab printer. Strain gauges are bonded to the four sides of the square prism on the base, and a contact microphone is glued to the top of the cap. The cap is then assembled onto the prism and secured with an M2 screw.

The PCB is prepared by soldering the connector and wiring the strain gauges and microphone. Then it is mounted beneath the base of the fingertip. The soft silicone skin is molded using Mold Star 20T and applied to the sensorized cap after curing.

Excluding skin curing time, the entire process takes around 30 minutes and the total cost is less than \$100. The fingertip base can be customized for various robotic hands, making the design scalable and batch-producible.

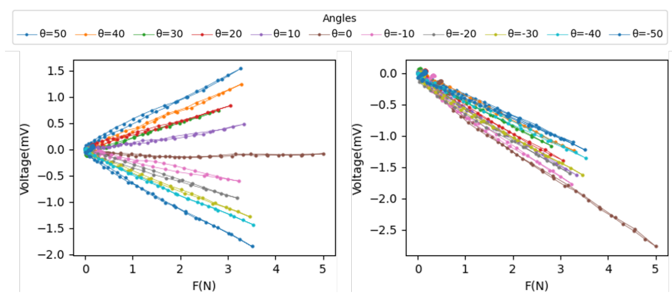

Fig. 4. Voltage response of strain gauges under varying force and angular conditions. (a) Strain gauge aligned parallel to the force direction. (b) Strain gauge aligned perpendicular to the force direction.

III. Experiments

To demonstrate the proposed fingertip capability for multimodal perception, we performed experiments of force estimation with strain gauge sensors and material classification with the contact microphone sensor. In addition, we show the application of using four tactile fingertips with a DeltaHand, and conduct a earphone flipping manipulation task which benefits from the novel structure and sensing capability of the design.

A. *Force estimation with strain gauges*

We evaluate the sensitivity and accuracy of force estimation from strain gauge sensor readings.

As the experimental setup, we use a UR5 robotic arm with a customized end-effctor (including a 3 mm cylindrical indenter) to actively interact with a fixed fingertip. The fingertip is rigidly mounted on top of a 6-DOF force torque sensor, which provides the ground-truth force readings. During data collection, the robot operated in *remote control* mode and followed a predefined trajectory.

During each data collection trial, the end effector incrementally indented the fingertip in the XY plane with a step size of 1.5 mm, continuing until a total displacement of 30 mm was reached, followed by retraction along the same path. At each step, the robot paused for 8 seconds to allow the system to stabilize before recording sensor values. This procedure was repeated in multiple angular orientations in the XY plane (from -50° to 50° in increments of 10°), and at varying contact heights along the Z-axis (from 0 mm to 5 mm in increments of 1 mm), with the fingernail tip defined as the zero reference point. To reduce sampling bias and ensure trial independence, the indentation angles and contact heights were randomized prior to each run.

We show the mapping between the raw sensor readings and the forces with the stepping input in Fig. 4. From the results, we show that at each fixed angle, the relationship between

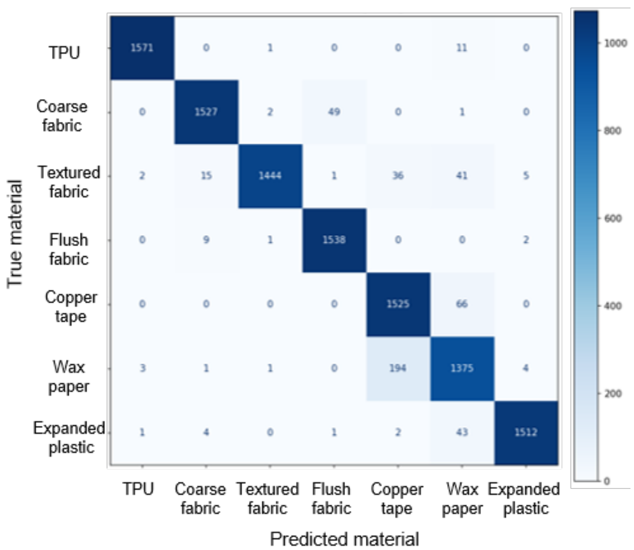

Fig. 5. Confusion matrix for material classsification: having an overall accuracy of 95.49% for 7 different materials. The primary source of misclassification was between *Copper Tape* and *Wax Paper*, likely due to the resemblance in their smooth surface characteristics.

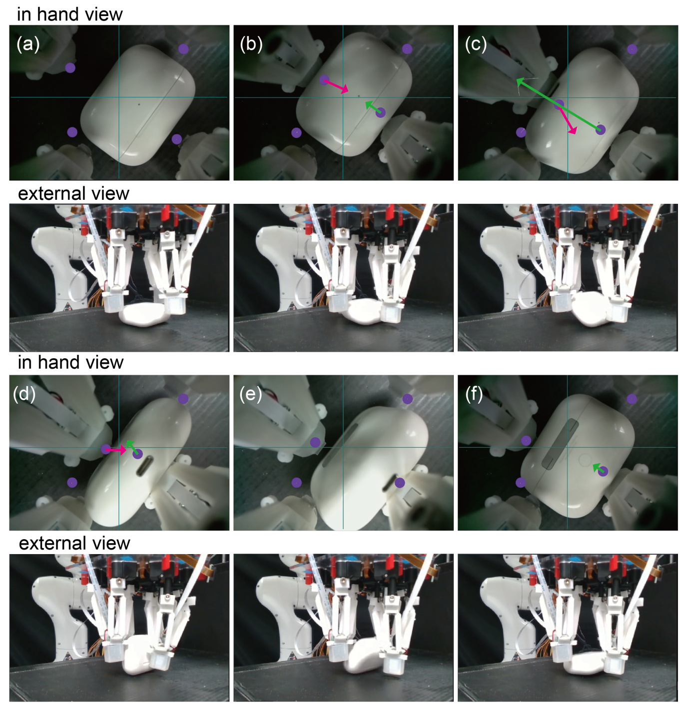

Fig. 6. Flip an AirPod case with a DeltaHand equipped with sensorized fingertips: (a) initial state with no contact; (b) insert the fingernail under the bottom edge of the case to establish contact; (c) raise the finger to hook and flip the case upward from its resting position; (d) manipulate the top of the case to bring it into an upright position; (e) move the opposite finger outward, allowing the case to naturally fall back against it; (e) final state where the case is flipped 180 degrees.

applied force and measured voltage remains approximately linear. Although some observable hysteresis is present in both configurations, it does not significantly compromise the linearity of the response, suggesting that reliable force estimation is still achievable under moderate dynamic conditions.

We then used the collected data to train a force estimator using a multilayer perceptron (MLP) network. The network successfully captured the underlying nonlinearities and angle-dependent variations in the signal. The resulting model achieved a mean squared error (MSE) of approximately 0.15 N^2, demonstrating its effectiveness in accurately estimating force from multichannel strain gauge voltage inputs.

B. Material classification with contact microphone

Contact microphone is sensitive to the vibration generated by dynamic interaction. We evaluated the efficacy of using the contact microphone sensor in material classification.

We use a set of seven materials including *TPU*, *Expanded Plastic*, *Copper Tape*, *Coarse Fabric*, *Flush Fabric*, *Wax Paper*, and *Textured Fabric*. We customize the end-effector of a UR5 and mount samples of these materials on different faces. For each material, we control the UR5 arm to rotate to its correponding sample, approach the fingernail, and slide perpendicularly to the fingernail while maintaining the contact.

We collect the raw audio signals during the sliding, and for each material, we collect 7000 data samples. For material classification, we first use Fast Fourier Transform (FFT) to transform the raw data from the time domain to the frequency domain. Then we train a multilayer perceptron (MLP) classifier by using the spectrograms as inputs and outputs a 7D vector as the material prediction probability.

Fig. 5 presents the confusion matrix of the classification results. The classifier achieved an overall accuracy of 95.49%, demonstrating strong performance in material discrimination. Most misclassifications occurred between *Copper Tape* and *Wax Paper*, likely due to the similarity in their smooth surface textures despite their different material compositions.

C. Application on manipulation tasks

We mounted four fingertips on a DeltaHand [16] and performed an in-hand object reorientation task by teleoperation [17]. To assist the operator, the predicted 2D forces from fingertips are visualized in real time on the graphical interface during teleoperation. Using only a pair of opposing fingers, we can successfully perform the task of flipping an AirPod case. Fig. 6 illustrates the six key frames of the flipping task, where the arrows labeled in in-hand view indicate the direction and magnitude of the contact forces.

IV. Conclusion

In this work, we present a low-cost, bio-inspired tactile fingertip design for robotic hands. By integrating strain gauges and a contact microphone, the fingertip enables multimodal sensing of both static force and dynamic interactions. Through characterization, we demonstrate that the fingertip is capable of estimating 2D planar forces within the range of 0–5 N and classifying different materials during sliding interaction with an accuracy of 95.49%. In the future, we aim to incorporate tactile sensing into the control loop of the robotic hands to achieve manipulation tasks with high precision requirement.

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