

Designing Closed-loop Sensing and Feedback Systems for Embodied Human Interaction

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A thesis
submitted in partial fulfillment of the
requirements for the degree of

Master of Science

University of Washington

2026

Committee:

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Program Authorized to Offer Degree:

Electrical and Computer Engineering

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Abstract

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Wearable and interactive systems create new ways to support embodied human interaction in real-world activities such as learning, physical training, and rehabilitation. In these activities, people rely on their bodies, tools, and surroundings to understand what is happening and decide what to do next. However, many existing systems still focus mainly on accurate sensing or computation, without fully supporting this ongoing process of sensing, acting, and adjusting. This thesis asks how interactive systems can support effective embodied human interaction in real-world use.

To answer this question, this thesis studies the design of closed-loop sensing and feedback systems through three human-centered projects. The first project, *BrailleRhythm*, supports early Braille learning by augmenting printed Braille cards with a flexible piezoresistive sensor, achieving over 92% Braille recognition accuracy. The system senses finger interactions on Braille symbols and provides real-time audio feedback, helping learners connect tactile symbols with their corresponding sounds. The second project is a closed-loop CPR self-training glove that helps users practice CPR outside of traditional training settings. The glove combines distributed tactile sensing and vibrotactile feedback to evaluate compression rate, force, and hand pose in real time, while reducing the need for external audio-visual interfaces. The third project, *MultiSensKnit*, is a multimodal knitted textile sleeve for rehabilitation monitoring. It integrates electromyography (EMG), electrical impedance sensing (EIS), and capacitive sensing into a wearable sleeve to capture muscle activity, tissue changes, and joint movement, and uses these signals to support real-time visualization and behavior understanding.

Across these projects, this thesis identifies design insights along three dimensions: form factor, sensing, and feedback. Form factor should preserve natural interaction through unobtrusive design, while balancing durability, portability, wearability, and signal quality. Sensing should capture task-relevant signals, while minimizing hardware complexity and modality interference. Feedback should match the task context, while remaining low-latency, low-burden, and clear across multimodal combinations. Together, these projects show that effective embodied interaction is not achieved by simply adding sensors or feedback. It requires designing the physical form, sensing method, and feedback strategy as one closed loop within the activity itself.

ACKNOWLEDGMENTS

I would like to express my deepest gratitude to my advisor, Prof. Yiyue Luo, for her continuous guidance, support, and thoughtful feedback throughout this thesis. Her mentorship has not only shaped this work, but also helped me grow as a researcher. I am also sincerely grateful to my committee member, Prof. Sam Burden, for reviewing this thesis and providing valuable feedback.

I would like to thank my collaborators, Qifeng Yang, Hongyu Mao, Sen Zhang, Jaeyoung Moon, Seokhyun Hwang, and Helen Lai. I am truly grateful for their generous help, insightful discussions, and contributions to the projects presented in this thesis. Without their support, this work would not have been possible.

I am also grateful to all members of the Wearable Intelligence Lab. It has been my great honor to join this big family and spend two wonderful years with such kind, talented, and supportive labmates.

Finally, I would like to thank my beloved family, my partner, Peng Zhang, and my friends, Jiaqi Dong and Yingchao Jian, for their love, encouragement, and support throughout this journey. Their presence has meant so much to me and has helped me move forward through every challenge.

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Chapter 1

INTRODUCTION

Human–computer interaction (HCI) has long studied how people interact with computational systems. Much of early and mainstream HCI was shaped by desktop computing, where interaction often happened through screens, keyboards, and mice [51, 78]. Later, ubiquitous computing [110] and tangible computing [51] expanded this view by moving computation into everyday environments and connecting digital information with physical objects and surfaces.

However, even as interaction moves into physical environments, many systems still treat the body mainly as a source of input or control. The body may trigger commands, gestures, or events, but the rich information produced through bodily action is often not fully used. In real-world activities, people rely on touch, movement, and resistance to understand what is happening and decide what to do next. Interaction in these settings is not a single input event. It is an ongoing process of sensing, acting, and adjusting.

This view is closely related to **embodied interaction**. Paul Dourish describes embodied interaction as “the creation, manipulation, and sharing of meaning through engaged interaction with artifacts” [25]. In this thesis, I use embodied interaction to refer to how people use their bodies, tools, and surroundings to understand a task and adapt their actions during real-world activity. This perspective is important for activities such as tactile learning, physical training, and rehabilitation, where people learn and improve through bodily action and feedback.

This thesis asks: **How can interactive systems support effective embodied human interaction in real-world use?** To answer this question, this thesis studies **closed-loop sensing and feedback systems** as a design approach.

Recent advances in sensing, materials, wearable computing, and feedback technologies make this approach increasingly possible. Sensors are becoming smaller, softer, and more diverse [55, 68, 76]. They can capture tactile interaction, muscle activity, body movement, and posture. At the same time, feedback technologies such as audio, visual, and haptic feedback can provide real-time

responses to guide user action [14, 49, 53]. However, effective embodied interaction is not achieved simply by adding more sensors or more feedback channels. The main challenge is designing how the physical form, sensing method, and feedback strategy work together within the activity itself.

This thesis investigates this challenge through three systems in different embodied interaction contexts. First, *BrailleRhythm* supports early Braille learning by sensing finger interaction on physical Braille cards and providing real-time audio feedback. Second, a CPR self-training glove supports physical training by sensing compression rate, force, and hand pose, then providing vibrotactile feedback to guide user action. Third, *MultiSensKnit* supports rehabilitation monitoring through a knitted textile sleeve that integrates electromyography (EMG), electrical impedance sensing (EIS), and capacitive sensing to capture muscle activity, inertial tissue impedance changes, and joint movement during exercise.

Overall, this thesis contributes three interactive system designs, implementation strategies for closed-loop sensing and feedback, empirical evaluations in application contexts, and cross-case design insights. These insights show that effective embodied interaction depends not only on sensing accuracy or computational performance, but also on how the system fits the body, captures meaningful signals, and provides feedback that supports ongoing action.

1.1 Thesis Structure

This thesis is organized around three systems that examine how interactive systems can support effective embodied human interaction in real-world use through the co-design of form factor, sensing, and feedback.

- **Chapter 1** introduces the motivation, research framing, and thesis structure.
- **Chapter 2** presents *BrailleRhythm: Enhancing Braille Character Recognition and Learning via Real-time Tactile Sensing and Audio Feedback*, an early Braille learning enhancement interactive tool that combines tactile sensing, real-time recognition, and immediate audio feedback.
- **Chapter 3** presents *A Closed-Loop CPR Training Glove with Integrated Tactile Sensing and Haptic Feedback*, a wearable CPR self-training glove that combines tactile sensing, real-time

interpretation of CPR performance, and vibrotactile feedback.

- **Chapter 4** presents *MultiSensKnit: Multimodal Machine-Knitted Sensing Sleeve for Upper Limb Rehabilitation*, a multimodal textile sleeve integrating EMG, EIS, and capacitive sensing with a visual interface for rehabilitation progress tracking.
- **Chapter 5** synthesizes findings across the three systems, discusses limitations, and outlines future research directions.

The following subsections briefly introduce Chapters 2–5.

1.1.1 *BrailleRhythm: Enhancing Braille Character Recognition and Learning via Real-time Tactile Sensing and Audio Feedback*

Braille is an important pathway to literacy for blind and low-vision (BLV) individuals, but Braille learning can be challenging without timely educational support at the early stage. Many existing tools support tactile exploration but provide limited real-time guidance or rely on sensing technology that is costly and less customizable. To address this gap, Chapter 2 presents an early Braille learning enhancement interactive tool that bonds a flexible piezoresistive sensor onto customized Braille cards and provides immediate auditory feedback through text-to-speech Web API on a mobile phone.

This chapter establishes a closed-loop interaction system for Braille learning. It emphasizes interaction compatibility in the form factor by preserving tactile exploration, uses tactile sensing for real-time Braille interaction recognition, and employs real-time audio feedback to reinforce learning during use. Chapter 2 describes the system design, implementation, and evaluation of *BrailleRhythm*, and discusses implications for unobtrusive learning support.

1.1.2 *A Closed-Loop CPR Training Glove with Integrated Tactile Sensing and Haptic Feedback*

High-quality cardiopulmonary resuscitation (CPR) requires correct compression rate, compression force, and hand posture, but many existing training systems depend on expensive manikins and

audio-visual guidance that may not support low-cost, self-directed practice. To enable more accessible training, Chapter 3 presents a wearable glove that combines a tactile sensing with vibrotactile feedback for CPR self-training.

This chapter examines closed-loop sensing and feedback in a wearable form factor and a dynamic physical task. It introduces real-time interpretation of CPR-related performance metrics from tactile sensing data and applies vibrotactile feedback as corrective task-specific guidance. Chapter 3 details the hardware design, control pipeline, user studies for haptic feedback design, technical evaluation, and user evaluation of the CPR self-training glove.

1.1.3 MultiSensKnit: Multimodal Machine-Knitted Sensing Sleeve for Upper Limb Rehabilitation

Rehabilitation monitoring and assessment often rely on separate sensing setups that require multiple devices, repeated calibration, and clinician supervision, which can limit use in home and everyday settings. To reduce setup burden while supporting richer physiological and biomechanical measurement, Chapter 4 presents a multimodal machine-knitted sleeve for rehabilitation monitoring in a unified sleeve structure.

The proposed system, *MultiSensKnit*, integrates EMG, EIS, and capacitive sensing in a textile wearable sleeve and provides a visual interface through a mobile application to support rehabilitation monitoring and progress tracking. Chapter 4 describes the system design, user interface, application scenarios, technical evaluation, and implementation details, and discusses implications for everyday rehabilitation monitoring.

1.1.4 Discussion, Conclusion and Future Research Directions

Chapter 5 synthesizes findings across the three systems and revisits the thesis question of how interactive systems can support effective embodied human interaction in real-world use. It summarizes cross-case lessons on the co-design of form factor, sensing, and feedback, discusses current limitations, and outlines future research directions for more robust, personalized, and deployable interactive systems.

These future directions include improving long-term wearability and comfort, strengthening real-time multimodal interpretation under real-world variability, and developing adaptive feedback

strategies that better match diverse users, tasks, and contexts. In general, Chapter 5 argues for a systems-oriented approach to embodied interaction design in which form factor, sensing, and feedback are jointly developed to support practical and effective real-world use.

Chapter 2

BRAILLERHYTHM: ENHANCING BRAILLE CHARACTER RECOGNITION AND LEARNING VIA REAL-TIME TACTILE SENSING AND AUDIO FEEDBACK

2.1 Background and Motivation

In 2020, an estimated 43.3 million people worldwide were blind and 295 million experienced moderate to severe vision impairment, with the number projected to reach 61 million by 2050 [38]. For individuals without usable vision, conventional printed text remains inaccessible, and written literacy can be difficult to achieve without appropriate assistive methods [26, 28]. Braille is a tactile reading and writing system that provides a pathway to literacy, enabling education, independence, and social participation for blind and low-vision (BLV) individuals [28, 113].

Despite its importance, Braille literacy remains low. Only around 10–25% BLV individuals in the United States are able to read Braille [1]. Learning Braille is challenging because it requires establishing reliable associations between tactile dot patterns and language. Sighted children naturally develop strong links between spoken language and visual symbols over many years, but learners with visual impairments may lack early exposure to an intuitive mapping between touch and written language [26]. As a result, early Braille learning often depends on repeated sensorimotor practice to build tactile discrimination, symbol recognition, and reading fluency.

Existing Braille learning tools commonly provide passive tactile practice, such as static dot boards or physical Braille cards, which preserve tactile exploration but provide limited instructional guidance [98]. Meanwhile, many recognition-based systems focus on converting Braille to digital text, rather than supporting the learning process itself. Image-based Optical Braille Recognition (OBR) systems can report high accuracy on benchmark datasets [4, 54], but camera-based capture and processing often decouple recognition from tactile exploration and typically provide limited real-time corrective feedback for learners. Sensor-based Tactile Braille Recognition (TBR) approaches can preserve physical interaction, but accuracy may degrade under natural sliding behaviors and many designs require complex hardware that is difficult to scale or customize across classrooms and

languages [37, 121]. These limitations highlight the need for learning-oriented systems that preserve tactile engagement while providing immediate guidance.

A multisensory approach combining tactile and auditory feedback can help reinforce the association between language and symbols by providing real-time confirmation and correction during exploration [26]. However, few multisensory systems are both affordable and customizable enough for broad deployment [6, 19]. To support early Braille learning in practical settings, an ideal system should preserve natural touch interaction, operate in real time without external interfaces, and enable low-cost customization of learning materials.

Motivated by these needs, this chapter explores a tactile-sensing Braille learning interactive tool that bonds a flexible piezoresistive sensor sheet onto customized Braille cards. The system detects pressing and sliding interactions while preserving the tactile experience of Braille reading, and provides immediate auditory feedback via on-device text-to-speech Web API to reinforce sensorimotor learning. Through a low-cost and modular design, the platform aims to support scalable deployment and simple extension to new exercises and languages.

2.2 Related Works

Automated Braille learning requires accurate and real-time Braille recognition systems, which is critical for BLV individuals to restoring access to written language. Such systems can be broadly categorized into two approaches based on the type of data they process: Optical Braille Recognition (OBR), which applies image processing techniques to Braille text images, and Tactile Braille Recognition (TBR), which detects physical inputs through sensing arrays. Both approaches incorporate machine learning or deep learning methods to interpret the acquired data.

2.2.1 Optical Braille Recognition

Convolutional neural networks (CNN) is of high popularity in character recognition and thus, it is also considered as a promising tool for Braille recognition [4, 81].

Kausar et al. [54] applied a two-stage automatic Braille character recognition algorithm on the English Braille and Chinese double-sided Braille image (DSBI) datasets with 95.2% and 98.3% accuracy, respectively. They improved the computational cost and recognition performance by replacing partial modules in original CNN with an inverted residual block (IRB) module. AlSalman

et al. [4] proposed an OBR system to convert Braille image to multilingual texts using a deep CNN (DCNN) model and multilingual character lookup table with 99.29% and 98.99% accuracy for two datasets. Byeong et al. [81] developed a model with Faster region-based convolutional neural network (R-CNN)–feature pyramid network (FPN)–ResNet-50 architecture pipeline to recognize Braille based on RGB images.

Although these OBR methods achieve high accuracy and are great for translation via text-to-speech, and digitizing and preserving Braille texts, their applicability to improving Braille literacy and accessibility is limited. They primarily function as conversion tools, losing out on the tactile experience of Braille reading that needs to be learned.

2.2.2 Tactile Braille Recognition

Matsuda et al. [72] designed a one-handed finger Braille recognition system for teaching purposes using piezoelectric accelerometers mounted on the rings to recognize the dotted fingers and dotted positions with a microphone to output the translated text. Rings must be worn on five fingers, but typically users may not use all fingers to recognize Braille. Ahmed et al. [2] utilized magnetic nanocomposite artificial cilia on magnetic micro sensors to measure the voltage drop on different dot positions of the Braille with the individual character recognition accuracy of 91-97%. In [81], Byeong et al. fabricated a three-layer sensor which has 5×5 conductive electrodes on the top, a 5×5 flexible capacitive pressure sensor array with $25 \text{ } 1.5 \text{ mm} \times 1.5 \text{ mm}$ sensors on the bottom, and a pressure-sensitive micro dome-structured array layer in the middle. Its performance has been visualized by the similarity between generated heat map images and the input Braille characters. However, both of them haven't tested their performance on data collected through sliding.

Zhiqiang et al. [37] proposed a piezoresistive and piezoelectric dual-mode tactile sensing scheme based on human finger tactile skin structure placed on a robot arm and used CNN-LTSM detection algorithm to achieve 84.28% accuracy for different sliding speed and directions. Xuefeng et al. [121], inspired from force perception layer-force treatment layer-force signal receiving layer structure of human skin, also created a similar three-layer flexible tactile sensor with the use of RDFA, achieving more than 99% accuracy in real time by pacing tubes on different sensors. These methods achieved high accuracy but have not conducted any experiment on real human, which might be different

from robot arms and tubes.

These tactile recognition systems provide valuable insights and technical foundations for Braille sensing, particularly in considering various sensor designs and machine learning approaches. While these systems report high accuracy in recognizing Braille through pressing, model performance often declines when being applied to data from sliding motions, highlighting a key challenge in TBR. Additionally, none of these systems were explicitly designed with Braille literacy education in mind, and therefore do not fully address the specific needs of a learning tool.

2.2.3 Commercial Braille Learning Tools

A number of commercial products support Braille learning through interactive physical interfaces, but they often trade off cost, flexibility, and scalability. *Taptilo* [80] as shown in Figure 2.1a is a multi-sensory learning device that provides guided practice, but its learning content is limited to short words, not supporting long sentences with only nine characters on the board, and the device cost is high (approximately \$1349). In addition, its customization workflow depends on entering words through a phone interface, which limits flexibility for multilingual learning and classroom-scale deployment.

BrailleCoach (Figure 2.1b) supports personalized learning by allowing users to enter a “record mode” that links a recorded audio cue with a Braille pattern printed on cards. However, its system relies on RFID-enabled, disposable printed cards and remains expensive (approximately \$2750). Furthermore, customization requires pairing with an additional Braille label maker (Figure 2.1c), increasing both cost and setup complexity [62]. In contrast, *BrailleTeach* (Figure 2.1d) is relatively low cost (approximately \$140), but its functionality is restricted to fixed patterns and primarily supports basic letters, numbers, and symbols, limiting its coverage of richer learning content and progression [12].

Beyond character learning, *BrailleDoodle* (Figure 2.1e) focuses on tactile creativity and exploration, enabling learners to create tactile graphics with high flexibility at a relatively low cost (approximately \$179). While this design supports open-ended interaction and customization, it does not provide auditory feedback and lacks support for punctuation and contractions, which are important for advancing beyond introductory Braille practice [102]. Finally, the *Perkins Smart*

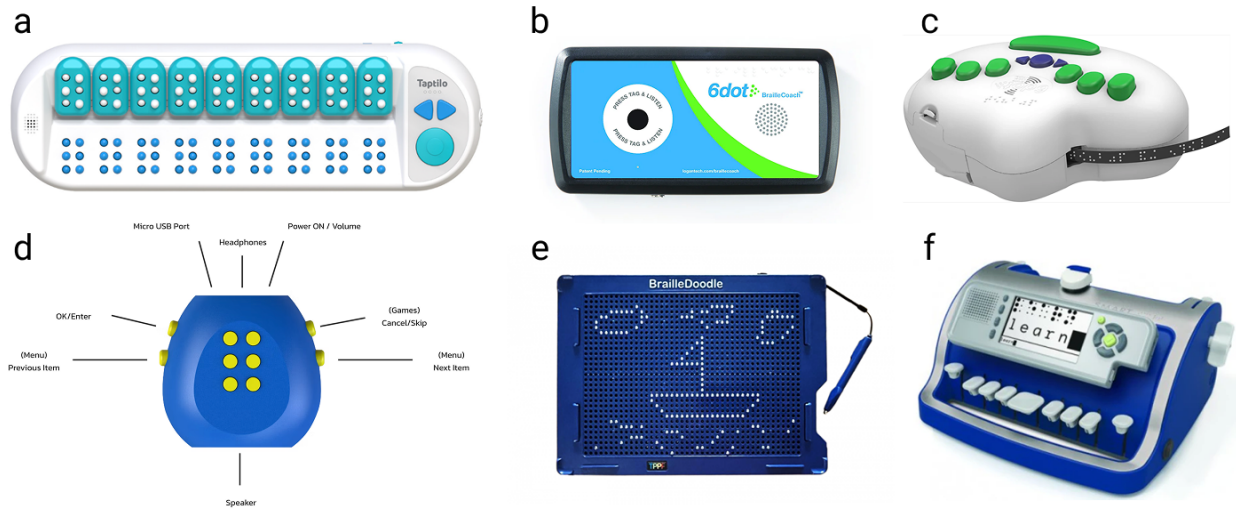


Figure 2.1: Current commercial braille learning tools. (a) Taptilo [80], (b) BrailleCoach recorder [62], (c) BrailleCoach label maker [62], (d) BrailleTeach [12], (e) BrailleDoodle [102], (f) Perkins Smart Brailier [85]

Brailier (Figure 2.1f) is a typing-oriented learning device that provides both tactile and audio feedback and supports multiple languages. However, it resembles a dedicated workstation, similar to a small computer or printer and requires learners to map key positions to Braille dot locations, which can increase learning overhead and reduce portability for everyday, in-situ practice [85].

Overall, these products demonstrate strong interest in multisensory and interactive Braille learning, but many remain constrained by high cost, limited content coverage (e.g., short sequences or a fixed set of characters), and restricted scalability for multilingual or classroom-based learning.

These gaps motivate learning-oriented systems that preserve authentic tactile engagement, provide immediate guidance, and remain affordable and customizable across diverse learning scenarios. Our system, *BrailleRhythm*, addresses this need by integrating a flexible piezoresistive sensor sheet that detects Braille dots under both pressing and sliding motions and supports real-time auditory feedback for interactive learning. *BrailleRhythm* extends tactile Braille recognition from passive detection to a complete and customizable learning platform, facilitating the transition from reliance on assistive devices to independent Braille reading.

2.3 BrailleRhythm

2.3.1 Sensor Design and Fabrication

We printed 26 standard English Braille alphabet cards (3×2 dot matrix) at three times the standard dimensions [23, 57] in modalur and full-block form using a Stratasys F120 printer as shown in Appendix Figure B.1. We adopted enlarged Braille because prior work [8, 80] shows that larger dot patterns can be learned significantly faster during early training and can improve subsequent learning of standard-sized Braille.

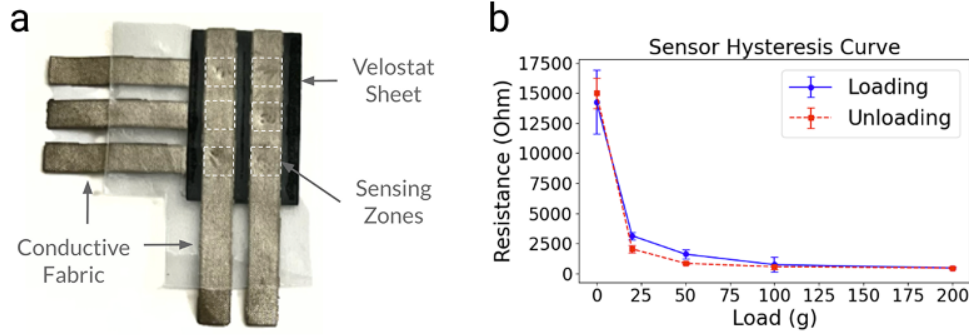


Figure 2.2: (a) A Tactile Sensor Sheet sandwiched by a Velostat sheet and conductive strips. (b) Hysteresis evaluation of the sensor from a loading-unloading experiment.

Each enlarged dot measures 3.6 mm in diameter with 6.75 mm inter-dot spacing. Adjacent cells are separated by 10.5 mm horizontally and 11.4 mm vertically, and all components are 1.5 mm thick. To sense user input, we laser-cut an 18.3×30 mm piezoresistive Velostat sheet and six conductive fabric strips, then laminated them in a tape-reinforced sandwich so that their intersections align with the six Braille positions (Figure 2.2a) [118]. A rear-mounted frame clips onto rails milled into the cards, ensuring precise alignment and smooth sliding. The sensor performance was evaluated through hysteresis using calibration weights and a digital multimeter. Hysteresis tests followed a 0-200 g load-unload protocol, measuring resistance 10s after each step and repeating five times for a more accurate measurement. The hysteresis results in Figure 2.2b exhibit the characteristic viscoelastic response of Velostat, demonstrating both recoverability and time-dependent

deformation.

2.3.2 Circuit Design and Web application

Due to the piezoresistive behavior, our Velostat sensor sheet exhibits decreased resistance under increasing force: raised Braille dots concentrate pressure on aligned sensing zones, enabling unobtrusive dot detection via measured resistance drops. The sensing hardware comprises two analog multiplexers, an XIAO ESP32C3 microcontroller (MCU), and a pull-up resistor of 3.3 k Ω . One multiplexer selects each row strip of the sensor, which is tied through the resistor to the power supply, while another grounds the chosen column strip, forming a voltage divider. Circuit block diagram is shown in Figure 2.3a and the front and back side of our customized printed circuit board (PCB) are also illustrated in Figure 2.3b and c. The sensor voltage data are transmitted over Bluetooth Low Energy (BLE) to PC for real-time processing at around 11 Hz frame rate.

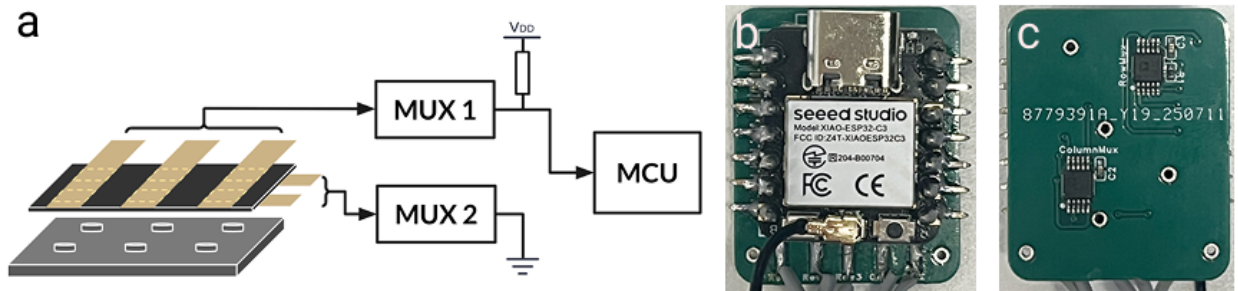


Figure 2.3: Circuit Design of BrailleRhythm. (a) A Velostat sensor sheet over a Braille card is read via voltage divider circuit with two multiplexers and streamed to a host for audio feedback. (b) PCB front side: XIAO ESP32C3 MCU and connectors to the tactile sensor. (c) PCB back side: Multiplexers, resistors, and capacitors.

Besides hardware, we also developed a web interface (Figure 2.4) that visualizes live six-channel voltages as a 3 $\times$ 2 white-to-red heatmap, manages “dip” onset and release signals to drive a 2.5 s classification countdown (the countdown time can be adjusted manually to achieve faster response), and streams recognized characters with their dot patterns and pressure data via Socket.IO. Detected letters are vocalized immediately using the Web Speech API and accumulate into a “current word”

buffer. When space is detected, the assembled word will be vocalized as well. Speech synthesis by default provides synchronized visual and auditory feedback that reinforces tactile-to-symbol mapping for effective Braille learning.

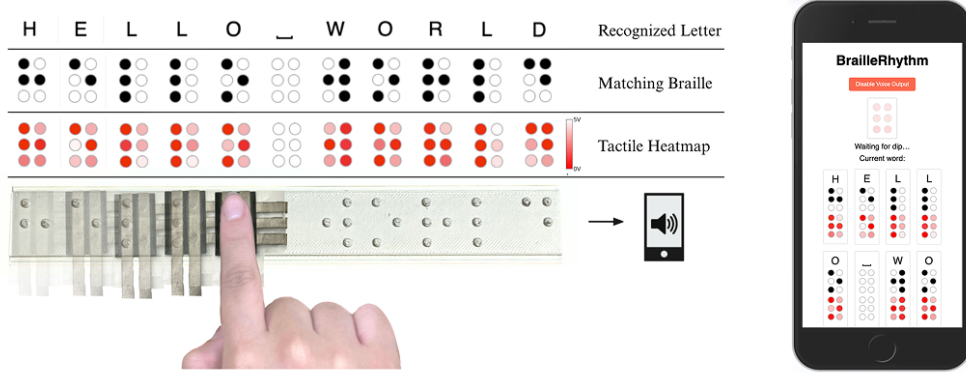


Figure 2.4: BrailleRhythm Web Interface. Left: Braille recognition pipeline: by placing fingers on the "HELLO WORLD" braille card, the system shows the pressure distribution via tactile heatmaps and localizes the recognized Braille letters with their true patterns; Right: Web interface on smartphone showing real-time heatmaps and character recognition and providing audio feedback.

2.4 Implementation

We collected data from three participants (P1, P2, P3), each asked to glide their finger to locate dots and then press to confirm. Data quality deemed "high" when a sensor threshold could be found to reliably match the known Braille pattern. It was generally satisfactory, with slightly lower performance for the participant with the largest fingertip (Figure 2.5a). We also observed that lighter presses degrade signal quality as illustrated in Figure 2.5b.

To ensure generalization of our recognition method, we employed a machine learning method based on K-fold cross validation, which is better suited for our small dataset (520 files) collected under the refined pipeline. Here we set $K=5$ for our 5 datasets – P1, P2, P3 with high force, P1 with medium force, and P1 with low force. It splits the dataset into 5 folds, on each fold, 4 are used for training and the remaining for testing. This utilizes the whole dataset in the training process, improving the model's ability to generalize. To maximize recognition accuracy, we evaluated

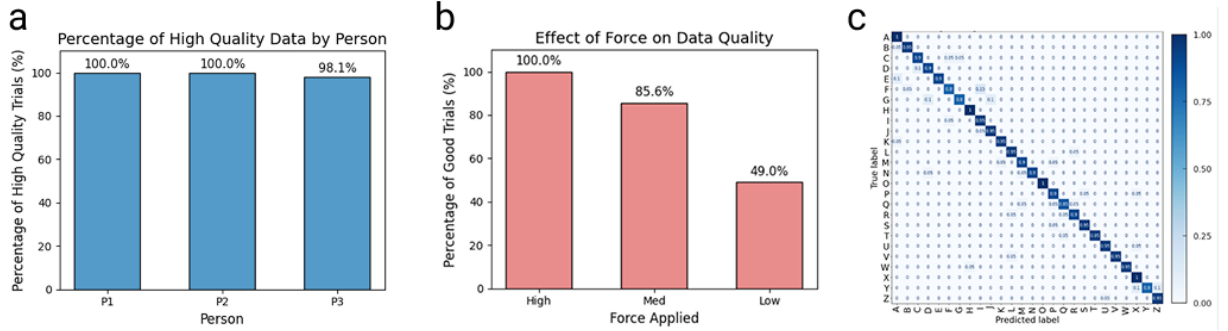


Figure 2.5: (a) Percentage of high-quality sensor recordings retained for each participant (P1-P3). (b) Effect of applied finger force from high to low on the proportion of usable data. (c) Confusion matrix of our trained LR model under 5-fold cross validation.

Random Forest (RF), Support Vector Classifier (SVC), K-Nearest Neighbor (KNN), and Logistic Regression (LR) under five-fold cross-validation after hyperparameter tuning as shown in Table 2.1. Logistic Regression (C=10, L2 penalty, lbfgs solver) achieved the highest mean accuracy and relatively low standard deviation accuracy ($92.31 \pm 2.36\%$) with its confusion matrix illustrated in Figure 2.5c.

Table 2.1: Per-fold classification accuracies for the four classifiers and their mean $\pm$ standard deviation over 5 folds.

Fold	RF (%)	SVC (%)	KNN (%)	LR (%)
1	86.54	89.42	89.42	92.31
2	86.54	89.42	88.46	90.38
3	93.27	93.27	95.19	96.15
4	87.50	89.42	86.54	89.42
5	87.50	87.50	86.54	93.27
Mean $\pm$ Std	88.27 $\pm$ 2.54	89.81 $\pm$ 1.88	89.23 $\pm$ 3.18	92.31 $\pm$ 2.36

2.5 Discussion and Future Work

We demonstrated that our newly fabricated velostat-based sensor sheet enables an average of 92% under five-fold cross-validation using logistic regression model. This system is low-cost, potentially portable, and encourages interactive learning through a Scrabble-like design by sticking cell magnets to Braille cards. Despite these successes, it has not yet been tested with visually impaired users, and its long-term durability under daily use has yet to be evaluated. The significant drop in accuracy under light presses (49%, Figure 2.5b) indicates a need for more sensitive transduction or active force feedback for novice users. By linking touch to real-time audio feedback, *BrailleRhythm* supports multisensory learning and may serve as a supplementary learning tool in educational settings. Its wireless architecture enables future integration with mobile learning platforms.

Future work will prioritize full system portability by embedding both the recognition model and text-to-speech engine on the MCU. Card dimensions and surface textures will be refined to emulate real-world Braille on embossed paper, signage, or standard publications. Concurrent efforts will target power consumption reductions and mechanical robustness enhancements to ensure long-term durability. Comprehensive, user-centered evaluations involving individuals with visual impairments will assess usability, accessibility, and learning efficacy. Numerals, punctuation, contracted, and multilingual Braille will be included to facilitate complete deployment across diverse educational contexts.

2.6 Conclusion

In this chapter, we introduced *BrailleRhythm*, an interactive Braille recognition system that combines tactile sensing with real-time audio feedback to support multisensory learning. Our prototype addresses accessibility challenges faced by individuals with visual impairment as a low-cost and intuitive tool for literacy acquisition. While the current implementation is best suited to function as a supplementary aid, our results demonstrate the feasibility of accurate, real-time Braille recognition using simple materials and off-the-shelf components.

Although further developments are needed in areas such as improving portability, enhancing sensor durability, and refining usability features, *BrailleRhythm* lays a solid foundation for a future fully developed Braille learning tool, as well as for other inclusive educational technologies. Through

the use of a piezoresistive sensor sheet, we are able to link touch to language in a way that preserves the authentic Braille reading experience while enhancing it with an auditory component. With continued refinement and usability testing, *BrailleRhythm* has the potential to expand access to tactile literacy and meet a wide range of learning needs.

Chapter 3

A CLOSED-LOOP CPR TRAINING GLOVE WITH INTEGRATED TACTILE SENSING AND HAPTIC FEEDBACK

3.1 Background and Motivation

Cardiopulmonary resuscitation (CPR) is a critical life-saving procedure, and effective training is essential for improving survival rates in cardiac arrest situations [18, 22, 44, 66, 79]. Traditional CPR education typically occurs in instructor-led sessions with hands-on coaching, yet many trainees have limited opportunities for continued practice after formal training. This gap has motivated increasing interest in self-training approaches that enable independent practice and skill maintenance in everyday settings [3, 47, 56, 64].

Prior work has explored CPR self-training systems that monitor performance and provide immediate feedback to guide users toward proper technique. However, many existing solutions depend on smart manikins paired with audio-visual interfaces [89, 109], which can be costly and less accessible for frequent practice. In addition, guideline-based targets do not always translate cleanly to everyday users: achieving recommended compressions can require substantially different forces across rescuers and contexts, reported to span roughly 250–600 N [9, 32, 43, 104]. These challenges motivate self-training systems that are portable, low-distraction, and adaptive to individual users.

In this chapter, we present a closed-loop CPR self-training glove that integrates tactile sensing with vibrotactile feedback (Figure 3.1). By sensing distributed pressure on the hand during compressions, the glove enables on-device estimation of the three core CPR metrics—compression rate, compression force (as a proxy for depth), and hand pose—and delivers immediate, localized haptic feedback to help users correct errors without relying on external screens or continuous audio prompts. To support individual differences, the system incorporates an adaptive force-to-target strategy that translates measured effort into appropriate training targets rather than assuming a single uniform depth requirement.

We evaluate the proposed approach through technical characterization of the sensing and end-

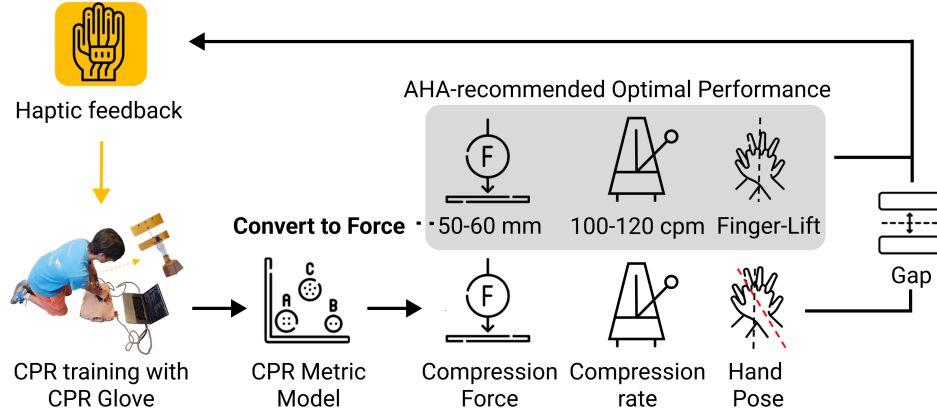


Figure 3.1: Our Closed-Loop CPR Self-training System Overview.

to-end closed-loop responsiveness, and a user study comparing haptic guidance with conventional audio-visual (AV) feedback. Across these evaluations, we identify practical trade-offs in feedback design, including reduced visual distraction with haptics alongside risks of information overload and motion-induced masking, and distill design directions for improving wearable, closed-loop CPR self-training.

3.2 Related Work

3.2.1 Tactile Sensing

Researchers use different methods for dynamic pressure sensing, and the most common ones are optical, capacitive, and resistive. Optical tactile sensors capture deformation in a soft elastomer or changes in illumination to recover high-resolution contact maps (e.g., GelSight [119], DIGIT [59], Gelslim 3.0 [101]). However, camera-based modules have strict size and shape constraints. They often depend on specialized optics and can be blocked easily, which reduces scalability and flexibility. Capacitive sensors measure capacitance changes between electrodes separated by a compressible dielectric [40, 114]. Although sensitive and low-power, they typically require guarded/shielded layouts and dedicated readout circuits to mitigate electromagnetic interference (EMI) and drift from bending or humidity [96], and are more commonly used for binary touch detection than continuous pressure measurement [42]. Resistive sensing works by placing a piezoresistive layer

between orthogonally routed electrodes [48, 58, 77]. Electrode size and density can be easily scaled. This allows thin, flexible, and wide-area sensing skins with simple electronics for continuous pressure estimation. Based on these trade-offs, we adopt a resistive tactile sensor design for the proposed glove.

3.2.2 Existing CPR self-training systems with Audio-Visual Feedback

A common design choice across prior CPR self-training tools is the use of audio and visual cues to guide performance in real time. To meet the growing need for self-directed CPR practice, researchers have developed systems that monitor compression behavior and provide immediate feedback to guide users toward proper procedures [27, 84, 86, 89, 95, 105, 109, 120]. Across these systems, as shown in Figure 3.2, feedback is commonly delivered through phone screens, indicator lights, dials, and metronomes, which can effectively communicate target compression rate and depth. However, many solutions are designed around instrumented manikins or dedicated feedback devices, making them comparatively costly and limiting accessibility and portability for everyday use.

Early mobile and consumer tools show the strengths and limitations of screen-based guidance and real-time prompts. iCPR [89] provides audio-visual feedback by displaying estimated compression rate and counts on the screen through a mobile application while pacing users with a built-in metronome. Zoll PocketCPR™ [120] uses an accelerometer to estimate compression frequency and depth when placed on the chest, providing optional audio prompts and LED-based feedback to reflect guideline targets. However, sensing with only an accelerometer can miss important aspects of technique, such as incorrect compression angles, which may lead to inadequate compressions as reported in evaluations of Zoll PocketCPR™. In addition, the time from device setup to the first chest compression was longer with Zoll PocketCPR™, suggesting that device interaction may delay CPR initiation and potentially worsen outcomes in time-critical situations. [120].

Stand-alone feedback devices often leverage force or pressure sensing to better estimate compression depth and release, but they still mainly focus on depth and rate. CPR-Plus [27] was an early stand-alone device that provided feedback on compression depth and incomplete release using a pressure-sensitive compression plate and metronome pacing. Comparative studies [27] reported reductions in incorrect compressions and fatigue, along with improved accuracy and more consistent



Figure 3.2: Existing CPR self-training systems. (a) iCPR [89], (b) CPR-Plus [27], (c) CPREzy™ [84], (d) CPRmeter™ [86], (e) Zoll PocketCPR™ [120] (f) Cardio First Angel™ (CFA) [105], (g) TrueCPR [95]

hand positioning among nurses when using the device. CPREzy™ [84] provides an LED display of applied force and has been reported to improve compression rate and depth, especially under fatigue [11]. However, its hardware design can introduce new issues, including hand injuries and discomfort, and clinical trials did not show consistent improvements in patient outcomes despite gains in manikin performance. [84].

More recent devices combine multiple sensing modalities to improve robustness, but continue to emphasize a narrow set of CPR metrics. CPRmeter™ [86] integrates an accelerometer with a pressure sensor and provides depth and rate feedback through a bar-and-target-zone display and a speedometer-like indicator. Studies reported improved depth and rate and reduced irregular inclinations, and users found it easy to adapt with minimal training [94]. TrueCPR [95] uses Tri-axis Field Induction (TFI) to measure the distance between a chest pad and back pad via a three-dimensional magnetic field, enabling accurate depth measurement and real-time feedback on

a highly visible dial along with metronome prompts. These systems are typically evaluated using manikin models [35, 71], which support controlled comparisons but may not capture the variability encountered across users and real emergency contexts. In parallel, Cardio First Angel™ (CFA) [105] demonstrates a purely mechanical feedback approach, emitting an audible click when the correct compression depth is reached and a second sound upon full recoil, confirming both phases of the compression cycle without electronics or displays.

Despite differences in sensing and form factor, existing self-training tools share several limitations that motivate a low-cost, portable, and adaptive alternative. First, their audio-visual cues require sustained attention to external displays or device-generated prompts, which can distract trainees and does not reflect realistic emergency scenarios where attention must remain on the patient and maintaining correct hand posture. Second, while the American Heart Association (AHA) guidelines emphasize compression depth, compression rate, and hand pose as key metrics of high-quality CPR [75], most systems primarily provide feedback on depth and rate, leaving hand pose largely unaddressed. Third, many devices implicitly assume a uniform “correct” compression depth without accounting for variability in body size, gender, or physical capability across rescuers. In practice, achieving guideline-recommended depth can require substantially different forces—reported to range roughly from 250 N to 600 N [9, 32, 43, 104]. Together, these gaps highlight the need for CPR self-training systems that are not only accurate, but also low-distraction, portable, and adaptive to individual users.

3.3 A Closed-loop CPR self-training glove

Our closed-loop CPR self-training glove consists of three main hardware components: tactile sensors that capture user interactions during CPR, haptic units that provide feedback to guide proper performance, and a control circuit that serializes sensing signals and drives the vibrotactile actuators, as illustrated in Figure 3.3. All the components are implemented via flexible printed circuit board (FPCB) for accessible manufacturing and assembly. The system is designed as a combination of a tactile sensing glove and control and haptic wristbands for portable and wearable applications.

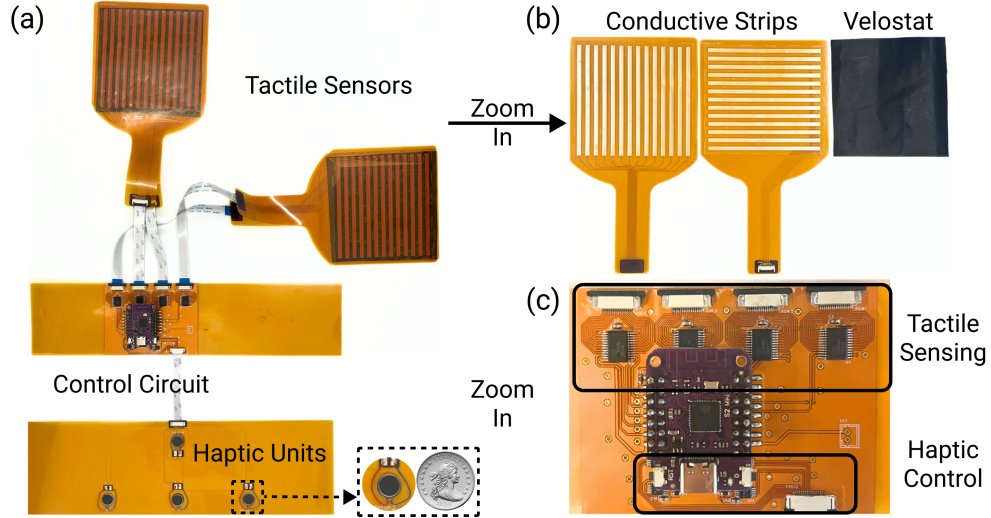


Figure 3.3: (a) CPR self-training glove with integrated tactile sensors, vibrotactile haptics, control circuit and FPCB connectors. (b) The tactile sensing array is made by sandwiching a Velostat layer between two flexible polyimide sheets with orthogonal copper traces. (c) Close-up of the custom control board with tactile sensing and haptic control circuits.

3.3.1 Tactile Sensors and Vibrotactile Haptics

We design and implement two tactile sensing arrays, one on the palm of the bottom hand and one on its back, to capture CPR activity. The tactile sensor is implemented as a piezoresistive sensing array. A palm-sized semi-conductive Velostat sheet (Adafruit) is sandwiched between two sets of orthogonally arranged electrodes. In our design, each set of electrodes is fabricated using an FPCB process, with copper traces patterned on polyimide substrates (Figure 3.3b). Each intersection of the orthogonal conductive traces defines a sensing cell. When pressure is applied, the carbon particles in the Velostat compress, lowering resistance and converting pressure stimulation into electrical signals [76].

We use eccentric rotating mass (ERM) 1030 coin vibration motors (AEDIKO) for vibrotactile haptics. It is positioned on the forearm to ensure adequate spacing between units, reliable contact area, and a comfortable wearable form factor. Because effective haptic feedback depends on how users perceive and interpret signals, we designed the placement, patterns, and intensities of the

haptic units through expert co-design and user studies, ensuring they reliably convey key CPR metrics. The details of the studies are described in Section 3.4 and Section 3.5.

3.3.2 Control Circuit Design

Our control circuit is also implemented on an FPCB and positioned over the wrist, making the system a fully integrated, portable wearable interface (Figure 3.3c). The circuit performs two main functions: serializing tactile data and driving the haptic units.

The tactile signals from the sensor array are serialized by scanning rows and columns using two 16:1 analog multiplexers. Readout is performed through a voltage divider circuit with a $4.7\text{ k}\Omega$ pull-up resistor and a 13-bit analog-to-digital converter (ADC). Two independent voltage-divider networks are implemented to instrument the palm-side and dorsum-side sensor arrays, both managed by the same MCU (ESP32S2-Mini) to provide synchronous sampling and unified data collection. Each ERM is driven by a DRV2605 haptic driver via Inter-Integrated Circuit (IIC). To accommodate multiple motors while avoiding IIC address conflicts, we route the bus to individual driver channels using a TCA9548 IIC multiplexer. This allows sequential and parallel control of the full haptics set through a single MCU port. Powered via USB, the MCU runs a Wi-Fi SoftAP and sends UDP packets to downstream devices, enabling closed-loop sensing and control.

3.4 User study #1: Haptic Placement and Pattern Design

The patterns of haptic feedback to convey a user’s CPR performance were designed through a co-design workshop with four haptics experts of 4+ years experience. After explaining the objectives and constraints of this study, each expert independently proposed candidate designs, implemented them with available vibration units, and iteratively refined the patterns through peer evaluation and feedback. The most critical design constraint was to deliver independent feedback for the three CPR metrics (compression rate, force, and hand pose) using a minimal number of vibration units, such that a single vibration pattern at any moment conveys all three. The final design mapped compression rate to pulse count, compression force to vibration intensity, and hand pose to the spatial position of the vibration unit (Table 3.1).

Table 3.1: Haptic Feedback Patterns.

Dimension	Attribute	Condition	Pattern
Compression Rate	Pulse Count	Too Slow	Single Pulse
		Correct	Double Pulse
		Too Fast	Triple Pulse
Compression Force	Intensity	Too Weak	Maximum Intensity
		Correct	Medium Intensity
		Too Strong	Minimum Intensity
Hand Pose	Position	Left/Right Skewed	Left/Right Unit
		Correct	Center Unit
		Finger Release	Lower $\leftrightarrow$ Center Units

3.5 User Study #2: Haptic Intensity Range Selection

To convey compression force appropriately, we conducted a pilot study with five participants (4 male, 1 female; 25.8 ± 4.5 years old; arm circumference 25.0 ± 2.6 cm) to identify the three settings for minimum perceivable intensity (*low*), maximum comfortable intensity (*high*), and the medium intensity that can be clearly distinguished from the other two intensity levels (*mid*). We controlled vibration intensity by adjusting the effective voltage (V_{eff}) with pulse-width modulation (PWM, range 0-128). Higher V_{eff} increases both amplitude and frequency in ERMs.

For each participant, we asked them to experience a set of vibrations with a specific PWM. The minimum perceivable intensity *low* was identified by verifying their perception through three questions: “Did you feel it?”, “How many pulses?”, and “Which motor?” The maximum tolerable intensity *high* was then identified by gradually increasing PWM values and asking participants to rate their comfort on a 5-point scale (1 = very comfortable, 5 = very uncomfortable). The results show that the *low* intensity spans from PWM 38 to 58 across users because of different skin sensitivity, and all participants could tolerate the *high* vibration intensity of PWM 128.

The *mid* setting needed to provide clear discriminability and lie approximately at the midpoint between each participant’s minimum and maximum thresholds. To satisfy these criteria, participants experienced randomized sequences of vibrations at their personalized *low*, *mid*, and *high* PWM values. After familiarization with these three reference levels, they labeled each vibration as *low*, *mid*, or *high*, reported the perceived order, and rated their confidence on a 5-point Likert scale (1 = not confident, 5 = very confident).

As demonstrated in Figure 3.4, all intensities spanning from 38 to 58 were reliably identified as *low*, consistent with prior findings. Thus, the mean value 50 was selected as the final *low* value. In contrast, participants sometimes confused *mid* and *high*, so rather than choosing the intensity being recognized as *mid* responses most frequently, we selected the *mid* level that is most distinguishable from *high*, yielding PWM = 73. The resulting PWM values of **(50, 73, 128)** were used as *low*, *mid*, and *high* intensities in all subsequent experiments.

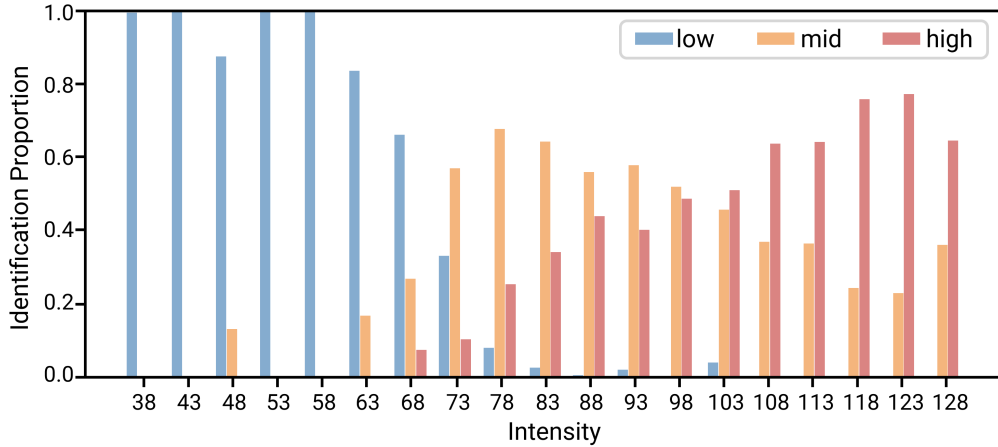


Figure 3.4: Haptic Intensity Range Validation Results. Confidence-weighted proportion of each intensity being recognized as *low*, *mid*, and *high*.

3.6 Implementation

To develop our model, we recorded synchronized tactile signals and ground-truth compression forces from two participants with different body size, weights, and genders. Ground-truth compression

force was measured using a SparkFun OpenScale ¹ load cell amplifier (≈ 10 Hz) connected to a commercial scale with a manikin placed on top. The OpenScale system reports applied force in kg, which corresponds to kilogram-force (kgf). To obtain the standard SI unit of force, Newton (N), we converted the readings by multiplying by the standard gravitational acceleration (9.81 m/s^2); *i.e.*, $1 \text{ kgf} = 9.81 \text{ N}$. The tactile sensor was sampled at 14.3 Hz. Force values were aligned to the closest tactile timestamps.

As shown in Figure 3.5, we first recorded ten seconds of baseline signals, which were used to estimate the offset of each tactile channel. Then, participants were asked to perform a step pressing with 10 N increments (three-second press, one-second release) until maximum compression (Stage 1), a continuous ramp-up to maximum force followed by a ramp-down (Stage 2), and lastly 20 free-style compressions without predefined targets (Stage 3). To capture pose data, participants executed 100 compressions under four conditions: correct, left-skewed, right-skewed, and loose finger lifting (Figure 3.6). We later simplified the 3-stage data collection procedure when applying our system to user study participants, using it as a calibration data collection process for training personalized models. More data captured by our system during CPR with ground truth is shown in Appendix Figure B.2

3.7 Technical Evaluation

We evaluated our system through glove tactile sensor characterization, and a user study on CPR self-training experience.

3.7.1 Tactile Sensor Characterization

The tactile sensors are evaluated through hysteresis measurement, cyclic repeatability test, and signal-to-noise ratio (SNR) estimation.

To support the compression force applied during CPR with different body weights, we designed the sensor to resolve forces across 0-600 N and to retain stable performance under repeated loading. We evaluated three conductive strip widths (1 mm, 3 mm and 6 mm) by fabricating test matrices and subjecting them to quasi-static loading and unloading cycles across the target range. For each

¹<https://www.sparkfun.com/sparkfun-openscale.html>

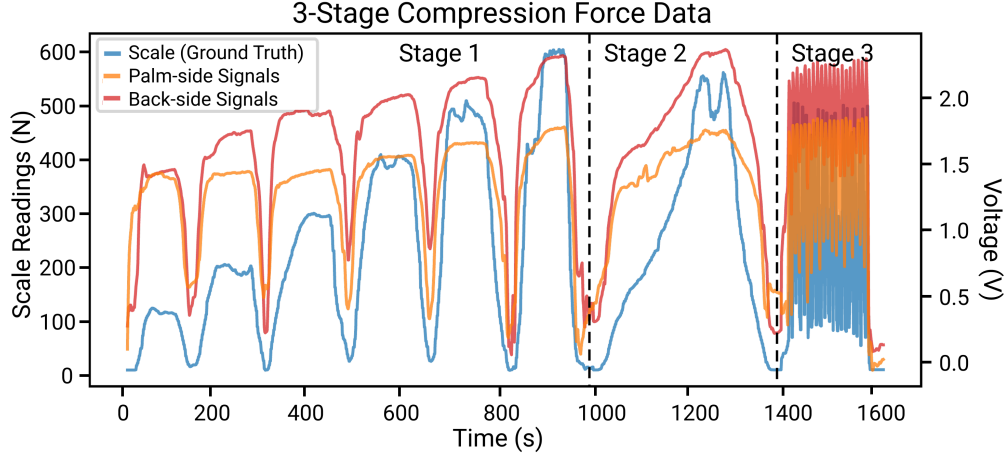


Figure 3.5: Examples of the 3-stage compression force data. Stage 1: Applying and releasing pressure in 10kg increments; Stage 2: Gradually increasing and decreasing pressure; Stage 3: Simulating random compressions.

geometry we measured the resistance-force curve, quantified hysteresis under repeated cycles, and assessed repeatability via a 300-cycle repeatability test. Force per sensing cell was inferred from $Pressure = Force/Area$ on the pressed 5×5 sensor matrix area ($27.2 \text{ mm} \times 27.2 \text{ mm}$).

As demonstrated in Figure 3.7, the width of electrodes affects the wide-range sensitivity and dynamic range of the tactile sensors. The 3 mm matrix provides the best tradeoff between sensitivity and robustness. It shows the largest normalized resistance change over 0-600 N ($\Delta R/R_0 \approx 0.85$), clearly exceeding the 1mm strips (≈ 0.10) and the 6mm strips (≈ 0.03). Hysteresis, quantified by the loading-unloading loop-area ratio, is also lower for 3mm (56.04%) than for 1mm (99.57%), while 6mm remains low (22.39%) but with poor sensitivity. Over 300 cycles, the 3 mm strip exhibited an average peak-valley amplitude drift of 11.05%, indicating relatively good stability.

To quantify how reliably the sensor distinguishes true contact signals from background artifacts, we estimate local and global SNR from the 300-cycle test data based on different definitions of *Noise*. *Signal* is defined by the median of the average voltage drops across 300 cycles on the pressed cells. *Local Noise* is the unwanted response on the surrounding unpressed cells, affecting localization and edge cases. *Global Noise* is the unwanted signal on all unpressed cells, affecting thresholding and

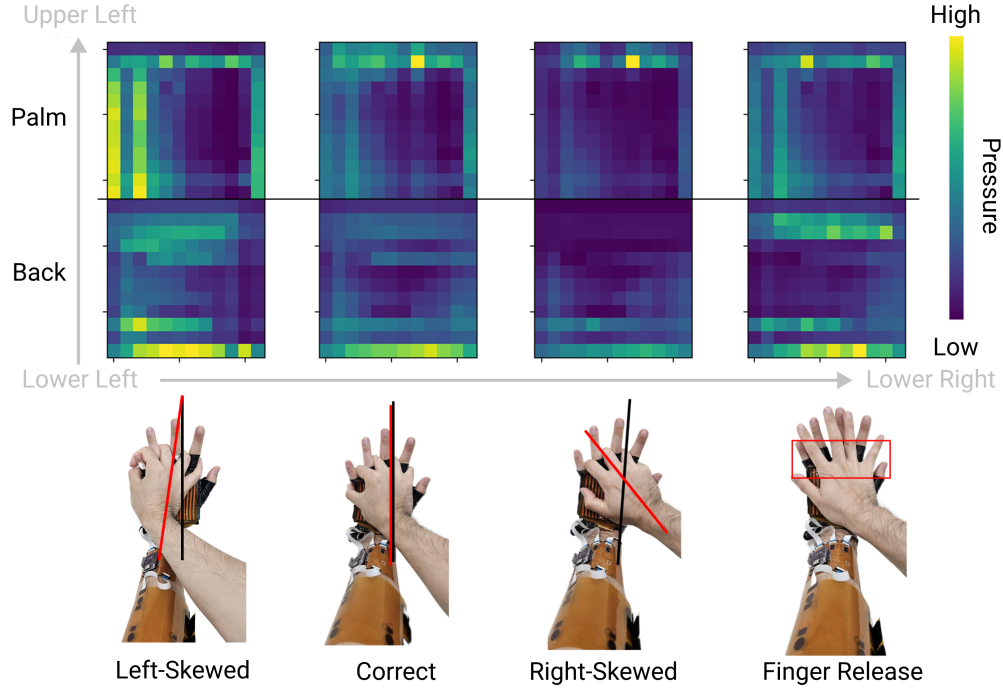


Figure 3.6: Heatmap of average pressure distribution on the sensor for each hand pose case. Brighter areas represent higher pressure.

calibration drift. Based on these definitions, local and global SNR can be computed using

$$\text{SNR}_{\text{dB}} = 20 \log_{10} \left(\frac{\text{Signal}}{\text{Noise}} \right) \quad (3.1)$$

As illustrated in Figure 3.8, the SNR increases monotonically with applied force and saturates in the 500-600 N range. Global SNR is higher because the surrounding unpressed cells are more susceptible to proximal artifacts (18.90 ± 2.41 dB at 600 N). Overall, the SNR remains sufficiently high to support meaningful data analysis.

3.7.2 User Evaluation

We evaluated the effectiveness of our CPR training glove on users and compared it with conventional AV feedback interface on a mobile application.

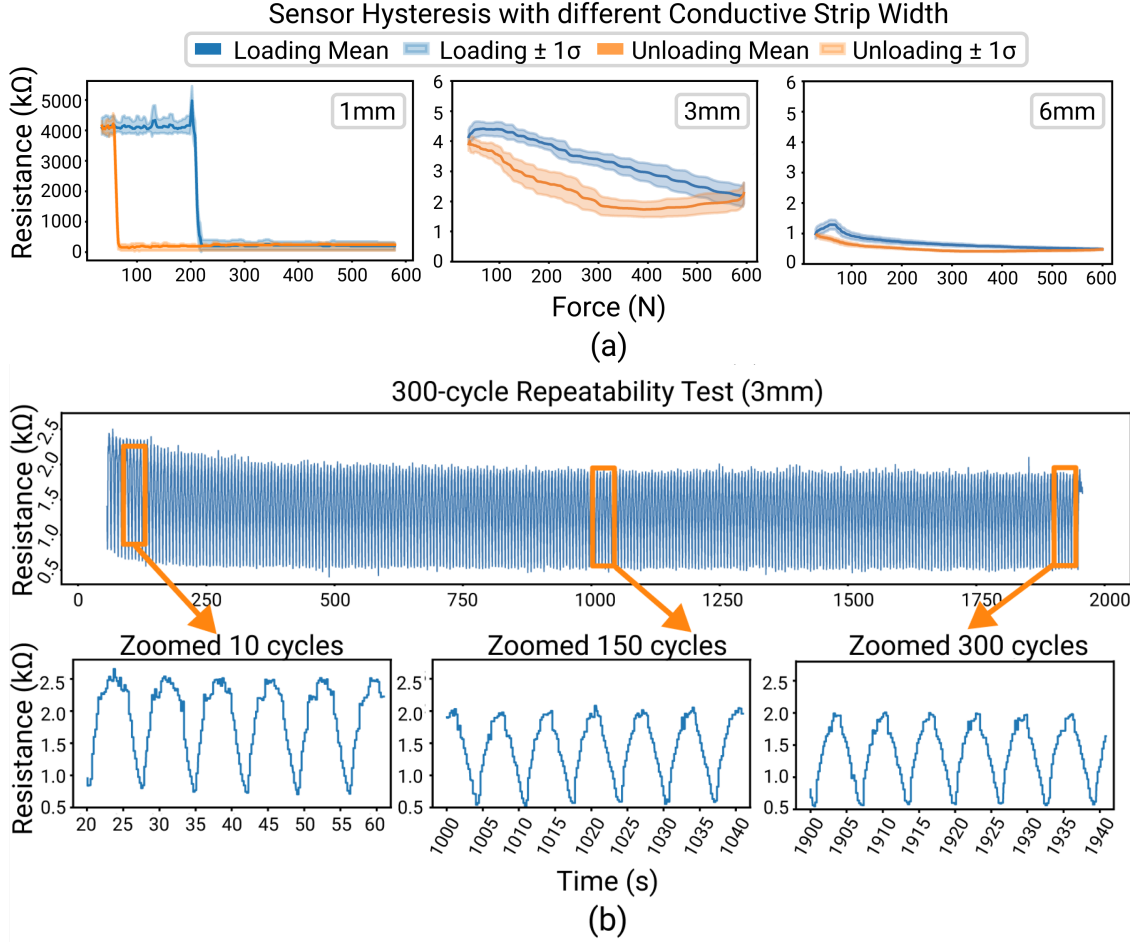


Figure 3.7: Tactile sensor characterization. (a) Hysteresis performance of sensors with 1 mm, 3 mm, and 6 mm conductive strips. (b) 300-cycle repeatability test on the sensor with 3 mm conductive strips.

3.7.2.1 Baseline Implementation

We implemented AV feedback on a mobile application (Figure 3.9), following modalities commonly adopted in prior studies and commercial products [27, 84, 86, 95, 105, 120]. The app communicates with the MCU via SoftAP Wi-Fi. Compression rate was conveyed through audio beeps (metronome at 110 cpm with short beep/long beep/buzz variations depending on deviation). Compression force was shown on a triangular indicator (one yellow, two green, or three red segments). Hand pose

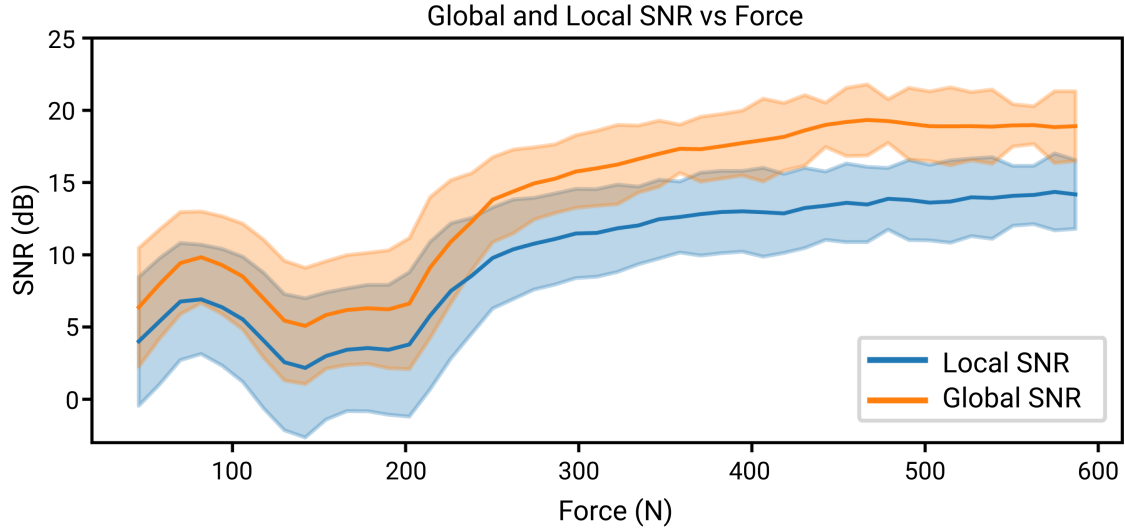


Figure 3.8: Global and Local SNR of tactile sensors under 0-600N force.

was represented by three circular indicators (all green when correct; corresponding red circles for incorrect alignment).

3.7.2.2 Procedure

We recruited 8 participants (6 male, 2 female; 24.63 ± 4.96 years old; five < 70 kg, two 70-80 kg, one 80-90 kg) for the between-subject study. Four participants experienced the proposed haptic feedback, and four received conventional AV feedback with additional hand-pose cues.

All participants successfully completed the simplified calibration procedure explained in Section 3.6 prior to practice, performing a reduced set of 20 compressions per condition. After collecting the calibration data, they had feedback familiarization session for 5 minutes. Subsequently, they performed two pre-practice sessions (30 compressions and 10 seconds of break each) without a feedback system to get accustomed to the task. Each then performed five practice sessions consisting of 30 compressions followed by a 10-second rest with each feedback system.

After the sessions, participants completed a short questionnaire on a 5-point Likert scale, covering perceived physical workload, mental workload, and ease of use. Semi-structured interviews further revealed their subjective impressions. The interview probed three aspects: the perceived

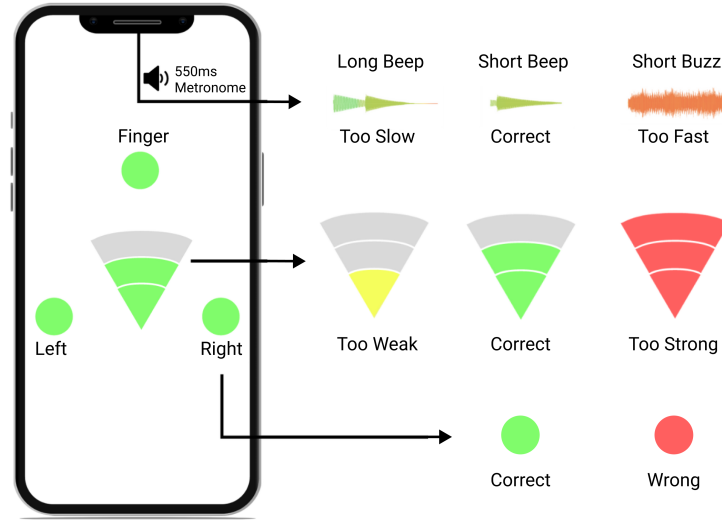


Figure 3.9: Baseline AV Feedback Design for CPR on the mobile application

helpfulness of the system for CPR training, the effectiveness of feedback delivery during compressions, and suggestions for feedback system improvement. The details of the questionnaire and interview are included in Appendix A.

3.7.2.3 Result

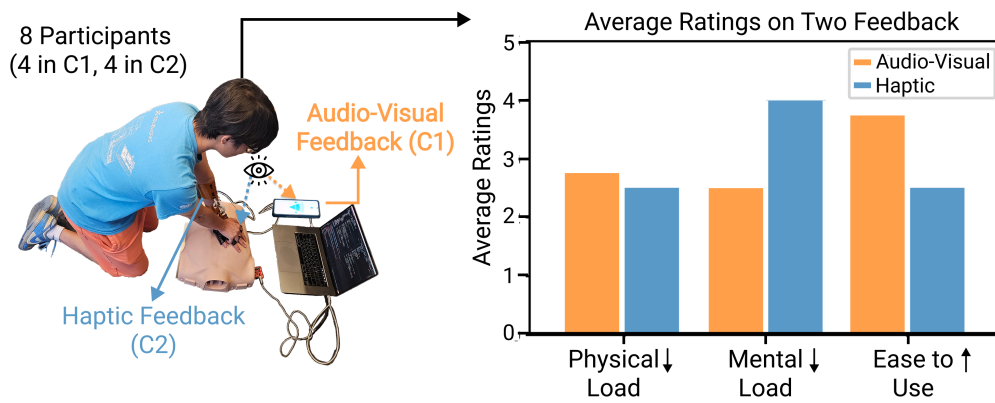


Figure 3.10: Results of user study responses. ↓ denotes that lower values are better, and ↑ denotes higher values are better

This section reports the usability of the proposed CPR self-training glove based on both qualitative (interview) and quantitative (survey) results. The interview transcripts were analyzed using Braun and Clarke’s thematic analysis [13]. Figure 3.10 presents participants’ ratings of physical load, mental load, and ease of use when practicing CPR with either haptic or audio-visual feedback. Lower scores indicate lower workload (physical and mental), whereas higher scores indicate better usability (ease of use). By integrating the quantitative and qualitative results, we identified three main themes.

General usefulness of the glove: In post-study interviews, all participants agreed that the system was helpful for CPR training. Without feedback during the pre-practice phase, they reported being uncertain about their performance; in contrast, with feedback (both audio-visual and haptic), they felt more confident in assessing their compression quality. In particular, they emphasized that the feedback was highly effective in maintaining compression rate. However, some participants noted drawbacks: audio-visual feedback could lead to visual distraction, whereas haptic feedback posed challenges in perception and signal clarity under physical exertion.

Visual distraction from audio-visual feedback: Quantitative results (Figure 3.10) showed that haptic feedback yielded slightly lower physical workload than audio-visual feedback. This suggests that reliance on an external visual channel distracted participants’ attention during compressions. In the experimental demo on the left side of Figure 3.10, it can be seen that when using audio-visual feedback, the participant’s gaze deviates significantly from the manikin. Indeed, two of the four participants using audio-visual feedback explicitly mentioned visual distraction. For example, P5 stated, “... I kept having my attention drawn to the app, I found it difficult to focus well on checking the patient’s [Manikin’s] condition.” Similarly, P1 remarked, “For the sound feedback it is effective, but for the force feedback [the light] it is hard to follow.” Notably, P5 further suggested that incorporating “another modality such as haptics”, which does not require conscious visual attention, could alleviate this issue.

Complexity of haptic feedback: Despite showing lower physical workload, haptic feedback scored worse in mental workload and ease of use. All participants in this group reported difficulty perceiving vibrations during compressions, due to motion-induced vibrotactile masking and unstable glove-skin contact rather than increased physical exertion. While the perceivable intensity study (Section 3.5) confirmed that three intensity levels were distinguishable under static conditions, par-

ticipants indicated that minimum and medium intensities were often imperceptible in practice. As P7 noted, “..., sometimes I felt barely nothing during the CPR and sometimes I felt strong vibrations ...,” suggesting that only maximum intensity was reliably detected. In addition, participants reported cognitive challenges in recalling the meanings of multiple vibration codes. For instance, P8 remarked, “... hard to recall the meaning of vibration,” while P7 explained, “... The vibration patterns are too many to be remembered, and it is hard for me to realize their meanings during CPR ...” These findings suggest that the number of vibration patterns should be reduced, intensity margins should be increased to remain perceivable under dynamic conditions, and a longer familiarization period should be provided. Indeed, all haptic participants expressed the need for extended familiarization, and P8 further suggested distributing feedback across modalities, “... The number of patterns should be reduced (just for one or two metrics) and mix additional modalities to support the remaining metrics.”

3.8 Discussion and Future Work

Future work included the development a standalone glove system that integrates simplified haptic-audio feedback without external devices. While the current model requires a relatively long calibration stage, larger datasets and advanced learning methods could make it more adaptive across users and environments, enabling more robust and generalizable performance. Second, CPR metrics are currently computed on an external computer, which constrains mobility. Integrating a lightweight processor would allow the glove to function as a fully standalone device. Also, our evaluation focused primarily on hardware validation and model accuracy. Future research should include structured user studies to directly assess the system’s educational impact on CPR learning outcomes. Lastly, haptic feedback design remains an open challenge: participants noted difficulty distinguishing multiple vibration patterns and occasional masking during active movements. Simplifying and refining feedback patterns could improve clarity and reliability. These directions provide a clear roadmap toward more robust, usable, and effective wearable CPR self-training systems.

3.9 Conclusion

In conclusion, we propose a closed-loop CPR training glove that integrates a high-resolution tactile sensing array and vibrotactile actuators for self-directed practice. The tactile sensing array measures

distributed pressures across the palm and dorsum to enable real-time estimation of compression rate, force, and hand pose. Based on these estimations, the glove delivers immediate haptic feedback to guide the user for proper CPR, reducing reliance on external AV displays. We quantified the tactile sensor performance by measuring wide-range sensitivity (≈ 0.85 over 0-600 N), computing hysteresis (56.04%), testing stability (11.05% drift over 300 cycles), and estimating global signal-to-noise ratio (18.90 ± 2.41 dB at 600 N). Our closed-loop pipeline provides continuous modeling and feedback of key performance metrics essential for high-quality CPR. Our user study (N=8) showed that haptic feedback reduced visual distraction compared to audio-visual cues, though simplified patterns were required for reliable perception under dynamic load. These results highlight the potential of the tactile sensing and haptic glove for CPR self-training, underscoring the glove’s potential as a practical tool to enhance CPR learning beyond traditional instructor-led methods.

Chapter 4

MULTISENSKNIT: MULTIMODAL MACHINE-KNITTED SENSING SLEEVE FOR UPPER LIMB REHABILITATION

4.1 Background and Motivation

In 2021, there were 93.8 million stroke survivors worldwide, and the need for stroke rehabilitation remains substantial [30, 31]. The World Health Organization estimates that 86 million people need rehabilitation due to stroke, with much of this need still unmet [111]. Effective recovery often depends on repeated practice over extended periods and on the ability to assess progress beyond brief clinical visits. Recent advances in sensing technologies have enabled increasingly rich measurement of rehabilitation-relevant physiological and biomechanical signals, supporting new opportunities for quantitative assessment and personalized care [69, 108].

Post-stroke rehabilitation monitoring commonly relies on multiple sensing modalities [69, 108]. Electromyography (EMG) measures muscle activation and coordination, impedance-based sensing can capture changes in tissue properties and internal dynamics, and kinematic measurements quantify joint motion and movement quality [16, 60, 88, 90]. Traditionally, these measurements are obtained using clinic-bound systems such as wired EMG with gel electrodes, optical motion capture, ultrasound, or standalone measurement devices that require careful setup and calibration [90, 108]. While such systems can provide high-fidelity data, they introduce significant practical barriers for everyday use.

Despite ongoing progress, clinical rehabilitation remains fragmented, costly, and complex [65, 112]. In typical workflows, multiple standalone devices must be set up and calibrated separately, resulting in lengthy sessions that contribute to fatigue and limit the number of repetitions a patient can perform. More importantly, these systems are often operated by trained clinicians in specialized facilities, meaning that quantitative data collection is limited to infrequent clinical visits. This makes it difficult to track rehabilitation progress, evaluate day-to-day variability, and provide continuous support outside the clinic.

Wearable sensing offers a promising direction for bridging this gap. Soft, body-conforming wearables can reduce setup time, improve comfort, and enable in-situ measurement during natural movements. However, designing wearable systems for everyday rehabilitation introduces several key challenges. First, physiological sensing quality varies across sessions due to changes in electrode contact, motion artifacts, and user differences. Second, deploying multiple modalities in one wearable interface increases hardware and wiring complexity, often worsening wearability. Third, effective rehabilitation monitoring requires not only raw sensing, but also real-time processing and interpretable metrics that can be used by patients and clinicians.

To address these challenges, this chapter explores a multimodal smart-textile sleeve that enables continuous and real-time rehabilitation monitoring in a garment-like form factor. Three complementary sensing modalities, EMG for muscle activation dynamics, electrical impedance sensing (EIS) for inertial tissue impedance monitoring, and capacitive sensing for joint bending angle estimation, are integrated within a single knitted substrate. By embedding sensing within a textile interface and reducing the number of required electrodes through a shared-electrode architecture, the sleeve targets practical wearability while supporting multimodal measurement. Custom data acquisition hardware and software that support efficient serial/wireless data acquisition, and adaptive handling of multimodal data streams are developed to enable real-time monitoring. Together, these design goals aim to reduce setup burden, improve comfort, and enable quantitative rehabilitation monitoring that is feasible beyond specialized clinical environments.

4.2 *Related Work*

4.2.1 *Smart Textiles for Physiological Sensing*

Smart textiles provide a promising approach for unobtrusive physiological sensing by embedding conductive materials into garments. Prior work has explored textile-based electrodes for capturing biopotential signals such as EMG and ECG, offering improved comfort and long-term wearability compared to traditional gel-based electrodes [73, 97]. Knitted and woven conductive fabrics have been shown to provide conformal contact with the skin while maintaining breathability and flexibility, making them suitable for everyday use [29, 50].

However, textile electrodes introduce challenges related to contact stability, motion artifacts,

and variability in skin–electrode impedance [117]. Several studies have investigated material selection, electrode geometry, and fabrication techniques to improve signal quality and durability [63]. Washability and long-term robustness remain critical concerns, as repeated use and laundering can degrade electrical performance [52].

Most prior work focuses on single-modality sensing, typically EMG or ECG. In contrast, our work explores how textile electrodes can be designed to support multiple sensing modalities simultaneously with a minimal number of electrodes needed, requiring careful co-design of electrode placement, material properties, and electrical interfaces.

4.2.2 *Multimodal Sensing in Rehabilitation*

Multimodal sensing has been widely studied for rehabilitation assessment, as combining complementary signals can provide a more comprehensive understanding of motor function. EMG is commonly used to assess muscle activation patterns, while kinematic sensing (e.g., IMU or motion capture) provides information on movement trajectories [100]. Impedance-based sensing has also been explored for monitoring tissue properties and muscle condition [41].

Recent systems have begun to integrate multiple sensing modalities to improve robustness and enable richer analysis. For example, combinations of EMG and motion sensing have been used for gesture recognition and motor assessment [7]. Other work explores sensor fusion for rehabilitation robotics and assistive systems [24]. However, these systems often rely on separate sensing modules, leading to increased hardware complexity and reduced wearability.

Instead, our work studies a shared-electrode multimodal sensing approach, where one set of textile electrodes supports EMG, EIS, and capacitive sensing. This design reduces hardware redundancy and enables a more compact and wearable system.

4.3 *MultiSensKnit*

Our sleeve is designed for upper-limb rehabilitation and captures muscle activation intensity via EMG, inertial tissue impedance change via EIS, and joint bending angle via capacitive sensing in real time within a wearable form factor. To balance wearable design and sensing performance, our intelligent sleeve uses a shared-electrode architecture, where a minimal set of electrodes enables multimodal sensing, ensuring exact same muscle to be monitored across modalities simultaneously.

As illustrated in Figure 4.1d, the shared-electrode design is made possible by the inherent electrical-based sensing principles and the strategic placement of electrodes on the arm. In Figure 4.1e, EIS requires 4 electrodes distributed circumferentially around the upper arm and forearm, with one pair of electrodes injecting current and another pair measuring resultant voltage alternatively. EMG requires 2 electrodes aligned along each of the muscle groups, including Biceps, Triceps, Brachioradialis, and Forearm Flexors. Joint angles are captured via capacitive sensing with an electrode positioned across the elbow and another electrode connected to the human body. Because these sensing modalities naturally require electrodes in overlapping regions, around key muscle groups and across the joint, we reuse the same electrodes whenever possible. This shared-electrode approach eliminates redundant hardware, reduces wiring complexity, and maintains the lightweight and wearable form factor of the sleeve.

Figure 4.1b–c depicts the smart sleeve in use, where the inner electrodes make direct contact with the skin for biopotential and impedance measurements, while the outer electrodes serve as the motion-sensing component. During elbow flexion, the capacitance increases as the distance between the capacitor plates decreases (Figure 4.1e). Simultaneously, EMG electrodes detect muscle activation in the biceps, and EIS measurements indicate tissue impedance change associated with muscle contraction. Collectively, the results demonstrate that the three sensing modalities exhibit consistent and well-aligned trends during arm bending, highlighting the robustness of the integrated multimodal sensing framework.

Our sleeve is digitally designed and fabricated using industrial machine knitting, a scalable textile manufacturing method. The knitting machine produces a full garment by forming looped structures with different yarn types. The main fabric is made from acrylic yarn, while conductive electrodes are integrated at selected locations using stainless-steel threads. We use a double-layer structure to separate inner and outer electrodes. The knitted structure makes the sleeve flexible and stretchable, allowing it to conform to the body during movement and maintain stable contact with the skin. The textile design also preserves the natural breathability of fabric, supporting comfort during extended wear. The detailed knitting process is shown in Appendix Figure B.6a.

Multimodal signals from the shared electrodes are scheduled and serialized by an integrated readout circuit operating at up to 6.25 Hz. The circuit includes a programmable analog front end and a multiplexing module that allocates electrode pairs for EMG, EIS, or capacitive sensing

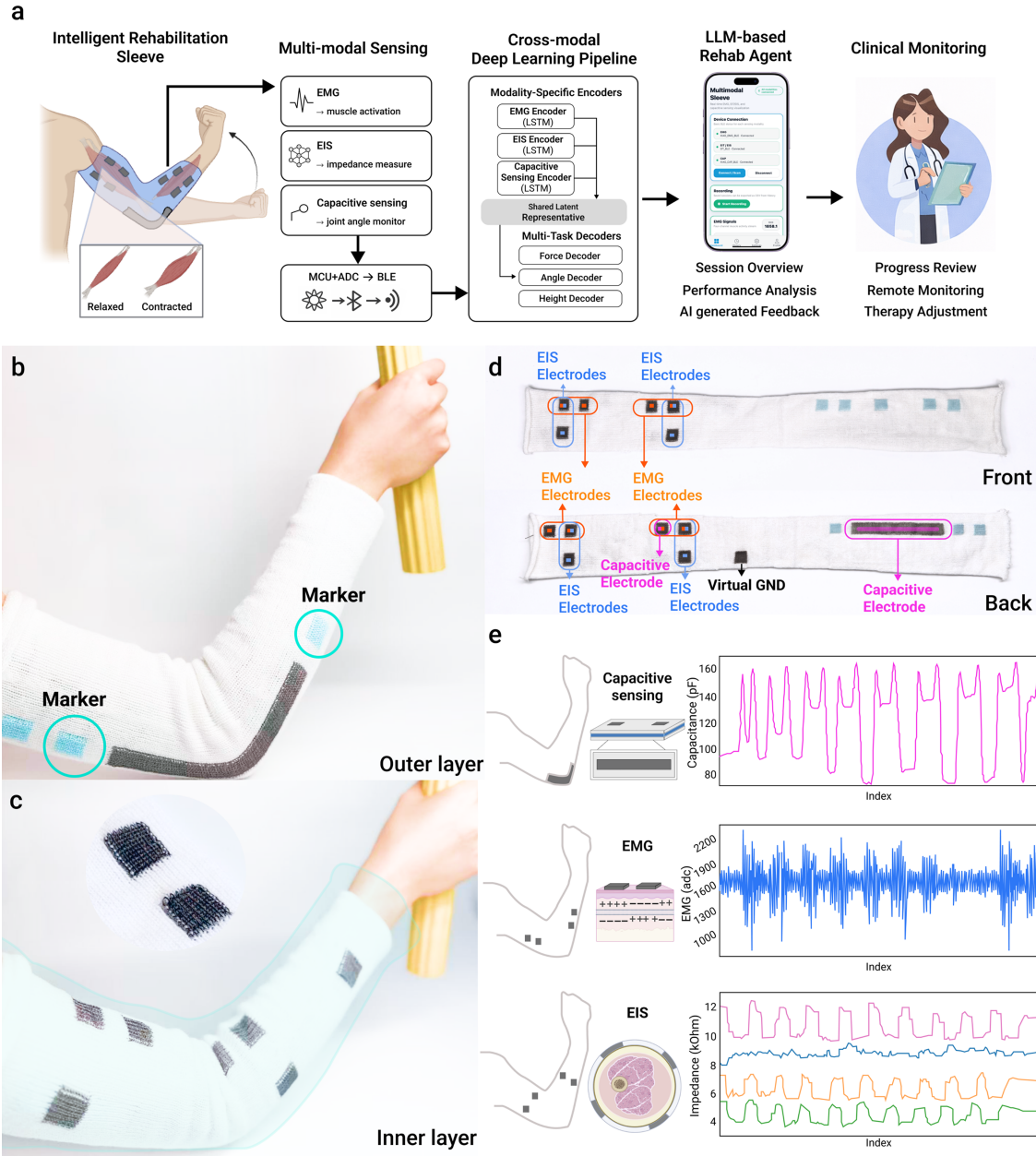


Figure 4.1: Overview of *MultiSensKnit*. (a) The overall working pipeline of the system. (b–c) The sleeve design, shown from the outer and inner sides. (d–e) Electrode placement for each sensing modality with example signals.

at each time step. After amplification, filtering, and digitization, the data stream is serialized and transmitted to a laptop or mobile application for visualization and processing. The mobile app provides real-time monitoring of EMG levels, impedance maps, and joint-angle trajectories, enabling clinicians and patients to view rehabilitation progress during and after use.

4.3.1 Multimodal Circuit design

Our sleeve integrates three sensing modalities, EIS, EMG, and capacitive sensing, with an electrode-selection network. The system uses a Teensy 4.0 microcontroller (MCU) for EIS and Seeed Studio XIAO ESP32S3 for EMG and capacitive sensing. The block diagram of our circuit design is shown in Figure 4.2a. The MCUs coordinate stimulation and sampling, control multiplexers and relays, and packetize data for wireless transmission over BLE to a host computer for further processing and model training. We use the Teensy for EIS due to its high sampling rate and abundant GPIOs, and we add an external 16-bit ADC on the EIS path to maintain throughput and resolution before data reach the MCU. The Seeed Studio XIAO ESP32S3 supports EMG and capacitive sensing with integrated BLE for real-time data transmission.

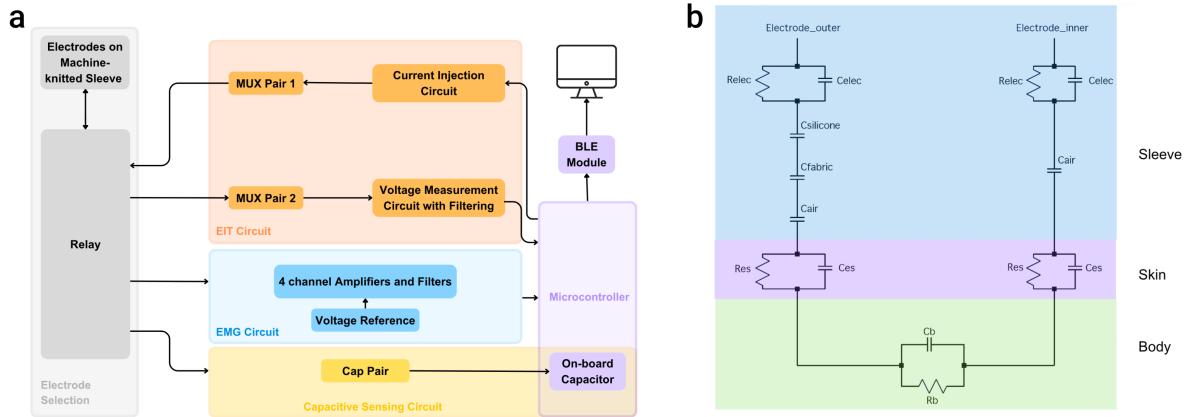


Figure 4.2: (a) *MultiSensKnit* circuit architecture design (b) Equivalent capacitance model of *MultiSensKnit* for joint angle monitoring

EIS is used to monitor bio-impedance changes related to muscle contraction and relaxation. Two electrode pairs are distributed around the arm; one pair injects current and the other senses

voltage. A waveform generator, driven by the MCU, produces a sinusoid that is converted to a differential, voltage-controlled current using a mirrored, modified Howland source, and this current is sequentially injected into selected electrode pairs via two multiplexers. The pickup voltage from a different pair is AC-coupled through a high-pass filter with a cutoff near 1.6 kHz and amplified by an instrumentation amplifier before conversion by the external 16-bit ADC. The four-multiplexer (MUX) topology (two for current injection, two for voltage measurement) allows rapid scanning without fixing the drive or sense locations of EIS.

EMG measures myoelectric potentials between bipolar electrode pairs placed along muscle fibers. In our design, each electrode pair connects directly to a dedicated EMG circuit, and four channels are read in parallel using analog input pins on the Seeed Studio XIAO ESP32S3. Each channel feeds an instrumentation amplifier with a gain of about 101. To achieve the desired EMG bandwidth, the signal passes through a second-order 20 Hz high-pass filter and a second-order 500 Hz low-pass filter, forming a band-pass response. A second gain stage (about $101\times$) scales the signal to match the MCU ADC range. EMG signals are referenced to a stable midpoint rather than earth ground. We generate this mid-supply reference using a resistor divider and buffer it to provide high input impedance, which helps stabilize the baseline and reduce drift.

Capacitive sensing measures the capacitance between human skin and the outer electrode. The equivalent capacitance model of our system is illustrated in Figure 4.2b, where C_{silicone} is the most significant factor causing capacitance change. We designed the capacitive sensing circuit to monitor this change following the voltage divider principle, in which the series resistors are replaced by capacitors – the unknown textile capacitor fabricated on the sleeve and a known on-board parasitic capacitance between two GPIOs. A PWM-driven square wave from the MCU provides the AC excitation; the node voltage between the two capacitors is sampled to infer capacitance changes that are subsequently mapped to joint angle during elbow flexion.

To ensure effective signal capture while preserving the signal quality, the sampling frequency of each modality is carefully chosen based on its sensing mechanism. EMG measures muscle electrical activity, which can be up to approximately 500Hz. Thus, the EMG stream was sampled at approximately 1000 Hz according to the Nyquist sampling theorem, preserving the main components of the raw signal before rectification, envelope extraction, and smoothing. In contrast, EIS and capacitive sensing capture slower movement-related changes. EIS measures impedance varia-

tions associated with muscle deformation, limb posture, and internal tissue geometry rather than raw electrophysiological activity. Each EIS sample consists of an eight-channel impedance vector, and the measured effective EIS frame rate was approximately 18.3Hz, corresponding to a Nyquist frequency of 9.15Hz. This rate is sufficient for capturing the slower impedance changes during squeezing, rotation, and joint-angle tasks. The capacitive sensing stream measures joint bending angle at an effective sampling frequency of approximately 102Hz and a Nyquist frequency of 51Hz. This provides sufficient temporal resolution for tracking joint motion while allowing smoothing for stable angle estimation.

To minimize hardware on the sleeve while avoiding cross-talk between active and passive modalities, electrodes are shared and time-multiplexed. The upper EMG electrodes are reused for the EIS circular electrode array and the lower EMG electrodes for the capacitive sensor. Since EIS and capacitive sensing actively inject current, whereas EMG is purely passive, we adopted relays driven by the MCU through N-MOSFET to isolate the EMG front-end during EMG acquisition and reconnect the electrodes to the EIS/capacitive paths otherwise. In practice, the MCU alternates measurement phases: during EMG windows, the relays disconnect the injection circuits and route the bipolar pair to the EMG amplifier; during EIS or capacitive windows, the relays engage the corresponding paths, and the multiplexers scan the electrode configurations. This scheduling strategy provides effective signals from all three modalities, maintains high data rates over BLE, and keeps the electrode count low without sacrificing measurement fidelity. The switching mechanism is explained in Appendix Figure B.3. The actual PCB of each modality and the stacked version is illustrated in Appendix Figure B.4.

4.3.2 UI Design

To support rehabilitation monitoring with *MultiSensKnit*, we developed a mobile application that receives multimodal data from the smart sleeve over BLE and presents the signals through a multi-screen interface for real-time monitoring and longitudinal review (Figure 4.3). The main dashboard provides immediate session-level information, including connection status, recording controls, and modality selection, allowing users to confirm that the sleeve is connected and streaming before beginning an exercise session.

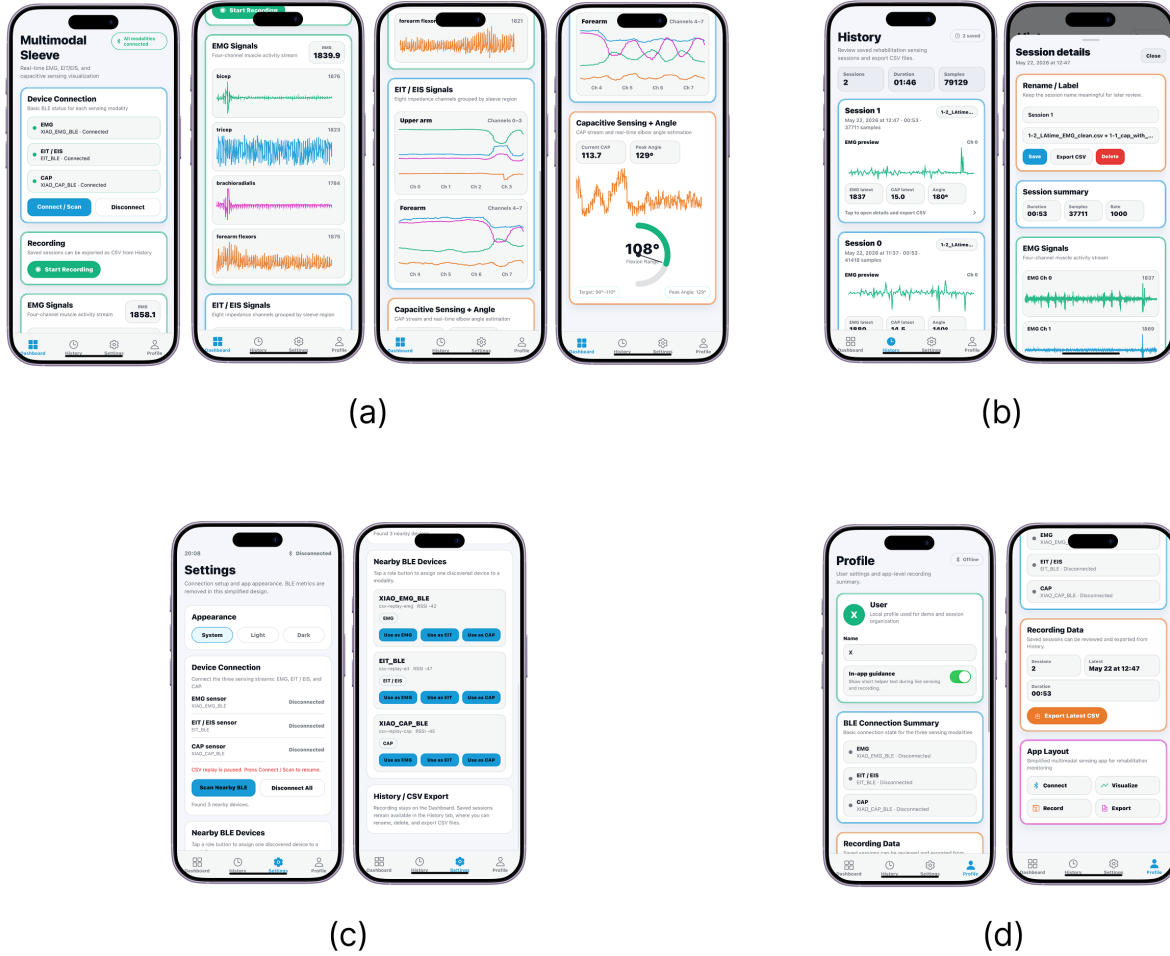


Figure 4.3: UI design of the mobile application for *MultiSensKnit*. (a) Dashboard Screen (b) History Screen (c) Setting Screen (d) Profile Screen.

The dashboard (Figure 4.3a) is organized into separate views for EIS, EMG, and joint angle sensing. These views allow users to observe multimodal signals during arm movement in real time. The EIS view shows multi-channel impedance traces, which reflect changes in muscle activity and help assess signal consistency and channel quality. The EMG view displays electrical muscle activity across channels, revealing activation patterns during rehabilitation tasks. The joint-angle view presents elbow motion in an intuitive way, making flexion and extension easy to interpret and relate to the corresponding EIS and EMG signals. Together, these views support quick cross-modal

inspection of movement and sensing quality during rehabilitation.

In addition to the real-time dashboard, there is a History screen for session management and progress tracking (Figure 4.3b). This screen allows recorded data to be stored and exported as CSV files for later review. By preserving time-series records across sessions, the History interface supports both patients and clinicians in visualizing rehabilitation progress over time, comparing performance across sessions, and incorporating recorded data into downstream analysis workflows.

The application also includes a Settings screen (Figure 4.3c), which provides controls for device connection and system configuration. This screen allows users to scan and connect to nearby BLE devices for EMG, EIS, and capacitive sensing, and to monitor the connection status of each modality. It also includes basic interface options, such as appearance settings, to support a consistent user experience. By centralizing device management and configuration, the Settings screen helps ensure reliable data acquisition during real-time monitoring.

We further designed a Profile screen (Figure 4.3d), which provides a dedicated space for user-specific information and app-level preferences. It allows users to manage personal settings and export recorded sessions, supporting data sharing and long-term tracking.

Overall, the interface is designed to reduce cognitive load while preserving clinically useful information. The card-based layout and clear visual hierarchy help users focus on key signals. The interface separates real-time monitoring from historical data, supporting both in-session use during rehabilitation and later review of recovery progress outside controlled settings.

4.4 *Technical Evaluation*

4.4.1 *Electrode dimension characterization*

We optimized the electrode dimensions, width and length, to ensure reliable performance across all sensing modalities. Electrode size directly affects the skin-electrode bioimpedance and therefore influences the SNR of EMG and the sensitivity of EIS and capacitive sensing. The electrode width is limited by the arm circumference, so we fixed the width at 20 mm and fabricated samples with varied electrode length from 10 mm to 30 mm with a step size of 5mm. We evaluated performance using modality-specific metrics: capacitance change ratio for joint-angle sensing (Figure 4.4a), EMG SNR (Figure 4.4b), and EIS bioimpedance (Figure 4.4c) – each representing the primary indicator

of sensing quality.

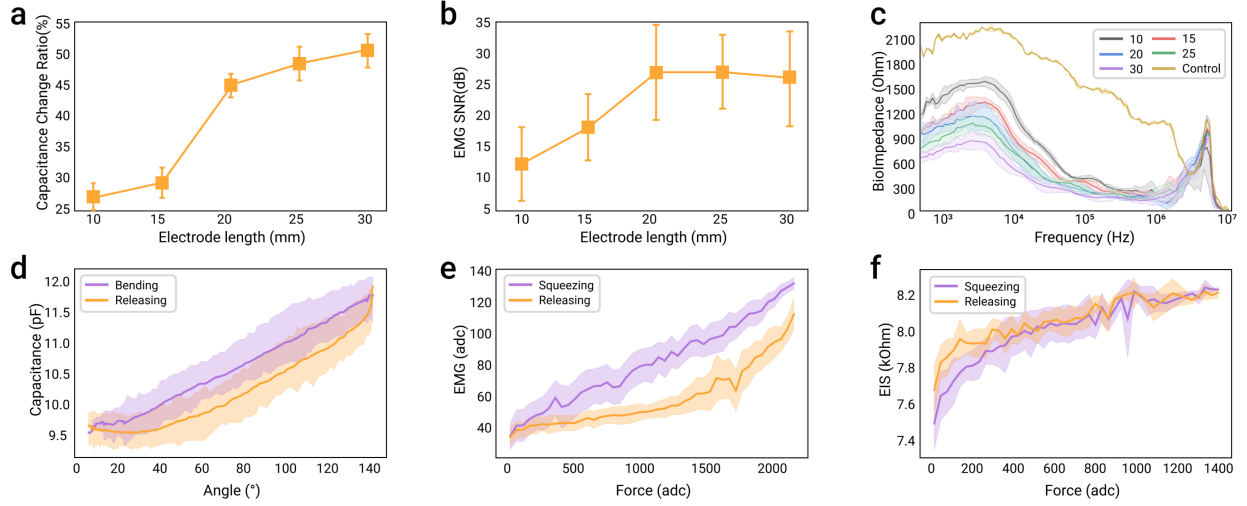


Figure 4.4: Electrode dimension characterization and hysteresis characterization experiments results of the three sensing modalities. (a) The capacitance change ratio of electrodes with different dimensions during elbow flexion from 0° to 150° , (b) The SNR measured from bicep EMG electrodes with different dimensions when holding a 25lb weight, (c) The bioimpedance of electrodes with different dimensions evaluated across a 100Hz–10MHz frequency range compared to a commercial electrode (control). (d) Capacitance response during elbow bending and releasing as a function of joint angle. (e) EMG amplitude during ball squeezing and releasing as a function of applied force. (f) EIS impedance response during ball squeezing and releasing as a function of applied force.

The performance of the capacitive sensor was evaluated by measuring the capacitance change ratio during elbow flexion from 0° to 150° . Electrodes of lengths from 10 mm to 30 mm attached on the 2 mm silicone strip were also prepared for the electrode dimension experiment (Figure 4.4a). The capacitance change ratio was calculated using Equation 4.1:

$$\text{Capacitance change ratio} = \frac{C_1 - C_0}{C_0} \times 100\%, \quad (4.1)$$

where C_0 denotes the capacitance when the arm is fully extended, and C_1 represents the capacitance when the arm is flexed to around 150° (the maximum bending angle that participants could

achieve).

As shown in Figure 4.4a, the capacitance change ratio increased as the electrode length increased. Smaller electrodes produced a weaker response during elbow flexion, while larger electrodes produced a stronger capacitive response. The increase became less pronounced at larger electrode lengths, suggesting that the sensing performance gradually approached saturation. This trend is likely due to the finite conductivity of the fabric electrode and the impedance at the electrode-skin interface. Compared with an ideal metal electrode, conductive fabric introduces additional resistance, which slows the charging and discharging process of the capacitive sensing node. For smaller electrodes, the higher effective impedance can prevent the node from fully settling before sampling, leading to a lower apparent capacitance change. As the electrode length increases, the effective sensing area becomes larger and the influence of electrode/interface impedance is reduced. Therefore, the measured capacitance change ratio increases for the same elbow bending motion.

To quantitatively measure the SNR of EMG signals acquired by different samples, the electrodes were placed on the same location on the biceps and tested while the arm held a 25 lb weight. Each sample was tested using three independent specimens. The SNR was calculated using Equation 4.2:

$$\text{SNR}_{\text{dB}} = 20 \log_{10} \left(\frac{\text{RMS}(V_{\text{active}})}{\text{RMS}(V_{\text{rest}})} \right) \quad (4.2)$$

where $\text{RMS}(V_{\text{rest}})$ denotes the root mean square (RMS) voltage when the arm was fully relaxed, and $\text{RMS}(V_{\text{active}})$ represents the RMS voltage when the arm was under load while holding the weight.

As shown in Figure 4.4b, the EMG SNR increased as electrode length was extended from 10 to 20 mm, indicating improved signal capture. However, further increasing the length from 20 to 30 mm resulted in little additional improvement, with SNR plateauing at approximately 25 dB. This suggests that once the electrode area is sufficient to capture representative muscle activity, additional surface area does not enhance EMG performance.

We further evaluated the bioimpedance of electrodes with different dimensions and compared them with a commercially available electrode as a control (Figure 4.4c). Bioimpedance measurements were performed across a broad frequency range (100 Hz–10 MHz) to identify electrode materials and dimensions that provide stable performance and low skin–electrode impedance through a

frequency response analysis (FRA) approach. Each electrode's impedance was characterized using a TL082 operational amplifier with a 1 k Ω feedback resistor. A 1 V peak-to-peak sinusoidal signal, sweeping from 100 Hz to 10 MHz, was generated by the built-in FRA module of an oscilloscope. Channel 1 (CH1) on the oscilloscope recorded the input to the electrode, while Channel 2 (CH2) measured the output across the electrode. The gain and phase responses obtained from the two channels were used to calculate the complex impedance over the full frequency spectrum. Each sample electrodes was tested using three independent specimens. The results demonstrate that bioimpedance decreases with increasing electrode size, attributable to the larger electrode-skin contact area that reduces interface resistance.

Based on the results of the three experiments, electrodes with dimensions of 20 mm $\times$ 20 mm offer a balance between EMG, EIS, and capacitive sensing performance. This size is therefore chosen for the final sleeve design.

4.4.2 *Silicone thickness characterization*

The silicone strip thickness is a key parameter influencing capacitance. The performance of the capacitive sensor was evaluated by measuring the capacitance change ratio during elbow flexion from 0° to 150°. Silicone strips of varying thicknesses (2, 4, 6, and 8 cm) were incorporated into the sensors, with three specimens prepared for each thickness condition. The capacitance change ratio was calculated using Equation 4.1.

As shown in Figure 4.5, the capacitance change ratio decreased with increasing silicone thickness. This is attributed to two factors: (1) thicker silicone strips require greater force to deform during bending, and (2) the increased electrode separation in thicker strips results in a lower baseline capacitance (below 10pF), such that changes after stretching remain difficult to detect. By contrast, thinner silicone strips exhibited superior performance, as they deformed more easily and provided higher measurable capacitance values. Therefore, we adopted a silicone thickness of 2cm for the final sleeve design. The 2cm silicone is illustrated in Appendix Figure B.5.

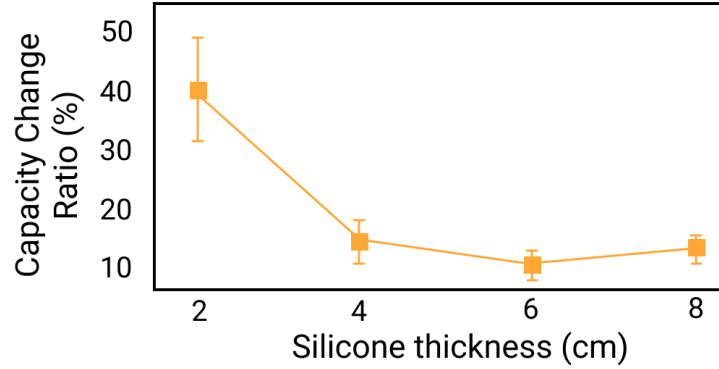


Figure 4.5: Capacitance change ratio during arm bending using capacitors fabricated with silicone of 2cm, 4cm, 6cm, and 8cm thickness

4.4.3 Hysteresis characterization

After determining the electrode dimensions and silicone thickness for sleeve fabrication, we characterized the hysteresis of each sensing modality against its corresponding reference variable. Capacitive sensing was evaluated against elbow bending angle, while EMG and EIS were evaluated against the applied force during ball squeezing. As shown in Figure 4.4d–f, capacitance increases monotonically with elbow angle, and both EMG amplitude and EIS impedance increase with squeezing force. The bending/releasing and squeezing/releasing curves remain closely aligned, especially for EIS, indicating low hysteresis and reliable signal tracking across repeated loading and unloading cycles. These results demonstrate that the sleeve can capture angle-, muscle activation-, and tissue impedance-related signals with clear and consistent trends.

4.4.4 Electrode reduction rate evaluation

We also compared the number of electrodes needed for the traditional design, where each modality does not share any electrode with that of our design where electrodes are shared across modalities. Our current design supports 4-channel EMG signals and 8-channel EIS signals under 1-channel capacitive sensing measurement, but is expected to increase the number of channels for more accurate and localized monitoring. With this expectation, we calculated the number of electrodes

that could be reduced under different channel combinations across modalities and then obtained the corresponding electrode reduction rate using Equation 4.3.

$$\text{Electrode reduction ratio} = \frac{N_{noShare} - N_{Share}}{N_{noShare}} \times 100\%, \quad (4.3)$$

where $N_{noShare}$ denotes the number of electrodes needed under traditional non-sharing architecture, and N_{Share} represents the number of electrodes required using our sharing structure.

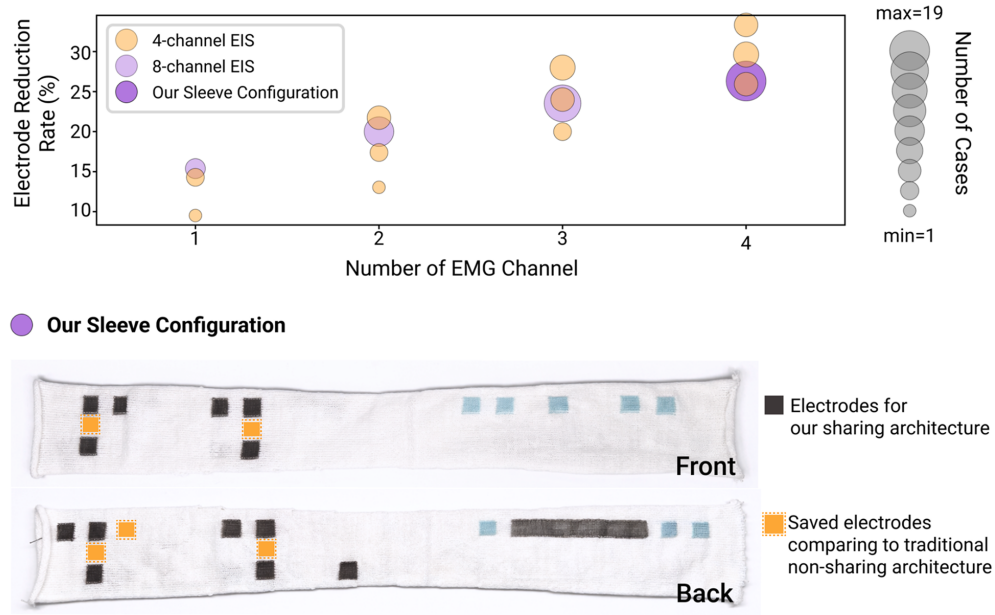


Figure 4.6: Electrode reduction rate by comparison between our shared design and traditional non-sharing design with an example of the comparison under our sleeve configuration.

With our design, the electrodes needed could be reduced by 26.32% as illustrated in Figure 4.6 and could reach up to 33%, significantly saving the materials and simplifying the hardware setup.

4.4.5 Washability and Gel necessity characterization

Washability is a critical requirement for wearable systems, as it directly impacts both sustainability and practical usability. To assess the wash durability of the knitted electrodes, we fabricated sleeves

containing four electrode pairs and subjected them to repeated laundering in a full-scale commercial washing machine (Maytag Washer; 30 min per cycle). After each wash cycle, the sleeves were air-dried at room temperature, and EMG signal quality was evaluated using SNR. As shown in Figure 4.7, the knitted electrodes preserved stable EMG performance after repeated washing when conductive gel was applied. Across wash cycles, the gel-assisted knitted electrodes achieved SNR values of approximately 22–23 dB, which were slightly higher than those of the commercial electrodes (21.04 dB). By contrast, the dry knitted electrodes exhibited SNR values near 0 dB or below, indicating that the absence of conductive gel led to high skin–electrode impedance and substantially degraded signal acquisition. These findings demonstrate that the machine-knitted electrodes are washable and mechanically robust, while also highlighting the importance of conductive gel in maintaining reliable EMG measurements. The stretchability and washability of our sleeve is shown in Appendix Figure B.6b–c.

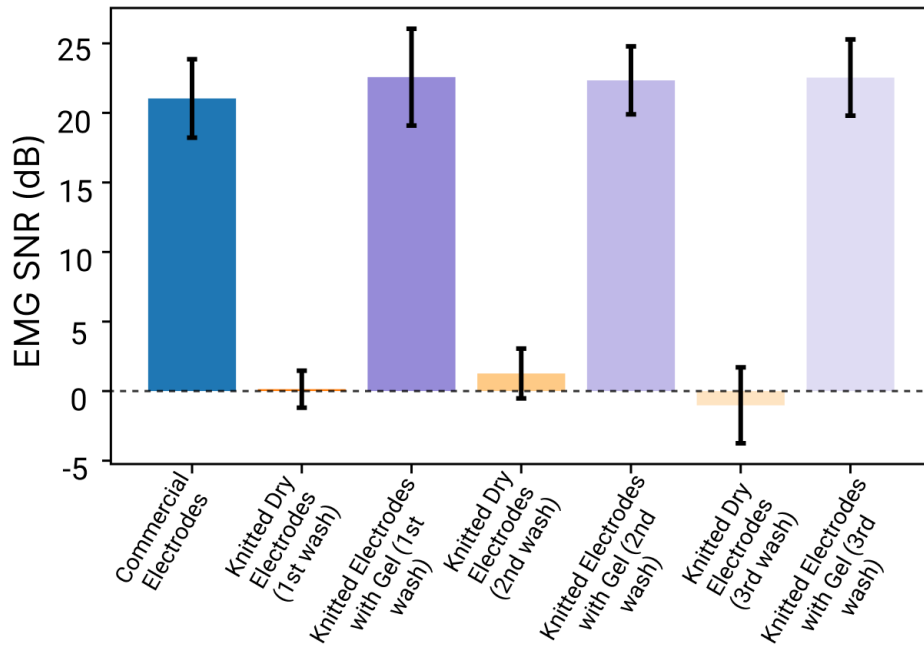


Figure 4.7: EMG SNR measurement before and after washing compared with commercial electrodes.

4.4.6 Signal quality evaluation under different Relay switching frequency

Relay is a mechanical switch that we used to switch shared electrodes between modalities physically by disconnecting and connecting the pads under the electromagnetic effect. The complete turn-on and turn-off enable reliable signal capture across modalities, eliminating the influence of EIS and capacitive sensing (active sensing) on EMG (passive sensing). However, too frequent switching could cause an unstable connection and shorten relay life. To balance the system's durability and signal stability with real-time sensing, we assess signal quality via EMG SNR evaluation across different relay switching frequencies. As shown in Figure 4.8, the EMG SNR remains stable for switching times greater than or equal to 100 ms, staying around 25 dB with small variation on Biceps. For switching times below 100 ms, the signal quality decreases and becomes less stable, as indicated by the larger variation. According to the results, we finally chose 80ms switching intervals, which ensure real-time, stable signal capture. Under this condition, our system could achieve a 6.25Hz frame rate.

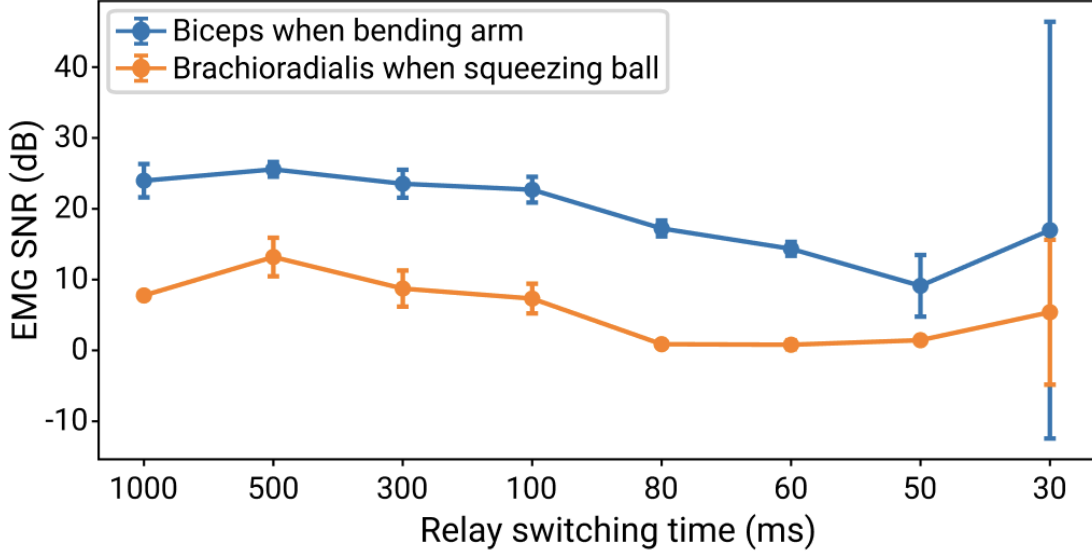


Figure 4.8: EMG SNR measurement under different relay switching intervals.

4.4.7 Bluetooth Low Energy (BLE) evaluation

To evaluate the wireless communication performance of the multimodal sensing system, we measured BLE metrics for all three sensing modalities. We report latency, throughput, and dropout rate, and evaluate these metrics on both a PC-based receiver and a customized mobile application to compare BLE behavior across development and deployment platforms. Throughput was defined as the total number of successfully received payload bytes divided by the measurement duration, i.e., $\text{Throughput} = B_{\text{rx}}/T$, where B_{rx} denotes the total received bytes and T denotes the duration of the measurement window. Dropout rate was calculated based on packet sequence continuity as $\text{Dropout Rate} = (N_{\text{expected}} - N_{\text{received}})/N_{\text{expected}}$, where N_{expected} is the expected number of packets inferred from the observed sequence range and N_{received} is the number of successfully received packets. Latency was defined as the elapsed time between data generation on the microcontroller and reception at the host, given by $\text{Latency} = t_{\text{host}} - t_{\text{device}}$, where t_{device} is the device-side timestamp and t_{host} is the corresponding host-side timestamp. On the PC, t_{host} corresponds to the packet reception time, whereas on the mobile application it corresponds to the reception or rendering time used by the interface pipeline. The resultant metrics measured on PC and the mobile application are listed in Table 4.1. The PC receiver achieves near-lossless transmission with lower latency. Throughput remains similar across PC and mobile platforms. Although EMG exhibits a drop rate of up to 20% on the mobile application, its high sampling rate (1000 Hz) still enables real-time visualization.

4.5 Implementation

4.5.1 Data Collection

We collected synchronized multimodal signals to support cross-modality prediction and rehabilitation task assessment using 4-channel EMG, 8-channel EIS, and 1-channel capacitive sensing. Data were acquired via serial communication with USB power and continuously logged to CSV files. During collection, we provided real-time visualizations of all streams to verify signal quality and to quickly detect potential issues such as signal dropouts, saturation, electrode contact changes, or labeling mistakes. The protocol involved one participant, seated on a chair, performing four rehabilitation exercises same as the ones in the real rehabilitation scenario. During the whole

Table 4.1: BLE transmission performance across sensing modalities on PC and mobile application.

Platform	Modality	Latency	Throughput	Drop Rate
PC	EIS	29.6 ± 11.6 ms	0.98 KB/s	0%
	EMG	36.8 ± 5.4 ms	5.6 KB/s	0%
	Capactive sensing	21.1 ± 14.9 ms	0.86 KB/s	0%
Mobile app	EIS	43.1 ± 34.7 ms	1.05 KB/s	0%
	EMG	44.1 ± 27.4 ms	6.06 KB/s	20%
	Capactive sensing	48.9 ± 30.1 ms	0.96 KB/s	9.1%

data collection process, the ground truth joint bending angle was captured in real time through Mediapipe using a camera mounted on the laptop.

For Task 1 (Squeeze Ball), each repetition cycle began with the participant picking up the ball, during which the arm naturally bent, followed by returning to a comfortable position to perform three consecutive squeezing actions. The participant then extended the arm to drop the ball and placed the hand on the table for rest. This sequence was repeated six times per trial, with a total of 10 trials. The ground-truth squeezing force was measured using four force-sensitive sensors distributed on the ball.

For Task 2 (Rotate Flexbar), each repetition cycle followed a similar structure: the participant first picked up the Flexbar with a natural arm bending motion, returned to a comfortable position, and performed three rotation actions. Afterwards, the arm was extended to drop the Flexbar, followed by placing the hand on the table for rest. Each trial consisted of six such cycles, with a total of 10 trials. The ground-truth rotation angle (degrees) was estimated from video tracking using ArUco markers implemented in OpenCV. Two ArUco tags were attached to the Flexbar linearly, and their 2D pixel coordinates were detected in each video frame. We computed the marker centers as the average of the four detected corner points, then connected the two centers to form a line. The bar rotation was calculated by comparing the line angle relative to the horizontal axis, using the formulation $\theta = \text{atan2}(-\Delta y, \Delta x)$ (in degrees), where $-\Delta y$ accounts for the image coordinate

convention. To reduce detection noise, we applied a short median filter over a 5-frame window.

For Task 3 (Bend Flexbar), each repetition cycle also began with picking up the Flexbar, followed by returning to a comfortable position to perform three bending actions. The participant then extended the arm to drop the Flexbar and placed the hand on the table for rest. Each trial consisted of six such cycles, with a total of 10 trials. The ground-truth Flexbar bending angle was captured using three ArUco markers placed at the center and two ends of the Flexbar. The marker positions were tracked from video frames using OpenCV, and two vectors were formed from the center marker to the two side markers. The Flexbar bending angle was then calculated as the angle between these two vectors.

For Task 4 (Touch Ruler), we formulated an 8-class classification problem where the participant sequentially touched one of eight discrete heights (0, 5, 10, 15, 20, 25, 30, 35 cm). After each touch, the hand returned to a consistent resting position on the knees before proceeding to the next height. One repetition consisted of completing the full sequence from 0 to 35 cm with 5 cm increments. Each trial repeated this sequence six times, and a total of 10 trials were collected. Labels were defined based on the target height, and 10 cm was set as the participant’s natural horizontal reach without raising or lowering the arm. To standardize execution and reduce labeling ambiguity, we recorded a video during collection to further improve consistency across sessions.

Overall, the full data collection session lasted approximately 3.5 hours including rest periods. We also recorded session notes on any irregularities while ensuring that visualization and file logging remained synchronized without observable delay.

4.5.2 Data Processing

All recorded signals were processed offline in Python before multimodal synchronization and the results are shown in Figure 4.9. Since EMG, EIS, capacitive sensing, joint-angle, flexbar rotating and bending angles, and force signals were obtained at different effective sampling rates, each stream was first processed separately and then aligned using timestamps. Raw timestamps were standardized across files, converted to datetime format, and sorted in chronological order. Invalid timestamps and non-numeric signal values were removed. For mixed log files, signals were separated by modality before further processing.

EMG signals were first cleaned to remove transient artifacts caused by relay switching. Each channel was then median-centered and rectified:

$$e_c(t) = |x_c(t) - \text{median}(x_c)|,$$

where $x_c(t)$ is the raw EMG signal from channel c , and $e_c(t)$ is the rectified signal. Remaining spikes were suppressed using an adaptive threshold. EMG envelopes were then extracted using a moving RMS window and smoothed with a moving-average filter. The resulting envelopes were normalized per channel for comparison across trials.

EIS signals were processed from the eight impedance channels. Invalid low-value samples caused by relay switching or inactive measurement periods were removed using an adaptive threshold that separated each channel into low-value and high-value groups. Large outliers and sudden jumps were removed based on channel-specific statistical thresholds. The remaining signal was smoothed using a moving-average filter, and short missing regions introduced during filtering were filled using forward and backward filling.

Capacitive sensing signals were processed by removing samples outside the expected measurement range and trimming unstable samples near relay transitions. The remaining samples were re-indexed to form a continuous sequence and smoothed using a moving-average filter. For angle-based tasks, the processed capacitive signal was later aligned with joint-angle measurements using timestamps.

Joint-angle signals were cleaned by removing invalid values and suppressing large spikes. For rotation-based and bending-based tasks, the angle sequence was unwrapped to avoid discontinuities at wrap-around boundaries, interpolated on the time axis, smoothed with a rolling window, and then wrapped back into the desired angular range.

After modality-specific processing, all signals were synchronized into a common analysis table. EMG was used as the reference timeline because it had the highest sampling rate. EIS, capacitive sensing, joint-angle, flexbar rotation and bending angles, and force signals were aligned to the nearest EMG timestamp using modality-specific tolerance windows. Duplicate timestamps in lower-rate streams were averaged before synchronization. Samples without a nearby valid measurement were kept as missing values rather than being artificially interpolated across inactive sensing periods.

The final synchronized data contained the processed EMG envelopes, cleaned EIS channels,

smoothed capacitive signal, joint-angle measurements, flexbar rotating and bending angles, and force signals when available. Signal quality and temporal alignment were checked by plotting the processed streams on a shared time axis.

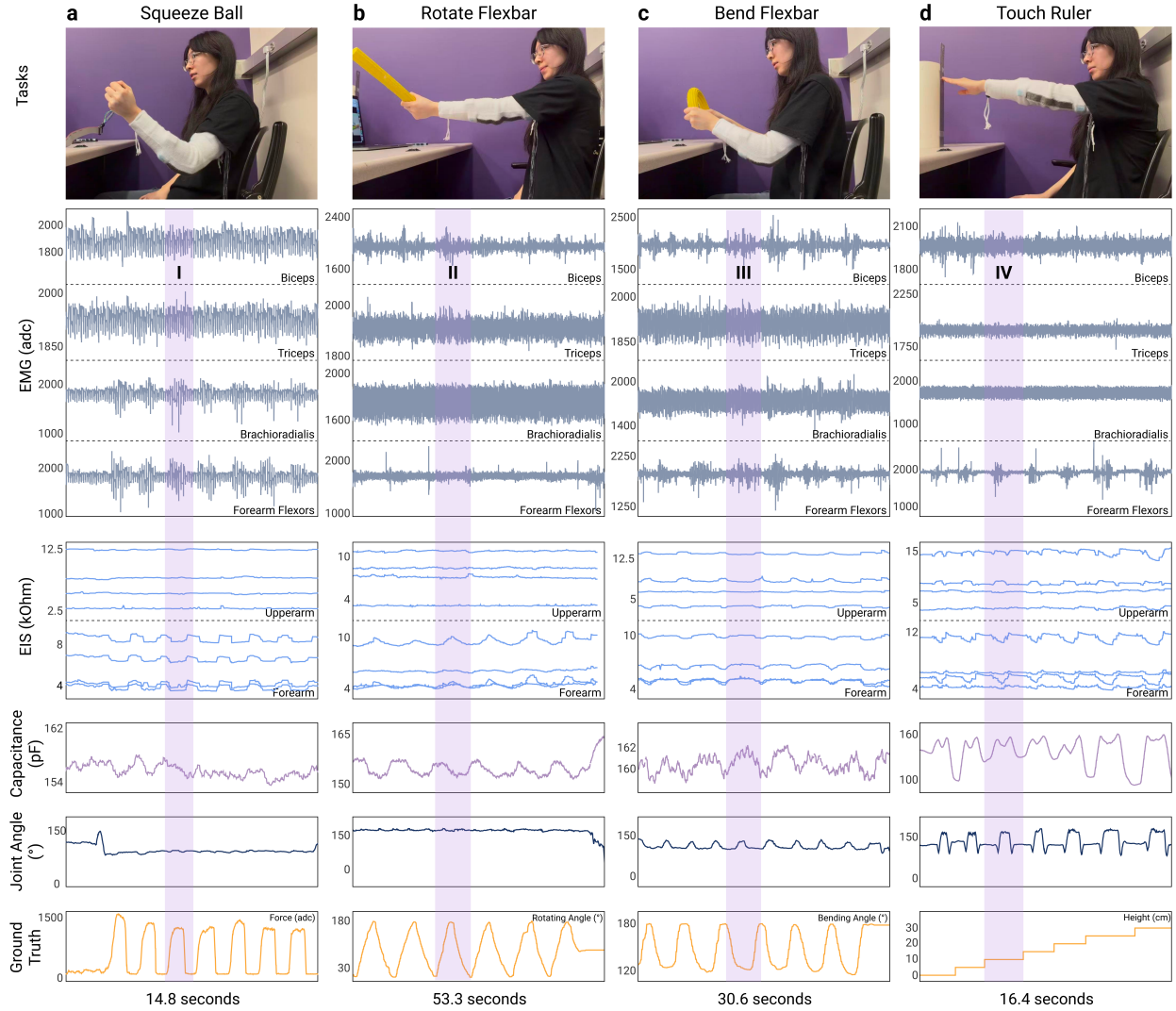


Figure 4.9: Signals of all three modalities, joint bending angle and the corresponding ground truth collected when the participant is perform four typical rehabilitation tasks: (a) Squeezing Ball, (b) Rotating Flexbar, (c) Bending Flexbar, and (d) Touching Ruler. Highlighted section I, II, III, and IV mark one active action for each tasks.

As illustrated in Figure 4.9, each modality captures distinct yet complementary patterns across tasks. In Task 1, when the participant squeezed the ball, the EMG signals increased mainly in the forearm, while the upper-arm signals did not change much. This suggests that the squeezing motion mainly used the forearm muscles for hand and finger force. The EIS signals showed a similar pattern: most changes appeared in the forearm, while the upper arm stayed almost unchanged. This makes sense because the task did not involve elbow bending or arm rotation, so the capacitive sensing signal also stayed mostly stable. In Task 2, the participant kept the arm lifted and rotated the Flexbar. Most EMG channels did not show large changes, except for the biceps. This may be because the arm and forearm muscles were already holding a steady force to keep the Flexbar horizontal, so their EMG did not change much over time. The biceps may have changed more because it helped support the arm and contributed to the rotation. However, the EIS signals changed clearly in both the upper arm and forearm. This shows that EIS can capture changes that EMG may miss, especially when muscle activation stays relatively steady but the muscle shape and tissue pressure change during movement. The capacitive sensing signal also changed during rotation, which may come from changes in contact between the electrodes and the skin.

In Task 3, during Flexbar bending, the forearm and biceps EMG signals increased at each bend. The greatest changes appeared in the forearm flexors and the biceps, suggesting that these muscles were highly involved in the bending motion. The EIS signals also changed clearly with each bend, showing that the tissue inside the arm changed during the movement. In Task 4, the participant reached forward to touch the ruler at different heights. The forearm flexor EMG signals changed the most, likely because these muscles were stretched and engaged during the reaching motion. As the touch height became higher, the reaching distance increased, and the EMG signals from these muscles also became larger. The EIS signals also responded consistently to the reaching motion. As the reaching distance increased, the EIS signal variation lasted longer, indicating that EIS can capture the duration and extent of muscle/tissue deformation during the movement. The capacitive sensing signal change reflected the general trend of the participant's behaviour, which involved bending and extending arms repeatedly.

Overall, we observe the following insights: (1) Capacitive sensing and EIS provide intuitive information about elbow motion and internal tissue changes. (2) EIS captures complementary information beyond visible motion and EMG activation. (3) All three modalities align during

task execution while emphasizing different aspects of movement. The dataset captures meaningful relationships between muscle activation, tissue deformation, and joint motion across clinically grounded tasks. The design, based on real rehabilitation routines with varied force and movement levels, suggests its potential to generalize to broader clinical settings and support future studies.

4.6 Discussion and Future Works

This work demonstrates that multimodal rehabilitation monitoring can be achieved within a wearable textile form factor by jointly considering sensing performance, hardware integration, and usability constraints. By integrating EMG, EIS, and capacitive sensing into a shared-electrode architecture, *MultiSensKnit* reduces hardware redundancy while preserving signal quality across modalities. This result suggests that multimodal sensing systems do not necessarily require independent sensing interfaces, and careful co-design of sensing principles and electrode placement can significantly simplify system complexity.

Our findings further highlight important trade-offs between electrode design and sensing performance. Increasing electrode size improves EMG SNR, reduces bioimpedance for EIS, and enhances capacitive sensitivity by improving electrical coupling. However, these benefits saturate beyond a certain size, indicating diminishing returns once sufficient contact area is achieved. This suggests that optimal electrode design should balance sensing performance with wearability constraints, such as comfort, breathability, and garment fit.

The shared-electrode and time-multiplexing strategy also introduces system-level considerations. While relays and multiplexers enable efficient reuse of electrodes, they impose constraints on sampling rate and require careful scheduling to avoid cross-modal interference. Our evaluation shows that an 80 ms switching interval achieves a balance between signal quality and system stability, resulting in a 6.25 Hz multimodal frame rate. Although sufficient for many rehabilitation tasks, this rate may limit applications requiring higher temporal resolution, such as rapid motor control analysis.

From a usability perspective, embedding sensors into a knitted garment improves comfort and reduces setup burden compared to traditional systems. The breathability and washability of the textile electrodes support long-term use, which is critical for rehabilitation scenarios that require repeated daily practice. However, the current system still relies on conductive gel to ensure reli-

able skin contact, which introduces additional steps and may limit user adoption in fully at-home settings.

Finally, while our pilot study demonstrates the feasibility of multimodal monitoring and cross-modality learning, the evaluation remains limited in scale. The current dataset was collected from a single participant under controlled conditions, and further validation is needed to assess generalizability across users, sessions, and real-world environments.

Several directions can further extend the capabilities and applicability of *MultiSensKnit*.

First, improving the skin–electrode interface by developing dry or semi-dry textile electrodes that maintain low and stable impedance without conductive gel will be considered. Possible approaches include surface treatments, hybrid materials, and designs that apply consistent pressure to improve contact during movement.

The current system relies on external power and wired connections between the sleeve and control electronics. Future designs will integrate a compact battery-powered module with optimized energy use to enable fully untethered operation. This requires evaluating power consumption across sensing, BLE transmission, and real-time processing for extended daily use.

While this work focuses on the upper limb, the design can be extended to other body regions such as the knee, wrist, or fingers. This will support a wider range of rehabilitation tasks but requires adjustments in electrode placement, textile structure, and sensing models to match different body parts.

Future designs should also improve scalability and personalization. The system should support multiple garment sizes and adaptive fitting for different body shapes. It should also include calibration methods and adaptive models to account for differences in physiology and movement across users.

A key next step is to conduct studies with a larger and more diverse population, including stroke survivors with different levels of impairment. Long-term studies in home settings will help evaluate how multimodal sensing can track recovery over time and support clinical decisions.

This work also points toward closed-loop rehabilitation systems that continuously sense, interpret, and guide user behavior. Future research can study how multimodal signals can be translated into actionable feedback that improves motor learning, adherence, and rehabilitation outcomes in everyday settings.

4.7 Conclusion

In this work, we presented *MultiSensKnit*, a multimodal sensing sleeve that integrates EMG, EIS, and capacitive sensing within a seamlessly knitted textile architecture. By embedding co-located electrodes into a machine-knitted sleeve and coupling them with portable electronics, firmware, and a mobile interface, we established a scalable and wearable platform for synchronized multimodal data acquisition and real-time visualization.

Our results demonstrate that the knitted electrode design enables robust acquisition of muscle activity, tissue conductivity, and joint kinematics in a form factor that resembles everyday clothing. Through systematic optimization of electrode geometry, silicone dielectric thickness, and fabrication parameters, we achieved reliable signal quality across modalities while preserving comfort, washability, and breathability. Comparative evaluations confirmed that knitted electrodes outperform conventional hydrogel electrodes in long-term usability, while maintaining equivalent or superior sensing fidelity.

A user-guided design process further refined the garment’s comfort, stability, and social acceptability, ensuring its suitability for both clinical and in-home use. Pilot deployments validated the feasibility of continuous multimodal monitoring during rehabilitation exercises, with multimodal signals exhibiting aligned and interpretable trends. These datasets supported the development of machine learning models capable of fusing heterogeneous signals to assess motor function, predict recovery trajectories, and provide clinically meaningful feedback.

Taken together, this study establishes a comprehensive platform that bridges textile engineering, wearable electronics, and rehabilitation science. *MultiSensKnit* advances the state of the art by demonstrating that intelligent textiles can provide clinically relevant, multimodal measurements in real-world settings. The methods and insights generalize to broader contexts, including neuromuscular disorders, orthopedic recovery, and athletic training. By uniting scalable textile manufacturing with a mobile interface, this work paves the way for patient-friendly, data-driven rehabilitation systems that extend continuous care from the clinic to the home.

Chapter 5

DISCUSSION, CONCLUSION, AND FUTURE RESEARCH DIRECTIONS

5.1 General Discussion

This thesis investigated how closed-loop sensing and feedback systems can support embodied human interaction in real-world settings. Across three projects, the systems explored different contexts: Braille learning, physical training, and rehabilitation monitoring. Although the applications are different, they share the same goal: to sense user action during an activity, interpret task-relevant information, and provide feedback that supports the user’s next action.

Across these projects, three design aspects appeared repeatedly: form factor, sensing, and feedback.

In *BrailleRhythm*, the form factor needed to remain unobtrusive during tactile exploration. The system used a thin, flexible, and lightweight Velostat sheet placed under customized Braille cards. This design preserved the user’s tactile perception of the Braille symbols while adding sensing capability to the learning material. The sensing method also needed to match the task. Since BLV learners mainly rely on touch when learning Braille, the system used tactile sensing rather than an indirect sensing method. This allowed the system to capture finger interaction directly and recognize Braille input with high accuracy. For feedback, the system needed to respond quickly and clearly. Audio feedback was simple and directly connected to the user’s touch, helping rebuild the link between tactile symbols and auditory language information. Overall, *BrailleRhythm* shows how a closed-loop system can support tactile learning by integrating sensing and feedback into the Braille learning process.

In the CPR self-training glove, the form factor needed to support repeated, high-force compression. The sensors were integrated into the glove, while the circuit was placed on the wrist to keep the system wearable and portable. Because CPR practice involves repeated pressure and deformation, durability and robustness were also important. The repeatability test helped evaluate whether the sensing surface could remain stable under repeated use. For sensing, many CPR

feedback systems can measure compression force or depth, but they do not always capture hand pose. Hand pose could be measured using an additional camera-based system, but this would increase system complexity and reduce portability. Instead, tactile sensing allowed the glove to capture pressure distribution from the hand itself. The same sensing surface could support force, rate, and hand-pose estimation without requiring extra hardware. For feedback, the system should convey three CPR metrics at the same time. Audio feedback can be immediate, but it is difficult to interpret many correction patterns at once. Visual feedback can show more information, but it may distract the user from the physical task. Haptic feedback keeps guidance on the body, but vibration patterns can be harder to learn and may be masked during movement. This suggests that feedback should guide the user without overwhelming them. In future versions, combining haptic and audio feedback may help use the advantages of both modalities. Overall, this project shows how a wearable closed-loop system can support dynamic physical training.

In *MultiSensKnit*, the form factor highlights the importance of balancing wearability and signal quality. The textile-based sleeve supports more natural use in at-home rehabilitation settings, but long-term wearing can affect signal quality due to less stable contact with the skin after movement or prolonged use. This shows that soft wearable systems need to consider not only comfort, but also contact stability, durability, and long-term reliability. For sensing, the system integrated capacitive sensing, EMG, and EIS to capture joint movement, muscle activity, and tissue-related changes during rehabilitation exercises. More sensing modalities can provide richer information, but they also introduce interference and system complexity. For example, combining passive EMG with active EIS and capacitive sensing required careful switching and isolation to reduce cross-modality interference. For feedback, the strategy needed to match the rehabilitation context. The goal of this system was not only immediate correction, but also monitoring and progress tracking. Therefore, visualization was more appropriate than complex haptic or audio feedback. It allowed users and clinicians to observe multimodal signals, understand changes over time, and record the progress easily. Overall, *MultiSensKnit* shows how textile-integrated multimodal sensing can support rehabilitation monitoring during natural body movement.

To summarize, for interactive systems that support embodied interaction in real world, their form factor should preserve natural interaction through unobtrusive design, while balancing durability, portability, wearability, and signal quality. Their sensing methods should capture task-relevant

signals, while minimizing hardware complexity and modality interference. Their feedback strategy should match the task context, while remaining low-latency, low-burden, and clear across multi-modal combinations.

5.2 Future Work

These projects also reveal several challenges that remain open for future work.

First, future systems need to become more robust for long-term use. Soft and textile-based systems can improve comfort and preserve natural interaction, but they still face challenges such as durability, repeated deformation, washing, and stable skin contact. These issues are especially important when systems move from short studies to daily use.

Second, future systems need better personalization. Users differ in body size, movement patterns, skin properties, force perception, and feedback sensitivity. These differences can affect both sensing quality and feedback effectiveness. Future systems should support calibration and adjustable hardware while keeping the setup process simple.

Third, future systems need stronger generalization across users, tasks, and environments. Real-world use introduces motion, noise, contact variation, and behavioral differences that are difficult to fully capture in controlled studies. Future work should improve sensing and feedback strategies so that systems remain reliable across these variations.

Together, these directions point toward embodied interaction systems that are more robust, adaptive, and ready for real-world deployment.

5.3 Conclusion

This thesis explored how closed-loop sensing and feedback systems can support embodied human interaction across Braille learning, physical training, and rehabilitation monitoring. Through three interactive systems, it showed that effective embodied interaction depends on the co-design of form factor, sensing, and feedback.

The three projects show that form factor affects how naturally users can interact with the system, sensing determines what task-relevant information can be captured, and feedback shapes how users understand and adjust their actions. These aspects cannot be designed separately. They need to work together within the activity itself.

Overall, this thesis contributes three system designs, implementation strategies, empirical evaluations, and cross-project design insights. These contributions show that closed-loop interactive systems can better support real-world embodied activities when they fit the body, capture meaningful signals, and provide feedback that supports ongoing action.

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Appendix A

CPR STUDY QUESTIONNAIRE AND POST-INTERVIEW QUESTIONS

This appendix lists the questionnaire and post-interview questions used in the CPR training study. Participant responses are not included.

A.1 System Evaluation Questionnaire

After completing the CPR training session, participants answered the following system evaluation questions on a 5-point Likert scale. For agreement-based items, 1 indicated strongly disagree and 5 indicated strongly agree. For workload items, 1 indicated very low demand and 5 indicated very high demand.

1. I was able to clearly understand what the system conveyed.
2. The system was helpful for learning CPR.
3. The system was easy to use.
4. This training system increased my confidence in performing CPR in a real-life situation.
5. Mental demand required to use the system.
6. Physical demand required to use the system.

A.2 Post-interview Questions

After the system evaluation questionnaire, participants answered the following post-interview questions.

1. What feedback type did you experience?

2. Do you think the system you used was helpful for CPR training? If yes, why? If not, why not?
3. During CPR training, was the feedback provided by the system delivered effectively? Were you able to clearly distinguish the content of the feedback received? For participants who had no feedback, how did you recall the video instruction during training and apply it?
4. If there were any difficulties with the feedback system, including the no-feedback condition, what aspects were inconvenient?
5. What suggestions do you have for improving the feedback system?

Appendix B

ADDITIONAL FIGURES

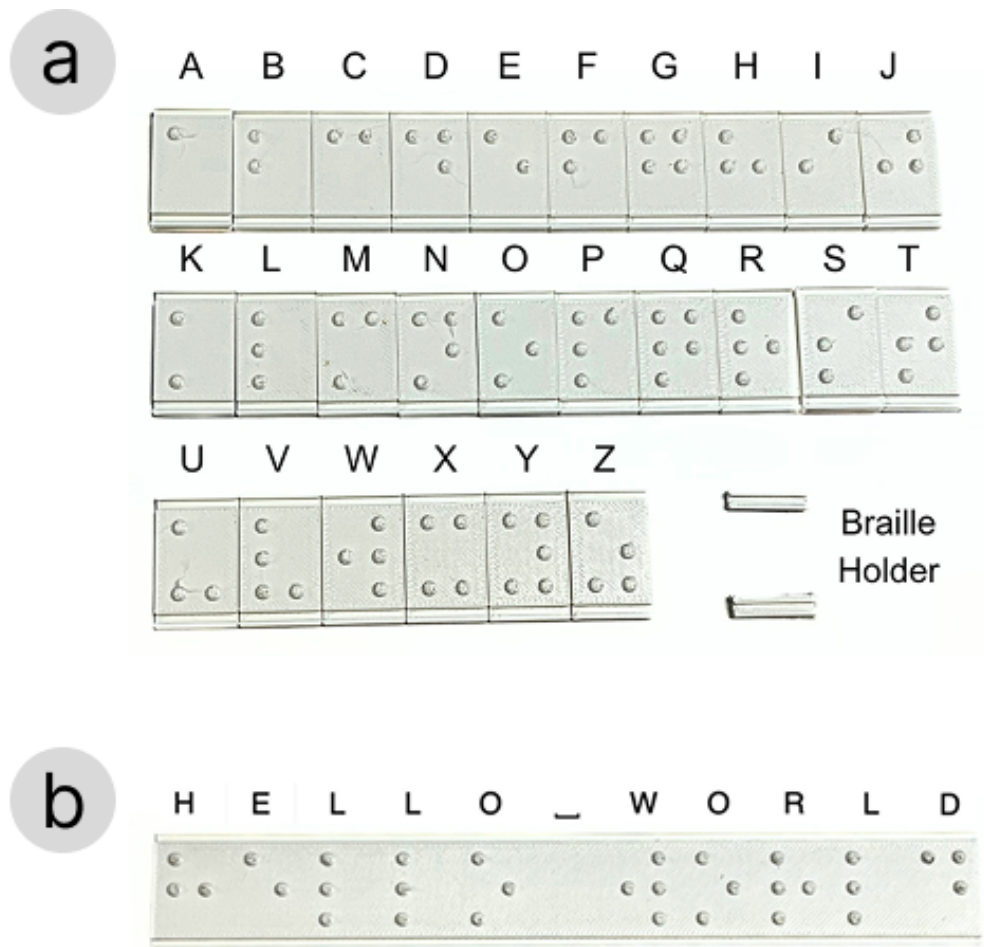


Figure B.1: Customized 3D-printed Braille cards (a) in modularized form, and (b) full-block form.

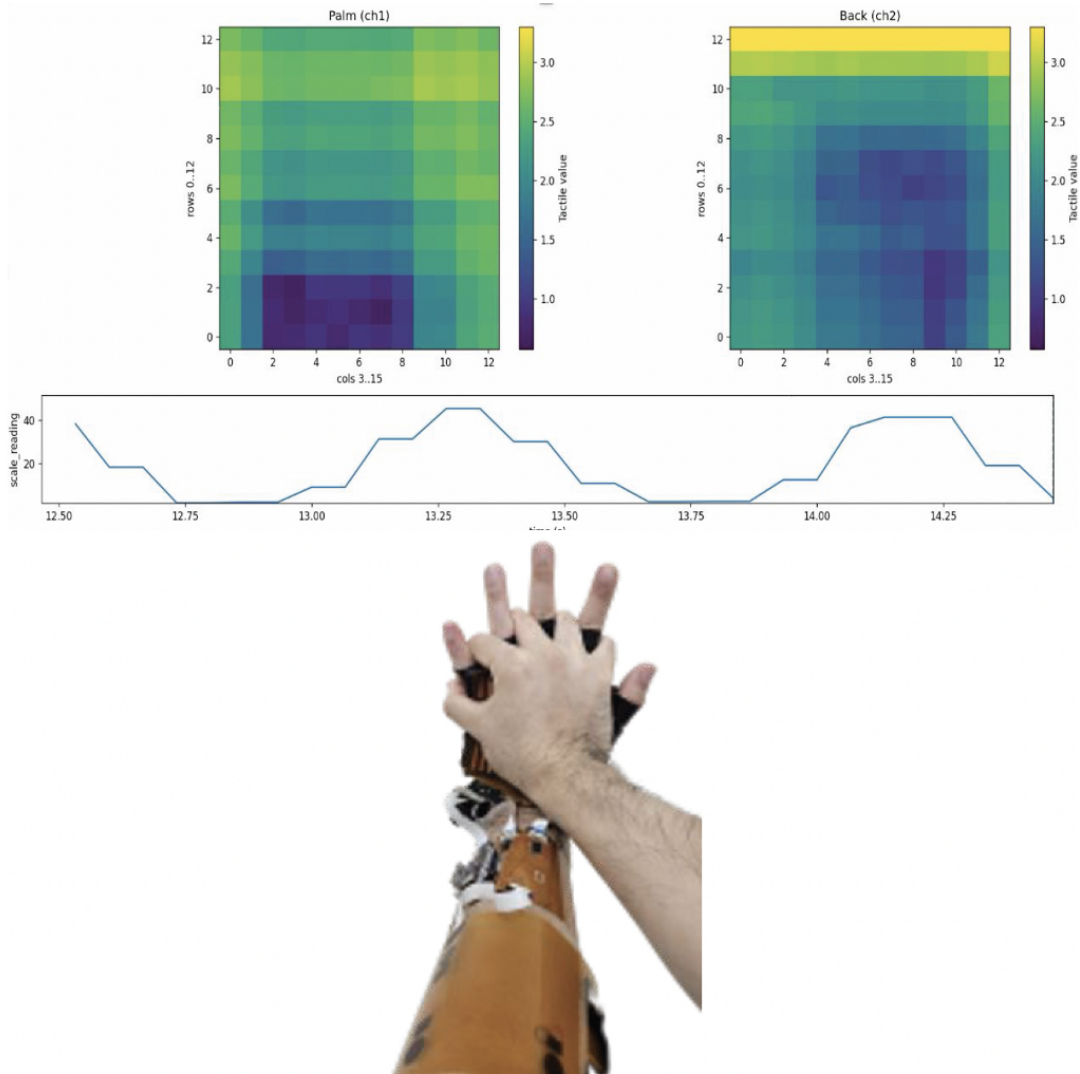


Figure B.2: Tactile heatmaps from sensor during CPR compression. First row demonstrates the distributed tactile heatmap obtained from the sensor. The second row shows the scale readings when users are performing CPR. The bottom figure illustrates how users wear our system and perform CPR.

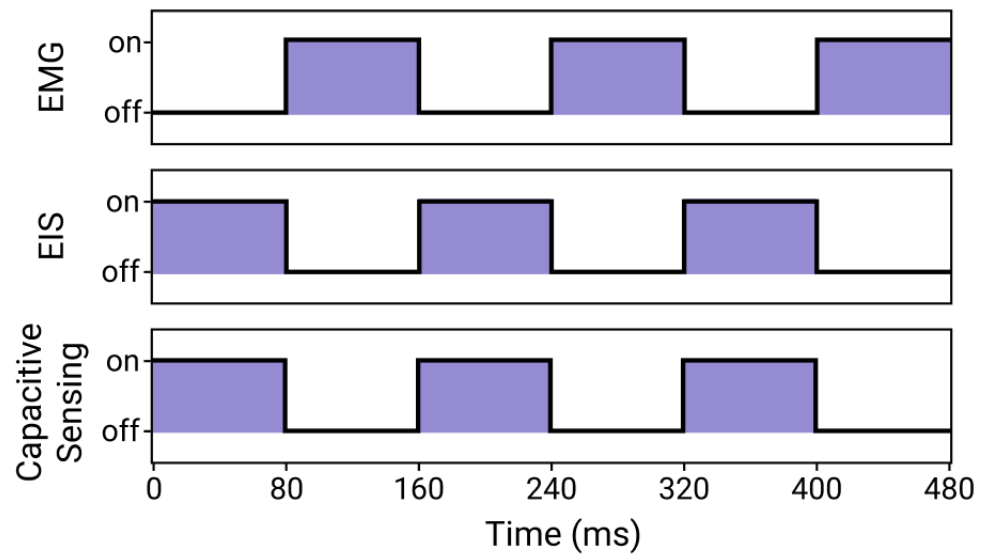


Figure B.3: Multi-modality switching (Time-multiplexing) mechanism of *MutliSensKnit*

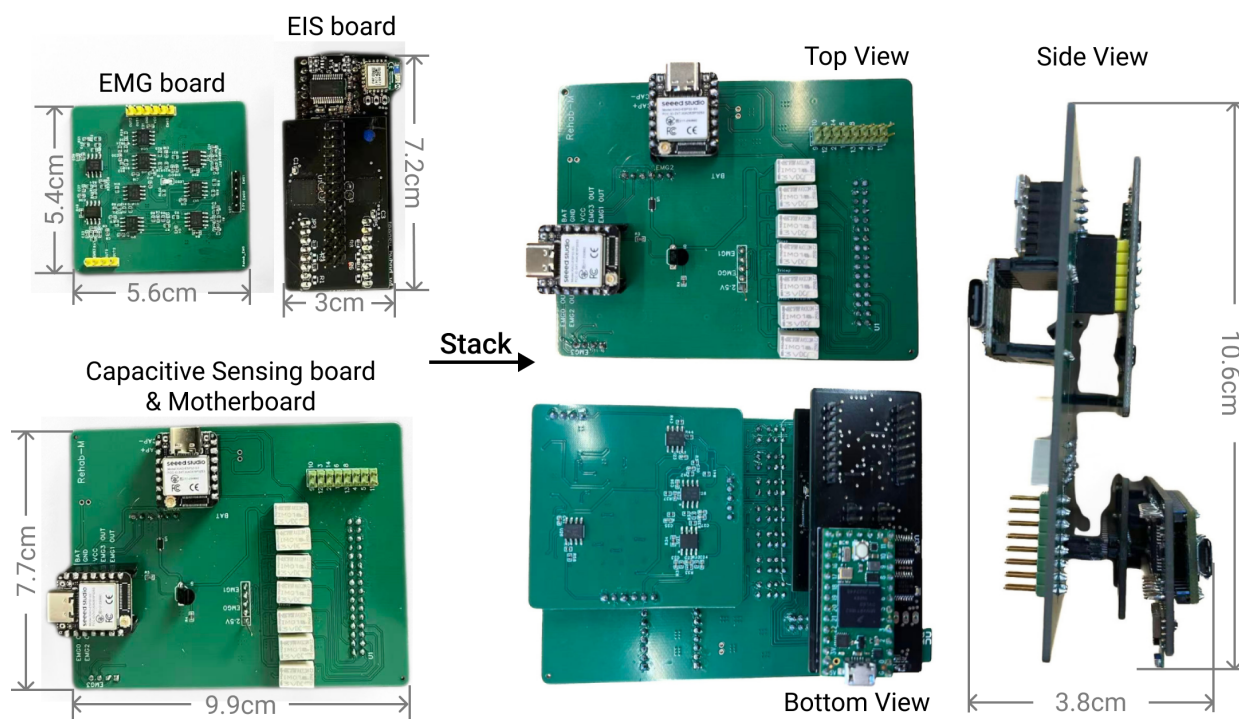


Figure B.4: PCB of *MutliSensKnit*. Left side is the PCBs for each modality and Right side shows by stacking the PCBs together, the board can be more compact.

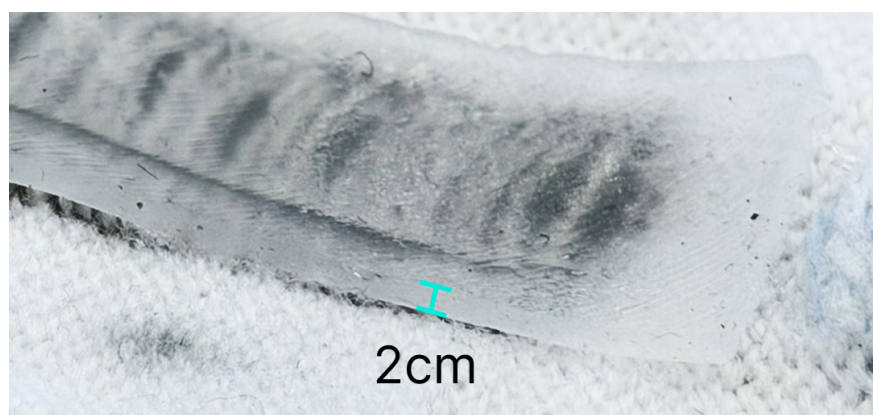


Figure B.5: Dielectric (silicone) layer of the customized capacitor in *MutliSensKnit*

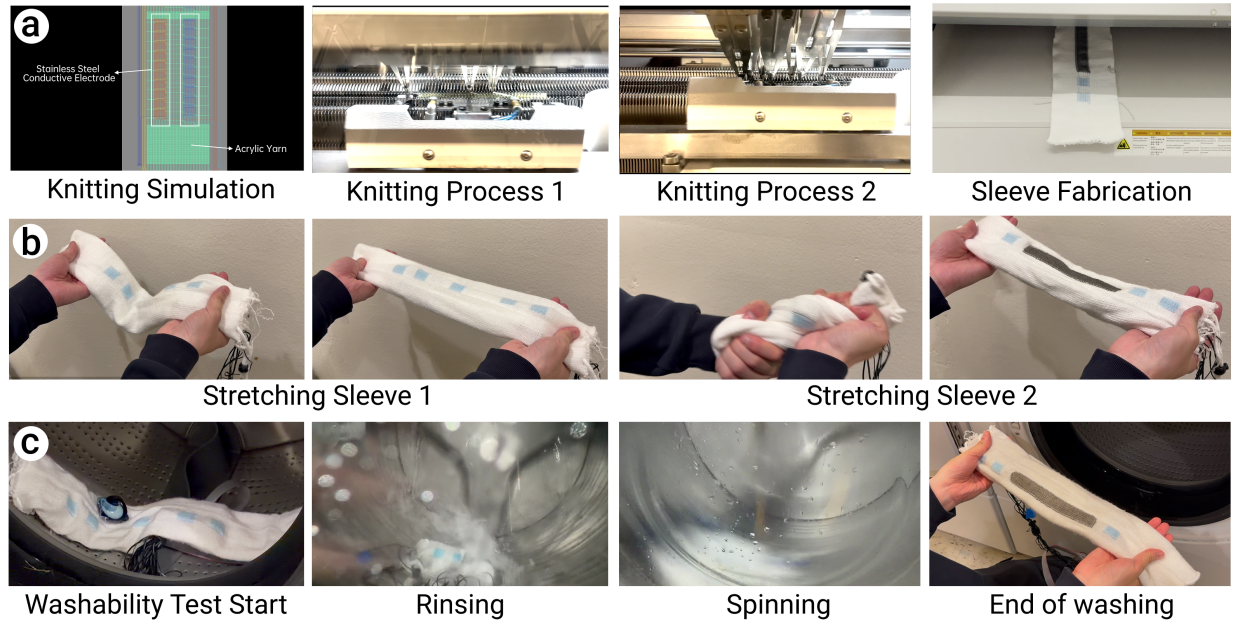


Figure B.6: (a) Knitting process of the sleeve fabrication. (b) Stretchability and (c) washability process of *MultiSensKnit*