

Capacitivo: Contact-Based Object Recognition on Interactive Fabrics using Capacitive Sensing

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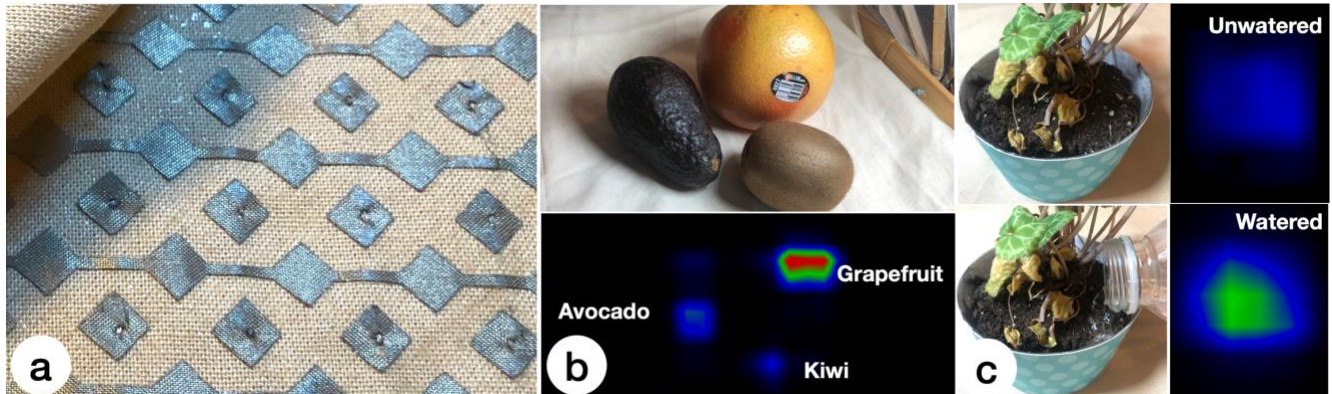


Figure 1 (a) Capacitivo is an interactive fabric, capable of sensing a wide variety of non-metallic daily objects it is in contact with. (b) For example, the fabric sensor can sense different types of fruits. (c) It can also sense if the soil of a table plant is wet or dry.

ABSTRACT

We present Capacitivo, a contact-based object recognition technique developed for interactive fabrics, using capacitive sensing. Unlike prior work that has focused on metallic objects, our technique recognizes non-metallic objects such as food, different types of fruits, liquids, and other types of objects that are often found around a home or in a workplace. To demonstrate our technique, we created a prototype composed of a 12 x 12 grid of electrodes, made from conductive fabric attached to a textile substrate. We designed the size and separation between the electrodes to maximize the sensing area and sensitivity. We then used a 10-person study to evaluate the performance of our sensing technique using 20 different objects, which yielded a 94.5% accuracy rate. We conclude this work by presenting several different application scenarios to demonstrate unique interactions that are enabled by our technique on fabrics.

Author Keywords

Capacitive sensing; Interactive Fabrics; Object Recognition

CSS Concepts

•**Human-centered computing** → **Human computer interaction (HCI); Interaction devices.**

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INTRODUCTION

Interactive fabrics enable numerous applications for smart everyday “things” and beyond (e.g., garments, furniture, and toys) [1, 7, 23, 40]. However, with existing sensing techniques, input through a fabric is primarily carried out by a user performing an action, such as touching [1, 23, 30] or deforming [6, 25, 36]. This means that the fabric lacks awareness of its context of use, such as what types of objects it is in contact with. Thus, there are several opportunities missing for new applications and interaction techniques.

In this paper, we present a contact-based object recognition technique on interactive fabrics using capacitive sensing. Our technique senses and recognizes non-metallic objects that are common in homes or workspaces, such as food items, dinnerware, plastic, and paper products. When an object is in contact with the fabric, our technique recognizes the object based on its capacitance footprint. Consequently, a desired action can be triggered. For example, a smoothie recipe can be suggested to a user based on what fruit or vegetable the user has inside a basket, detected through its cloth lining (Figure 1b). Aside from recognizing the contacted object, our system can also sense the change of what is inside a container. For example, a tablecloth can detect whether the soil of a table plant is wet or dry, enabling the system to remind a user to water the plant (Figure 1c).

We demonstrate the technical feasibility of our approach through the implementation of a proof-of-concept prototype called Capacitivo. Our prototype is composed of a grid of 12 × 12 electrodes made of conductive fabric that is attached to a textile substrate (Figure 1a). The electrodes are connected

by rows and columns, allowing a contacted object to be recognized based on its material as well as the shape of the contact area using mutual and self-capacitive sensing. We carefully designed the size of the electrodes and the distance between them, to maximize the sensitivity of our prototype when placed flat on a tabletop. In a controlled experiment, we tested the recognition accuracy of our approach with 20 daily objects, ranging from food to plastic and dinnerware (empty or filled with water or soup). Our results suggested that the prototype could achieve a real-time recognition accuracy of 94.5%.

The contributions of this work include: (1) a non-metallic object recognition technique on interactive fabrics using capacitive sensing; (2) the result of an experiment measuring the accuracy of our technique; and (3) usage scenarios demonstrating unique applications enabled by Capacitivo.

RELATED WORK

We briefly discuss the literature for input on fabrics, object recognition using capacitive sensing, and the sensing techniques for context-aware applications.

Input on Interactive Fabrics

There are two types of input: *explicit* and *implicit* input. Explicit input refers to the input carried out in the fore of the user's consciousness [12]. Research on interactive fabrics has been primarily focused on explicit input using touch [1, 24, 33] or deformation gestures [6, 28, 36]. The earliest exploration of this space was the Musical Jacket [23], which allows a user to interact with a computer using a fabric-based touch keypad embroidered on a jacket. Jacquard [34] from Levi's and Google is one of the first commercial products in this space. It allows touch gestures to be carried out on the sleeve cuff of a jacket made of touch sensitive fabric using conductive yarn. Recent work from Wu, et al. [40] shows that touchless hand gestures, like swipe, are also possible on interactive fabrics using Doppler motion sensing. Aside from touch and touchless gestures, deformation gestures have also been studied for explicit input on fabrics. StretchEBand [36], for example, allows a user to interact with computing devices by stretching, folding, and pressing a soft fabric band made of a textile stretch sensor. SmartSleeve [25] enables even an even wider range of deformation gestures on the sleeve using a pressure-sensitive textile sensor.

In contrast to explicit input, implicit input does not require explicit action from a user to interact with a computer. It is widely used for activity tracking or for contextual interactions. In comparison to explicit input, there is little research on implicit input for interactive fabrics. eCushion [41] is one of them. The technique uses a pressure sensitive fabric developed in the form of a seat cushion to infer a user's seated posture. Rofouei et al.'s work [28] uses the pressure footprint (e.g., weight and shape) to distinguish objects placed on the fabric. No evaluation was conducted to inform how well this technique works. Tessutivo [7] is the most relevant work to our research, but the technique only works on metallic objects. In contrast, our work focuses on non-

metallic objects that are also common in daily life. It complements existing research in the literature with a new sensing technique based on capacitance.

Capacitive Sensing for Object Recognition

Capacitive sensing is a well-known technique that has been used in prior research for numerous applications, including sensing touch input [5, 18, 19, 29, 48], mid-air hand gesture and postures [8, 22, 34, 48], differentiating people [11, 29], sensing the distance or displacement of an object [14, 31, 39], and analyzing the material of an object [8, 32, 38, 43]. An overview of capacitive sensing and its applications was described by Grosse-Puppenthal, et al. [10].

For object recognition, a common approach is to tag the target object. For example, TUIC [46] identifies tagged objects through a commodity touchscreen (i.e. mutual capacitive sensing) by recognizing the geometrical pattern of the tag. With Capacitive NFCs [9], target objects are instrumented using an active tag. Aside from detecting them, the motion of the objects can also be tracked using self-capacitive sensing. Zanzibar [35] uses both mutual and self-capacitive sensing in a single device to sense touch and touchless hand gestures. Object recognition was implemented using NFC tags. While tagging can be an effective approach in some applications (e.g., tangible interaction), usability can be a concern in contextual applications if it is a requirement for a user to tag every object involved in an application.

This has led to numerous techniques being developed to sense untagged objects. One of the more common techniques in this body of research is Electrical Capacitance Tomography (ECT) [43, 44]. The technique measures the distribution of capacitance across sensor electrodes affected by the target object. Unlike the other approaches, where the electrodes can be connected by rows or columns, systems using ECT require each individual electrode to be connected to the sensor board separately. This may increase the complexity of the system. Our technique is also based on capacitive sensing, but with a simpler structure suitable for interactive fabrics. In comparison to existing work, our approach is unique in that we combined both mutual and self-capacitance in a single package, to recognize an object based on the material and shape of the contact area of the object.

Sensing Techniques for Context Awareness

Aside from capacitance, implicit input can also be sensed using GPS or motion sensors on a smartphone [12], millimeter wave radar [45], computer vision [20], acoustics for objects that emit a sound [15], electromagnetic noises in the environment [17], and contact vibrations when people use their hands [16]. Within existing research, techniques like EM-Sense [17] and ViBand [16] leverage the intrinsic electric or mechanical properties of home appliances (e.g., electromagnetic noises or mechanical vibrations) to infer a user's activities and how devices are used by users. Other lines of research in this space focus on the recognition of objects based on the difference in the material of the objects,

and thus work with a large variety of passive objects or even liquids. Radarcat [45], for example, is a technique based on millimeter wave radar. It can recognize passive and active objects as well as different parts of the body. Furthermore, TagScan [37] identifies different types of liquids using RFID. Unlike the existing work, where objects can only be detected at a single location of a rigid sensor, our technique is designed for soft fabrics to cover a broader surface area.

CAPACITIVO SENSING TECHNIQUE

Our object recognition technique is based on sensing the change in the capacitance of electrodes, affected by the presence of an object. For example, when a non-metallic object is in contact with the electrodes, the electric field applied from the electrodes causes an electric displacement within the object. The amount of the electric displacement varies among different objects, depending on the permittivity of the objects. The electric displacement changes the charge stored in the electrodes, and in turn alters the capacitance. It is thus possible to detect or recognize an object based on how much of a shift is observed in the measured capacitance. When a metallic object is in contact with the electrodes, the shift in the measured capacitance is primarily caused by short circuit or the dielectric (e.g. air) in the tiny spaces between the uneven contact surfaces of the object and the electrode. The change in the capacitance is thus not related to the material and cannot be used for recognition of objects.

Unlike sensing gestural input from fingers, object recognition relies on precise sensor readings from different types of objects. Traditional methods, like time-based capacitance measurement, lack precision. We employed a resonance-based approach, where the sensing unit is composed of an LC resonant circuit [33], including an inductor and capacitor (sensor electrodes). By precisely measuring the resonant frequency (f) of the circuit, the capacitance (C) of the electrodes can be calculated using the following formula:

$$C = \frac{1}{4\pi^2 f^2 L} \quad (1)$$

where L is the known inductance. The capacitance measured using this approach is composed of the capacitance of different types occurring in the circuit, primarily the mutual and self-capacitance in our case (details provided later).

Unlike alternative methods, the resonance-based approach has two major advantages that are essential for robust object recognition. First, it is less susceptible to EMI noises, thus having a better signal-noise-ratio (SNR). Second, it allows the capacitance to be measured in a wider range (1pF to 250nF) with an ultra-high resolution (0.08fF) [32].

HARDWARE IMPLEMENTATION

We present the implementation details of Capacitivo using conductive fabrics and customized hardware.

Sensor Design

Our sensor is composed of coplanar electrodes connected by rows and columns and a ground plane (Figure 2). With this

setup, two types of capacitance occur primarily: mutual and self-capacitance. Mutual capacitance is the capacitance between the adjacent electrodes while self-capacitance is the capacitance between the electrodes and the ground plane. Both are affected by a contacted object. We used the aggregation of them to allow the signal to be more pronounced in response to the small change in the capacitance. For each capacitance measurement, one row and one column are selected to form a mutual capacitor. The selected electrodes also act as capacitors coupling to the ground, so the changes in both types of capacitance together affect the sensor readings (oscillation frequency). The impact caused by a contacted object can thus be measured by scanning all the row and column electrodes. However, the challenge with this approach is that due to the coupling of the electrodes to the ground (self-capacitance), sensor readings at a location are interfered with all electrodes connected in the same row or column, which we call a *crossing effect* (Figure 3b). This affects the sensing accuracy due to the noise outside the object's contact area.

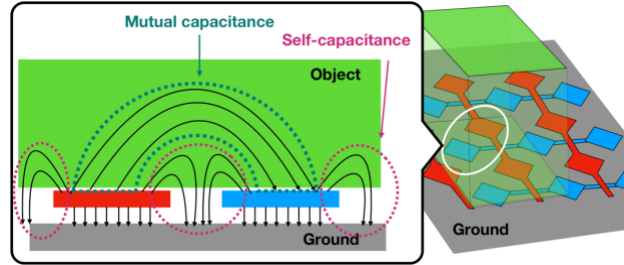


Figure 2. An illustration of the mutual and self-capacitance formed by our sensor.

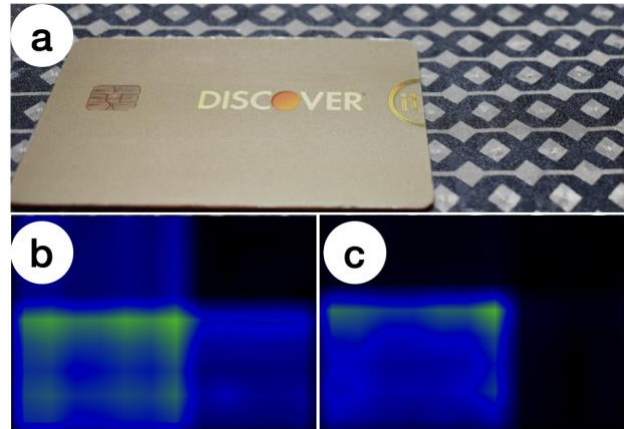


Figure 3. (a) A credit card placed on our textile sensor. (b) The footprint of it measured by the resonance-based approach. (c) The footprint of it measured by the mutual capacitive sensing.

One approach in solving this problem is to connect each individual electrode to the sensor board separately, but it comes at the cost of system complexity and scalability. We addressed the crossing effect issue by additionally measuring the contour of the contact area of the object and gathering sensor readings from only inside of the contour. The shape of the contact area of the object can also be useful for object

recognition. With our sensor setup the shape of the contact area of the object can be roughly captured using mutual capacitive sensing (Figure 3c). The issue, however, is that the current resonance-based approach cannot measure the mutual capacitance in isolation. We thus had to use a separate circuit, employing a method commonly used for mutual capacitive sensing by measuring the displacement current from a transmitter to a receiver (discussed later). In comparison to the resonant-based approach, this method is less sensitive to the difference in object material, so it was only used for sensing shape of the contact area of the object.

Fabricating Sensor Electrodes

We describe the fabrication approach to create the fabric sensor using three layers of conductive and non-conductive (substrate) fabric.

With our approach, electrodes are created using conductive fabric attaching to a layer of non-conductive substrate. We began by attaching conductive fabric (we used Adafruit conductive woven fabric) to a cotton substrate using an iron-on adhesive [2]. After the adhesive dried, we used a low-cost cutting machine (Cricut Air Explorer) to cut the conductive layer into diamond shaped electrodes (Figure 4a). In principle, the electrodes can be made in any shape. We used the diamond shape to maximize the sensing region in a 2D space. We carefully adjusted the cutting force of the cutting machine so that it only cuts the conductive layer without damaging the substrate. Once the cut was completed, we heated the fabric again to soften the adhesive to allow the unwanted piece to be peeled off the substrate (Figure 4b). We designed the electrode pattern using graphics programming software (e.g., Processing) and then saved into an SVG file that was readable by the cutting machine. In comparison to alternative methods like embroidering [26], knitting [13], weaving [27], our approach creates electrodes that are precise in shape and location, while keeping the costs low.

For the electrodes on rows, we also cut the connection lines between them. Column electrodes were connected from the back using conductive threads so that they are electrically disconnected from the row electrodes. This can be done by hand or using a home sewing machine (Figure 4c). When using a sewing machine, the standard stitching process pushes the threads through the substrate and electrode layer. This connects the front and back of the sensor, which is

needed to route the column connection lines to the back. The issue, however, is that the conductive threads left on the front may cross the connection lines of the row electrodes, which causes short circuits between the rows and columns.

We solved this problem by controlling when the conductive thread could be pushed to the front side of the sensor. This was done by fine-tuning the tension and speed of the sewing machine. We first adopted the method discussed in Dunne et. al.'s work [10], and carefully tuned the tension of the top thread (e.g., non-conductive thread) to ensure that when the machine is sewing at a high speed, the conductive thread (LIBERATOR 40) on the back only floated on the surface of the substrate without penetrating it. Adjusting the machine to sew at a low speed allowed the conductive thread to be pushed through and land on the front side of the sensor (e.g., connecting to an electrode). To force the machine to sew at a low speed, we let it turn at a sharp angle (90°) at the location where the penetration of the conductive thread was needed. Like similar products in the consumer market, our sewing machine sews at a low speed at the corners

Finally, we added a grounded shielding layer (i.e. ground plane) made of a knit conductive fabric (Adafruit knit jersey conductive fabric) on the back side of the sensor (Figure 4d). The knit conductive fabric is attached to the back of the sensor on its non-conductive side to avoid shorting the column electrodes. An optional layer of fabric can be used to cover the electrodes for the aesthetic sake. Our prototype employed a 12×12 grid layout of electrodes (15.6 × 15.6 cm), taking 20 minutes to complete the fabrication process, with a total material cost under \$30 USD.

Customized Sensing Board

Our customized sensing board (Figure 5) uses an LC circuit with a FDC2214 chip from Texas Instruments. The FDC2214 chip measures the joint effect of mutual and self-capacitance. To capture the contour of the contact area of an object and to mitigate the crossing effect, we used a separate mutual capacitive sensing circuit, similar to the one described in prior work [47]. On the transmitter side (column electrodes), the circuit is composed of a wave generator (AD5930, Analog Device) and an amplifier (AD8066ARZ, Analog Device), which generates an excitation signal using a 100k Hz sine wave with a 5V peak-to-peak voltage. The excitation signal is routed to the row electrodes via

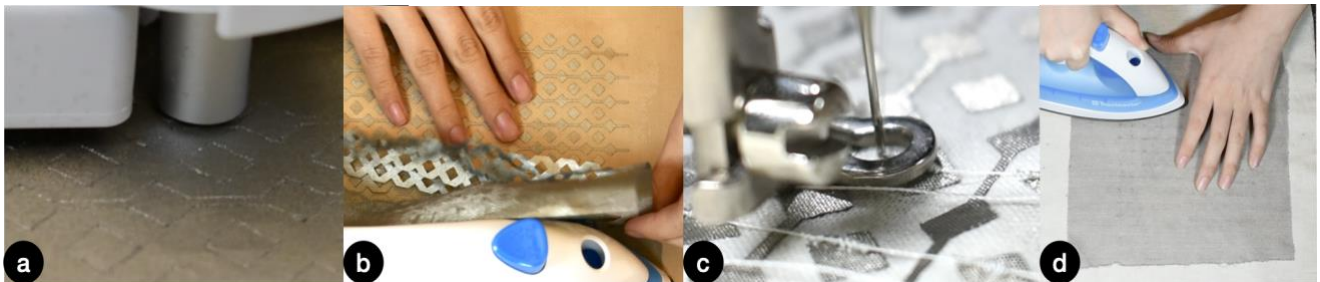


Figure 4. Fabrication process of sensor electrodes. (a) The electrodes are being cut using a low-cost cutting machine. (b) Unwanted piece is being peeled off the substrate. (c) Connecting the column electrodes from the back using a sewing machine. (d) A grounded shielding layer is being attached to the back side of the sensor.

multiplexers. On the receiver side (row electrodes), the displacement current from the column electrodes was converted and filtered to an amplified voltage signal using two amplifiers. The system then reports the capacitance by calculating the RMS value of the voltage signal using a window size of 100 samples with a sampling rate of 1MHz.

Aside from the two capacitive sensing circuits, our sensing board also has an ARM-based flash micro-controller (ATSAM3X8EA-AU) powered by Arduino Due Firmware, a Bluetooth module (RN42, Microchip) for wireless communication, and eight 4:1 multiplexers (FSUSB74, ON Semiconductor) to drive the electrode arrays. Each multiplexer further connects to two switches (TMUX154EDGSR, Texas Instruments) to allow the system to switch between the two capacitive sensing circuits. Note that we used two switches instead of one, because we found that the sensor readings interfered with each other if the two circuits are connected to the same switch.

Note that when the system is in one of the two capacitive sensing modes (e.g., resonance-based or mutual), the circuit for the other mode is turned off to avoid crosstalk. With our current implementation, the prototype runs at 3 - 4 Hz for the 12×12 layout of electrodes. The speed bottleneck is in our mutual capacitive sensing. But this issue can be mitigated in the future using better sensing chips (e.g. MTCH6303 [21]).



Figure 5. Capacitive sensing board. The button and header pins are used for debugging.

Wire Connection

The sensor board is connected to the fabric electrodes through electric wires and conductive threads. We used a method similar to the one suggested in prior research [7] to connect the lead threads and wires together using twist splice. We used hot glue to strengthen and fixed the connection. Although it is clunky, this type of wire connection is stable and performed well in our experiments.

DETERMINING ELECTRODE SIZE AND SEPARATION

For a given input voltage (e.g., 5V in our case), the size of the electrodes and the distance between two adjacent electrodes (called separation as shown in Figure 6), may affect the intensity of the electric field [42], thus affecting sensor sensitivity to the small changes in the capacitance

caused by objects of different materials. In theory, increasing the size of the electrodes increases the intensity of the electric field. The tradeoff, however, is that larger electrodes reduce the sensing resolution in 2D. The effect of separation adds more complexity. For example, reducing the separation may increase the intensity of the electric field for mutual capacitance since the electrodes become closer. However, an opposite trend may be observed for self-capacitance since the space between the electrodes becomes smaller. We conducted two experiments to determine the proper size and separation for our implementation.

Electrode Size

For the study about electrode size, we created three sensors with different electrode sizes (7mm, 14mm, and 21 mm in diagonal distance). 7mm was chosen to be the smallest size for our study because it was nearly the smallest electrode that could be robustly fabricated using the low-cost cutting machines that are widely available to the research and maker communities. The electrodes of the sensors were made in a 2×2 grid with a fixed 2 mm separation. For each electrode size, we also created five replications of the same sensor for data collection, to accommodate any potential variations in sensor readings caused by inconsistency in fabrication.

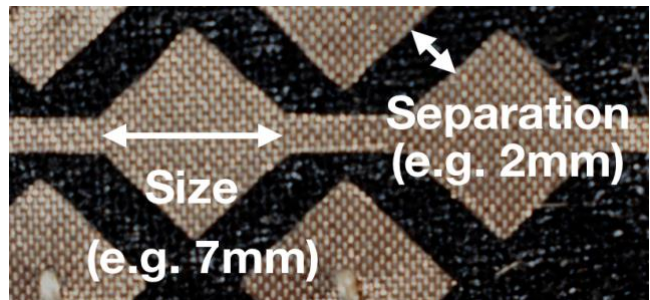


Figure 6. An illustration of electrode size and separation.

To acquire the sensor data for comparison, we used a thin plastic sheet as a dummy object (60 mm ×60 mm ×1 mm), 3D printed using PLA filament. We chose PLA because it has a relatively low permittivity (e.g., ~3.5 F/m [4]), allowing us to better measure the size effect of the electrodes in reaction to a small change in capacitance. For each trial, we placed the plastic sheet on top of the sensor and covered all electrodes. We measured the sensor readings for each column-row pair of the electrodes to calculate a SNR. The average SNR was then calculated for all the pairs of the sensor and then all the five replications of the same sensor.

Results

As we expected, increasing the size of the electrodes increases SNR. The SNR achieved from size 21mm is nearly five times as high as that achieved from size 7mm. The tradeoff is of course sensing resolution in 2D. To consider both SNR and 2D resolution, we calculated an overall score for each electrode size, using the following equation. The higher the score is, the better the size is for the electrode to satisfy our sensing needs.

$$Score = \frac{SNR}{SNR_{highest}} + \frac{Resolution_Score}{Resolution_Score_{highest}}$$

where *Resolution_Score* represents the number of electrodes per square meter. The result is shown in Table 1. Among all the tested electrode sizes, 7 mm scored the highest despite being the lowest on SNR. We thus used 7 mm in our implementation.

Electrode Separation

For the separation study, we created three sensors each with different separation distances (2mm, 3mm, and 4 mm). The sensors were created using 7mm electrodes. 2mm was chosen to be the smallest separation for our study because again it was approximately the smallest separation that can be robustly fabricated using the low-cost cutting machines. Similar to the size study, we also created five replications of the same sensor for data collection. All other study protocols remained the same.

Results

Interestingly, increasing the distance between two adjacent electrodes also increases SNR. This suggests that self-capacitance may have dominated the sensor signal. Regardless, using the joint effect from both types of capacitance leads to higher SNR. The overall scores shown in Table 1 suggest that the separation of 4 mm has the highest score amongst the tested values. It increases SNR for about twice as high without significantly impacting 2D resolution. We thus used the 4mm separation in our implementation. Note that it was not our goal to identify the most optimal size or separation, thus we left them for future research.

	Size (Separation = 2mm)			Separation (Size = 7mm)		
	7 mm	14mm	21mm	2mm	3mm	4mm
SNR	5.29 (std:1.22)	11.32 (std:1.43)	25.54 (std:3.3)	5.29 (std:1.22)	7.17 (std:1.11)	9.87 (std:1.06)
Resolution	101 x 101	59 x 59	41 x 41	101 x 101	88 x 88	79 x 79
Overall Score	1.21	0.78	1.16	1.53	1.49	1.61

Table 1. The results of our size and separation experiment. The columns shaded in grey were used in our implementation.

OBJECT RECOGNITION

Our system recognizes non-metallic objects based on the capacitance footprint of the object’s contact area. This section presents our object recognition pipeline.

Data Processing

When an object is in contact with the fabric sensor, the sensor reports two 12×12 arrays of capacitance values, one from the LC circuit (more precise for sensing material) and the other from the mutual capacitive sensing circuit (more precise for sensing shape). Before the raw sensor data was used for object recognition, we subtracted background noise from the sensor readings for all the column and row electrode pairs. To handle this in an efficient way, we created a 2D noise profile, which represents the background noise across

the entire sensor. The noise profile was constructed by averaging the sensor readings at all locations within a sliding window of size 5. It was updated automatically when no object was detected and when no location reported a delta in sensor value (current value minus initial value) exceeding a preset threshold (e.g., 3000 units of FDC2214’s raw sensor reading). When an object was in contact with the sensor, our system detected the presence of the object if the average of the sensor data across all the locations is over a threshold (5000) while the standard deviation is below a threshold (1000). We then extracted the 2D capacitive footprint of the object by taking the LC circuit data from the contact area of the object. The contact area of the object is determined by getting the locations, whose sensor data is above 30% of the maximum value of the mutual capacitive sensor. The footprint data was then smoothed using a median filter to reduce the fluctuations in sensor readings. In addition, by placing the objects on the sensor one by one, the footprints of multiple objects can be detected. To get a high-resolution visualization of the counter image, we multiplied the data from the LC circuits with the normalized data from the mutual capacitive sensing at each location and scaled up the resulting data map using linear interpretation.

Machine Learning

Object recognition was carried out using the Random Forest technique. In comparison to the alternative methods (e.g., Hidden Markov Models and Convolutional Neural Networks), Random Forest is accurate, robust, and more efficient in computation, thus suitable for real-time applications in low-power embedded platforms. Features used for training and testing are primarily based on two types of information, the material and shape of the contact area of the objects, where the shape data was acquired using the interpolated image of the data map. Based on our observation and initial tests, we derived 33 material-related features and 53 shape-related features (Table 2).

Shape-related Features (53)	<ul style="list-style-type: none"> Local Binary Pattern (36) Hu Moments (7) Object Area (1): Number of pixels the object covers Object Edge (1): Number of pixels on object's edge Average Distance (4): Average distance from object's pixels to object's center of gravity and geometric center (2), average distance from object's edge pixels to object's center of gravity and geometric center (2) Number of Blobs (1), Average Diameter of Blobs (1)
Material-related Features (33)	<ul style="list-style-type: none"> Statistical Functions (13): Mean per mode (2), Max (1), Binned Entropy (1), Local Maximum Numbers (1), Median (1), Quantiles (3), Count above/below mean (2), Variance(1), Absolute energy of the object's pixel values (1) Ten-Fold Stats (20): Sort and divide the object's pixel values into 10 folds and average for each fold (10), Divide grayscale values (e.g., 0~255) into ten intervals and count the number of the pixels in each interval (10)

Table 2. The feature set extracted for training our machine learning model.



Category	Tested Objects
Personal items	AirPods Case (A), Lipstick (B), Discover Credit Card (C), JCPenney Rewards Card (D)
Food items	Kiwis (E), Avocados (F), Grapefruits (G), Cheese Slices in Plastic Wrap (M)
Kitchen items	Table Salt in a Round Package (L), Glass Candle (O), Empty Water Glass (J), Water Glass Filled with Water (K), Empty Bowl, (H) Bowl Filled With Clam Chowder (I)
Office items	Portable External Hard Drive (T), Hand Sanitizer (N), Crouching Figure Statue (S), Book (R), Tabletop Plant (Q), Tabletop Plant After Being Watered (B)

Figure 7. The full list of tested nonmetallic objects.

SYSTEM EVALUATION

We conducted an experiment to measure the recognition accuracy of our prototype for daily objects commonly found at home or in an office environment.

Participants

Ten right-handed participants (average age: 22.9, 6 males, 4 females) were recruited for the study to reduce tested objects being placed at the same locations or orientations.

Objects

We tested our prototype using 20 everyday objects (Figure 7), ranging from food, to personal items and things that are commonly seen in kitchens and offices. The tested objects vary in geometrical (e.g., size, shape) and material properties, which is useful for demonstrating the capability of our sensing technique. We also purposefully included container-like objects, such as a water glass and bowl, to test how reliable it is for our system to recognize the different statuses of containers. For example, we tested how well it could be recognized if a container was empty versus when it was filled with water (e.g., water glass filled with water) or soup (e.g., bowl filled with clam chowder). Similarly, we tested if the system can correctly differentiate between dry and wet soil for a small tabletop plant. This is to show the potential of our system in wider application scenarios. For food items, we bought two packs of the same type of food from different markets or brands. We used those from one pack for training and the other pack for testing. For example, we used cheese from Velveeta for training and cheese from Kraft for testing. We used 3 kiwis, 3 avocados, and 3 grapefruit from one pack for training and same amount of them from another pack for testing.

Data Collection

Our study protocol was similar to that of prior work [7]. Three days before the study, a volunteer was invited to collect the training data for the machine learning model. The volunteer was asked to place each of the tested objects inside the sensing area in a random location, orientation, and order. No other instruction was given in terms of how the objects should be presented to the sensor. Fifty samples were collected for each object to train the model. During data collection, the sensor was placed in a horizontal position on a table to mimic a common tablecloth scenario. The device

was powered by a wall outlet (earth ground). The same procedure was used for collecting the testing data, except that 10 new participants were recruited for the task. Ten samples were collected per object for testing. Real-time recognition accuracy was recorded for analyzing the study results.

Results

Overall, our system yields an accuracy of 94.5% (SD = 4.5). The confusion matrix of the study result shows that 18 out of the 20 tested objects achieved an accuracy higher than 90% (Figure 8). This is a promising result considering that many of the tested objects are similar in shape, and in a few cases, also in material. For example, the Empty Water Glass, Empty Bowl, and Table Salt are all round in their contact area, but they could be recognized by the system with a relatively high accuracy. While the JCPenney Rewards Card scored lower than 90%, it was still differentiable from the Discover Credit Card, which is almost identical in shape and size. Since the two cards are both made of plastic, they are differentiable by the system through the difference in internal structure (e.g., with vs without the chip) and magnetic strip.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T
A	86	0	0	6	1	0	0	0	0	0	0	0	0	0	0	0	7	0	0	0
B	0	98	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0
C	0	0	91	0	0	0	0	1	0	3	2	3	0	0	0	0	0	0	0	0
D	0	0	0	85	4	0	0	0	0	0	0	0	0	4	3	1	0	0	3	0
E	0	0	0	0	92	8	0	0	0	0	0	0	0	0	0	0	0	0	0	0
F	0	2	0	0	0	97	1	0	0	0	0	0	0	0	0	0	0	0	0	0
G	0	1	0	0	0	1	98	0	0	0	0	0	0	0	0	0	0	0	0	0
H	0	0	5	0	0	0	0	95	0	0	0	0	0	0	0	0	0	0	0	0
I	0	0	0	0	0	0	0	0	97	0	3	0	0	0	0	0	0	0	0	0
J	0	0	0	0	0	0	0	0	0	94	6	0	0	0	0	0	0	0	0	0
K	0	1	0	0	0	0	0	0	0	1	97	1	0	0	0	0	0	0	0	0
L	0	0	8	0	0	0	0	0	0	0	0	91	0	0	0	0	0	0	0	1
M	0	0	0	0	0	0	0	0	0	0	0	0	100	0	0	0	0	0	0	0
N	0	0	0	0	0	0	0	0	0	0	0	0	0	91	7	0	0	2	0	0
O	0	0	0	0	0	0	0	0	0	0	0	0	0	1	98	1	0	0	0	0
P	5	0	0	5	0	0	0	0	0	0	0	0	0	0	0	90	0	0	0	0
Q	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	99	0	0	0
R	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100	0	0
S	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	99	0
T	0	0	7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	91

Figure 8. The confusion matrix of the study result across 10 participants. Results are shown in percentage.

The system also performed relatively well on food items. For example, the differences between the Kiwis and Avocados could be discerned with good accuracy despite their size and shape are not very much different from each other. Grapefruits have a unique capacitive footprint among all the tested objects, which allowed them to be recognized with a good accuracy of 98%. In addition to the objects, we found that the status of the container could also be well tracked. For example, the system could distinguish between the Empty Water Glass and the one filled with water with an accuracy of 94% and higher. It could also correctly recognize the Empty Bowl versus the one filled with clam chowder in all the 20 tested instances. Finally, the system was able to differentiate between wet and dry soil for the table plant with 99% accuracy. This is a promising result considering that all the containers, despite their status, are well recognizable among all the other tested objects.

Misclassifications typically occurred when an object failed to have a clear capacitance footprint in our current implementation, such as those with low permittivity (e.g., Credit Cards, Book). The JCPenney Rewards Card is an example, which is one of the two most difficult objects to recognize (85% accuracy). The problem was more pronounced when a part of the card lost contact with the sensor electrodes, which is a common scenario since the fabric sensor is not entirely flat. In this case, neither the shape nor the material could serve as a reliable indicator for the system to recognize the object. This is partially why the system can get confused between the JCPenney Rewards Card and the Apple AirPods Case.

SUPPLEMENTARY STUDIES

Aside from the main study, we conducted two supplementary studies to push the limit of this fabric sensor further. We first preliminarily evaluated how well the system can recognize different types of liquids. We then investigated how well the objects can be recognized by the sensor in a vertical placement (e.g., in a pocket form factor) to mimic another common use scenario. These two studies were carried out with a single participant (female, right-handed, 25 years old).

Liquid Recognition

To understand how well the proposed technique may work for a wider variety of drinks, we extended our apparatus to six liquids, including Cold Water, Hot Water, Coke, Apple Cider, Milk, and Beer (Pabst blue ribbon). According to prior work [3, 37], the permittivity of these liquids varies due to the difference in temperature and also in the concentration of sugar and salt. However, unlike the objects tested in the main study, liquids are different in a much more subtle way.

The result of our initial testing revealed poor performance of our system on the tested liquids, primarily attributed to the small inconsistency in the sensor readings at different locations of the current prototype. We thus only report the performance of the system measured at a fixed location, picked randomly inside the sensor (Figure 9 right). While this setup clearly limits the utility of the system, some

applications may still benefit from it, including the one related to the smart coaster described in the demo section. We see that this inconsistency issue can likely be resolved by using an industrial grade fabrication process.

Data Collection

The study had two sessions, one for training and one for testing. For the training session, data was collected by the participant putting the glass filled with one of the tested liquids anywhere inside a sensing region, made of 7×7 electrodes. All the liquids were at room temperature ($\sim 23^\circ\text{C}$) except the hot water, which was measured at 80°C . Aside from the liquids, we also included an empty glass in this study, resulting in a total of 8 conditions. The liquids were tested in a random order. We collected 20 samples for each type of liquid. The same procedure was used in the testing session, which took place six hours later.

Result

The study result was analyzed using a twofold cross-validation. Overall, the system achieved an average accuracy of 90.71% (SD=14.6). Figure 9 (left) shows the confusion matrix of the result across all the tested liquids, amongst which, Beer had the lowest accuracy of 65%. It was confused by the system with several other liquids, such as Coke, Apple Cider, and Milk. This is likely because of the similarity in sugar concentration, but it must be confirmed with a careful study. The recognition accuracy increased to 96.67% (SD=6.0) after we removed the Beer from the tested objects.

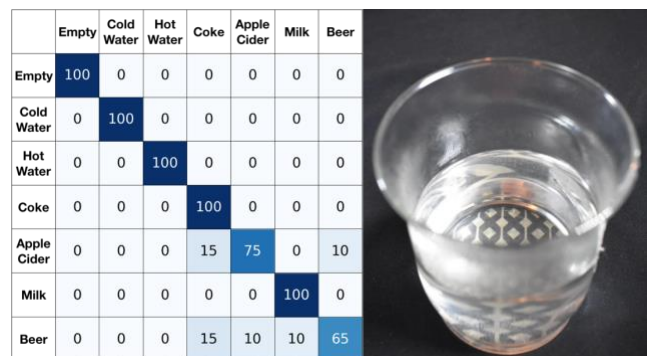


Figure 9. Left: the confusion matrix of the study result. Right: the sensor at a fixed location was used for this study.

Vertical Sensor Placement

The goal of the second preliminary study was to measure the performance of the sensor in a vertical placement. The study apparatus included the proposed fabric sensor implemented in a pocket form factor (15.6×15.6 cm; Figure 10 right), similar to the ones on used on winter jackets. When in a vertical position, the sensor deformed slightly due to gravity. We left it as is to simulate more realistic scenarios.

Data Collection

Out of the 20 objects tested in the main study, nine can be fit into the pocket prototype. These include an AirPods Case, Lipstick, Kiwis, Avocados, Cheese Slices in Plastic Wrap, a Discover Credit Card, a JCPenny Rewards Card, a Book, and a Portable External Hard Drive. We used all except the

JCPenny card because its footprint was too weak to be recognized by the pocket prototype. Data was also collected in two sessions with one for training and the other for testing. Similar to the first preliminary study, the two sessions were set 6 hours apart. In each session, the volunteer randomly chose an object and placed it inside the pocket. No instruction was given regarding how the item should be placed inside the pocket in terms of location, or orientation. We collected 20 samples per item for training and testing.

Result

The study result was analyzed using a twofold cross-validation. On average, the system could recognize the eight tested objects at an accuracy of 70% (SD = 15.5). That is nearly 25% lower than the accuracy achievable with even more items when the sensor is in the horizontal placement. This is understandable because our sensing technique is contact based. When the sensor is placed vertically, the contact between the object and the sensor cannot be guaranteed since the object may partially lean against the sensor or due to the deformation of the sensor itself.

Figure 10 (left) shows the confusion matrix, which demonstrates that the system performed poorly with objects that had square edges (e.g., Book and Lipstick). This is because the contact area of the objects varied randomly depending on how they were placed and leaned against the sensor inside the pocket. If we removed the Book and Lipstick from the dataset, the recognition accuracy increased to 80% (SD = 6.3). While Avocados were confused by the system with Kiwis for 10% of the tested instances, the accuracy was not worse than when the sensor was in the horizontal position. If Avocados were removed from the dataset, the system could recognize the remaining objects (e.g., AirPods Case, Kiwis, Cheese Slices in Plastic Wrap, Discover Credit Card, and Portable External Hard Drive) at an accuracy of 87% (SD = 6.7). We think this is encouraging because the result suggests the potential of the sensor in a vertical placement in applications suitable for a small set of objects.



Figure 10. Left: the confusion matrix of the study result. Right: the sensor in a pocket form factor

DEMO APPLICATIONS

In this section, we present eight usage scenarios of Capacitivo to demonstrate new applications enabled.

Small devices, like AirPods, have become an important part of the ecosystem of the wearables people use in everyday

life. However, despite being convenient to carry and use, their small and portable nature has made them easy to lose and hard to find. For example, people often forget where they leave their AirPods case when the headphones need to be charged. We implemented an interactive pocket on a jacket, which senses if the case is left inside the pocket (Figure 11-a). The user can thus be notified where to find it when the battery of the headphones is low.

At home or at a workspace, a table is another location where personal or shared items can be found. We implemented our sensor on a tablecloth, which detects the items that are placed on the table. Our system uses a smart speaker to remind a user if something important is left on the table for too long (e.g., credit card) or if they forget to take it before their day begins. In our implementation, we remind the user to take personal items (e.g., lipstick in our example) that are often forgotten when rushing out in the morning (Figure 11-b).

When a user registers or shops at a website for the first time, the tablecloth recognizes the credit card placed on the table and automatically fills in the card information for the user (Figure 11-c). This is convenient for some users, as entering a card number can be error prone and tedious. Further, the tablecloth can detect if the user's table plant needs watering, reminding a user when the soil is dry.

Capacitivo can also be useful in a kitchen for cooking and eating. For example, cooking is a process which often relies on following a procedure. Thus, a smart kitchen capable of detecting the ingredients and seasonings available on a table, can be helpful for informing a user about the order and timing in which ingredients should be added to a dish that is being prepared. Our implementation can detect avocado, cheese, and salt on the table and provide a user with suggestions on how to make avocado soup (Figure 11-d).

Sometimes cooking also needs spontaneity. When the user does not know what to make for dinner or to drink, it can be helpful to suggest the user recipes based on what is available at home. In our implementation, the system can suggest to the user a smoothie recipe based what fruit and vegetables they have in a basket (e.g., kiwis, avocados, grapefruits), detectable by the cloth lining of the basket.

During dinner, the system infers what a user drinks based on sensing the liquid inside the glass. It automatically updates their diet tracking app (Figure 11-e). Finally, the system can remind the user to clean the table after the empty bowl used for soup was left on the table for several hours (Figure 11-f).

LIMITATIONS AND FUTURE WORK

We discuss the insights gained from this work, the limitations of our approach, and future research directions.

Sensor Deformation. Our proposed fabric sensor is deformable, making it suitable for objects or containers with a curved surface (e.g., basket). To accommodate this, the machine learning model needs to be trained with the sensor in the corresponding curved form factor. This allows the

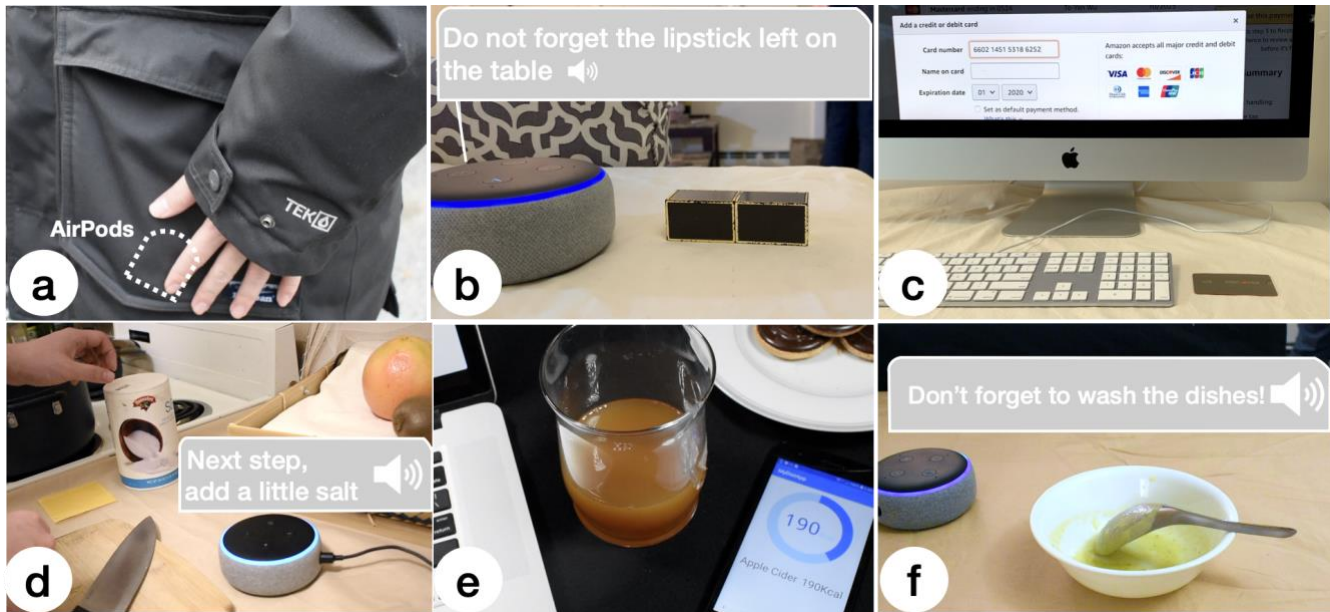


Figure 11. The demo applications of Capacitivo. (a) A user can be notified that they’ve left their airpods inside their jacket pocket; (b) A tablecloth can remind a user to not forget a personal item through a smart speaker; (c) Credit card information can be auto filled while shopping, by placing it on a tablecloth; (d) Guided cooking instructions by detecting different food items; (e) A user can track the beverage they are consuming; (f) A user can be gently reminded to clean up after a meal.

sensor to be used in a wide variety of different application scenarios. However, the problem with the current implementation is that if the electrodes are deformed after the machine learning model is trained, sensor readings are affected, which consequently introduces false recognition. This is an issue with many of the existing fabric sensors and requires careful research in the future. We are investigating methods that can model the shape deformation of the sensor using the unique sensor readings introduced by folding the electrodes at different locations, degrees, and angles. However, many of the application scenarios foreseeable for the proposed sensor, (e.g. those in this paper) allow the sensor to work under relatively stable conditions without being prone to significant deformation.

Touch Input. As our technique uses capacitive sensing, it is expected that finger touch gestures can be sensed. This enables new applications on top of what are proposed here in the paper. We left this part of research for future work because our prototype in its current form was developed with a focus on object recognition. Sensing the movement of the finger or a detected object requires a higher frame rate from a system than what is developed in the current prototype (3 – 4 Hz). As mentioned earlier, the frame rate of our system is currently limited by the chip used for mutual capacitive sensing. It can be increased with better hardware.

Contact-Based Sensing. Our technique requires the full contact area of the object to be presented to the sensor for the object to be correctly recognized. In some scenarios, a firm contact may not be guaranteed as shown in our preliminary study with the sensor in the vertical placement. This largely impacts sensing accuracy. A potential solution to this

problem is to optimize sensitivity also in the Z direction so that objects can be sensed in the near field of the electrodes.

Fabrication. With our current implementation, sensor readings vary slightly at different locations of the electrode array. This made it difficult for the system to sense small differences between the impact in the capacitance caused by the different types of liquids. Future work will focus on improving the fabrication process to assure the consistency in sensor readings across the surface of the sensor. Solving this means recognition accuracy of the system over other types of daily objects can be further improved.

Sensing Metallic Objects. Our technique does not work with metallic objects. This is a limitation of capacitive sensing. We expect that a hybrid approach combining capacitive sensing with the other types of sensing techniques, such as inductive sensing, has the potential to solve this problem. This may require changing the geometry of the electrodes to accommodate both types of sensing.

CONCLUSION

This paper demonstrates a technique for contact-based object recognition on interactive fabrics, enabling them to detect everyday objects. We first discussed our sensing principle and investigations into the size and separation between electrodes that were optimal to enable our approach. We then built a prototype with a 12 x 12 grid of electrodes made from conductive fabrics, which was chosen based on our earlier investigations. Using a ten-participant study, we found our approach demonstrated a 94.5% real time classification accuracy with 20 different objects, enabling a new set of application scenarios. We believe our approach is a critical step for increasing the input space of interactive fabrics.

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