Force and Thermal Sensing with a Fabric-based Skin

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***Abstract*— We present a novel fabric-based multimodal tactile sensing skin with three sensing modalities: force, actively heated temperature sensors to measure heat transfer and passive, unheated temperature sensors. In our evaluation, the skin recognized two materials during pressing and sliding tasks. Our method thermally distinguished pine wood from aluminum after detecting the contact force. With a support vector machine (SVM) classifier trained on 0.25 s of data, our method achieved a recognition accuracy of 96% for the pressing task and 73% for the sliding task.**

I. Introduction

Multimodal tactile sensing can provide valuable information for robot manipulation in unstructured environments with proximity to people. Force-based sensing has been used to recognize the stiffness/compliance and movement of objects [1]. Actively heated temperature (active thermal) sensing shows promise for recognizing materials based on their thermal properties and unheated temperature (passive thermal) sensing can be effective at recognizing heat-generating objects such as the human body [2]. As shown in [3], multimodal tactile sensing can enable robots to recognize materials that may be difficult to distinguish using a single modality.

In this work we present a multimodal tactile sensing skin prototype that could be used to cover a robot's entire arm. This builds upon our previous work with a single rigid multimodal sensor attached to a handheld data acquisition device [4]. In contrast to other multimodal tactile sensing skins [5], [6], we implemented both active and passive thermal sensors and used a fabric-based design. We used the skin to perform two representative manipulation tasks. Finally, we present our results of material recognition with the skin on samples of pine wood and aluminum using both thermal modalities.

II. Device Description

Figure 1 shows the fabric-based multimodal tactile sensing skin prototype. The skin has 5 force sensing taxels, 1 at the end (area = 9 cm^2) and 4 around the circumference (each of area = 17 cm^2). Each taxel has 7 fabric layers as shown in Fig. 1 (bottom) and has two active and passive thermal sensors.

A. Hardware Specifications

The skin's force sensing modality uses fabric-based tactile sensors as described in [7]. Each force sensing taxel features a layer of resistive fabric sandwiched between two layers of conductive fabric. Each of these taxels has four fast response 10 kΩ thermistors (EPCOS B57541G1103F). Two are heated by a 15 mm wide carbon fiber resistive heating strip [8] for active thermal sensing while the other two are used for passive thermal sensing, similar to our work in [2].

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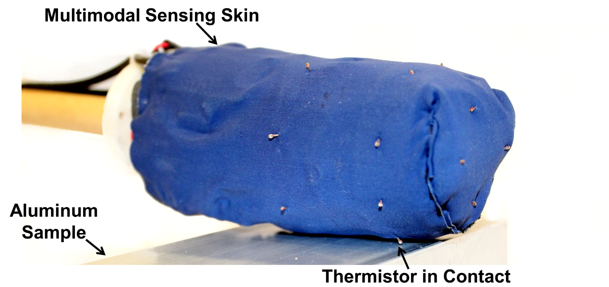

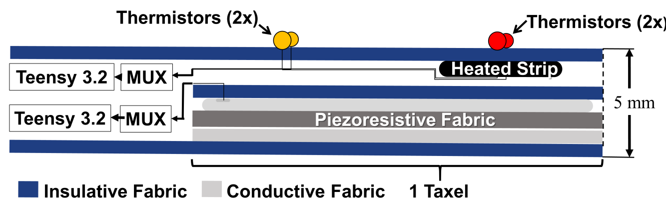

Fig. 1: *Top: multimodal fabric-based tactile sensing skin prototype covering a 3D printed cylinder. Bottom: design of fabric-based skin.*

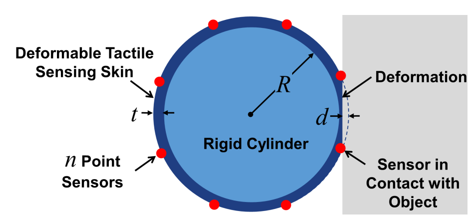

Fig. 2: *Model used to evaluate thermistor spacing.*

B. Spacing of Discrete Thermal Sensors

Because the active and passive thermal sensing modalities rely on thermistors of small cross-sectional area (0.015 cm^2) compared to our force sensing taxels, we consider them point sensors. To gain insight into the spacing for the thermistors along the circumference of the cylinder, we developed a planar model for the number of point sensors that will make contact when the cylinder touches a flat surface. Figure 2 shows a rigid cylinder of radius R covered with the deformable tactile sensing skin of thickness t. During contact, the skin compresses a distance d with a small applied force. The model yields

$$k_c = \lfloor \frac{n}{\pi} \arccos(1 - \frac{d}{R+t}) \rfloor \tag{1}$$

where n is the number of point sensors evenly spaced around the circumference of the skin and k_c is the minimum number of point sensors that will contact the surface. For

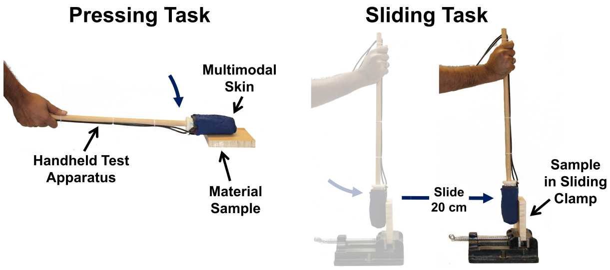

Fig. 3: *Experimental procedure for the pressing and sliding tasks.*

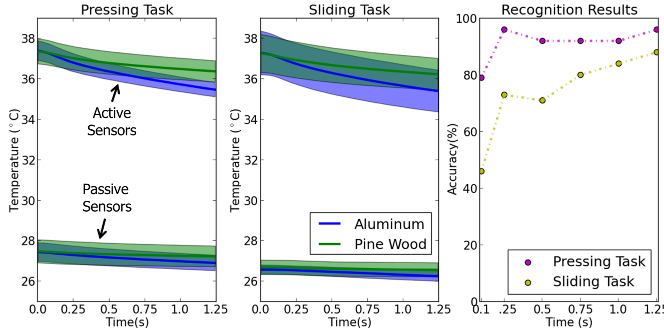

Fig. 4: *Left, middle: thermal sensor data (mean ± standard deviation) recorded with 10 material samples each of aluminum and pine wood during two manipulation tasks. Right: recognition accuracy with varying contact time.*

our prototype, $R = 17\,\text{mm}$, $t = 5\,\text{mm}$ and $d = 3\,\text{mm}$ which yields $k_c = 1$ for $6 \leq n \leq 11$. Thus our model predicts that for our design with $n = 8$ thermistors, at least one should make contact when the cylinder touches a flat surface.

III. Experiments

Figure 3 illustrates the experimental procedure we used to evaluate the skin. Our objective was to distinguish aluminum from pine wood during two tasks that robots could do while performing manipulation in cluttered environments [1]: pressing a stationary object and sliding an object so that it moves. We covered a 3D printed rigid cylinder with the skin and attached it to a 50 cm long wooden dowel to represent a robot arm. We performed each task shown in Fig. 3 with 10 material samples each of aluminum and pine wood. In the first task, we pressed the skin to each material sample for 4 s. In the second task we placed the sample in a movable clamp and used the skin to push and slide it a distance of 20 cm in approximately 2 s. In both cases, we held the skin and rigid cylinder flat against the sample. We used a force detection threshold of 0.1 N to determine the start of contact and recorded data at 100 Hz. To ensure that the active thermal sensors were in a thermal steady state before each task, we waited for 60 s before moving on to the next sample.

IV. Analysis and Results

To determine which heat transfer sensor came in contact with the material during a trial, we analyzed data from active thermal sensors that exhibited a negative change in temperature at each time step for 1.25 s. We ensured that the corresponding force sensing taxel measured a force greater than 0.1 N. This provided evidence that the thermistor was in contact with the material sample, which was at ambient temperature. Based on this approach, we determined that one or two active thermal sensors were in contact with the sample during each trial, a range that agrees our model in Section II-B. Because we tested the skin with the cylinder flat against the surface, we assumed that both the active and passive thermal sensors at a particular circumferential position would simultaneously contact the sample. Based on this, with each active thermal sensor time series used, we also used data from the passive sensor in the same circumferential position. Figure 4 (left, middle) shows the first 1.25 s of active and passive thermal sensor data (mean ± standard deviation) collected with 10 material samples each of aluminum and pine wood for the pressing and sliding tasks.

Based on our previous work in [2], we used a binary support vector machine (SVM) classifier with a linear kernel to recognize aluminum vs. pine wood based on the active and passive thermal sensor data and the time derivative of the active data. We truncated the data to begin at the estimated onset of contact using a force threshold of 0.1 N. To study the effect of contact duration on our recognition accuracy, we truncated the time series to include the first 10, 25, 50, 75, 100 and 125 samples corresponding to the first 0.10, 0.25, 0.50, 0.75, 1.00 and 1.25 s of contact respectively. Figure 4 (right) shows the SVM's recognition accuracy over the time duration considered for both the pressing and sliding tasks. With 3-fold cross-validation, the average recognition accuracy for the pressing task was 96% with 0.25 s of data and 92% with 1.0 s of data. For the more challenging sliding task, the accuracy was 73% and 84% for 0.25 s and 1.0 s of data, respectively. This demonstrates the feasibility of our fabric-based multimodal skin that could cover a robot's arm and provide information about the environment.

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