Data-Driven Thermal Recognition of Contact with People and Objects

Tapomayukh Bhattacharjee, Joshua Wade, Yash Chitalia, and Charles C. Kemp

***Abstract*— Many tactile sensors can readily detect physical contact with an object, but tactile recognition of the type of object remains challenging. In this paper, we provide evidence that data-driven thermal tactile sensing can be used to recognize contact with people and objects in real-world settings. We created a portable handheld device with three tactile sensing modalities: a heat-transfer sensor that is actively heated, a small thermally-isolated temperature sensor, and a force sensor to detect the onset of contact. Using this device, we collected data from contact with the arms of 10 people (3 locations on the right arm) and contact with 80 objects relevant to robotic assistance (8 object types in 10 residential bathrooms). We then used support vector machines (SVMs) to perform binary classifications relevant to assistive robots. When classifying contact as person vs. object, classifiers that only used the temperature sensor performed best (average accuracy of 98.75% for 3.65s of contact, 93.13% for 1.0s, and 82.13% for 0.5s). When classifying contact into two task-relevant object types (e.g., towel vs. towel rack), classifiers that used the heat-transfer sensor together with the temperature sensor performed best. Performance was good when generalizing to new contact locations in the same environment (average accuracy of 92.14% for 3.65s of contact, 91.43% for 1.0s, and 84.29% for 0.5s), but weaker when generalizing to new environments (average accuracy of 84% for 3.65s of contact, 71% for 1.0s, and 65% for 0.5s).**

I. INTRODUCTION

In this paper, we provide evidence that data-driven thermal tactile sensing can be used to recognize contact with people and objects in real-world settings. Unlike approaches that attempt to classify objects into a large number of categories, we focus on task-relevant binary classification. Robots operating in human environments would benefit from the ability to recognize when contact has occurred with a person versus objects in the environment. For example, a robot might regulate the force it applies to a person or monitor contact with a person for communicative signals. When manipulating objects, distinguishing between contact with an object of interest and a nearby object could also be useful. For example, a robot might use this capability to better maneuver its end effector to grasp a target object. In general, we expect that the task being performed by the robot and observations of the local environment can be used to reduce the tactile recognition problem to one of categorizing contact into a small number of categories.

We train support vector machines (SVMs) to classify time series from a temperature sensor and a heat-transfer sensor. As we demonstrate, temperature sensing is useful for detecting contact with a person's body versus the environment.

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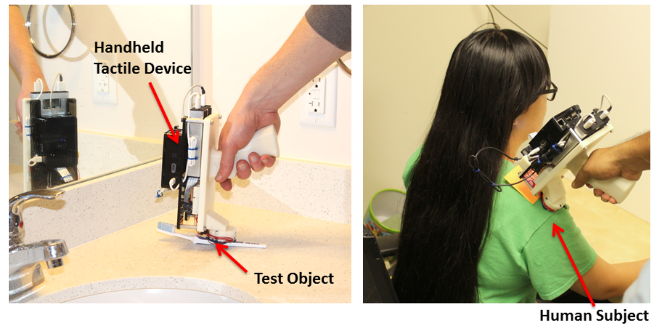

Fig. 1: *A person using a handheld device to make contact with a toothbrush on counter in a bathroom (left), and a human participant's shoulder (right).*

Temperature sensing is well matched to this classification problem, since the human body actively generates heat, while most objects in the environment are thermally passive and close to the ambient temperature. We also show that heat-transfer sensing can be informative for distinguishing between task-relevant objects. This is in part due to heat-transfer sensing being able to distinguish materials with different thermal effusivities, such as metal and plastic.

Data-driven approaches for tactile perception have shown promise [1], but suitable training data is lacking. To help address this challenge, we developed a portable handheld device (see Fig. 1) [2] for the efficient acquisition of heat-transfer and temperature sensing data from objects in their natural settings. Robot vision and audition, including face detection and speech recognition, have benefited greatly from large labeled data sets of pictures, videos, and audio collected by people. One of our motivations for creating this device is to enable people to efficiently acquire tactile training data for robots, so that tactile perception systems for robots can similarly benefit. Our data-driven recognition algorithm uses this data to train the classifiers for thermal recognition of contact with people and objects.

Thermal recognition of objects in situ entails distinct challenges from material recognition and laboratory-based studies. In contrast to recognition of material samples, objects will often be composed of multiple materials with distinct thermal properties, such as different thermal effusivities. Objects will also have geometries that affect heat transfer, such as by altering the contact area between thermal sensors and the object. Also, different objects in the same object category can be made of thermally distinct materials, such as a plastic fork and a metal fork. In contrast to laboratory-based studies, objects in their natural settings and thermal sensors making contact with them will be influenced by more varied thermal phenomena. These include sunlight through windows, heating, ventilating, and air conditioning (HVAC), body heat, and complex connections between objects and the

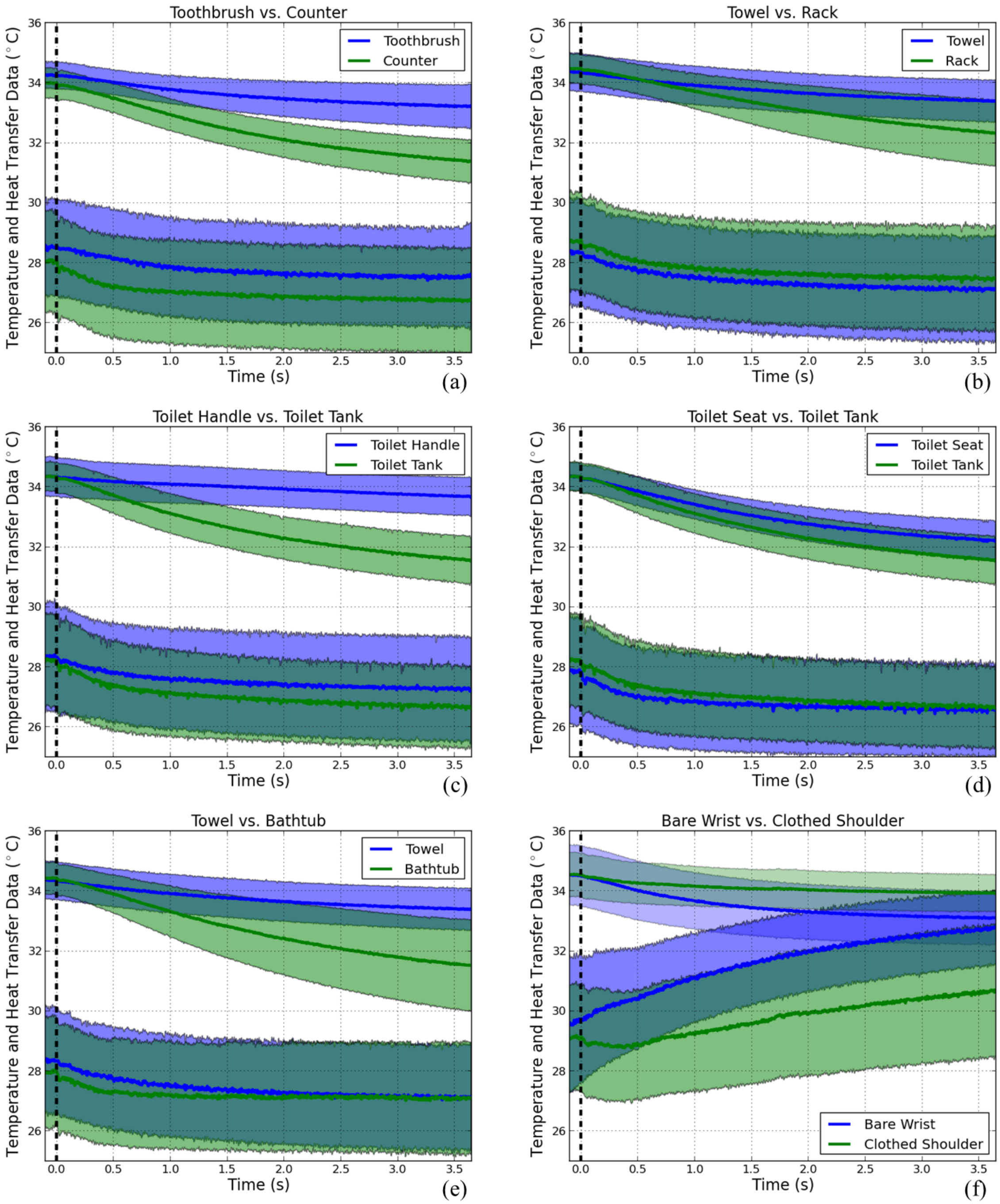

Fig. 2: *Tactile sensor response with average (solid lines) and standard deviation (shaded) values for both heat-transfer (top two regions in each graph) and temperature (bottom two regions in each graph) sensors for contact with task-relevant objects and locations on human arm. Black dashed lines show the onset of contact.*

interiors and exteriors of buildings.

To evaluate our approach, we collected two data sets. For the first, we collected data from contact with 3 different locations on the right arms of 10 human participants. For the second, we collected data from contact with 80 objects, consisting of 8 object types from 10 residential bathrooms. We considered objects in the bathroom because many activities of daily living (ADLs) with which robots might provide valuable assistance take place in bathrooms, such as hygiene, grooming, bathing, showering, toileting, transfers, and dressing [3]–[5]. We selected these objects because they are related to ADLs and are commonly found within residential bathrooms in the United States.

In our evaluation, we only consider binary classification problems. Due to the existence of only two categories (i.e., two object types or two contact types), we use terms like 'distinguishing', 'classifying', and 'recognizing' nearly interchangeably.

Our evaluation of human vs. object recognition focuses on distinguishing contact with a human arm from contact with task-relevant objects associated with ADLs. This recognition problem has additional challenges due to factors such as clothing, the location of contact on the person's body, and physiological differences among people (See Fig. 2(f)).

Our evaluation of task-relevant object recognition focuses on distinguishing a target object, which we refer to as the tactile foreground, from an object in its immediate surrounding, which we refer to as the tactile background. Each foreground/background pair corresponds with two objects relevant to a specific task. For example, the task of placing a towel on a towel rack and the task of picking up a toothbrush from a counter (See Fig. 2).

II. RELATED WORK

Most previous tactile recognition studies focus on data taken from material samples or objects in a controlled laboratory setting. However, our work focuses on task-relevant object recognition using data gathered from in situ objects in homes. Also, contact based material recognition studies in the literature have often focused on deliberate exploratory contact behaviors. These behaviors help in controlling the sensing to maximize the information retrieval for material recognition. Our work uses a single instance of sustained contact.

A. Human vs. Object Recognition

Humans represent an important class of object in the world that merits special consideration by machines. Research communities devoted to other perceptual modalities, such as audio and video, have emphasized machine perception of signals resulting from people, such as face detection [6]. In contrast, detecting when tactile signals result from human contact has been relatively unexplored [7]. In [8], we used heat flow to classify contact with medium-density fiberboard versus a persons bare forearm. The closest other work of which we are aware investigated multimodal tactile sensing for affective interaction with the Huggable, a small robotic teddy bear for companionship [9], [10]. The Huggable used distributed electric field, temperature, and force sensors [10] to categorize gestures based on 200 examples from a single person using his/her hand to make communicative contact. In contrast, we focus on discriminating contact between objects and people under varying conditions, such as location and presence of clothing, and investigate the relevance of these capabilities for tasks related to ADLs. [11] uses SVMs and carefully designed features to detect collisions from physical interactions between a robot and a human. Kerr et al. [12] used the BioTAC^{TM} sensor to infer properties of a human body by detecting pulse, classifying the heart rate and analyzing pulse-to-pulse intervals.

There have also been studies on detecting people using non-contact thermal sensors such as thermal cameras [13]. This body of work generally relies on the fact that there is a temperature difference between a heat-generating object like the human body and surrounding objects. Researchers have also used other non-contact thermal sensors such as pyrometers to measure skin temperature [14]. [15] gives an overview of the temperature of the human body, explains the source of heat generation, and discusses its variability depending on the location on the body.

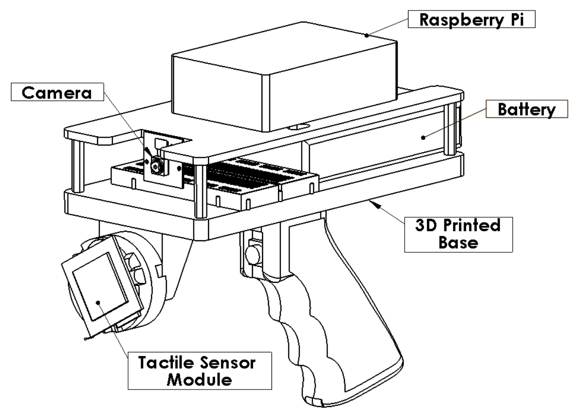

Fig. 3: *Design of handheld haptic data acquisition device.*

B. Object vs. Object Recognition

1) Thermal Sensing Only: There have been many studies on material recognition using only thermal sensing. For an overview of such material recognition studies, please refer to [8], [16]–[20].

There have also been studies in which researchers have used thermal sensing in conjunction with other sensory modalities for material recognition purposes.

2) Thermal and Force Sensing Modality: Engel et al. [21], [22] developed a flexible multimodal tactile sensing system using pressure and thermal sensing and achieved 90% accuracy over 50 trials for recognizing 5 materials. Siegal et al. [23] developed a multimodal sensor consisting of an 8 x 8 array of capacitive tactile sensors with a 4 x 4 array of thermal sensors. Takamuku et al. [24] designed an anthropomorphic finger consisting of 3 strain gauges and 4 thermistors with a heating element arranged in a layered format. They successfully classified 5 materials using a combination of strain gauge information and thermal sensing. Yang et al. [25] constructed a 32 x 32 array of conductive rubber based force sensors and absolute temperature measurement chips mounted on both sides of a flexible substrate.

Yuji et al. [26] developed a tactile and thermal sensor using a single pressure-conductive rubber sheet with unequally spaced electrodes to infer both temperature and contact force. They used a common heating element to warm a 2x2 array of sensing modules to 36°C and performed tests with two materials. Caldwell et al. [27] developed a multimodal tactile sensor to measure contact force and thermal response. They measured the contact force and robot position during specific exploratory behaviors to infer texture, stiffness and object profile, temperature and thermal properties. The thermal sensor used a temperature controlled heat source at a constant 40°C and a Peltier Effect sensor to identify 7 materials with different thermal properties. Castelli [28] developed an 8x8 array of capacitive-based tactile sensors using temperature-dependent semiconductors for absolute temperature measurement. Dario et al. [29] developed a polymer-based tactile and thermal sensor inspired by dermal and epidermal layers of human skin.

3) Thermal and Other Sensing Modalities: Taddeucci et al. [30] used a multimodal haptic sensing finger with thermal and vibration feedback and a high resolution array of tactile

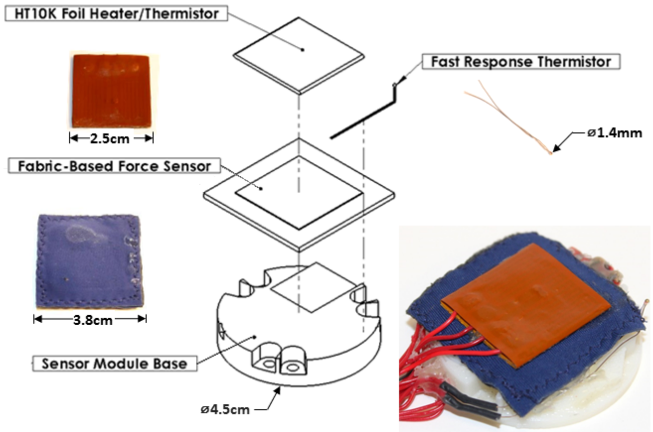

Fig. 4: *Exploded view of tactile sensor module.*

sensors to identify 14 objects during idealized sliding contact using neural networks. [31]–[33] used the BioTAC™ sensor with thermal feedback to classify objects using Bayesian learning techniques, ANNs and HMMs.

Mittendorfer et al. [34] developed hexagonal multi-modal sensing modules with optical proximity, thermal and acceleration-vibration modalities combined to form an array on a robot arm. In [35], the authors developed a prosthetic skin that used strain, pressure, temperature, and humidity sensors, along with electroresistive heaters.

III. DESCRIPTION OF THE HANDHELD DEVICE

Figure 3 shows the design of the complete handheld data acquisition device. Figure 4 shows the tactile sensor module that mounts to the front of the handheld device and comes into contact with objects. The tactile sensor includes a sensor for measuring heat transfer, a fast response thermistor for temperature sensing and a fabric-based force sensor for force estimation. The heat-transfer and temperature sensing modalities are used for recognition purposes. The force sensing modality is only used to detect the onset of contact and is not used for recognition.

The handheld device uses an onboard camera to save a picture of each object for documentation. The onboard Raspberry Pi 2 and 8 channel 12 bit ADS7828 analog-to-digital converter (ADC) record data to a USB flash drive from the force sensor at approximately 550 Hz and from the heat-transfer sensor and temperature sensor at approximately 110 Hz. To simplify analysis, we upsampled the data from the heat-transfer and temperature sensors to 550 Hz using zero-order hold interpolation in order to match the sample rate of the force sensor.

A. *Design Assembly of the Sensor Module*

Figure 4 shows the complete sensor with a 3D printed base. We used Surebonder 727 Hot Glue [36] to attach the passive fast response thermistor, and heat-transfer sensor on top of the force sensor, which is mounted on the 3D printed base. The heat-transfer sensor and fast response thermistor sit beside one another and form the outer-most sensing layer. They come into direct contact with the object, which allows for faster response times.

B. *Heat-Transfer Sensor*

We based the sensor for measuring heat transfer on our work in [8]. The sensor uses a Thorlabs HT10K - Flexible Polyimide Foil Heater with a 10 kOhm Thermistor [37]. This sensor uses the modified transient plane source technique for thermal property estimation [38]. In this technique, a resistive heater heats the sensor up before bringing it into contact with a uniform material sample at room temperature. With good contact and a large sample, the material's thermal effusivity [8] primarily determines the heat transfer from the sensor to the sample. This results in a characteristic temperature change measured by the HT10K's thermistor. We converted the raw ADC output from the thermistor in the heat-transfer sensor to degrees Celsius using a third-order polynomial fit ($R^2 = 0.994$) based on calibration data.

C. *Temperature Sensor*

Unlike our previous work in [8], we also used a small, passive EPCOS fast response 10K NTC thermistor to measure the approximate air temperature before contact and the object's temperature during contact. Though heat from the heat-transfer sensor's heater and other onboard electronics, as well as other environment factors tend to raise the temperature of the surrounding air, it is still possible to estimate the ambient temperature of the environment within approximately 1°C by recording the temperature sensor value prior to contact. We implemented a third-order polynomial fit ($R^2 = 0.994$) based on calibration data to convert the raw ADC output from the fast response thermistor to degrees Celsius (See [8] for details).

D. *Fabric-Based Force Sensor*

The force sensing modality uses a single 2.5cm square taxel of piezoresistive fabric in a voltage divider circuit based on the stretchable fabric-based force sensor described in [39]. We converted the raw ADC output from the taxel to force in newtons, assuming a uniform pressure distribution over the taxel, using a third-order polynomial fit ($R^2 = 0.984$) with calibration data collected using an ATI Mini45 Force/Torque sensor.

IV. EXPERIMENTS

We performed two sets of experiments to evaluate our device and methods.

A. *Experimental Procedure*

For both the experiments with humans and objects, we performed the following procedure for data collection.

- We identified the object or the location on the human arm and attached a sticky note adjacent to it identifying the object / location.
- Before a trial with any object or any location on the human arm, we allowed the heat-transfer sensor to heat for 3 minutes to allow it to reach a thermal steady state. This reduces variability in the sensor's initial conditions.
- We took a picture of the object/location using the camera mounted on the device.

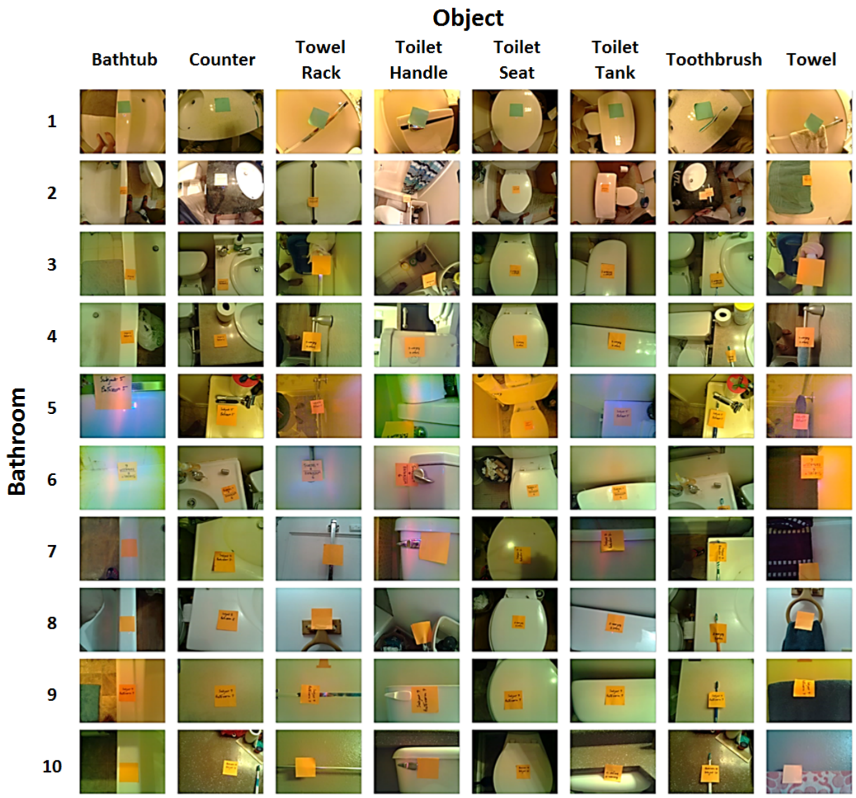

Fig. 5: *Test set consisting of 10 sets of common items found in a bathroom associated with activities of daily living (ADLs): bathtub, sink counter, empty towel rack, toilet handle, toilet seat, toilet tank, toothbrush and towel on towel rack.*

- We attempted to move the device in a linear motion normal to the surface of the object with constant velocity.
- We maintained contact with approximately constant pressure for 5s and waited for a beep from the device to break contact.

B. Experiments with human participants

For these trials, we used the handheld device to make contact with three locations on the human arm, namely the wrist, the forearm and the shoulder (covered by the sleeve of an article of clothing) as shown in Fig. 6. Each participant wore his/her own shoulder-covering clothing for the study. We recruited 10 participants via word of mouth. We had 3 female and 7 male participants from 21 to 49 years of age. We obtained informed consent from each participant. Our study was approved by the Institutional Review Board of the Georgia Institute of Technology. For each experiment, we asked the participant to keep his / her arm on a table-like surface while we applied the handheld device to three points on his / her arm.

We chose locations on the wrist, forearm and elbow of a human arm to be anatomically consistent across different participants in our controlled experiments (Fig. 6). For the wrist, we chose a location 1cm away from the triquetral bone towards the sagittal plane. For the forearm, we chose a location on the bulk of the flexor muscle, 5cm away (towards the wrist) from the line connecting the elbow pit and elbow bone. For the shoulder, we chose the location of the acromion scapula. We conducted 1 trial per location, thus collecting a total of 30 trials (3 locations X 10 participants). Figure 2(f) shows 3.65s of the data from all trials on the wrist and shoulder of human participants. As seen in the figure, the heat-transfer rate is higher for the bare wrist (and forearm) locations compared to the clothed shoulder potentially due to the thermal insulation provided by the clothing. Unlike the experiments with household objects, the temperature sensor warms up slightly after contact because it is in contact with a heat-generating object (human body). The temperature sensor is close to ambient temperature (within 1°C) before contact.

C. Experiments with household objects

Figure 5 shows the common household objects found in a bathroom from which we collected data. Our objective was to analyze recognition performance for the following task-relevant tactile foreground versus tactile background recognition problems: toothbrush vs. counter; towel vs. towel rack; toilet handle vs. toilet tank; toilet seat vs. toilet tank; and towel vs. bathtub.

1) Objects in the same bathroom: We used the handheld device to make contact with each of the 8 objects in the same bathroom. We collected 10 trials from 10 different locations on the same object while waiting for 3 minutes between each trial. After collecting the data, for each sensing modality, we subtracted the starting temperature of a trial from all subsequent measurements in the trial. We did this to avoid bias from spatially varying temperatures in the bathroom.

2) Objects from different bathrooms: We used the handheld device to make contact with each of the 8 objects once each in 10 different bathrooms for a total of 10 trials with

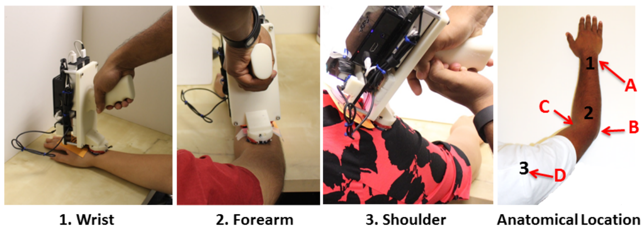

Fig. 6: *The three images on the left show data collection from three locations on the dominant arm of 3 different participants using the handheld device. The image on the right shows the test locations (black) [1-Wrist, 2-Forearm, 3-Shoulder] and the anatomical key points (red) [A-Triquetral bone, B-Elbow bone, C-Elbow pit, and D-Acromion Scapula].*

each object. Figure 2 shows 3.65s of the sensor data from all trials with different objects. As seen in the figure, the heat-transfer rate is higher for the counter when compared to the toothbrush. Also from the figure we see that the average room temperature measured by the temperature sensor before contact varies slightly between trials with toothbrushes and counters potentially due to variations in the temperature of the room while the data was recorded. After contact, the temperature sensor cools slightly for approximately the first 1s of contact before coming to thermal steady state with the object. Before contact the temperature sensor is heated approximately 1°C above the air temperature in the room, potentially due to heat generated in the heat-transfer sensor's heater and other onboard electronics.

D. Recognition algorithm

For each trial, we truncated the raw time series from the heat-transfer sensor and temperature sensor to include 2000 time samples from time of contact to approximately 3.65s after contact for each modality. To ensure accurate detection of contact, we checked each trial data visually and determined the time instant when contact occurred using the force sensor modality. We then used the same time instant for the thermal modalities in the same trial. Our methods also used estimates of the derivative (slope) of the heat-transfer data with respect to time by taking the first difference of the raw signals and then using a causal filter. The filter was an 8th-order digital low-pass Butterworth filter with Nyquist frequency of 100 Hz and cutoff frequency of 5 Hz.

We then normalized each modality by subtracting the mean and dividing by the variance across all of the modality's data, after which we vectorized each modality and concatenated the resulting vectors into a single vector. We used a binary support vector machine (SVM) classifier with a linear kernel and 5-fold cross-validation to recognize each object-object and human-object pair.

V. RESULTS AND DISCUSSION

A. Results with human participants

1) Effect of different modalities: Table I shows the results with different modalities and 30 trials across the human-participants experiment and 80 trials across the objects experiment. Results show that temperature is a valuable modality for distinguishing humans from their surroundings irrespective of location or clothing. This is intuitive as the human body generates heat which can be felt irrespective of clothing.

2) Effect of contact duration: For these analyses, we varied the duration of contact by truncating the data at different time intervals (0.5s, 1.0s, 2.0s, and 3.65s) to see how rapidly our algorithm could accurately classify. Table II shows the results for different contact durations. We chose passive temperature sensing because it gave the best results in Table I. Results show the highest accuracy was with the longest contact duration of 3.65s, as seen in Table II. However, results with just 0.5s of contact were above chance (82.13%) showing the potential of these methods for faster discrimination between humans and their surroundings.

TABLE I: Human vs. Object recognition.

Tasks		Accuracy with Different Modalities		
		Two Modalities	Single Modality	
		H+T+ Slope of H	H+ Slope of H	T
Brushing Teeth				
Human	Toothbrush	88%	72%	**100%**
Hand on Counter				
Human	Counter	97%	95%	**100%**
Wiping Face				
Human	Towel	95%	75%	**100%**
Flushing Toilet				
Human	Toilet Handle	93%	72%	**100%**
Flushing Toilet				
Human	Toilet Tank	95%	88%	**100%**
Lifting Toilet Seat				
Human	Toilet Seat	95%	88%	**97%**
Taking a Bath				
Human	Bathtub	**93%**	90%	**93%**
Placing a Towel				
Human	Rack	93%	90%	**100%**
Average Performance		93.63%	83.75%	**98.75%**

*H = Heat-Transfer, T = Temperature Sensor Modality

TABLE II: Human vs. Object recognition : Effect of contact duration.

Tasks		T Modality			
		0.5s	1.0s	2.0s	3.65s
Brushing Teeth					
Human	Toothbrush	80%	97%	97%	**100%**
Hand on Counter					
Human	Counter	85%	93%	97%	**100%**
Wiping Face					
Human	Towel	78%	97%	97%	**100%**
Flushing Toilet					
Human	Toilet Handle	85%	90%	97%	**100%**
Flushing Toilet					
Human	Toilet Tank	90%	90%	93%	**100%**
Lifting Toilet Seat					
Human	Toilet Seat	82%	93%	93%	**97%**
Taking a Bath					
Human	Bathtub	82%	88%	88%	**93%**
Placing a Towel					
Human	Rack	75%	97%	97%	**100%**
Average Performance		82.13%	93.13%	94.88%	**98.75%**

B. Results with objects in the same bathroom

Table III shows the results for objects in the same bathroom. Using both heat-transfer and temperature sensing gave the best results. For this experiment, we used two different towel conditions in dry and wet state as seen in Table III. Note that the rack in this bathroom had a rectangular cross-section, thus allowing more contact with the heat-transfer

TABLE III: Object recognition : Generalization to new locations.

Task Relevant Scenarios	Accuracy with Different Modalities		
	Two Modalities	Single Modality	
	H+T+ Slope of H	H+ Slope of H	T
Toothbrush on Counter	**95%**	90%	**95%**
Dry Towel on Rack	**100%**	**100%**	65%
Wet Towel on Rack	**100%**	**100%**	**100%**
Toilet Handle on Toilet Tank	**85%**	80%	**85%**
Toilet Seat on Toilet Tank	**75%**	65%	60%
Dry Towel on Bathtub	**95%**	**95%**	60%
Wet Towel on Bathtub	**95%**	**95%**	90%
Average Performance	**92.14%**	89.29%	79.29%

TABLE IV: Object recognition : Effect of contact duration on generalization to new locations.

Task Relevant Scenarios	H+T+Slope of H Modalities			
	0.5s	1.0s	2.0s	3.65s
Toothbrush on Counter	90%	90%	**95%**	**95%**
Dry Towel on Rack	95%	**100%**	**100%**	**100%**
Wet Towel on Rack	95%	**100%**	**100%**	**100%**
Toilet Handle on Toilet Tank	65%	75%	**90%**	85%
Toilet Seat on Toilet Tank	75%	**90%**	**90%**	75%
Dry Towel on Bathtub	90%	90%	**95%**	**95%**
Wet Towel on Bathtub	80%	**95%**	90%	**95%**
Average Performance	84.29%	91.43%	**94.29%**	92.14%

sensor. Table IV shows the effect of contact duration on the recognition problem. Even with just 0.5s of contact, the accuracy results are good because of less variability in object conditions in the same bathroom, as mentioned above.

C. Results with objects from different bathrooms

1) Effect of different modalities: Table V shows the results with one trial for each object in each bathroom for different modalities thus totaling 80 (10 bathrooms x 8 objects x 1 trial) trials. Results (Table V) show that heat-transfer with temperature sensing gave the best results, thus generalizing to different objects / bathrooms. Results in Table V are worse when compared with the results in Table III because 10 trials were taken from 10 different toothbrushes, counters, towels etc. that may be different in each of the 10 bathrooms. Results with towel and rack are low, possibly because racks varied with rectangular and circular cross-sections which affects the contact area with the heat-transfer sensor. Segregating the data with the rectangular rack, which allows more contact area with the heat-transfer sensor, resulted in 93% accuracy for towel-rack recognition with heat-transfer and temperature data.

2) Effect of contact duration: Table VI shows the results for different contact duration of 0.5s, 1.0s, 2.0s, and 3.65s. We used both the heat-transfer and temperature data because it gave the best overall results shown in Table V. Our methods achieved highest accuracy with the longest contact duration of 3.65s as seen in Table VI. With a duration of 1.0s, the accuracies are high except for recognition of towel vs. rack, due to different shapes of cross-sections of racks (See Section V-C.1). Recognition of towel vs. bathtub in such short intervals is also low, probably due to different wet and dry towel conditions.

TABLE V: Object recognition : Generalization to new environments.

Task Relevant Scenarios	Accuracy with Different Modalities		
	Two Modalities	Single Modality	
	H+T+ Slope of H	H+ Slope of H	T
Toothbrush on Counter	**90%**	85%	70%
Towel on Rack	**65%**	**65%**	55%
Toilet Handle on Toilet Tank	**95%**	**95%**	55%
Toilet Seat on Toilet Tank	**80%**	60%	35%
Towel on Bathtub	**90%**	75%	55%
Average Performance	**84%**	76%	54%

TABLE VI: Object recognition : Effect of contact duration on generalization to new environments.

Task Relevant Scenarios	H+T+Slope of H Modalities			
	0.5s	1.0s	2.0s	3.65s
Toothbrush on Counter	70%	80%	85%	**90%**
Towel on Rack	55%	50%	60%	**65%**
Toilet Handle on Toilet Tank	75%	90%	90%	**95%**
Toilet Seat on Toilet Tank	70%	75%	75%	**80%**
Towel on Bathtub	55%	60%	70%	**90%**
Average Performance	65%	71%	76%	**84%**

D. Discussion

Throughout this paper, we have referred to the actively heated sensor as the heat-transfer sensor. However, both thermal sensors rely on heat transfer. For example, the unheated temperature sensor is cooler than the human body, resulting in a distinctive signal due to heat transfer from the human body to the sensor.

We conducted our research with robots in mind. We expect our results to be relevant to robots that operate in close proximity to people and manipulate objects, such as assistive robots. However, other devices could potentially use similar methods to sense their surroundings and human interaction. For robots, a number of open questions remain. For example, more varied conditions associated with a task might degrade performance. During real-world use, we would expect greater variability in applied force, contact area, relative orientation of the sensor to the object's surface, reheat times, and other characteristics. Nonetheless, we expect data-driven thermal recognition to still be useful, given the strong performance of object vs. object classification when in a single environment and human vs. object classification.

VI. Conclusions

We investigated data-driven thermal recognition of contact with people and objects. Using a portable handheld data acquisition device, we collected data from 3 different locations on the arms of 10 different human participants, and from 8 types of task-relevant objects found in 10 residential bathrooms. We implemented SVMs to distinguish between contact with humans and objects, and between task-relevant object pairs. In our tests, classifying contact as people versus object worked well with temperature sensing alone in spite of clothing, individual variation, and different locations on the arm. Classifying contact into two task-relevant object types worked well when restricted to a particular bathroom. Heat-transfer sensing and temperature sensing had complementary value for this type of recognition problem. Recognition performed using both modalities outperformed recognition performed with either modality alone. Classifying contact in a new bathroom based on training data only from other bathrooms did not work as well. However, the classifiers did generalize to new bathrooms to some extent, as evidenced by their improved performance with longer contact duration.

ACKNOWLEDGMENTS

This work was supported in part by NSF Awards EFRI-1137229 and IIS-1150157, the National Institute on Disability, Independent Living, and Rehabilitation Research (NIDILRR) grant 90RE5016-01-00 via RERC TechSAge, and a Google Faculty Research Award. We thank Vincent Dureau for valuable discussions, and Phillip M. Grice and Yun Seong Song for their help with the human-subjects study.

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