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TacLight: A Six-Axis Soft Optical Tactile Sensor for Physical and Virtual Interaction

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Abstract

Tactile sensing is a fundamental enabler of robust interaction in environments characterized by dense and uncertain contacts. Yet, existing tactile sensors remain far from human inspiration: they are often mechanically rigid or restricted in the richness of the signals they provide. This paper aims to make a step towards solving this challenge by introducing TacLight: a compact, camera-free optical tactile sensor capable of detecting all six independent force/torque components—normal, shear, torsional, and twisting forces. The sensor is also capable of localizing the contact point. The sensing principle relies on infrared LEDs that emit light through a transparent porous elastomer, while a thin white reflective layer on top enhances light reflection, with distributed photoresistors registering transmitted intensities. Deformations of the porous medium perturb internal light paths, producing direct variations in the electrical output that encode contact mechanics without computationally heavy reconstruction. TacLight achieves high sensitivity (100 mV/N in the 0–3 N range), maintains excellent linearity ($R^2 > 0.95$) with a 10 mm elastomer layer, and preserves a compact, low-cost, and scalable architecture. Two demonstrations highlight TacLight’s versatility. In human–machine interaction, a joystick-like device enables intuitive drone control in a simulation environment. In robotic manipulation, tactile feedback improves the success rate of an imitation-learning-based peeling task compared with a baseline without tactile sensing.

Keywords: tactile sensing, light-based tactile sensor, human-robot interaction (HRI), imitation learning, soft sensor, control of soft robots

1 Introduction

Tactile sensing is essential for enabling robots to interact intelligently and safely with the physical environment [1, 2]. Unlike vision or hearing, tactile feedback provides direct and local information about contact events, for instance, how and where a robot physically interacts with objects, tools, or humans. This immediate sensing is critical for grasping [3–5], object recognition [6–9], and collaborative tasks [10, 11], where responsiveness and adaptability are key to performance.

As robotic systems become more autonomous and interactive, the demand for compact, responsive, and multimodal tactile sensors continues to grow. An ideal tactile sensor should be able to detect multiple wrench components (normal, shear, and torsional) while maintaining a soft form factor, a fast response time, and ease of integration. To meet these demands, a wide range of tactile technologies have emerged, including resistive [12–17], capacitive [18–21], barometric [22–25], and magnetic [7, 26–30]. Current tactile sensors are often limited in the types of deformation they detect. Many are optimized for normal or shear forces but overlook torsional interactions forces that are prevalent in natural tasks such as twisting, turning, or slip detection [31, 32].

This paper concerns itself with an interesting subclass of tactile sensors, which we believe holds the promise of solving this challenge: light-based ones - both optical [33–39] and vision-based [40–46]. They offer high sensitivity and detailed feedback by measuring how light paths change within a deformable medium under contact. However, existing devices rely on rigid optical paths or calibrated components (for optical) or even full-fledged internal cameras (for vision-based) - thus strongly limiting their flexibility and often resulting in large form factors, high power consumption, and slow processing.

A central limitation of current multimodal optical tactile sensors is that the material does not intrinsically encode how deformation affects the sensed signal. Most systems rely on geometric reconstruction, image processing, or learned models to infer forces, rendering the sensor a passive transducer whose interpretation is entirely dependent on external computation. This work introduces TacLight, a camera-free optical sensor that leverages distributed scattering in a porous elastomer to provide multi-axis tactile feedback in a fully soft and compact form factor.

To overcome the limitations mentioned above, we introduce *TacLight* (Figure 1), a compact, soft, and camera-free optical tactile sensor capable of resolving six independent deformation modes (shear, torsion, compression, and bending) and mapping them to the corresponding forces and torques. The architecture combines a porous elastomeric layer with a custom-printed circuit board (PCB) hosting arrays of infrared emitters and receivers. Contact-induced deformations of the porous medium alter the light transmission paths within the elastomer, generating distinct optical signatures for different modes of touch. As is often the case in soft robotics, the deformable structure

plays a dual role: it enhances sensitivity by producing large, tunable light modulation while ensuring the softness and compliance required for safe interaction. This capability arises because volumetric scattering physically encodes deformation direction and magnitude within the material, eliminating the need for geometric reconstruction.

Additionally, we highlight the versatility of TacLight through two substantially different applications. Firstly, we present a soft joystick integrating TacLight and demonstrate its use for intuitive drone control in a simulated environment. Secondly, we employ TacLight as a robotic tactile sensor in a food preparation task, where its output is integrated into an imitation learning architecture to teach robust yet gentle peeling operations (Figures 1D and E).

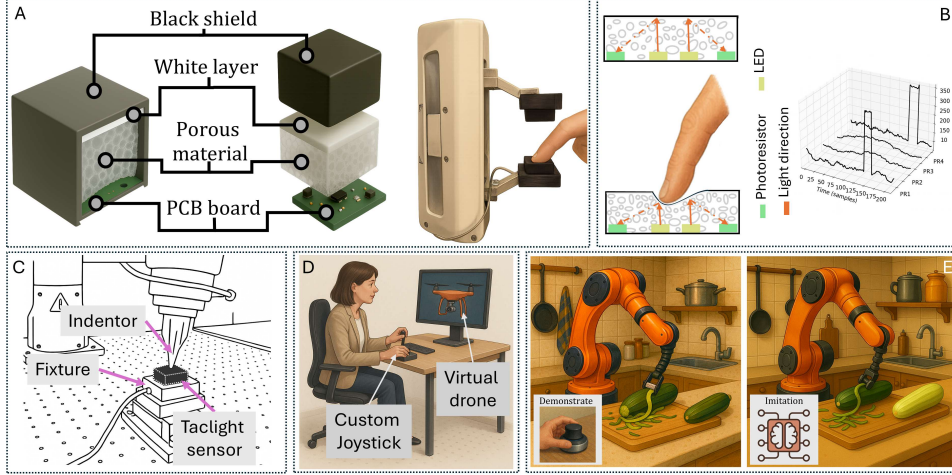


Fig. 1 Overview of the TacLight sensor and its applications. (A) Sensor design with assembled and exploded views, showing the transparent porous elastomer with a thin white reflective layer on top, integrated on a custom PCB, and enclosed by a black silicone shield. (B) Working principle, where deformation of the porous elastomer modulates infrared light propagation toward photoreceptors. (C) Contact-detection setup used to identify where the finger touches the TacLight surface. (D) Human-machine interaction, in which a TacLight-based joystick enables real-time control of a virtual drone in a game environment. (E) Human-robot interaction through imitation learning, where TacLight enables skill transfer for a contact-rich peeling task.

2 Results

We evaluate TacLight’s performance through controlled characterization experiments and two human-centered demonstrations. Section 2.1 introduces the sensor’s architecture and operating principle, followed by its characterization of six-axis deformation sensing in Section 2.2, and the capability of independently localizing a contact in Section 2.3.

We then demonstrate two examples of TacLight’s usage: (i) in real-time interaction for virtual drone control (Section 2.4) and (ii) in enabling a robot to acquire a force-aware peeling skill via imitation learning (Section 2.5).

2.1 Sensor Architecture and Sensing Mechanism

TacLight builds on a simple yet powerful principle: a soft medium serves as both a structural support and an optical channel. The key idea is to use the porous elastomer itself as the optical transduction medium, rather than relying on rigid optics or imaging. Local deformation perturbs the internal scattering field, producing mode-specific intensity changes at the receivers. Unlike marker tracking or waveguide deformation, porous scattering does not require geometric reconstruction. Because deformation alters scattering density and photon path-length distributions throughout the volume, each mechanical mode imprints a unique spatial modulation of light intensity. Compression yields symmetric attenuation, shear introduces directional gradients, and torsion induces rotational asymmetry. These structured optical fields arise within the material itself and are directly measurable at the photoresistors, providing intrinsic multi-axis encoding.

Infrared light is injected into this medium, and any local deformation perturbs its internal transmission paths (See Figure 1B). These perturbations generate distinct intensity variations at distributed detectors, which can be directly correlated with the underlying deformation through supervised calibration.

We implemented this principle in a compact design via three main components: (i) the deformable medium, a transparent porous silicone structure topped with a thin white reflective layer ($20 \times 20 \times 10$ mm), (ii) a thin black coating, shielding the sensing layer from environmental light, and (iii) a custom PCB (14×14 mm) with four radially arranged infrared (IR) LEDs¹ and four photoresistors (PR)² positioned at the PCB corners (Figure 1C).

When pressed, slid, or twisted, the porous matrix alters the light’s scattering and absorption within the medium. These changes modulate the intensity of IR light reaching each photoresistor, generating characteristic signal patterns that reflect both the direction and magnitude of the applied force. The symmetrical placement of LEDs and photoresistors ensures uniform coverage, allowing each interaction to produce a unique and distinguishable signal profile, which reflects the physically encoded differences among deformation modes.

The selected wavelength of the LEDs, at 940 nm, lies outside the visible spectrum, making them less sensitive to environmental lights and ensuring stable operation under different lighting conditions. With a wide viewing angle of 140° , the LEDs provide uniform coverage across the sensing layer while operating at low power. These properties make them well-suited for long-term use in portable or embedded robotic systems where energy efficiency is critical. In contrast to vision-based tactile sensors, which depend on high-resolution imaging and computationally intensive processing, TacLight offers a compact and efficient alternative. Sampling analog signals at 100 Hz delivers continuous, low-latency feedback. The porous silicone layer further enhances perconducted to demonstrateing light evenly, resulting in consistent responses without adding design complexity. Full details of the fabrication process, including material selection, mold design, layer assembly, and optoelectronic integration, are provided in the Supporting Information.

¹(15406094BA400A, 940 nm, Würth Elektronik)

²(1540601NBA500, 940 nm, Würth Elektronik)

2.2 Characterization of Six Independent Deformation Modes

The sensing performance of TacLight was evaluated under six independent deformation modes, including normal, shear, torsional, and twist forces around three axes (Figure 2). These experiments examined how reliably the sensor can distinguish different types of contact and how consistently it responds to changes in magnitude and direction. The setup, shown in Figure 2A, combined a Thorlabs NRT150/M linear stage for applying controlled normal and shear displacements with a Dynamixel motor (XM430-W210-R) for generating twisting about the yaw axis. The sensor was mounted on a 3D-printed holder that ensured precise alignment and mechanical stability and was coupled to a six-axis SensONE force/torque (F/T) sensor used as a reference. Motions were applied at a velocity of 5 mm/s and an acceleration of 5 mm/s² (Kinesis software, Thorlabs) to provide smooth and repeatable loading. Signals from the four photoresistors embedded in the sensing layer (PR1–PR4) were sampled through a 12-bit Analog-to-Digital Converter (ADC) at 100 Hz without filtering to preserve the full temporal response.

To assess 6D sensing capabilities, two main 3D-printed indenters were used, one with a flat surface and another with a 30-degree angled tip. The flat-surfaced indenter was used to test normal force (Fz), shear forces (Fx, Fy), and twisting moment (Mz). For Fz, the indenter was placed 2 mm above the sensor and moved 7 mm downward, resulting in a 5 mm displacement into the sensor. For shear (Fx, Fy), the indenter was slid 5 mm in both positive and negative directions. First, shear was applied along the x-axis, and then the sensor was rotated 90 degrees to apply shear along the y-axis. For twisting (Mz), the sensor was mounted on a base controlled by the Dynamixel motor, with a preload of 0.5 N to ensure firm contact between the sensor and the indenter. The motor was then rotated 40 degrees in both directions, applying twisting to the sensor.

After testing twisting (Mz), the indenter was swapped for the angled version, which was placed 2 mm above the TacLight sensor and moved 12 mm down to apply shear forces. The same procedure was repeated for Mx and My, where the indenter applied shear force. After each test, the indenter was rotated to test all four directions, ensuring thorough testing of the sensor’s response to shear forces.

Each deformation mode was tested independently. As shown in Figure 2B, the voltage outputs followed clear and characteristic patterns across all directions. Normal indentation (Fz) produced symmetric signal changes across the four channels, while shear along the x and y axes (Fx and Fy) caused polarity reversals between opposite photoresistors, revealing the direction of motion. Rotational deformations (Mx, My, and Mz) generated phase-dependent variations that remained stable over repeated trials and were clearly distinct from translational responses. The calibration curves in Figure 2C show linear relations between the applied loads and measured voltages, with coefficients of determination of $R^2 = 0.975$ for Fz, 0.967 for Fx, 0.958 for Fy, 0.991 for Mx, 0.986 for My, and 0.911 for Mz. The slightly lower linearity in twisting is attributed to the complex light-scattering paths formed during rotational deformation, whereas all other modes exhibit highly linear behavior above 0.95.

During static characterization, we also quantified the intrinsic electrical noise of the four channels over a 10-second duration without mechanical loading (Supplementary Figure S5). A histogram of the raw signal values and the corresponding summary Table

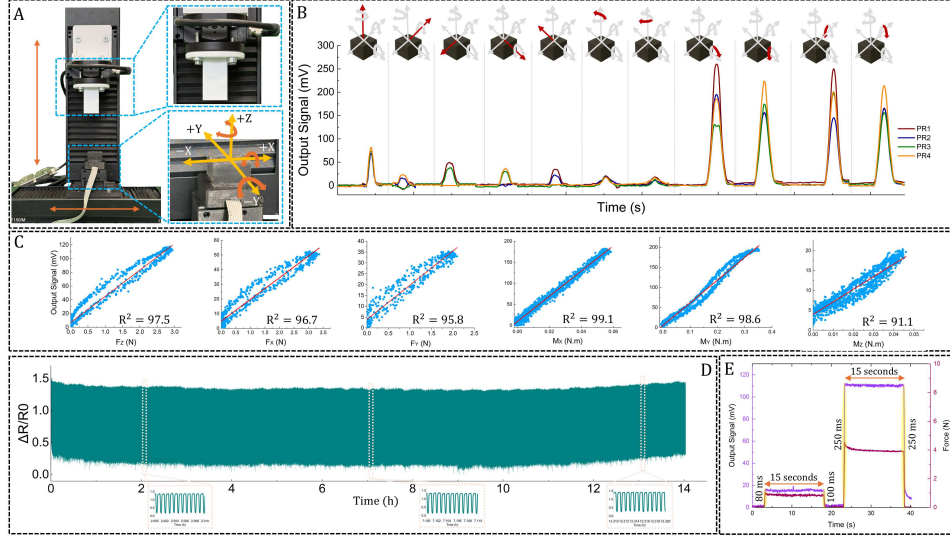


Fig. 2 (A) Experimental setup combining linear and rotational stages for applying normal, shear, and torsional loads. (B) Time responses of four photoresistors (PR1–PR4) under six deformation modes. (C) Calibration curves showing strong linearity ($R^2 = 0.975, 0.967, 0.958, 0.991, 0.986, 0.911$). (D) Long-term stability over 14 h under a 4 N load. (E) Dynamic response under 1 N and 4 N loads with rise and fall times of 80–100 ms and 250 ms, respectively.

S2 show that each photoresistor exhibits a narrow distribution, confirming that baseline fluctuations remain negligible compared to load-induced signal changes. This low noise floor ensures that small deformations are detectable without additional filtering and supports stable multi-axis calibration.

Long-term testing was carried out for 14 hours, corresponding to approximately ($\sim 14,000$ cycles) loading cycles under a 4 N normal force (Figure 2D). The normalized response ($\Delta R/R_0$) remained stable throughout the test, indicating reliable signal output during extended operation.

The dynamic response of TacLight reflects the evolution of volumetric light scattering within the porous elastomer during deformation. At low loads (1 N), only the upper region of the porous layer participates in the deformation, producing fast and highly repeatable optical changes (80–100 ms). At higher loads (4 N), a larger portion of the porous volume contributes to scattering modulation, which naturally requires more time to reach a steady optical configuration, resulting in rise times of 250 ms. This load-dependent transition is typical of compliant porous materials and shows that the sensing dynamics are governed by predictable deformation depth rather than electronic latency. During loading, the optical output remains stable for the full 15-second hold, indicating that the scattering field and mechanical structure maintain consistent behavior even under sustained deformation (Figure 2E).

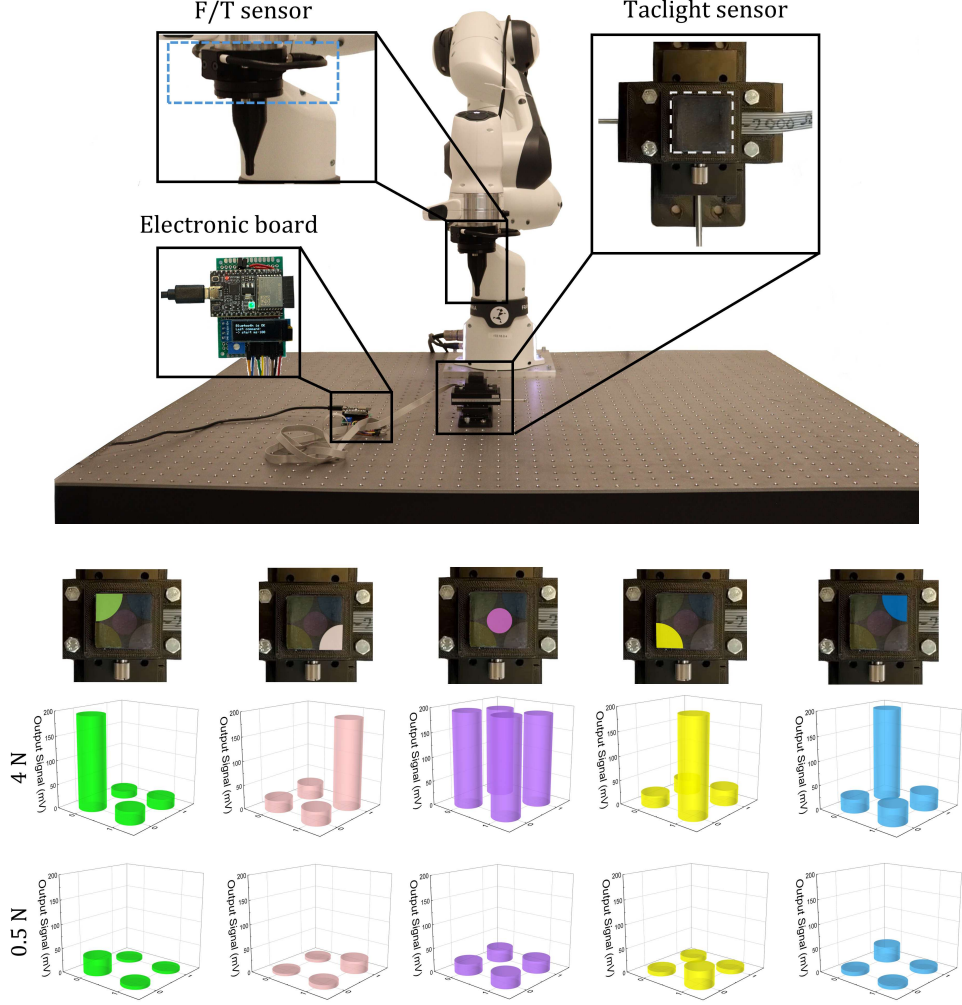


Fig. 3 Experimental setup and tactile characterization. (Top) A Franka Emika Panda robotic arm equipped with a force/torque (F/T) sensor at the wrist and the TacLight sensor for contact point evaluation. Insets show: I) F/T sensor, II) TacLight sensor with the sensing area, and III) electronic board for signal acquisition. (Bottom) Color-coded signal outputs corresponding to tactile interactions at distinct contact points under applied normal forces of 0.5 N and 4 N.

2.3 Contact Point Detection

To validate TacLight’s ability to accurately detect contact points, we performed tests using a Franka Emika Panda robotic arm equipped with the SensONE F/T sensor (Figure 3). The goal was to ensure that TacLight could reliably detect and localize contact locations when interacting with objects, which is crucial for tasks such as robotic manipulation. The Franka Emika Panda was chosen for its high precision and

fine control over force and positioning, allowing us to apply force at specific, well-defined points on the sensor’s surface. This setup ensured that we could test TacLight’s ability to detect contact points with known accuracy, mimicking real-world scenarios where precise interaction with objects is required.

During the test, the TacLight sensor was mounted below the robot’s end-effector. A 3D-printed indenter, attached to the F/T sensor, was used to apply contact to the TacLight sensor at specific points. The robot’s movements were controlled to apply force at defined positions across the sensor’s surface. The contact points included the center and four corners of the sensor, with each position being tested multiple times to verify repeatability and consistency.

For each applied contact point, the voltage response from TacLight was recorded. The sensor’s response showed clear and distinguishable variations for each location, with voltage shifts corresponding to the applied load. These variations allowed the sensor to accurately detect the position of contact.

The sensor’s ability to localize contact points was visually represented in Figure 3, bottom, which shows the voltage distribution for each contact point across the surface. The results confirmed that TacLight could reliably detect contact locations, making it well-suited for tasks involving precise object manipulation or interaction, where accurate localization of contact is required.

2.4 TacLight Joystick for Virtual Drone Control

To evaluate TacLight in an interactive control setting, we developed a custom joystick prototype embedding the sensor and interfaced it with a virtual drone simulator (Supplementary Figure S3). The goal of this experiment was to determine whether TacLight’s deformation signals could directly support navigation tasks without relying on machine learning, thereby assessing the interpretability and responsiveness of the outputs for real-time conditions.

As shown in the top part of Figure 4, two deformation modes were mapped to drone commands. Roll was assigned to forward motion, while yaw controlled left and right motion. This mapping provided two degrees of freedom (2-DOF), sufficient to investigate directional navigation. A threshold-based strategy was employed for signal interpretation: when the TacLight output associated with roll or yaw exceeded a predefined limit, the corresponding flight command was activated, and the velocity was scaled proportionally with the signal amplitude. This method enabled low-latency operation at 100 Hz without additional computation.

To evaluate manoeuvrability, we designed two flight scenarios shown in the lower panels of Figure 4. In the first scenario, the drone navigated between virtual trees, a task that required continuous adaptation rather than a fixed trajectory. Forward motion was achieved by applying roll, but successful completion demanded frequent alternating yaw commands to shift the drone left or right and pass through narrow gaps without collision. This scenario, therefore, tested TacLight’s ability to generate clear and separable roll and yaw signals in close succession, and the resulting voltage traces confirmed that both modes remained distinct and responsive during obstacle avoidance. In the second scenario, the drone was flown along a straight trajectory, where roll input dominated, and yaw was used only for minor corrections. This task

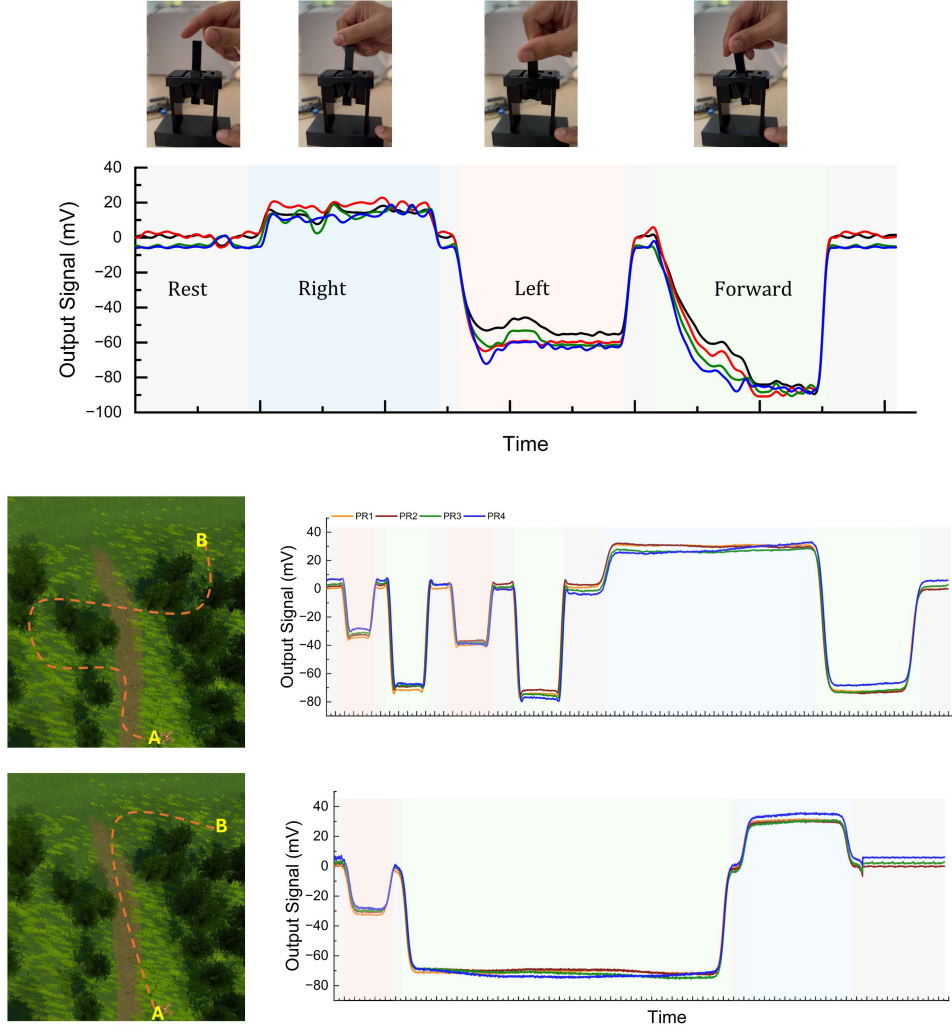


Fig. 4 Human-machine interaction using the TacLight-based joystick for drone navigation. (Top) The operation of the joystick, where directional manipulations (rest, forward, left, and right) generate distinct sensor responses that enable real-time control of a virtual drone. (Bottom) Two navigation scenarios are presented, in which the TacLight joystick enables the drone to follow predefined trajectories from point A to point B, with output signals demonstrating consistent correspondence between tactile inputs and drone maneuvers.

highlighted the stability of TacLight’s roll signals, demonstrating their capacity to provide reliable, continuous input for sustained forward navigation.

Together, these results demonstrate that TacLight delivers distinct roll and yaw signals that can be directly translated into reliable commands for real-time 2-DOF drone navigation. A real-time demonstration is provided in the Supporting Information (Supplementary Movie S1).

2.5 Learning Force-Aware Robot Policy via Imitation Learning

Tactile sensing enables robots to autonomously perform tasks that demand precise control of interaction forces. To evaluate this capability, we applied TacLight in a contact-rich zucchini-peeling task. The described task was chosen because it demands both dexterous tool use and continuous adaptation to varying surface conditions. The goal was to teach the robot a policy that removes the outer skin efficiently while controlling contact forces to prevent damage to the softer interior. This requires ongoing awareness of the interaction state, including whether the peeler’s blade is engaging the skin or encountering unexpected resistance. To provide this awareness, the TacLight sensor was integrated into a custom gripper specifically designed to hold a standard vegetable peeler. The gripper, attached to the flange of a KUKA LBR iiwa robot arm, positioned the sensor between the robot’s wrist and the peeler so that all interaction forces passed through its soft, porous surface. The peeler blade was mounted at a slight offset to maintain continuous contact along the zucchini’s curvature while enabling smooth slicing motions. In this configuration, every push, shear, and twist during peeling generated a distinct deformation signature. The data of completing this task are recorded using teleoperation by an operator. This data is then used to train a robot policy that can complete this task autonomously (Figure 5).

A real-time demo is shown in the Support information (Supplementary Movie S2), and full gripper design parts are given in the Supplementary Figure S4.

Interactive Data Collection We employ an Interactive Imitation Learning (IIL) algorithm [47] to teach the robot to accomplish this task. We model the problem as a Markov decision process (MDP). The state $\mathbf{s}$ captures the observations at each time step, including the robot end-effector pose and tactile sensor readings. The action $\mathbf{a}$ corresponds to a task-space velocity command applied to the end-effector. The objective is to learn a policy that outputs appropriate actions for each state in the peeling process. The policy π_θ , parameterized by a deep neural network with parameters θ , selects actions $\mathbf{a}$ given states $\mathbf{s}$. During the learning process, the robot takes actions $\mathbf{a}^r$ to peel zucchinis and can be intervened by a human teacher through a SpaceMouse teleoperation device. During each step of this intervention, the human teacher controls the robot with human action $\mathbf{a}^h$, while the robot policy still outputs $\mathbf{a}^r$ without being executed. This process results in an observed action pair $(\mathbf{s}, \mathbf{a}^h, \mathbf{a}^r)$ and is saved into a reply buffer $\mathcal{D}$. The robot policy π_θ can be updated using a loss function to imitate the behavior in $\mathcal{D}$. This process lasts for 95 minutes and results in 7865 data pairs inside $\mathcal{D}$.

Training Robot Policy with Collected Data To test the effectiveness of the tactile information of our sensor, we train the robot policy with two different datasets: (1) the original dataset, with each state $\mathbf{s}$ contains the tactile information and the robot pose; (2) the modified dataset with each state $\mathbf{s}$ contains only the robot pose, without any tactile information. After training the policies with 5000 episodes, we evaluated their performance in the post-training phase, by executing the robot policy without any human intervention. Each condition (with and without TacLight input) was tested in 10 independent trials to ensure consistency. The results, summarized in Table 1, show that the learned policy with access to tactile information achieved a higher success rate than the policy without this information. In the absence of

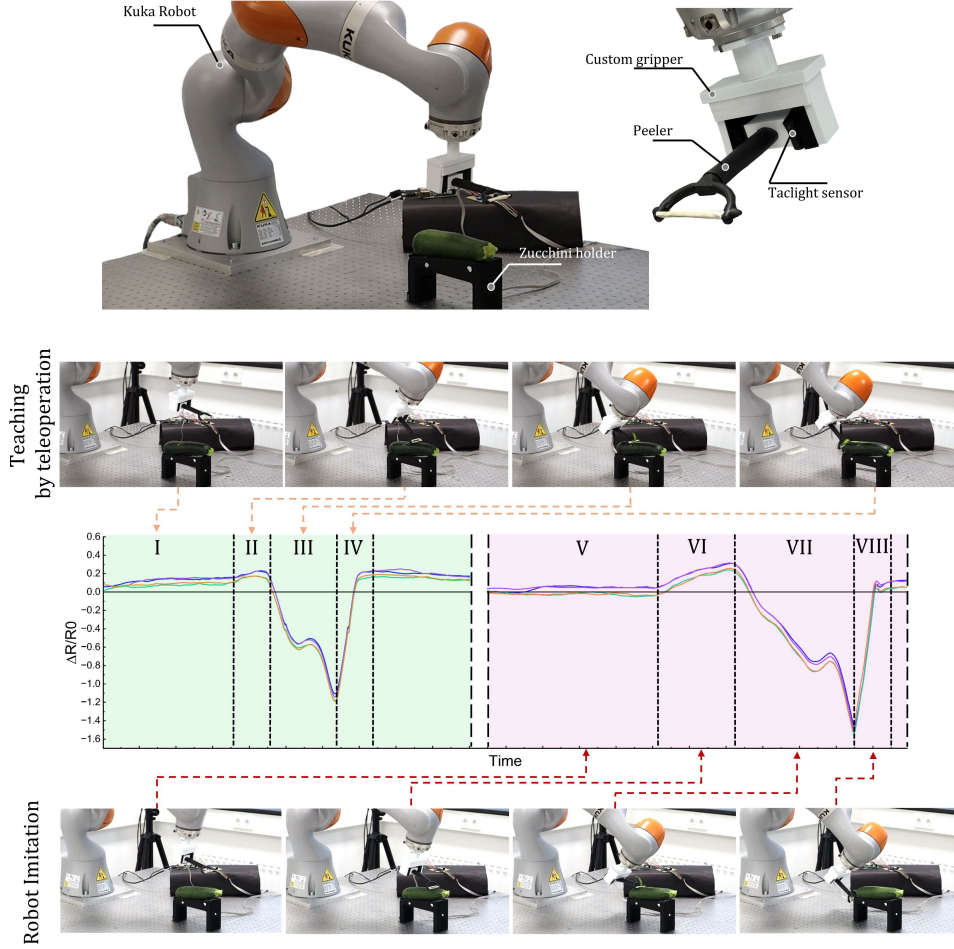


Fig. 5 Human demonstration and robotic imitation of a force-aware peeling task using the TacLight sensor. (Top) Experimental setup with a KUKA robotic arm, custom gripper, TacLight sensor embedded in a peeler, and a zucchini mounted on a holder. (Bottom) Teaching and imitation phases: during teaching (green background), a human operator teleoperates the robot to perform a peeling task while the TacLight sensor records contact forces, producing normalized resistance changes ($\Delta R/R_0$) across four sensing channels (PR1-PR4) segmented into eight phases (I-VIII). In the imitation phase (purple background), the robot autonomously replays the demonstrated motion, regulating contact forces based on the learned tactile profiles.

TacLight, the robot was unable to consistently identify the peeling state (Figure 6). This often resulted in two types of failures: misclassifying whether the zucchini surface was peeled or unpeeled, and colliding with the vegetable, which led to incomplete peeling. These failures align with the lower success rates in Table 1 and underline the essential role of tactile sensing in achieving stable, force-aware manipulation.

The signal patterns in Figures 4 and 5 appear with different patterns than those in Figure 2 due to differences in the acquisition pipeline. For sensor characterization (Figure 2), raw signals were collected with a custom board under controlled conditions,

Table 1 Success rates of the robotic peeling task trained with and without TacLight sensor input

	Without TacLight Sensor	With TacLight Sensor
Success rate	0.4	0.70

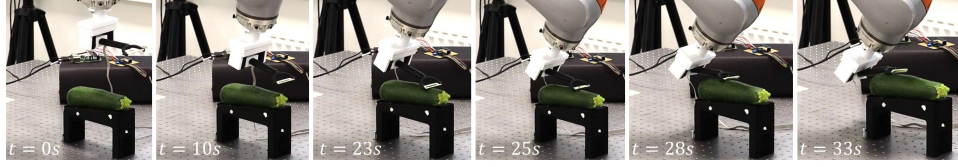


Fig. 6 Robotic execution of the zucchini-peeling task without TacLight sensing. In the absence of tactile feedback, the robot is unable to consistently identify the peeling state, resulting in frequent errors such as surface collisions and incomplete peeling.

highlighting the distinct response profiles of each deformation mode. In contrast, the joystick and peeling experiments (Figures 4 and 5) utilized a Raspberry Pi 4B for real-time signal acquisition, with a Kalman filter applied to reduce the noise and stabilize the outputs. This processing ensured reliable interaction during application tasks, though it naturally altered the visual appearance of the signals compared to the raw characterization data.

3 Discussion

TacLight demonstrates that deformation-induced optical scattering in a porous elastomer can serve as a compact and compliant route to multi-axis tactile sensing. The sensor produces distinct and repeatable patterns for normal, shear, bending, and twisting interactions, and it maintains stable behaviour during extended loading and real-time operation. These results show that the porous material not only hosts the sensor but also performs part of the computation. Volumetric scattering physically encodes deformation direction and magnitude into structured optical signatures that are directly separable at the hardware level. This intrinsic encoding explains why TacLight supports both direct, model-free interpretation for real-time control and high-bandwidth data, making it suitable for robot learning.

The comparison in Table S1 highlights the differences between TacLight and established optical tactile technologies. Camera-based sensors achieve high spatial resolution but depend on rigid housings, controlled illumination, and substantial computational resources. Optical-fiber designs offer sensitive strain measurements but rely on guided-light deformation and are not typically configured to capture multiple deformation modes within a single soft structure. TacLight provides an alternative optical pathway: a camera-free architecture in which the porous medium itself acts as the transduction substrate, enabling a fully soft form factor with minimal processing requirements.

The contact-point experiments indicate that the scattering field also carries spatial information, even with only four sensing channels. The two demonstrations further show how this sensing principle supports real-time interaction: the joystick experiment

uses raw signals as direct user input, while the peeling task illustrates how tactile feedback assists in regulating forces during manipulation.

TacLight operates within the boundaries set by its present architecture. The porous layer defines the usable compression range, and spatial resolution follows from the number of receivers; this study focuses on single-contact interactions. Future refinements, such as graded porosity or additional receivers, may extend the operating range and enhance spatial fidelity.

Overall, TacLight establishes a compact and simple alternative to existing optical tactile approaches, utilizing porous-medium scattering to deliver multi-axis sensing in a soft, camera-free architecture that is well-suited for embedded robotic and human-machine interaction tasks.

4 Method

Fabrication Process:

The multilayer structure was fabricated in sequential casting steps. The bottom layer was made from Dragon Skin 30 by mixing equal amounts of Part A and Part B, adding a small quantity of black pigment to ensure opacity, degassing the mixture in a vacuum chamber, and casting it into a flat mold. The layer was left to cure fully at room temperature. Once cured, the porous layer was cast directly on top of it. Ecoflex 00-30 Part B was mixed with salt crystals (250–500 μm) at a 1:1 weight ratio relative to the total silicone, then combined with Part A. The salt created sufficient internal porosity, eliminating the need for vacuum degassing. The mixture was poured onto the Dragon Skin base and cured at 60 °C for 30 minutes. A reflective layer was then formed by mixing Ecoflex 00-30 with white pigment, degassing it, and casting a thin, uniform coating on top of the dried porous structure. This layer cured at room temperature. To remove the embedded salt and form the pores, the sample was submerged in deionized water with repeated water replacement until dissolution was complete. The sample was subsequently dried in a vacuum oven at 40 °C for 1 hour. A very thin Sil-Poxy coating was applied next. This sealing step prevented the final silicone layer from penetrating into the porous-reflective interface.

The final optical-shielding layer was fabricated by mixing Ecoflex 00-10 with black pigment, degassing it, and casting it over the Sil-Poxy-sealed surface. After curing, this top layer formed a compliant, opaque barrier that protects the internal optical structure and blocks ambient light during sensing. Full details of mold design, layer assembly, and optoelectronic integration are provided in the Supplementary Figure S1.

Sensor Electronics: The TacLight sensor uses a compact electronic circuit built around four IR LEDs and four phototransistors arranged in emitter-receiver pairs. The LEDs are powered by a 3.3V supply and driven in a pulsed mode via a DMN3067LW-7 MOSFET, controlled by a digital pin on an ESP32-C3 microcontroller. This pulsing minimizes ambient light interference by synchronizing IR emission with signal sampling. Each phototransistor is configured with a 10 k Ω pull-down resistor and outputs an analog voltage proportional to the reflected IR intensity. These signals are digitized using the ESP32-C3’s 12-bit ADC at a rate of 100 Hz and filtered in firmware using a moving average. The design is low-power, compact, and

well-suited for integration into soft robotic systems. A complete schematic is provided in the Supporting Information (Supplementary Figure S2).

Human–Machine Interaction Test: A custom joystick was built to integrate TacLight sensors for directional control input. Each photoresistor outputs an analog voltage proportional to deformation. The signals were sampled at 100 Hz using the ESP32-C3’s 12-bit ADC, smoothed with a moving average filter, and transmitted via serial to a Raspberry Pi 4B.

A Python program on the Raspberry Pi processed the incoming voltages to classify joystick inputs into three commands: forward, left, and right. These commands were defined during a calibration step in which several users pressed the joystick in each direction. The collected voltage data were analyzed to determine threshold ranges that clearly separated the commands while allowing for variation in pressing position and force. The final thresholds were: forward (10–30 mV), left (–20 to –60 mV), and right (–60 to –90 mV). The Python program sent the classified commands to a Unity simulation of a quadrotor in a forest environment.

Methodology of Interactive Imitation Learning: We utilize the IIL algorithm, Contractive Learning from Interactive Corrections (CLIC) [48], to train the robot policy from human corrections. CLIC utilizes a loss function that avoids overfitting to a single action label and, therefore, can learn a more robust policy.

Given an observed action pair, CLIC creates a desired action space, which is a subset of the action space that includes optimal actions. This desired space provides useful information to the improvement of the robot policy by ruling out actions outside this space. Specifically, given the observed action pair $(\mathbf{s}, \mathbf{a}^h, \mathbf{a}^r)$, CLIC defines a desired action space with a circular geometry:

$$\hat{\mathcal{A}}(\mathbf{a}^r, \mathbf{a}^h) = \{\mathbf{a} \in \mathcal{A} | (1 - \varepsilon) \cdot D(\mathbf{a}^h, \mathbf{a}^r) \geq D(\mathbf{a}, \mathbf{a}^h)\}, \quad (1)$$

which is the circle centered at the human action $\mathbf{a}^h$ with radius $(1 - \varepsilon) \cdot D(\mathbf{a}^h, \mathbf{a}^r)$. The distance of two actions is defined as $D(\mathbf{a}_1, \mathbf{a}_2) = \|\mathbf{a}_1 - \mathbf{a}_2\|$. The hyperparameter $\varepsilon \in [0, 1)$ adjusts the radius of the ball.

Given the desired space, a target distribution $\pi^{\text{target}}(\mathbf{a}|\mathbf{s})$ can be defined to assign higher probability to actions within $\hat{\mathcal{A}}(\mathbf{a}^r, \mathbf{a}^h)$ than the current robot policy π_θ . The robot policy can be aligned with the desired action space by minimizing the KL divergence between the target and the policy distribution:

$$\ell_{KL}(\theta) = E_{(\mathbf{a}^h, \mathbf{a}^r, \mathbf{s}) \sim \mathcal{P}_{\mathcal{D}}} [\text{KL}(\pi^{\text{target}}(\mathbf{a}|\mathbf{s}) || \pi_\theta(\mathbf{a}|\mathbf{s}))] \quad (2)$$

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Supplementary information.

Fabrication Process

We first prepared the bottom layer using Dragon Skin 30. Equal amounts of Part A and Part B were mixed thoroughly, and a small amount of black pigment was added to make the layer opaque. The mixture was degassed in a vacuum chamber, poured into a mold, and left to cure completely at room temperature.

After the bottom layer cured, we prepared the porous layer using Ecoflex 00-30. Salt crystals (250–500 μm) were added to Part B in a 1:1 weight ratio to the total silicone, mixed well, and then combined with Part A. Because the salt creates inherent porosity, no vacuum degassing was needed. The mixture was poured directly onto the cured Dragon Skin layer and cured at 60 °C for 30 minutes.

Next, a thin reflective layer was prepared by mixing Ecoflex 00-30 with white pigment. The mixture was degassed, poured onto the dried porous structure, and cured at room temperature to form a uniform reflective surface.

To generate the pores, the sample was submerged in deionized water, with frequent water replacement, until all the salt was fully dissolved. The washed sample was then dried in a vacuum oven at 40 °C for 1 hour.

After that, a very thin coat of Sil-Poxy was applied on top. This sealing step prevents the final silicone layer from infiltrating the underlying reflective surface, ensuring clean adhesion.

A final black layer was then prepared by mixing Ecoflex 00-10 with black pigment. The mixture was degassed, poured over the Sil-Poxy-sealed surface, and cured. This outer black layer forms a soft optical shield that blocks ambient light and protects the inner layers.

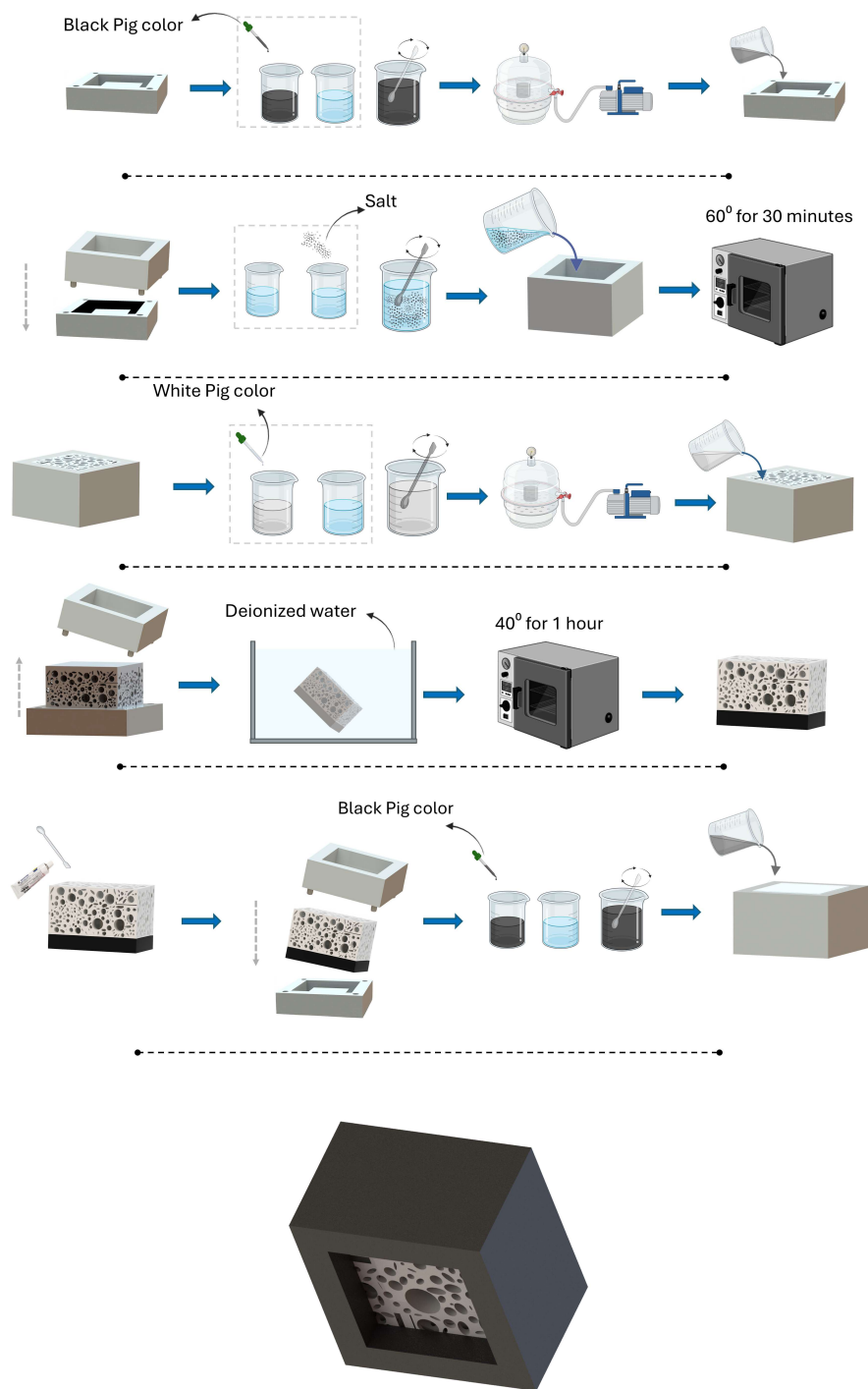


Fig. S1 Step-by-step process for creating the dual-colored porous structure: (1) preparation and infusion of the black pigment solution into the mold; (2) salt-templated casting and consolidation of the porous matrix; (3) infusion of the white pigment and thermal treatment at 60 °C for 30 min; (4) desalination and drying in deionized water at 40°C for 1 h; (5) selective re-pigmentation of the top layer using black pigment; and (6) final assembly of the composite block. The schematic illustrates the sequential processes of mixing, casting, washing, and curing required to achieve the final structured material.

Electronic Components and PCB Board

The Taclight sensor employs a compact optoelectronic system designed for infrared-based tactile signal acquisition. The complete circuit comprises four IR LEDs and four phototransistors arranged in spatially distributed emitter–receiver pairs. To ensure consistent brightness, each LED is current-limited using 15Ω resistors and powered by a regulated 3.3V supply.

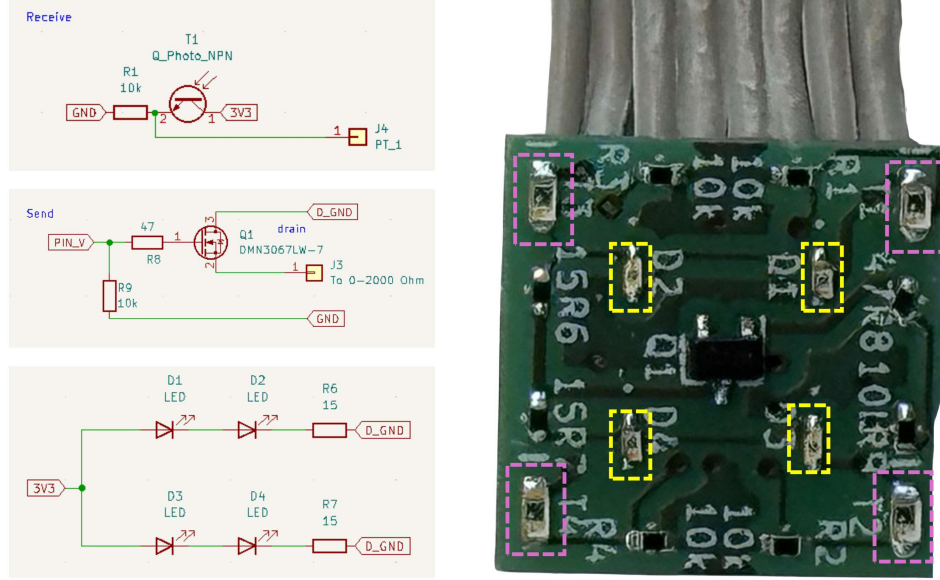


Fig. S2 Schematic diagram of the Taclight sensor electronics. The circuit includes four infrared (IR) LEDs configured in parallel with current-limiting resistors and powered by a 3.3 V supply. An N-channel MOSFET (DMN3067LW-7), controlled by the ESP32-C3 microcontroller, enables pulsed LED operation for improved robustness against ambient light. Four phototransistors serve as receivers, each connected in a voltage divider configuration with a 10 k pull-down resistor. The analog output from each receive is digitized by the 12-bit ADC of the ESP32-C3 at a sampling rate of 100 Hz. This setup provides a compact, low-power platform for capturing deformation-induced variations in IR intensity.

To suppress interference from ambient light, the IR LEDs are not powered continuously but are pulsed using a DMN3067LW-7 N-channel MOSFET, which is controlled by a digital output pin of an ESP32-C3 microcontroller. This configuration enables synchronized activation of the emitters and sampling of the phototransistor outputs. A pull-down resistor (10 k Ω) is connected to each phototransistor, forming a voltage divider that outputs an analog voltage proportional to the received IR intensity. The ESP32-C3's 12-bit ADC digitizes these analog signals at a sampling rate of 100 Hz. A simple moving average filter is applied in firmware to reduce high-frequency noise. The microcontroller also handles LED switching logic and communication with a host system for data logging and real-time control.

Custom Joystick

The Taclight sensor was mounted using a custom-designed fixture consisting of a joystick arm, clamp, and support base. The clamp securely holds the sensor without compressing or altering its soft layer, while the joystick arm enables fine manual positioning and repeatable alignment. This assembly was employed to ensure consistent orientation and contact during tactile response evaluations. All fixture parts were fabricated on a Prusa i3 (MK3S+ 3D) printer using PLA filament, providing sufficient stiffness and durability for repeated experiments.

The bottom panel illustrates the virtual drone navigation experiment. In this demonstration, the Taclight sensor functioned as a joystick-like interface: normal and shear deformations of the soft layer were mapped to translational and rotational commands of the drone in a simulated environment. The sequence of images shows different stages of drone motion, highlighting how the sensor’s multi-axis response enables smooth and continuous control. This experiment validates the capability of Taclight to serve not only as a tactile measurement device but also as an effective human–machine interface for real-time robotic applications.

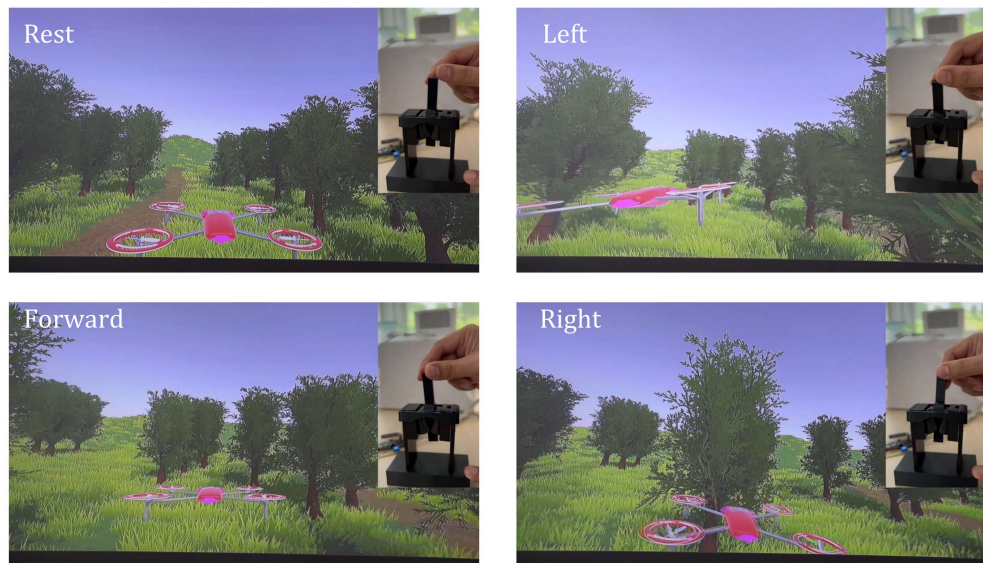
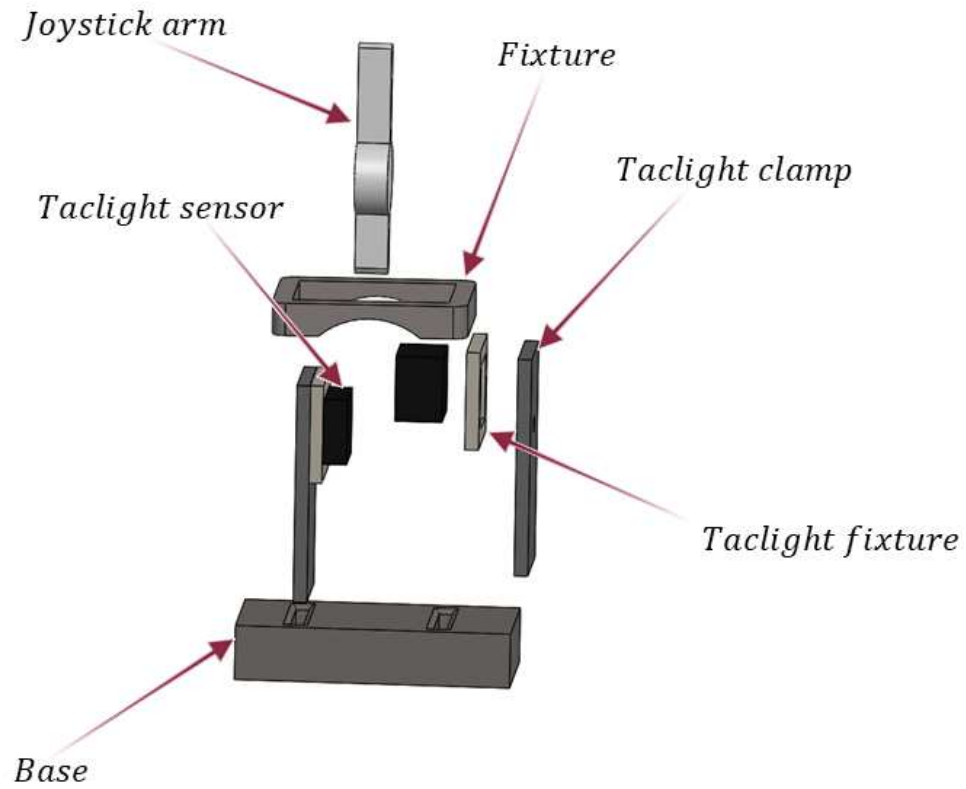


Fig. S3 (Top) Exploded view of the Taclight integration setup. The figure illustrates the mechanical components used to mount the Taclight sensor to control the virtual drone. (Bottom) Demonstration of drone navigation in a virtual environment using the Taclight-based joystick interface.

comparison soft optic sensors

Supplementary Table S1 provides an overview of representative optical tactile sensing technologies reported in the literature, comparing their core characteristics with those of the TacLight sensor. The table highlights key differences in sensing modality, mechanical structure, working principles, and performance metrics, including bandwidth, force resolution, and degrees of freedom. Unlike camera-based systems, TacLight operates without imaging hardware and instead relies on distributed IR scattering inside a dual-colored porous medium, enabling compact integration, low power consumption, and high robustness against ambient light.

Table ST1 Comparison of representative optical tactile sensing technologies.

Ref.	Camera	Working principle	DoF / Modality	Soft / Rigid	Performance	Bandwidth	Notes
TacLight (this work)	No	IR scattering in porous elastomer	6-axis + contact points	Soft	0.5 N	100 Hz	Camera-free 6-DoF sensor; low power
GelSight [44]	Yes	Marker deformation imaging	Geometry + shear + normal	Soft	μm -scale spatial accuracy	30–100 Hz	High-res tactile imaging
Insight [42]	Yes	Photometric stereo + structured light	3D force field	Soft shell	0.03 N; 5° error	10 Hz	Requires camera + ML
Optical Lace [36]	No	Stretchable optical fibers	Distributed deformation	Soft	0.3 N; 0.7 mm spatial	Up to kHz	Large-area deformation sensing
3D Optical Channels [37]	No	Optical waveguides in PDMS	Triaxial (Fx, Fy, Fz)	Soft	Linear response	100–300 Hz	No torque sensing
Evetac [40]	Yes	Event-based marker tracking	Shear, contact, vibration	Soft layer	Vibration up to 498 Hz	>1 kHz	High-speed slip sensing
Optoelectronic WG [38]	No	Stretchable waveguides	1–2 axis strain	Soft	Good strain resolution	–	Not multimodal
Soft Optical Fiber Sensor [39]	No	In-fiber interferometer	Normal force	Soft	Sub-N resolution	100 Hz	Local sensing only
TacTip [46]	Yes	Internal pins/markers	Geometry + shear	Soft dome	Sub-mm spatial	30–60 Hz	Camera required
T-Blep [9]	No	Inflatable membrane deformation	Force + stiffness	Soft	Stiffness class detection	10–100 Hz	Force + stiffness sensing

Custom Gripper

To integrate the TacLight sensor with the robotic setup, we designed a custom 3D-printed mounting structure that ensures stable alignment and repeatable positioning during all tactile experiments. The assembly consists of two main components: a robot connector that attaches directly to the robot's end-effector, and a sensor holder that provides a precise slot for positioning the TacLight module.

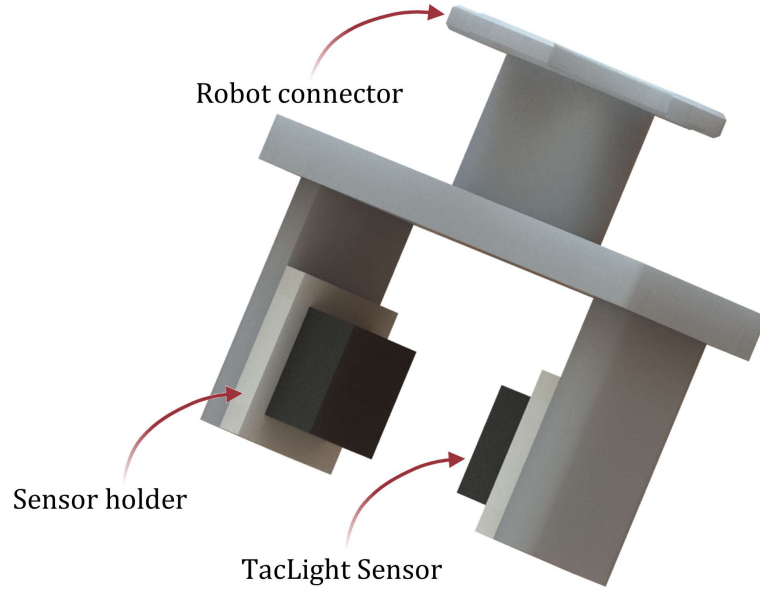


Fig. S4 Mounting assembly for integrating the TacLight sensor with the robotic end-effector. The structure includes a robot connector and a dedicated sensor holder that positions and secures the TacLight module. This configuration ensures stable alignment, minimizes ambient light interference, and preserves the sensor's optical geometry during tactile experiments.

Baseline Noise Characterization

To quantify the intrinsic noise floor of the TacLight sensor, we recorded a 10-second zero-load baseline at 100 Hz and analyzed the raw signals from all four photoresistor channels (PR1–PR4). The deviation-from-mean histograms (Supplementary Figure S5) show narrow, symmetric distributions centered around zero, indicating stable electronic behavior and the absence of low-frequency drift. The corresponding standard deviations, summarized in Supplementary Table S2, range from 1.1 to 1.6 mV, confirming that the sensor maintains a consistently low noise floor across channels. This baseline behavior establishes the reference level against which all deformation-induced signal changes are interpreted.

Table ST2 Baseline noise across photoresistor channels. Standard deviation computed from a 10 s zero-load interval (100 Hz).

Channel	Noise (std)
PR1	1.12
PR2	1.37
PR3	1.58
PR4	1.34

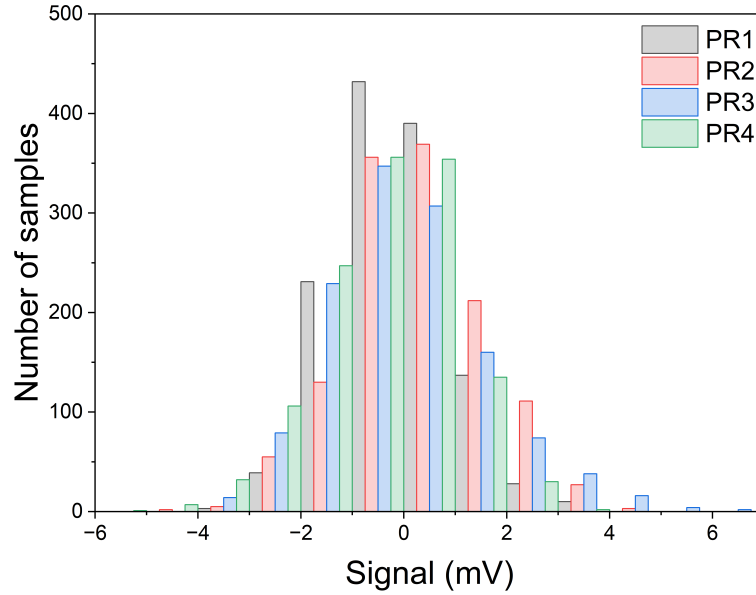


Fig. S5 Histogram of zero-load signals collected over a 10-second period. All four channels (PR1–PR4) exhibit narrow, symmetric noise distributions centered around zero, confirming stable optoelectronic behavior and a low intrinsic noise floor. The standard deviations fall within the 1–2 mV range across channels.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- [VideoS1.mp4](#)
- [VideoS2.mp4](#)