AnySkin: Plug-and-play Skin Sensing for Robotic Touch

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https://any-skin.github.io

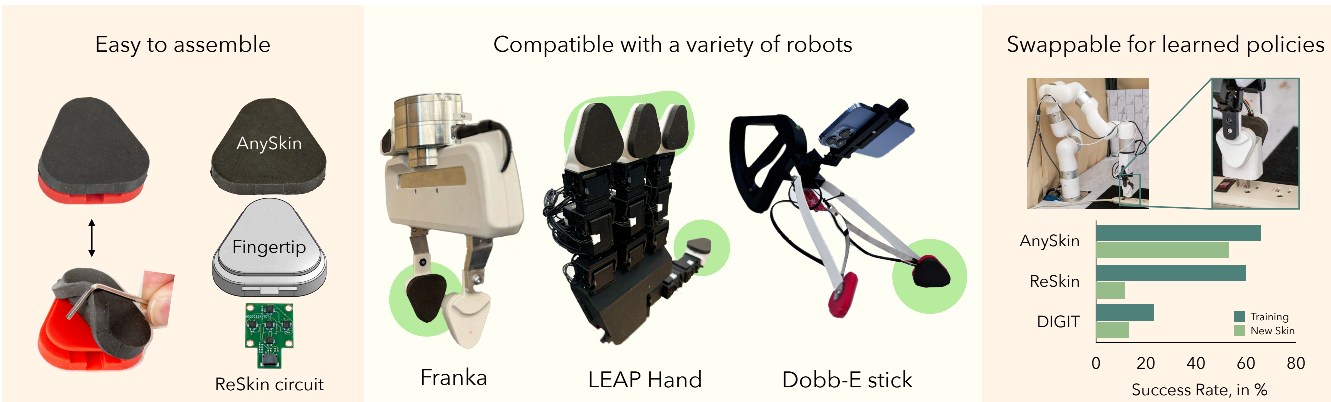

Fig. 1: We present AnySkin, a skin sensor made for robotic touch that is easy to assemble, compatible with different robot end-effectors and generalizes to new skin instances. AnySkin senses contact through distortions in magnetic field generated by magnetized iron particles in the sensing surface. The flexible surface is physically separated from its electronics, which allows for easy replacability when damaged.

I. Introduction

Touch sensing is widely recognized as a crucial modality for biological movement and control [1], [2]. Unlike vision, sound, or proprioception, touch provides sensing at the point of contact, allowing agents to perceive and reason about forces and pressure. However, a closer examination of robotics literature reveals a different narrative. Prominent works and current state-of-the-art in robot learning primarily utilize vision sensing in conjunction with proprioception to train manipulation skills [3], [4], [5], [6], often ignoring touch. If touch is indeed vital from a biological perspective, why does it remain a second-class citizen in sensorimotor control?

In this work we present AnySkin, a new touch sensor that is cheap, convenient to use and has consistent response across different sensor instances. AnySkin builds on ReSkin [7], a magnetic-field based touch sensor, by improving its fabrication, separating the sensing mechanism from the interaction surface, and developing a new self-adhering, self-aligning attachment mechanism. This allows AnySkin to (a) have stronger magnetic fields, which significantly improves its sensor response, (b) be easy to fabricate for arbitrary surface shapes, which allows easy use on different end-effectors, (c) be easy to replace the sensor without adversely affecting the data collection process or the efficacy of models trained on previous sensors (Fig. 1).

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We run a suite of experiments to understand the efficacy of AnySkin vis-a-viz other prominent touch sensors. Our main findings can be summarized below:

1) AnySkin can readily be used on a variety of robots including xArm, Franka, and the four-fingered Leap hand (See fabrication details in Section III).
2) AnySkin is compatible with ML techniques for slip detection and visuo-tactile policy learning for precise tasks such as inserting USBs (See learning details in Section IV).
3) AnySkin takes an average of 12 seconds to replace and can be reused after replacement (See replacement study in Section IV-C).
4) Models trained on one AnySkin transfer zero-shot to a different AnySkin with only a 13% reduction in performance on a plug insertion task compared to the 43% drop in performance with ReSkin [7] sensors.

AnySkin is fully open-sourced. Videos of fabrication, attachment, and robot policies are best viewed on our project website: https://any-skin.github.io/.

II. AnySkin: Components

AnySkin builds on ReSkin [7], a tactile skin composed of a soft magnetized skin coupled with magnetometer-based sensing circuitry. By detecting distortions in magnetic fields, ReSkin measures skin deformations caused by normal and shear forces [8], [7]. Its adaptability enables integration across various applications, from robotic hands [9], [10]

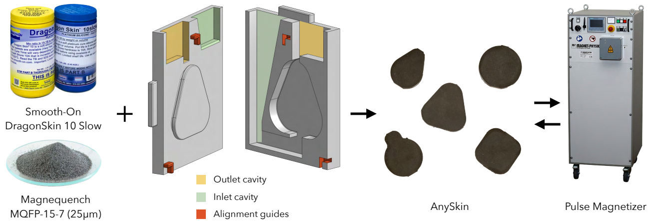

Fig. 2: AnySkin is made by mixing Smooth-On DragonSkin 10 Slow and MQFP-15-7(25μm) magnetic particles in a 1:1:2 ratio, and curing it in the two-part molds shown above. Cured skins are magnetized using a pulse magnetizer.

to arm sleeves and even dog shoes. AnySkin uses the same 5-magnetometer circuitry as ReSkin, while introducing key design and fabrication changes to the skin to improve durability, repeatability, and replaceability.

- Magnetizing skins post-curing using a pulse magnetizer.
- Introducing physical separation between magnetic elastomer and magnetometer circuit.
- Utilizing finer magnetic particles to achieve a more uniform particle distribution.
- Implementing a self-aligning design for reduced variability in the positioning of elastomers and circuitry.

These fabrication changes enable signal consistency across sensor instances that is leveraged in the following policy learning experiments.

III. AnySkin: Fabrication

The overall fabrication procedure follows the general outline of ReSkin as shown in Fig. 2. The shape of the fingertip-skin assembly is designed to be triangular as shown in Fig. 1 to improve reachability. We elaborate on the details of the fabrication procedure for AnySkin, and key changes to the ReSkin fabrication procedure that result in the paper.

IV. Experiments and Results

We perform extensive experiments to demonstrate the capabilities of AnySkin as a tactile sensor, and within the context of policy learning. Our experiments are designed to answer the following questions:

- How do the fabrication changes outlined in Section II influence signal characteristics?
- Can AnySkin sensors be used to detect slip?
- How does AnySkin's ease of replaceability compare with other sensors like DIGIT and ReSkin?
- How does replacing AnySkin affect the performance of learned policies, and compare with other sensors like ReSkin and DIGIT?

A. Comparison between ReSkin and AnySkin signal

We find that AnySkin signal is stronger and more consistent as a result of the pulse magnetization and the self-aligning design of AnySkin. Detailed quantitative results can be found in the paper.

B. Slip Detection

We quantify AnySkin's ability to detect slip through a controlled experiment. An object held by a human operator is grasped with an AnySkin-equipped gripper and lifted up. We use a set of 40 daily objects – 30 for training and 10 evaluation. A human annotator labels the sequences as slip or no-slip. We only use tactile signals as input to the slip detection model. The full set of training and test objects as well as videos of the learned policy can be found on our website. Our LSTM model is able to detect slip on unseen objects with 92% accuracy.

C. Ease of replaceability

We compare the ease of replaceability of AnySkin against the replaceability of other skins like DIGIT and ReSkin, and present the results in Table I.

TABLE I: Comparison of replaceability of different sensors

Sensor	Time to replace, in s	Reusable
ReSkin (adhesive)	82 ± 64	No
ReSkin (screws)	236 ± 64	Yes
DIGIT	58 ± 22	Yes
AnySkin	$\mathbf{12 \pm 5}$	Yes

D. Replaceability in Policy Learning

The most important consequence of the signal consistency and replaceability of AnySkin outlined so far, is its ability to enable policy generalization across different instances of the skin. We demonstrate the cross-instance generalizability of AnySkin across three precise manipulation tasks. We follow this up with a comparison of the cross-instance generalizability of policies trained on DIGIT, ReSkin and AnySkin on the plug insertion task. Table II presents a comparison between policy performance with the original and swapped skins for three precise, contact-rich tasks.

TABLE II: Success rates (out of 10) for policies when swapping out tactile skins. All statistics computed over 3 training seeds

Task	Cameras only	Cameras + Skin	
		Original skin	Swapped skin
Cross-instance generalization			
Plug Insertion	1.7 ± 0.6	6.7 ± 1.5	5.3 ± 2.5
Card Swiping	2.0 ± 1.0	7.0 ± 1.7	6.3 ± 0.6
USB Insertion	1.7 ± 1.2	5.7 ± 1.5	3.0 ± 1.0
Comparison across sensors – Plug Insertion			
AnySkin	1.7 ± 0.6	$\mathbf{6.7 \pm 1.5}$	$\mathbf{5.3 \pm 2.5}$
ReSkin	1.7 ± 1.2	6.0 ± 1.7	1.7 ± 1.2
DIGIT	1.7 ± 1.5	2.3 ± 0.6	1.3 ± 0.6

V. Conclusion

In this paper, we present AnySkin, a new magnetic tactile sensor. AnySkin is versatile, self-adhering and improves on signal consistency across different instances of the skin. Furthermore, to the best of our knowledge, AnySkin is the first sensor to demonstrate zero-shot generalization of visuotactile policies to new instances of the tactile skin.

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