Project Tasca: Enabling Touch and Contextual Interactions with a Pocket-based Textile Sensor

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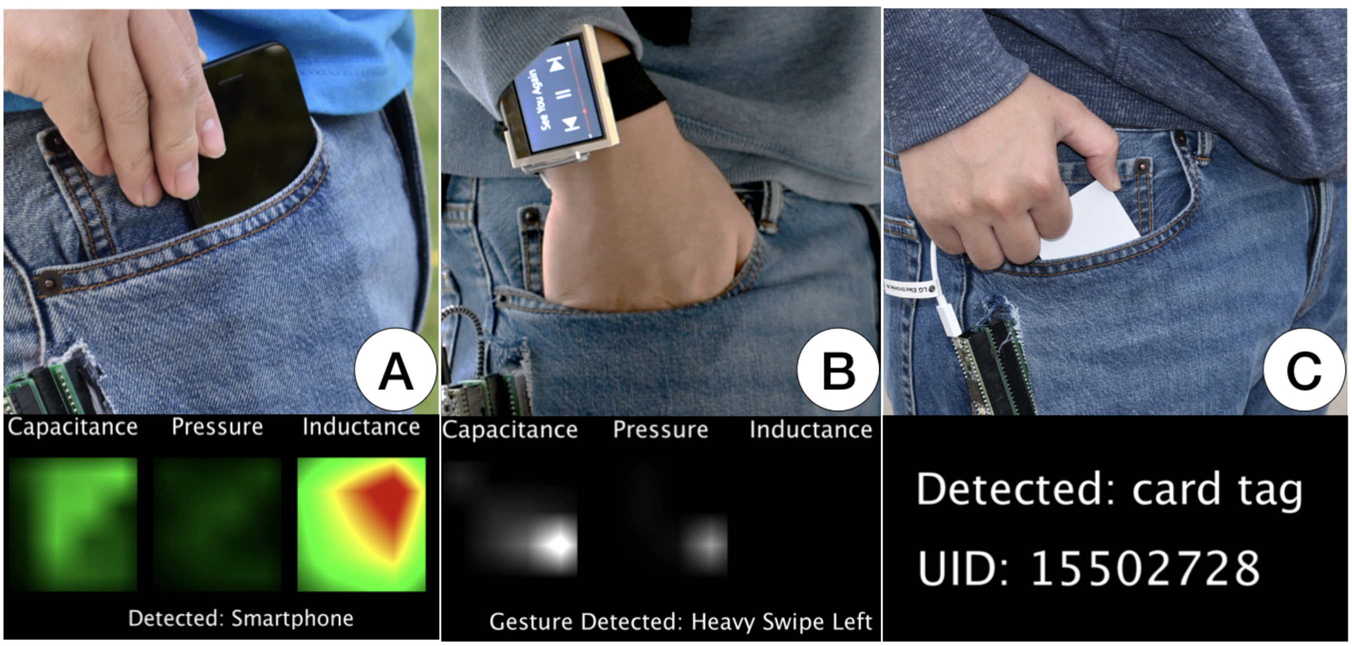

Figure 1: Tasca is a pocketed-based textile sensor, capable of sensing (A) common objects people carry in their pockets (e.g. a smartphone or car key), (B) touch and pressure gestures, and (C) NFC tags.

ABSTRACT

We present Project Tasca, a pocket-based textile sensor that detects user input and recognizes everyday objects that a user carries in the pockets of a pair of pants (e.g., keys, coins, electronic devices, or plastic items). By creating a new fabric-based sensor capable of detecting in-pocket touch and pressure, and recognizing metallic, non-metallic, and tagged objects inside the pocket, we enable a rich variety of subtle, eyes-free, and always-available input, as well as context-driven interactions in wearable scenarios. We developed our prototype by integrating four distinct types of sensing methods, namely: inductive sensing, capacitive sensing, resistive sensing, and NFC in a multi-layer fabric structure into the form factor of a jeans pocket. Through a ten-participant study, we evaluated the performance of our prototype across 11 common objects including hands, 8 force gestures, and 30 NFC tag placements. We yielded a 92.3% personal cross-validation accuracy for object recognition, 96.4% accuracy for gesture recognition, and a 100% accuracy for detecting NFC tags at close distance . We conclude by demonstrating the interactions enabled by our pocket-based sensor in several applications.

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CCS CONCEPTS

• **Human-centered computing → Interaction devices**.

KEYWORDS

Capacitive sensing; inductive sensing, resistive sensing, NFC, interactive fabrics, gesture recognition, object recognition, wearables, interactive pockets

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1 INTRODUCTION

In the era of smart "things", computing is becoming increasingly accessible and ubiquitous through new interface technologies developed on everyday objects in homes and work spaces, as well as those worn on the body. The interactivity available on these "things" that could be covered by (or made too) interactive fabrics (e.g., clothing, furniture, toys, and bags) enables numerous applications that were not previously possible [8, 20, 36, 41]. Concepts like interactive pockets (e.g., on a pair of pants) not only allow for touch interactions to occur beyond smartphones, watches or rings, but also be carried out in a comfortable, private, and always-available manner to use other computing devices (e.g., head-worn or wall-size displays [2, 34]) in ubiquitous computing environments. Furthermore, understanding the items that a user has in a pocket (e.g., a phone) also enables a new set of applications, such as activity tracking [28], placement-dependent notification [38], or providing new context to the information sensed from other devices [38].

While prior research has explored the concept of interactive pockets, much of the focus was demonstrating proof-of-concepts and application scenarios using mockups through rigid devices or sensors, such as a camera [34], optical sensor panel [28], or capacitive touch panel [2], which are unsuitable for practical and daily use.

In this paper, we introduce Tasca, an interactive pocket-based textile sensor integrated into a form factor that fits into the pocket of a pair of jeans (Figure 1). Tascais capable of sensing a wide variety of user input that exists in the current literature and beyond. Unlike the previous work that we build upon, our prototype was developed using an interactive fabric, and can sense touch [20], pressure [19], while also recognizing everyday items that people carry in their pocket such as keys, coins, electronic devices and some plastic items [28]. We developed our prototype using four different sensing techniques that have not been previously developed into a single fabric-based package: NFC, capacitive, inductive, and resistive sensing. These techniques were combined together to deliver a more practical solution for interactive fabrics in a wearable pocket context, in terms of robustness against sensor deformation (e.g. improved object recognition by fusing data from any pair of the sensors) and more capable in sensed object types (e.g. metallic, nonmetallic, and NFC tagged objects).

The contributions of our work include: (1) the sensor design of an interactive pants pocket, capable of sensing explicit user input and recognizing the objects a user carries in their pocket and (2) the result of an experimental evaluation of the sensing performance of our system.

2 RELATED WORK

We briefly discuss the literature for interacting with fabrics, the different sensing techniques for smart fabrics, and the area of smart pockets.

2.1 Interacting with Smart Fabrics

Smart fabrics use a number of sensing methods that enable interactions for users, including inductive sensing [4], capacitive touch and gestures, all of which can accomplished using different weaving, braiding, sewing and embroidery techniques [16, 17, 21]. Like other forms of input, smart fabric input can be broken into implicit and explicit input. Implicit input is often used for contextual interactions (e.g. activity tracking or adjusting an environment), and doesn't require an explicit action from a user. Examples of such research include using the pressure footprint of an object to detect different objects [23], using a pressure sensitive fabric approach [42]. For smart fabric interactions, implicit input has not been widely explored other than the work such as [4, 40].

Unlike implicit input on fabrics, explicit input techniques and their enabling technologies continue to be well explored. The most common technique for explicit input on smart fabrics is touch [18, 20] or manipulating the fabric itself (deformation) [15, 19]. The canonical example of explicit input on a textile is the Musical Jacket, where a fabric-based keypad was embroidered onto a jacket and allowed a user to play music. More recent examples include Project Jacquard [20] and GestureSleeve [27], both use touch gestures on different parts of a garment. Beyond touch based gestures, mid-air gestures also have been explored by Wu et al. [39], where Dopper motion sensing was integrated into fabric to enable different interactions. For deformation-based input techniques, SmartSleeve demonstrates how common fabric-based interactions such as folding, stretching and pressing can be augmented as a means of interacting with everyday objects [19].

While many of the input techniques for smart fabrics have been explored in individual prototypes, many have not been combined together, providing an interesting opportunity to explore novel implicit and explicit input techniques.

2.2 Sensing Techniques for Smart Fabrics

A number of techniques have been developed in the research literature for sensing using fabrics, with the most common enabling approach being the combination of fabrics and different sensing coils. Example application scenarios for fabrics and coils include include wireless power charging, and inductive heart sensors [13, 14, 32, 37].

Beyond using solely coils for sensing on smart fabrics, sensing techniques for textiles have included capacitive and NFC sensing, and object recognition, to name a few. Capacitive sensing involves particular challenges for fabrics and wearables [7], but ultimately it can enable touch input, hand gesture and posture detection (e.g. detecting large swipe gestures with an entire hand) [20], and material analysis [40]. A canonical example of capacitive sensing and textiles that is commercially available, is the Levi's Jacquard jacket

[20], where capacitive sensing is integrated into a jacket cuff and touch gestures are used to interact with a phone and other devices.

Combining different sensing approaches also leads to novel interactions. For example, Project Zanzibar [35] combines mutual and self-capacitive sensing to detect touch and hand gestures, and also used NFC tagging to detect objects. In our work, we also combine different sensing techniques, where we explored the fusion of inductive, capacitive, resistive, and NFC sensing to enable a wide variety of applications new to interactive pockets on a pair of jeans.

2.3 Smart Pocket Interactions

While the broader space of interactions as it relates to smart garments, and interactions on and around the body is well explored, areas located around the the thigh – specifically the pocket – have been under-explored comparatively [2, 34]. Prior work has demonstrated that in scenarios involving standing, sitting or kneeling, the front of the thigh is the most appropriate position to place a touchpad-like interface [33]. Similarly, Holleis et al. [10] used capactive buttons integrated into different garment form factors to demonstrate that the thigh area was potentially the most acceptable for touch-based wearable controls.

One critical factor for acceptable interactions around the pocket (and thigh area) is their social acceptability. For example, prior research has shown that people are comfortable with interactions above the belt, but not near the area around a belt buckle, due to social statements that could be perceived (e.g. a hand near the lower extremities) [1]. Profita et al. [22] has also demonstrated similar results that pockets are not as socially acceptable because of the physical location to different (private) parts of the body. This means that ideally, sociably acceptable interactions should be closer to a resting hand position for pockets (similar to [2]).

An early example of pocket-based interaction in the literature is PocketTouch [26], which demonstrated capacitive sensing through fabric. Their approach consisted of a capacitive sensing grid (connected to a smart phone) that enabled touch interaction through the pocket, as well as stroke-based gestures that could be performed on the outside of the pocket. Through-pocket techniques have also been demonstrated by others [11, 25] and often rely on using the sensors of a mobile phone in a pocket [2]. Smart pocket prototypes have also been created using cameras, and other more rigid materials, but aren't practical for an everyday pocket. The closest system that recognizes objects in a pocket was created by Shimozuru et al. [29], using an array of infrared sensors, but is also impractiable due to its rigidness.

In this work, we are the first to explore how multiple sensing techniques can be designed and developed in combination (rather than in isolation), to enable different types of interactions in an everyday pocket form factor. As part of this exploration, we identify unique challenges due to the constraints of a pocket and demonstrate promising solutions that are both applicable to pockets, as well as the wider space of smart fabrics.

3 PROJECT TASCA

Our goal was to implement Tasca as a pocket sensor that supports some of the most common input modalities, including: (1) 2D touch gestures commonly used on mobile and wearable devices and (2) force touch by pressing the fabric at different levels of pressure. Additionally, to allow for rich contextual interactions, we wanted the sensor to be able to (3) sense and recognize daily objects that users normally carry in their pants pockets. Finally, to allow customization and enable the system to handle objects that are not registered in our system, we wanted the sensor to be able to (4) sense tags that are easy to attach to objects (e.g., NFC). We detail the design and implementation of our prototype to handle all of these requirements using four sensing techniques.

3.1 Sensing Capabilities

Our prototype is capable of sensing touch, pressure, metallic objects, non-metallic objects, and tagged objects by integrating four different types of sensing methods, including inductive sensing, capacitive sensing, resistive sensing, and NFC. We investigated the sensing techniques that are contact-based or the ones working in a short range so the operation of our sensor does not interfere with other personal electronic devices.

3.1.1 Sensing Metallic Objects Using Inductive Sensing.

Metallic objects are recognized using inductive sensing based on Faraday's law of induction. When an alternating electrical current is flowing through a L-C resonator, composed of the spiral-shaped coil of the sensor (inductor) and a capacitor, an electromagnetic field is generated around the sensor. If a conductive object is brought into the vicinity of the sensor, the electromagnetic field will induce an eddy current on the surface of the object, which in turn generates its own electromagnetic field, which opposes the original field generated by the sensor. Therefore, a small shift in inductance can be observed through the sensor. The amount of the shift is related to the resistivity, size, and shape of the object when it is in proximity to the sensor. Inductive sensing works primarily with metallic objects (e.g., keys, coins) and those composed of metallic parts (e.g., electronic devices). To implement inductive sensing for our pocket, we used an approach similar to one described in the research literature [4]. However, the design of our coils is different because we also use the coils for NFC, which we discuss later.

3.1.2 Sensing Touch and Non-Metallic Objects Using Capacitive Sensing.

Touch input is sensed using capacitive sensing, which is a well-known technique used on everyday devices ranging from smartphones and watches to interactive garments (e.g., Jacquard [20]). Aside from touch input, capacitive sensing has also been used for object recognition [6, 43]. Unlike inductive sensing, capacitive sensing works better for non-metallic objects, such as food items, dinnerware, plastic, and paper products. As a complement for inductive sensing, we included capacitive sensing to recognize non-metallic objects (e.g. hand sanitizer and wallet), as well as sensing touch input, using a shared set of coplanar textile electrodes. For object recognition, we used a technique similar to the one described in the research literature [40]. Our system recognizes non-metallic objects based on their capacitance footprint introduced by the change in the capacitance of electrodes, affected by the presence of an object. When the electrodes are in contact with a non-metallic object, the electric field applied from the electrodes causes a certain amount of electric displacement within the object. Objects with different permittivity have different effects on the amount of the electric displacement, which alters the capacitance of the object. The shift in the capacitance can be measured using a resonance-based approach, which is known to be precise and less susceptible to environmental noise.

3.1.3 *Sensing Pressure Using Resistive Sensing.*

Pressure sensing is based on the change in the resistance of a piezo-resistive material when it is pressed or deformed. As an input method, this resistive sensing can be used for both sensing touch input [19] and recognizing objects [24]. For object recognition, unlike capacitive and inductive sensing, resistive sensing detects objects primarily based on the shape and amount of pressure exerted on the sensor by the objects. In the context of a pocket, using resistive sensing allows our system to infer the thickness of the objects since higher pressure can be observed with thicker objects. Fused with the data from the capacitive and inductive sensor, resistive sensing could potentially improve the robustness and accuracy of object recognition. Our fabric resistive sensor implementation involved creating a three-layer structure with a piece of pressure sensitive material (e.g., velostat) sandwiched between two layers of conductive fabric.

3.1.4 *Sensing Tagged Objects Using NFC.*

Tagged objects are sensed using Near Field Communication (NFC), which is a technique commonly used in applications involving contactless payments or tagged detection [35]. The technique uses alternating electromagnetic fields for sensing and transmitting data. When a NFC tag is triggered by an electromagnetic interrogation signal from a nearby antenna coil, it transmits its data to the sensor coil. In our implementation, we carefully designed the coil layout and its circuit to ensure that the sensor can not only detect tags, but can also function as an inductive sensor.

3.2 Sensor Design

To develop these four different sensor modalities in a single package, a naive approach would be to stack them four discrete sensors on top of each other. However, this would increase the thickness of the sensor and complexity of the fabrication process and interface circuitry. To overcome this challenge, we designed the sensor in a two-layer structure (Figure 2) with the top layer composed of a grid of fabric resistive sensors with conductive electrodes for both capacitive and resistive sensing and the bottom layer composed of a grid of embroidered coils for inductive and NFC sensing. We designed our sensor to cover the space of a 100 mm x 100 mm region, which is roughly the size of a jeans pocket.

3.2.1 *Inductive-NFC Sensing Layer Design.*

For object recognition, inductive sensing usually requires the sensor coils to be arranged in a grid layout to detect the rough geometry of the contact area of an object. The grid arrangement also ensures the NFC sensor is effective across the full area. However, a tag may not be recognized when it is placed between two adjacent coils. We overcame this challenge by introducing a small overlap between two adjacent coils (Figure 2). Note that the overlap may impact the sensing resolution of the inductive sensor in the 2D space. Our initial test suggests that with our coil design (see details below), a 5 mm overlap works best for balancing the coverage of NFC and the sensing resolution of the inductive sensor in the 2D space.

To maximize the sensitivity to objects of different materials and shapes, the size and shape of the coils for inductive sensing can be determined using the approach described in a previous work [4]. Once the design of the coils is determined, they are shared by the NFC and inductive sensing circuits. A multiplexer can be used to swap between the two circuits, as shown in the circuit schematic in Figure 3. The challenge, however, is that in practice, multiplexers introduce parasitic impedance that degreades performance. As such, we had to minimize the use of them in our design. Since the LDC1614 chip used in our implementation (more details later) supports four channels, this allowed us to implement our sensor using four coils without the need of any extra multiplexer except the one used for switching between the two circuits. This is why our current implementation has a grid of 2×2 coils. To support higher-resolution sensing the number of coils can be increased in the future with better hardware. Note that another limitation of the the current inductive sensing hardware is that operation becomes unreliable when the inductance of the coils is below 4 uH. As such, we designed our coils with an inductance of 4 uH (e.g., square shape, number of traces = 5). Figure 2 shows the detail of our coil design.

3.2.2 *Resistive-Capacitive Sensing Layer Design.*

To enable capacitive sensing we re-purposed the conductive fabric of the resistive sensor as the electrode for capacitive sensing. This approach is similar to what is described in zPatch [31]. However, unlike the previous work, recognizing objects and touch gestures requires the sensor to be arranged in a grid layout. In our implementation, we arranged the resistive sensors in a 4×4 grid. Note that the problem with the grid arrangement is the conflict between the design for the capacitive and resistive sensor. For example, the row and column electrodes of the capacitive sensor need to be electrically separated while the row and column electrodes of the resistive sensor need to be electrically connected. Thus in our implementation, we left the resistive sensors disconnected from each other. Each sensor was connected to the sensor board separately. This setup works well for a pocket.

3.3 Sensor Implementation

In this section, we detail the hardware implementation of the pocket sensor.

3.3.1 *Fabrication.*

The coils on the inductive-NFC sensing layer was created by stitching conductive wires onto a cotton substrate, as shown in Figure 4A. Since our design requires some of coil traces to overlap with each other, we had to use insulated wires to avoid short circuits. In our implementation, we used the standard enamel coated copper wire, widely used in the smart fabric industry. Based on some initial testings with a JGVA embroidery sampling machine [12], we opted for the 34 AWG wire (161 um diameter) as it is both thin and strong enough to stand the fabrication process. The enameled wire was applied to the fabric substrate using a fixation top thread (Polyneon #40 weight) interlocked with a bottom thread (polyester #150 weight).

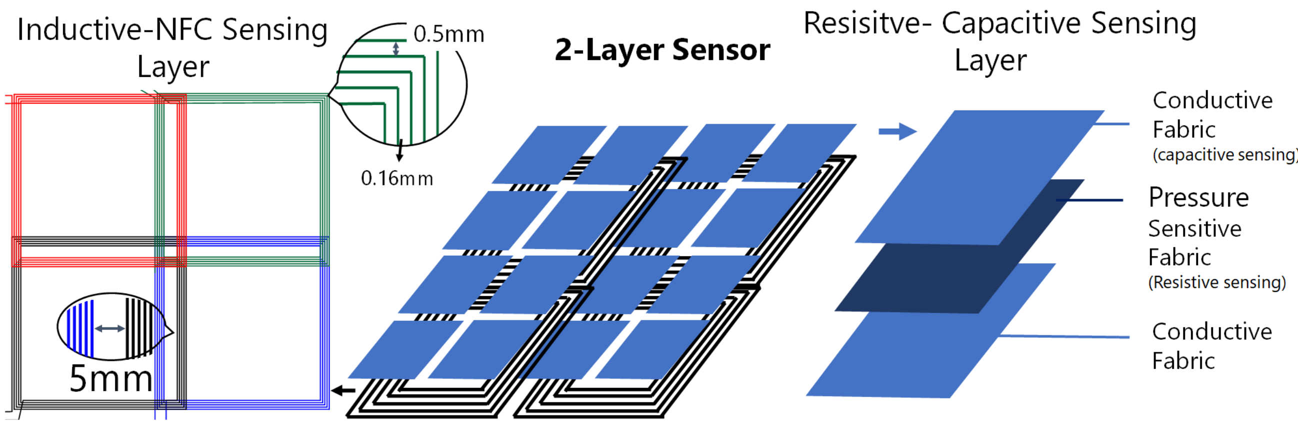

Figure 2: We use a two-layer structure for our sensor. The bottom layer is composed of a grid of embroidered coils for inductive and NFC sensing. The top layer is composed of a grid of fabric resistive sensors with conductive electrodes for both capacitive and resistive sensing.

To create the electrodes for the resistive-capacitive layer, we first stitched a sheet of conductive fabric (EeonTexTM NW170-PI-20) onto a cotton substrate. The stitches followed the grid layout of 16 square-shaped electrodes. The conductive fabric faces the inner side of the sensor to allow a contact with the middle layer of a pressure-sensitive material. Note that we chose the conductive fabric that was made of a non-metallic material (e.g., conductive polymer) to avoid interfering the signals of the other sensors (e.g., inductive sensor). Following the stitches, we cut the conductive fabric outside the electrodes using a cutting machine (Cricut Air Explorer). Next, we stitched a connection line from the top right corner of each electrode to the corresponding position of the pins on the sensor board using the same enameled wire. To prevent the fabric from being bent easily along the gap between two adjacent electrodes, we added a sheet of felt to hold the electrodes on their positions.

The resistive-capacitive sensor was completed by sandwiching a grid of 16 square-shaped pressure-sensitive fabrics (velostat) between the two electrode layers using stitches (Figure 4B). Note that in order for the pressure sensor to work properly, contact between the velostat layer and the connection lines of the electrodes needs be avoided. As such, the top right corner of the velostat pieces was removed and replaced with a piece of felt to create an insulation between the top and bottom electrodes.

The entire sensor was completed by stitching the two individual layers together into one piece. We also added a fabric ground shield on the bottom of it. To develop the sensor in a pocket form factor, we stitched it onto a piece of denim with an opining on the top. We then replaced the original pocket of a pair of jeans with our pocket sensor by attaching the sensor to the jeans using velcro (Figure 4C). In our current implementation, we placed the sensor in the front-right pocket as it is easy for people to perform touch input.

3.3.2 *Customized Sensor Board.*

Our customized sensor board is comprised of a multiplexer module, a sensor module and a processing module (Figure 3 and 5).

The multiplexer module connects the electrodes and coils to the corresponding sensor circuit. Our implementation has three

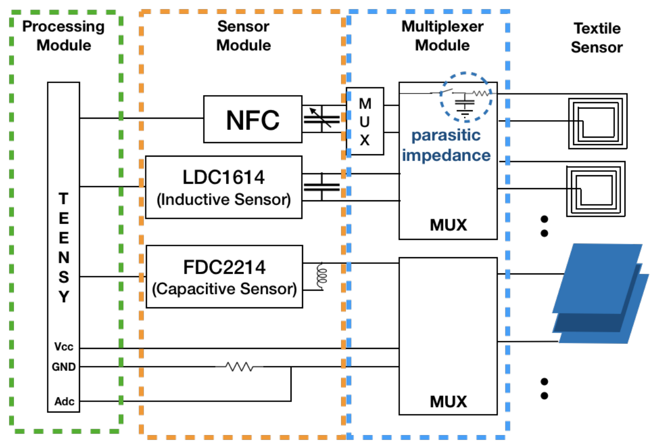

Figure 3: Tasca circuit consists of a processing module, a sensor module, and a multiplexer module. Due to the negative impact on inductive sensing from the multiplexers' parasitic impedance when the coils are shared between inductive and NFC sensing, we had to minimize the multiplexers in our circuit design.

four-channel 2:1 multiplexers (TMUX1574, Texas Instruments), two for the system to switch four coils between the inductive and NFC sensing circuits and the other one for the system to switch between the capacitive and resistive sensing circuits. Additionally, we used four two-channel 4:1 multiplexers (FSUSB74, On Semiconductor) to handle the 16 electrodes for the capacitive and resistive sensor. Further, we used an additional two-channel 4:1 multiplexer (FSUSB74, On Semiconductor) as the RF switching component to handle the 4 coils for NFC. No multiplexer is needed for the inductive sensor as the LDC1614 chip supports four channels.

Mounted on the multiplexer module, the sensor module hosts the necessary circuitry for the four different types of sensors. For inductive sensing, we used a LDC1614 4-channel inductive sensing

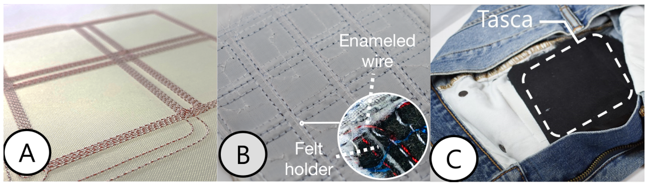

Figure 4: Tasca sensor. (A) The inductive-NFC sensing layer. The coils were created by embroidering enameled copper wires onto a cotton substrate. (B) The resistive-capacitive layer. The sensor grid was created by stitching the velostat pieces between two conductive fabric layers. (C) Tasca is installed on a front pocket of a pair of jeans using velcro

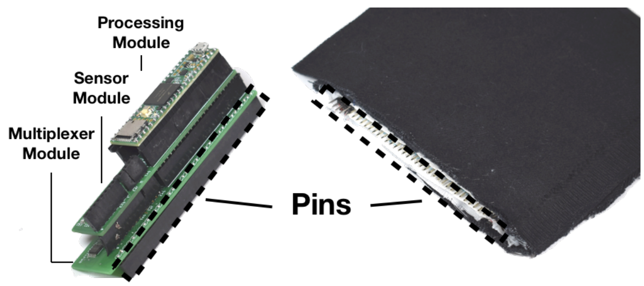

Figure 5: Our customized sensor board is a stack of a processing module, a sensor module, and a multiplexer module. A pluggable interface was implemented using pin headers to connect the sensor board to the textile sensor.

chip from Texas Instruments running at a circuit capacitance value of 680 pF (3 MHz operating frequency). The capacitive sensing was implemented using self-capacitance with a FDC 2214 capacitor sensing chip also from Texas Instruments. The resistive sensing was implemented using a voltage divider circuit for monitoring the change in the resistance of the pressure sensor. Finally, the NFC circuit used a MFRC522 reader chip. Note that the strength of RF signal fluctuates when small changes occur in coil inductance due to inevitable sensor deformation during use. This affected the signal strength of NFC sensing. To allow for the strength of the RF signals to remain at a relatively constant level, we included two programmable capacitors (NCD2100, IXYS) in the system. This enabled dynamic adjustment of signal strength based on the coil inductance detected using the inductive sensor.

Finally, mounted on top of the sensor module, the processing module is composed of a Teensy 3.6 development board. It reads the data from all the sensors at 10 Hz and transmits to a laptop via USB for computation.

3.3.3 Pluggable Connection.

The sensor board was connected to the fabric sensor through a pluggable interface implemented using pin headers (Figure 5). We soldered an array of male headers at the end of the sensor's connection lines and female ones on the sensor board. To ensure that the entire system can be worn on the body comfortably, we placed the rigid sensor board on the outside of the jeans.

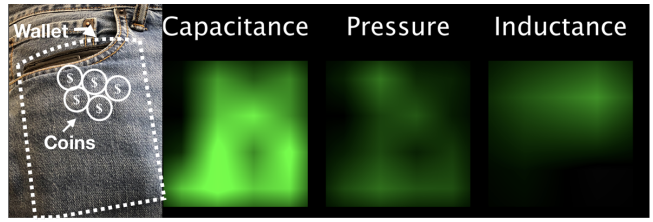

Figure 6: The heatmap images of the raw sensor data showing the capacitance, pressure, and inductance footprint of a wallet with coins.

3.4 Data Processing

For every 100 ms, the sensor reports a 4×4 grid of capacitance values, a 4×4 grid of pressure values, a 2×2 grid of inductance values, and NFC data. All the data, except from NFC, was used for object or gesture recognition. Before the raw sensor data was used for recognition, it was smoothed using a median filter with a sliding window of size 10. We then subtracted background noise from the sensor values using a 2D noise profile, created by averaging the sensor readings at all the locations of the sensor with a sliding

Table 1: The feature set extracted from each sensor data for training our machine learning model.

Shape-related Features (53)	• 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) • Object's center of gravity and geometric center(4)
Material-related Features or Pressure-related Features(33)	• Statistical Functions (13): Sum(1), Mean(1), 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)

window of size 10. For every 5s, we also updated the noise profile if the deltas between current sensor values and the initial ones were classified as noise by a machine learning model. Upon the presence of an object or hand, we upscaled the sensor data to a 240×240 heatmap image using linear interpolation. Figure 6 demonstrates an example of a a wallet with coins inside it and its corresponding sensor footprint shown in the heatmap image.

3.5 Object Recognition

Our system recognizes objects based on the inductance, capacitance, and pressure footprint of the contact area of the objects. For the data collected from each type of sensor, we derived 33 material- or pressure-related features and 53 shape-related features. We also added 16 pressure data collected when the sensor was in the idle model (e.g., without the presence of an object or hand). This data inferred how tight the sensor was worn on the user's body. In total, 274 features (see Table 1) were collected and used to train our machine learning model. We used Random Forest in our implementation because it has been found to be accurate, robust, and computationally efficient in applications involving small wearables and interactive fabrics [4, 5].

3.6 Finger Gesture Recognition

If a hand was recognized, the system switched to the gesture recognition mode. Finger gesture recognition assumed the palm remains in a relatively stable position. This allowed us to use background subtraction to remove the palm in the heatmap image. We then detected the moving fingers by using OpenCV's blob detection to look for blobs smaller than a threshold size. Gestures were recognized if the finger's moving distance exceeded a certain threshold. This is similar to the method described in [30]. The normal force of the finger pressing the sensor was detected using the resistive sensor.

4 INTERACTION TECHNIQUES

Tasca's unique sensing capabilities enable five different input modalities in one fabric-based sensor: object recognition, touch gesture, pressure input, and activity tracking. In this section, we describe several example applications to illustrate potential uses of these modalities through eyes-free, private, always-available, and context-driven interactions.

4.1 Object Recognition

Tasca understands what objects a user carries in the pants pockets. This enables richer contextual interactions in wearable scenarios beyond what is currently offered by existing wearable devices, such as smartwatches or head-worn displays. For example, knowing what the user has or does not have in their pocket, Tasca can provide better personal assistance. In our implementation, the system can detect whether the user carries loose change (e.g., coins) (*metallic*) in their wallet that can be used to pay for street parking or to purchase an item from a vending machine. A reminder is sent to the user before they travel,if their empty wallet (*non-metallic*) is detected.

In VR games, tagged objects (*NFC*) can be used as tangible tokens to enable a more immersive gaming experience by allowing the user to physically interact with virtual items in the digital world. For example, when the user encounters a weapon in a game, they could pick it up and place its physical counterpart (e.g., the weapon token) in their pants pocket. This adds the item to the user's virtual inventory. When the user wants to use it, they can grab the physical token from their pocket (Figure 7).

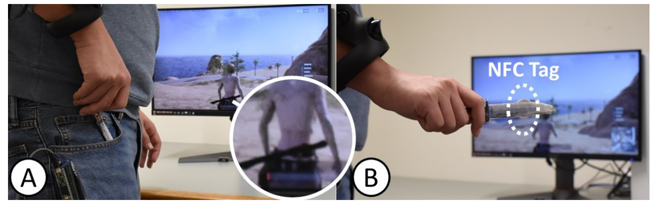

Figure 7: An NFC tagged toy sword is used as a tangible token in a VR game. (A) A user can carry the sword in their pocket, which is used as a physical extension of the user's virtual storage for their weapons in the game. (B) The user can switch to the sword from the fist by grabbing the sword token from their pocket.

4.2 Gestural Input Using The Hand

Unlike existing work [28], our system can differentiate between the hand (*body*) and other objects. Since the pocket is where hands can naturally reside, Tasca provides a useful input mechanism for a user to interact with computing devices. For example, a user can use touch gestures inside the pocket to interact with a head-worn display or a smartwatch. This subtle and eyes-free input method can be useful especially in the public settings, where repeatedly interacting with the device might be considered inappropriate. When Tasca is used to interact with a smartwatch using the same-side hand wearing the smartwatch (Figure 1B), one-handed interaction becomes possible on a smartwatch. This type of interaction can be beneficial in situations where the other hand is occupied by holding objects or is busy with other tasks.

4.3 Pressure Input

In addition to 2D touch gestures, pressure as an input modality enables a new dimension of interaction with computing devices through the pocket. Prior research has shown the promise of pressure sensing in gestural input on smartphones [9] or text input on small head-worn displays [44]. In our implementation, a user can perform directional swipes with two levels of pressure, low and high. Unlike the pressure input on a rigid-body touch panel, where the amount of normal force is only perceived through the fingertip, pressing inside a pocket allows the user to feel the normal force also through the thigh. Therefore, in-pocket touch input through pressure not only expands the vocabulary of touch gestures, it also enriches the haptic feedback that the user can perceive to better support eyes-free input.

4.4 Activity Tracking

Sensing the hands of a user inside the pants pockets can also provide rich contextual information related to their current activity. For example, a hand inside a pocket while interacting with a smartphone

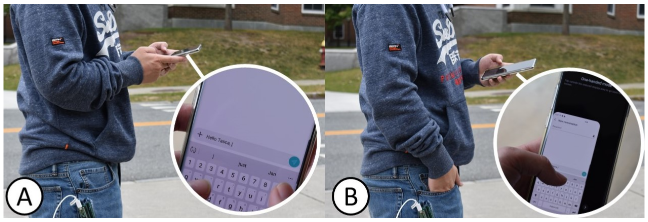

Figure 8: Our system can sense user activity by tracking if a user puts their hands in the pocket. (A) When typing using both hands, the keyboard is configured in its maximum width. (B) The system detects that the user puts their hand in the pocket. (C) The system automatically switch the keyboard to a narrower version to facilitate typing using one hand.

using the other hand indicates one-handed use of the smartphone. As such, the smartphone UI can be adjusted accordingly to facilitate input using the thumb (e.g. a narrower keyboard for one-handed typing) (Figure 8).

In social scenarios, the body language expressed by the user putting their hands in the pants pocket is often associated with certain social meanings. For example, hands in a pocket when standing can be considered as a sign of low confidence [3]. Self-correction is often hard since body posture is driven by a subconscious process. The system can be setup to notify the user about their hand position through the vibration of a smartwatch.

5 EVALUATION 1 - OBJECT RECOGNITION

The goal of this study was to validate the object recognition accuracy of our prototype and its robustness against individual variance among different users.

5.1 Participants and Apparatus

Ten participants (age: 18-34, 4 males, 6 females) were recruited to participate in this study. The size of their hip ranged from 33 inch to 40 inch (average: 37.5, SD = 2.2) and the size of their upper thigh ranged from 17 inch to 22 inch (average: 20.0, SD = 1.6). We customized our sensor for each participant by installing it in the front right pocket of a pair of skinny jeans purchased at their size. They wore the jeans during the study. Our study was conducted by following an approved Institutional Review Board (IRB) protocol developed specifically to ensure the safety of our researchers and participants during a pandemic.

5.2 Objects

We tested our prototype using 10 objects that are often carried by people in their pants pocket (Figure 9). The tested objects vary in geometrical (e.g., size and shape) and material properties. Some of them were pure metallic or non-metallic, while many were made of a mixture of metallic and non-metallic materials. For the non-metallic objects, we included a leather wallet and a bottle of hand sanitizer. For the metallic object, we included a door key. For the hybrid ones, we included a signature pen, multitool knife, car key, earbuds charging case, and LG Rebel 4 smartphone. We also purposefully included an empty sanitizer bottle and a few coins in the wallet to measure how well our system can recognize different statuses of a container. For example, we tested how well the system can recognize if the sanitizer bottle is empty or if there are coins in the wallet. We let our participants to randomly choose how many coins they wanted to put in the wallet. We ended up collecting the data ranging from five to ten coins. Further, we included the hand in our study to test how well our system can differentiate between the hand and all the other tested objects.

5.3 Data Collection

The study was conducted with our participants performing the task in a standing position to simulate the common use scenarios of a pants pocket. Participants were asked to place each of the tested object in their pocket 10 times at a random order. Further, to test whether user activities such as walking may cause confusion to the system between the tested objects, we collected noise data by asking participants to walk for 30 seconds. In total, it took about 20 minutes for the participants to complete the task. In total, we collected 1100 samples (10 participants × 11 objects × 10 repetitions) for analysis.

5.4 Result

We present our results using within-user accuracy and cross-user accuracy. Additionally, we discuss how data from different sensors contributed to the accuracy of object recognition.

5.4.1 *Within-User Accuracy.*

Within-user accuracy is the measurement of prediction accuracy, where training and testing data are from the same participant. For each participant, we conducted a five-fold cross validation, where 4/5 of the data was used for training and the remaining data used for testing. We then calculated the overall within-user accuracy by averaging the results from all the participants. The result yielded an accuracy of 92.3% (SD = 3.2%). Figure 9 shows the confusion matrix. A close look at the study result reviewed that most objects received an accuracy over 90%. The noise could be reliably distinguished from the tested objects and hand. The major source of error, however, was from the confusion of the system between the full and empty bottle of hand sanitizer, which suggests that very small differences in the material property of the objects is still challenging to distinguish. One of the potential reasons of this issue is related to the small inconsistency in sensor readings at different locations of the current prototype. Further, the tightness inside the pocket also varied at different locations. When the variation in sensor readings at different locations was somewhat closed to the impact caused by the change in the material property of an object (e.g., with vs without liquid in this case), a reduction in system performance was observed. We were thus interested in knowing whether system performance could be improved after removing the data from the most confusing object. We found that the accuracy increased to 95.5% (SD = 2.2%) without the empty hand sanitizer. Aside from the hand sanitizer, the system also sometimes confused the multitool with the signature pen. This is primarily due to the similarity in the shape and material of these two objects. We except

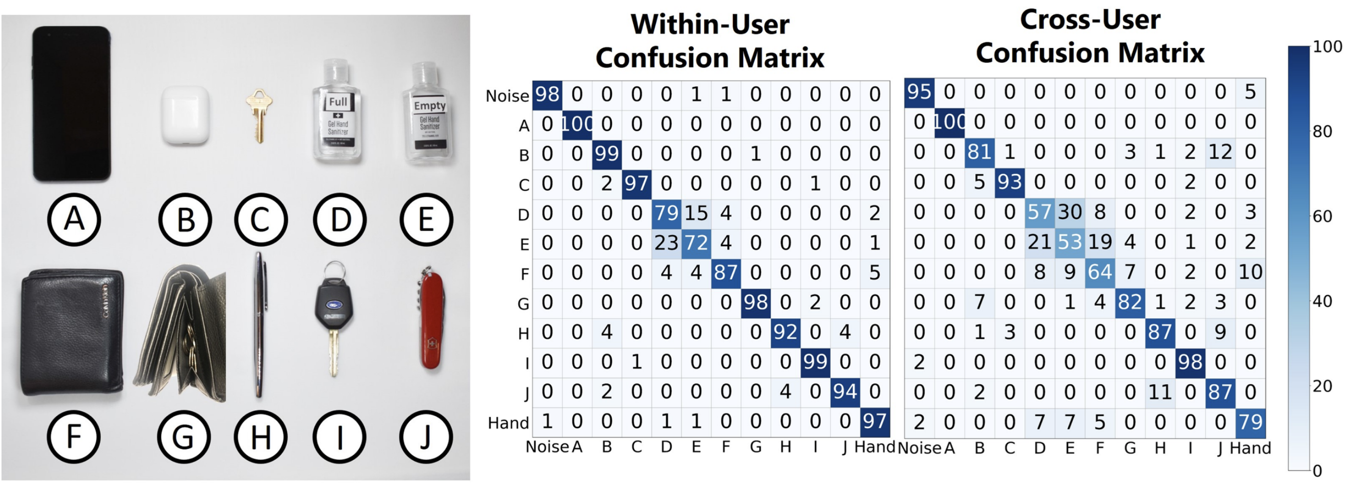

Figure 9: (Left) Objects tested in the study: (A) LG Rebel 4 smartphone, (B) earbuds charging case, (C) key, (D) full bottle of hand sanitizer, (E) empty hand sanitizer bottle, (F) wallet without coins, (G) wallet with coins, (H) signature pen, (I) car key, (J) multitool knife. (Right) The within-user confusion matrix and cross-user confusion matrix.

that this problem can be solved by improving the 2D resolution of the sensor.

5.4.2 *Cross-User Accuracy.*

Across-user accuracy (or universality) measured how well our model works across different users. We calculated the accuracy by using the data from nine participants for training and the remaining one for testing. The overall accuracy was then calculated by averaging the accuracy of all the ten combinations of training and test data. The result yielded a 81.3% accuracy (SD: 6.0%). The reduced accuracy was expected as the sensor deformed differently across the users, which had made it more difficult for the machine learning model to handle. Figure 9 shows the confusion matrix. Similar to the within-user condition, the full (57%) and empty hand sanitizer bottle (53%) contributed to most of the classification errors. Additionally, objects that are similar in shape or made of similar materials began to be less distinguishable across different users. Examples include signature pen (87%) versus multitool knife (87%) and wallet (64%) versus empty hand sanitizer bottle (53%). The decline in system performance is primarily because of the individual difference in the shape and diameter of the thigh, which had led to variations in the footprint of the tested objects. For example, the footprint of the hand sanitizer was wider for the participants who had plump thighs than those who had slim thighs because the sensor was worn flatter in the former case, thus increasing the contact area between the objects and the sensor. Removing the signature pen, full and empty sanitizer bottle from the training/testing set increased the recognition accuracy to 90.3% (SD:6.2%). This is in fact quite promising as it suggests that it is technically feasible to use a general model across different users without a impact on the type of objects that the system can correctly recognize.

5.4.3 *The Contribution of Different Sensors.*

Aside from recognition accuracy, we were also interested in understanding how system performance was affected by the availability of the data form different types of sensors in our system. We included the analysis of the same set of objects except that the most confusing ones (e.g., empty hand sanitize bottle in the within-user condition) were removed so the system worked in an "ideal" situation. We then calculated the recognition accuracy using only a subset of the sensor data. As shown in Figure 10, object recognition accuracy was affected by which sensor(s) was involved and how they were combined. As one may expect, no single sensor could reliably handle our diverse set of objects. However, if we combined any two of the sensors, the accuracy was improved. For instance, the combination of capacitive and resistive sensing yields a better accuracy (within-in user: 80.5%, SD = 6.7%; cross-user: 55.1%, SD = 9.4%) than using the capacitive (within-in user: 73.0%, SD = 5.7%; cross-user: 47.3%, SD = 6.2%) or resistive sensing along (within-in user: 73.2, SD = 11.3; cross-user: 42.9%, SD = 6.6%). This suggested that even the pressure data along was unreliable for object recognition, it worked well as an addition to improve the performance of capacitive sensing when the sensor was deformed by the body. The same pattern was observed for inductive sensing with performance increased to above 80% for both within- and cross-user conditions. Considering that the 2D sensing resolution for the inductive sensing is quite low in the current implementation ($e.g.$, 2×2), we expect that the overall accuracy of our system can be improved by improving the 2D resolution of the inductive sensor.

6 EVALUATION 2 - GESTURE RECOGNITION

The goal of this study was to measure how accurate our system can sense some of the most common touch gestures in daily computing tasks. We were also interested in understanding the whether users can use our system to perform the gestures with different levels of pressure (e.g., low vs high).

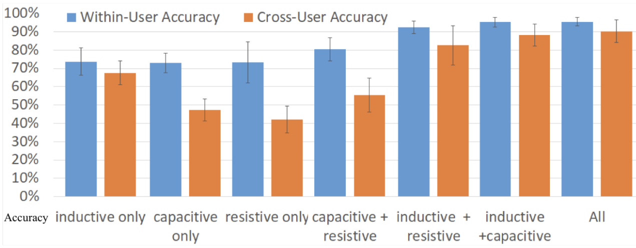

Figure 10: The within-user and cross-user accuracy using a different sensor data set. The error bars are two standard deviations.

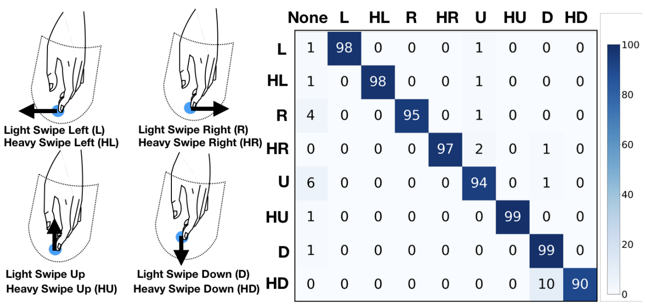

Figure 11: Left: An illustration of the tested gestures. Right: A confusion matrix showing how well the system can detect the gestures.

6.1 Participants and Apparatus

We invited the same group of participants to participate in this study. The study apparatus was also same as in Evaluation 1.

6.2 Gesture Sets

We included in our study four directional strokes (left, right, up, down) that are commonly used on touchscreen devices or for navigating large workspaces (e.g., a map or long list) (Figure 11). Note that our sensor can detect other types of common gestures for interactive fabrics (e.g., deforming the fabric [19]) but according to our pilot study, most of them require relatively large hand motion that are uncomfortable to perform in a small jeans pocket. For each tested gesture, participants were asked to perform the gesture with low and high pressure. Note that our pilot study suggested that the perception of low versus strong force varied across different people. Therefore, we let each participant to perform the force gestures at their own pressure levels.

6.3 Data Collection

Similar to Experiment 1, the study was conducted with participants performing the task in a standing position. Before we started the experiment, participants were given several minutes to learn the 8 gestures. During this short training session, we also customized the pressure threshold for each participant. After this short training session, each participant performed a gesture inside the pocket using their right hand (Figure 11). The order of the tested gestures was randomly assigned. Each gesture was repeated 10 times and the entire experiment took less than 20 minutes to complete. In total, we collected 800 samples (10 participants × 4 gestures × 2 forces × 10 repetitions). Real-time recognition accuracy was recorded for analyzing the study results.

6.4 Result

Overall, our system yielded an average gesture recognition accuracy of 96.1% (SD = 3%). The confusion matrix shown in Figure 11 suggests that 6 out of the 8 tested gestures could be correctly recognized by the system with an accuracy of over 95%. Some of the gestures were harder to perform than the others. For example, users with long nails often performed the light swipe up (94%) by scratching the sensor using the nail. This has caused difficulties for the system to properly detect the touch gesture. Further, performing the swipe down gesture (90%) using two levels of pressures was more challenging than the other tested gestures because participants naturally exerted more force when pushing the finger downwards even in the low pressure condition. It was thus more challenging for the system to distinguish between the two swipe down gestures with different levels of pressure.

7 EVALUATION 3 - NFC TAG DETECTION

The goal of this study was to evaluate the robustness of our NFC sensor in different tag position and distance to the sensor.

7.1 Participants and Apparatus

The same group of ten participants were invited to participate in this study. We tested our system using two common types of NFC tags, card and key tag (Figure 12). The distance between a tag and the sensor was controlled by attaching the tag to an acrylic sheet of certain thicknesses (Figure 12).

7.2 Data Collection

The data was collected with the tag placed in the center as well as at the four corners of the sensor. We chose these locations because sensor signals are weaker at the edges of the coils. Similar to Experiment 1 and 2, participants were instructed to place the tags in the tested locations in a standing position. Note that the tags may appear at a small distance away from the sensor when attaching to an object of a certain thickness. So in this study, we also included three tag distances at each of the tested locations (near, medium, and far). In the near condition, the tag was placed in a direct contact with the sensor. The medium and far conditions were controlled at 3 mm and 6 mm (about the thickness of a smartphone) respectively for the key tag. Note that sensor signals are stronger for the card, so we increased the distances for medium and far conditions for the card to 10 mm and 20 mm, which is about the thickness of a wallet. Each trial was repeated 3 times and the entire study took less than 15 minutes to complete. In total, we collected 900 samples (10 participants × 2 tags × 5 locations × 3 distances × 3 repetitions) for analysis.

7.3 Result

Figure 12 shows the result of the experiment. Overall, the recognition success rate for the card was 98% across all the locations

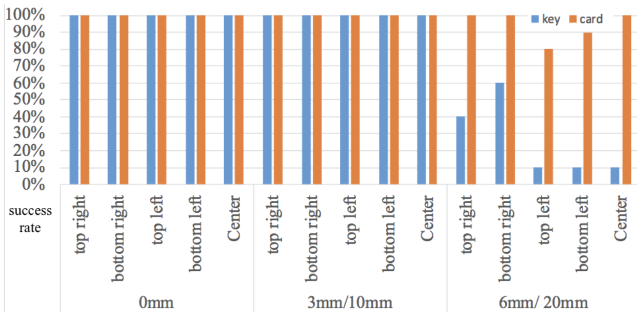

Figure 12: Recognition success rate of our system with the NFC tags placed at different locations and distances to the sensor

and distances. The success rate of the card dropped at both corners near inner thigh (e.g., left corners) at the longest distance of 20 mm. We found that the signal was weaker on that side of the pocket, especially for those who had slim thighs. This is possibly because of the increase in senor deformation at the far end, which consequently increased the distance of the tag. The system was able correctly recognize the small key tag at all the tested locations in the 0 mm and 3 mm distance conditions. However, due to the drop of the signal strength at the 6 mm distance, the key tag could not be reliably detected.

8 LIMITATIONS AND FUTURE WORK

In this section, we discuss limitations of our work and suggest future research for exploring the space of interactive pockets.

8.1 Sensor Hardware

We demonstrated that our system can recognize some everyday objects, as well as simple finger gestures. The sensing accuracy of our system for both object and gesture sensing can be improved in the future with the availability of better hardware (e.g., multiplexer). As shown in our study, the number of electrodes and coils impacted recognition accuracy of the tested objects in both within- and cross-user conditions. We expect that including a denser array of electrodes and coils will allow the system to be more capable of sensing user input. Furthermore, going beyond the focus of our current research, incorporating different types of hardware design for sensing will likely open opportunities for a completely new set of applications in pocket-based computing. As a next step for future research, we will focus on new capabilities, such as wireless power transfer for charging electronic devices inside the pocket.

8.2 Effect of Body Motion

As a flexible wearable sensor, the readings of our prototype are affected by the motion or posture of a user's body. For example, actions such as sitting down or jogging may introduce noises that can be hard to handle using a machine learning model trained in a stationary condition. Our initial investigations demonstrated that noises caused by walking had no noticeable effect on how well the system could distinguish between different types objects or hands. Our next step is to investigate whether our system can handle other types of body motion, identify other issues unique to the context of an interactive pocket, and explore practical solutions to overcome the challenges.

8.3 Beyond Jeans Pockets

In the context of object recognition, our current research focuses on pockets in a pair of jeans. This led to the design of our sensor primarily using contact-based techniques that require an object to be in contact with the sensor. This requirement can mostly be guaranteed on a pair of jeans, especially with popular skinny styles as the pockets are tight to the body. The shape of the sensor conforms with the user's body, thus largely reducing the possibility of it to be deformed in a random way and consequently affect sensor readings. However, in other wearable scenarios beyond jeans (e.g., pockets in a hoodie, or a jacket), firm contact between an object and the sensor may not be guaranteed, so it is unknown how well our current object detection method can work in these situations. Future work can further look at understanding the challenges for our system to be used in scenarios beyond jeans and identify novel contactless solutions (e.g., EM- or thermal-based sensing) to overcome the challenges.

8.4 Fabric Flexibility

With multiple layers of electrodes, coils, and substrates, it is expected that our implemented jeans pocket is harder than it was before instrumentation. Preserving the softness of the fabric sensor is also an important consideration in our future explorations. We see it as a interesting future research direction to investigate ways to optimize the sensor based on the material properties of the substrates and wires, which can lead to improvements in softness and comfort of the sensor.

9 CONCLUSION

In this paper, we demonstrate a technique that combines inductive sensing, capacitive sensing, resistive sensing, and NFC into a multi-layered fabric that is integrated into a pocket of a pair of jeans. First, we discussed our sensing principle and approaches to optimize the layering, which was selected based on careful research. With a ten-participant study, we found our approach demonstrated a 92.3% with-user classification accuracy with 11 different objects, 96.4% accuracy for gesture recognition and 100% accuracy for NFC tag detection at a maximum distance of 3mm (key tag) or 10mm (card). We demonstrated a set of new application scenarios, and believe it is an important step to enabling new types of interactions with an everyday part of garments, as well as expanding the broader input space for interactive fabrics.

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