Comparing Piezoresistive Substrates for Tactile Sensing in Dexterous Hands

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Abstract—While tactile skins have been shown to be useful for detecting collisions between a robotic arm and its environment, they have not been extensively used for improving robotic grasping and in-hand manipulation. We propose a novel sensor design for use in covering existing multi-fingered robot hands. We analyze the performance of four different piezoresistive materials using both fabric and anti-static foam substrates in benchtop experiments. We find that although the piezoresistive foam was designed as packing material and not for use as a sensing substrate, it performs comparably with fabrics specifically designed for this purpose. While these results demonstrate the potential of piezoresistive foams for tactile sensing applications, they do not fully characterize the efficacy of these sensors for use in robot manipulation. As such, we use a low density foam substrate to develop a scalable tactile skin that can be attached to the palm of a robotic hand. We demonstrate several robotic manipulation tasks using this sensor to show its ability to reliably detect and localize contact, as well as analyze contact patterns during grasping and transport tasks. Our project website provides details on all materials, software, and data used in the sensor development and analysis: https://sites.google.com/gcloud.utah.edu/piezoresistive-tactile-sensing/.

I. INTRODUCTION

Existing robotics research clearly establishes the benefits of tactile sensing for manipulation [1–4]. Researchers have consistently shown the benefit of tactile sensing over vision-based perception alone, particularly in the context of manipulation under uncertainty or involving unknown or unmodeled objects [3–8]. Tactile sensing has been shown to improve grasp execution and evaluation [4,7,9–11]; predict and arrest slip [1,3,12–14]; perform 3D object reconstruction [2,15,16] and localization [17–19]; identify objects [17,20] and their materials [21] among other properties [22–24]; and enable dexterous in-hand manipulation [1,8]. Why then, given over 30 years of active research in robotics [1,2,25], are large-scale tactile skins still not commonplace?

In the context of manipulation, tactile sensing has primarily focused on the use of high-fidelity sensing at distal phalanges [22,26–29]. Fewer works examine the use of tactile sensing throughout the finger [30–32] or in the palm [32] typically at the loss of sensor acuity or modalities. This reliance on sensing only at the fingertips neglects the potential feedback from the palm and fingers, which could improve spatial coverage in many of the above use cases.

Tactile sensing skins have more commonly been employed for contact detection along the length of robotic arms [33,34]. Robots can successfully use such sensors to improve arm navigation through cluttered environments [35]. These existing tactile skins have been shown to be reliable and responsive to contact, but typically rely on highly specialized components, such as conductive fabrics or custom circuit boards, which can be difficult to source or construct.

Furthermore, commercially available sensors can cost thousands of dollars. These issues compound making tactile
sensors prohibitively expensive either in cost or time for most researchers to install. The research community’s lack of use further hinders deployment in commercial applications given the lack of common methods for using tactile sensing. Thus, there remains a need for easily producible and affordable tactile sensors which can cover larger portions of a robot.

To address these issues we propose a novel tactile sensor design for use as a tactile skin on a dexterous multi-fingered hand. Our sensor design can be constructed from multiple types of piezoresistive material enabling us to test and compare alternative substrates for tactile skins. Additionally, our tactile elements are of smaller scale than previously shown in order to apply them directly on the robot palm.

In this paper, we analyze the performance of two known piezoresistive fabrics compared to two types of anti-static foam which, by nature of their construction, exhibit piezoresistive properties. These substrates can be seen in Figure 2. Our motivation for using foam comes primarily as we found the fabrics used in previous work [34–36] to be extremely difficult to source, while foam could be easily ordered from numerous vendors. We highlight other potential benefits of foam in our discussion in Section V.

We summarize our contributions as follows: (1) we show the efficacy of using a novel sensing substrate (foam) instead of the more difficult to source fabric for piezoresistive tactile sensing. (2) We design an affordable, scalable tactile sensing skin for use directly on robot hands for manipulation; (3) we demonstrate the ability of using smaller scale tactile elements compared with similar, previously developed sensors. (4) We extensively evaluate the sensor on goal-driven robot manipulation and object recognition tasks to highlight its utility for tactile perception and feedback control. We provide explicit links to all materials, software, and data used in the sensor development and analysis as well as video at our project website: https://sites.google.com/gcloud.utah.edu/piezoresistive-tactile-sensing/.

In the next section we provide a more detailed discussion of the related literature. In Section III we discuss the sensor design and evaluate multiple piezoresistive substrates. Section IV reports the details of manipulation experiments using our sensor. We conclude in Section V.

II. RELATED WORK

In this section we discuss the use and design of tactile sensing for robot manipulation. We primarily focus on the design aspects of different sensing modalities used for tactile skins or in robot hands for grasping. We then discuss the details of piezoresistive materials for tactile and capacitive sensing that relate most closely to the sensor proposed in this paper.

A. Tactile Hands for Manipulation

While tactile skins have become more popular in recent years, they are primarily used as low resolution contact sensors along the length of the robotic arm for navigating through clutter or collision avoidance [34,35,37,38] or on limited regions of a robotic hand [26,28]. There has not been a significant amount of research into using tactile skins on robotic hands to improve grasp performance.

Tactile-enabled grasping improves success over vision-only grasping [4,9,10]. This fact motivates robotics researchers to provide tactile sensing to robotic systems [26,28,39]. Fingertip sensors such as the GelSight [28] and BioTac [26] measure the material distortion within the sensor when contact is made. While fingertip sensors are highly sensitive and can collect high resolution tactile information about surfaces, they neglect the potential of feedback from the remainder of the hand, namely the palm and fingers.

The most prominent existing tactile skin used in robotic grasping is the Takktile [31] array of sensors. These have been installed along the fingers and in the palm of hands [32], including the commercially available Reflex hand. These barometric sensors are open source and can be assembled in a matter of days for very little cost. Although they can be manufactured in different sizes, Takktile sensors are only practical for fine resolution sensor arrays and not for coarse large area sensing over the entire robotic hand-arm system. Other existing tactile skins utilize capacitive [33,37,40] or resistive [34,36,41] properties of materials to detect collisions. Capacitive sensors require lower power consumption compared to resistive sensors. However, as our sensor will always be wired to power, the difference in power consumption was not a significant factor to be accounted for in our design. Another cause for the popularity of capacitive sensors derives from their high sensitivity; Gray et al. [42] report that an 8×8 capacitive sensing array with 1 mm² taxels was at least ten times more sensitive than a human.

The capacitive sensors from [33] enable large area contact detection along the surface of an iCub humanoid robot. The
skin is divided into a series of interconnected triangular modules, each containing up to 192 taxels. These patches can be combined to achieve large area coverage over the entire robot. While the iCub tactile skin (and PCB sensors generally) can be customized to some extent for different applications, the versatility is limited by the fixed, large size of the triangular modules defining a patch of sensors. This restricts the ability to vary tactile spatial resolution across the robot as needed by the desired application. In contrast the piezoresistive sensors we leverage in this work scale more easily to different sized taxels and different array shapes.

B. Piezoresistive Materials for Tactile Skin

There have been several tactile skins developed which utilize stretchable and piezoresistive fabrics by Eeon-Tex [34,36]. These sensors use a similar design to ours where conductive fabric acts as electrodes against the resistive substrate as illustrated in Figure 3. Both of the aforementioned sensors utilized EeonTex LG-SLPA-16K resistive fabric to detect contact with a robotic arm. Our sensor is designed to be versatile, with the ability to swap out the resistive material without recreating the entire sensor from scratch. This is beneficial for experimenting with a wide variety of materials in order to find the optimal substrate for a given task. The tactile sensor array designed in [36] required fewer wires than other designs by using overlapping rows and columns of conductive fabric on either side of the resistive substrate. This design, however, was plagued by cross talk as there was no way to distinguish between signals if multiple taxels were activated at once. For this reason, we opt for separate electrodes per taxel in order to achieve more reliable results.

This design, however, was plagued by cross talk as there was no way to distinguish between signals if multiple taxels were activated at once. For this reason, we opt for separate electrodes per taxel in order to achieve more reliable results at the cost of more wires. The sensor in [34] was designed for large area tactile sensing covering the entire robotic arm with taxels ranging in size from 4 to 2 cm². To match our use of sensing on the robot palm we build 1 cm² taxels.

For many years, foam has been used in capacitive sensors for microphones [43] and more recently has made its way into sensing for robotics [40] and sport impact analysis [44]. It is a desirable substrate because it is inexpensive and can be tailored to different applications by tuning parameters such as the thickness and size of the pores to achieve different performance. One intriguing property that was exhibited by piezoresistive foam constructed out of silicone was significant resistance to drift [45]. Despite these factors which make foam a versatile, inexpensive and reliable sensing substrate, to the best of our knowledge it has never been used in any tactile sensing applications. In this paper, we will show that our novel piezoresistive foam sensor is not only comparable to piezoresistive fabrics common in tactile sensing, but that it provides the necessary sensations for both contact detection and object recognition.

III. TACTILE SENSOR DESIGN

In this section we detail the design and construction of our sensor. We then provide a comparative analysis between four piezoresistive substrates which can be used in the sensor. Importantly, we construct our sensor in such a way to directly compare different substrates within a common form factor.

### A. Sensor Design and Construction

Figure 3 shows the design of the tactile sensor. The bottom and top non-conducting fabrics act to electrically insulate the sensor from the robot and environment. The three layers making up the active elements of the sensor correspond to a piezoresistive substrate, $R_{\text{tax}}$, sandwiched between two conductive layers: a lower ground plane and upper electrode. By providing a constant input voltage to the sensor network and connecting an electrode in series with a reference resistor, $R_{\text{div}}$, we form a voltage divider that can detect an applied load by measuring the change in output voltage.

We follow previous designs [34,46] and construct soft tactile sensors using commonly available conductive fabric for the two conductive layers of the sensor. We design and construct our sensor in such a way that we can directly compare different piezoresistive substrates in identical sensor form factors. This enables us to compare the use of piezoresistive foam to the previously used piezoresistive fabrics.

As commonly done for tactile sensing, we decompose our sensor into an array of tactile elements or “taxels.” Each taxel corresponds to an electrode pad made out of conductive fabric. In order to ease the construction and design of the sensor, all taxels in the array share a single ground plane created from a single piece of conductive fabric. This means that the size and quantity of the taxels are defined solely by the size and density of the electrodes. A layer of non-conductive fabric was used to hold the entire sensor together. Each of the electrodes and the ground plane were attached to the non-conductive fabric layer using an iron-on adhesive. The full list of materials that we used to construct our sensor can be found on our website.

![Fig. 3: Five layers of non-conductive, conductive and resistive fabric that make up our tactile sensor array.](image)

![Fig. 4: Sensor network diagram for the 34-taxel sensor that was mounted to the Allegro robotic hand.](image)
tuning the value for each material. After testing a variety of \( R_{\text{div}} \) values, we chose a value of 5.1k\( \Omega \) because it offered the largest full-scale-range for all of the substrates. The signals from each voltage divider are passed through a multiplexer to an Arduino Nano that collects and sends each taxel’s value to the robot. Since the Arduino Nano has a 10 bit analog to digital converter (ADC), the digital signal of each taxel is represented by Eq. (1).

\[
ADC = \frac{1024 R_{\text{taxel}}}{R_{\text{div}} + R_{\text{taxel}}} \tag{1}
\]

We now describe how we construct our sensor. Both the electrodes and ground plane are attached to a layer of non-conductive fabric using an iron on adhesive, a fast and simple step. Conductive threads coated in an insulating layer of nail polish carry the electrodes signals to the rest of the circuit. Our sensor is constructed as a pouch such that different substrates can be inserted between the ground and electrode planes with ease. The pouch is closed at the top with a thin strip of hook and loop fastener. While this construction method was ideal for easily switching out the substrate for comparisons, it comes at the cost of not having the substrate rigidly attached to the electrode and ground plane. It has been shown that having a stable, rigid connection between the electrode and the substrate can improve the signal-to-noise ratio of a sensor [47]. For the benchtop experiments outlined in this paper, we secure the electrode to the substrate by lightly sewing them together. Even with the pouch structure of our sensor, we were able to obtain clear signals sufficient for both contact detection and object recognition. Figure 5 shows the layout of our 34 taxels, each with a 1 cm² footprint, spaced to cover the palm of the Allegro hand.

Since the size of each taxel is determined solely by the area of the electrodes, taxel areas can be increased or decreased to achieve different spatial resolutions at different positions of the array. This variable spatial resolution provides the benefits of higher resolution where needed, such as along the palm and fingers of the hand, while simplifying the wiring and construction in areas where lower spatial acuity suffices, such as the back of the hand or the robot arm.

B. Sensor Characterization

We compare four different piezoresistive substrates in the sensor: two types of fabric and two types of foam. The fabrics used were the EeonTex NW170SLPA-2k and Wearic piezoresistive fabric. The EeonTex and Wearic fabrics were both designed for use in tactile sensors. In contrast, both of the foams were designed as anti-static packaging for electronic components. One foam we refer to as high density due to its smaller pores and firmer structure while the other is referred to as low density due to its larger pores and softer structure. Both foams were 1/4 inch thick anti static foam. We used a National Instruments 9237 Strain/Bridge Input Module with a 10 kHz sampling frequency to record the data referenced in this section.

Despite their intended use, the foams demonstrated similar time responses as the fabrics when a weight was placed and then removed from a single taxel. The time response plots illustrated in Figure 7 were obtained with a 20g hexagonal weight with a 5.85 cm² footprint placed in the center of a single 1 inch² taxel. Figure 7 shows the averaged responses of 15 trials for each material with the region within one standard deviation shaded. We measured the rise and fall times as the time it took the signal to change between 10% and 90% of its final steady state value.

The foam substrates exhibited similar responses to the piezoresistive fabrics as well as comparable rise and fall times as shown in Figure 6. The high density foam exhibited a secondary rise after appearing to have settled, indicating that there was more unexpected variations between trials of the high density foam than with other materials. This could be due to artifacts from previous trials being exhibited, implying that it may be less accurate in detecting forces made in quick succession compared to the other substrates.

In order to determine the sensitivity to changes of pressure for each of the substrates, we recorded data from a single 1 inch² taxel for 5 seconds after loading the sensor with a weight. Weight was added to the sensor in increments of 5 from 0 to 100g. Each time after a new weight was added to the sensor, several seconds were given before data began to record to ensure that only steady state data for each weight was recorded. The pressure applied to the sensor was then calculated for each weight. Figure 8 shows the results of this experiment using a total of 1,625 samples from the sensor for each weight increment on each of the tested substrates. While the EeonTex fabric had the most linear response, each
of the other materials followed predictable curves.

As can be seen, the low density foam has a much larger signal change over pressures less than 300Pa, making it well suited for applications where quickly detecting small amounts of force is necessary, such as in contact detection. The high density foam, which is able to detect a larger range of forces before saturating is better equipped for tasks such as object classification. This difference in sensitivity range between the high and low density foams grants researchers much more freedom to fine tune the foam substrate to best fit the needs of their system. Another benefit of using a foam substrate instead of fabric for tactile sensing in robots is that the 1/4 inch thick foam offers a small amount of mechanical compliance which the fabric does not. This allows the robot a small window of reaction time between initial contact with the foam and contact with the rigid body of the robot. This increases safety by both protecting the robot from collisions with an unmovable object as well as in the case of a collision with a human where the foam would soften the impact significantly.

With a thicker form factor, comes the potential for hysteresis to make it more difficult to detect when contact has occurred. To test this, we recorded the hysteresis for each time the 20g weight was placed and removed from each of the materials. An average of 20 full cycles of placing and removal of the weight were used per material to determine the average hysteresis for each. While we expected to see a higher hysteresis in the foams, they performed very similarly to the fabrics, 17.77% and 24.14% hysteresis for the low and high density foams versus 15.15% and 23.98% hysteresis for the Wearic and EeonTex, respectively.

In summary, we find that our easily procurable foams provide results comparable to previously developed soft, resistive sensors which are much harder to obtain. They also allow researchers more freedom to choose the sensitivity of their substrate to best suit their application. Furthermore while the foams provided slightly noisier responses and showed higher nonlinear response across load, we believe the signals are sufficiently predictable for use in robotics application when coupled with standard signal processing tools.

In our first set of experiments we examine the ability for the sensor to detect contact fast enough to allow the robot arm to stop before damaging itself or its environment. Such an ability is paramount for minimizing forces while reaching in clutter [35] or performing 3D object reconstruction from touch [16]. In our second set of experiments we examine the utility of our sensor for object and shape recognition.

A. Contact Detection and Motion Arrest Experiments

For our first experiment we compare the high density and low density foams’ ability to robustly detect contact while moving. We use a simple random forest classifier trained on sensor data collected from 15 different objects. The data was collected using two different methods with 10 objects selected for each:

Method 1: The robot arm approached each object moving in a straight horizontal line. Once the sensor made contact with an object, it would push the object until the trajectory was completed. For each selected object, this test was repeated five times.

Method 2: The robot arm approached each selected object from a total of five different trajectories. Once contact with the object was made, the robot was commanded to halt movement by the press of a button by the experimenters. In order to limit the effect of human error, after the data had been recorded, the instant in which contact was made or lost, in the cases where the object fell over, was refined using the timestamps on images from an RGB-D camera.

The classifier was trained on a total of 57,334 sensor readings. In 45% of these readings, the sensor was in contact with an object. For each trial, a baseline reading was selected when the sensor was known to not be in contact. We zeroed the sensor prior to each experiment by subtracting this baseline signal. When using the pre-recorded data from the

![Fig. 7: Time response of each material averaged over 15 trials where a 20g weight was placed and then removed from the testing sensor. One standard deviation from the mean has been depicted with the shaded regions on the graph.](image)

![Fig. 8: Comparison of normalized sensitivity of each piezoresistive material. For each material, weights from 0 to 100g were placed on a single 8 cm² taxel in increments of 5g. The weights were placed in the center of the taxel had a footprint of 5.85 cm². After each weight was placed, voltage was recorded for 5 seconds and then averaged to create a single number per weight measurement.](image)
trials described above, the random forest achieved an f1 score of 0.99 when trained to detect contact and 0.98 when trained to identify which object has been contacted.

We conduct a simple motion feedback control experiment to compare the low and high density foams contact detection performance. The robot moves in a straight line in the task space from a starting pose towards a goal pose, where an unknown object sits between the two. If the robot detects contact using the classifier described above, it commands the controller to stop. We measure if the sensor detects contact and if so, what happens to the object.

![Image](image_url)

**Fig. 9:** Contact detection experimental setup: (left) the arrow indicates the robot’s motion; (right) objects used: pitcher, drill, u-tower, llama, cheezeit, and bleach

We have the robot perform a total of 18 probing actions for each foam across 6 different objects of differing geometry. Figure 9 shows the experimental setup and the 6 test objects. We place each object in the same location, 12 cm from the starting pose. We perform one trial for each of three different orientations per object to test the sensor’s detection ability against different local geometries. The results are presented in Figure 10. Videos of all experiments can be found at our website.

![Image](image_url)

**Fig. 10:** Results comparing high (HD) and low density (LD) foam for contact detection.

We find that the **low density foam detected contact in every trial**, while the high density foam detected contact in 14 of the 18 trials. The high density foam never detected contact with the u-tower, and failed in one trial with the cheezeit box. The u-tower is constructed from a set of non-rigidly attached wooden cubes. Thus it loads only a minor force on the sensor prior to falling apart, which our simple classifier has difficulty detecting. Similarly, a contact with cheezeit isn’t registered at some orientations where only a slight force is sufficient to knock it over.

The results show that both substrates can detect contact fast enough to not knock down the heavier objects. We believe learning a more sophisticated contact classifier from labeled data (e.g. [3]) as well as rigidly mounting the electrodes to the substrate as was demonstrated in [46] could significantly improve the quality of contact detection for both substrates.

### B. Object Recognition Experiments

Based on the findings of the contact detection experiments, we selected to further evaluate the low density foam in the context of object recognition and contact localization. In order to further measure the effectiveness of the sensors ability to distinguish between a variety of forces, we performed object recognition on a set of 20 unique objects with a 5x4 rectangular taxel array with the low density foam as the sensing substrate. The objects that were used for this experiment can be seen in Fig. 11.

![Image](image_url)

**Fig. 11:** Objects used for object detection using a 20-taxel sensor.

We performed a total of three data collection trials between which the order of the objects was randomized. This was done in order to avoid any artifacts left on the sensor from heavier items such as the cat and bunny which each weighed more than 100 grams. Each object was sampled in multiple orientations throughout each trial. The objects were picked up and replaced into the center of the sensor array for each data point. This granted a large variety of samples from every angle of each object to be stored into the dataset. In the end, over the 20 different objects we collected a total of 1172 samples.

We trained a random forest classifier from scikit-learn[48] on this data with a 80/20 train test split. Using this method, we achieved 36.2% accuracy and a confusion matrix depicted in Fig. 12. While this number may seem low, recall that randomly guessing only provides a 5% chance of guessing the correct object, so learning is taking place. Further, as can be seen in the confusion matrix, objects with similar weights and sizes were difficult to distinguish such as the bunny and cat or the dongle and lead objects.

One approach to overcome the limitation in performance shown here is to leverage the change in contact information over time during a grasping process. To do so we examined the tactile signals present during object lifting when using a state-of-the-art grasp planner [49] to generate grasps for unknown objects with only partially observed geometry from an RGB-D camera.

We can see in Figure 1 that a different set of taxels activates during grasping and lifting of the same object.
Our sensor was constructed with the piezoresistive substrate in a 34-taxel sensor array, mounted to the palm of an Allegro robotic hand. We tested the performance of the sensors to detect and localize contact, as well as analyze the performance of autonomous grasp executions. We found the sensor to provide useful and meaningful response, enabling the robot to stop fast enough to not knock over objects it made contact with and provide distinct signatures corresponding to different grasping configurations.

These results show that foam has a significant potential for use in tactile skins. These skins could both be applied on hands for manipulation as in this work or to cover robot arms to improve reaching in clutter or operating around humans as previously shown with piezoresistive fabric sensors [34–36]. We note that the mechanical compliance offered by the foam can likely be leveraged to offer additional safety for the robot and its surrounding including human users and compatriots.

There are numerous advantages for utilizing foam instead of fabric as a sensing substrate, one of which is being easy to source. Piezoresistive fabric is only sold by a small handful of manufacturers. The primary manufacturer of piezoresistive fabric, Eeonyx, has discontinued production of it which has made it even more difficult to source. By contrast, foam is an extremely common material which can be readily purchased from many different sources. Recent work has indicated that any open-cell polyurethane foam can be converted into a reliable piezoresistive sensor by applying a coating of conductive ink [46]. This greatly increases the variety of foams which can be purchased and converted into sensors.

Our experiments, coupled with this ability to easily transform any foam into a suitable substrate, opens the door to much exciting future work in developing a piezoresistive foam that is optimized for tactile sensing applications. This includes reducing hysteresis and drift observed by the foam sensors. Due to its porous nature, foam has been shown to be very successful in detecting vibrations [43]. This means that there is a potential for foam substrates to detect slip and other tactile events. Finally, we note that this increased spatial resolution of tactile sensing on hands can enable improved grasp analysis, including automatic detection and learning of grasp type [50].

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