

Advancing Ubiquitous Tactile Sensing through Comprehensive Tooling for Resistive Matrix-Based Sensors

by

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B.S. Electrical Engineering and Computer Science, Massachusetts Institute of Technology,
2022

Submitted to the Department of Electrical Engineering and Computer Science
in partial fulfillment of the requirements for the degree of

MASTER OF ENGINEERING IN ELECTRICAL ENGINEERING AND
COMPUTER SCIENCE

at the

MASSACHUSETTS INSTITUTE OF TECHNOLOGY

September 2025

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ABSTRACT

Resistive matrix-based tactile sensors offer a scalable and intuitive approach to capturing human-environment interactions, yet deploying them in real-world systems remains challenging because they must remain portable, adaptive, and long-lasting. This thesis presents the WiReSens Toolkit, an open-source hardware and software platform for developing resistive tactile sensing systems that meet the demands of real world applications. The toolkit features adaptive hardware for interfacing with resistive sensors and a web-based GUI that mediates access to otherwise complex functionality, including 1) multi-device programming and wireless visualization across three distinct communication protocols 2) autocalibration methods for adaptive sensitivity and 3) intermittent data transmission for low-power operation. As a use case for the toolkit, the thesis then introduces a method for the automatic design and fabrication of custom tactile sensing gloves using flexible printed circuit boards (FPCBs), enabling rapid, scalable production. Together, these contributions lower barriers to adoption and support broader exploration of tactile sensing in HCI, robotics, and ubiquitous computing.

Thesis supervisor: Wojciech Matusik

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Acknowledgments

I am deeply grateful for the support of the incredible mentors, friends, and family who made this thesis possible.

First, I would like to thank Ridwan Alam, for the opportunity to return to MIT as a TA for Biomedical Signal and Image Processing. I am grateful to Tiffany Louie and Young Joong Lee for introducing me to this line of research in the CDFG lab, and for Young's early contributions to the flex-glove concept outlined in this thesis. I am especially thankful to Yiyue Luo, who generously invested time to advise on many aspects of this work. Her thoughtful insights into tactile purpose and her research guidance were deeply impactful, shaping my identity as a researcher.

Thank you to my lab mates in the CDFG, especially my close collaborators Crystal Owens and Yichen Li, for your valuable feedback and stimulating discussions. I am also grateful to my peers in the Multisensory Intelligence group for fostering such a joyful and collegial lab environment.

It has been a privilege to mentor four exceptional undergraduate researchers—Layla Stanton, Isabel Wabno, Eden Hen, and Nicolas Valayannopoulos-Akrivou—whose dedication and hard work played a critical role in bringing this thesis to life.

Thank you to my academic advisor, Katrina LaCurts, for her wise and generous guidance on graduate studies and academic life. I am also thankful to my faculty advisors at MIT—Antonio Torralba, Paul Pu Liang, and Wojciech Matusik—for their support throughout my M.Eng journey, the professional growth opportunities they provided, and their advice on the work presented here.

Finally, to my friends and family—thank you for grounding me, for bringing peace and perspective, and for fostering a sense of belonging throughout my M.Eng. Your support has meant the world.

Publications

Chapter 4 of this thesis was published in the Extended Abstracts of the 2025 ACM CHI Conference on Human Factors in Computing Systems:

D. Murphy et al. “Fits like a Flex-Glove: Automatic Design of Personalized FPCB-Based Tactile Sensing Gloves”. In: *Proceedings of the Extended Abstracts of the CHI Conference on Human Factors in Computing Systems*. CHI EA '25. Association for Computing Machinery, 2025. ISBN: 9798400713958. DOI: [10.1145/3706599.3720147](https://doi.org/10.1145/3706599.3720147). URL: <https://doi.org/10.1145/3706599.3720147>

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Chapter 1

Introduction

Tactile sensing endows humans and everyday objects with the ability to capture, interpret, and respond to physical interactions. As such, it plays a growing role in cyber-physical systems [2], the Internet of Things (IoT) [3], and Human-Computer Interaction (HCI) [4, 5]. While a variety of sensing principles have been employed to record tactile interactions, resistive sensing has emerged as a widely adopted approach due to its simplicity, scalability, and compatibility with low-cost materials [6–9]. Typically, resistive tactile sensors are constructed by sandwiching a piezoresistive material between orthogonally arranged electrode arrays, forming taxels that measure pressure through changes in resistance. This matrix-based structure reduces wiring complexity [10] and has been implemented using a variety of fabrication techniques—from embroidery and 3D printing to conductive knitting and beyond [8, 11, 12].

Despite the growing popularity of resistive sensing, realizing scalable, robust tactile sensing systems—particularly for dynamic, real-world applications—remains challenging. To move toward ubiquitous tactile sensing and large-scale understanding of human-environment interaction, researchers need more than just sensor fabrication methods; they require robust infrastructure for system deployment. For example, consider a pair of resistive tactile sensing gloves used to capture bimanual manipulation tasks. These gloves must transmit data wirelessly, raising questions of protocol choice (Bluetooth? Wi-Fi?), synchronization across hands, and power consumption—each of which introduces practical barriers to deployment. Moreover, resistive sensors often require calibration tailored to each fabrication run, user, or application context. Without infrastructure to support such configuration and adaptation, tactile sensing systems remain fragile, difficult to scale, and impractical for many researchers or longitudinal studies.

To address these challenges, this thesis introduces the WiReSens Toolkit, an open-source¹ hardware and software platform designed to simplify and accelerate the development of resistive tactile sensing systems. The toolkit supports three wireless communication protocols, facilitates data calibration and synchronization, and is designed to accommodate a range of form factors and use cases. By making system-level concerns more manageable, the WiReSens Toolkit enables researchers to focus on application-level questions and opens new avenues for experimentation with tactile interaction.

¹[WiReSens Toolkit Site](#)

I subsequently detail the automated design and fabrication of custom tactile sensing gloves² as an example application made possible by the toolkit. These gloves represent a compelling use case for resistive sensing, as human dexterous manipulation remains a central topic across robotics, rehabilitation, and immersive computing [13–15]. While several glove designs have leveraged resistive sensing principles [16–18], many rely on hand-built or hard-to-access manufacturing methods. This thesis demonstrates how flexible printed circuit boards (FPCBs), which are already widely adopted in wearable electronics due to their compatibility with digital fabrication workflows [19–21], can be used to streamline glove production.

This thesis begins by providing background on the resistive pressure sensing principle, related toolkits, and tactile sensing gloves. It then describes the design, implementation, and evaluation of the WiReSens Toolkit. The next chapter discusses the automatic design and manufacturing of custom tactile sensing gloves as one example of an in-depth use case of the toolkit: understanding human dexterous manipulation. Finally, I outline directions for future work and discuss broader implications for ubiquitous, accessible tactile sensing.

²FPCB Glove Website

Chapter 2

Background and Related Works

This thesis presents hardware, software, and fabrication tools for resistive matrix-based pressure sensors and is therefore most similar to prior works which facilitate the creation of interactive touch-sensing systems. Here I provide an overview of resistive pressure sensing before situating this thesis within the landscape of toolkits designed for tactile sensing. I then examine the principle’s use in tactile sensing gloves—a key form factor for understanding human–environment interaction, and the focus of the novel design and fabrication tools introduced in this thesis.

2.1 Resistive Pressure Sensing

Past research has explored various methods for dynamic pressure sensing, with optical, capacitive, and resistive techniques being among the most widely used. Optical tactile sensors, such as GelSight [22], analyze light pattern changes caused by material deformation under pressure. While offering high resolution and performance, these sensors often rely on proprietary hardware and face limitations in scalability and flexibility due to visual occlusion challenges. Capacitive sensing, on the other hand, typically involves two conductive electrodes separated by a deformable dielectric layer, where applied pressure alters capacitance [23]. However, capacitive methods often require shielding layers to mitigate stray noise induced by neighboring conductive elements [24, 25]. Additionally, capacitive sensing is more commonly

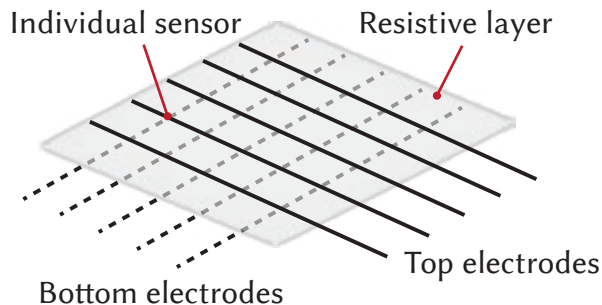


Figure 2.1: Typical layout of a resistive matrix-based pressure sensing form factor, with a resistive layer sandwiched between two sets of orthogonally positioned electrodes.

used in a mutual [26] or swept-frequency [27] setup for binary touch detection or proximity sensing [28] rather than precise pressure measurement. This thesis therefore focuses on resistive pressure sensing.

In resistive pressure sensing, orthogonally arranged electrodes sandwiching a piezoresistive layer (usually carbon-based) form a 2D sensing matrix, where pressure is measured via resistance changes at electrode intersections [29] (Fig. 2.1). This approach avoids the scalability problem that is present in optical pressure sensors, as wires can easily be added or removed and spaced tighter or more spread out. When combined with digital fabrication approaches like machine knitting [8], digital embroidery [11], 3d printing [12], and flexible circuit printing [1], it has allowed resistive sensing to be incorporated in a variety of form factors like hand bags [30], carpets [7, 31], and even hair extensions [32]. The toolkit platform contributed by this thesis is adaptable to these various fabrication approaches, as detailed in its *Sensor Adaptivity* section.

Pressure signals are typically read from a resistive sensing matrix using a zero potential scanning readout circuit [33], the hardware on which WiReSens Toolkit is also built. The circuit topology is well established and widely adopted due to its ability to reduce crosstalk between neighboring electrode. Although some works provide similar open-source hardware [34, 35], WiReSens Toolkit supports a higher density (up to 1024 pressure sensing locations), and is the first among the cited open-source hardware to include a digital potentiometer in this architecture for tuning sensitivity.

2.2 Tactile Sensing Toolkits

A range of toolkits have been developed to facilitate prototyping touch sensing applications, with early works focusing primarily on capacitive sensing. CapToolKit by Wimmer et al. [36] and Midas by Savage, Zhang, and Hartmann [37] were among the first to provide open-source hardware and software to streamline the prototyping of capacitive touch interfaces. Midas lowered the barrier to designing custom capacitive sensors which could be fabricated using digital manufacturing techniques such as inkjet printing, vinyl cutting, and CNC milling. These contributions allowed researchers and designers to rapidly iterate on new touch-sensing applications without needing deep expertise in circuit design or signal processing. Building on this foundation, the Multi-Touch Kit [38] further abstracted capacitive sensor processing by introducing an Arduino library for mutual capacitance-based multi-touch arrays. This allowed capacitive touch sensors to be implemented using only a standard microcontroller (MCU). While these toolkits provided valuable abstractions for capacitive touch sensing, they primarily supported binary multi-touch detection.

Support for resistive touch sensing is typically limited to specific application contexts and sensor types. The E256 project by Donneaud, Honnet, and Strohmeier [35] provides open-source Arduino firmware for denoised readout of resistive matrix-based eTextiles designed for musical expression. By leveraging a fabric-based piezoresistive sensor, E256 enables pressure-sensitive interaction beyond simple binary touch detection. Similar to the Multi-Touch kit, it includes Processing software for real-time visualization of sensor readings. Additionally, the 3D ViTac system by Huang et al. [34] has expanded accessibility within robotics communities by offering a hardware guide, Arduino firmware, and Python ROS libraries for parallel gripper

resistive tactile sensors.

	CapToolKit [36]	Midas [37]	Multi-Touch Kit [38]	E256 [35]	3D ViTac [34]	Ours
Sensing principle	Capacitive	Capacitive	Capacitive	Resistive	Resistive	Resistive
# of sensors per device	8	9	256	256	256	1024
# of sending devices	1	1	1	1	4	5
Sensitivity calibration	✗	✗	✗	✗	✗	✓
Wireless protocol support	✗	✗	✗	✗	✗	✓
Power-saving mode	✗	✗	✗	✗	✗	✓
Visualization	Static	Configurable	Static	Static	Static	Configurable

Table 2.1: In contrast to existing open-source tactile sensing toolkits, WiReSens enables sensing on a larger scale (4x the number of sensors and 5x the number of devices), automatic sensitivity calibration, wireless protocol support, and power-saving operation modes.

WiReSens Toolkit builds upon these prior works (Table 2.1) across key areas of HCI toolkit contributions as identified by Ledo et al. [39] and this thesis’ design goals of portability, adaptivity, and efficiency. With built-in wireless communication support for up to five devices, each capable of sensing dynamic pressure at 1024 unique locations, WiReSens Toolkit extends beyond individual sensors to enable the development of distributed multi-sensor interactive systems. This allows novice users to explore tactile interaction design on a larger scale. By integrating features such as automatic sensitivity calibration and power-saving modes, it simplifies access to more complex functionality, enabling users to rapidly prototype tactile sensing systems which are adaptable and sustainable in addition to functional. Finally, WiReSens is the first of these toolkits to be evaluated with first-time users, demonstrating that even those without prior experience can set up a functional tactile sensing system in 5 minutes.

2.3 Tactile Sensing Gloves

A tactile sensing glove captures touch sensations on the hand, contributing to studies in human behavior monitoring [40], robotics [41], and human-computer interaction [42]. Recently, a few commercial tactile sensing gloves [43–45] are available, but they are relatively costly and have limited sizing options. Sundaram et al. [16] introduced a high-resolution resistive tactile sensing glove by manually arranging orthogonal electrodes over a resistive layer, enabling the capture of a large and diverse dataset for human-object interactions. Other tactile sensing gloves have been fabricated using techniques like manually integrated fluidics [46] and hand-sewn conductive yarns [18]. Compared to sensing mechanisms such as capacitive, piezoelectric, and triboelectric sensors [9], resistive tactile sensing gloves offer notable advantages, including simple design, robust performance, and low power consumption. Further, to scale up the fabrication process, digital fabrication methods, including machine knitting [17], digital embroidery [47], and laser cutting [48], have been deployed to create resistive tactile sensing interfaces. However, current automated manufacturing processes face significant challenges, including the need for advanced equipment, difficulties in interfacing with readout electronics, and a reliance on one-size-fits-all designs. Flex-PCB technology has emerged as a promising solution to these limitations, with recent advancements in

capacitive sensing [49] and microelectromechanical systems [50]. This thesis presents a flex-PCB approach for personalized resistive tactile sensing gloves, enabling mass manufacturing through established industries and making the technology accessible and customizable to a broader community.

Chapter 3

A Toolkit for Interfacing with Resistive Tactile Sensors

This chapter presents the WiReSens Toolkit (Fig. 3.1). Inspired by sensing toolkits that simplify prototyping through domain-specific abstractions [37, 51, 52], it consists of a web-based GUI that interfaces with open-source hardware, making it easier for novices in embedded sensing to develop portable, adaptive, and efficient resistive tactile sensing systems. It includes methods for sensor array readout, wireless communication via three distinct protocols (Wi-Fi, Bluetooth Low Energy (BLE), and ESP-NOW), real-time interactive data visualizations, automatic sensitivity calibration, and intermittent data transmission for energy savings, all of which are lacking in existing open-source solutions for tactile sensing [35, 38, 53].

I provide a technical evaluation of the toolkit, evidencing its ability to provide robust multi-sender wireless communication across all three protocols, optimized pressure resolution during sensor readout, and up to a 42% increase in tactile sensing device lifetime. I then present results from a user study with 11 novice users, which demonstrated that the platform has excellent usability, streamlines access to complex functionality, and helps users better interpret pressure data visualizations. I finally demonstrate the flexibility of the toolkit by using it to rapidly prototype various applications, including musical gloves, shoe soles for gait

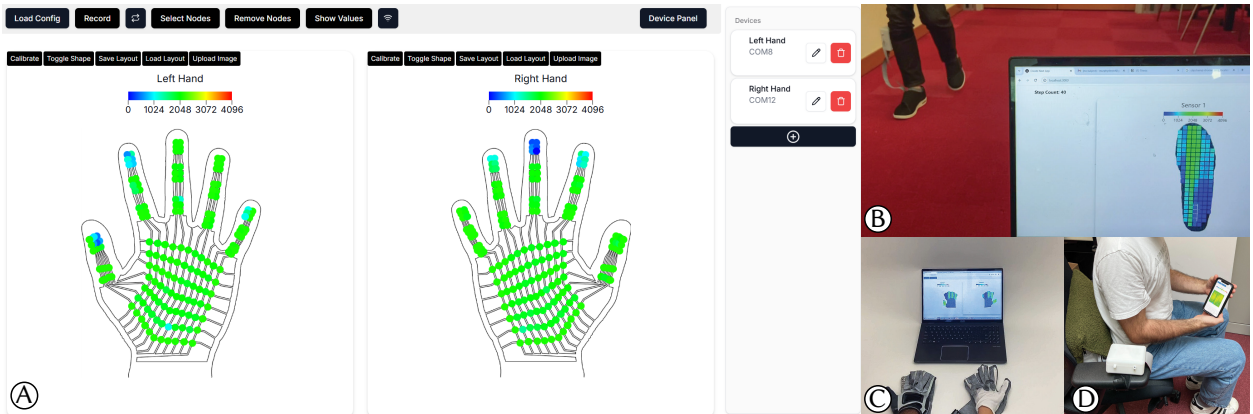


Figure 3.1: WiReSens Toolkit provides open-source hardware and software to enable the development of portable, adaptive, and efficient resistive tactile sensing systems.

monitoring, a pillow for posture monitoring and remote control, and a smart home welcome mat.

3.1 Design Requirements

To ensure the WiReSens Toolkit is effective for developing scalable tactile sensing systems, I outline several key goals for its design.

Portability: Tactile sensing devices must be easily repositioned to capture interactions across different surfaces and environments. This means wireless communication is a necessity, especially in wearable applications where wires can restrict movement. While many sensing toolkits adopt a single communication protocol (often Bluetooth [51, 54, 55]), different protocols offer distinct advantages [56]. For example, Wi-Fi offers excellent speed and reliability indoors but is difficult to access outdoors, where Bluetooth communication is more viable. A toolkit that simplifies switching between protocols would broaden the range of environments where tactile sensing systems can be effectively implemented.

Adaptivity: A key challenge with resistive tactile sensors is that the resistance-force relationship varies across fabrication techniques, and different applications require distinct force sensitivity ranges. In these different contexts, the same readout circuit can either overamplify or underamplify signals, limiting pressure resolution [57]. Additionally, resistive sensing array data is typically displayed statically, with each sensing node fixed in place. However, the real-world positioning of these nodes can shift when different users wear the same sensor or as conditions change over time. An adaptive visualization that accounts for these shifts could help users interpret tactile interactions more accurately and intuitively.

Efficiency: Wireless communication is power-intensive, which limits device lifetime and poses challenges for sustainable development [58, 59]. Low-power operation is therefore important to enable large-scale data collection over extended periods of time, though it can affect the computational capabilities of devices. Users should have access to methods that allow them to navigate this trade-off. Additionally, users may invest significant time and resources into developing interactive systems, so reconfiguring them for different form factors, users, and applications should be seamless, minimizing hardware and firmware modifications.

3.2 System Overview

This section illustrates an example of setting up a tactile sensing system using a digitally embroidered 32×32 node resistive sensor and the WiReSens Toolkit. While this example uses a specific fabrication method, I reemphasize that the toolkit is agnostic to sensor construction and supports resistive sensors produced through a wide range of manufacturing techniques.

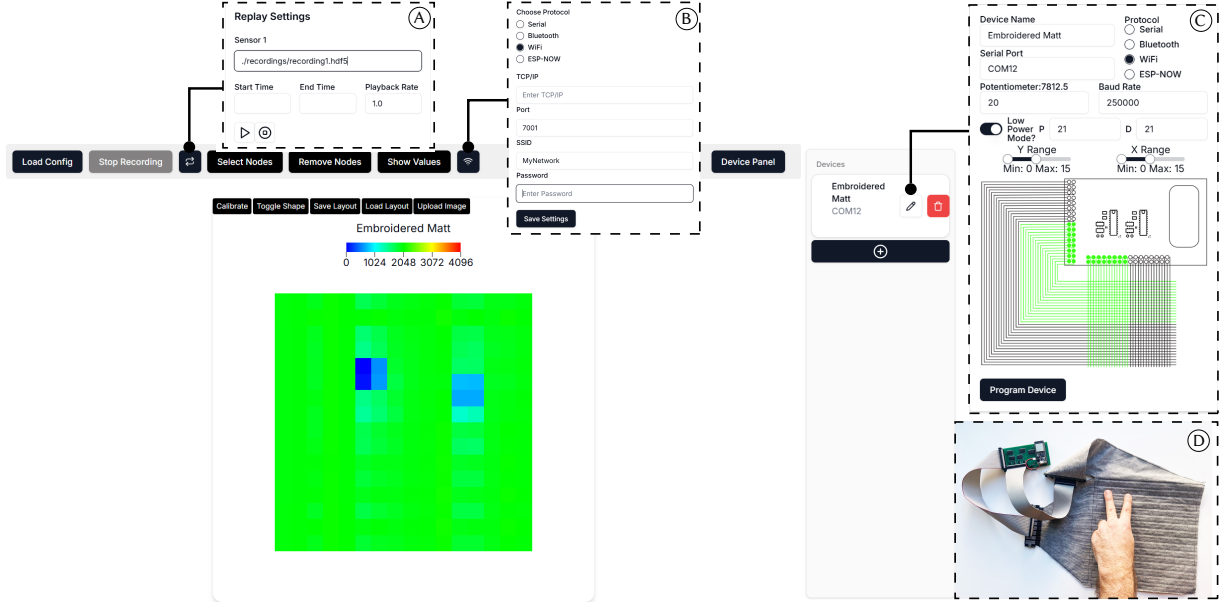


Figure 3.2: The WiReSens Toolkit web-based programming interface wirelessly records and displays pressure data from sensing devices (D) in real time, with panels to replay recordings (A), configure wireless protocols (B), and configure the devices themselves (C). The embroidered matt is configured to read only from the top-left quadrant and send readings via WiFi.

Hardware Setup To begin, the user connects the horizontal and vertical electrodes of their sensor to one of the zero-potential scanning readout circuits available in large (32×32) and small (16×16) configurations (Fig. 3.2D). The large circuit interfaces with the sensor via ribbon cables and the small circuit does so via flex cables. In this case, the user selects the large circuit and connects the ESP32 microcontroller which controls it to their laptop via USB. The user then uploads the Arduino-based firmware, which handles sensor readout and communication. This upload is a one-time step—subsequent configuration is performed entirely through the web GUI.

Configuring the Readout Area With the hardware connected, the user starts the Python backend and opens the web GUI in their browser. Using the Device Manager, they add a new device and access the configuration panel (Fig. 3.2C). The user decides they only need the top-left portion of the 32×32 array for their application, so they configure a smaller readout area of 16×16 nodes to improve the effective frame rate. A graphical interface allows intuitive selection of rows and columns, dynamically highlighting the chosen electrodes in green and providing a clear preview of the active sensing region.

Setting up Wireless Communication Next, the user configures wireless communication. The toolkit supports multiple protocols, including USB-serial, Wi-Fi (TCP), Bluetooth Low Energy (BLE), and ESP-NOW (Espressif’s peer-to-peer communication protocol [60]). The user selects Wi-Fi for its low latency and uses the wireless configuration panel (Fig. 3.2B) to enter parameters such as the laptop’s IP address and the network credentials.

Programming the Device Once satisfied with the configuration, the user clicks “Program Device” to send the updated settings to the MCU via USB. If adjustments are needed later, the configuration can be updated directly through the web GUI, allowing for rapid iteration. The user then unplugs the device, connects a battery, and can begin using the device for their application.

Recording, Visualization, and Playback By clicking “Record,” the user begins data acquisition across all configured devices, using their selected communication protocols and readout areas. They’ve also written a custom method for tracking touch points in Python, which hooks into the toolkit backend and runs concurrently with recording and visualization. Real-time pressure data is displayed as a heatmap of square “sensing pixels” representing the active readout regions. Users can reposition sensing pixels via drag-and-drop during recording to support flexible sensor layouts, in addition to saving these layouts and uploading background images for contextual visualization. Data is stored locally in HDF5 format, and a built-in replay feature enables playback with adjustable timestamps and speed controls (Fig. 3.2A).

Turning on low-power mode Aware of Wi-Fi’s energy demands, the user enables power-saving mode through the configuration panel (Fig. 3.2C) to extend device lifetime during battery powered use. Using a Python utility which takes their pressure recording file as input, they obtain optimized intermittent transmission parameters that balance power efficiency with sensing quality for their specific application, and input these values into the configuration panel. They reconnect the MCU to their laptop using a USB cable and click the "Program Device" button, reconfiguring the device to operate in the low-power mode.

Sensitivity Calibration During playback, the user notices that the sensor is less responsive than desired. By clicking “Calibrate,” they initiate an automatic gain calibration routine that optimizes voltage output range for the application at hand. During the 10-second calibration period, the user engages the tactile sensor in a way that reflects the range of pressures it would experience under normal operation. At the end of this interval, the firmware sets the amplification gain based on the recorded range of voltages, improving the sensor’s responsiveness for future interactions.

3.3 Implementation

Here I provide further implementation details behind the toolkit’s functionalities.

Web GUI and Python Library The WiReSens Toolkit web GUI provides a visual programming interface for control of the toolkit’s functionalities. It is implemented via NextJS and communicates with a locally running Python Flask backend through WebSockets. The Python backend serializes each device’s data in a separate thread, where each frame is timestamped using the desktop’s local Unix time and saved to an HDF5 file, ensuring synchronized data across devices. It also provides a library with utility functions for analyzing

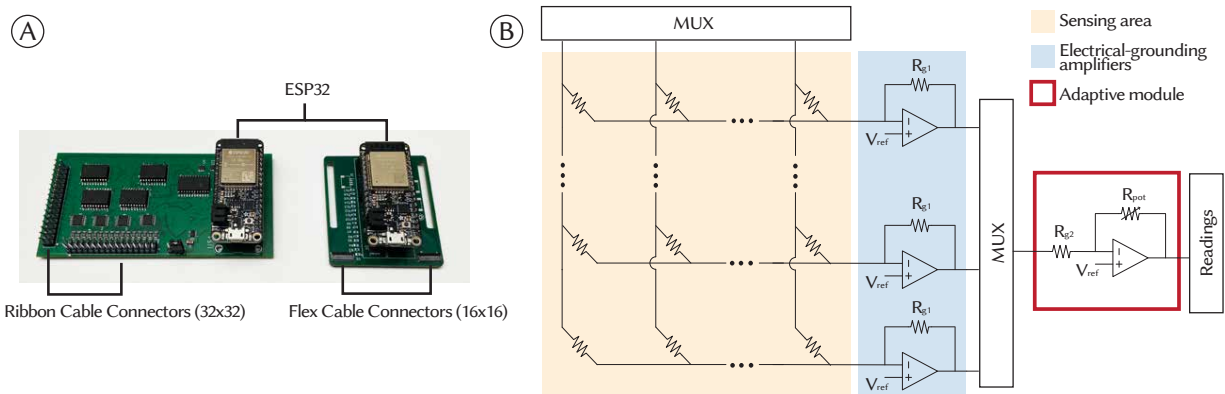


Figure 3.3: (A) Adaptive zero-potential readout circuit open-sourced by WiReSens Toolkit in large (left) and small (right) sizes (B) Schematic of general zero potential readout circuit (left) with additional opamp and digital potentiometer for adaptivity (red).

sensor recordings, optimizing parameters for low power consumption, and executing custom methods on sensor data in real time.

Adaptive Readout Circuit The WiReSens Toolkit provides two open source zero-potential readout circuit PCBs which can be manufactured and assembled using the gerber files provided for \$90.26 and \$140.92 USD, respectively, via JLCPCB (Fig. 3.3A). In this architecture, each electrode layer is connected to a digital multiplexer (MUX). To measure resistance at a specific node, the ESP32 controls one MUX to ground an electrode in one layer while the other MUX selects an electrode in the opposing layer for measurement. The voltage at this electrode is passed through an operational amplifier (LMV324, Texas Instruments) and digitized by the ESP32’s Analog-to-Digital Converter (ADC1) at a continuous sampling rate of 150 kHz using direct memory access with Espressif’s Inter-IC sound API. To allow tuning of tactile sensor sensitivity and avoid the problems of ADC underutilization and op-amp output saturation, I introduce an additional operational amplifier (TLV9152, Texas Instruments) in inverting configuration with variable gain (Fig. 3.3B). The gain is controlled by a 50 k Ω digital potentiometer (MCP4018, Microchip), denoted as R_{pot} .

Wireless Communication The toolkit firmware employs a batched transmission scheme for efficient data throughput, sending data in batches of 120 samples. All supported protocols—WiFi (TCP), BLE, and ESP-NOW—use a unified packet format: the first byte encodes the sender ID, the next two bytes specify the start index of the 120-sample segment within the sensing array, the next 240 bytes contain the sample data, and the last four bytes encode a unique packet ID. Users can optionally configure a protocol-specific delay (in milliseconds) via the wireless settings panel, which the device observes before transmitting each packet. This delay helps stagger transmissions across devices, reducing the likelihood of packet collisions when multiple devices are active.

Low-Power Mode To enable low-power operation modes, I employ intermittent sending, conserving power by minimizing data transmission for signals that are easy to predict or

unchanging. The MCU predicts the voltage at a sensor node before reading it using the window-based time series forecasting equation:

$$v[n+1] = v[n] + \frac{1}{p} \cdot (v[n] - v[n-1]) \quad (3.1)$$

where $v[n]$ represents the ADC voltage reading at time step n and p is a parameter controlling how responsive the prediction is to recent shifts in voltage. The ESP32 will only send the data packet if the average error between all readings and predictions is below some user defined threshold d . If the data packet is not sent, the Python library will predict its value using the same forecasting method as the ESP32 (3.1), ensuring that the average error across each data packet remains below the specified threshold d . This is modeled after the method proposed by Suryavansh et al. [61], which was chosen due to its low computational complexity and memory requirements, making it ideal for implementation on a MCU.

To help select the parameter p and error threshold d , I provide a utility function which takes any tactile recording as input and performs a grid-based optimization. The optimization minimizes an objective function based on the normalized root mean square error (NRMSE) of the predicted tactile frames E and the percentage of transmitted data r :

$$\alpha * E + (1 - \alpha) * r, \quad (3.2)$$

where α is an adjustable parameter managing the trade-off between accuracy and transmission percentage. The script generates a visualization of the objective function, allowing users to refine and adjust the search space for further optimization.

Automatic Sensitivity Calibration The automatic calibration sequence sets the resistance R_{pot} that best optimizes the tactile sensor’s range of voltage output for a particular application. Upon start, the MCU scans the sensor array using the minimum possible value of R_{pot} for a configurable duration (defaulting to 10 seconds) and keeps track of the minimum sensor output voltages during this time. At the end of the calibration duration, the method then calculates the average of these minimum sensor output voltages V_{min} and determines the value of R_{pot} that will make the output of the opamp in the adaptive module V_{out} equal to 0 volts according to equation 3.3, obtained from analysis of the readout circuit topology in Fig. 3.3, where the denominator 264Ω represents the smallest detectable resistance by the readout circuit (as set by $V_{\text{ref}} = 1.8V$ and $R_{g1} = 220\Omega$ in this implementation).

$$V_{\text{out}} = V_{\text{ref}} - \frac{R_{\text{pot}}}{264\Omega} \times (V_{\text{ref}} - V_{\text{min}}). \quad (3.3)$$

This effectively maps the minimum pressure applied to the maximum sensor output (V_{ref} Volts) and the maximum pressure applied to the minimum sensor readout (0 Volts), ensuring that the full range of the ADC is used and pressure resolution is maximized.

3.4 Evaluation

In this section I detail a technical and user evaluation of the WiReSens Toolkit, focusing on speed and reliability of the multi-sender wireless communication, automatic calibration performance, power-reduction capabilities, and usability of the web-GUI interface.

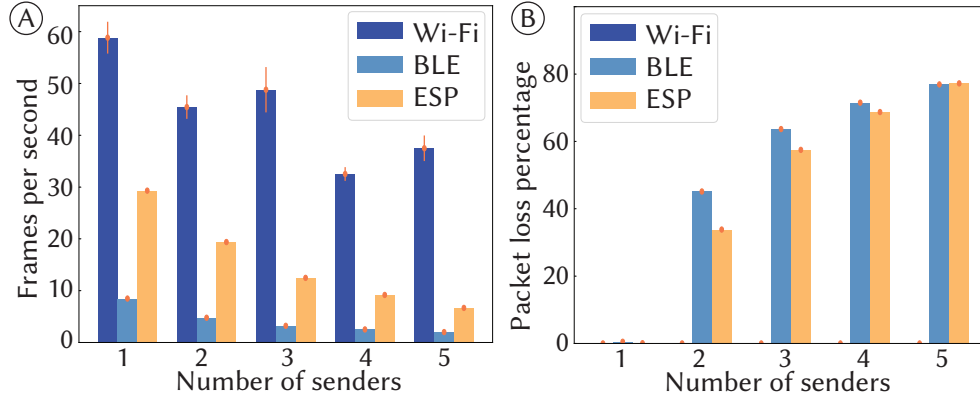


Figure 3.4: Average throughput (A) and average percentage of packets lost (B) per sender during multi-sender wireless communication using Wi-Fi, BLE, and ESP-NOW.

3.4.1 Wireless Communication

To assess the scalability of the wireless communication abstractions in WiReSens Toolkit (including Wi-Fi, BLE, and ESP-NOW), I programmed 1 to 5 devices to wirelessly send tactile sensing data from a 32x32 sensing matrix to a laptop running the Python backend. Each protocol and sender combination was tested for three minutes, repeated three times. Fig. 3.4 reports the average and standard deviation of throughput (in frames per second) and packet loss percentage per sender across all three tests. Here, one frame corresponds to approximately 2108 bytes.

Throughput generally decreases and packet loss increases as the number of senders grows across all protocols, due to limited bandwidth. However, Wi-Fi exhibited some exceptions to this trend, likely due to network variability. It consistently delivered the highest performance, achieving 58.84 fps with 0% packet loss for a single sender and 37.49 fps with no loss even with five senders. In contrast, the narrower bandwidths of BLE [62] and ESP-NOW [60] led to higher collision rates in multi-sender, high-throughput scenarios, resulting in substantial packet loss. ESP-NOW was the next most reliable protocol, with 29.30 fps and 0% packet loss for a single sender, dropping to 6.67 fps and 77% loss with five senders. BLE consistently showed the lowest performance, with 8.48 fps and 0.5% loss for one sender and just 2 fps and 76% loss with five. Accordingly, WiFi is recommended for high-throughput use cases, and ESP-NOW for offline scenarios where internet connectivity is unavailable.

The WiReSens Toolkit allows users to manage the trade-off between throughput and reliability by tuning the transmission frequency via protocol-specific delays. For example, with three senders, adding a 157 ms delay to BLE reduced the frame rate to 0.75 fps per sender but kept packet loss below 1%. ESP-NOW achieved similar reliability with only a 10 ms delay, maintaining a higher throughput of 11.76 fps per sender. These results suggest that BLE and ESP-NOW are viable alternatives to Wi-Fi for scenarios where lower power consumption or extended range is prioritized, without significantly compromising data integrity.

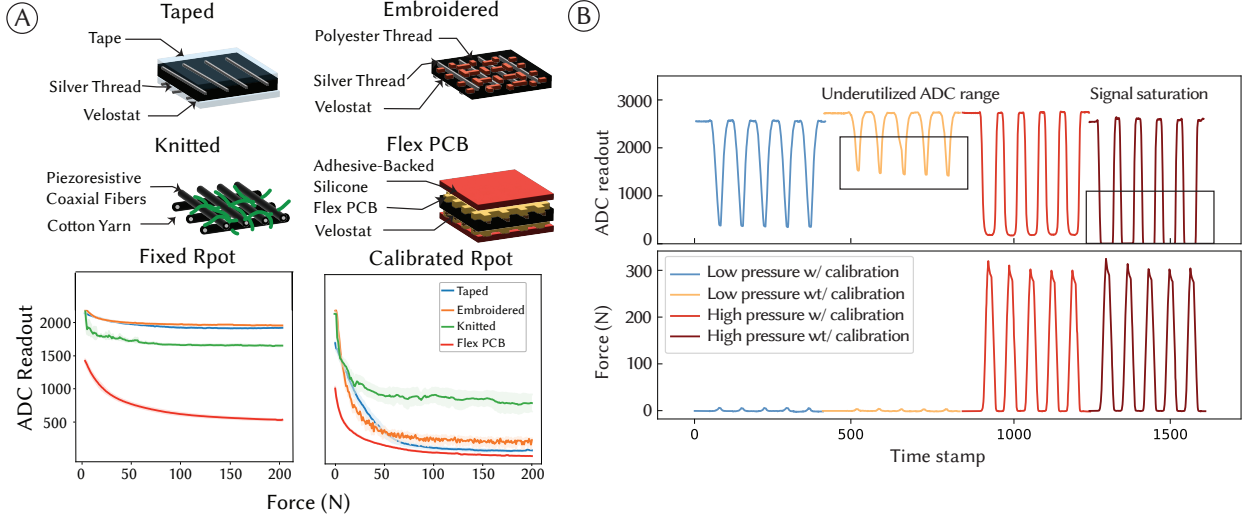


Figure 3.5: WiReSens Toolkit calibrates readout for different sensors and application scenarios (A) Average and standard deviation of ADC readout for four different resistive pressure sensors during cyclical force tests, before and after calibration. (B) Average ADC readout during low and high-pressure application cycles, before and after calibration. Low-pressure calibration maximizes pressure resolution (blue and yellow curves) and High-pressure calibration avoids saturation (red and brown curves).

3.4.2 Sensor Adaptivity

Here I evaluate the effectiveness of the proposed calibration algorithm in two scenarios: adapting to different sensor fabrication techniques and different application contexts. Both experiments used a mechanical tester (Shimadzu AGX-V2) to apply an adjustable normal force over an area of 9 cm^2 to a resistive sensor.

Calibrating for Different Sensors Four resistive matrix-based pressure sensors were fabricated using three established methods—taping copper threads [6], digital embroidery [11], and machine knitting [7]—as well as a flexible printed circuit board (FPCB) approach developed as part of this thesis. For each sensor, the mechanical tester applies a cyclic force to a 3×4 node region at its center for five cycles, with the digital potentiometer’s resistance (R_{pot}) set to 787Ω . Fig. 3.5A presents the mean and standard deviation of the ADC readout within the actuated region as a function of applied force for each fabrication method. Due to the inverting topology of the op-amp, the ADC readout is inversely correlated with force, exhibiting two approximately linear regions. Notably, the taped, embroidered, and knitted sensors display a significantly smaller overall change in ADC readout across the force range when using the default resistance, thereby reducing their effective pressure resolution.

Next, the auto-calibration procedure is applied while maintaining a 200N applied force, yielding calibrated R_{pot} values of 8661Ω , 4724Ω , 9055Ω , and 1181Ω for the taped, knitted, embroidered, and FPCB sensors, respectively. Repeating the cyclic force test, enhanced pressure resolution is observed in all four sensors post-calibration, as evidenced by the increased ADC output range over the same applied force range (Fig. 3.5A).

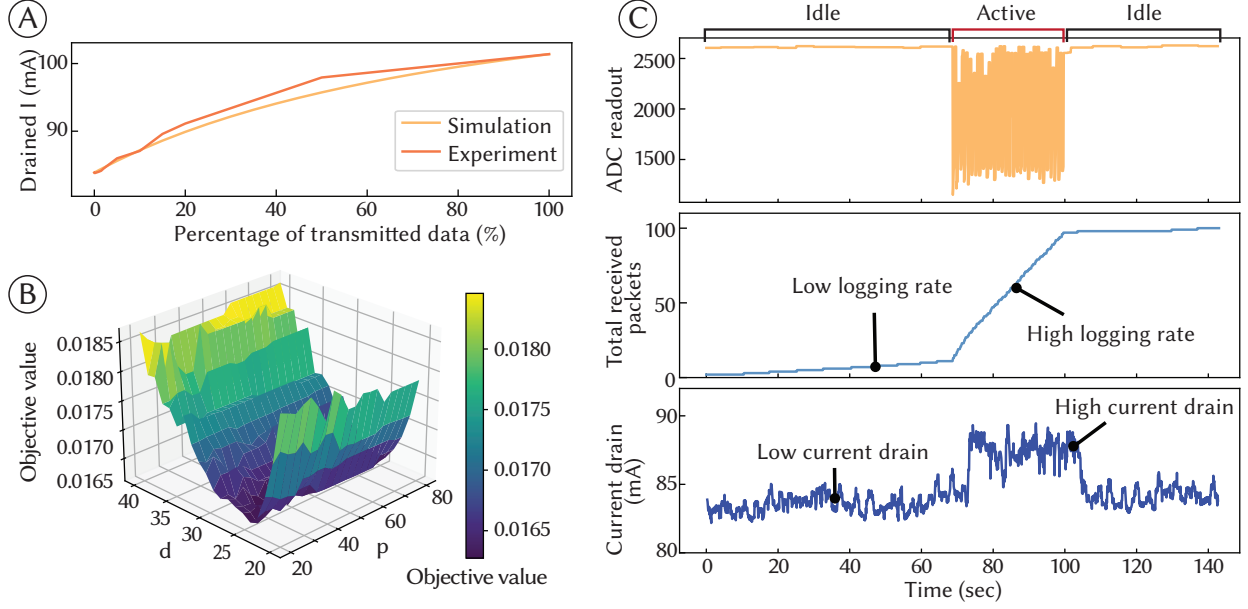


Figure 3.6: Characterization of intermittent sending performance. (A) Simulated and observed average current draw (mA) from a tactile sensing device as a function of the percentage of data transmitted during BLE operations. (B) Visualization of objective function used to select intermittent sending parameters. (C) Average ADC readout, received packet count, and current draw over time during periods of no applied pressure (Idle) and repeated pressure (Active). Low current drain indicates power is saved during Idle periods.

3.4.3 Wireless Power Reduction

I first investigate how packet transmission rate affects power consumption in a tactile sensing device using the BLE protocol. Let us use an abstraction where the device alternates between two states: sending data (state A) or idle (state B). Then, the average current drained during device operation is calculated as

$$I_A * t_A + I_B * (1 - t_A), \quad (3.4)$$

where I_A and I_B is the average current draw during states A and B , respectively, and t_A is the time percentage state in state A . I_B is measured while the MCU samples but does not send pressure data, and I_A is estimated by subtracting I_B from the measured current while data is sent continuously. Using a Nordic Semiconductor Power Profiler, the current (mA) from a 3.3V 1200mAh battery is logged over three minutes to obtain these averages.

I then simulate how the percentage of transmitted data changes t_A , and thus the average current draw of the device. I validate this simulation by fixing packet transmission frequency at 10 different values between 0 and 100% and recording the average current draw. Fig. 3.6A shows the simulated and observed trends, with results indicating that sending 1% of packets could extend the device lifetime by over 20% for BLE. Using similar calculations with data collected under Wi-Fi operation, this could increase to 42 % longer battery life, as Wi-Fi operation is generally more power-intensive than BLE (152.47 mA vs 101.31 mA for BLE).

To further validate the intermittent sending performance, I use a mechanical tester to apply a series of repeated presses to a 32x32 tactile sensor during intermittent operation.

Using the Python utility, I optimize the transmission parameters p and d ($p = 29$ and $d = 26$, Fig. 3.6B) and use them to program the device for the live pressure test. The results (Fig. 3.6C), indicate that when the sensor is inactive, packet transmission is minimal with low average current drain compared to when the sensor is active. The optimized values achieved packet transmission just under 5% with a NRMSE of around 0.012. With a 1200mAH battery, it is estimated this would extend the device’s lifetime by over 2 hours, while ensuring the predicted tactile frames differed from the ground truth frames by approximately only 1.2% of the full-scale range.

3.4.4 User Study

A user study was conducted to assess whether first-time participants found the WiReSens Toolkit easy to use and to what extent it simplifies prototyping resistive tactile sensing systems. Participants completed three tasks: (1) programming a new sensor, (2) calibrating a sensor, and (3) reproducing recorded pressure data. This study was approved by the MIT Committee on the Use of Humans as Experimental Subjects (COUHES) under protocol 2411001482.

Participants 11 participants (4 female, 7 male) aged 19–32 ($M = 22.64$, $SD = 3.87$) were recruited through university mailing lists and word of mouth. Only two had prior experience with resistive pressure sensors, and none had used any part of the WiReSens Toolkit before.

Task 1: Programming a Device To evaluate the toolkit’s learnability and usability, participants were tasked with using it to program a new device. They first received an overview of the resistive pressure sensing principle and were introduced to a 32×32 digitally embroidered sensor. The study moderator then demonstrated how to configure a device to read and record pressure data over Bluetooth using the web GUI. After the demonstration, participants could ask questions before attempting the task independently. They were asked to configure the device to read and record data from a new sensor—an 8×24 shoe sole—without guidance. They could reconfigure the device until they were confident in their setup. Both the time taken and the configured readout area were recorded. At the end of the study, participants completed a System Usability Scale (SUS) survey [63] to evaluate their experience.

Task 2: Calibrating a Device Next, I assessed the extent to which the auto-calibration procedure simplifies the calibration process. The study moderator preconfigured a new device to read from a 3×2 node area of a flex PCB sensor while a constant force of 3.0 kg was applied. Participants were given background information on the sensitivity calibration challenges of resistive sensors and were then instructed to manually adjust the digital potentiometer value through the web GUI to find the minimum amplification such that all six nodes displayed an ADC reading of zero. The time taken for this task and the user-selected value were recorded. The study moderator then asked the participant to perform the same calibration using the "Calibrate" button, which ran for a fixed duration of 10 seconds, and recorded the auto-calibrated potentiometer value.

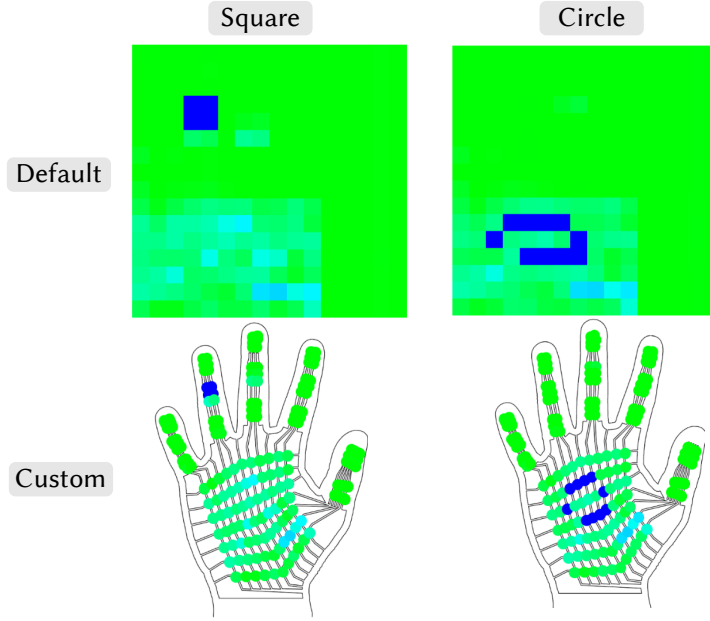


Figure 3.7: Study participants are asked to reproduce one square press and one circle press from either a default or custom visualization.

Task 3: Interpreting Visualized Pressure Data Finally, I examined whether the toolkit’s customized visualizations improve spatial reasoning about tactile data. Participants were shown two WiReSens Toolkit visualizations of presses on a sensing glove—one created with a circular object and one with a square object. Each visualization was presented in one of two formats: either a custom layout configured to match the glove’s shape or a default square layout (Fig. 3.7). The order of presentation was counterbalanced across participants. Participants were asked to reproduce the two presses using the objects and could adjust their attempt until they felt confident. The time taken was recorded and participants were asked to complete a survey assessing their confidence and perceived difficulty during each task on a Likert scale rating from 1 (Not Difficult/Not Confident) to 7 (Very Difficult/Very Confident).

Results On average, participants took less than 5 minutes ($M = 4.15$, $S.D = 1.71$) to program a new sensor, achieving an average readout area accuracy of 96% ($S.D = 4.3\%$) on their first attempt. The average SUS rating was 82.5 ($S.D = 9.68$), considered excellent and falling in the highest quartile of usability scores [64, 65]. Open-ended feedback further highlights the toolkit’s novice-friendly nature, as reflected in P11’s comment: *“It was very cool to work with hardware integrated with the toolkit software because it made the learning process more smooth and approachable. It was also beginner-friendly, and I could see myself using this for a project.”*

The toolkit expedites the tedious task of calibration. While all participants found the optimal R_{pot} value through manual calibration, this took 2.1 minutes on average ($S.D = 1.15$). The auto-calibration always found the same user-identified optimal gain, but with a fixed calibration duration of 10 seconds, was over 10x faster. Three participants mention the auto-calibration as their favorite feature in open-ended feedback - P2 notes: *“I liked the*

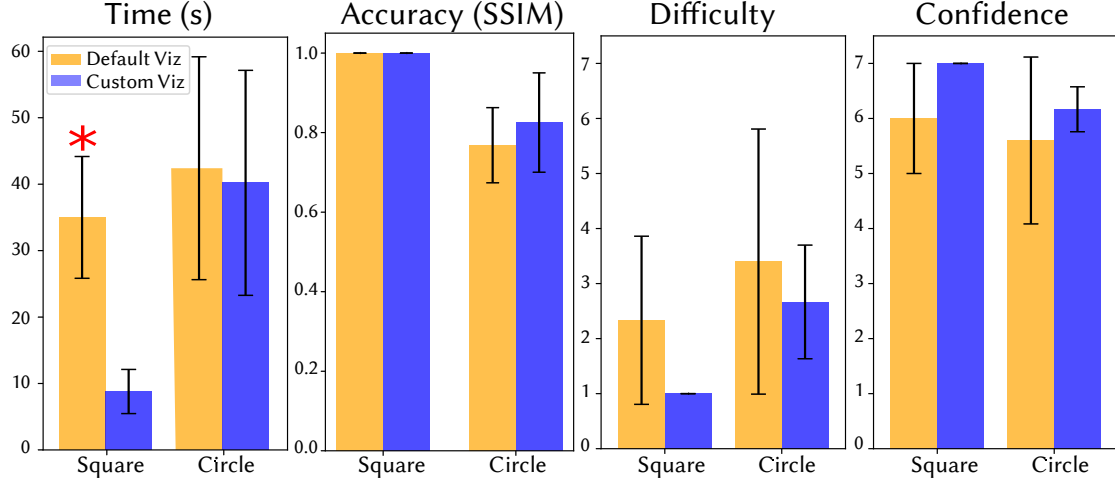


Figure 3.8: Mean and standard deviation of time (lower is better), accuracy (higher is better), difficulty (lower is better), and confidence (higher is better) for square and circle press tasks. Results are shown for default (orange) and custom (blue) visualizations.

auto-calibration tool because it seemed quite tedious to find the resistance yourself."

Finally, the WiReSens Toolkit’s custom visualization improves spatial reasoning of tactile data. I evaluate its effectiveness by analyzing participants’ task completion time, Likert scale ratings for difficulty and confidence, and accuracy of reproduced presses using the Structural Similarity Index Measure (SSIM) between binary thresholded participant and ground truth presses (Fig. 3.8). Participants using the custom visualization in the square press task took significantly less time ($M = 8.79$, $S.D = 3.32$, Welch’s t-test $p < 0.05$) than those using the default ($M = 35.0$, $S.D = 8.79$) and reported less difficulty ($M = 1.0$ for custom, $M = 2.33$ for default) and greater confidence ($M = 7.0$ for custom, $M = 6.0$ for default) on average. While there are not significant differences between visualization groups in the more challenging circle press task, participants using the custom visualization on average took less time ($M = 40.2$ for custom, $M = 42.4$ for default), reproduced presses more accurately ($M = 0.83$ for custom, $M = 0.77$ for default), and expressed higher confidence ($M = 7.0$ for custom, $M = 6.0$ for default) than those using the default visualization. Six participants highlighted the visualization tools as their favorite feature, with P8 stating: *“The layout is my favorite feature, the ability to hide and reconfigure layouts to match the shape of the object.”*

3.5 Applications

In this section, I demonstrate the utility of WiReSens Toolkit by using it to prototype a range of resistive tactile sensing systems. The tactile sensors were constructed with silver thread and Velostat, using digital embroidery [11] and direct taping [66]. Each application was prototyped in under 10 minutes.

Musical Gloves Taking inspiration from gloves that offer new means of musical expression [67, 68], I used WiReSens Toolkit to program two Wi-Fi-enabled tactile sensing gloves for

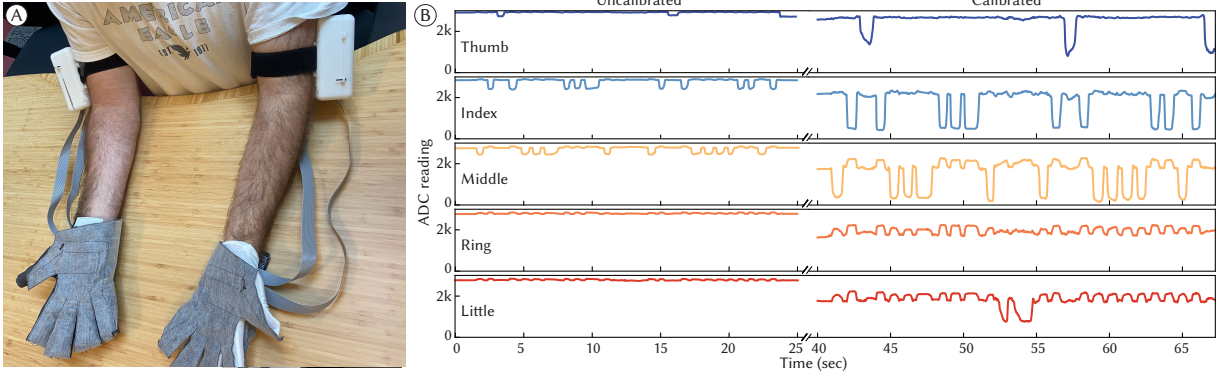


Figure 3.9: Wireless Musical Gloves: (A) Depiction of tactile sensing array, with readout circuit affixed to the arm via velcro straps (B) Average ADC readout in the Thumb, Index, Middle, Ring, and Little finger regions of one glove during "Mary Had a Little Lamb", before and after calibration, showing higher sensitivity after calibration.

playing a virtual piano, showcasing its potential for enhancing real-time, expressive musical performance. I recruited two users—one for the left-hand glove and one for the right-hand glove—to perform a piano duet both before and after calibration. The ADC readout in each finger region is shown in Fig. 3.9 for one of the users. After calibration, each user reported feeling like their glove was more responsive to their applied pressure, which can be evidenced by the greater range of ADC readout shown in Fig. 3.9B.

Gait Monitoring Shoe Soles Prior research has demonstrated interest in gait monitoring as a valuable tool for understanding overall health [69, 70]. I programmed a BLE-enabled pressure monitoring shoe sole, recorded pressure data during 5 minutes of walking and standing still, and used the toolkit's interactive visualization to replay the wirelessly recorded gait. As shown in Fig. 3.10, the device consumes considerably less power while the user is standing still than when they are stepping. The significant increase in packet transmission during the walking periods evidences that this is a direct result of the intermittent send algorithm ensuring efficient use of the onboard communication modules.

Other applications Because the sensitivity of readout can adaptively change during device operation, WiReSens Toolkit enables the development of tactile sensing devices that can be repurposed for different applications. I use this feature to develop a tactile sensing pillow that can serve both as a passive recording device (higher sensitivity) for posture monitoring and as an active input interface (lower sensitivity) for remote control of media playback (Fig. 3.11). I also developed a smart home IoT welcome mat (Fig. 3.12) for user identification [71]. The system includes a tactile sensing mat and a separate ESP32-controlled lamp. The mat captures tactile data, which is wirelessly transmitted using ESP-NOW to another microcontroller responsible for turning the lamp on when an authorized user is standing on it. In future iterations, WiReSens Toolkit could be used to enable seamless integration with other smart home devices, such as doorbells or security cameras.

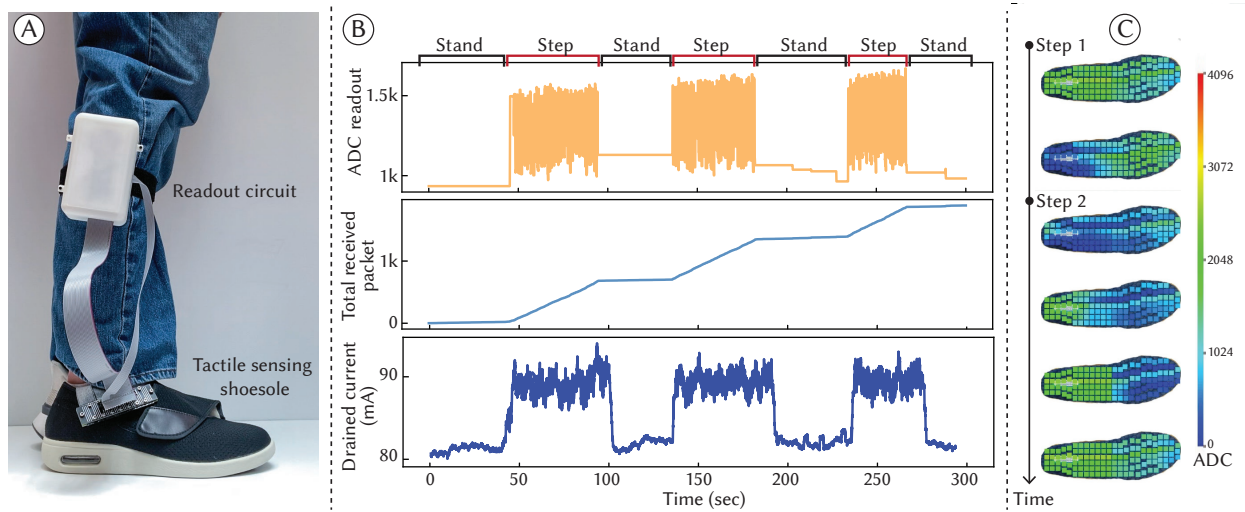


Figure 3.10: Gait Monitoring Shoe Sole: (A) Tactile sensing shoe sole form factor and readout circuit. (B) Power efficient operation using intermittent sending, with reduced current drain during periods of standing still and (C) Customized visualization for gait monitoring and step tracking.



Figure 3.11: Tactile Sensing Pillow: Used for (A) Posture monitoring, from left to right: leaning right, leaning left, leaning back, sitting up straight and (B) Remote Control, from left to right: Play, Pause, Volume Up, Volume Down.

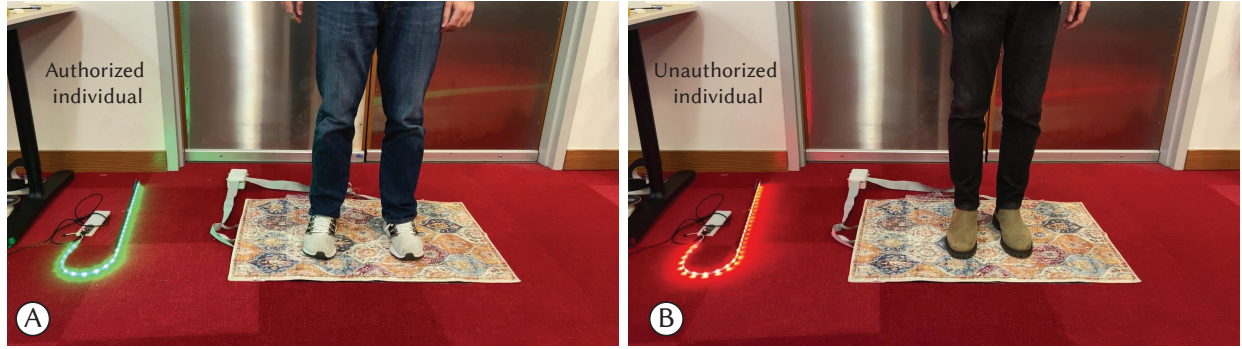


Figure 3.12: Smart Home Welcome Mat: IoT lamp processes tactile sensing data from a welcome mat to turn green when (A) an authorized individual enters the home and red when (B) an unauthorized individual enters the home.

3.6 Limitations

While the WiReSens Toolkit can be used in remote settings, portability may be limited by the fact that BLE and ESP-NOW communication are fundamentally lower-throughput, lower-range protocols [56] and backend support is restricted to desktop computers. This can be addressed by adding support for multiple receivers to balance the data load more effectively and implementing the backend within a mobile application. Additionally, we chose intermittent data transmission as a computationally efficient and intuitive means of power reduction that would not hinder sensing capability, but energy savings may be limited when compared to battery-free systems [72, 73]. Future work may explore ultra-low-power wake-on-motion sensing or energy harvesting techniques to extend operational lifetime without compromising sensing fidelity. Moreover, while the ESP32 microcontroller was chosen for accessibility, it imposes constraints on sample rate, power consumption, and form factor. Using ASIC or FPGA-based sensor readout could enhance the system’s ability to detect finer-grained or fast-changing pressures, such as vibrations, while reducing power consumption and size.

Chapter 4

Automatic Design and Manufacturing of Custom Tactile Sensing Gloves

Building on the software platform introduced in Chapter 3, which lowers the barrier to working with resistive tactile sensors through abstraction and visualization tools, this chapter focuses on democratizing the design and fabrication of the sensors themselves. I present a pipeline that automatically generates FPCB-based resistive sensing electrode arrays from a simple photograph of a hand taken on legal-size paper. Personalized to the unique contours of individual hands, these designs can be fabricated by commercial manufacturers—or "board houses"—at a cost of less than \$130 per glove. Assembly is straightforward, requiring less than 15 minutes and utilizing pressure-sensitive adhesive pre-applied to the components. To evaluate the approach, I characterize the sensors' response to varying pressure loads and conduct a preliminary user study with four personalized designs. The results demonstrate sensitivity and repeatability comparable to commercial solutions while highlighting the potential benefits of personalization, such as improved signal consistency over repeated use and reduced obstructiveness. I conclude by discussing challenges related to FPCB durability under repeated bending and present an evaluation of recommendations from expert engineers to improve robustness in future designs.

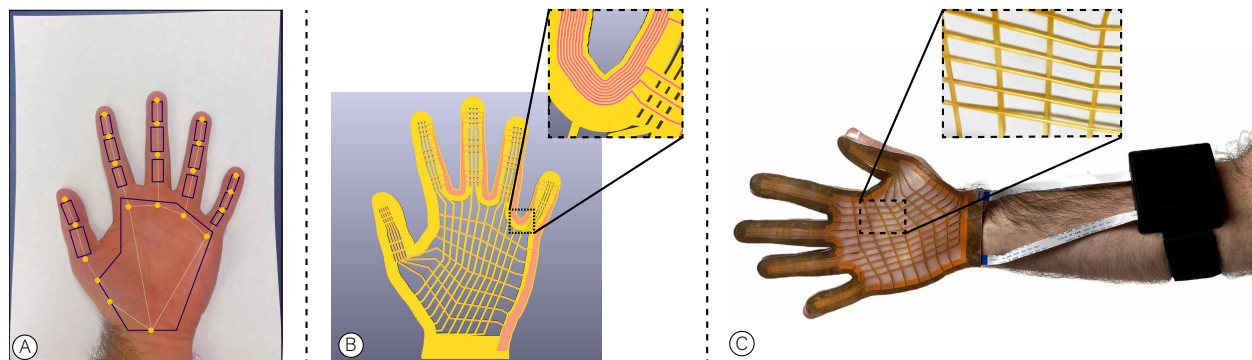


Figure 4.1: (A) A simple hand photo on legal-size paper is used to automatically generate manufacturing files (B) for personalized flexible printed circuit board tactile sensing gloves, ready to be ordered from a board house (C)



Figure 4.2: Automated FPCB design and sensor assembly. (A) Sensing regions are detected and orthogonally arranged electrodes are generated within them. (B) The binary mask of the hand is used to extract its contour, which serves to connect electrodes across neighboring regions. (C) Supporting layers of the PCB are generated and used to create Gerber files which can be sent directly to PCB manufacturers. (D) Sensor assembly using materials totaling under \$130 dollars by sandwiching 5 layers together with pressure-sensitive adhesive.

4.1 FPCB Design Algorithm

This section presents the algorithm that automates the design of personalized FPCB-based resistive tactile sensors, optimized for seamless integration with sensor readout electronics and fabrication by standard PCB manufacturers. The algorithm generates all necessary design components, including electrode traces, a coverlay mask, and an adhesive region. These sensors feature orthogonally arranged electrodes on a pair of top and bottom FPCBs, enabling straightforward assembly through the sandwiching of the two FPCBs, a middle piezoresistive layer, and silicone encapsulation layers on both sides.

The algorithm takes as input an image of the user hand laid on a legal size paper and outputs the FPCB sensor design components that can be readily fabricated by manufacturers (Fig. 4.2). I present the algorithm as three steps: automatic hand landmark detection for sensing region electrode placements, binary hand mask and connecting trace generation, and supporting layer generation.

Hand Landmark and Electrode Placement The objective is to arrange orthogonally positioned electrodes within regions of interest on the hand, specifically each digital pad and the palm. Starting with an image of a hand placed on a legal-size sheet of paper (8.5" x 11"), I first calculate the pixel-to-inch conversion ratio to scale the design file. I then use the open-source MediaPipe library [74] to detect 21 hand landmarks, which form the 2D hand skeleton, and automatically generate an approximate layout for the 15 regions of interest

(three for each finger, two for the thumb, and one for the palm). To define the finger regions, I compute the vector direction along each skeleton segment and generate a rectangular sensing region along this direction, with the width set to half the segment's length. The length of the rectangles above the palm is determined using standard ratios from the metacarpophalangeal (MCP) joints to the proximal interphalangeal (PIP) joints for each finger [75]. The palm region is represented as a 7-point polygon, defined by projecting the hand landmarks in the palm area along various parts of the skeleton. Within each sensing region, the algorithm creates orthogonally positioned horizontal and vertical traces by evenly sampling along the edges, generating unique sensing taxels at the intersections of these traces. For the initial design, I pre-define the resolution for each region (3x2 for each finger pad, 4x3 for the top of the thumb, 4x2 for the middle of the thumb, and 7x11 for the palm), totaling 167 unique pressure-sensing nodes.

Binary Mask and Connecting Trace Generation The generated electrodes must connect to a readout circuit, with all horizontal copper traces routed to a single connector and all vertical copper traces similarly routed. The algorithm begins by connecting neighboring traces that can be directly linked without crossing the hand's contour. This includes connecting vertical traces along the finger regions to one another and to the palm, as well as connecting the four horizontal traces in the thumb regions to each other and to the bottom four horizontal traces of the palm. For the remaining connections, the algorithm routes the traces along the hand's contour. To do this, it first generates a binary mask to segment the hand from the paper background using HSV thresholding, then automatically generate dense line segments representing the hand's contour from the mask. The trace thickness is set to 0.1 mm and slight inward extrusions of 0.2 mm are applied to create 16 connecting traces for both the horizontal and vertical electrodes, ensuring no trace clearance requirements are violated. By connecting the bottom right-most electrodes to the innermost connecting trace and the top electrodes to the outermost trace, any unconnected electrodes in the sensing regions are linked to the nearest points on the corresponding contour (Fig. 4.2B).

Supporting Layers Generation The FPCB requires additional layers for functionality: the coverlay mask, adhesive, and edge cut layers (Fig. 4.2C). Coverlay is a polyimide film normally laminated over copper traces to provide flexibility and electrical insulation. However, resistive sensing requires direct electrode contact with the piezoresistive layer, so a coverlay mask is defined as the convex hull of the sensing regions on the fingers with an inward extrusion of the hand contour. Adhesive layers, securing the piezoresistive layer, occupy the area between the hand's outer contour and the coverlay mask. The edge cut layer, marking where the board will be laser-cut, includes both the hand's outer contour and inner cuts to enhance flexibility and dexterity [76]. These inner cuts are created by outwardly extruding copper traces by 0.5 mm (to stay within most manufacturer's edge clearance requirements [77]) and subtracting the union of horizontal and vertical trace polygons from the coverlay mask.

The horizontal and vertical traces along with their supporting layers are exported into two different SVG files representing the front FPCB and back FPCB of the sensor, and converted into KiCad PCB footprints [78] using the open-source "gerbolyze" tool [79]. From KiCad,

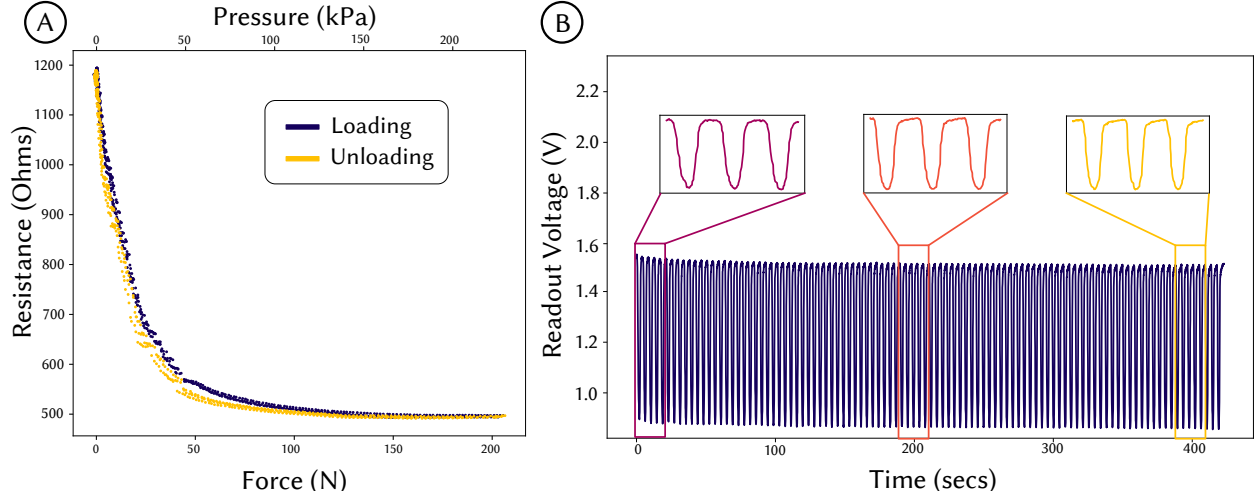


Figure 4.3: Sensor Characterizations: (A) Resistance variation during three loading and unloading cycles. (B) Consistent performance is captured by the readout circuit under a load of 12 N/cm^2 for 100 cycles.

the Gerber files, component placement, and bill-of-materials for each PCB can be exported and sent to a board house for manufacturing.

4.2 Sensor Assembly

The hand contour from the generated SVG file is used to laser cut two mirrored layers of silicone rubber ($1/32''$ thickness, 10A durometer) with adhesive backing. The perimeter and internal cutouts are then used to laser cut a single layer of piezoresistive Velostat®. I created an offset 3D-printed model of the hand outline from the SVG file, which served as a guide for accurately aligning and assembling the five layers that make up each glove. Assembly requires only the bonding of these layers using pressure-sensitive adhesive already deposited on the FPCB and silicone layers by manufacturers. For user evaluation, I also used each hand's contour to sew a classic fabric glove. This process involved laser cutting three layers of fabric with seam allowances based on the hand's outline: two layers surrounding the sensor assembly and one forming the back of the glove. The three layers are sewn together, and the sensor is then inserted into place. The horizontal and vertical electrodes of the sensor connect to a readout circuit via 16 pin 0.5mm pitch flat flexible cables (FFCs). I 3d-printed an enclosure for the readout circuit for ease-of-use during evaluations (Fig. 4.2D). Table A.1 shows a detailed cost breakdown of the necessary components for manufacturing, totaling under \$130 USD per glove.

4.3 Sensor Characterization

I conducted two experiments to characterize the response of the FPCB sensor. First, a mechanical tester (Shimadzu AGX-V2) applied adjustable normal forces over a contact area

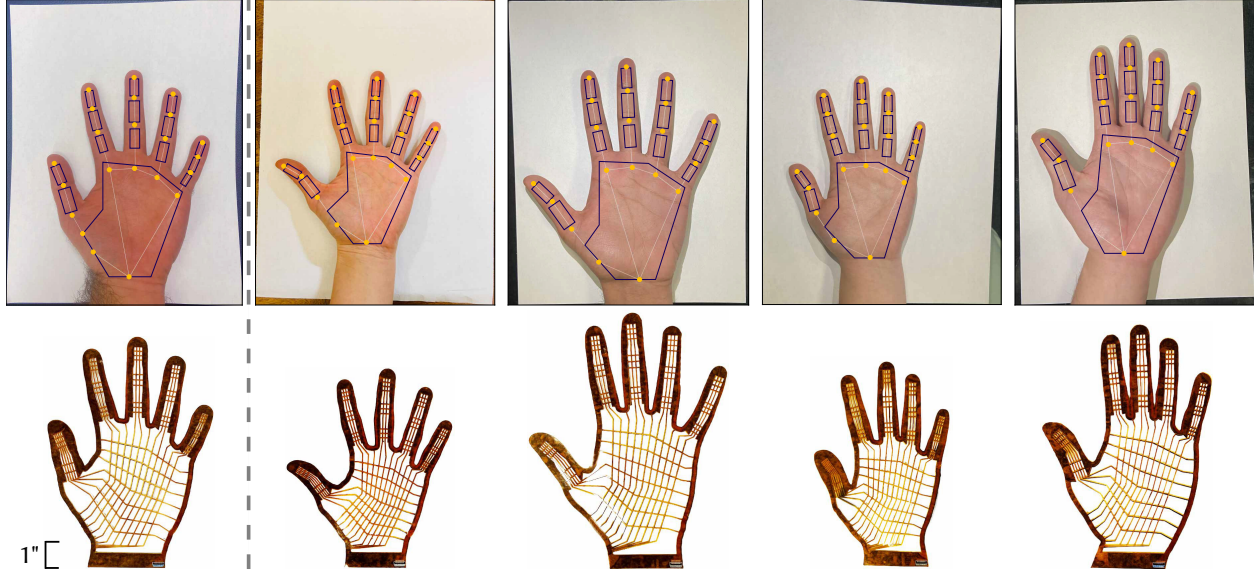


Figure 4.4: Automatically designed and manufactured FPCB tactile sensors for five individuals. Left: The sensor with median perimeter is used as the basis for a generic glove.

of 9 cm^2 . Using a digital multimeter (DMM), changes in resistance at a single node in the palm region were recorded across three loading and unloading cycles (Fig. 4.3A). The results demonstrated the expected inverse relationship between applied pressure and resistance, with two distinct linear regions and sensitivity up to 175 kPa , matching the performance of commercial solutions [44]. In the second experiment, a load of 12 N/cm^2 was applied repeatedly for 100 cycles over the same contact area. Voltage readings were acquired using the WiReSens Toolkit introduced in Chapter 3. The measurements were taken using a readout circuit based on a standard zero-potential architecture [33]. The sensor exhibited stable performance across all cycles, demonstrating repeatability under extended use (Fig. 4.3B).

4.4 User Evaluation

A preliminary user study was conducted ($N=4$) to assess the reliability and comfort of personalized FPCB tactile sensing gloves as compared to a generic, non-personalized glove. Using the presented pipeline, design components were generated for five right-handed individuals, and the hand with median perimeter was selected as the basis for the generic glove. The FPCB layers were manufactured by JLCPCB within nine days of order approval. Following the process in Section 4.2, one generic glove and one personalized glove was assembled per participant, resulting in eight gloves total (Fig. 4.4). Manufacturing costs per sensor (two FPCBs) ranged from $\$22.78$ to $\$27.55$ (Mean = $\$24.93$, S.D = $\$1.62$), with sensor assembly averaging 14 minutes.

Participants performed two experiments using their generic glove ("Glove A") and personalized glove ("Glove B") on their dominant hand. Each experiment was completed with Glove A first, followed by Glove B. In the first experiment, participants wore the glove, pressed their hand onto a table, and removed the glove, repeating this sequence three times

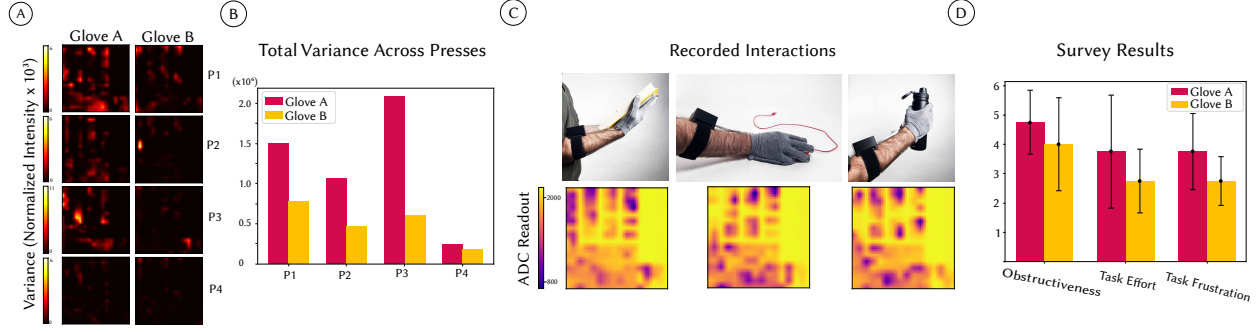


Figure 4.5: User study results from generic (Glove A) and personalized (Glove B) gloves. (A-B) Personalized gloves demonstrate reduced variance across repeated full-hand presses. (C) Over 42,00 tactile frames are collected while users perform three tasks—opening a book, using a mouse, and pouring water from a bottle. (D) Users rate personalized gloves as less obstructive and report that tasks require less effort and cause less frustration compared to using generic gloves, on average.

while pressure signals were recorded. In the second experiment, participants completed a series of tasks across different stages: opening/closing a book, sliding a mouse (right/left), left-clicking, picking up a water bottle, pouring, straightening the bottle, and setting it down. Each task was repeated 15 times, with video recorded for synchronized task-stage annotation. After the experiments, participants completed a survey assessing obstructiveness, task effort, and frustration for both gloves. The study was approved by the MIT COUHES under the protocol number 2411001482.

4.4.1 Evaluation and Discussion

Figure 4.5 presents the results of the two experiments. In the hand press experiment, pressure frames (frame count $\times 16 \times 16$) were loaded and the frame with the highest average pressure was identified for each press. The average pressure reading over a 50-frame window (1.3 seconds) centered at this press was calculated, normalized to its minimum and maximum values, converted to pixel intensity (0–255), and interpolated from a 16×16 resolution to 64×64 for enhanced visualization. Figure 4.5A shows the variance in pixel intensity across all presses for each participant (P1–P4) using both the generic and personalized gloves. Across all participants, the personalized gloves exhibited lower overall pixel variance, suggesting that personalized designs reduce hand placement variability and improve consistency across repeated presses (Fig. 4.5B).

I extracted variable-length pressure data sequences for each task stage using start and end times from video annotations, yielding a dataset with 1,076 tactile sequences, totaling over 42,000 frames of pressure data across nine task classes, four participants, and two glove types (Fig. 4.5C). Excerpts from the dataset demonstrate expected pressure correlations for associated tasks, such as high activation of the index finger region while clicking the mouse and high activation of the palm while holding the water bottle. While analyzing recorded data I observed some loss of sensitivity in the finger regions, averaging 25 taxels per glove due to fractures in the copper traces. I discuss the nature of these fractures further in Section 4.5.

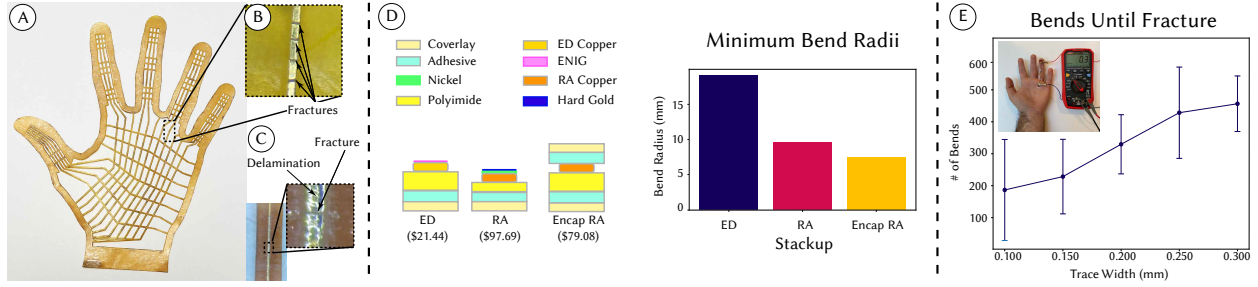


Figure 4.6: Mechanical investigation. (A) Failure location on the glove. (B-C) Brittle failure was observed in the electrodeposited (ED) copper design while ductile failure and delamination was observed with the rolled annealed (RA) copper design. (D) Comparison of three designs showing the estimated minimum bending radius before failure. In units of μm , **ED stackup**: coverlay-12.5, adhesive-15, polyimide-25, base ED copper-11.6, and an ENIG overlayer-25 nm, from JLCPCB. **RA stackup**: coverlay-12.5, adhesive-12.5, polyimide-12.5, base RA copper-12, a nickel overlay-3 and hard gold coating-76 nm, from PCBWay. **Encapsulated RA stackup**: coverlay-12, adhesive-15, polyimide-25, base RA copper-12, adhesive-15, and coverlay-12, from PCBWay. (E) Manual bending tests show increasing trace width improves RA stackup durability, averaging 330 bends to a tight fist before failure.

In the survey, participants evaluated the gloves on a 7-point scale for obstructiveness (1 = Not noticeable, 7 = Very obstructive), task effort (1 = Very low, 7 = Very high), and task frustration (1 = Very low, 7 = Very high). The personalized gloves were rated as less obstructive (Mean = 4.0, SD = 1.58), requiring less effort (Mean = 2.75, SD = 1.09), and causing less frustration (Mean = 2.75, SD = 0.83) (Fig. 4.5D). While the small participant pool limits generalizability, the results provide interesting insights for future work. For example, participants whose hand sizes most deviated from the generic design showed a stronger preference for personalized gloves and future studies might consider grouping participants by hand size (e.g., small, medium, large), instead comparing personalized designs to generic gloves in multiple sizes. Open-ended feedback also revealed that some participants (P2 and P3) preferred the generic glove due to discomfort from sensor slippage in the personalized design, highlighting the importance of attachment mechanisms for improving comfort and usability. Future research could focus on optimizing these mechanisms.

4.5 Limitations

Mechanical failure is the greatest limitation of this device, particularly when the glove must bend sharply for difficult or skilled tasks. For this initial study, all FPCBs were manufactured using electrodeposited (ED) copper (JLCPCB) with a coating of electroless nickel and gold (enig), as the lowest-cost option. ED copper is brittle, and we found fractures in the upper palm region after making one or two fists to stress-test the gloves (Fig. 4.6A, B). This strongly limits their usability as some gestures cannot be made while wearing them.

Switching from ED to rolled-annealed (RA) copper with a hard gold coating doubled cost but showed enhanced durability and caused ductile failure (Fig. 4.6C). Encapsulation of the copper between two coverlayers, as recommended by expert engineers at Epec Engineered

Technologies [80], is predicted to further improve the lifespan of the gloves. A mechanical analysis of bending failure shows that the ED copper design is expected to begin to fail when bent more than a bending radius of 19 mm, about the radius of a ping pong ball, for RA copper 9.5 mm, about the radius of a penny, and for encapsulated RA copper 7.5 mm, about the radius of an AA battery (Fig. 4.6D). Calculations of bending stress used the standard formula $\sigma = My/I$ for stress σ , bending moment M , maximum height of the copper from the neutral axis y , and second moment of area of the cross-section I , with tabulated material properties [81, 82]. Finally, increasing trace width was found to more than double the number of cycles the traces can endure for the RA stackup design when directly taped to the hand (Fig. 4.6E). To further evaluate durability, we conducted a cyclic bending test on a glove fabricated with the RA stackup, where FPCBs were embedded between two silicone layers as proposed in this work. After 10,000 cycles at a 2.5 mm bending radius, no fractures were observed, suggesting that silicone encapsulation may prevent creasing and subsequent trace failure. These design parameters—conductive material, stackup geometry, and trace width—offer tunable trade-offs between cost and durability for future designs.

Finally, while flexible PCBs offer a convenient manufacturing medium, they can be stiffer than purely textile-based approaches. The total thickness of the FPCB glove is approximately 4 mm — about eight times that of standard nitrile gloves, which may impact wearability. Additionally, like other piezoresistive sensors, we observed motion artifacts caused by bending in the absence of normal force. These artifacts may be mitigated using adaptive strain interference suppression methods, such as those proposed by Jiang, Xu, Li, et al. [18].

Chapter 5

Future Work

This chapter outlines potential directions for extending the work presented in this thesis, including applications, technical improvements, and broader research trajectories made possible by the WiReSens Toolkit.

5.1 Toolkit Adoption

As with any integrated software-hardware platform, continued improvements and updates are both expected and necessary. For example, future iterations may benefit from more compact form factors or modular designs tailored to specific applications. While this thesis centers on resistive tactile sensors, the WiReSens Toolkit could be extended to support other sensing modalities that rely on changes in conductivity. These include thermistors for temperature, moisture sensors, chemiresistors for gas detection, and photoresistors for light intensity.

This versatility positions the toolkit as a general-purpose platform for large-scale, multimodal physical sensing. Beyond touch, it can support applications in environmental monitoring and human-worn sensing systems. I envision this platform advancing tactile sensing as a privacy-conscious and efficient alternative to vision-based systems. Unlike images or video, resistive tactile data is typically lower in resolution and not easily interpretable by humans, making it inherently less invasive.

5.2 Automated Sensor Design for Arbitrary 3D Surfaces

Although our automated pipeline generalizes well to the geometry of human hands, it currently cannot generate sensor designs for arbitrary 3D surfaces—a key step toward ubiquitous tactile sensing. Prior work by Palma et al. [83] has demonstrated general-purpose solutions for mapping mutual capacitance sensors onto 3D surfaces using 3D printing with conductive filaments. TacDes [84] makes early progress in this direction for resistive sensor types.

One promising future direction involves leveraging mobile phone LiDAR sensors to capture 3D surface geometry. This captured mesh could be algorithmically unfolded, allowing users to define sensing regions and trace connections. Solving the resulting autorouting problem—particularly for convex surfaces—may build on the contour-based routing strategy

introduced in this thesis. Extending this approach to more complex geometries would significantly broaden the applicability of the tools presented in this thesis.

5.3 Software-Hardware Co-Optimization

Future work can explore co-optimization strategies where hardware configuration and software parameters adapt dynamically to specific applications. For example, in a wearable health-monitoring scenario, the system could automatically recalibrate sensors in response to changes in the wearer’s physiology, such as swelling, posture, or muscle activation, ensuring sustained sensing accuracy over time.

Additionally, sensor form factor data could be used to identify regions especially susceptible to noise due to bending or motion. The system could then recommend alternative electrode layouts or routing paths to mitigate such issues, ultimately improving robustness and performance.

5.4 Multimodal Tactile Sensing

Human tactile perception is inherently multimodal, involving not just pressure, but also shear, temperature, and vibration. Expanding the WiReSens Toolkit to support multimodal sensing would offer a more complete approximation of human touch perception, with potential implications for both robotics and human-computer interaction.

This expansion could involve multiplexing the resistive electrode array with alternate signal processing circuits or adapting firmware to support multiple sensing modes. Additionally, experimenting with different materials or metamaterial-inspired sensor stack-ups [85] could enable the detection of new tactile dimensions. Such enhancements would deepen our understanding of tactile perception and support richer forms of haptic feedback and robotic manipulation.

Chapter 6

Conclusion

This thesis introduced the WiReSens Toolkit, a hardware and software platform designed to facilitate the creation of portable, adaptive, and long-lasting resistive matrix-based tactile sensing systems. The toolkit supports variably sized sensor arrays, wireless communication via Wi-Fi, BLE, or ESP-NOW, adaptive sensitivity through auto-calibration, and power efficiency via intermittent computing. It also simplifies real-time data logging and visualization across multiple devices. Through technical evaluations, I demonstrated the toolkit’s ability to maintain consistent sensor performance across pressure intensities, support robust multi-sender wireless communication, and operate efficiently under power constraints. Application prototypes and a comprehensive user study further validated its usability and utility for developing interactive systems grounded in resistive tactile sensing.

Complementing the toolkit, this thesis contributed a rapid design and fabrication pipeline for personalized FPCB-based tactile sensing gloves, leveraging accessible digital manufacturing workflows. The gloves deliver pressure sensitivity and signal consistency on par with established methods, while user feedback highlights the benefits of personalized form factors for comfort and long-term wearability. Although challenges remain with mechanical durability, stress testing indicates these can be mitigated through design optimizations, positioning this approach as a viable, scalable alternative to traditional glove fabrication techniques.

Together, these contributions lay groundwork for the future of ubiquitous tactile sensing. By lowering the technical and logistical barriers to developing high-quality tactile systems, this work enables broader participation in tactile interaction research across domains such as HCI, robotics, and digital health. As wireless sensor networks, digital manufacturing, and machine learning continue to evolve, tools like WiReSens can bridge sensors, systems, and applications to support continuous, real-world sensing of touch at scale. In doing so, this thesis contributes not only practical methods, but also a vision for more accessible, adaptive, and embedded tactile sensing in everyday life.

Appendix A

Supplementary Information

Item	Cost (USD)
FPCBs	24.93
Velostat	2.50
Silicone rubber	29.20
Fabric	4.62
Readout Circuit	64.66
Flex cables	0.79
Total	126.70

Table A.1: Detailed cost breakdown for one glove

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