

Intelligent Textiles for Physical Interactions

by

Yiyue Luo

B.S., University of Illinois Urbana Champaign (2017)

M.S., Massachusetts Institute of Technology (2020)

Submitted to the Department of Electrical Engineering and Computer Science in Partial
Fulfillment of the Requirements for the Degree of

Doctor of Philosophy

at the

MASSACHUSETTS INSTITUTE OF TECHNOLOGY

September 2024

©2024 Yiyue Luo. All rights reserved.

The author hereby grants to MIT a nonexclusive, worldwide, irrevocable, royalty-free license to exercise any and all rights under copyright, including to reproduce, preserve, distribute and publicly display copies of the thesis, or release the thesis under an open-access license.

Authored By: Yiyue Luo
Department of Electrical Engineering and Computer Science
August 21, 2024

Certified By: Wojciech Matusik
Professor of Electrical Engineering and Computer Science
Thesis Supervisor

Certified By: Tomás Palacios
Professor of Electrical Engineering and Computer Science
Thesis Supervisor

Accepted By: Leslie A. Kolodziejcki
Professor of Electrical Engineering and Computer Science
Chair, Department Committee for Graduate Students

Intelligent Textiles for Physical Interactions

by

Yiyue Luo

Submitted to the Department of Electrical Engineering and Computer Science
on August 21, 2024, in partial fulfillment of the
requirements for the degree of
Doctor of Philosophy

Abstract

Human-environment interaction is a fundamental aspect of our daily lives, involving the constant use of our sensory and motor systems to extract, process, and communicate information. However, capturing, analyzing, and reproducing these interactions pose significant challenges due to their pervasive, variable, and prolonged nature, as well as their unique character for each individual. Despite these challenges, it is essential to develop systems that can accurately capture and reproduce human-environment interactions for a wide range of applications, including human behavior studies, health monitoring, human-computer interactions, and robot imitation learning. This thesis focuses on developing seamlessly integrated, scalable manufactured sensing and actuating systems, as well as advanced computational pipelines to capture, analyze, and reproduce adaptive ubiquitous physical human-environment interactions.

Acknowledgments

Reflecting on my Ph.D. journey, I am filled with gratitude for the abundance of joy amidst the inevitable challenges and surprises.

First and foremost, I extend my deepest appreciation to my advisor, Professor Wojciech Matusik, for his unwavering support and trust over the years. He consistently encouraged and guided me to explore new and ambitious ideas, always believing in my capabilities. I still remember my first year when he asked me to present at an annual funding review session, where all the other projects were presented by faculty members. Initially, I thought he was too busy, but he showed up at the review. It became clear that he wanted to give me the opportunity to present and receive feedback, helping me improve my soft skills. I am truly grateful for all the opportunities, trust, and support Wojciech has offered throughout the years. His support during the highs and lows of my Ph.D. journey has not only shaped my academic path but also taught me invaluable lessons on the significance of trust and mentorship.

I am equally thankful to my co-advisor, Professor Tomás Palacios, whose consistent encouragement and support have been a source of strength and confidence throughout the academic journey. In the past 6 years, I often experienced an identity crisis, unsure of which academic community I belonged to. Tomás always encouraged me to embrace this uniqueness and view it as a strength rather than a challenge. He has always inspired me to think big and provided resources to navigate the intricate landscape of interdisciplinary research.

I am extremely grateful for the insightful perspectives and unwavering support of my committee members, Professor Antonio Torralba and Professor Daniela Rus. I feel extremely fortunate to have had the opportunity to collaborate with them in the past years. I really appreciate the opportunity to extend my research into different areas, and I am grateful for all the innovative insights and unique perspectives on my projects and life throughout the years. Their feedback and advice have shaped my research vision and career path in so many ways.

I extend my heartfelt thanks to Professor Stefanie Mueller and Professor Jessica Hodgins,

for their roles as extraordinary role models, mentors, and collaborators. I would love to share my special thanks to Professor Elfar Adalsteinsson, my course advisor, whose brief yet impactful interactions during the semesterly advising sessions have always encouraged me to pursue my goals with confidence. I am particularly grateful to Dr. Yunzhu Li and Dr. Kui Wu, who mentored me when I was a junior Ph.D. student and shaped the way I approach and conduct research.

My Ph.D. journey would not be possible without collaboration with exceptional individuals. I would like to thank all of my collaborators. They have also significantly contributed to the works I will discuss in the dissertation: Michael Foshey, Chao Liu, Joseph DelPreto, Wan Shou, Young Joong Lee, Beichen Li, Andrew Spielberg, Junyi Zhu, Jie Xu, Mantian Xue, Jiadi Zhu, Alexandre Kaspar, Liane Makatura, Qiang Zhang, Junchi Yan, Joshua B Tenenbaum, Lara Zlokapa, Pulkit Agrawal, Bolei Deng, Liang Shi, Marek Hempel, Elaine McVay, Kewang Nan, Pratyusha Sharma, Cedric Honnet, Yunho Choi, SeungJun Kim, and Kyung-Joong Kim. I extend my appreciation to my current and former labmates in the Computational Fabrication Group for their friendship and collegiality, which have made the research environment truly inspiring: Timothy Erps, Petr Kellnhofer, Changil Kim, Mina Konaković Luković, Bohan Wang, Minghao Guo, Yichen Chen, Yifei Li, Pingchuan Ma, Yunsheng Tian, Donghun Ryu, James Minor, Taehyun Oh, Subra Sundaram, Megan Tjandrasuwita, Yichen Li, Allan Zhao, and Lara Zlokapa.

I have also received tremendous support from people at various institutions during my faculty job search. They have navigated me through the stressful but rewarding process. I would love to extend my sincere thanks to Adriana Schulz, Yuzhe Yang, Xuhai Xu, Nevidita Aurora, Scott Hudson, Xing-Dong Yang, Huaishu Peng, Vanessa Sanchez, Josiah Hester, Sean Follmer, Thijs Roumen, and Cindy Kao.

The assistance from the fantastic staff members at MIT has also made my Ph.D. life much easier and more enjoyable. I would like to share special thanks to Roger White, Mieke Moran, Janet Fischer, and the Infrastructure Group (TIG) at MIT CSAIL for their help through different stages of my Ph.D.

Last but not least, I am grateful to my friends and my family for their company and support. Your love and belief in me have been the driving forces behind my achievements. I

am extremely grateful to my parents, grandparents, and my husband Zeyu Wu, who have unconditionally supported my decisions throughout the years.

THIS PAGE INTENTIONALLY LEFT BLANK

Contents

List of Figures	15
List of Tables	21
1 Introduction	23
1.1 History of Smart Wearables	25
1.2 Human Data Capturing and Learning	27
1.3 Thesis Overview	28
 I Intelligent Textiles to Sense Human-Centered Physical Interac-	
tions	31
 2 Intelligent Carpet for Pose Estimation	33
2.1 Overview	33
2.2 Fabrication	35
2.3 Dataset	35
2.3.1 Data Collection	35
2.3.2 3D Pose Label Generation	36
2.3.3 Data Augmentation	38
2.4 3D Pose Estimation	39
2.4.1 Model	39
2.4.2 Single Person Pose Estimation	41
2.4.3 Multi-Person Pose Estimation	44

2.4.4	Failure Cases	46
2.5	Discussion	47
3	Digital Machine-Knitted Interactive Sensing Interfaces	51
3.1	Overview	51
3.2	Design and Fabrication	53
3.2.1	Knitted Resistive Sensors	53
3.2.2	Knitted Conductive Traces	55
3.3	Evaluation	56
3.3.1	Conductive Yarns	56
3.3.2	Number of Short-Rows.	57
3.3.3	Size of Sensing Unit	58
3.3.4	Washing Test	58
3.3.5	Performance under Deformation	59
3.3.6	Continuous Sensing Responses	59
3.4	Application	60
3.4.1	Interactive Textiles	60
3.4.2	Interactive Wearable	61
3.4.3	Tactile Sensing Wearables	62
3.4.4	Artificial Robot Sensing Skin	63
3.5	Discussion	64
4	Dynamic Modeling of Hand-Object Interactions via Tactile Sensing	67
4.1	Overview	67
4.2	Method	69
4.2.1	Tactile Sensing Glove	69
4.2.2	Dynamics Prediction Model	69
4.2.3	Pinball Loss for Uncertainty Estimation.	70
4.2.4	Contrastive Learning for Object Embeddings	71
4.2.5	Overall Loss and Evaluation Metrics.	72
4.3	Experiments	73

4.3.1	Data Collection	73
4.3.2	Results on “Wave” and “Throw”	74
4.3.3	Ablation Study on the Tactile Resolution	76
4.3.4	Results on “PingPong” and “Balance”	77
4.4	Discussion	78

II Intelligent Textiles to Augment Human-Centered Physical Inter- actions 80

5 Digital Machine-Knitted Pneumatic Assistive Wearables 81

5.1	Overview	81
5.2	Design and Fabrication	82
5.2.1	Pneumatic Actuators	82
5.2.2	Resistive and Capacitive Sensors	85
5.3	Evaluation	86
5.3.1	Pneumatic Actuators	86
5.3.2	Resistive and Capacitive Sensors	88
5.4	Interactive User Design Interface	89
5.4.1	Design Interface	89
5.4.2	Predictive Simulation	90
5.4.3	Knitting Instruction Generation	91
5.4.4	User Study	92
5.5	Application	95
5.5.1	Assistive Wearables	95
5.5.2	Soft Hand	96
5.5.3	Sensorized Two-Finger Grippers	97
5.5.4	Pneumatic Quadrapedal Robots	98
5.6	Discussion	99

6 Digital Machine-Knitted Passive Haptics 103

6.1	Overview	103
-----	--------------------	-----

6.2	Design and Fabrication	105
6.2.1	Principle	105
6.2.2	Designs for Various Motions	109
6.2.3	Parametric Templates	111
6.3	Evaluation	112
6.3.1	Passive Haptics	112
6.3.2	Binary Sensing	113
6.3.3	Preliminary User Evaluation	115
6.4	Application	117
6.4.1	Input Wearables	118
6.4.2	Soft Game Controller	120
6.4.3	Furniture Coverings	120
6.4.4	Virtual Texture Rendering	120
6.5	Discussion	122
7	Adaptive Tactile Interaction Transfer via Digitally Embroidered Smart Gloves	125
7.1	Overview	125
7.2	Design and Fabrication	127
7.2.1	Resistive Tactile Sensors	128
7.2.2	Vibrotactile Haptic Matrix	128
7.2.3	Integrated Tactile Sensing and Haptics Glove	130
7.3	Characterization	131
7.3.1	Resistive Tactile Sensors	131
7.3.2	Vibrotactile Haptics	132
7.4	Readout and Driving Circuits	134
7.4.1	Readout Circuit for Tactile Sensing Matrix	135
7.5	Driving Circuit for Vibrotactile Haptic Matrix	135
7.6	Perception of Vibrotactile Haptic Feedback	136
7.6.1	Pilot Study	136
7.6.2	Tactile Interaction Transfer for Tactile Occlusion Alleviation	138

7.7	Adaptive Tactile Interaction Transfer across Users	139
7.7.1	Method	139
7.7.2	Data Collection	141
7.7.3	Experiments	142
7.7.4	Results	143
7.8	Tactile Transfer for Teleoperation	146
7.8.1	Setup	146
7.8.2	Results	147
7.9	Discussion	148

III Intelligent Textiles for Robotics 151

8 Digitally Embroidered Impedance Sensors for Liquids Manipulation 153

8.1	Overview	153
8.2	Design and Fabrication	155
8.2.1	Embroidered Electrode Array	155
8.2.2	Read-out Circuit	157
8.3	Liquid Classification	158
8.3.1	Data Collection	158
8.3.2	Model	159
8.3.3	Results	160
8.4	Liquids Manipulation	161
8.4.1	Data Collection	161
8.4.2	Ground Truth Generation	161
8.4.3	Model	164
8.4.4	Results	164
8.4.5	Ablation Study	167
8.5	Discussion	168

9 Multi-Modal Digitally Embroidered Sensors for Tactual Perception 171

9.1	Overview	171
-----	--------------------	-----

9.2	Design and Fabrication	173
9.2.1	Tactile Sensing Matrix	173
9.2.2	FPGA-Enabled High-Speed Readout Circuit	174
9.2.3	Quantization Error Reduction	175
9.3	Evaluation	177
9.3.1	Shear Sensing	177
9.3.2	Vibration Sensing	178
9.3.3	Automatic Sensor Calibration	179
9.4	Application	180
9.4.1	Tactile Sensing Shoe Sole	180
9.4.2	Two-Finger Grippers with Integrated Tactile Sensors	181
9.4.3	Tactile Sensors for Robot Arm	181
9.5	Discussion	182
10	Conclusion and Future Work	183

List of Figures

1-1	Paradigm of a wearable intelligent assistant.	25
1-2	Comparison between smart wearables, epidermal electronics, 3D-printed electronics, and intelligent textiles.	26
1-3	History of smart textiles.	26
1-4	Overview of the thesis.	29
2-1	Pose estimation using an intelligent carpet.	33
2-2	Overview of resistive pressure-sensitive intelligent carpet.	35
2-3	Representative tactile images.	36
2-4	3D pose label generation.	37
2-5	Overview of the model for 3D human pose estimation.	39
2-6	Quantitative results on single person pose estimation.	42
2-7	Qualitative results of single-person 3D pose estimation across time steps.	42
2-8	Ablation studies.	43
2-9	Generalization results.	45
2-10	Quantitative results on multi-person scenarios.	46
2-11	Qualitative results of multi-person 3D human pose estimation.	46
2-12	Failure cases.	47
2-13	Intelligent carpet for VR locomotion.	48
2-14	Intelligent walker.	49
3-1	Example applications of KnitUI	51
3-2	KnitUI sensing structure.	54

3-3	Overview of KnitUI design and fabrication.	55
3-4	Characterization on numbers of short-rows, sizes, and washing cycles. . . .	57
3-5	Characterization on sensors with deformation.	59
3-6	Continuous resistance profile.	60
3-7	Interactive educational toys.	60
3-8	Interactive textile-based game controller.	61
3-9	Interactive wearables.	62
3-10	Tactile sensing socks.	63
3-11	A robot arm (KUKA) with knitted sensing covering.	63
4-1	Hand-object interactions using a tactile glove.	67
4-2	Dynamics prediction model.	70
4-3	Data collection setup and motion examples.	73
4-4	Qualitative visualizations for "Throw" and "Wave".	75
4-5	Ablation study on the resolution of the tactile glove.	77
4-6	Qualitative visualizations for "Ping-Pong" and "Balance".	77
5-1	Example applications of machine-knitted pneumatic actuators.	81
5-2	Overview of a machine-knitted sensing-integrated actuator	83
5-3	Illustration of three-layered structure knitting.	84
5-4	Actuator characterization.	86
5-5	Sensor characterization	88
5-6	Interactive user design interface.	89
5-7	Comparison between simulated and fabricated actuator shapes.	91
5-8	Task setups.	92
5-9	User study results.	93
5-10	Example designs by participants.	94
5-11	Assistive wearables	96
5-12	Soft hand	97
5-13	Two-finger gripper	97
5-14	Quadrupedal robot walking forward	98

5-15	Quadrupedal robot turning.	99
6-1	Example applications of <i>MagKnitic</i>	103
6-2	Principles of <i>MagKnitic</i>	106
6-3	Fabrication materials.	107
6-4	Knitting structures.	107
6-5	<i>MagKnitic</i> motions.	109
6-6	Example parametric design template for a <i>MagKnitic</i> design for angular interactions.	111
6-7	Characterization schematics.	112
6-8	Force response of ferromagnetic patches along vertical displacement.	113
6-9	Force response of ferromagnetic patches along horizontal displacement.	113
6-10	Binary sensing characterization.	114
6-11	Results of user study on user perception.	116
6-12	Results of user study on user input.	117
6-13	<i>MagKnitic</i> in wristbands.	118
6-14	Wearable T9 input interface with haptic feedback.	119
6-15	Sleeve-based shape input device and an interactive hat with haptic feedback for music control.	119
6-16	Knitted soft game controller.	120
6-17	Furniture covering	121
6-18	Interactive wearables for AR/VR.	121
6-19	Digitally embroidered electromagnet	123
7-1	Fabrication and structure of tactile interaction transferring smart gloves.	125
7-2	Applications of tactile interaction transferring smart gloves.	126
7-3	Materials and fabrication of the smart gloves.	127
7-4	Embroidered vibrotactile haptic matrix of various design variables	129
7-5	Design and fabrication procedures of the smart gloves.	130
7-6	Characterization of embroidered tactile sensor.	131
7-7	Simulation of embroidered magnetic coils.	132

7-8	Simulated and experimental magnetic flux from embroidered magnetic coils.	133
7-9	Vibration amplitudes of the vibrotactile units.	133
7-10	Resonant frequency of vibrotactile haptic units	134
7-11	Sensing readout and vibrotactile driving circuit.	134
7-12	Vibration displacement of neighboring haptic units.	135
7-13	Perception of vibrotactile haptic feedback of different amplitudes and frequencies.	137
7-14	Perception of vibrotactile haptic feedback of different spatial and temporal patterns.	137
7-15	Transfer physical tactile interaction for one person.	138
7-16	An overview of the pipeline for human model learning and inverse haptics optimization.	140
7-17	Illustration of the forward model	141
7-18	Offline validation of haptic output optimization.	143
7-19	Illustration of the forward model featuring an adaptive module.	144
7-20	Overview of the teleoperation experiment setup	145
7-21	Teleoperated grasping with optional tactile information transferring through haptic feedback.	147
7-22	Quantitative evaluation of teleoperated grasping.	148
8-1	System overview.	153
8-2	Embroidered impedance sensing matrix.	155
8-3	Embroidered electrode designs and characterization.	156
8-4	Read-out circuit diagram.	157
8-5	Sample impedance spectroscopy data for liquid classification.	159
8-6	Results of liquids classification.	160
8-7	Representative impedance responses for liquid state estimation.	162
8-8	Ground truth generation.	162
8-9	Results on liquid state estimation.	165
8-10	Model evaluation and ablation study.	167

9-1	Overview of multimodal tactile sensors.	171
9-2	Design and fabrication of multimodal tactile sensors.	173
9-3	FPGA-based readout circuit diagram.	174
9-4	ADC signal distribution over different gain values.	176
9-5	Results on quantization error reduction.	177
9-6	Characterization on shear force sensing.	178
9-7	Example responses on vibration sensing.	179
9-8	Automatic sensor calibration via a robot arm.	180
9-9	Shoe sole with integrated normal and shear pressure sensors.	180
9-10	Tactile sensors for two-finger grippers.	181
9-11	Tactile sensors for robot arm.	182
10-1	Future directions.	183

THIS PAGE INTENTIONALLY LEFT BLANK

List of Tables

2.1	Average keypoint localization error of the predicted single-person 3D skeleton (unit: cm).	41
2.2	Ablation studies on different modeling decisions.	44
2.3	Average keypoint localization error (unit: cm) of the predicted multi-person 3D skeleton.	46
3.1	Characterization on conductive yarns.	56
4.1	Quantitative results for “throw” and “wave”.	76
4.2	Quantitative results for “PingPong” and “Balance”.	78
5.1	Fabrication and assembly time for different pneumatic actuator designs. . .	100

THIS PAGE INTENTIONALLY LEFT BLANK

Chapter 1

Introduction

Humans constantly interact with the physical environment through sensory inputs and motor actions [74, 9]. For instance, when you sit on a chair, your tactile sensory system captures the real-time force distribution exerted by your sitting posture. This data is sent to your brain, which processes the information and generates signals to actuate the corresponding muscles, enabling a change in posture.

Extending such capabilities beyond our human body, to a wearable intelligent assistant (Figure 1-1) that can sense, model, and augment such physical human-environment interactions, is fundamental to understanding human behaviors [77, 84], promoting health monitoring and delivery [131], and fostering human-centric intelligent system designs [61]. However, challenges arise from the pervasive and diverse nature of physical human-environment interactions. These interactions occur across the human body, under various scenarios, and at extended durations. They are also subjectively perceived by individuals and involve diverse input-output modalities.

Picture an elderly person walking wearing *intelligent socks*, which detect motion anomalies, log data for disease pre-diagnosis, and facilitate their movement. Imagine a humanoid robot dressed in *intelligent textile outfits*, which equip them with human-like sensory abilities to perceive pressure and temperature, and textures when interacting with objects, and allow it to mimic human behaviors and interactions like hugging. Such practically deployable integrated interfaces for physical human-environment interactions are required to be scalable, seamlessly integrated, robust, and adaptable. Following these parameters, I have been

striving towards a wearable intelligent assistant: to record, model, and augment physical human-environment interactions via intelligent textiles, empowered by advances in both digital fabrication and artificial intelligence.

I aim to address the following research questions:

- How to efficiently scale up the physical human-environment interaction interfaces so that they can sense and actuate across the entire human body, from hands and torso to feet?
- How to seamlessly integrate functionalities in physical human-environment interfaces so that they enable unobtrusive, extended-duration use??
- How to ensure the robust performance of physical human-environment interaction interfaces despite the diverse events in our lives?
- How to adapt physical human-environment interactions interfaces to diverse individuals despite our subjective perceptions?

I believe that integrated intelligent textile-based systems will enable seamless yet comprehensive observation of human activities, deepen scientific understanding of our behaviors and interactions with the physical surroundings, and offer innovative strategies to augment human behaviors and intelligent systems. In this thesis, I exemplify my approach with individual projects following the three key thrusts:

- I. Functionality Integration via Digital Fabrication.** I aim to seamlessly integrate functionality into flexible and conformal platforms, scale up the density and lower the cost of functional systems, and enable customized design and fabrication catering to diverse needs, overcoming the restrictions of traditional manual fabrication.
- II. Large-Scale Multi-Sensory Data Capturing and Modeling.** Leveraging the scalable interfaces, I aim to capture large-scale multimodal physical human-environment interactions, employ advanced AI for scientific analysis of human behavior, and apply these insights to augment human behaviors and intelligent systems.
- III. Integrated Systems for Humans and Robots.** I aim to combine Thrust I and II to develop integrated systems for healthcare and robotics, enable understanding of human behaviors, inspire intelligent system designs, and promote human-human, human-object, and human-robot interactions.



Figure 1-1: **Paradigm of a wearable intelligent assistant.**

1.1 History of Smart Wearables

Scalability in terms of coverage area and seamless integration of functionality are contradictory design parameters for physical interaction interfaces (Figure 1-2). Localized smart wearables, such as smart watches, seamlessly integrate functionalities in a wristwatch form factor. However, they are limited to very localized measurements, only signals from the wrist, from the finger, and from the eye. Recent developments in epidermal interfaces enable functionalities in a skin-like form factor, with bigger and more conformal coverage on our body. However, most of them require delicate and manual fabrication, which limits their scalability. Digital fabrication, such as 3D printing, opens up opportunities for customizable and scalable fabrication of soft functional systems. However, they are still limited to polymer-based materials, which are obtrusive to our daily wearing. Intelligent textiles, on the other hand, obtain advantages in such design space.

Textiles have a long history in human civilization, playing pivotal roles in our culture, art, and daily activities [122]. Their unique softness, flexibility, and breathability make them ubiquitous and seamlessly integrated into our daily lives. It is one of the few interfaces that enable direct and prolonged contact between humans and their environment over a large area. As Mark Weiser envisioned a future where technologies seamlessly weave themselves into the fabric of everyday life [120], research into intelligent textiles has been initiated.

Intelligent textiles are fabrics and garments with integrated functionalities that can sense,

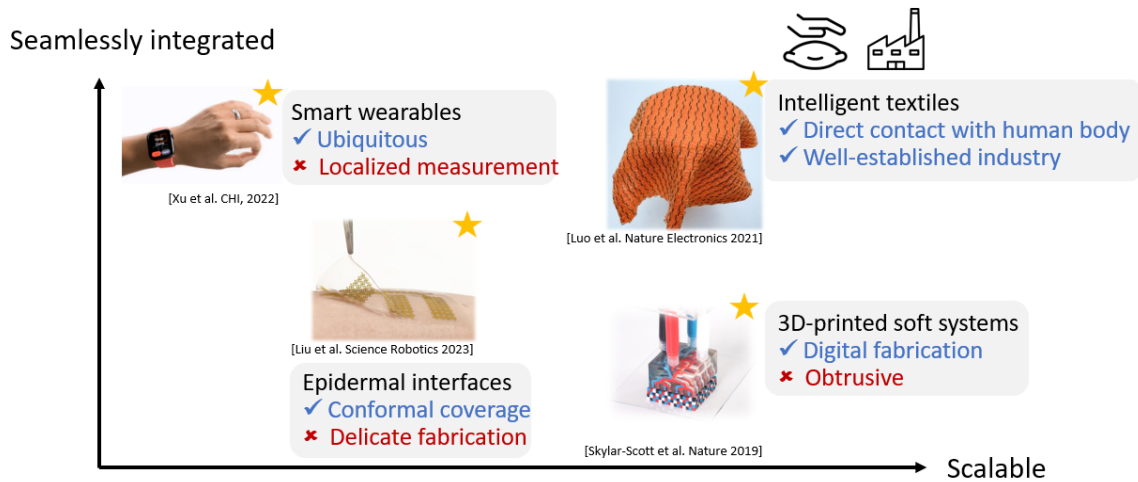


Figure 1-2: Comparison between smart wearables, epidermal electronics, 3D-printed electronics, and intelligent textiles.

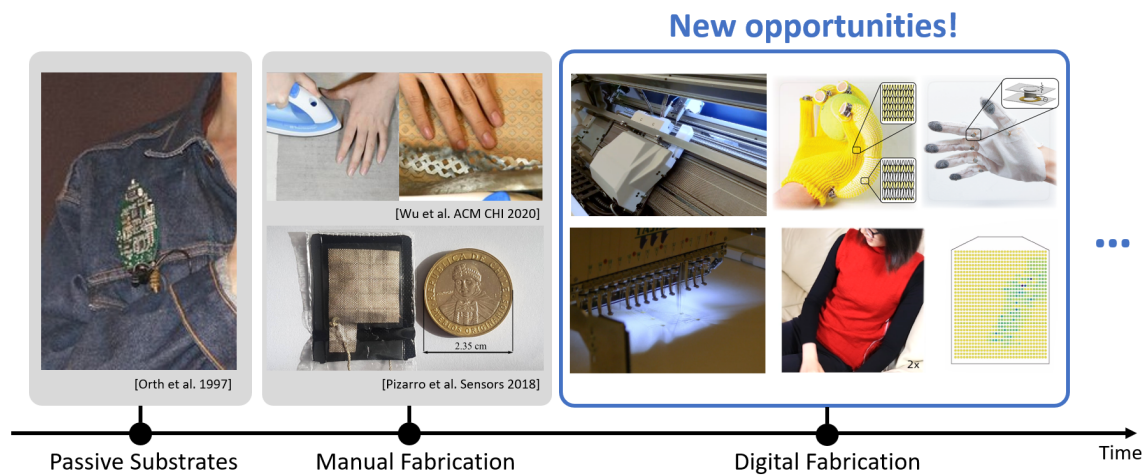


Figure 1-3: History of smart textiles.

store, process, and communicate information in a seamless, scalable, and unobtrusive manner [62, 129]. Compared to other form factors of smart wearables, such as smartwatches [97] and polymer-based epidermal electronics [53], intelligent textiles offer distinct advantages due to their seamless integration into our daily lives, spanning from our garments to everyday furniture, and their compatibility with long-established mass manufacturing facilities. They open up vast opportunities, ranging from seamless monitoring of physiological signals [121] and daily physical interactions [71, 96] to powering smart home applications [18].

Back in the 90s, researchers presented intelligent textiles by using the fabric as a passive

substrate and attaching [11]. Later, to further leverage the softness and flexibility of textiles, researchers investigate the seamless integration of diverse functionalities in the form factor of fibers [138]. However, such integration remains localized, with smart fibers typically manually integrated into larger-scale textiles, which constrains design flexibility, fabrication efficiency, and functional component density. Recently, advances in computational design tools for digital textile fabrication have promoted an accessible, interactive, and rapid design process [82, 51].

My work has leveraged such new opportunities to develop integrated systems for the recording, modeling, and augmentation of physical human-environment interactions (Figure 1-3). I leverage computational design to develop intelligent textiles with complex and conformal geometries, such as full-sized gloves with sensing and actuation capabilities. This demonstrates the huge potential for democratization and personalization. Also, I leverage digital fabrication to unlock the scalability of both the interfaces and datasets. For example, users wear a tactile sensing vest just like regular garments throughout the day. It captures pressure distributions spanning the back of users during their diverse daily activities without any obstruction to their behaviors. Such large and diverse datasets are valuable assets in our era with skyrocketing AI technology.

1.2 Human Data Capturing and Learning

Capturing and understanding human-centered data, including physiological signals [90], biomechanical behaviors [123], and physical interactions [23], are crucial for healthcare, interactive technologies, and robotics applications. However, different from visual, audio, and text information, which benefits from the availability of off-the-shelf input and output interfaces and extensive datasets, (e.g., users input text through keyboards and receive visual feedback through display easily), investigation in human-centered data suffered from the lack of accessible and standardized input and output interfaces

In the past decades, as computer vision skyrockets, extensive human data has been captured and analyzed through cameras and convolutional neural networks. Examples include leveraging visual information for physiological signal monitoring [116, 124], person

identification [45, 118], interactions estimation [101, 85], and so on.

However, while such vision-based human data capturing and learning systems are unobtrusive, accuracy is still limited. For more advanced tasks, especially in biomedical domains, researchers leveraged specialized sensors and developed modality-specific machine-learning models. However, such approaches suffer from obtrusive data collection as well as limited and non-generalized datasets. There is a growing need for scalable, ubiquitous, democratized, sensing interfaces and algorithms to power human data capturing and learning. Such integrated systems will facilitate ubiquitous health sensing, human-machine interactions, as well as imitation learning.

My work has been focused on developing scalable intelligent interfaces for unobtrusive human data capturing, as well as to leverage skyrocketing AI to extract high-level information from such collected datasets. The computational design and digital fabrication pipeline of such interfaces unlock the scalability of the available datasets, and therefore, opens up opportunities for human data capturing and learning.

1.3 Thesis Overview

In my thesis, I investigate intelligent textiles as a scalable, cost-effective, seamlessly integrated interface for recording, analyzing, and reproducing adaptive ubiquitous physical interactions. This thesis sits at the intersection of digital fabrication, human-computer interaction, and applied machine learning, addressing key questions and demonstrating advances in the three primary thrusts discussed earlier. A summary of the thesis highlights is presented in Figure 1-4.

Part I of this thesis focuses on intelligent textiles to sense human-centered physical interactions. Chapter 2 explores the development of a large-scale pressure-sensing carpet, which serves as an ambient sensing platform to capture and understand the physical interactions between humans and their environment. This chapter covers the detailed fabrication process, data collection pipeline, and demonstration of 3D pose estimation using the carpet. It also discusses various extended applications of such sensing interfaces. Chapter 3 showcases digital machine-knitted interactive sensing interfaces for diverse applications including

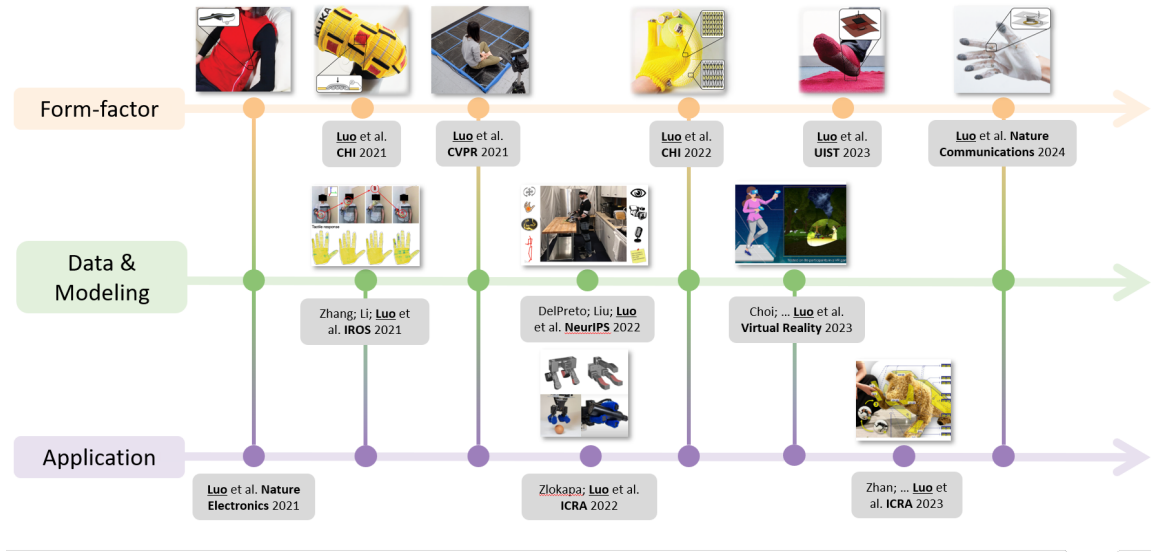


Figure 1-4: **Overview of the thesis.**

educational interfaces and interactive wearables. Chapter 4 discusses the dynamic modeling of hand-object interactions via a high-resolution tactile sensing glove.

Part II of this thesis will extend the application of intelligent textiles to augment human-centered physical interactions. Chapters 5 and 6 delve into the intricate integration of sensing and actuation capabilities within textile-based wearables using digital machine knitting techniques. These chapters showcase specific examples of textiles and garments equipped with integrated resistive pressure sensors, pneumatic actuators, and passive haptics. The design, fabrication methods, and diverse applications of these smart textiles are provided. In Chapter 6, the focus shifts to a closed-loop human-machine interface driven by digital embroidery technologies. This chapter elucidates the fabrication pipeline involved in combining sensing and actuation interfaces within textiles. It introduces novel algorithms designed to adaptively transfer tactile interactions, showcasing practical applications across various domains such as healthcare, gaming, and communication. This chapter demonstrates a simple example of a wearable intelligent assistant.

Part III of this thesis explores the application of intelligent textiles for robotics. Chapter 8 introduces a digitally embroidered sensing array designed for robot grippers, enabling liquid identification and manipulation. Chapter 9 presents a multimodal tactile sensing system for normal pressure, shear forces, and vibration sensing. This system is designed

for scalable integration with robotic arms and grippers, enabling enhanced interaction with objects and humans.

Chapter 10 serves as a culmination of the thesis, summarizing the key findings and highlighting the significant results obtained from the research. Furthermore, it offers a compelling future outlook on wearable intelligence, envisioning potential advancements and applications in this rapidly evolving field.

Part I

Intelligent Textiles to Sense Human-Centered Physical Interactions

THIS PAGE INTENTIONALLY LEFT BLANK

Chapter 2

Intelligent Carpet for Pose Estimation

2.1 Overview

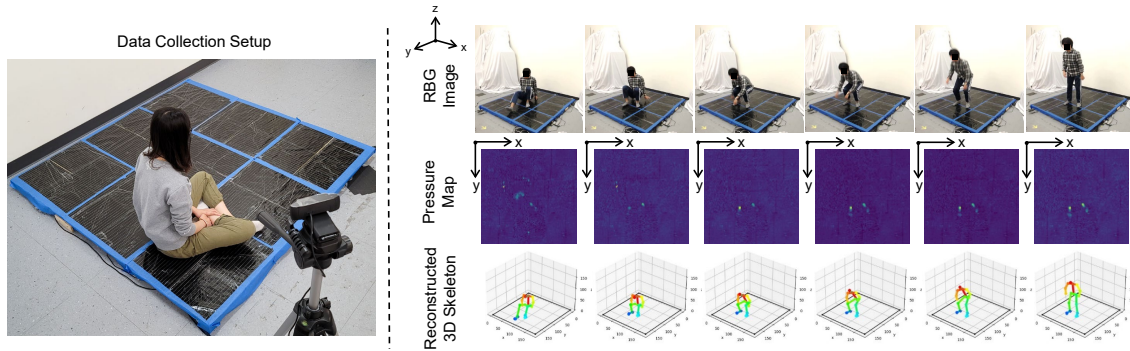


Figure 2-1: **Pose estimation using an intelligent carpet.** A low-cost, high-density, large-scale intelligent carpet system to capture the real-time human-floor tactile interactions (left) and the inferred 3D human pose from the captured tactile interactions of a person standing up from a sitting position (right).

Human pose estimation is critical in action recognition [58, 110], gaming [52], healthcare [144, 83, 46], and robotics [79]. Significant advances have been made to estimate human pose by extracting skeletal kinematics from images and videos. However, camera-based pose estimation remains challenging when occlusion happens, which is inevitable during daily activities. Further, the rising demand for privacy also promotes development in non-vision-based human pose estimation systems [140, 141]. Recently, inspired by the fact that most human activities are dependent on the contact between human and the environment,

researchers have proposed pose estimation approaches using tactile interactions between humans and the ground. various smart floor or carpet systems have been proposed for human movement detection [27, 4, 105, 16, 5, 133, 94, 36, 87], and posture recognition [50, 107]. Previous work has also demonstrated the feasibility of using pressure images for pose estimation [15, 19, 20]. However, these studies mainly focus on the estimation of poses where a large portion of the body is in direct contact with the sensing surface, e.g., resting postures. A more challenging task is to infer 3D human pose from the limited pressure imprints involved in complicated daily activities, e.g., using feet pressure distribution to reconstruct the pose of the head and limbs.

In this work[69], we propose a 3D human pose estimation approach using the pressure maps recorded by a tactile carpet as input. We build a low-cost, high-density, large-scale intelligent carpet, which enables the real-time recordings of human-floor tactile interactions in a seamless manner (Figure 2-1 left). We collect a synchronized tactile and visual dataset on various human activities. Employing a state-of-the-art camera-based pose estimation model as supervision, we design and implement a deep neural network model to infer 3D human poses using only the tactile information (Figure 2-1 right). Our pipeline can be further scaled up to multi-person pose estimation and applied for down-streamed application, i.e., action classification.

The following sections describe details of the system, experiments, and results. The contributions are summarized below.

- We build a low-cost, high-density, large-scale intelligent carpet, which enables the real-time recordings of human-floor tactile interactions in a seamless manner.
- We collect a synchronized tactile and visual dataset on various human activities. Employing a state-of-the-art camera-based pose estimation model as supervision,
- we design and implement a deep neural network model to infer 3D human poses using only tactile information.
- We evaluate our system and demonstrate its potential applications in diverse fields.

2.2 Fabrication

Our tactile data acquisition is based on a custom, high-density, large-scale piezoresistive pressure sensing carpet, which spans over 36 ft^2 and contains 9,216 sensors with a spacing of 0.375 inches, as demonstrated in Figure 2-2 left. The carpet is composed of a piezoresistive pressure sensing matrix fabricated by aligning a network of orthogonal conductive threads (2-ply stainless steel thread) as electrodes on each side of the commercial piezoresistive films (Velostat with the thickness of 2 mil). A thin adhesive tape (3M 468MP) secures the electrodes and a thin plastic film (Saran wrap) serves as the outermost protective layer. Each sensor locates at the overlap of orthogonal electrodes and is able to measure pressure up to 14 kPa with the highest sensitivity of 0.3 kPa (Figure 2-2 right). Our tactile sensing carpet is low-cost ($\sim\$100$), easy to fabricate, and robust for large-scale data collection. Using the coupled readout circuit, we collect the tactile frames with 9,216 individual sensing readouts at a rate of 14 Hz.

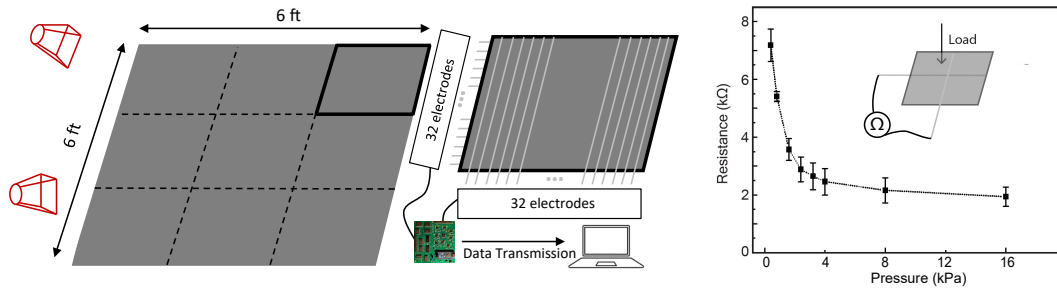


Figure 2-2: **Overview of pressure-sensitive intelligent carpet.** Our recording set-up includes a tactile sensing carpet spanning 36 ft^2 with 9,216 sensors, the corresponding readout circuits, and 2 cameras. Each sensor is able to convert pressure stimulus into electrical signals via the drop of resistance.

2.3 Dataset

2.3.1 Data Collection

We have collected over 1,800,000 synchronized tactile and visual frames on 10 volunteers with 2 rounds of 15 different actions, including walking, squatting, waist turning, arm-

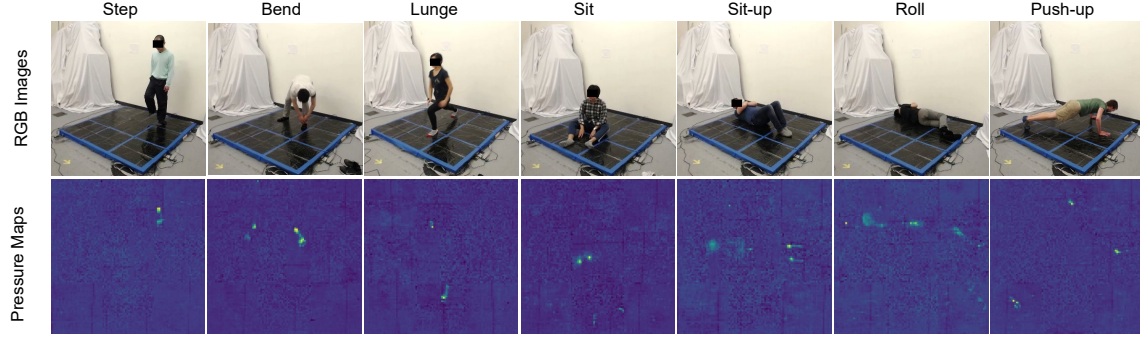


Figure 2-3: **Representative tactile images.** Typical pressure maps captured by the carpet from diverse human poses and activities.

waving, twisting, standing on toes, side-walking, lunging, lying, rolling, sit-ups, push-ups, bending, sitting, and stepping, where each action takes about 1 minute (800 frames). No additional instructions were provided, and the volunteers performed the actions in their own ways at random positions and orientations. With such a large-scale high-resolution tactile sensing platform, we can not only capture people’s foot pressure maps, which most of the previous work focused on, but also capture the full tactile interactions between the human and the floor when people are performing complex activities. As shown in Figure 2-3, our carpet captures the feet pressure maps when people perform activities in upright positions, as well as the physical contacts between the human body (e.g., hands, limbs) and the floor when people perform exercises and complex actions (e.g., push-ups, sit-ups, and rolling). Visual data is captured with 2 cameras that are synchronized and calibrated with respect to the global coordinate of the tactile sensing carpet using standard stereo camera calibration techniques. Our tactile acquisition set-up and the captured dataset are open-sourced to facilitate future research in the field.

2.3.2 3D Pose Label Generation

We design and implement a pipeline to generate the training pairs, i.e., synchronized tactile frames and 3D keypoint confidence maps. In order to annotate the ground truth human pose in a scalable manner, we leverage a state-of-the-art vision-based system, OpenPose [13], to generate 2D skeletons from the images captured by the cameras. Once we have obtained the 2D skeletons generated from the calibrated camera system, we triangulate the keypoints to

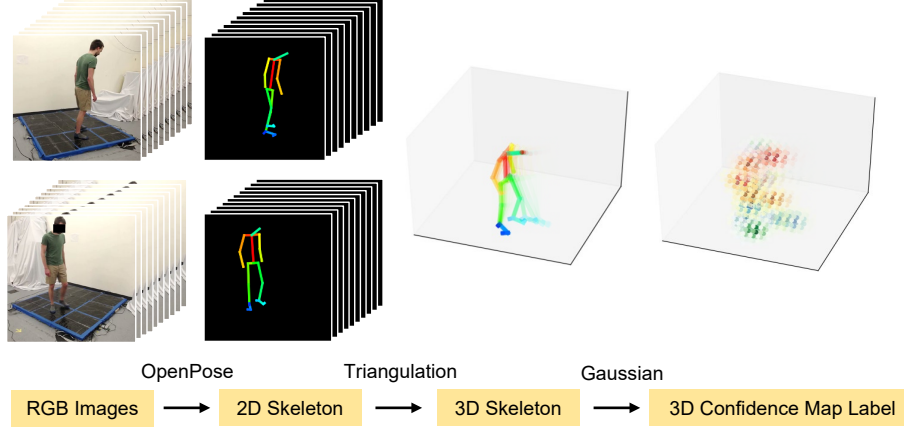


Figure 2-4: **3D pose label generation.** The ground truth voxelized 3D keypoint confidence maps are annotated by first extracting 2D skeleton keypoints from RGB images using OpenPose [12], then generating 3D keypoints through triangulation and optimization, and finally applying a 3D Gaussian filter.

generate the corresponding 3D skeletons.

The triangulation results may not be perfect in some frames due to perception noise or misdetection. To further optimize the triangulated 3D skeleton, we add a post-optimization stage to constrain the length of each link. More specifically, we first calculate the length of the links in the skeleton using the median value across the naively triangulated result for each person. For this specific person, we denote the length of the i^{th} link as K_i . We then use q^A and q^B to represent the detected N keypoints at a specific time step from the two cameras, which lie in a 2D space, where $q^A = \{q_1^A, \dots, q_N^A\}$ and $q_k^A = (u_k^A, v_k^A)$. We then calculate the length of each link $\hat{K}_i$ from the naive triangulation result and optimize the 3D location of the keypoints $p = \{p_1, \dots, p_N\}$ by minimizing the following loss function using stochastic gradient descent:

$$\begin{aligned}
 \mathcal{L}^{\text{skeleton}} = & \sum_{k=1}^N \|P^A p_k - q_k^A\| + \sum_{k=1}^N \|P^B p_k - q_k^B\| \\
 & + \sum_{i=1}^{N-1} \|\hat{K}_i - K_i\|
 \end{aligned} \tag{2.1}$$

where there are N keypoints and $N - 1$ links, $p = \{p_1, \dots, p_N\}$ lie in 3D space spanned by the world coordinate, $p_k = (x_k, y_k, z_k)$. P^A and P^B are the camera matrices that project the

3D keypoints onto the 2D image frame. In our experiments, we use $N = 21$. The accuracy of the 3D pose label and the effectiveness of our optimization pipeline are further analyzed in supplementary materials.

Given the optimized 3D positions of the 21 keypoints on the human skeleton, we further generate the 3D keypoint confidence maps by applying a 3D Gaussian filter over the keypoint locations on a voxelized 3D space (Figure 2-4).

2.3.3 Data Augmentation

We perform data augmentation on experiments for both single-person and multi-person pose estimation. When projecting the human skeletons to the x-y plane (Figure 2-3), we find a spatial correspondence between the projection and the tactile signals, which allows us to augment our dataset by rotating and shifting the tactile frames and the corresponding human skeletons. This allows us to easily obtain a larger number of diverse training pairs.

Additionally, this data augmentation overcomes the limitations imposed by social distancing and the size of the sensing carpet, which restrict data collection to one person at a time. The multi-person dataset is synthesized by combining multiple single-person clips. In other words, we add up the synchronized tactile frames and the generated 3D keypoint confidence maps from different recording clips. More specifically, since people rarely perform actions with one on top of the other, we assume that the pressure maps induced by the actions of different people will not overlap at the given time. We specify the location of each person by creating anchor boxes of the human skeleton projected onto the floor plane. We remove frames with the Intersection over Union (IoU) larger than 0.1 to ensure that the skeletons and tactile signals from different people do not overlap with each other. Note that the training of our models in the experiments is entirely based on the single-person dataset and the synthetic multi-person variants. We also record synchronized visual and tactile data for multiple people but only for evaluation purposes.

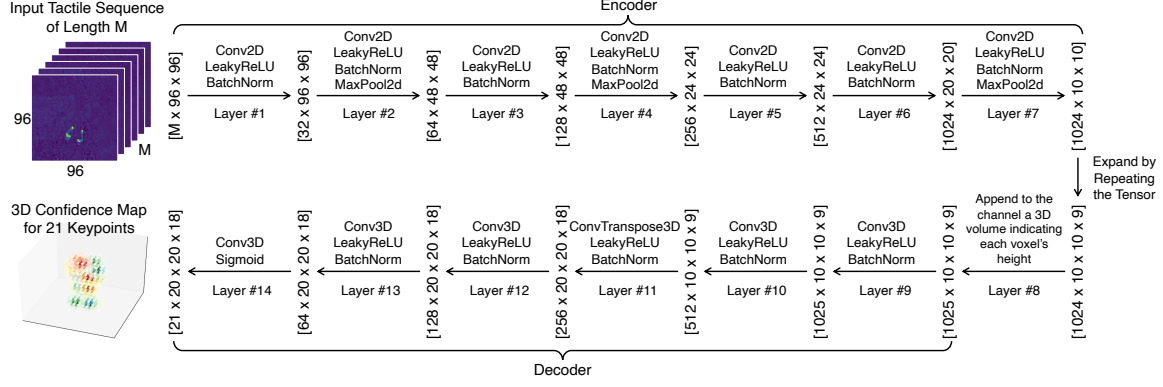


Figure 2-5: **Overview of the model for 3D human pose estimation.** Our model consists of an encoder and a decoder. The encoder maps the input tactile sequence into a 10×10 feature through 7 blocks of Conv2D-LeakyReLU-BatchNorm. We then expand the feature and repeat along the last dimension to transform the 2D feature map into a 3D feature volume. After appending an indexing volume indicating the height of each voxel, the feature goes through a set of decoding layers to generate the predicted confidence map for each keypoint.

2.4 3D Pose Estimation

We aim to develop a machine-learning pipeline, which takes the tactile frames as input and predicts the corresponding 3D human pose. We take the ground truth human pose estimated from our multi-camera setup as the supervision and train our model to predict the 3D confidence map of each of the 21 keypoints, including head, neck, shoulders, elbows, waists, hips, knees, ankles, heels, small and big toes.

2.4.1 Model

To include more contextual information and reduce the effects caused by the sensing noise, instead of taking a single tactile frame as input, our model takes a sequence of tactile frames spanning a temporary window of length M as input (Figure 2-5). For each input segment, the model processes the spatio-temporal tactile information and outputs the keypoint confidence maps in 3D that correspond to the middle frame.

As shown in Figure 2-3, the input tactile frames lie in 2D space, which has a nice spatial correspondence with the human skeleton over the x-y plane (the floor plane). Our model builds on top of a fully convolutional neural network to exploit such spatial equivariance. The encoder of our model uses 2D convolution to process the tactile frames. Then, to regress

the keypoints in 3D, we expand the feature map by repeating it along a new dimension in the middle of our network (Figure 2-5), which essentially transforms the 2D feature map into a 3D feature volume.

However, naive 2D to 3D expanding via repetition will introduce ambiguities as subsequent convolutional layers use shared kernels to process the feature - it is impossible to tell the height of a specific voxel, making it hard to regress the keypoint location along the z-axis. To resolve this issue, we add a new channel to the 3D feature map with a 3-dimensional indexing volume, indicating the height of each voxel. We then use 3D convolution to process the feature and predict the 3D keypoint confidence map for each of the 21 keypoints. The detailed architecture and the size of the feature maps along the forwarding pass are shown in Figure 2-5.

We optimize the model by minimizing the Mean Squared Error (MSE) between the predicted keypoint heatmap and the ground truth using Adam optimizer [55]. We also use spatial softmax to transform the heatmap into the keypoint location and include an additional loss term $\mathcal{L}^{\text{link}}$ to constrain the length of each link in the skeleton to lie in the range of normal human limb length. For each data point, the loss function is defined as:

$$\mathcal{L} = \frac{1}{N} \sum_{i=1}^N \|H_i - \hat{H}_i\| + \frac{1}{N-1} \sum_{i=1}^{N-1} \mathcal{L}_i^{\text{link}}, \quad (2.2)$$

where N denotes the number of keypoints, $N - 1$ is the number of links in the skeleton, H_i and $\hat{H}_i$ represent the ground truth and the predicted 3D keypoint confidence maps. The link loss is defined as the following:

$$\mathcal{L}_i^{\text{link}} = \begin{cases} K_i^{\min} - \hat{K}_i, & \text{if } \hat{K}_i < K_i^{\min}. \\ \hat{K}_i - K_i^{\max}, & \text{if } \hat{K}_i > K_i^{\max}. \\ 0, & \text{otherwise,} \end{cases} \quad (2.3)$$

where $\hat{K}_i$ is the link length calculated from our prediction, $K_i^{\min}$ and $K_i^{\max}$ represent the 3th and 97th percentile of each of the body limb length in the training dataset.

Our network is implemented using PyTorch [95]. We train the model by minimizing

Eq. 2.2 using a learning rate of $1e^{-4}$ and a batch size of 32. As shown in Figure 2-5, the encoding part of our network consists of 7 groups of layers. The Conv2D in the first 5 and the 7th layers use 3×3 kernels and 1×1 padding. The 6th uses 5×5 kernels and zero padding. A 2×2 MaxPool2D is also applied in the 2nd, 4th, and 7th layers to reduce the resolution of the feature maps. We expand the tactile feature maps to 3D by repeating the tensor 9 times along the last dimension, and then append the channel with a 3D indexing volume indicating the height of each voxel. The decoding network takes in the resulting tensor and predicts the 3D confidence maps of the keypoints. The decoder is composed of 5 layers of $3 \times 3 \times 3$ 3D convolution with a padding of $1 \times 1 \times 1$. The 11th layer uses a kernel size of $2 \times 2 \times 2$ with a stride of 2 to increase the resolution. We also apply batch normalization and Leaky ReLU after each layer except the last one, where we use the Sigmoid activation function to regress the confidence value.

2.4.2 Single Person Pose Estimation

Experiment. We used one round of the recorded data for training and split the other for validation and testing. Single-person pose estimation is trained with 135,000 pairs of tactile and visual frames and validated on 30,000 pairs of frames. The performance is tested on a held-out test set with 30,000 tactile frames. We use Euclidean distance (L2) as the evaluation metric to compare the predicted 3D human pose to the corresponding ground truth human pose retrieved from the visual data.

Axis	Ave.	Head	Shoulder	Elbow	wrist	Hip	Knee	Ankle	Feet
X	6.8	6.4	6.3	8.9	10.9	4.6	5.8	5.6	6.4
Y	7.2	8.0	6.5	8.8	10.9	5.2	5.8	5.7	6.7
Z	6.8	9.6	7.0	8.9	14.4	4.0	4.0	3.1	3.5

Table 2.1: Average keypoint localization error of the predicted single-person 3D skeleton (unit: cm).

Results. The L2 distance of each keypoint and the localization error of each body part are listed in Figure 2-6 and Table 2.1.

Generally, keypoints on the lower body (e.g., knee and ankle) and the torso (e.g., shoulder and hip) hold higher accuracy compared with the keypoints on the upper body (e.g., wrist

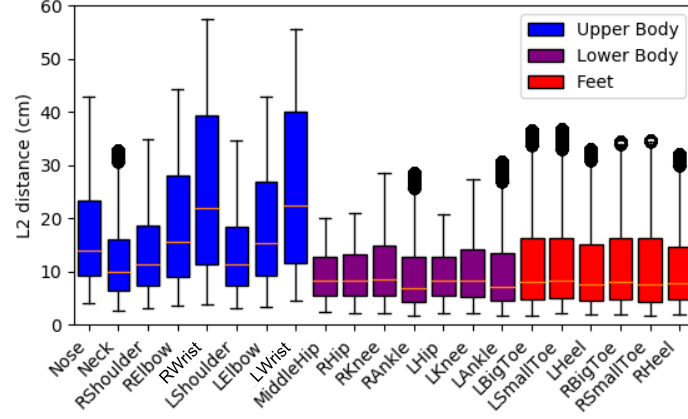


Figure 2-6: **Quantitative results on single person pose estimation.** The Euclidean distance between the predicted single-person 3D skeleton (21 keypoints) and the ground truth label (unit: cm).

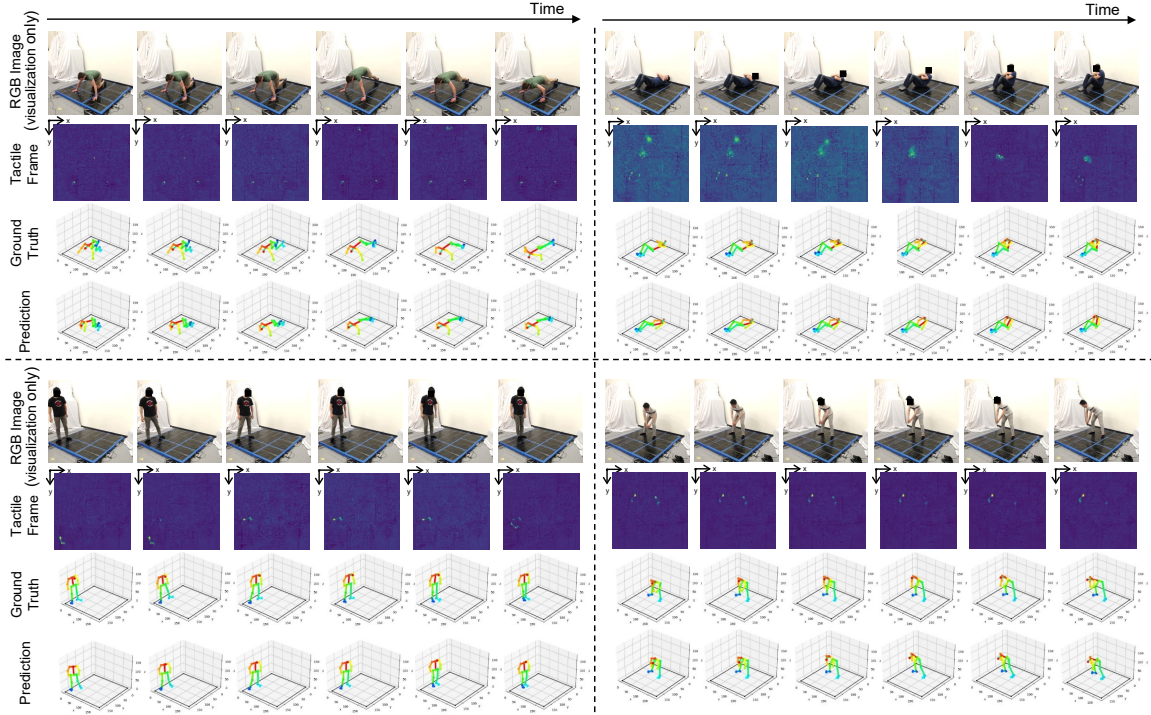


Figure 2-7: **Qualitative results of single-person 3D pose estimation across time steps.** For each sequence, from top to bottom, we show the RGB image as ground truth annotation (only used here for visualization purpose), the captured tactile frame, ground truth 3D skeleton, and predicted 3D skeleton from our model using only the tactile frames (unit: cm). The predicted poses are consistent over time with a smooth transition along the corresponding trajectories.

and head). The observation agrees with our intuition that changes in pressure maps are primarily determined by the positions of the lower body and the torso. We also note that the

model obtains better predictions if the keypoints are closer to the torso on the skeleton tree - the prediction error increases as we move further away from the torso, e.g., shoulders to elbows, and then to the wrist. Figure 2-7 shows some qualitative results on the 3D human pose predictions, along with the input tactile frames, ground truth pose extracted from the RGB image, over a continuous time sequence.

Ablation study. We perform ablation studies on the sensing resolution of the intelligent carpet. To ablate the tactile sensing resolution, we reassign the value in each 2×2 grid with the average of the four values, which reduces the effective resolution from 96×96 to 48×48 . We then use the same training pipeline to derive the predictions. A similar procedure is employed for evaluating the model performance with the effective sensing resolution of 24×24 and 12×12 . As Figure 2-8 illustrates, the prediction accuracy decreases with the decrease of sensing resolution, which reiterates the importance of our high density, large-scale tactile sensing platform. We also perform an ablation study on the number of input frames, where the best performance was obtained with 20 input frames (~ 1.5 sec, Figure 2-8).

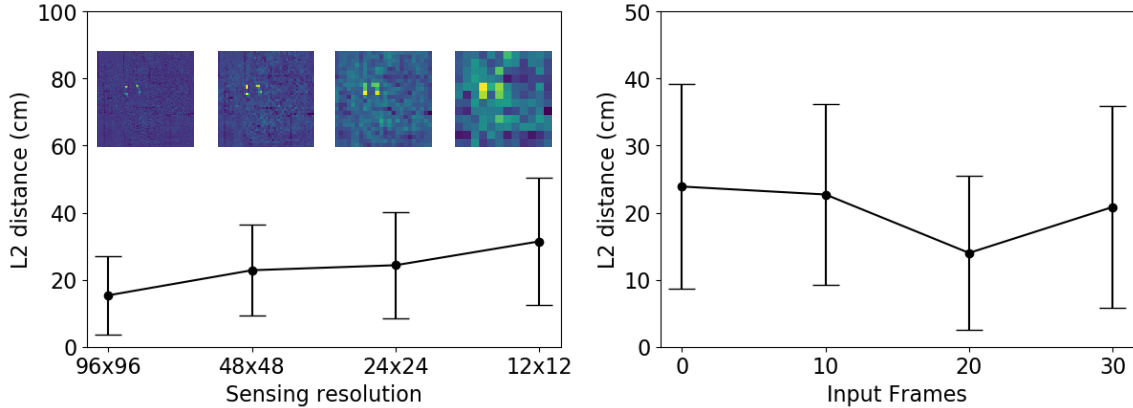


Figure 2-8: **Ablation studies.** Model performance with different sensing resolution (left) and the number of input frames (right).

Additionally, we performed additional ablation studies on our 3D pose estimation model by quantitatively evaluating the effectiveness of the 3D indexing volume (Layer #8 in Figure 4) and the link length loss. We also performed an ablation study on the repeating tensor along the last dimension (between Layer #7 and #8) by comparing the performance of our

model to a model where the tactile feature maps were expanded to 3D by zero-padding along the last dimension. As demonstrated in Table 2.2, our model obtains the best performance.

	Our model	W/o 3D indexing volume	Zero-padding expansion	W/o link length loss $\mathcal{L}^{\text{link}}$
L2 (cm)	14.0 ± 11.4	19.8 ± 12.0	66.5 ± 29.7	15.8 ± 11.5

Table 2.2: Ablation studies on different modeling decisions.

Generalization. We evaluate how well the model generalizes to unseen individuals and activities. As demonstrated in Figure 2-9, our model generalizes to unseen people with a negligible increase of the keypoint localization error. On the other hand, our model has a varying performance on different types of unseen tasks.

The learned model easily generalizes to poses with the pressure maps similar to what the model is trained on but delivers poor performance with tactile imprints that the model has never encountered before. For example, our model generalizes to the lunging pose, where the pressure maps are mainly directed by the human’s center of mass; however, it fails to predict the push-up pose, which induces pressure imprints that are vastly different from the training distribution. When deploying the system for practical use in real life, it is essential to perform a more systematic data collection procedure covering more typical human activities to achieve a more reliable pose estimation performance.

2.4.3 Multi-Person Pose Estimation

Experiment. When moving into multi-person scenarios, each keypoint confidence map can contain multiple regions with high confidence that belong to different people. Therefore, we threshold the keypoint confidence map to segment out each of these high-confidence regions, and then calculate the centroid of each region to transform it into the 3D keypoint location. To associate the keypoints that belong to the same person, we start from the keypoint of the head and traverse through the person’s skeleton (represented as a tree) to include the remaining keypoints. Every time we want to add a new keypoint to the person, e.g., the neck, we select the one among multiple extracted keypoint candidates with the closest L2 distance to its parent, e.g., head, which has already been added to the person on

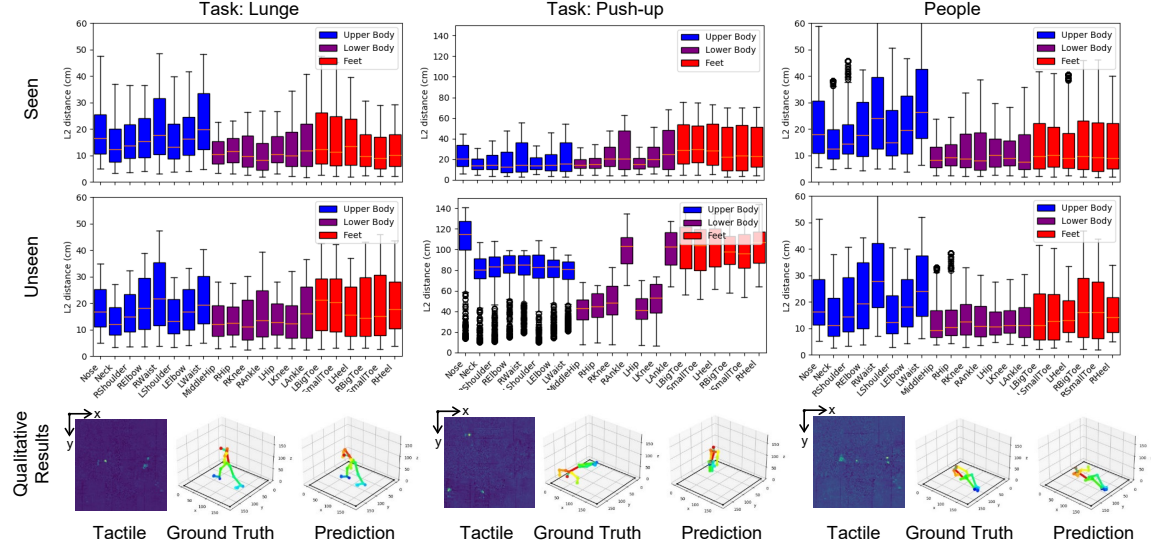


Figure 2-9: **Generalization results.** Top: Localization error of predictions on seen tasks and individuals, where the training was performed on the full dataset including all tasks and individuals. Middle: Localization error of predictions on unseen tasks and individuals, where the training was performed on a split dataset excluding specific actions and individuals. Bottom: Qualitative results on unseen tasks and individuals (unit: cm).

the skeleton tree. This method is simple but works well when people are kept at a certain distance from each other. More complicated and effective techniques could be used to handle cases where people are very close to each other [13]. Since it is not the main focus of this project, we plan to explore this direction in the future.

Results. The multi-person pose estimation model is trained and validated with 112,000 and 10,000 pairs of synthesized tactile frames and keypoint confidence maps. Performance is evaluated with 4,000 recorded tactile frames of two people performing stepping, sitting, lunging, twisting, bending, squatting, and standing on toes. The L2 distance of each keypoint and the localization error of each body part are listed in Figure 2-10 and Table 2.3. Examples of the multi-person pose prediction are shown in Figure 2-11. Purely from the tactile information, our network successfully localizes each individual and predicts his or her 3D pose with a localization error of less than 15 cm. The predictions do not rely on any visual information and, therefore, are unaffected by visual obstructions or a limited field of view, which are common challenges in vision-based human pose estimation.

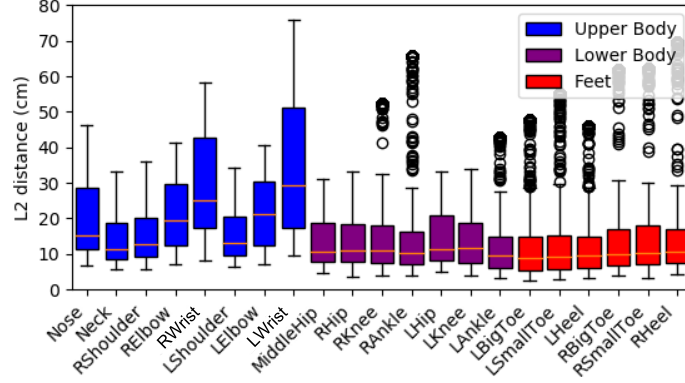


Figure 2-10: **Quantitative results on multi-person scenarios.** Euclidean distance between the predicted multi-person 3D skeleton and the ground truth (unit: cm).

Axis	Ave. Head	Shoulder	Elbow	wrist	Hip	Knee	Ankle	Feet
X	14.5	14.1	10.1	15.3	24.7	10.2	12.6	14.1
Y	12.9	13.9	10.8	15.9	21.6	10.1	11.0	9.7
Z	12.7	16.6	13.2	17.3	23.9	10.0	8.0	6.5

Table 2.3: Average keypoint localization error (unit: cm) of the predicted multi-person 3D skeleton.

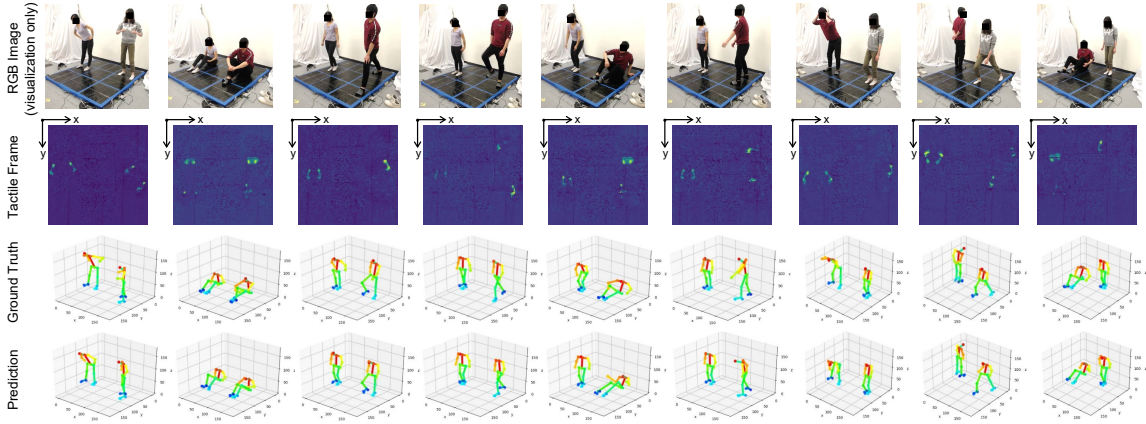


Figure 2-11: **Qualitative results of multi-person 3D human pose estimation.** From top to bottom, we show the RGB image for ground truth annotation, the captured tactile frame, ground truth 3D skeleton, and the predicted 3D skeleton from our model using only the tactile frames (unit: cm). Our network learns to localize each individual and predict the corresponding 3D pose.

2.4.4 Failure Cases

As demonstrated in Figure 2-12, the typical failure cases can be categorized into three main types. First, the model fails to predict the position of the wrist and the head (Figure 2-12

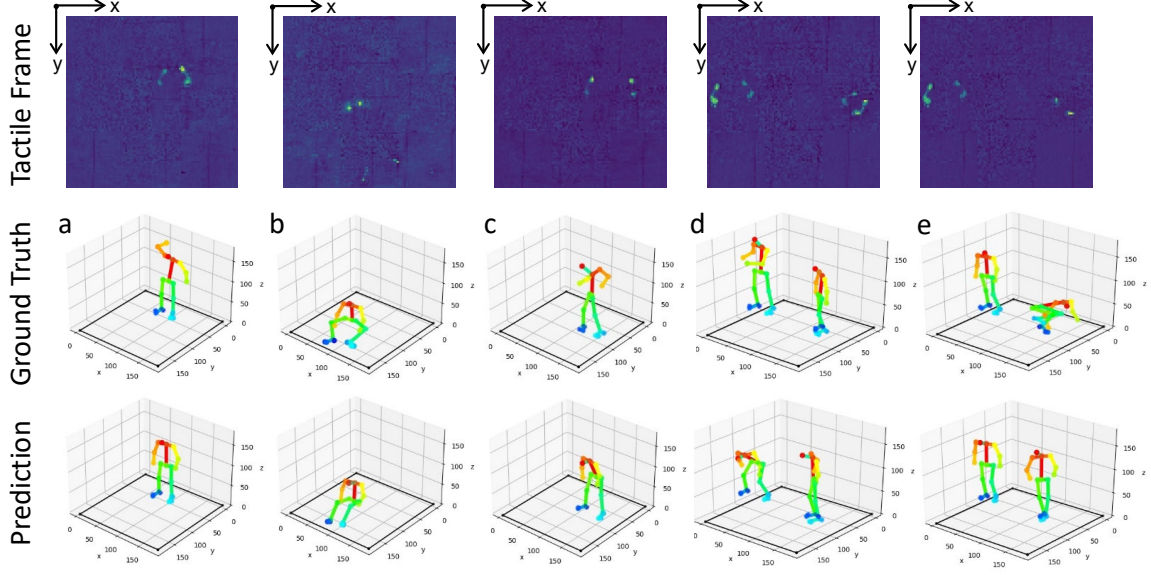


Figure 2-12: **Failure cases.** Our model fails due to the lack of discernible physical contact with the floor (a-b) or the ambiguity of the tactile signal (c-e).

a). This is expected as we observe that the pressure distributions of the tactile maps are rarely or not affected by the movement of the head and wrist when a person is standing on feet. Also, the model fails to predict the poses where actions are performed without notable physical contact with the floor, e.g., free-floating legs during sit-ups and twisted torso during the standing-up process (Figure 2-12 b and e). Furthermore, different actions may induce very similar pressure imprints, e.g., bending and twisting, causing trouble for the model to distinguish the activities due to the intrinsic ambiguity of the tactile signal (Figure 2-12 c and d). As for the multi-person pose estimation, additional errors can happen because of the ambiguity underlying the tactile signals from different individuals, where the model fails when two people are too close to each other. This type of data is not included in our synthetic training dataset.

2.5 Discussion

We built a low-cost, high-density, large-scale tactile sensing carpet and captured a large tactile and visual dataset on humans performing daily activities. Leveraging the perception results from a vision system as supervision, our model learns to infer single-person and

multi-person 3D human skeletons with only the tactile readings of humans performing a diverse set of activities on the intelligent carpet. This work introduces a sensing modality that is different and complementary to the vision system, opening up new opportunities for human pose estimation unaffected by visual obstructions in a seamless and confidential manner, with potential applications in smart homes, healthcare, and gaming.

Limitation. We observe that even with the constraint on the human body link lengths, some predicted human poses appear unrealistic in real life. Therefore, adversarial prior can be imposed to further constrain the predicted 3D human pose. Also, we currently use the same model for the single-person and multi-person pose estimation, which suffers from the ambiguity of the tactile signal induced by multiple people that are too close to each other. To obtain more accurate predictions on multi-person pose estimation, a region proposal network can be applied to localize the tactile information belonging to each of the individuals, which will then respectively pass through the pose estimation network to predict the pose of each person [30, 99, 37]. Estimation and modeling of multi-person interactions from tactile information would be another interesting future direction.

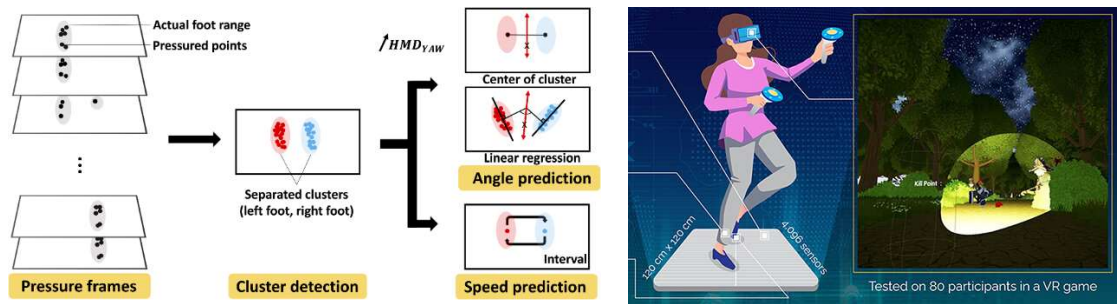


Figure 2-13: **Intelligent carpet for virtual reality locomotion.** Multiple frames are input into a machine-learning model that clusters pressure points to identify foot positions and estimate movement (left) for VR locomotion (right).

Extended application for virtual reality (VR) locomotion. The intelligent carpet system we have developed not only enables human pose estimation that remains unaffected by visual obstructions but also opens up possibilities for various downstream tasks. In an extended study, we leverage the intelligent carpet for VR locomotion (Figure 2-13). We leverage

multiple consecutive images (e.g., 14 frames in this study) as input to a machine-learning model that identifies pressure points from the area stepped on. The model uses K-means clustering to detect two clusters representing the left and right feet. Based on these clusters, the model estimates the angle and speed of movement. This information is then used for VR locomotion.

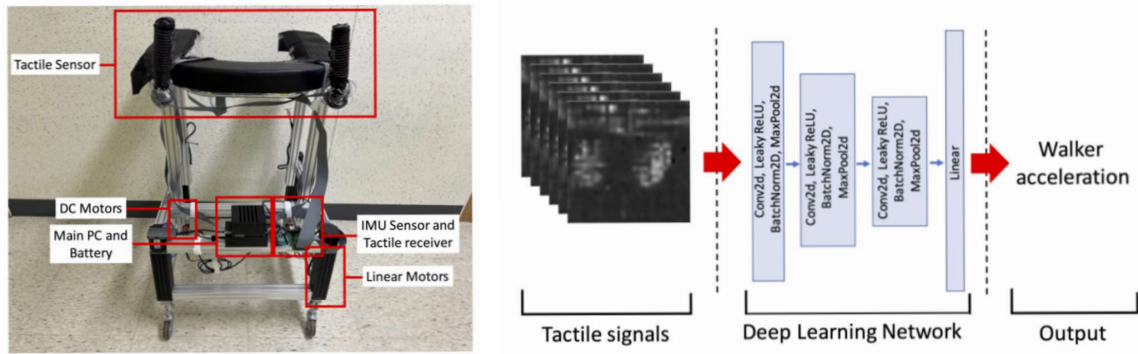


Figure 2-14: **Intelligent walker.** Left: the intelligent walker is integrated with tactile sensors, DC motors, IMUs, and the main PC for operation. Tactile sensors are distributed on the cushions and handles while the IMUs are located at the bottom. The sensors transmit information to the main PC, which actuates the motors based on the received information. Right: ten continuous tactile frames, which capture pressure distribution from the hands and upper arms, are fed into a compact deep-learning network to predict the walker's acceleration.

Extended application for intelligent walker. We extend the intelligent carpet interface further to an intelligence walker system (Figure 2-14) that recognizes human intention to move forward or stop. Through tactile sensing, it collects tactile signals occurring when a person intends to move forward or stop, and learns from these signals. Then, by capturing users' movement by tactile sensor on the walker, moves according to the user's intention, even without the user having to manually press a button or manipulate a joystick.

THIS PAGE INTENTIONALLY LEFT BLANK

Chapter 3

Digital Machine-Knitted Interactive Sensing Interfaces

3.1 Overview



Figure 3-1: **Example applications of KnitUI.** Example applications include interactive educational toys, game controller, music controller glove, numpad wrist wrap, tactile sensing socks, and tactile robotic skin.

Envisioned in ubiquitous and wearable computing, the seamless integration of technology in our everyday environments enables less obtrusive and less constrained interactions in

richer contexts [119]. To overcome the boundary between rigid electronic devices and the ideal soft form factor, previous researchers developed diverse flexible and wearable interfaces [113, 33]. Among them, smart textiles exhibit a few clear advantages. As the fabric is flexible, lightweight, and breathable, it provides comfort during natural human activities. Textiles also offer seamless integration of functionalities in daily human life due to their wide variety of everyday applications, spanning apparel, furniture, and plush toys, which can be fabricated and tailored using existing manufacturing methods. There are several common textile manufacturing methods (*e.g.*, weaving, sewing), but we focus on knitting, which offers several clear advantages. First, the latest advances in digital machine knitting allow designers to create the whole garment with versatile geometries, patterns, and colorworks in one machine run [117], which can eliminate manual tailoring. Furthermore, the continuously interlocking “loop-through-loop” structure makes knitted fabrics extra deformable and stretchable.

In this chapter, we present *KnitUI*, a machine-knitted textile-based interactive sensing interfaces that leverage Jacquard and plating knitting techniques to create a two-layered structure [70]. Conductive yarns are embedded automatically into the knitted fabric during knitting to form resistive pressure sensing units. To provide a solution for connecting the sensing matrix with the readout circuit, we introduce a design for knitted conductive traces, which also leverages a two-layered structure with conductive yarns and conventional knitting yarns. We investigate the design parameters for optimized sensing and interactive performance. Thanks to the stable knitting structure with the conventional yarn and conductive yarn, our resulting sensors are deformable, portable, and washable. To help users better utilize *KnitUI*, we present an interactive design interface for users to customize sensing units’ colors, sizes, positions, and shapes. We demonstrate the capability of *KnitUI* with various example applications designed by our interface, including interactive educational toys, portable soft game controllers, and wearable user interfaces. Coupled with the existing machine learning techniques, *KnitUI* can also be used as tactile sensing wearables to record, monitor, and learn physical human-environment interactions. Further, using the knitting shaping technique (*i.e.*, short-rows), we integrate *KnitUI* with a full-sized conformal sensing sleeve for a commercial robot arm, offering an inexpensive, large-scale, lightweight, and

conformal tactile robotic skin.

The following sections describe details on the design, fabrication, evaluation, and application scenarios. The contributions are summarized below.

- We present a knitted deformable, portable, and washable user interface, integrating interactivity and sensing capability with digital machine knitting.
- We introduce the designs of knitted resistive pressure-sensitive sensing units and the corresponding conductive traces, which require minimal manual post-processing to assemble and connect to the readout circuit.
- We develop an interactive design interface for users to customize the graphic designs (e.g., shapes and colors) of KnitUI, and to convert the designs into low-level machine knitting instructions.
- We characterize and evaluate the impact of various design variables for the optimized sensing performance, including sensor sizes, number of conductive rows, and the type of conductive yarns.
- We demonstrate the capability of KnitUI, with a diverse set of example applications, including interactive textiles/wearables interface, tactile sensing wearables, and artificial robot sensing skin.

3.2 Design and Fabrication

3.2.1 Knitted Resistive Sensors

Our method builds on a double-layered knitting structure that utilizes both front and back needle beds from the v-bed knitting machine (*SWG091N_2*, Shima Seiki). As shown in Figure 3-2, the sensing capability is enabled by inserting conductive yarns at specific locations on both top and bottom layers separately. At the rest state without any externally applied pressure, only a limited number of conductive paths exist inside the sensing unit because the knitted conductive yarn loops interlock loosely. When applying a load, the top and bottom layers collapse, and the interactions among the conductive yarn loops increase, creating more electrically conductive paths and significantly reducing the resistance.

To further increase the sensitivity and expand the detection range of sensing units, we utilize a traditional knits shaping technique, *short-row*, to pile up more conductive yarn loops at the bottom layer, which can provide more potential conductive paths. *Short-row* refers to partial rows, where only some stitches of the full row are worked. This structure is commonly used to expand the surface locally and induce curvature, *e.g.*, in the heel of a sock. In this work, multiple conductive short-rows at the bottom layer naturally form visible bumps. These offer similar geometry of a typical interactive button. Also, more potential interactions among loops enable the sensing unit to be sensitive to the physical perturbation and sustainable within the large sensing range.

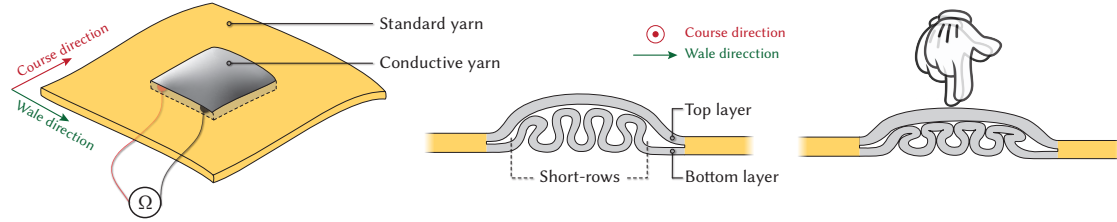


Figure 3-2: **The sensing structure.** Left: A double-layered sensing unit knitted with conventional and conductive yarns. Middle: the cross-sectional view (along the wale direction) of the sensing unit, with conductive short-rows on the bottom layer to increase sensitivity. Right: When pressure is applied, the interactions between conductive yarn loops increase, leading to the drop of resistance.

Figure 3-3 right demonstrates knitting our sensing unit with needle $\times$ time “bed view”, where each row represents the front and back needle beds, and each circle represents the corresponding needle holding a loop. Yellow indicates the standard yarn, and grey indicates the conductive yarn. The bed views are aligned vertically to show the construction time along the upward direction. In the beginning, a two-layered interlocked structure is constructed via Jacquard knitting, which provides a mechanically flattened structure without the curling that typically happens in single-sided all-knits fabrics. To create the sensing unit, we split the interlocked structure to the front and back beds to establish a double-layered structure. Then, we plate both standard and conductive yarns at the same stitches in the sensing unit for two reasons. First, it makes the conductive layer as thick as the rest of the fabric, as the conductive thread is typically much thinner than the standard yarn. Further, plating allows us to further embed graphic designs (*e.g.*, patterns and colors) in front of the sensing unit

with different yarns.

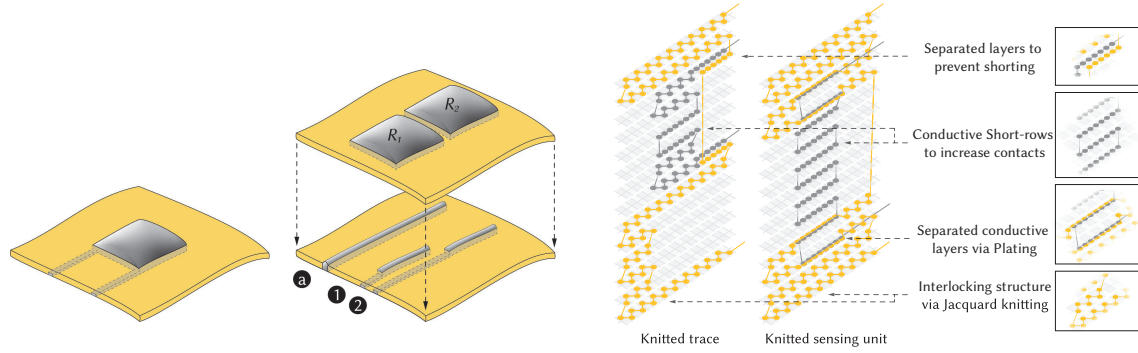


Figure 3-3: **Overview of KnitUI design and fabrication.** Left: For a single sensing unit, the conductive traces are knitted on the backside. However, due to the limited space, conductive traces are knitted on a separate fabric for designs with multiple sensing units. Conductive yarn is knitted on the bottom layer for the connection on the side but is only knitted around the contact area (with the sensing unit) on the top layer to avoid shorting. Right: Needle $\times$ time “bed view” for the sensing units and traces knits (starts from bottom). Note that we highlight each component created by knitting techniques on the right as small insets.

3.2.2 Knitted Conductive Traces

To connect the knitted sensing unit to the readout circuit with minimal labor, we create coupled conductive traces at the bottom layer on the same fabric (Figure. 3-3 left). However, for sensing matrices with more than one sensing unit aligned in the same row, it is hard to knit an isolated conductive path for each sensor due to the limited space. Hence, to avoid shorting among sensing units, we further design an extra fabric with coupled conductive traces to connect sensing units with the external readout circuit (Figure 3-3 right). Each unit connects to one unique conductive trace and shares another conductive trace with all other sensors on the same row. By that, our method not only accomplishes the essential electrical routing with minimal manual work but also preserves the soft and flexible form factor of our sensing units.

For each conductive trace, the conductive thread is always knitted at the bottom layer to form the complete conductive paths. Meanwhile, the conductive yarn is only knitted at the top layer at specific locations to construct the electrical connection with the sensing units.

Short-rows are added at the top layer with conductive yarns to create local curvatures for better contact between the sensing units and the knitted electrical traces. Figure 3-3 right illustrates the needle $\times$ time “bed” view for knitting one trace at the fabric.

3.3 Evaluation

We characterize our knitted sensors as an electric switch and a tactile sensor unit, respectively. The resistance profiles are measured with a digital multimeter (DMM 4050, Tektronix), while an adjustable normal force is applied to the fabricated sensing unit by a mechanical testing system (Instron 5944).

3.3.1 Conductive Yarns

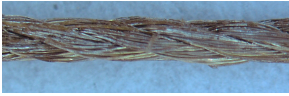
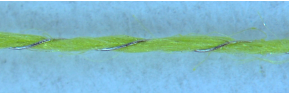
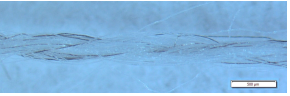
Conductive yarn		Type 1	Type 2	Type 3
Microscope image				
Materials		Stainless steel 100%	Stainless steel 35% Silk 65%	Stainless steel 20% Polyester 80%
Thickness (μm)		450	180	300
Resistance (Ω/m)		30	700	4000
ON	Mean ($k\Omega$)	0.021	19.3	64.7
	STD ($k\Omega$)	0.002	19.8	13.3
OFF	Mean ($k\Omega$)	0.549	9.9e6	533
	STD ($k\Omega$)	0.107	< 0.001	42.9

Table 3.1: The characteristics of different conductive yarns and the performance profile of the typical sensing units fabricated with each of them.

Our proposed knitting structure is functional with standard off-the-shelf conductive yarns. To evaluate how the characteristics of different conductive yarns impact the sensing performance, we knit sensing units with 28×28 stitches and two backside short-rows using three different commercial conductive yarns. The characteristics of yarns and the performance evaluations are listed in Table 3.1. The first conductive yarn (type 1) is made of 100% stainless steel and thus has high conductivity; however, the sensor resistance is too

small ($\ll 1 \text{ k}\Omega$) for the readout circuit to capture the difference when pressure is applied. Besides material composition, the sensing performance highly depends on the yarn structure. For instance, Yarn 2 is made by intertwining a single stainless steel fiber with silk fibers. As shown in the first row of Table 3.1, the conductive component is only exposed to the exterior in a small region. This structure restricts the stable interactions between the conductive yarns within the knitted sensing unit, leading to a significant variation in the resistance at the “ON” state. On the other hand, Yarn 3 is made of short steel fibers mixed with polyester. It obtains higher unit resistance ($4 \text{ k}\Omega$) due to the lower conductive composition percentage. However, compared with the intertwined structure of Yarn 2, the conductive composition in Yarn 3 is distributed throughout the yarn volume more homogeneously, which provides uniform and reliable electrical contacts among the conductive yarns when the unit is compressed. Therefore, we use Yarn 3 in the rest of the paper because of its reasonable resistance range and response variations.

3.3.2 Number of Short-Rows.

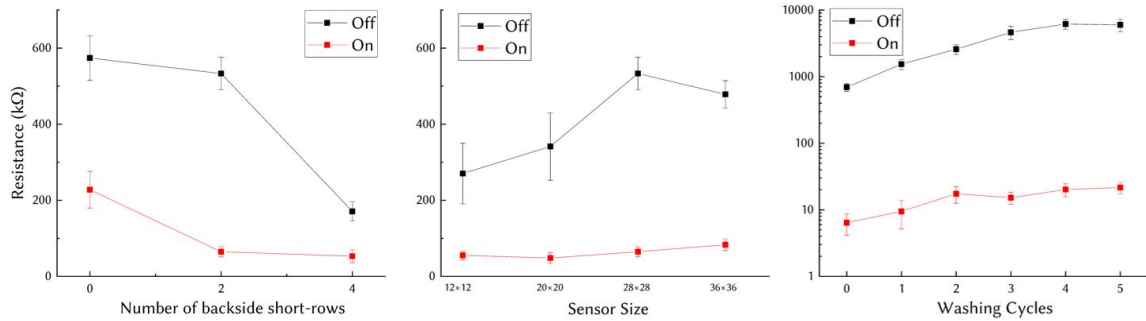


Figure 3-4: **Characterization on numbers of short-rows, sizes, and washing cycles.** Resistance at the “ON” and “OFF” states of the sensors fabricated with different numbers of short-rows (left), sensing sizes (middle), and washing cycles (right).

Conductive short-rows on the backside of the sensing unit can improve the electrical contact. Here, we evaluate the performance of sensing units (28×28 stitches) with 0, 2, and 4 backside conductive short-rows. As shown in Figure. 3-4 left, with no conductive short-rows, only a small amount of conductive yarn is embedded in the sensing unit; this causes the electrical interactions to be unstable. Therefore, the resistance is relatively high with significant variation in both “ON” and “OFF” states. In contrast, with more short-rows, the

sensing unit demonstrates lower resistance. This is expected because more conductive yarns are integrated, enabling more extensive potential electrical contacts. However, integrating with too many short-rows also reduces the resistance difference between the “ON” and “OFF” states. The crowded conductive yarns consistently interact with each other to some extent, even when no physical perturbation is applied. This increases the undesirable false-positive detection rate. Hence, to achieve a well-distinguished resistance gap between “ON” and “OFF” states with low variance, we use the design of two short-rows for the rest of the paper.

3.3.3 Size of Sensing Unit

We also measure the performance of sensors of different sizes. To be specific, we knit and measure the resistance profiles of sensing units with 12×12 , 20×20 , 28×28 , and 36×36 stitches, respectively. The actual physical size of the sensor with 12×12 stitches is $17\text{ mm} \times 15\text{ mm}$. As shown in Figure. 3-4 middle, all of them maintain reasonable resistance differences between two states with low variations. A clear threshold between the “ON” and “OFF” states can be retrieved at the resistance of $150\text{ k}\Omega$.

3.3.4 Washing Test

Like other knitted daily goods, our sensors are also washable. We perform a washing test with an industrial washing machine (*GFWN1600J1WW*, GE Appliances) and gas dryer (*GFD45ESSK0WW*, GE Appliances). Each washing cycle lasts for 52 mins in the delicate mode with liquid laundry detergent (Tide), and laundry sanitizer (Lysol), and each drying cycle lasts for 60 mins in the *delicate* mode. After each washing cycle, we measure the resistances of the sensing unit at the “ON” and “OFF” states. Figure. 3-4 right shows that the resistance slightly increases in both states but remains stable after the third cycle. The interlocked structures of the conductive yarn get disturbed by the first few washing (and drying) cycles but become stable eventually. Most importantly, even after our washing tests, the sensing unit remains fully functional, with a significant resistance difference and a small variation at the two states.

3.3.5 Performance under Deformation

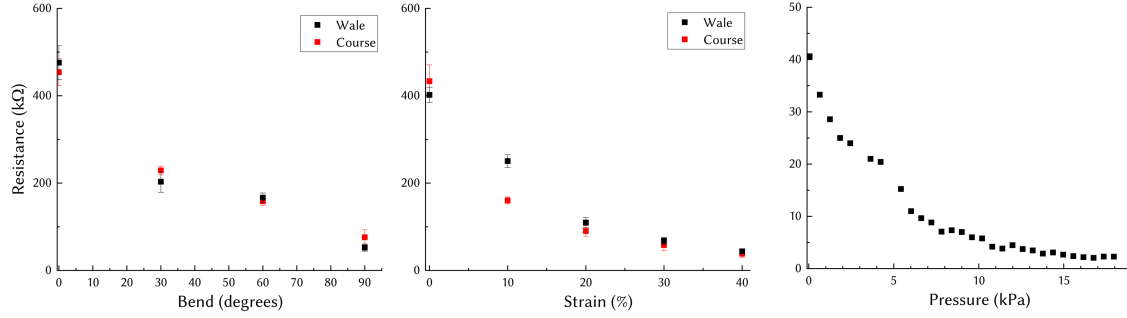


Figure 3-5: **Characterization on sensors with deformation.** Resistance of a sensor at the “OFF” states of the sensors under bending (left) and stretching (middle). The resistive profile of a sensor under 40% strain along the course direction in response to the applied pressure (right).

We investigate the influence of deformation by measuring the sensing unit’ at “OFF” state under different levels of bending and stretching. Due to the anisotropy of the knitting structures, we perform the characterization along with the wale and course directions, respectively. Generally, as demonstrated in Figure. 3-5 (left and middle), the sensing unit’s resistance drops under deformation because the electrical contacts among the knitted conductive yarns increases during bending and stretching. In the worst case, the sensor ensures the largest resistance drops from 420 $k\Omega$ to 160 $k\Omega$ to 38 $k\Omega$ under 40% strain along the course direction. To demonstrate the usability of our device under large deformation, we evaluate the performance of a sensing unit under 40% strain along the course direction (Figure. 3-5 right); The signal under the increasing pressure from 0 kPa to 17.5 kPa is still detectable with a 10-fold change in magnitude, with the resistance drops from 38 $k\Omega$ to 0.7 $k\Omega$. It is also worth noting that knits are usually used as conformal coverings so that we wouldn’t expect KnitUI under large deformation in real usability scenarios.

3.3.6 Continuous Sensing Responses

Lastly, we characterize our 28×28 -stitch sensing units as tactile sensors. Figure. 3-6 shows that the resistance profile of a typical sensing unit under continuously increasing and decreasing of applied pressure. The resistance drops from 190 $k\Omega$ to 25 $k\Omega$ in response to

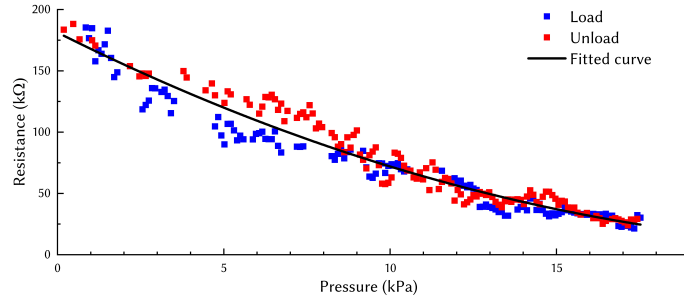


Figure 3-6: **Continuous resistance profile.** Continuous resistance profile of a typical knitted sensing unit in response to the load and unload of pressure.

a continuously increasing applied pressure from 0 kPa to 17.5 kPa . The peak hysteresis is around 16%. Among six tests on the same sensing unit, when the applied pressure is small, resistance variation is inevitable due to the flexibility of the knitted fabric and the local movement of the layered structures. This artifact is alleviated eventually when the applied pressure increases. It is worth noting that the response variation can be compensated easily by deploying current machine learning techniques. We will show a few applications in tactile sensing in the next section.

3.4 Application

We demonstrate application of KnitUI in diverse using scenarios.

3.4.1 Interactive Textiles



Figure 3-7: **Interactive educational toys.** The front and back of “Apple”, “Flower”, “Cloud and Sun”, and “Shark and Jellyfish”.

KnitUI provides an entirely knitted interface that is soft, washable, and ecofriendly. More importantly, it allows users to customize the color and shapes of each sensing unit and

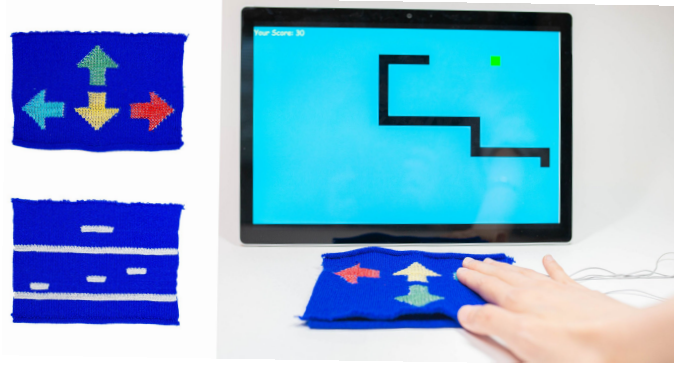


Figure 3-8: **Textile-based game controller.** Playing “Snake” game using our knitted controller.

interface. All the mentioned features make KnitUI perfect for early education toys. Here, we present four knitted patches with diverse graphic designs (Figure. 3-7). In particular, each patch contains two sensing units for children’s interactive learning. For example, the “apple” patch contains two sensing units in the “apple” and “leaf” regions, respectively; the corresponding word will be pronounced when the sensing units are pressed. As shown in Figure. 3-7 right, the coupled conductive traces are integrated on the backside of the same fabric with the sensing units, which enables the simple and removable electrical connection to the readout circuit.

KnitUI can be used as a soft controller. Figure. 3-8 demonstrates the user plays “Snake” game using our knitted controller. Since there are three sensing units aligned in the same row, instead of knitting the conductive traces in the same patch as the sensing units, we knit a separate patch to connect to the readout circuit. Both the sensing and connection patch are knitted fully automatically. Electrical connections are created by stacking the two patches together.

3.4.2 Interactive Wearable

Thanks to the recently introduced whole garment digital knitting machine, the fabrication of whole garments with complex geometries, *e.g.*, gloves and apparel, can be realized without further manual cutting and sewing. These garments are fully customizable and can be adapted to individual shape, size, surface texture, and color preferences, meeting the



Figure 3-9: **Interactive wearables.** Conductive traces are added to existing knitted glove design for gloves with different controller designs.

needs of personalization and fashion design. KnitUI can be integrated into a whole garment seamlessly, which enriches the interactive modalities and broadens the application scenarios of KnitUI. We demonstrate an example on the daily human goods with the most complex geometry – glove, in Figure. 3-9. The interactive glove is composed of a patch with the sensing units of desired shapes and colors and a full-sized glove embedded with electrical traces at specific locations. The full-sized glove is designed by adapting the existing design (Shima Seiki) through *KnitPaint* [108]. This design process reiterates the straightforward design transfer to an existing complex knitting design using our method, which maximizes the usage of existing designs and boosts design efficiency. Moreover, the double-layer structure offers an opportunity to use the same glove in conjunction with multiple sensing units designed for different applications. Here, the interactive glove can be used for either direction indications or music control, just by switching the directional pad to the other designed controller pad, respectively.

3.4.3 Tactile Sensing Wearables

KnitUI can be further used as tactile sensing wearables for recording, monitoring, and learning on physical human-environment interactions. As a proof of concept, we present a pair of socks (Figure. 3-10), each of which contains a 2×5 sensing array, to capture the real-time tactile information when the wearer performs a diverse set of actions. A deep neural network is trained to classify the wearer’s actions given sequential sensing data as

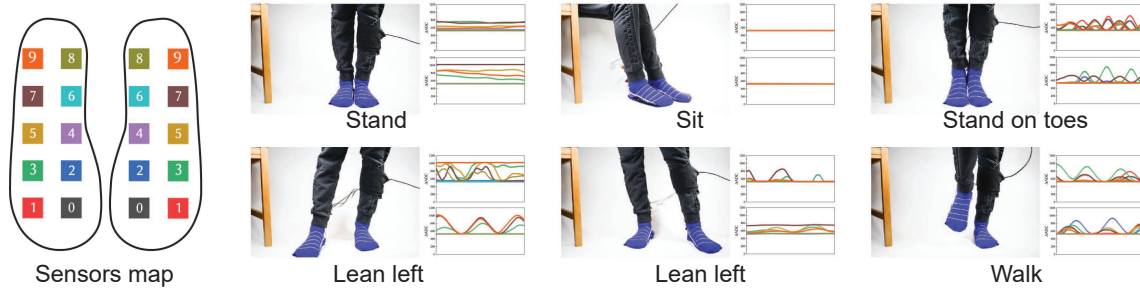


Figure 3-10: **Tactile sensing socks.** Sensor map and the corresponding pressure signals during six actions.

input. Specifically, we use the Temporal Convolutional Network (TCN) [6], a benchmarking network, and one of the most widely used ones for sequential modeling tasks. To train the TCN, we collect a training dataset (5400 tactile frames) that includes actions of stand, lean left (left), lean right (right), stand on toes (toes), sit, and walk (Figure. 3-10). The training details primarily follow the settings in the original paper of Bai et al. [6], except that we set the number of input channels to 20, the total number of input sensors. The training converges in 20 epochs.

3.4.4 Artificial Robot Sensing Skin



Figure 3-11: **A robot arm (KUKA) with knitted sensing covering.** Conformal robot arm sleeve with sensors in red and conductive traces in grey.

Unlike humans, modern robots lack tactile feedback; touch sensors have been demonstrated as a critical step towards the promotion of physical human-robot interactions and the improvement of robot manipulation. However, it is still challenging to obtain a 3D conformal

soft robot skin. In this work, we demonstrate that KnitUI can produce full-sized soft conformal robot skins, which are light, inexpensive, customizable, and easy-to-manufacture. This capability will facilitate physical human-robot interactions through collision detection and real-time tactile sensing. As shown in Figure. 3-11, We present a full-sized conformal sensing sleeve for a commercial robot arm (a link with a dimension of $50\text{ cm} \times 20\text{ cm} \times 20\text{ cm}$, LBR iiwa, KUKA). The artificial robot skin is composed of two parts: individual patches with sensing units and a conformal robot arm covering with integrated conductive traces. The machine knitting instructions for the conformal covering is generated from the KUKA arm mesh directly using Stitch Meshes [125, 88]. By placing individual sensing units at desired locations, we endow the robot arm with real-time tactile feedback. Since our sensors are knitted separately, we can easily adjust the densities and positions of individual sensing units along the conductive traces to perform recordings at desired spots over the robotic arm surface. Our method demonstrates the potential for applications in unobtrusive tactile sensing, multi-point collision detection for robot manipulation and control, and physical human-robot interaction.

3.5 Discussion

We presented KnitUI, a knitted interactive and sensing user interface based on resistive pressure sensing. KnitUI offers a user interface that is deformable, portable, breathable, washable, robust, and lightweight. This is useful in a wide range of application spaces, including education, entertainment, tactile sensing, and human-robot interaction. KnitUI builds on a machine-knitted double-layered structure using conventional yarns and conductive yarns. KnitUI also includes a machine-knitted conductive trace design, which allows users to connect the sensor with a read-out circuit quickly with minimal manual post-processing. The resulting knitted fabrics can be integrated with any existing knitted garment designs easily. We also presented an interactive design interface for users to customize the sensor’s shape. We performed characterization and evaluation of the impact of various design variables for the sensor, including sensor sizes, number of conductive rows, and the types of conductive yarns. We demonstrated several example applications of KnitUI,

including interactive textiles, tactile sensing wearable, and artificial robot skin. We believe KnitUI opens up possibilities in endowing everyday objects with sensing capability at a low cost by bridging the gap between interactive textile and industrial-scale manufacturing.

Limitation. Due to the thickness of the yarn and the knitting mechanism, the minimum size for a knitted sensor that can produce stable sensing is limited to 2 to 3 stitches (5 mm width). Although our digital knitting machine enables knits of up to 90 cm, sensor performance degrades with too-small or too-large sensing units. Also, KnitUI relies on the interactions among the integrated conductive yarns, whose performance variation is unavoidable due to the softness and flexibility of the knitted textiles and the double-layered structure. Therefore, it is vital to record a training dataset coupled with machine learning techniques for reliable quantitative measurement extraction.

THIS PAGE INTENTIONALLY LEFT BLANK

Chapter 4

Dynamic Modeling of Hand-Object Interactions via Tactile Sensing

4.1 Overview

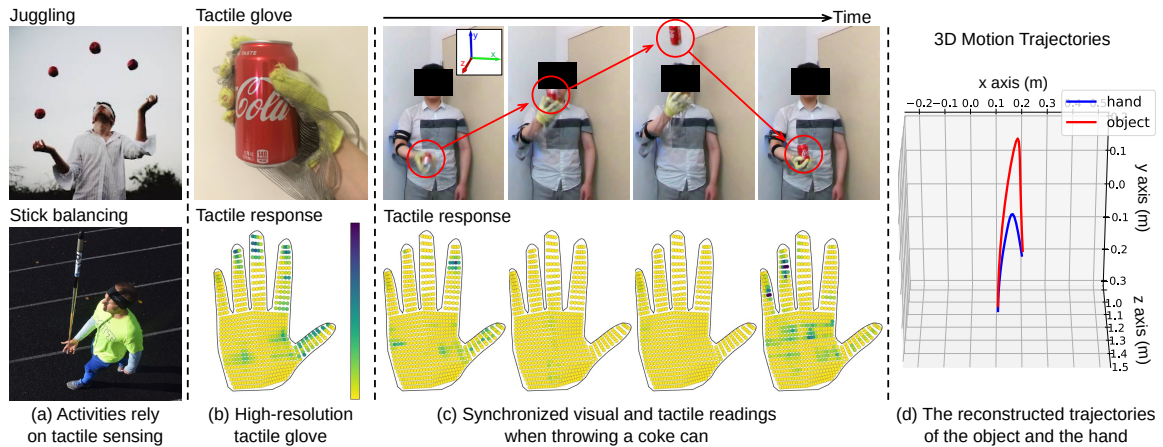


Figure 4-1: **Hand-object interactions using a tactile glove.** (a) Daily activities involving hand-object interactions require tactile sensing and an intuitive understanding of real-world dynamics. (b) We employ a high-resolution tactile glove [115] to obtain the tactile signal when interacting with objects. (c) When throwing an object in the air and catching it, different tactile patterns appear during the process. (d) We model the dynamics of this interaction and reconstruct the 3D trajectories of both the object and the hand using only tactile data.

When interacting with diverse objects using our hands, humans can feel and sense the contacts, enabling a strong intuitive understanding of the dynamics of the interactions

(Figure 4-1 a). This understanding allows us to predict how the environment will evolve and be influenced by these interactions, which is tremendously helpful for accomplishing daily manipulation tasks. To further our understanding of human activities, it is desirable to develop techniques that can model the dynamics of hand-object interactions, especially in highly dynamic scenarios.

In this work, we aim to model the dynamics of hand-object interactions in highly dynamic tasks using a high-resolution tactile glove (Figure 4-1 b). Specifically, we employ a cross-modal learning framework, where we collect synchronized RGBD images and tactile readings. During training, we use a visual processing pipeline to estimate the ground truth trajectories of both the object and the hand, which act as the labels to supervise the tactile model. During the test time, we only assume to have access to the tactile inputs and predict the corresponding system’s states using the trained tactile model.

We consider diverse activities, including holding an object and waving it in the air, throwing an object upwards and catch it (Figure 4-1 c), bouncing a ping-pong ball up and down using the racket, and balancing an umbrella to prevent it from falling. Our goal is to predict the motion trajectory of the hand and the object purely based on the tactile readings (Figure 4-1 d).

Our tactile model builds on top of a predictive model that takes the current state of the system, i.e., the positions and velocities of the object and the hand, and the tactile reading as input, then predicts the system state at the next time step. We add to the model an object encoder that produces object-centric embeddings calculated from a short sequence of interaction data that implicitly encodes the object-specific information like the mass and geometry. Experiments show that our model can reason about the interaction patterns from the tactile data, model the dynamics of the interactions, and quantify the uncertainty of the prediction. The use of the object encoder also allows an improved performance when generalizing to unseen objects. We also provide detailed ablation studies regarding the resolution of the tactile sensing and the visualizations of the predicted trajectories. This work moves in the direction of dynamics modeling in hand-object interactions from dense tactile sensing, which we hope can facilitate future studies and applications in multiple domains, including computer vision, graphics, and robotics.

The following sections describe details on the method, experiment, evaluation, and application scenarios. The contributions are summarized below.

- We capture a synchronized visual and tactile dataset featuring on humans’ dexterous and dynamic interactions with the objects.
- We develop cross-modal learning framework to model dynamic hand-object interactions from tactile sensing.
- We perform experiments to validate that our model can reason about the interaction patterns from the tactile data, model the dynamics of the interactions, and quantify the uncertainty of the prediction.

4.2 Method

4.2.1 Tactile Sensing Glove

We use the tactile glove proposed by Sundaram et al. [115] to collect the hand-object interaction touch data (Figure 4-1 b). There are about 680 sensors covering the palm area of the glove that can measure the applied forces. We record the tactile signal at each time step as an image of 32×32 resolution at a rate of around 15 Hz.

4.2.2 Dynamics Prediction Model

The overall dynamics model is defined as the following:

$$\hat{s}_{t+1} = f(s_t, g_t, e_i), \quad (4.1)$$

where s_t denotes the state of the system at time t , g_t indicates the tactile embedding derived from the current tactile input, and e_i is the object embedding that is shared across all time steps, containing contextual information like the mass and geometry of object i .

We represent the state of our system using the states of both the object and the hand,

$s_t = (s_t^{\text{object}}, s_t^{\text{hand}})$, each of which is a concatenation of its position and velocity,

$$s_t^{\text{hand}} = (q_t^{\text{hand}}, \dot{q}_t^{\text{hand}}), \quad s_t^{\text{object}} = (q_t^{\text{object}}, \dot{q}_t^{\text{object}}), \quad (4.2)$$

where $q_t = (x_t, y_t, z_t)$ indicates its 3D location.

To calculate the tactile embedding g_t , we take a small temporal window of M tactile frames as input, $\mathcal{T}_t = \{T_{t-M+1}, \dots, T_{t-1}, T_t\}$, concatenate them to form a tensor of shape $M \times 32 \times 32$, and then feed it through an encoder (Figure 4-2 b). We implement the encoder as a three-layer convolutional network with channel sizes of 32, 64, 128, individually. The dynamics prediction module (the green box in Figure 4-2) is an MLP (Multi-Layer-Perceptron) that predicts the next state $\hat{s}_{t+1}$ by taking as input the concatenation of the tactile embedding g_t , the object embedding e_i , and the system state s_t at the last time step.

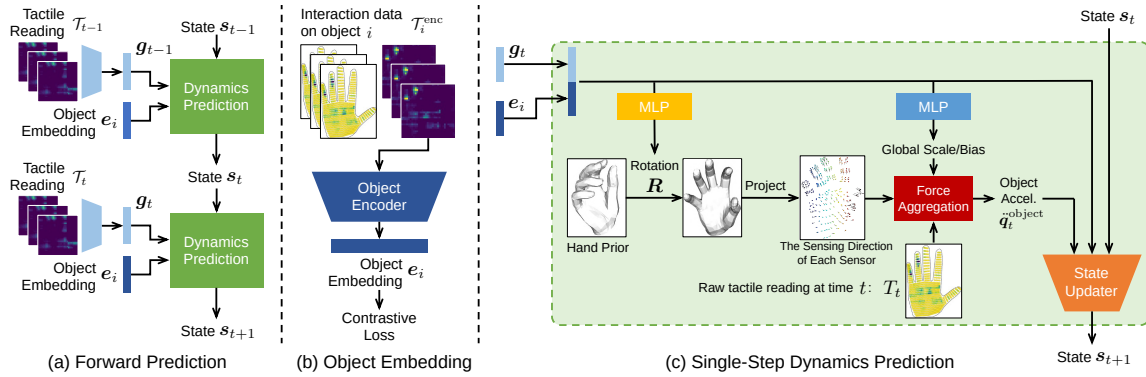


Figure 4-2: Dynamics prediction model. (a) The object embedding e_i is derived by encoding a short period of interaction data into an implicit object-specific representation containing information like the mass and geometry. (b) Our model builds on top of a dynamics prediction model, which takes (i) the current state s_t , i.e., the positions and velocities of the object and the hand, (ii) the tactile embedding g_t , and (iii) the object embedding e_i as input, and then predicts the system state at the next step.

4.2.3 Pinball Loss for Uncertainty Estimation.

To quantify the uncertainty in state prediction, we use a pinball loss function [56] to predict both the mean value and the 10% and 90% quantiles. The intuition is that for a given set of inputs, the model estimates through a single forward pass both the expected future state and a cone of error within which the ground truth should lie 80% of the whole time.

More specifically, the outputs of the dynamics prediction module contain both the state $\hat{s}$ and the offset from the expected state, $m\sigma$, such that $\hat{s} + m\sigma$ is the 90% quantile of its distribution while $\hat{s} - m\sigma$ is the 10% quantile. Assuming that the ground truth future state is s , the pinball loss is calculated as the following:

$$\mathcal{L}_{\text{pinball}}^\tau = \max(\tau \hat{p}_\tau, -(1 - \tau) \hat{p}_\tau), \text{ where} \quad (4.3)$$

$$\hat{p}_\tau = \begin{cases} s - (\hat{s} - m\sigma), & \text{for } \tau \leq 0.5 \\ s - (\hat{s} + m\sigma), & \text{otherwise.} \end{cases}$$

We use the L1 regression loss and this pinball loss for both the predicted state and the quantiles at $\tau = 0.1$ and $\tau = 0.9$, making $m\sigma$ a measurement of the difference between the 10% and 90% quantiles and the expected value. The final loss for future state prediction is then:

$$\mathcal{L}_{\text{state}} = |s - \hat{s}| + \mathcal{L}_{\text{pinball}}^{0.1} + \mathcal{L}_{\text{pinball}}^{0.9}. \quad (4.4)$$

4.2.4 Contrastive Learning for Object Embeddings

To improve our model’s generalization ability to unseen objects, we propose to encode a short period of interaction data into an implicit object embedding containing object-specific information like the mass and geometry. The intuition here is that when we humans have interacted with an object for a while using our hands, we can develop a better intuitive understanding of the object’s dynamics and give better estimates of the object’s physical properties like mass.

We subsample a short sequence from the interaction dataset of the object i and denote it as $\mathcal{T}_i^{\text{enc}}$. An encoder, implemented as a convolutional neural network, maps $\mathcal{T}_i^{\text{enc}}$ into its object embedding e_i (Figure 4-2 a). When predicting multiple steps into the future using the dynamics prediction module, the tactile embedding g_t is changing as it is derived from the current tactile inputs. In contrast, the object embedding e_i is kept the same throughout the prediction horizon (Figure 4-2 b), which we hope can help the model disentangle the object-related information from the motion-related features, facilitating generalization to unseen objects.

Inspired by recent developments in contrastive representation learning [91], we introduce an auxiliary contrastive loss to help the object encoder learn more meaningful representations. We use the object embeddings calculated from the same object as the positive pair and embeddings from different objects as the negative pair. We then define the auxiliary contrastive loss as the following:

$$\mathcal{L}_{\text{obj}} = \mathbb{E}_e \left[\log \frac{\exp(e^T \cdot e^+)}{\exp(e^T \cdot e^+) + \sum_{j=1}^{N_{\text{sample}}-1} \exp(e^T \cdot e^-)} \right], \quad (4.5)$$

where e is the reference embedding, e^+ and e^- are positive and negative embeddings respectively, and N_{sample} denotes the number of samples.

4.2.5 Overall Loss and Evaluation Metrics.

The overall loss of our framework is then a weighted sum of the future state prediction loss $\mathcal{L}_{\text{state}}$ and the contrastive loss for learning the object embeddings $\mathcal{L}_{\text{obj}}$:

$$\mathcal{L} = \mathcal{L}_{\text{state}} + \lambda_{\text{obj}} \mathcal{L}_{\text{obj}}. \quad (4.6)$$

We evaluate the performance of our dynamics modeling framework using two different metrics: (1) the L1 distance between the predicted state and the ground truth over different time steps, and (2) the Hausdorff distance [44] between the predicted and ground truth trajectories. Given the ground truth trajectory $A = \{s_t, s_{t+1}, \dots\}$ and the predicted trajectory $B = \{\hat{s}_t, \hat{s}_{t+1}, \dots\}$, the Hausdorff distance measures the similarity based on the shape of the trajectories and is defined as the following:

$$H = \max \left\{ \max_{a_i \in A} \min_{b_j \in B} d(a_i, b_j), \max_{b_i \in B} \min_{a_j \in A} d(b_i, a_j) \right\}, \quad (4.7)$$

where $d(\cdot, \cdot)$ denotes the Euclidean distance.

4.3 Experiments

4.3.1 Data Collection

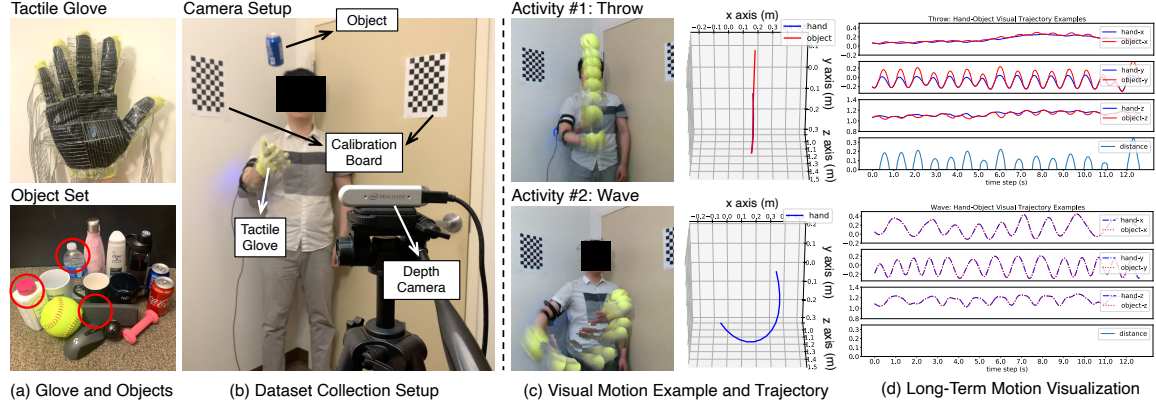


Figure 4-3: **Data collection setup and motion examples.** (a) The tactile glove and the object set for performing “wave” and “throw” activities. Objects used for evaluating the model’s generalization ability are marked using red circles (unseen during training). (b) A depth camera collects RGBD videos, which we use to project the hand and object’s motion to 3D. (c) Here we show a visual example and the corresponding 3D trajectory for each activity. (d) shows long-term visualizations of typical motions in each axis and the distance between hand and object for the two activities.

The primary focus of this work is the dynamics modeling of hand-object interactions from tactile sensing. Given that there is still a huge performance gap between the state-of-the-art dexterous hand robotic system [54, 1, 3, 86] and human capabilities, we ask a human subject to wear the glove and perform various interaction tasks instead of using a robot system, which allows us to study more dexterous and dynamic interactions.

Figure 4-3 b shows the setup for data collection, where a human subject faces a depth camera and performs various hand-object interaction activities. The RGBD camera and the tactile glove collect synchronized visual and tactile data with a framerate of 20 Hz and 15 Hz, respectively. To obtain the ground truth locations of both the hand and the object, we first segment the image according to the depth map and use the CSRT tracker [64] implemented in the OpenCV library to track their locations. We also calibrate the camera to ensure that we can interpret the ground truth labels in real physical units like meter and second. Compared with motion capture systems using markers on the object/hand, this RGBD-based caption

system is simple, cheap, and easy to use. See the accompanying videos for visualizations of the tracking results.

We first consider the *Wave* activity, where the human subject holds an object in hand and wave it in the air. This activity is to verify the feasibility of the task: only when there exists a strong correlation between the tactile signal and the object’s acceleration can we predict the motion trajectories purely from touch. This intuition on the correlation between different sensory modalities originates from Newton’s second law of motion, which builds the connection between force (perceived by the tactile signal) and motion (the object’s acceleration). Then we extend the system to more complicated activities where there can be large relative motion between the object and the hand:

- *Throw*: throw an object upward and catch it,
- *PingPong*: bounce a ping-pong ball using the racket,
- *Balance*: balance an umbrella to prevent it from falling.

Examples of the four activities are shown in Figure 4-3 and Figure 4-6 respectively. For *Wave* and *Throw*, we collect data for interacting with 15 different objects (Figure 4-3 a), where we constantly change the in-hand position of the objects to increase the diversity of the dataset. We then split them into 12 seen and 3 unseen objects. Among the data for the seen objects, 80% of them are used for training, while the remaining 20% are for evaluation.

4.3.2 Results on “Wave” and “Throw”

This section presents the experimental results on the *Wave* and *Throw* tasks. We first evaluate the model’s performance by training separate models for each object. Then, we train a single model on all objects to test the model’s multi-object generalization ability and show the benefits brought by the object embedding.

We train a separate model for each object by minimizing the loss function defined in Equation 4.6 for 50 epochs using Adam optimizer [55] and a learning rate of 0.0005.

We compare our model with the following two baselines: (1) Random: For each testing example, we randomly sample another trajectory from the dataset and measure

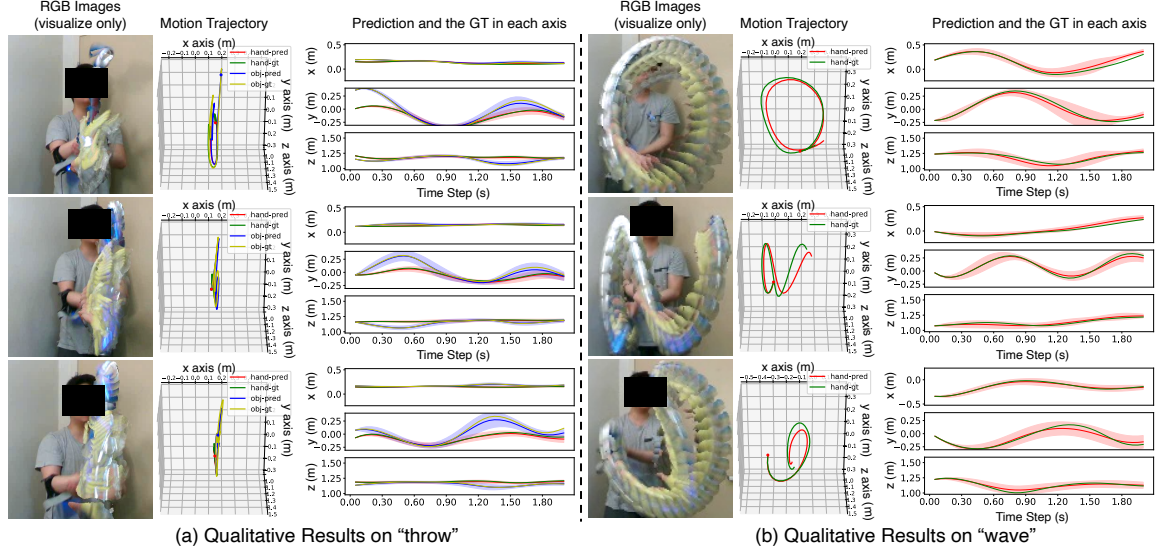


Figure 4-4: **Qualitative visualizations for “Throw” and “Wave”**. (a) Visualization of the results in the “throw” activity. From left to right, we show the reference images (only used for visualization), the predicted and the ground truth trajectory in 3D, and the individual comparison in each axis. The shaded area indicates the estimated uncertainty from our model that corresponds to the 10% and 90% quantiles. (b) The same set of visualizations for the “wave” activity. Our model’s predictions closely resemble what’s happened in the real physical world.

their difference using the metrics discussed earlier, which acts as a lower bound for the performance. (2) w/o Touch: In this baseline, we remove the tactile input and only use the state at the previous time step (s_t in Figure 4-2 b) as the input to the dynamics prediction module. This baseline serves to show the benefit of the tactile information in dynamics modeling.

The left part of Table 4.1 illustrates the quantitative results. It is clear from the table that the touch information is critical for predicting the dynamics. We also include some qualitative results in Figure 4-4 for each activity by showing a side-by-side illustration of the original RGB image, the motion trajectories in 3D, and the estimated uncertainty in each axis. Our model can generate trajectories that closely match the ground truth, where the hand and object’s movements consistently lie in our model’s predicted confidence interval.

We also evaluate the model’s ability to generalize across multiple objects. We use an object encoder to extract the implicit embeddings for each object that contain object-related information like the mass and the geometry (Figure 4-2 a). To optimize our model, we first

Exp. type		Single object		Multi-object			
Setting		Average		Seen		Unseen	
Throw	Random	w/o Touch	Ours	w/o Embed.	Ours	w/o Embed.	Ours
L1@20	0.992	0.341	0.227	0.281	0.254	0.312	0.265
L1@50	1.005	0.547	0.288	0.323	0.297	0.391	0.305
Hausdorff	1.169	1.007	0.659	0.868	0.775	0.918	0.842
Wave	Random	w/o Touch	Ours	w/o Embed.	Ours	w/o Embed.	Ours
L1@20	0.308	0.186	0.108	0.135	0.116	0.154	0.129
L1@50	0.309	0.212	0.132	0.161	0.137	0.182	0.154
Hausdorff	1.671	1.498	0.917	1.154	1.025	1.308	1.119

Table 4.1: Quantitative results for “Throw” and “Wave”. Here we assess our model’s ability for predicting the dynamics of a single object and that of cross-object generalization. We evaluate the performance using the Hausdorff distance as well as the average L1 distance between the prediction and the ground truth when rolling 20 or 50 steps into the future. In both the “Throw” and the “Wave” activities, our model outperforms a random baseline and a baseline that does not use the touch information, which is in line with our intuition that touch plays a critical role in modeling the dynamics. The use of object embeddings also improves the performance, especially when encountering objects that are not seen during training.

train the object encoder using contrastive loss, where the positive and negative samples are from the same object and different objects separately. Each sample is a 20-step touch segment uniformly sampled from all touch data sequences. We then fix the object embedding for each object and concatenate it with the tactile embedding as the input feature for the subsequent computation (Figure 4-2 b). During the test time, we choose the touch sequence from the first 20 steps and feed it into the object encoder to obtain the object embeddings.

We compare our model with a baseline that does not use the object embedding (w/o Embedding). The right half of Table 4.1 presents the quantitative results on cross-object generalization performance, which shows the benefit of the object embedding for improving the generalization ability.

4.3.3 Ablation Study on the Tactile Resolution

In this section, we aim to evaluate the importance of sensor resolution in dynamics modeling. We downsample the input tactile image from original 32×32 resolution to 24×24 , 16×16 , 12×12 , 8×8 , and 6×6 respectively, and evaluate the performance on the “Billiard”

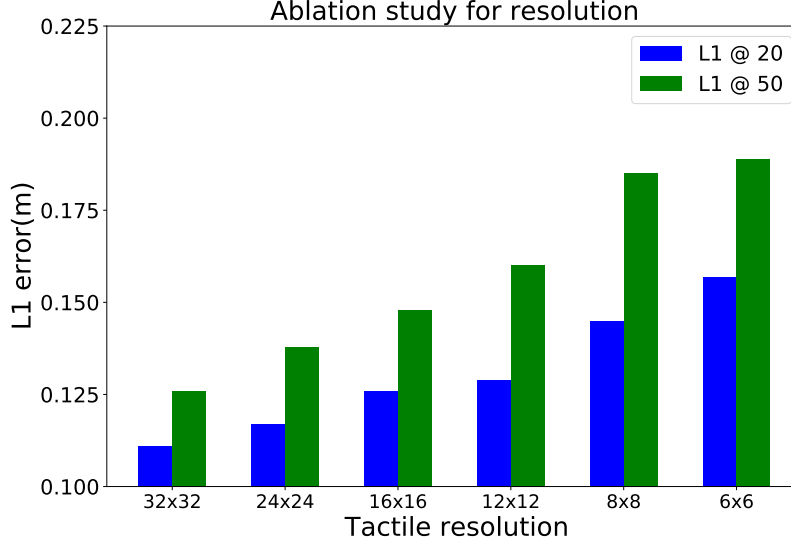


Figure 4-5: **Ablation study on the resolution of the tactile glove.** The error bars show the L1 error of the prediction at 20 or 50 steps into the future when using tactile images of different resolutions, ranging from 32×32 to 6×6 . Higher resolution can, in general, achieve better performance.

dataset from the “Waving” task. As shown in Figure 4-5, with the decrease of the effective resolution, the prediction performance drops notably, showing the importance of the sensor count in dynamics modeling.

4.3.4 Results on “PingPong” and “Balance”

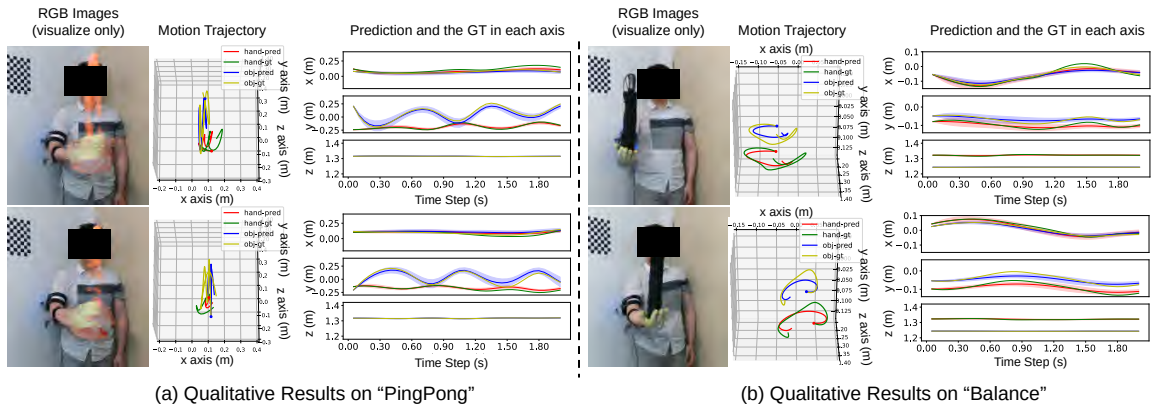


Figure 4-6: **Qualitative visualizations for “PingPong” and “Balance”.** We show the reference images, the predicted and the ground truth 3D trajectory, and individual comparisons in each axis. The state of the object s_t^{object} is represented as the position and velocity of the ping-pong ball and the upper tip of the umbrella in these two activities, respectively. Again, our model’s prediction closely matches the evolution of the actual physical systems.

PingPong	Random	w/o Touch	Ours
L1@20	0.205	0.164	0.092
L1@50	0.207	0.185	0.109
Hausdorff	0.725	0.293	0.162
Balance	Random	w/o Touch	Ours
L1@20	0.183	0.139	0.076
L1@50	0.187	0.175	0.103
Hausdorff	0.835	0.453	0.267

Table 4.2: Quantitative results for “PingPong” and “Balance”. Our method outperforms two baselines on all the metrics, demonstrating the effectiveness of our dynamics prediction model and the critical role tactile sensing played in the process.

We also evaluate our model’s performance on the two other hand-object interaction activities: *PingPong* and *Balance*. The training and test numbers are 15k and 3k, respectively, for both of these two activities. Our model takes the tactile sequences as input and predicts the movements of the ping-pong ball and the umbrella. In *PingPong*, the state of the object s_t^{object} is represented as the position and velocity of the ping-pong ball, while in *Balance*, we use the position and velocity of the umbrella’s upper tip as the object state. The quantitative results and the qualitative results are shown in Table 4.2 and Figure 4-6, respectively.

4.4 Discussion

In this paper, we study the problem of dynamics modeling in hand-object interactions using tactile sensing, where a human subject acts as a proxy for a robotic system to investigate more dexterous and dynamic interactive activities. The human subject wears a high-resolution tactile glove to perform four different interactive tasks with a range of diverse objects. We build a model that predicts how the environment is expected to evolve with time by only taking the current state and the subsequent tactile information as input. We further augment the model using an object-centric encoder to facilitate multi-object generalization. Experiments show that our model can predict the dynamics of the interactions, quantify the uncertainty of the prediction, and generalize to unseen objects. Through this work, we hope to draw people’s attention and inspire future investigations to build better perception systems and intuitive models of the environment via the lens of different sensing modalities.

In the future, we desire to predict not only the position but also the orientation of the object, where we plan to combine the proposed framework with other sources of information like IMUs, or human (or robot) joint states (e.g., positions, torques), which we believe would improve and scale up the framework for more complicated applications and tasks.

Part II

Intelligent Textiles to Augment Human-Centered Physical Interactions

Chapter 5

Digital Machine-Knitted Pneumatic Assistive Wearables

5.1 Overview



Figure 5-1: **Example applications of machine-knitted pneumatic actuators.** Example applications include assistive glove, soft hand, interactive robot, and pneumatic quadrupedal robot.

Over the last decade, soft actuators have shown enormous promise in applications such as assistive wearables, soft robotics, and interactive devices. In particular, pneumatic actuation is attractive due to its low response time and relatively large output power density. Despite its potential, design and fabrication remain challenging: most common established methods for fabricating soft pneumatic actuators remain slow and manual [73, 111]. Further, incorporating sensorization into such workflows is rarely considered, and simple, established recipes for doing so are lacking.

To overcome the shortcomings of current workflows, in this chapter, I present a workflow

for computationally designing and digitally fabricating soft pneumatic actuators via a machine knitting process [68]. Machine knitting is attractive as a fabrication process because it is fast, digital (programmable), and provides access to a rich material library of functional yarns for specified mechanical behavior and integrated sensing. Our method uses elastic stitches to construct non-homogeneous knitting structures, which program the bending of actuators when inflated. Our method also integrates pressure and swept frequency capacitive sensing structures using conductive yarns. The entire knitted structure is fabricated automatically in a single machine run. We further provide a computational design interface for the user to interactively preview actuators’ quasi-static shape when authoring elastic stitches. Our sensing-integrated actuators are cost-effective, easy to design, robust to large actuation, and require minimal manual post-processing. We demonstrate five use cases of our actuators in relevant application settings (Figure 5-1).

The following sections describe details on the design, fabrication, evaluation, and application scenarios. The contributions are summarized below.

- We propose a method for rapidly fabricating digitally machine-knitted, customizable pneumatic actuators with integrated pressure and swept frequency capacitive sensing;
- We develop an interactive graphical user interface for design, which allows users to specify and preview actuator behavior easily;
- We perform characterization on our actuation scheme and evaluate the integrated sensing capabilities;
- We demonstrate our actuator in assistive wearables, interactive input devices, and soft robotics.

5.2 Design and Fabrication

5.2.1 Pneumatic Actuators

Our actuator is composed of two parts: an off-the-shelf thin-wall silicone tube, which serves as the base pneumatic channel, and the knitted sheath with programmed stitches, which wraps over the silicone tube and confines the shape of the inflated actuator.

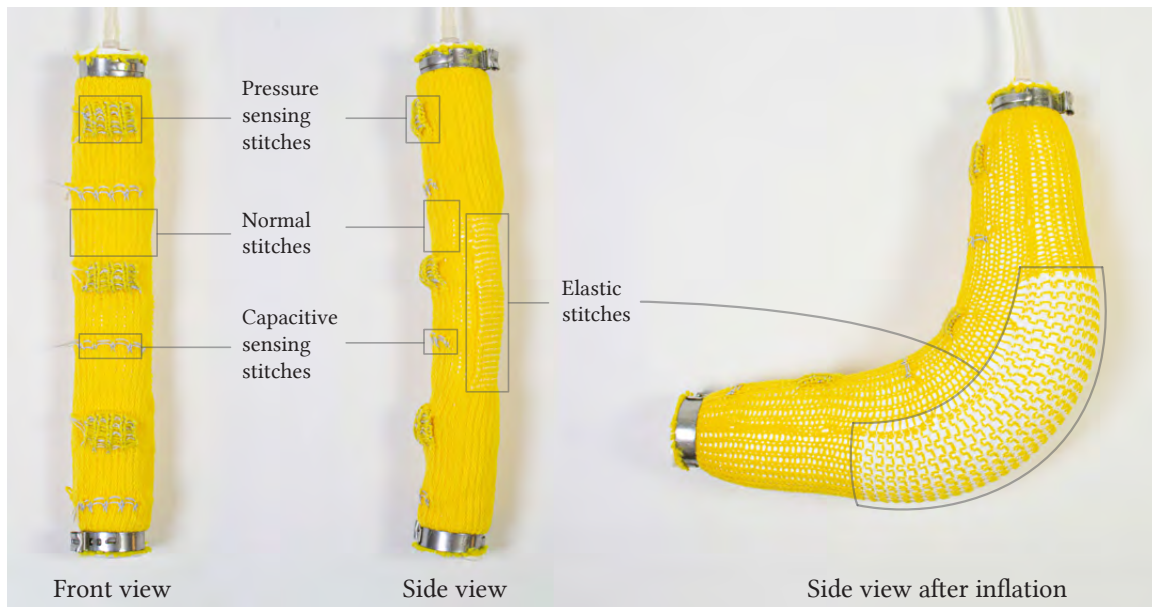


Figure 5-2: **Overview of a machine-knitted sensing-integrated actuator.** Three spaced pressure sensors and three spaced electrodes for swept frequency capacitive sensing are located at the front of the knitted sheath; the elastic stitches at selective locations in the back of the knitted sheath enable the bending of the actuator.

The deformation of the actuators is mainly defined by the knitted sheath with locally variable extensibility. We manipulate the extensibility of the knits with two parameters: stitch densities and stitch types. Using only one of every two or four needles on the knitting machines, we can generate half gauge or quarter gauge knits with higher flexibility and extensibility. Moreover, varying stitch types offers distinction in mechanical performance. In particular, we use an elastic yarn (Lycra, Uppingham Yarns), which is about 100 times more extensible than acrylic yarn. An elastic feed device enables the knitting of elastic yarn, which pre-stretches the elastic yarn and controls its advancement using a stepping motor. To stabilize the knitting process and maintain the straight tubular configurations of the knitted sheath, we integrate the elastic yarns in the form of short-rows, which are only knitted locally at selective locations.

As an example, an actuator design is demonstrated in Figure 5-2. The front of the tubular knits is constructed with normal acrylic knitting yarn (normal stitches), and the back of the tubular knits is constructed with a mixture of normal stitches and elastic stitches. More specifically, the elastic stitches are composed of knits with normal acrylic yarn and

short-rows with elastic yarn. We then wrap the knitted sheath over the silicone tube and anchor both ends of the wrapped tube with clamps. When the silicone tube is inflated, the elastic stitches at the backside tend to extend more than the non-elastic stitches, forcing the tube to bend to another side. It is noted that the knitted sheath maintains a straight tubular shape before the actuator is inflated, as shown in Figure 5-2 left. This is a consequence of the design: the short-rows of elastic yarn tend to shrink once released from the machine, and both the front and back sides obtain the same number of knitting courses by acrylic yarn. By placing the normal stitches and elastic stitches at designed locations, we can program the shape of the inflated actuators.

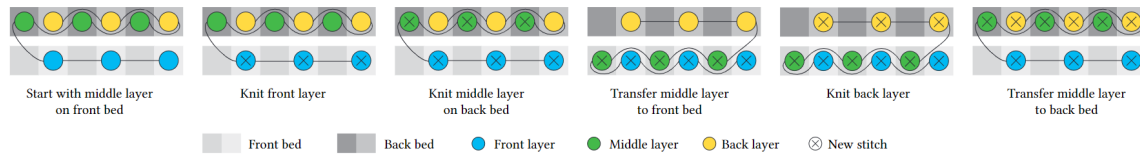


Figure 5-3: **Illustration of three-layered structure knitting.** Our three-layered knitting structure is enabled by the recurrent transferring of the middle layer between the front and back bed.

In this project, we demonstrate our actuation principle on assistive wearables and grippers, which may have multiple actuators each requiring a single degree of freedom; but, further, we also demonstrate a soft locomoting robot whose motion requires actuators with multiple degrees of freedom. To this end, we design and fabricate a three-layered knitted structure, which can hold a pair of actuators to enable the structure to bend along both forward and backward directions. In particular, the front and back layers are composed of elastic stitches. The middle layer is composed of normal stitches and shared by both silicone tubes. Since we use a v-bed knitting machine with two needle-beds, front and back, a special treatment is needed to knit the three-layered structure. To be more specific, the stitches in the middle layer are recurrent transferred between the front and back beds. For example, in each knitting cycle, we first knit the back layer on the back bed while temporally holding both the front and middle layers on different sets of needles (half gauge) in the front bed. Then, we knit the middle layer on the front bed and transfer it to the back bed (Figure 5-3). Lastly, we knit the front layer, transfer the middle layer back to the front bed, and start a new cycle. We repeat this knitting cycle until we have the full sheath.

5.2.2 Resistive and Capacitive Sensors

Further, we integrate two different sensing capabilities into our machine-knitted pneumatic actuators: resistive pressure sensing and swept frequency capacitive sensing. Both sensing capabilities are enabled by the usage of standard off-the-shelf conductive yarns (80% polyester and 20% stainless steel). We optimize the design so that our resistive and capacitive sensors are not affected by the inflation and bending of the actuators.

Resistive pressure sensors. We leverage the plating technique to insert conductive yarns at specific locations. Specifically, the conductive yarns are blended with normal acrylic knitting yarn *via* a pressure-sensing stitch. The knitted conductive yarn loops interlock loosely when there is no external pressure. The conductive loops collapse when applying a load, resulting in more electrical paths; thus, the resistance drops. The sensor measurements are amplified and converted to a digital signal by a read-out circuit.

One of the biggest challenges is to make the pressure sensor insensitive to actuator-driven expansion. Since the resistive pressure sensors share the same base knitted substrate with the pneumatic actuators, previous knitted sensor designs, like [70], cannot provide reliable pressure sensing when the actuator is inflated, stretching the pressure sensor and collapsing the conductive loops. To this end, we propose a new pressure sensor design with a few special treatments. First, by splitting and transferring the existing yarn loops, we construct the pressure-sensing stitches on a separate layer on the stiffer side of the actuator. Moreover, as shown in Figure 5-2, we design the pressure sensor with lower stitch density and larger local curvatures by using a quarter gauge and short-rows. Therefore, our pressure sensor obtains minimal connections with the base knitting substrate and additional flexibility and surface area compared with the base knitting structure. As a result, our design prevents the pressure sensors from being stretched when the actuators activate and ensures the reliability of pressure sensor performance.

Capacitive sensors. Swept frequency capacitive sensing leverages the fact that alternating current (AC) signals of different frequencies flow through different paths at the capacitive interface between the electrode and body-contacted objects [104, 39]. By collecting amplitude

responses over a range of frequencies, we retrieve information on the existence of human touch or human-contacted objects. We generate square wave sweeps from 100 kHz to 1.6 MHz in 5 kHz steps (300 steps in each sweep) and transform them to sinusoidal waves using an LC (inductor-capacitor) oscillator. We measure the return voltage signal over a 1 M Ω resistor. We use an Adafruit Metro M4 (ATSAMD51) for signal processing.

Like the integrated pressure sensor, we use a separated layer to construct the electrode for swept frequency capacitive sensing, but we knit the capacitive sensing stitch with conductive yarn only instead of plating normal and conductive yarns. We separate capacitive sensing stitches and pressure sensing stitches with at least two courses of normal stitches to prevent shorting among the integrated conductive yarns and reduce interference. To aid readers in better understanding our knitted structure, we also include a sample .knitout code in the supplemental material. This code enables knitting of the actuator (Figure 5-2) with pressure and capacitive sensors using the V-bed knitting machine (SWG091N2, Shima Seiki) as well as visualization through an online knitout visualization tool [134].

5.3 Evaluation

5.3.1 Pneumatic Actuators

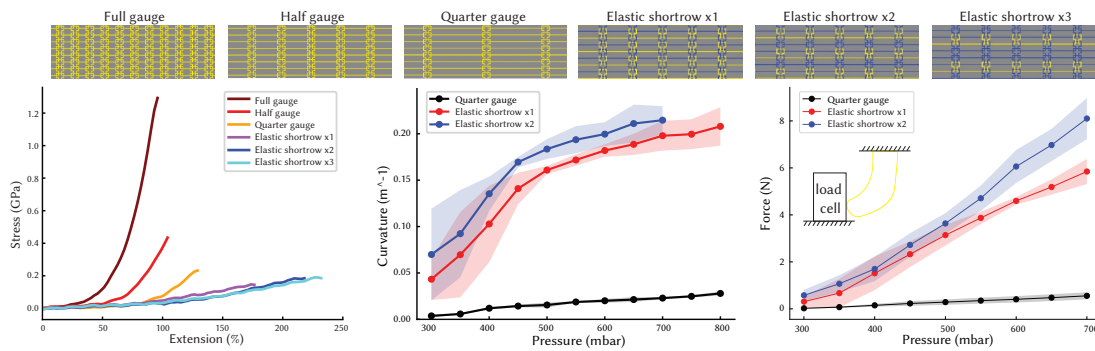


Figure 5-4: **Actuator characterization.** Illustrations of different knitting structures (normal yarn in yellow, elastic yarn in blue) (visualizing in the web-based UI [134]). Left: Stress-strain characteristics of knits with different structures. Middle: Curvature of pressurized actuators with different knitting structures. Right: Exerted force of pressurized actuators with different knitting structures (measurement set-up illustrated in the sub-plot). Characterization is done on three different samples.

The ability of our actuator to reach desired deformations relies on the extensibility variation enabled by knit structures and stitch types. Therefore, we first perform tensile testings (Shimadzu AGS-X) on knitted fabrics ($3\text{ cm} \times 6\text{ cm}$) with different normal stitch densities and elastic short-row densities. Generally, compared with knits with low stitch density (quarter gauge, Young's modulus of 0.18 GPa and tensile strength of 0.24 GPa), knits with higher stitch density (half gauge or full gauge) demonstrate higher Young's modulus (0.22 GPa for half gauge 0.54 GPa for full gauge) and tensile strength (0.44 GPa for half gauge 1.29 GPa for full gauge). Moreover, since the elastic yarn is more extensible than the acrylic knitting yarn, given the same stitch density (half gauge), knits with the higher compositions of elastic yarn demonstrate lower Young's modulus (as low as 0.18 GPa) and higher elongation (up to 230 %), as shown in Figure 5-4 left.

We fabricate multiple knitted sheaths to characterize the bending performance of actuators that are composed of different sets of knitting structures. In particular, the front is always composed of half-gauge normal stitches, and the back is composed of either quarter-gauge normal stitches or half-gauge elastic stitches with different densities (one or two elastic short-rows). We then wrap them around silicone tubes (1.5 mm in thickness) and assemble them into actuators (2 cm in diameter and 16 cm in length). We measure the bending radius (curvature) when the actuators are activated up to 800 mbar (Figure 5-4 middle). We further measure the forces exerted by the actuator at the tip. We measure the response from the fixed load cell when the actuators are activated. The testing setup is shown in the inset figure. Our actuators can bend with curvatures up to 0.2 m^{-1} and exert forces up to 9 N at the tip (Figure 5-4 right), which is comparable to previous work in fabric-based pneumatic actuators [14].

To prevent breakage, we need to keep the extension of the knitted fabric below its yield strain. Both normal knits and elastic knits are strong enough to endure the expansion even with more than 100% of extension, which is much higher than the experienced stretch of our actuators at this stage. We also performed 100 cycles of an inflate/deflate test with air pressure at 700 mbar, the maximum pressure we used for our applications. We observe the actuator obtains stable performance without any breakage of yarn.

5.3.2 Resistive and Capacitive Sensors

Our typical pressure sensor is about $2\text{ cm} \times 1\text{ cm}$, realized as 5×12 stitches in quarter gauge. We characterize the performance of our pressure sensors by measuring resistance (DMM 4050, Tektronix) while applying loads up to 5.5 N at various actuator pressurizations. A typical sensor's resistance drops when the applied load increases from 1.5 N to 5 N. As shown in Figure 5-5 left, the resistance profile of our pressure sensor is barely affected by the activated pressure, which demonstrates the ability of our knitted structure design to operate accurately under a wide range of actuation.

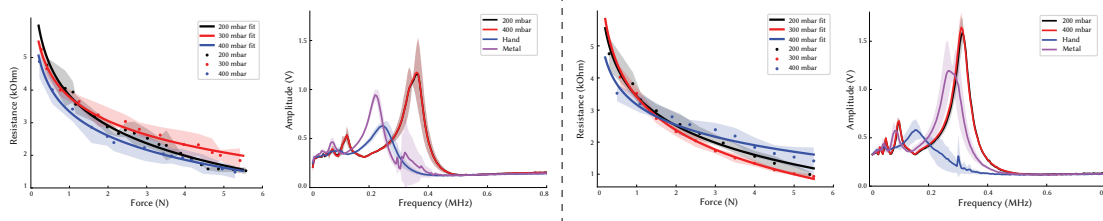


Figure 5-5: **Sensor characterization.** Left: Resistance profile of the integrated pressure sensor under load and representative amplitude responses from swept frequency capacitive sensing. Right: Our pressure and capacitive sensors obtain similar performance after a regular washing and drying cycle. All characterizations are performed on three samples.

Figure 5-5 left shows the characteristic amplitude responses from the swept frequency capacitive sensing. The black and red curves almost coincide, indicating that the actuating pressure similarly does not affect the swept frequency capacitive sensing performance. On the other hand, the amplitude responses, in terms of the peak position and magnitude, vary significantly when the electrode is in contact with the human body or human-contacted conductive substrate, making this sensing modality useful for human interaction.

We further perform a washing test to verify the reliability of our sensors. We measure the performance of our the pressure and capacitive sensors after a regular warm washing and medium drying cycle. As demonstrated in Figure 5-5 right, the performance of both sensors after the washing cycle is very similar to that without washing.

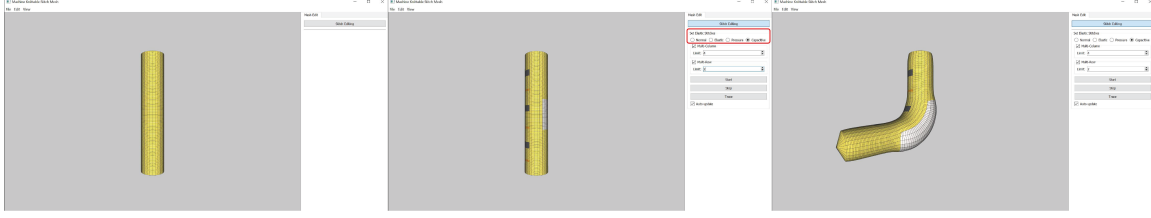


Figure 5-6: **Interactive user design interface.** Left: The user starts with a sketch tube, which is a simple tubular knit structure with all normal stitches. Middle: The user paints the tube with different stitch types highlighted in red. Right: The predicted (actuated) actuator shape based on user’s design. Yellow, white, black, and orange faces indicate normal, elastic, resistive sensing, and capacitive sensing stitches, respectively.

5.4 Interactive User Design Interface

To allow users to design and preview inflated actuators quickly, we provide an interactive design system by which users are free to specify the locations of elastic stitches, pressure sensors, and captive sensors (Figure 5-6). Our system can then convert the user’s design into low-level machine instructions for immediate digital fabrication.

5.4.1 Design Interface

Our design interface is built on quad Stitch Meshes [70], where each stitch structure is abstracted as a quad mesh face. Users mark each face with one of four stitch types. The *normal stitch* (yellow faces) is knitted with standard acrylic yarn as the base structure. Our actuation programming principle is based on inserting short-rows (additional partial rows in the middle of other full rows) that are fully knitted using elastic yarns. However, inserting a short-row would require modifying the mesh topology. To preserve the same mesh topology during stitch type authoring, we use the *elastic stitch* (white faces) to represent one normal stitch and two elastic stitches next to each other along the elongated direction. Both the *pressure sensing stitch* (black faces) and the *capacitive sensing stitch* (orange faces) represent double-layered structures where the front layer is knitted with conductive yarn. As shown in Figure 5-6 left, the user starts by generating a tube by inputting a specific number of rows and columns. Each quad represents one stitch and is marked as a normal stitch by default. Then, the user can design the actuator by labeling individual faces or sets of faces with the desired stitches (Figure 5-6 middle).

5.4.2 Predictive Simulation

Our system also provides an interactive preview of the actuator’s shape when the user adds or removes elastic stitches (Figure 5-6 right). To achieve this, we deploy a physically-based simulation. The simulation is optimized by minimizing the potential energy $E(\mathbf{x})$ when the physical system is at equilibrium under pressurization, meaning sum of the internal force $\mathbf{f}_{\text{int}}$ and the pressure force $\mathbf{f}_{\text{pressure}}$ should be zero at any point on the actuator’s surface.

We formulate the equilibrium problem as solving for $\mathbf{x}$ such that

$$\mathbf{f}_{\text{pressure}}(\mathbf{x}) - \sum_i w_i \nabla E_i(\mathbf{x}) = \mathbf{0} \quad (5.1)$$

where $\mathbf{x}$ is a vector corresponding to the vertex positions in the quad mesh state, and E_i is defined as three different types of constraints based on our observation of knit behaviors.

First, we use a rectangle constraint to enforce each face to be rectangular since the course edges and wales edges are typically perpendicular to each other for a *knit* stitch. To solve this, we first project the corners of the quad face onto their least-squares plane and then fit the rectangle in 2D as mentioned in [8]. The anisotropic deforming behavior for each knit face is modeled as distance constraints with different stiffnesses for wales edges and course edges, respectively. Thirdly, bending constraints are added to the adjacent quads to minimize the difference between the mean curvature of the deformed and undeformed quad surface [7]. Like [112], The pressure force on each quad is defined as

$$\mathbf{f}_{\text{pressure}}(\mathbf{x}) = A(\mathbf{x})P\mathbf{n}, \quad (5.2)$$

where P is the pressure value, $\mathbf{n}$ is the outward face normal, and $A(\mathbf{x})$ is the quad area that depends on node position $\mathbf{x}$. To solve Eq. 5.1, we use Projective Dynamics [7], which uses a pre-factorized system matrix to achieve the interactive frame rate for the simulation.

To obtain a realistic simulation result, we use a data-driven strategy to capture the shape of individual normal and elastic stitch faces under pressure. In particular, we first inflated two actuators: one with all normal stitches and one with all elastic stitches. Then, we measured the length and radius of those two actuators, respectively, and converted them to

the width w and height h of the individual face. During simulation, we use w and h as the rest width and height for each quad. To verify our result, we fabricated four actuators with 120 rows and 28 stitches per row as shown in Figure 5-7. Under 500 mbar, our predicted results are qualitatively similar to the physical experimental results for the actuators with 10, 20, 30, and 40 elastic short-rows.

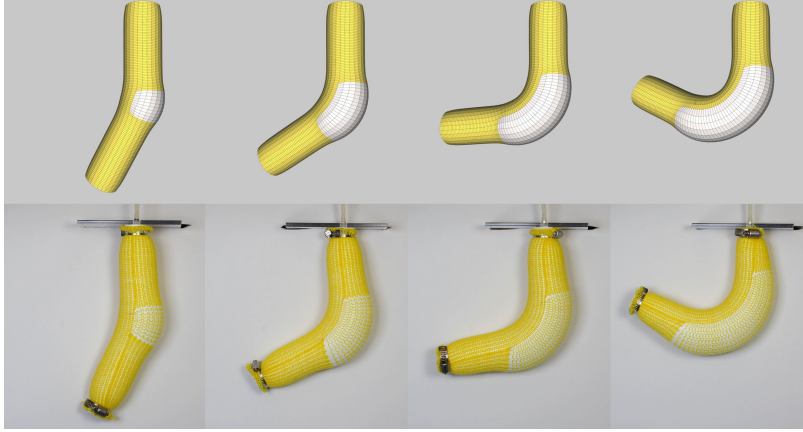


Figure 5-7: **Comparison between simulated and fabricated actuator shapes.** Predicted results from our simulator (top) and fabricated pneumatic actuators (bottom) with 10, 20, 30, and 40 rows of elastic stitches. Yellow faces represent normal stitches and white faces represent elastic stitches.

5.4.3 Knitting Instruction Generation

Since we insert a silicone tube with a uniform radius inside the knitted sheath, we only consider tubular knitted structures with the same number of stitches every row. From this constraint, it is straightforward to trace the knitting patch from the bottom to the top and schedule the needle location for each face. To generate the machine instructions, we first pre-trace the current row to check if sensor stitches exist. If so, we split the stitches at sensor stitch locations and merge them back after knitting the sensors. The elastic stitches can be added easily by knitting additional short-rows at elastic stitch locations after finishing the current row.

5.4.4 User Study

We conducted an experiment to evaluate the usability and effectiveness of our computational design interface. Our goal is to investigate whether our design interface, which incorporates predictive simulation, improves design efficiency.

Procedure. Eleven participants (3 female) between 21 and 30 participated in the study. We first provided participants with a tutorial of our design user interface. We then let users design a simple “S” shape actuator with the feedback from the predictive simulation to ensure they were familiar with the interface. Next, we asked participants to perform two tasks that have been widely used for evaluating soft robot design [40, 26, 2]. The first task asked users to design an actuator such that the endpoint of the actuator would make contact with a specified location (red dot) when inflated. The second task asked users to design an actuator that can circumnavigate a specified obstacle (gray cylinder) *while* hitting the target (red dot) when inflated. The task setups are shown in Figure 5-8. During the study, we first asked all participants to perform those tasks without simulator feedback. Users were not informed on the actuated shape of their designs during or after designing. Those designs were used as our baseline. Then, we asked all participants to perform the same tasks again with the predictive simulation enabled, which offers intermediate feedback during the design process. We used the output designs as the experimental group.

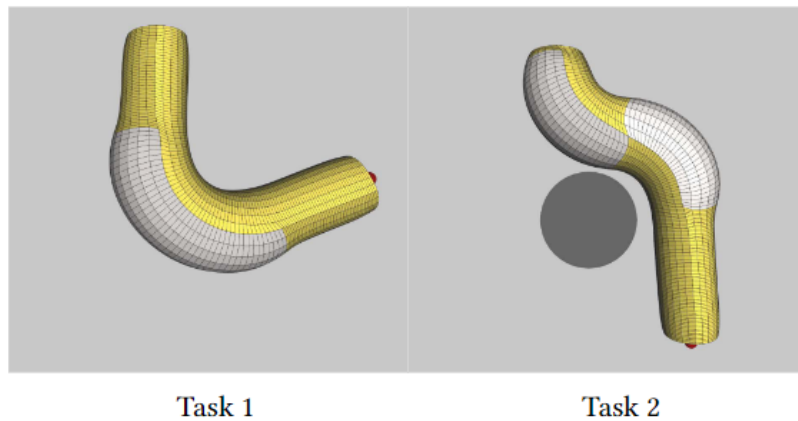


Figure 5-8: **Task setups.** left, task 1 asked users to design an actuator whose end would hit the target (red dot) when actuated; right, task 2 asked users to design an actuator that would hit the target (red dot) and avoid the obstacle (gray cylinder).

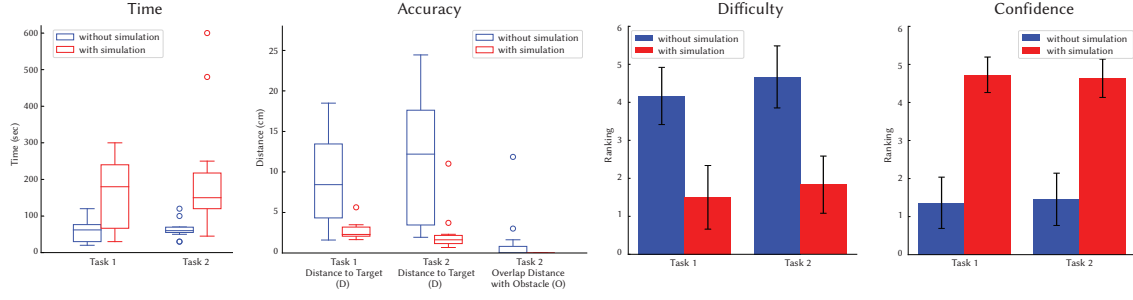


Figure 5-9: User study results. Left: Design time for each task. Middle left: Quantitative design accuracy. Middle right: Subjective rating of difficulty of each task (scale 1 to 5, where 1 represents the easiest and 5 represents the most difficult). Right: Subjective rating of confidence on the designs (scale 1 to 5, where 1 represents the least confidence and 5 represents the highest confidence).

To quantitatively and qualitatively measure the usability and effectiveness of our method, we define four metrics, *time*, *accuracy*, *difficulty*, and *confidence*, in which the first two are objective, and the latter two are subjective. Our method has high *usability* if participants can design actuators with high accuracy while using a small amount of time. Our method has high *effectiveness* if the participants believe the tool is easy to use and feel confident in their designs. We tracked the amount of time participants spent on each task and measured the accuracy of participants' designs by calculating the distance D between the end of the actuator and the target and the overlapping distance O between the actuator and the obstacle. After the study, participants filled out a post-experiment questionnaire, where they indicated subjective ratings for the difficulty of each task (with and without predictive simulation), as well as the confidence of whether the fabricated designs would behave as desired using a continuous numerical scale.

Overall results. All participants indicated a positive experience (4.73 ± 0.47 given the scale from 1 to 5, where 1 is the worst and 5 is best). The design time and accuracy on each task, as well as participants' subjective ratings on task difficulty and confidence on designs, are demonstrated in Figure 5-9. We also fabricated six randomly selected participant designs as examples and compared them with our simulation results. The fabricated and simulated results are shown in Figure 5-10. In general, participants achieved higher accuracy in both tasks, considered the tasks easier, and obtained more confidence in their design when our

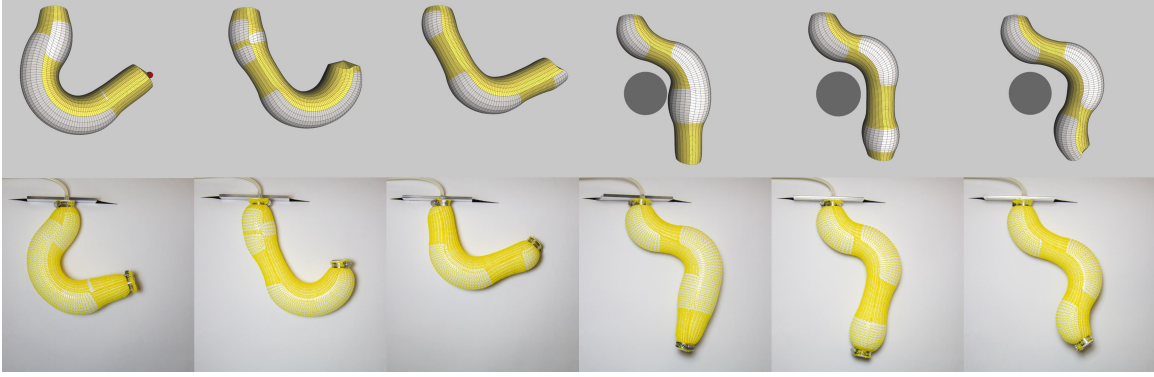


Figure 5-10: **Example designs by participants.** top, participants' designs in our design pipeline with predictive simulation; bottom, the corresponding fabricated actuators.

predictive simulation tool was provided. Such results indicate the usability and effectiveness of our design pipeline.

Design time. Participants finished the designs within 2 minutes on average without the predictive simulation and within 5 minutes when given the simulation. Participants generally spent more time on designing when the predictive simulation was included in the pipeline, which is expected as we observed that our tool with predictive simulation offered participants an opportunity to iterate on and improve their designs.

Design accuracy. All designs are 19 cm long with the radius of 2 cm without inflation. Assuming the axis and radius of the cylindrical obstacle are L and R ($R = 2.83$ cm), we computed O as R minus the closest distance between the actuator and the axis L . Ideally, we expected D is close to zero, indicating hitting the target, and O is smaller or equal to zero, indicating no collision between the actuator and obstacle. As demonstrated in Figure 5-9 middle left, when offered our predictive simulation pipeline, participants were able to create designs with higher end-effector accuracy. Most actuators designed while using simulator feedback could reach within 5cm of the target. Furthermore, all participants could create designs that bypassed the obstacle when using our predictive simulator, which wasn't always true when the simulation was disabled. Although participants spent more time designing when relying on simulator feedback, the resulting designs were expected to be much more effective.

Difficulty. Regarding the difficulty, participants gave 4.17 ± 0.75 for task 1 and 4.67 ± 0.82 for task 2 when predictive simulation was disabled, which indicates that participants found both tasks very difficult without the predictive simulation. Here, the score range is from 1 to 5, where 1 represents the easiest and 5 represents the most difficult). In contrast, when the predictive simulation was offered, the difficulty score decreased to 1.5 ± 0.83 and 1.83 ± 0.75 for task 1 and task 2, respectively. We can conclude that those participants found the tasks significantly easier when predictive simulation is available.

Confidence. When designing with the predictive simulation, participants were very confident that the fabricated actuator would behave as desired (4.73 ± 0.47 for task 1 and 4.64 ± 0.50 with the scale from 1 to 5, where 1 represents the least confidence and 5 represents the most confidence). In contrast, participants were generally not confident with their designs without the predictive simulation (1.36 ± 0.67 for task 1 and 1.45 ± 0.69). We further validate our predictive simulation by fabricating three randomly selected designs from each task. Figure 5-10 demonstrates the fabricated actuators obtain quantitatively similar behavior as the simulated prediction.

5.5 Application

We demonstrate diverse application scenarios of our digital machine-knitted pneumatic actuators with integrated sensors, spanning from assistive wearables to soft robots.

5.5.1 Assistive Wearables

Soft actuated wearables serve as attractive solutions for assistance in medical and health applications. Our machine-knitted pneumatic actuators have outsized potential as assistive wearable solutions because they are low-cost, lightweight, breathable, conformal to the human body, and compatible with the current garment manufacturing processes. We demonstrate our actuators' potential and capability in wearable devices by seamlessly integrating them into knitted garments such as gloves and sleeves. An assistive glove with 5 actuators on the top surface of each finger is demonstrated in Figure 5-11. The whole

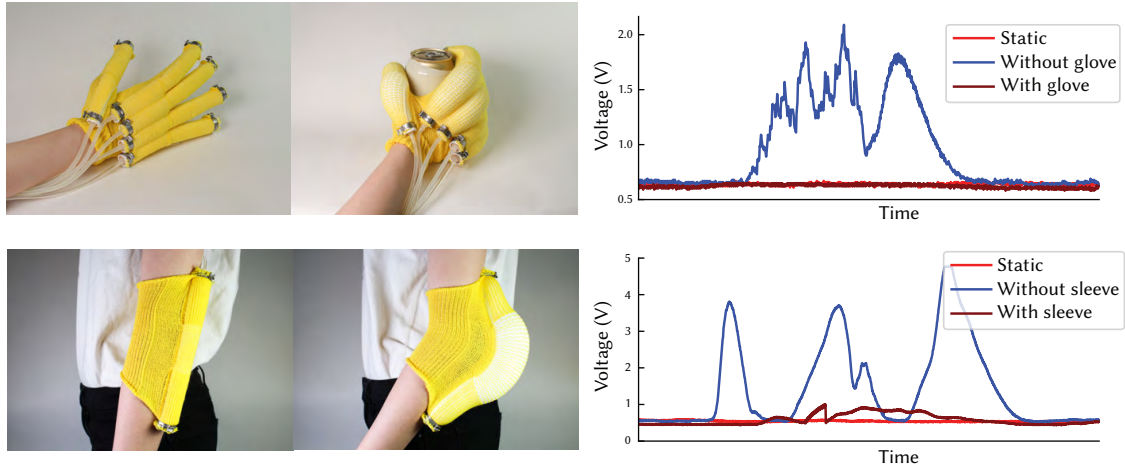


Figure 5-11: **Assistive wearables.** Top: The activated assistive glove facilitates the grasping of a filled can with minimal muscle activities. Bottom: The assistive sleeve facilitates the bending of the elbow.

glove is knitted in one machine run. Each actuator is designed to enable the forward bending motion, which facilitates the corresponding finger flexion. The assistive glove enables geometrically and materially diverse objects to be grasped securely within approximately 1.5 seconds. We also designed and fabricated a shirt sleeve with actuators that can assist in elbow bending. We demonstrate the utility of our assistive wearables by comparing electrical activities of muscles under different circumstances, which are measured by placing an electromyography (EMG) sensor (Advanced Technologies) at the extensor digitorum communis (EDC) muscles. Minimal muscle activities are observed while completing tasks and motions when using the assistive glove and assistive sleeve, as shown in Figure 5-11 (plots on the right).

5.5.2 Soft Hand

We design and fabricate a soft hand with six individual machine-knitted actuators. We specifically incorporate two actuators for the thumb to mimic the utility of human thumb opposability. The actuators are mounted on a 3D printed palm-shaped holder. As demonstrated in Figure 5-12, by activating different sets of actuators, we can perform diverse grasps on objects of various sizes, geometries, and weights, from a tennis ball to a wooden block, in a reliable manner.



Figure 5-12: **Soft hand.** The actuation of each finger is individually addressable by a pneumatic valve system, allowing us to realize a variety of hand poses and grasp objects with different shapes, textures, and weights.

5.5.3 Sensorized Two-Finger Grippers

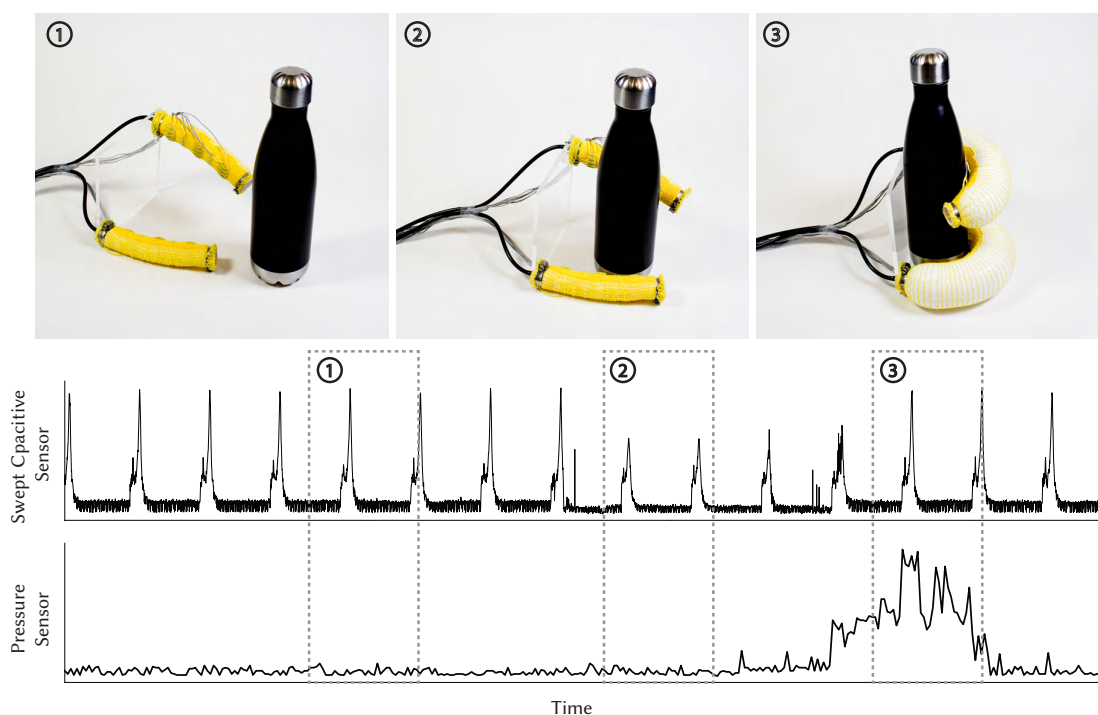


Figure 5-13: **Two-finger gripper.** A typical grasp sequence of the two-finger gripper alongside the average recorded signal of the 6 integrated pressure sensors and the recorded amplitude response from the capacitive sensor.

We demonstrate a two-finger gripper with integrated pressure sensors and swept frequency capacitive sensing. We integrate three pressure sensors and two electrodes for swept frequency capacitive sensing on each finger. The amplitude response from swept frequency capacitive sensing offers real-time feedback on the presence of objects along with the finger interior. The integrated pressure sensors provide real-time feedback on the quality of the grasp. Figure 5-13 presents a montage of a typical grasp procedure. First, the pressure and

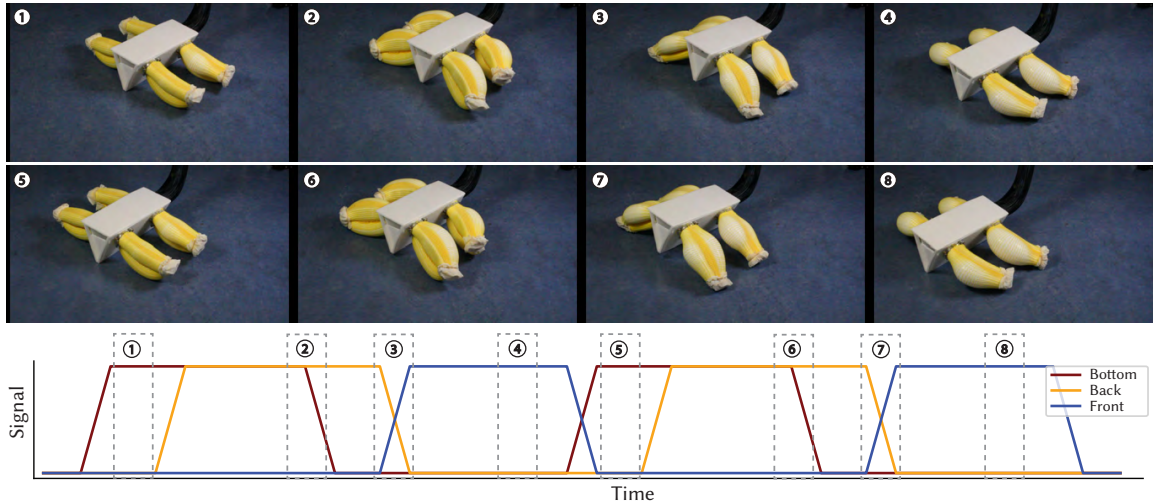


Figure 5-14: **Quadrupedal robot walking forward.** Status of the robot walking forward at different stages of the leg actuation sequence.

capacitive sensors exhibit the default response when the gripper is not yet in contact with the object. Second, the gripper establishes loose contact with the water bottle, whose conductive bottom induces a change in the capacitive signal. The pressure sensors exhibit no response at this stage. Lastly, the actuators are activated to power grasp the object once the object is detected. The signal from the pressure sensors increases, corresponding to the rise of force between the actuators and the object. Once the pressure sensor reading exceeds a threshold, the grasp is registered as successful. The success of the grasp is confirmed by lifting and shaking the gripper while maintaining the stability of the grasped object; more details can be found in the supplementary video.

Our machine-knitted actuator with integrated swept frequency capacitive sensing can be used as an interactive robot. We assemble four separate actuators, each integrated with an electrode for the swept frequency capacitive sensing. Real-time sensing feedback allows the robot to respond interactively: when a human's touch is detected with an actuator, they either activate (if inactive) or deactivate (if active).

5.5.4 Pneumatic Quadrupedal Robots

Our machine-knitted pneumatic actuators can further be arranged as legs for a soft quadrupedal robot (Figure 5-14 and Figure 5-15). Each of the four legs consists of three actuators, two of

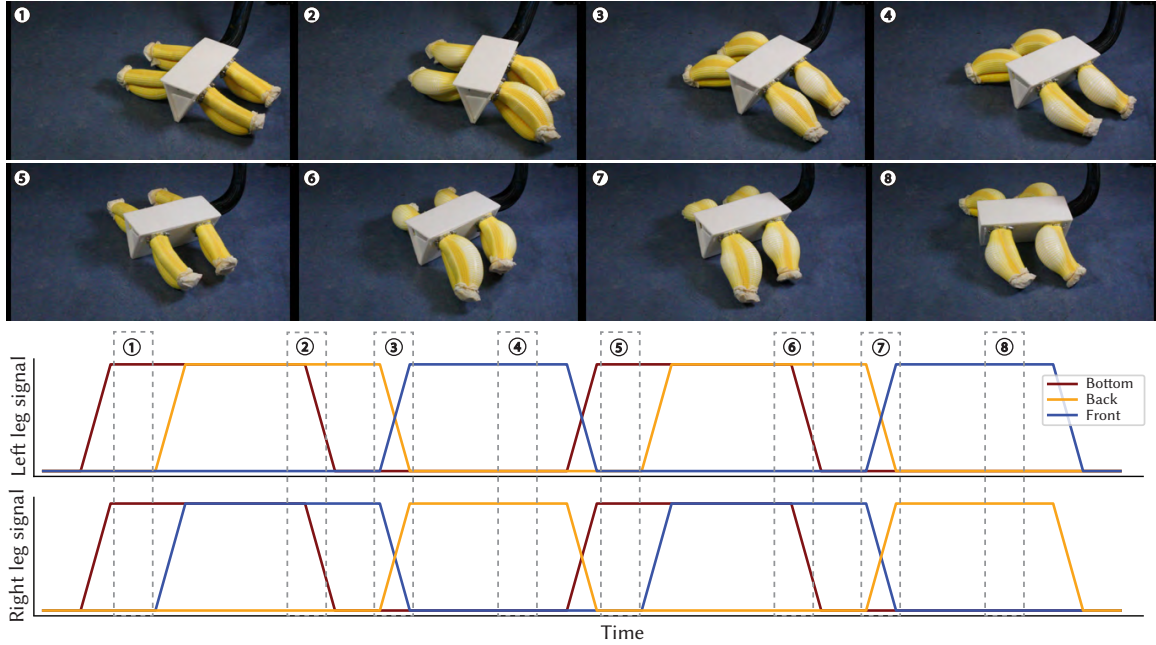


Figure 5-15: **Quadrupedal robot turning.** Robot turns to right by actuating legs on the left forward and legs on the right backward.

which antagonistically bend in the lateral direction (forward and backward) while the third turns the leg upward vertically. We note that it is hard to knit multiple layers in the V-shape knitting machine. As a solution, we design and knit each of the four legs in two machine runs: one run to fabricate a pair of horizontal actuators and the other to fabricate the vertical actuator. Then, the vertical actuator is sewed and affixed to the pair of horizontal actuators. The horizontal actuators are designed and manufactured explicitly as a pair in one run to reinforce each other's motion relative motions, and their movements in the vertical direction are minimized.

5.6 Discussion

We have presented a method for rapidly digitally fabricating sensing-integrated pneumatic actuators *via* machine knitting. By programming our actuators at the stitch level, we can elicit desired deformation behavior. Resistive pressure sensors and swept frequency capacitive sensing electrodes can be integrated through conductive yarns while remaining resilient to the effects of large actuation. We offer a design interface for users to interactively

Example	Glove	Sleeve	Soft hand	Gripper	Int. robot	Quad. robot
Knitting time	35 min	8 min	15 min	14 min	14 min	45 min
Assembly time	8 min	2 min	15 min	6 min	8 min	30 min

Table 5.1: Fabrication and assembly time for different pneumatic actuator designs.

program and preview the bending of actuators and the positions of the integrated sensors. We evaluate the usability and effectiveness of our design pipeline, reliability of our actuation, and capability of our sensing component. We demonstrate the application of our design tool to assistive wearables and soft robotics. We highlight that our design and fabrication pipeline is fully digital. Typically, the user only needs to spend a few minutes customizing and finalizing the actuation design. Then, the designs are knitted automatically in an industrial knitting machine. We record the knitting and assembly time in Table 5.1, which shows that our proposed machine-knitted pneumatic actuator system is easy and fast to fabricate and assemble. We are excited to see our methodology deployed in other application domains in the future.

Complex actuator and sensing design. Currently, it is challenging to incorporate our sensors over the entire body of the actuator, given the extensive stretching of the elastic yarn. Also, our V-bed knitting machine only allows for fabricating actuators with bending motion along one specific direction at a time, which limits the actuators’ degrees of freedom. For the quadruped example in Figure 5-14, separated knitting processes and manual sewing post-processing steps are needed to make the leg bend into multiple directions. Further, we would like to extend our design tool to incorporate task-driven, optimization-based design, where users specify target poses and optimal stitch patterns can be synthesized automatically.

Actuators of diverse shapes and sizes. As demonstrated by recent work [88, 126], machine knitting is compatible with complex 3D geometry. The same principle of actuation and sensing can be extended to any geometries and size as long as the corresponding pneumatic channels are available. For ease of rapid fabrication, in our experiments, we use only one type of thin-walled commercial off-the-shelf silicone tubes. However, if commercial thin-walled silicone bladders of other shapes and sizes were made available, our

method should be directly applicable for actuators with diverse shapes, sizes, and bending performance, opening up new potential applications. It would be worthwhile to verify this in future work.

The granularity of actuation. The bending performance of the actuator is determined by the knitted sheath designs as well as pneumatic channel properties, *e.g.*, wall thickness, radius, and materials. Those parameters and the air pressure level further determine the overall volume of inflated actuators. Our predictive simulation model is guided by the experimental results of inflated actuators using only one type of thin-walled silicone tube. It would be interesting to build an automatic system identification pipeline for actuators with different pneumatic channels and elastic yarns in the future.

Sensing. As one limitation, during grasping, we notice that direct contact with grasped objects mostly occurs at the fingertips, which limits the utility of our integrated sensors distributed throughout the actuators. As a salient avenue for future work, it would be very useful to develop strain sensing capability, which would offer proprioception information for the actuators and robots. It would be interesting to explore knit architectures that could provide more spatially-rich contact information; approaches (*e.g.*, [43]) that combine learning with sensor data could be helpful here. Furthermore, coupling the sensing capabilities of our actuators with modern machine learning techniques could enable diverse cognitive robotics tasks such as grasped object classification, human interaction classification, or learning-based control.

THIS PAGE INTENTIONALLY LEFT BLANK

Chapter 6

Digital Machine-Knitted Passive Haptics

6.1 Overview



Figure 6-1: **Example applications of *MagKnitic*.** Example applications include a rotary wristband, a glove numpad, VR socks, and a sofa covering, offering passive haptic feedback during users interactions.

Haptics is a critical component in designing interactive systems for tangible digital interfaces. Haptic interaction and feedback can be categorized into two primary types, active and passive. Passive haptics, in contrast to active haptics, utilize non-powered or non-motorized interfaces, such as physical props and textured surfaces, to provide tactile sensations to users during their active movement. These passive interfaces require minimal power consumption, have a lower cost, and are less complex to design [35]. Such features make passive haptics a great fit for large-scale deployment and portable environments [102].

Conventional passive haptic devices rely on mechanical structures such as buttons, springs, and gears to generate haptic feedback. However, these devices are often rigid

and inflexible, which poses a challenge when integrating them with the user's body form or wearable devices. To address this challenge, researchers have been investigating new approaches to create flexible and stretchable passive haptic interfaces by leveraging soft and stretchable materials, such as elastomers and hydrogels [80]. However, such soft passive haptic interfaces are usually fabricated manually with complex and time-consuming procedures.

To overcome these drawbacks, we propose *MagKnitic*, a novel design and fabrication pipeline for textile-based passive haptic interfaces with integrated binary sensing via digital machine knitting (Figure 6-1). Digital machine knitting is a highly versatile fabrication method that can create lightweight and stretchable fabrics with conformal shapes in a customizable, scalable, and programmable manner. Knitting is also compatible with a rich material library of functional yarns for various mechanical and electrical features. To convert users' interaction with *MagKnitic* as passive force feedback, we integrate commercially available permanent magnets and ferromagnetic yarns into fabrics by digital machine knitting seamlessly. Our approach expands the design space for haptic experiences through digital fabrication technology, enabling haptic interfaces that are soft, lightweight, and conform to the user's body shape while providing strong, interactive, and responsive force feedback.

MagKnitic supports fully programmable and customizable designs, which enable precise control of the placement and density of the magnets and ferromagnetic yarns within the fabric through a parametric design pipeline. Six design templates for passive haptic interactions enable fast prototyping, including linear, polar, angular, planar, radial, and free motions. In addition, *MagKnitic* enables further programming of passive force sensations through post-fabrication techniques such as embroidering and altering the arrangement of the permanent magnets. This feature provides a high degree of customization and adaptability, allowing users to fine-tune the haptic feedback to their specific needs and preferences. In addition to providing passive force feedback, *MagKnitic* can also integrate resistive binary sensing capability via the high conductivity of integrated ferromagnetic yarn and permanent magnets. Such a sensing mechanism works in tandem with the passive force feedback generation, enabling interface designs with both input and output capabilities.

The following sections describe details on the design, fabrication, evaluation, and

application scenarios. The contributions are summarized below.

- We propose a programmable fabrication pipeline for textile-based passive haptic interfaces with integrated resistive binary sensing capability using industrial digital knitting machine and commercially available functional yarns.
- We develop interactive parametric design templates for fast prototyping and customization on designs, enabling passive force feedback for linear, polar, angular, planar, radial, and free interactions, as well as binary sensing capability.
- We evaluate the performance of passive haptic feedback and sensing capability of *MagKnitic* with different ferromagnetic knitted patterns and layouts.
- We perform preliminary user studies on the effectiveness of *MagKnitic* for the passive haptics feedback.
- We demonstrate various *MagKnitic* prototypes across diverse interactive application scenarios.

6.2 Design and Fabrication

6.2.1 Principle

The passive force feedback in *MagKnitic* was generated through the interaction between permanent magnets and ferromagnetic yarns. The ferromagnetic yarn (Filix) is made of stainless steel fiber, which comprises iron and exhibits the unique ability to interact with a magnetic field and get magnetized. A typical passive haptic unit is made of knitted fabric with plated ferromagnetic patches and another knitted fabric with a split pocket for the permanent commercial magnet (K&J, Neodymium, N52, axially magnetized) insertion. When the permanent magnet approaches a knitted fabric integrated with ferromagnetic yarn caused by a human's motion, an attractive force between two pieces of fabric is generated and transmitted to the user through the fabric, providing them with customized feedback (Figure 6-2 left). Our force feedback mechanism operates with zero energy consumption. Unlike active haptics, our passive haptic design eliminates wiring, batteries, and driving

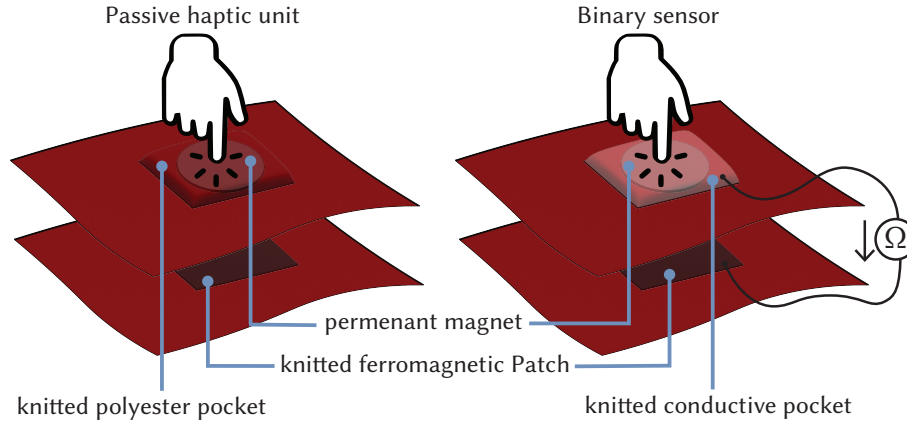


Figure 6-2: **Principles of *MagKnitic*.** Left: In general, *MagKnitic* comprises an integrated ferromagnetic patch and a split pocket for permanent magnet placement. As the user moves, bringing the inserted permanent magnet closer to the integrated ferromagnetic yarn, an attractive force is generated and transmitted to the user as a passive force feedback to a specific interaction. Right: To enable binary sensing, we further integrate commercial conductive yarn into the split pocket. Thanks to the high conductivity of permanent magnet and ferromagnetic yarn, as the user’s motion brings the plated conductive pocket with inserted magnet into contact with the integrated ferromagnetic yarn, active electrical paths form and the measured resistance significantly drops, enabling binary sensing on the user’s interaction accompanied by the passive haptic feedback to the user.

circuits. This not only conserves energy, but also facilitates seamless integration into wearable devices, enabling unobtrusive passive force feedback during user interactions.

We further augment *MagKnitic* with a binary sensing capability by utilizing the high conductivity of ferromagnetic yarn and the permanent magnet. We achieve this by placing the permanent magnet in a split pocket plated with conductive yarn (Figure 6-2 right). As the user brings the pocket with inserted magnet into direct contact with the ferromagnetic patch, the resistance drops significantly due to the activated electrical paths. This drop in resistance allows us to detect the presence of user motion or interaction by measuring the resistance between the knitted pocket with inserted magnet and the integrated ferromagnetic patches. In this work, we focus on passive force feedback that provides a single instantaneous response to the user upon interaction with the interface. Therefore, binary sensing, which detects the presence or absence of interaction, is preferable over continuous monitoring of the applied force level. Note, unlike passive haptic, power supply is needed for sensing signal serialization and visualization.

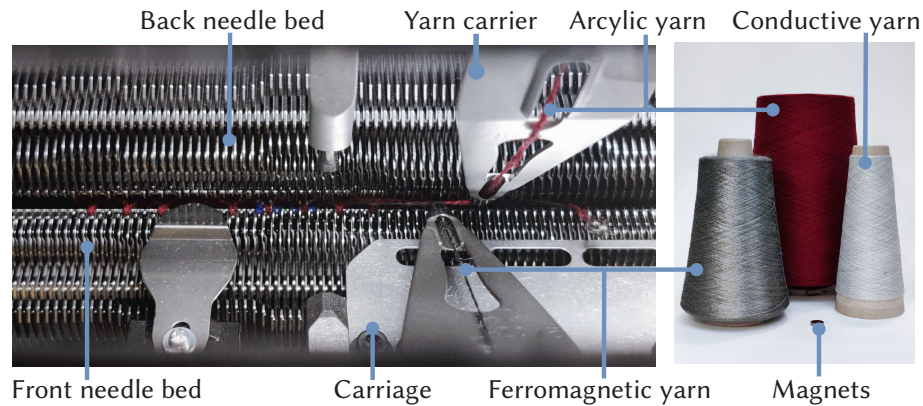


Figure 6-3: **Fabrication materials.** *MagKnitic* is made of acrylic yarn, ferromagnetic yarn, conductive yarn, and permanent magnets. All specimens are automatically fabricated by an industrial digital knitting machine.

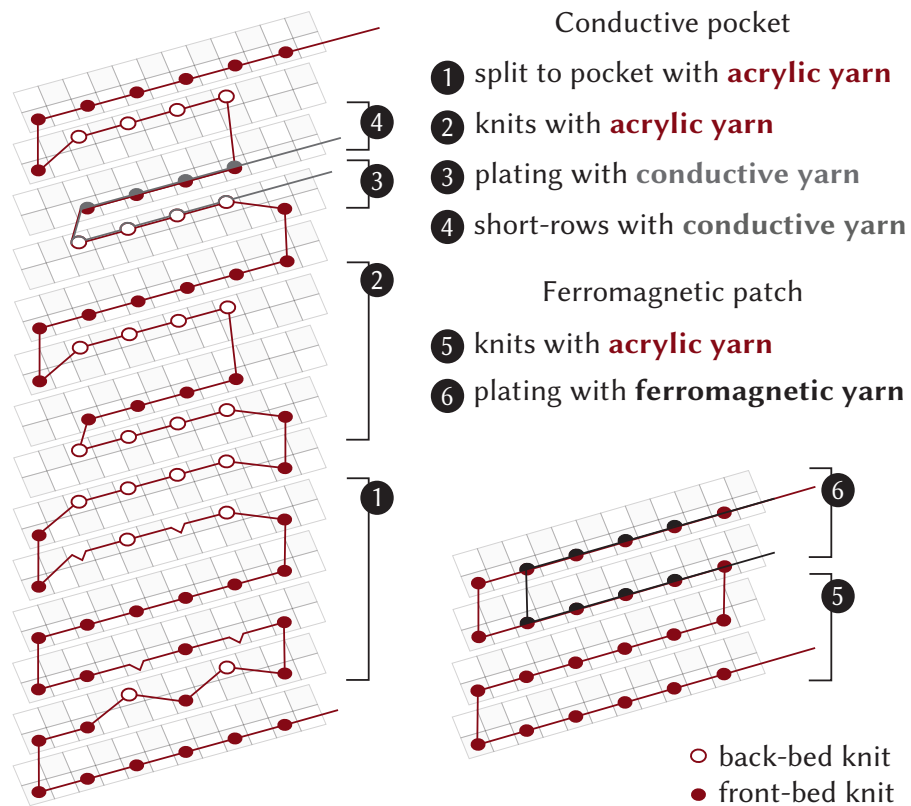


Figure 6-4: **Knitting structures.** The knitting machine bed-view of the knitting structure of the conductive pocket for permanent magnet placement (left) and the ferromagnetic patch (right).

MagKnitic can be fabricated automatically using a digital machine knitting (Shima Seiki SWG091N2G, 14 gauge). The digital knitting machine comprises a front and a back needle back (Figure 6-3), which enables the fabricating of full-sized garments, e.g., socks, and gloves in a single machine run. Fabrics of different geometries, patterns, and textures are generated using the different operations of needles, including knits, purls, tucks, and so on. The fabrication of *MagKnitic* leverages the knitting technique of *splitting* and *plating*. Splitting is a technique to extend a second sheet from the base sheet. This technique creates pockets or separates fabric sections from the base designs. Plating is a technique of using two different yarns together in the knitting process to create a single layer of fabric. In plating, one yarn is knitted on the front of the fabric, while the other is knitted on the back. Plating can combine different colors or properties in a single layer of fabric. We use 1-ply acrylic knitting yarn (Uppingham) for the base structures, stainless steel yarn (Filix) as ferromagnetic yarn and polyester yarn with 20% micro stainless steel fiber as conductive yarn. All samples are knitted using half-gauge, meaning every other needle is used during the knitting.

A pocket for permanent magnet placement can be created by splitting a second knitted layer from one side of the needle bed at specific locations. This is achieved with a sequence of transferring and tucking. To further enable binary sensing, conductive yarn is integrated into the split pocket by plating (Figure 6-4 left).

The ferromagnetic yarn is compatible with all needle operations so can be knitted, plated, transferred, and inlaid by the industrial knitting machine. The ferromagnetic patches are incorporated into the knitted fabric at predetermined locations by plating the ferromagnetic yarn with the standard acrylic knitting yarn at specific needles (Figure 6-4 right).

After the samples are knitted, we manually place the commercial permanent magnets into the corresponding knitted pocket. To enable binary sensing, electrical connections are established by entangling read-out cables with the plated conductive yarns in the split pocket and the ferromagnetic patch.

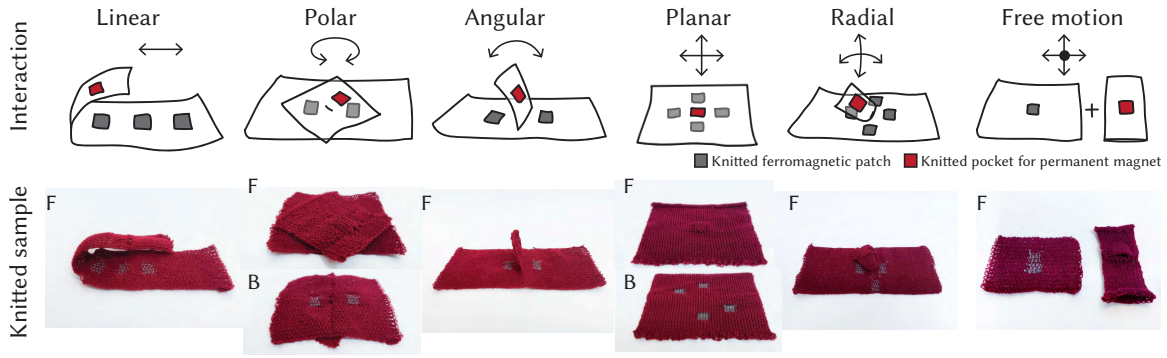


Figure 6-5: **MagKnitic motions.** *MagKnitic* enables passive haptics during linear, polar, angular, planar, radial, and free interactions.

6.2.2 Designs for Various Motions

Inspired by previous works on magnet-based passive haptic interactions [143], we propose designs for six different passive haptic interactions that involve linear, polar, angular, planar, radial, and free motions (Figure 6-5). Here, we describe their interaction principle and how we leverage machine knitting to fabricate them.

Linear motion Interacting with linear motion involves pushing or pulling along a straight path, which was often implemented as a slider. *MagKnitic* featuring passive force feedback during linear motion is knitted as a flat sheet, with plated ferromagnetic patches and a split pocket for magnet placement in a linear arrangement.

Polar motion Interacting with polar motion involves spinning or rotating around a fixed point or axis, which was often implemented as a knob. *MagKnitic* featuring passive force feedback during polar motion is implemented as a double sheet structure by knitting on both the front and back beds. The front sheet obtains a split pocket for magnet placement, and the back sheet obtains plated ferromagnetic patches at desired locations. The two knits are interconnected by transferring two stitches at the center from the front bed to the back bed, which serves as the spinning fixed axial point.

Angular motion Interacting with angular motion involves flipping around an axis within a two-dimensional plane, which was often implemented as a switch. *MagKnitic* featuring

passive force feedback during polar motion is fabricated by knitting on both beds. The out-of-plane flipping patch with the split pocket for magnet placement is knitted on the front bed, while the base structure with plated ferromagnetic patches is knitted on the back bed. All stitches from the front knitted flipping patch is transferred and merged to the base structure on the back bed. The merged seam serves as the flipping axis. The integrated ferromagnetic patches are arranged linearly and separated by the merged seam of the flipping patch, offering passive force feedback during the angular flipping interactions.

Planar motion Interacting with planar motion involves panning along a two-dimensional plane, often implemented as a thumbstick interface. *MagKnitic* featuring passive force feedback during planar motion is based on tubular knitting with an enclosed bottom and top. During tubular knitting, stitches are made across both the front and back beds. The split pocket is integrated into the front knits, and the plated ferromagnetic patches are integrated into the back knits at desired locations.

Note that the tubular knitted structures as the essential shape primitive of knitting is also supported by our planar motion intersection. In that case, two encased tubes can move freely along the axis direction and rotate to enable the passive haptic feedback.

Radial motion Interacting with radial motion involves adjusting the angle and direction along a circular path with the combination of rotating and flipping motion, often implemented as a joystick. *MagKnitic* featuring passive force feedback during radial motion obtains similar designs to the one featuring angular motion. The radial patch with the split pocket for magnet placement is knitted on the front bed, while the base structure with plated ferromagnetic patches is knitted on the back bed. Stitches from the front knitted radial patch first decrease into two stitches and are transferred and merged to the base structure on the back bed. Since there are only a few interconnected stitches, the out-of-plane knit could be flipped and rotated, enabling radial interactions.

Free motion Interacting with free motion involves controlling the movement in a three-dimensional space. *MagKnitic* featuring passive force feedback during radial motion is enabled with two separated fabrics, one flat sheet with plated ferromagnetic patches knitted

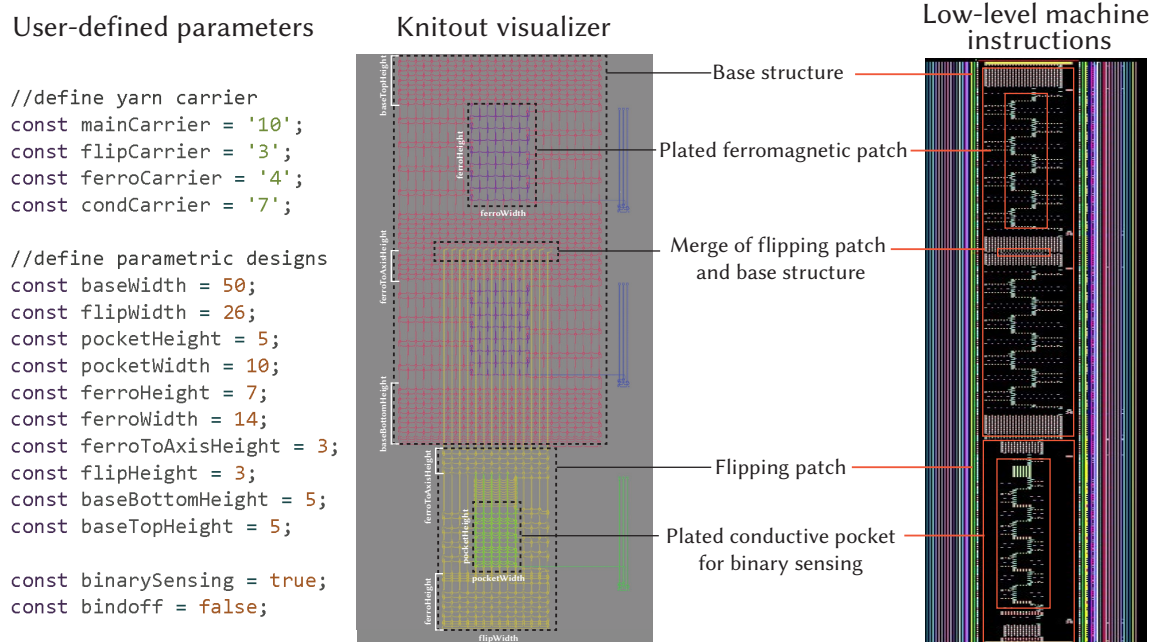


Figure 6-6: Example parametric design template for a *MagKnitic* design for angular interactions. Users are able to define design-specific parameters, such as the dimensions of the flipping patch and base structure, as well as the placement of plated ferromagnetic patches, and split pockets. In the middle Knitout visualization, the user-defined parameters are in white. With the user-defined parameters, our pre-programmed design templates output the corresponding .DAT file on the right using the Knitout compiler, encoding low-level knitting machine instructions and can be imported to the machine for automatic fabrication.

on the front bed and another flat sheet or tubular structure with split pockets for magnet placement.

6.2.3 Parametric Templates

We offer interactive parametric design templates for *MagKnitic* designs featuring passive haptic feedback during each interaction. Our design templates are compiled and visualized based on .Knitout [81, 134]. Figure 6-6 shows an example template on a design enabling angular interaction. Users can define various parameters, including which yarn carrier to use, with or without the integration of conductive yarns for binary sensing, the size of the base structure, the placement of ferromagnetic patches, and so on. Our templates take all user-defined parameters to the .Knitout compiler, which outputs the corresponding low-level machine instructions (.DAT files). The digital knitting machine is able to fabricate the

defined designs automatically after importing the output machine instructions.

6.3 Evaluation

6.3.1 Passive Haptics

The passive haptic feedback is affected by both the amount of integrated ferromagnetic yarn, which varies based on the knitting designs, and the magnitude of the applied magnetic field, which is determined mainly by the size of the integrated permanent magnet.

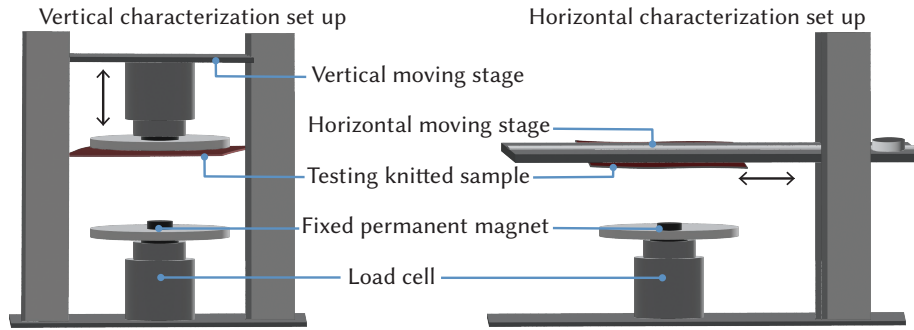


Figure 6-7: **Characterization schematics.** The customized characterization schematics featuring vertical motion (left) and horizontal motion (right).

We characterized the effectiveness of various knitting patterns by approximating the force generated between knitted ferromagnetic patches with varying designs and a fixed magnet. The measurement was done on a customized mechanical testing setup, where a permanent magnet was fixed on the bottom plate integrated with a load cell, and the ferromagnetic knitted patches were fixed on the top plate. The top plate can move vertically, where the distance between the two plates and the reading from the load cells can be recorded simultaneously (Figure 6-7 left). As demonstrated in Figure 6-8 left, patterns with higher ferromagnetic yarn compositions, such as seed, knit with tucks, and jacquard knits, obtain steeper force response curves, indicating stronger force feedback. On the other hand, the quarter gauge knit obtains the weakest force response due to its lower ferromagnetic yarn composition. In this work, we opt for a stronger force response; to further optimize for the knitting complexity, we select seeds for most of our ferromagnetic patch designs. Figure 6-8 right shows the force response between a plated ferromagnetic patch and permanent

magnets of different sizes (diameters of 1/4", 1/2", and 1", the thickness of 1/16"). A larger magnet generates a stronger force response due to the introduction of a stronger magnetic field. However, we also note that larger magnets are heavier, which must be taken into consideration for real-life applications.

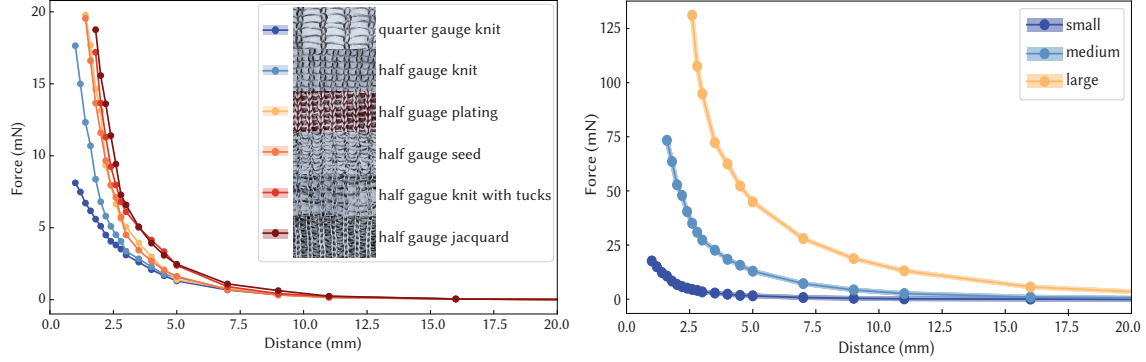


Figure 6-8: **Force response of ferromagnetic patches along vertical displacement.** We measure the force responses of ferromagnetic patches along vertical displacement toward a fixed permanent magnet. Different knitting patterns (left) and patch sizes (right) are evaluated.

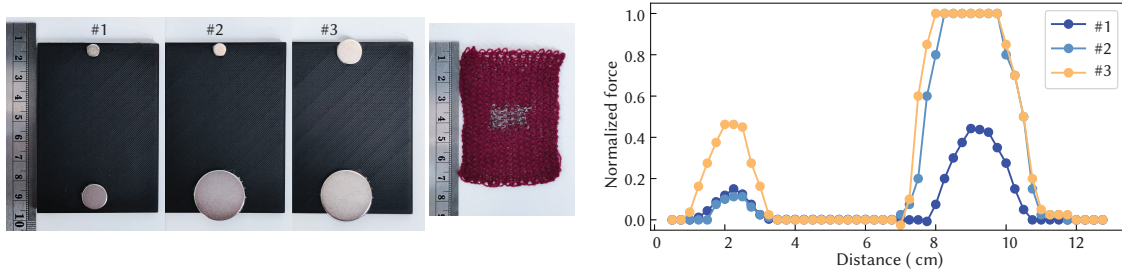


Figure 6-9: **Force response of ferromagnetic patches along horizontal displacement.** We measure the force responses of a ferromagnetic knit along horizontal displacement towards different permanent magnet arrangements.

6.3.2 Binary Sensing

Within the context of passive interactive haptics, we specifically focus on binary sensing in this work. Coupling passive haptic feedback with binary sensing, which enables the detection of the presence or absence of an interaction, we are able to create a more sophisticated and versatile interactive system.

We evaluated the binary sensing performance with different commercial conductive yarns, including ferromagnetic yarn (50 Ω/m), polyester yarn with 20% dispersed stainless steel fiber (4000 Ω/m), and silk yarn with intertwined single stainless steel thread (700 Ω/m). To quantify the performance, we focused on the angular interaction mode. The out-of-plane flipping knits were machine-knitted using three different conductive yarns in pure or plated designs. Resistance was measured between the flipping knits with inserted permanent magnet and the ferromagnetic patch during the characterization. The resistance is overloaded when the flipping knits are not in contact with the ferromagnetic. On the other hand, when the flipping knits come into contact with the ferromagnetic patch during the angular interactions, the measured resistance drops dramatically due to the formed electrical paths (Figure 6-10). Compared with designs made of plated conductive yarn, designs with pure conductive knits enable larger contact areas for electrical paths and hence obtain lower resistance during the interaction. Since ferromagnetic yarn has the lowest resistance, designs made of ferromagnetic yarn obtain the lowest resistance when the interaction occurs. It is also interesting to note that designs with plated silk-based conductive yarns are overloaded during the interactions; this is because the intertwined structure in silk-based conductive yarn and the plating structure limit the exposed area of the conductive stainless steel thread and restricts the stable electrical interactions between the flipping knits and ferromagnetic passive haptic patches.

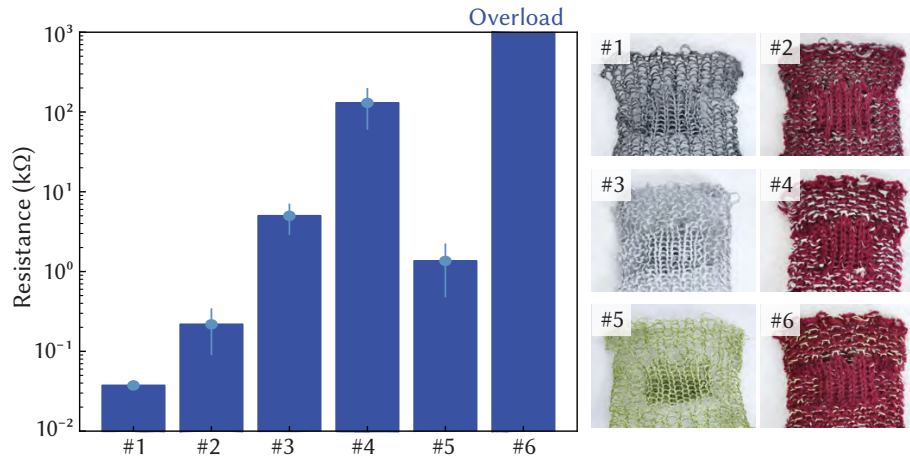


Figure 6-10: **Binary sensing characterization.** The resistance between the conductive pocket with different knitting structures and materials and the ferromagnetic patch upon contact.

In this work, we select plated polyester yarn with 20% dispersed stainless steel fiber (design #4). Its distinct change in resistance range (overload to $k\Omega$ range) makes it effective for binary sensing. Additionally, unlike ferromagnetic yarn, the polyester-based yarn does not interfere with the designed passive force feedback. Moreover, plating is a straightforward technique for integrating functional yarn into textiles, which made it a practical choice for our implementation.

6.3.3 Preliminary User Evaluation

User perception. In our first user study, we investigated the effectiveness of our passive haptic feedback by evaluating users' perceptions toward diverse force feedback characteristics generated by *MagKnitic*. We recruited 8 participants (3 female, 5 male) aged 24-32 years ($M=27.37$, $SD=3$). All participants were right-handed and used their non-dominant hands for the study.

During the study, participants wore a machine-knitted glove with an integrated ferromagnetic patch at the index fingertip. Participants first got the opportunity to experience the passive haptic feedback generated via *MagKnitic* by approaching a permanent magnet. Then, they were asked to identify the predefined 9 textured surfaces by hovering their index fingertip above different permanent magnet layouts. The magnet layouts varied in each magnet's magnetic flux density and spacing, which were expected to create different force curves during the participant's finger movement. A piece of paper was placed on top of the magnet layouts so they were invisible to the participants. Participants were free to interact with the surface until they were confident about their answers. We recorded the participants' answers once they confirmed their selections.

Figure 6-11 demonstrated the confusion matrix depicting the identification of experienced force curves by participants, which were generated by different magnet layouts. In general, participants achieved 93.1% accuracy in identifying the textured surfaces. Accuracy is almost perfect except for designs #3 and #9. This suggests that users had a distinct perception of the presence of passive force feedback, the spacing between every single peak of the provided force feedback, and the intensity of the force feedback when a reference

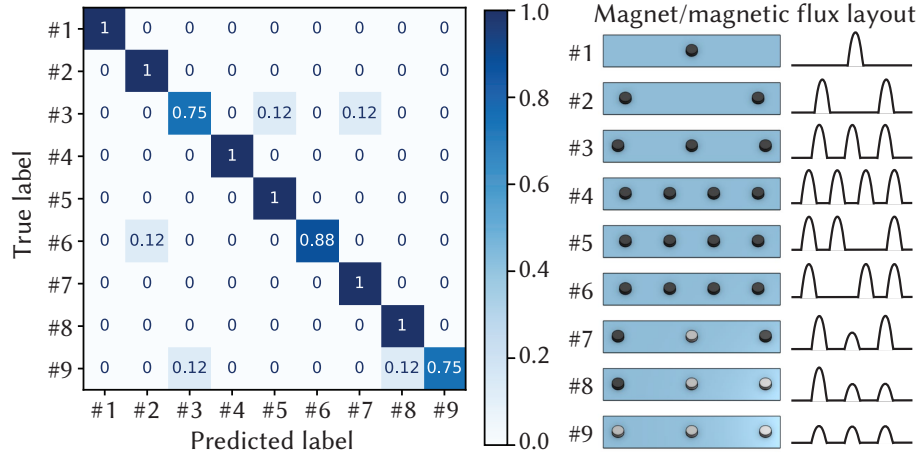


Figure 6-11: **Results of user study on user perception.** User classification on force feedback generated by diverse magnet arrangements. The magnet flux layouts generated from different magnetic amplitudes and spacing are plotted on the right.

was provided (i.e., when both the strong and weak feedback were provided).

User input. In this user study, we investigated the effectiveness of MagKnitic for user input. We recruited 6 participants (3 female, 3 male) aged 24-27 years ($M=25.75$, $SD=1.26$). All participants were right-handed and used both hands for the study. The participants were asked to interact with a swatch enabling polar interactions. The swatch was integrated with two ferromagnetic patches at the bottom layer and a pocket for permanent magnet insertion at the top. Before the study, we let the participants experience the generated haptic feedback when they rotated the top layer. During the study, the participants were asked to rotate the top layer 30, 60, 90, 120, and 150 degrees, respectively, to the target position, where the integrated ferromagnetic patch was located. The same procedure was performed both with and without the permanent magnet inserted to provide haptic feedback. Participants were free to interact with the swatch until they felt confident that they had rotated to the target position. We recorded the time each participant took to complete the task and their accuracy.

Overall, participants reported experiencing higher resistance during rotation when the inserted magnet aligned with the ferromagnetic patches. As shown in Figure 6-12, the integration of passive force feedback results in higher accuracy on the rotation task. This is because the passive force feedback gave users a tactile cue to indicate whether they were reaching the target position. It is also noted that in the absence of integrated force feedback,

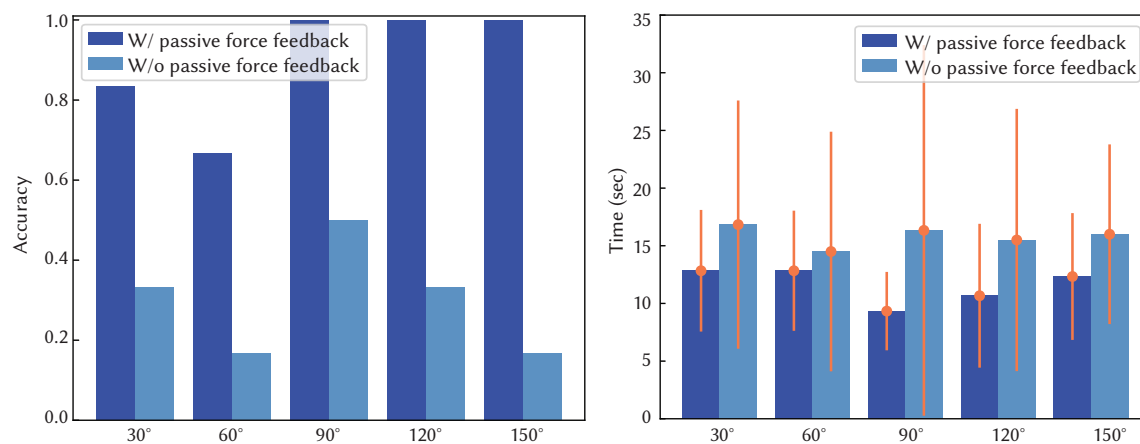


Figure 6-12: **Results of user study on user input.** Time consumption and input accuracy featuring polar interactions with and without *MagKnitic* passive haptic feedback.

participants achieved the highest accuracy when performing 90-degree rotations. This is because the 90-degree rotation is a more familiar and intuitive task for the participants. We have also observed that, on average, it takes users a long time to complete the rotation. However, 2 out of 6 participants performed the rotation faster when passive force feedback was not integrated. According to the 2 participants, without integrated force feedback, they lacked a means of determining whether their actions were correct. Consequently, they had to perform the task randomly, which may be efficient but not accurate.

The high accuracy exhibited by users in distinguishing between various force feedback characteristics and the improved accuracy observed in rotation tasks confirms the effectiveness and capability of *MagKnitic*, reiterating its potential for real-world applications.

6.4 Application

Thanks to the digital design and fabrication pipeline, we are able to integrate *MagKnitic* into textiles spanning from compact wearables to full-sized furniture coverings and carpets in a seamless and salable manner. In this section, we discuss applications of *MagKnitic* in passive yet interactive textile-based input wearables, soft game controllers, and large-scale objects like furniture coverings. All examples are built with our parametric design templates and fabricated in one go.

6.4.1 Input Wearables

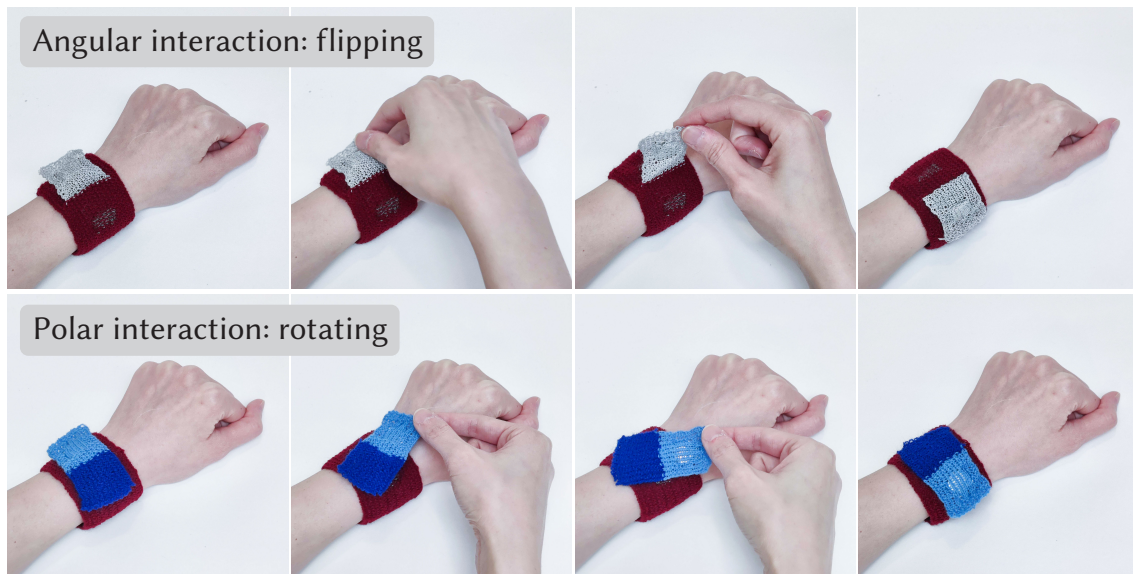


Figure 6-13: **MagKnitic in wristbands.** Knitted wristbands with haptic feedback as wearable input interfaces, enabling angular and polar interactions.

MagKnitic is uniquely suitable for integration into full-sized garments due to its compatibility with the industrial textile manufacturing process. As demonstrated in Figure 6-13, wristbands embedded with *MagKnitic* enable angular and polar interactions, which can serve as a customizable flip and rotary interface for wearable devices, such as for mode switch controls (focus, driving modes etc.) on mobile devices.

Coupling with binary sensing, *MagKnitic* offers solutions for wearable input interfaces with programmable haptic feedback. For example, we developed a custom text input device in the form of a glove (Figure 6-14). The digitally knitted glove includes 10 ferromagnetic patches along the index, middle, ring, and pinky fingers, as well as a conductive pocket with an embedded magnet on the thumb. Each of the ferromagnetic patches is designed as one key of the T9 predictive text input, plus one patch for the space & delete key. Together it can serve as a wearable keypad for user input. The user can perform input by getting the thumb tips towards a specific ferromagnetic patch, which causes the resistance to drop dramatically between the pocket and the patch, indicating the press input from the user. At the same time, the user receives haptic feedback through the generated attractive force as a confirmation of

successful recordings of the input.

This setup can also be incorporated similarly into a sleeve and a hat with various ferromagnetic patch layouts as wearable shape input or music control interfaces for mobile devices (Figure 6-15). By wearing a glove with a conductive pocket for an embedded magnet at the index fingertip, users will be able to input commands through different finger movements while perceiving tactile feedback that enhances their experience with the wearable input interface. These eyes-free interactions [142, 49] can be important for safety and convenience in various situations. For example, users can control their music or make phone calls while they are driving or walking in the street.



Figure 6-14: **Wearable T9 input interface with haptic feedback.**

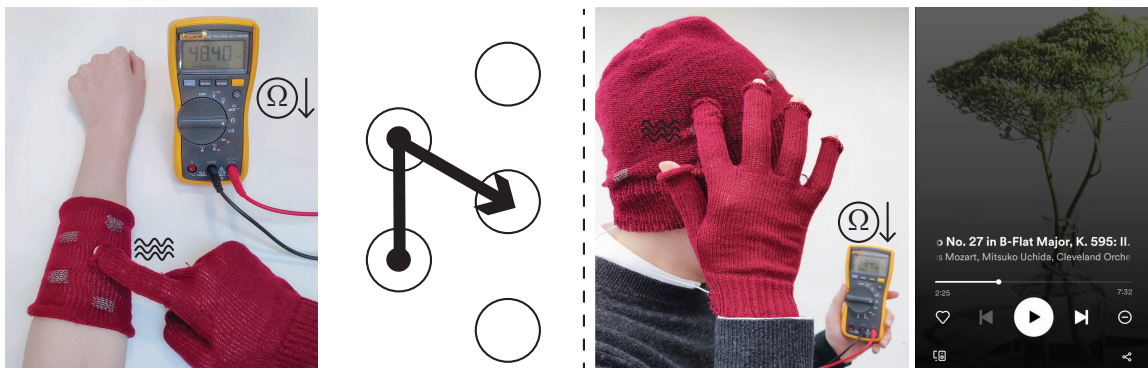


Figure 6-15: **Sleeve-based shape input device and an interactive hat with haptic feedback for music control.**

6.4.2 Soft Game Controller

To demonstrate *MagKnitic*'s capability for planar interactions, we implement a textile-based thumbstick-like game controller interface (Figure 6-16). This soft custom controller is designed for adolescents or users with small hands, for whom the conventional game controllers are too big. Integrated with four ferromagnetic patches, this soft and flexible controller enables binary directional sensing, allowing users to input through planar motion. In addition, it provides passive haptic feedback that enhances the users' sense of immersion during their planar interaction.



Figure 6-16: **Knitted soft game controller.**

6.4.3 Furniture Coverings

Unlike traditional passive haptic technologies that require rigid mechanical components and are challenging to be scaled up, *MagKnitic* can be seamlessly integrated into large-scale objects, such as furniture coverings. For example, it could be used to create interactive tablecloths and sofa coverings (Figure 6-17) that provide users with both comfort and aesthetic appeal and an immersive and tactile user interface with passive haptic feedback.

6.4.4 Virtual Texture Rendering

Passive haptic provides a natural and comfortable experience for VR/AR applications while keeping the cost and complexity of the device at a minimum. We propose potential applications of *MagKnitic* as easily integrated into AR/VR wearables, providing a subtle and



Figure 6-17: **Furniture covering.** Leveraging digital design and fabrication pipeline, *MagKnitic* can be integrated into furniture coverings, including table cloth, and sofa coverings, for diverse user interactions with passive haptic feedback. Using scenarios include tangible and interactive task checklists, ubiquitous user input interfaces, and so on.

realistic tactile sensation to the user and enhancing the sense of presence and immersion in the virtual environment in a passive manner. For instance, by wearing the socks and stepping towards a floor area or a knitted carpet with embedded magnets arrays, users will experience the sensation of walking on the muddy wetland, feeling the resistance and texture of the surface (Figure 6-18 right). Similarly, wearing the gloves and moving across a magnet array, users will experience touching a rough stone surface and feeling the bumps and irregularities of the texture (Figure 6-18 left). As demonstrated in preliminary user evaluation, our passive haptic feedback allows the user to feel the differences between various magnet layouts and magnetic flux densities, which demonstrate potential for embodying different textures in VR, e.g. mudding wetland, clean trail, and rough stone surface, in a soft, flexible, conformal, and natural form factor. More user studies will be planned to validate users' sensation over *MagKnitic* in VR environments.



Figure 6-18: **Interactive wearables for AR/VR.** Potential application of passive yet interactive gloves and socks for surface textures rendering in VR environments.

6.5 Discussion

We present *MagKnitic*, which integrates passive force feedback and resistive sensing into fabrics via digital machine knitting. With its soft, flexible, and lightweight nature, *MagKnitic* conforms to the human body and provides unique and natural tactile sensations, as well as perceivable haptic feedback during users' interactions and motions. Coupling with the complementary binary sensing feature, which detects users' interactions, *MagKnitic* provides users with tangible cues to interact with physical interfaces in diverse ways. We also provide parametric design templates for users to customize *MagKnitic* layouts and patterns, which support passive haptic interactions featuring 6 different motions. Technical evaluations and user studies validate the effectiveness of our approach. Finally, various application scenarios at different scales, from wearable input interfaces like glove-based text input and sleeve-based shape input devices, soft game controllers, to passive haptics systems for VR/AR environments, and large scale objects like interactive furniture coverings, demonstrate the potential of *MagKnitic* in different domains. This research opens up new possibilities for incorporating passive haptic feedback into fabrics, paving the way for the development of innovative and more immersive interactive systems.

Use of permanent magnets. In this work, we used permanent magnets rather than electromagnets to provide a magnetic field for force feedback due to several reasons. First of all, conventional electromagnets are based on coil structures, which are not feasible through digital machine knitting. While electromagnets are feasible through digital embroidery, another scalable textile manufacturing technique (Figure 6-19), the magnetic flux generated by an embroidered electromagnet powered by a 3.7 V battery is more than 1000 times weaker than that produced by a permanent magnet of the same size. Additionally, although electromagnets offer the advantage of programmable and active haptic feedback, they also raise concerns about safety due to the current and generated heat. They are also subject to significant energy consumption. These limitations make textile-based electromagnets less practical for wearable applications.

Taking into account the constraints of electromagnets in textile-based wearable applications, we opted to use permanent magnets for their simplicity, reliability, and energy efficiency. Our integrated permanent magnets are comparable in size to rigid buttons and zippers commonly found on garments (radius $< 1/2''$ and thickness $< 1/16''$). Despite adding a non-textile-based component to the systems, the small permanent magnets provide a strong and constant magnetic field without adding significant stiffness to the textile substrate. In the future, we also plan to explore the integration of polymer-based magnets [80] with textiles to enable a fully soft interface.

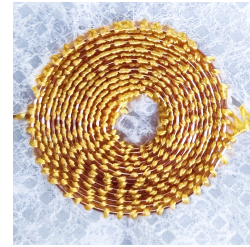


Figure 6-19: **Digitally embroidered electro-magnet.**

Alternative fabrication methods. Throughout the course of this project’s development, our knitting machine encountered mechanical complications, thereby requiring a significant amount of time to address. Consequently, this issue limited the number of applications that we can present in this submission. Such issues may prompt contemplation on alternative production techniques, which could be advantageous for readers seeking to prototype comparable systems.

Before committing to a complex knitted design, hand sewing can enable rapid prototyping to determine the dimensions and positions of the ferromagnetic zones for example. This can also be performed using simple sewing machines, and if a knitting machine is not accessible, an embroidery machine might produce satisfactory and consistent results too. However, it is important to emphasize that embroidery introduces an additional layer, which compromises the flexibility of the material.

Limitation. *MagKnitic* is a passive interface that benefits from being scalable, portable, low-cost, and low-power. However, it also suffers from common limitations of passive haptics, the lack of specificity and real-time response. *MagKnitic* needs to be pre-programmed and does not respond to real-time changes. This may limit the realism and effectiveness of the haptic feedback in high-speed or unpredictable environments, especially for AR/VR applications. Also, because ferromagnetic materials can only be attracted to the magnetic

field, *MagKnitic* can only utilize the attractive force between the ferromagnetic yarn and the magnet. This means that the system is limited to providing passive haptic feedback in a single direction, namely towards the magnet. While this may be sufficient for most applications for tangible user interfaces, it may not be ideal for more complex interactions that require feedback in multiple directions. Also, the spatial resolution of passive haptic units and binary sensors are inherently constrained by the resolution of knitting structures.

Chapter 7

Adaptive Tactile Interaction Transfer via Digitally Embroidered Smart Gloves

7.1 Overview

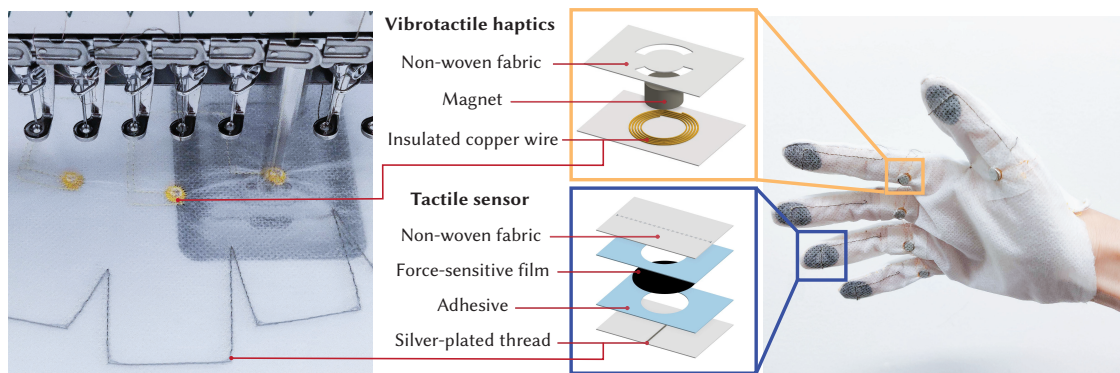


Figure 7-1: **Fabrication and structure of tactile interaction transferring smart gloves.** A full-sized textile-based glove with integrated tactile sensors (in orange box) and vibrotactile haptics (in blue box) is digitally designed and automatically fabricated using a digital embroidery machine.

Humans rely on their senses, including sight, hearing, and touch, to gather information about the environment and each other for everyday activities [74, 9]. Physical tactile feedback, in particular, serves a critical role in learning, movement, communication, and environmental awareness [47, 77, 84]. As technology continues to evolve and its capacity to understand and assist more complex scenarios increases, there is a growing need to leverage

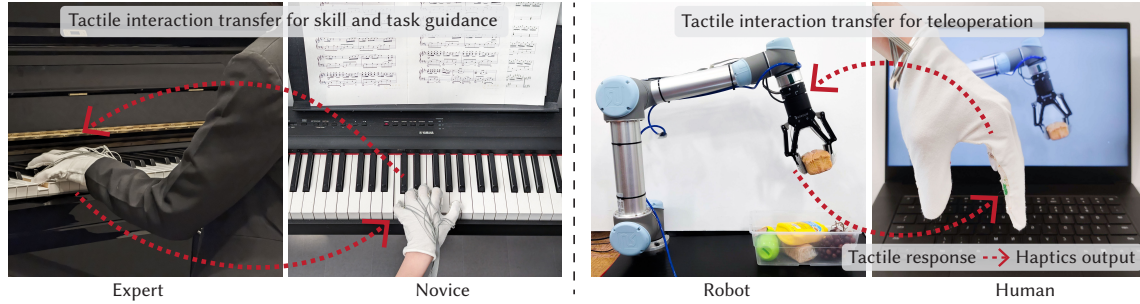


Figure 7-2: **Applications of tactile interaction transferring smart gloves.** Leveraging these gloves with integrated sensing and haptic capabilities, we demonstrate adaptive physical interaction transfer across people for skill development (left) and physical interaction transfer between humans and robots for teleoperation (right).

such physical tactile experiences to enrich technology-mediated interactions among humans and between humans and machines [38, 131]. Indeed, studies have demonstrated how sharing tactile information across humans and machines can be fundamental to personalized medicine and treatment [130, 127], robot-assisted surgery [89], human-robot interactions [98, 61, 139], augmented reality (AR)/virtual reality (VR) [78], and even everyday human activities [31, 25].

Enabling intuitive tactile interaction transfer remains challenging since it requires scalable and conformal tactile sensing and haptic display systems that can be seamlessly integrated into our daily lives [42, 59]. To combine tactile sensing and haptic feedback, recent soft systems have explored hand-based epidermal closed-loop human-machine interfaces [135, 114, 109, 60]. While previous works demonstrated the exciting potential of such systems, they also highlighted challenges such as their complex and delicate fabrication process that can limit scalability, robustness, customizability, and compatibility. Moreover, the variation in humans' perception of haptic feedback makes effective and reliable human-machine communication difficult since per-user calibration should also be minimized to create a seamless experience. Thus, scalable, compact, conformal, and adaptive human-machine interfaces with both tactile sensing and haptic display capabilities remain limited but obtain great potential for diverse real-world applications.

We aim to move towards addressing these challenges by presenting a textile-based wearable human-machine interface as well as its digital fabrication approach and adaptive

control algorithms [66]. More specifically, focusing on tactile interactions of the hands, we present a diverse set of gloves with integrated tactile sensors and vibrotactile haptic actuators (Figure 7-1). We integrate tactile sensing and vibrotactile haptic feedback using a customizable and scalable computational fabrication pipeline, develop designs that can be applied to various domains, and create a machine-learning pipeline for per-user haptic optimization. Experiments demonstrate its ability to record, reproduce, and adaptively transfer physical interactions in a variety of contexts (Figure 7-2).

The following sections describe details of the system, evaluation, and results. The contributions are summarized below.

- We develop a digital design and fabrication pipeline for wearables with integrated tactile sensors and vibrotactile haptic actuators.
- We evaluate the performance of the sensing and haptic components.
- We investigate users' perception on vibrotactile haptic feedback via a series of user studies.
- We develop a machine-learning pipeline that adaptively optimizes haptic feedback parameters for individual users.
- We exemplify the potential of tactile interaction transfer through end-to-end systems.

7.2 Design and Fabrication

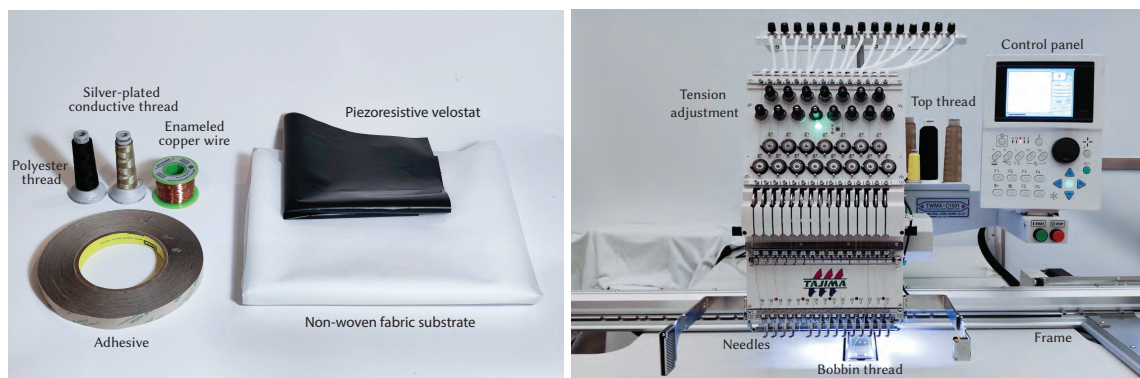


Figure 7-3: **Materials and fabrication of the smart gloves.** The smart gloves are made of polyester thread, silver-plated conductive thread, enameled copper wire, piezoresistive film, non-woven fabric, and adhesive (left), via digital embroidery (right).

The textile-based smart gloves, integrated with tactile sensing and vibrotactile haptic capabilities, are rapidly fabricated via a digital embroidery machine with minimal manual assembly (Figure 7-1). The smart glove offers a comparable level of wearability to regular gloves, comparable in terms of size, flexibility, and weight. The structures of tactile sensors and vibrotactile units are demonstrated in Figure 7-1, respectively. The digital design and fabrication pipeline allows the smart gloves to be modularly designed and customized for the unique requirements of individual users or specific tasks; this includes rapidly adjusting the density, layout, and size of tactile sensors or vibrotactile haptic units.

7.2.1 Resistive Tactile Sensors

Each of the tactile sensing units is based on a triple-layer design (Figure.7-1 orange box), where a piezoresistive layer (Velostat, Figure.7-3 left) was sandwiched between two fabric substrates with embroidered conductive yarns (Madeira HC40, polyamide/silver plated) as electrodes. We first embroidered the horizontal and vertical electrodes on separate fabrics. We then sandwiched the piezoresistive film at specific locations between the two fabrics using shaped adhesive (3M 468MP, Figure.7-3 left), which was pre-cut hollow in the center to enable direct contact between the electrodes and piezoresistive film (Figure.7-3 right).

7.2.2 Vibrotactile Haptic Matrix

Our vibrotactile haptics are based on a linear resonant actuator structure, including an electromagnetic coil and a moving mass (Figure.7-1 blue box). More specifically, our typical vibrotactile haptic unit consists of two fabric layers, a bottom layer embroidered with enameled copper coils (Fig.2a, 32 AWG, 5 winds), and a top layer with pre-cut symmetry circular slits. These slits generate a pair of symmetric fabric links with an angle of 30 degrees, accommodating a permanent magnet (K&J, N52 NdFeB) at the center. The two layers are affixed with thin adhesive. When an alternating pulse-width modulation (PWM) square wave signal is applied to the embroidered coil on the bottom layer, alternating magnetic flux is generated and leads to the vibration of the mounted permanent magnet on the top layer with a perceptible force and displacement. The symmetric pre-cut slits on the

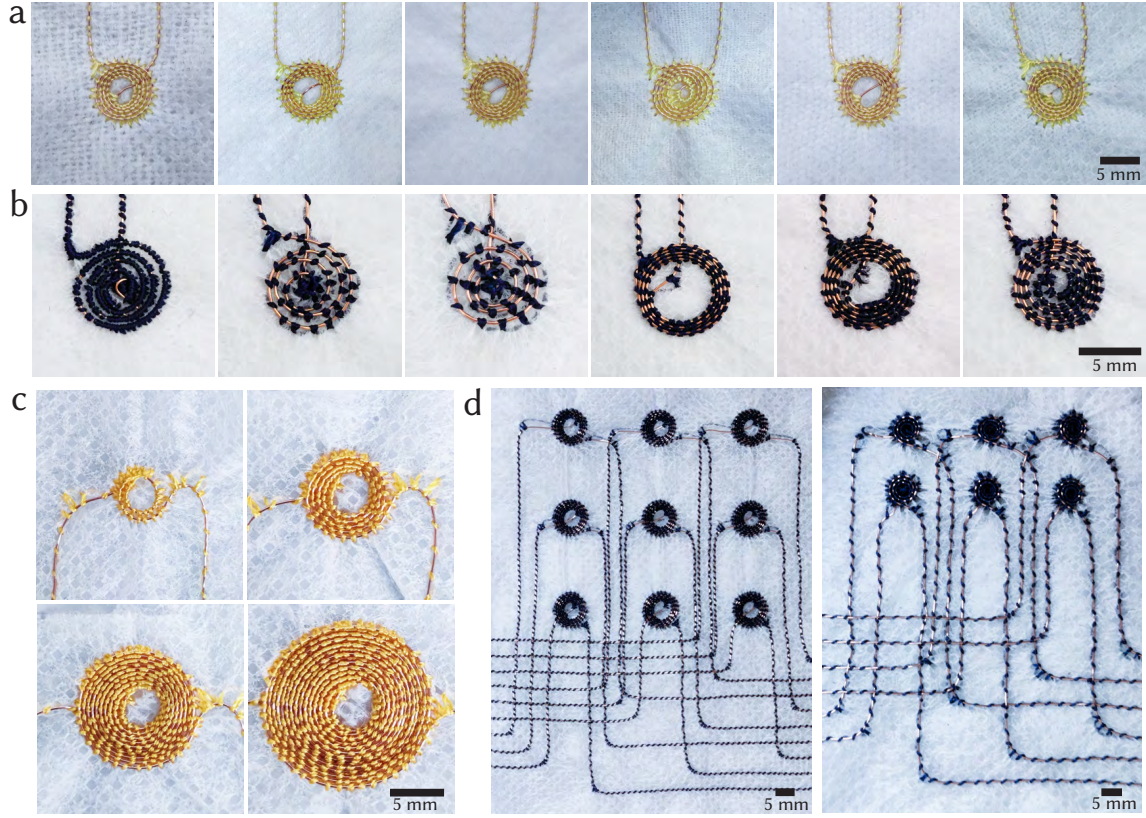


Figure 7-4: **Embroidered vibrotactile haptic matrix of various design variables.** (a) Embroidered coil on canvas, silk, cotton, mixed polyester-cotton, polyester, and poly-cotton substrate. (b) Embroidered coil with various stitch pitch (p_s) and coil pitch (p_c). (c) Embroidered coils with 2, 5, 10, and 15 winds (outer radius of 3.25, 4, 5.25, 6.5 mm). (d) Embroidered coil arrays with different spacing and arrangements. Both ends of the coils are arranged to the side for electrical connections to the driving board.

top layer allow for vertical movement of the attached magnets while effectively securing them at specific locations. The vibration frequency and amplitude of the haptic unit are contingent upon various factors, including the design of the embroidered copper coil, the size of the permanent magnets, and the duty cycle of the alternating PWM input.

The magnetic wire (BNTECHGO 32 AWG enameled copper wire) was embroidered as an electromagnetic coil on the fabric substrate at the speed of 700 stitch/min. Since the copper thread is stiffer than the usual embroidery threads (Madeira 100% polyester), we used it as a bobbin (bottom) thread, which experienced less strain during the embroidering process and thus ensured a stable fabrication process. Different design parameters of the embroidered copper coil, including inner radius r_{in} , outer radius r_{out} , coil pitch p_c , and stitch

pitch p_s are investigated and optimized (Figure 7-4). Based on the size of magnets (diameter = 6.3 mm) and the size of copper thread (diameter=0.2 mm), we set the inner radius r_{in} as 3 mm, outer radius r_{out} as 4 mm, coil pitch p_c as 0.25 mm (Figure 7-7). Stitch pitch p_s was set as 1 mm to maintain the optimal tension of the embroidered coil. The top fabric was first laser-cut to generate a circular slit with pre-defined angles. Commercial permanent magnet (K&J, N52 NdFeB, thickness = 1.6 mm) of different sizes (diameter = 3.2 mm, 6.3 mm, 12.7 mm,) was affixed to the center of slits by thin adhesive (3M 468MP). The top fabric with the affixed magnet was aligned to the embroidered coil matrix and affixed with adhesive. In this work, the vibrotactile haptic units were fabricated using non-woven fabric as a substrate; however, the same fabrication process is feasible for a wide range of substrates.

7.2.3 Integrated Tactile Sensing and Haptics Glove

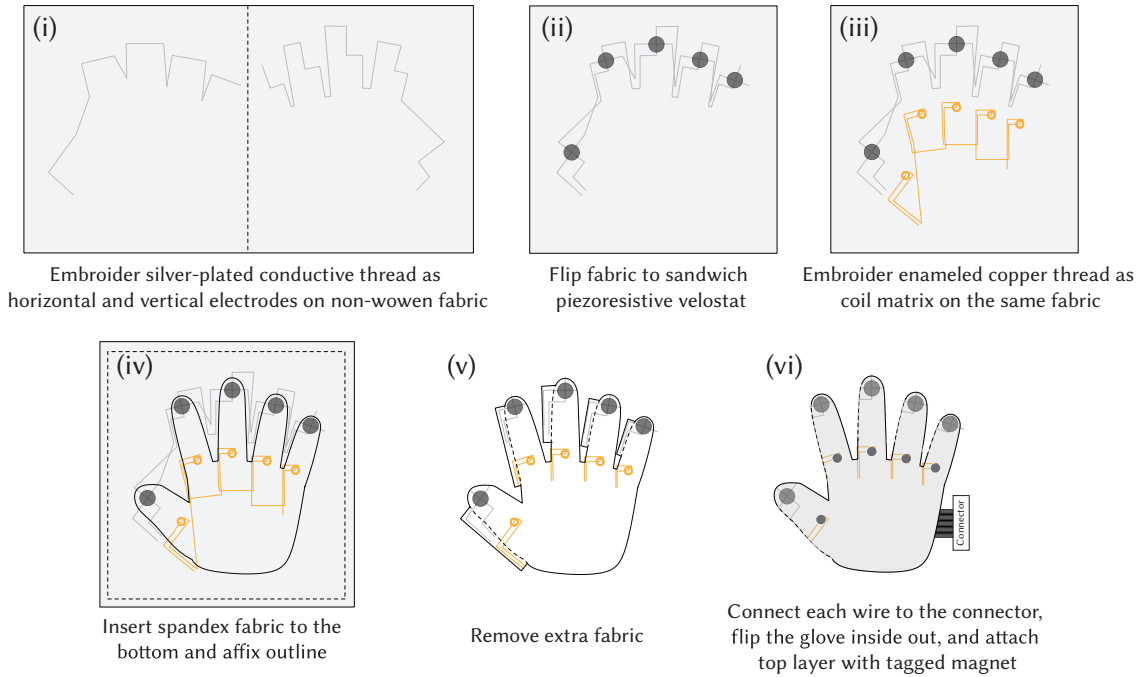


Figure 7-5: Design and fabrication procedures of the smart gloves. A full-sized glove with tactile sensing array and vibrotactile haptic array can be fabricated in sequential machine runs. First, we embroider the silver-plated thread as vertical and horizontal electrodes of the tactile sensing array (i). We then sandwich piezoresistive films with embroidered electrodes (ii). The same procedure for textile-based vibrotactile haptic array can be applied on the fabric with an integrated tactile sensing array (iii-vi).

The fabrication of full-size textile-based gloves with seamlessly integrated tactile sensors and vibrotactile haptic units is composed of 6 steps. First, we embroidered the silver-plated conductive thread as horizontal and vertical electrodes for the tactile sensors (Figure 7-5b(i)). We then affixed the piezoresistive layer at specific locations and flipped the fabric with vertical electrodes over to the one with horizontal electrodes, forming the three-layer sensing structure (Figure 7-5b(ii)). The electromagnetic coils were then embroidered onto the same fabric (Figure 7-5b(iii)). To further offer flexibility to the glove design, we applied Spandex fabric to the bottom of the embroidered fabric and stitched the outline of the glove design (Figure 7-5b(iv)). We then cut the excess fabric (Figure 7-5b(v)). Lastly, we flipped the embroidered glove inside out to avoid visible seams, and aligned and attached the laser-cut top fabric with the tagged permanent magnets onto the embroidered coil matrix. The tactile-vibrotactile glove would be fully functional after connecting the tactile sensing electrodes and the extended copper thread to the readout and driving circuits (Figure 7-5b(vi)).

7.3 Characterization

7.3.1 Resistive Tactile Sensors

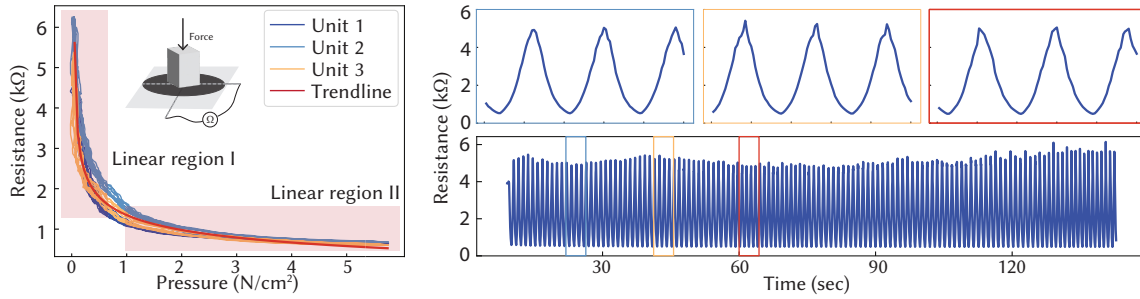


Figure 7-6: Characterization of embroidered tactile sensor. Left: Resistance profiles are consistent across three individual embroidered tactile sensors under pressure, with two linear regions. Right: Consistent performance of an embroidered tactile sensor was captured during 500 pressure (5 N/cm^2) loading and unloading cycles.

The resistance profile of a typical tactile sensor was measured by a digital multimeter (Tektronix DMM4050) with a loading normal pressure of up to 35 N/cm^2 (Shimadzu AGS-X). Each tactile sensor obtains a minimum detection limit of 0.35 N/cm^2 and a maximal

detection limit at 20 N/cm^2 . When the applied normal pressure is increased up to 6 N/cm^2 , the resistance of tactile sensors drops from $6 \text{ k}\Omega$ to $0.8 \text{ k}\Omega$, with two linear sensing regions. Consistent performance was retrieved from multiple individual tactile sensors, reiterating the advantages of standardized digital design and fabrication pipeline. Our sensor functions with minimal hysteresis during pressure loading and unloading cycles at with minimal hysteresis (Figure 7-6 left). The stability and durability were further demonstrated by the stable sensing performance of our sensors by applying 0.35 to 5 N/cm^2 loading and unloading cycles at the rate of 3 mm/min (Figure 7-6 right).

7.3.2 Vibrotactile Haptics

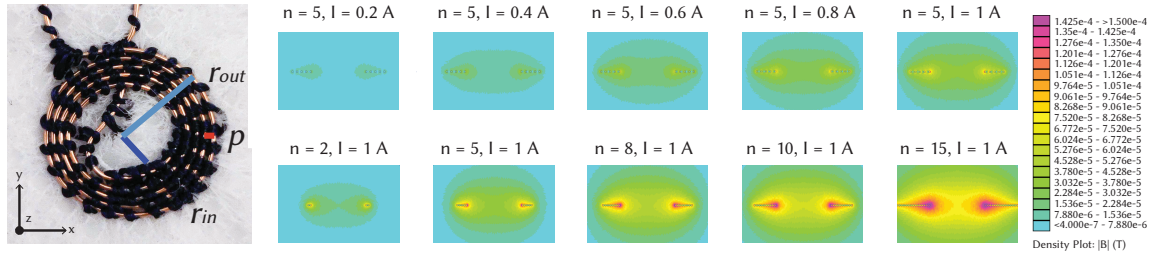


Figure 7-7: **Simulation of embroidered magnetic coils.** Left: Photograph on a typical embroidered magnetic coil showcasing inner and outer radii (r_{in} and r_{out}) and the pitch (p) of neighboring coil winds. Right: Simulation demonstrating magnetic flux at the cross-section when subjected to various winds and input currents.

Figure 7-7 demonstrates a representative design of an embroidered copper coil and the corresponding simulated magnetic flux heatmap with different current inputs, respectively. In particular, we performed a finite element method (FEM) simulation to compute the magnetic flux density and compared it with the actual magnetic flux density we measured from the physical samples. All our simulations are conducted using Finite Element Method Magnetics (FEMM) [29]. We considered our design as a symmetric structure and used FEMM to solve the axisymmetric problem with one cross-section slice. We also measure the magnetic flux of different embroidered coil designs via a Gauss meter (FW Bell 9500) using a probe of around 5 mm by 5 mm surface area. The measured magnetic flux from the embroidered magnetic coils (subjected to a full-scale duty cycle input) agrees with the simulation result (Figure 7-8). The magnetic flux generally decreases with the increase in

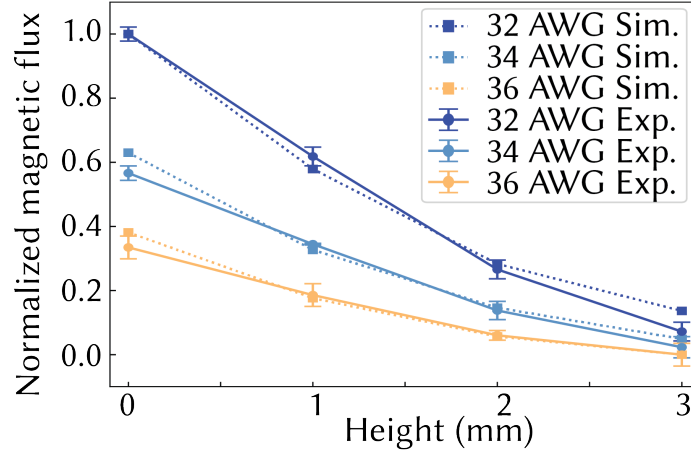


Figure 7-8: **Simulated and experimental magnetic flux from embroidered magnetic coils.** Comparison of normalized simulated and experimentally measured magnetic flux from embroidered coils with varying gauge numbers of magnetic wire at different heights. Error bars indicate the standard deviations (SD) across measurements.

sensing height and magnetic wire gauge.

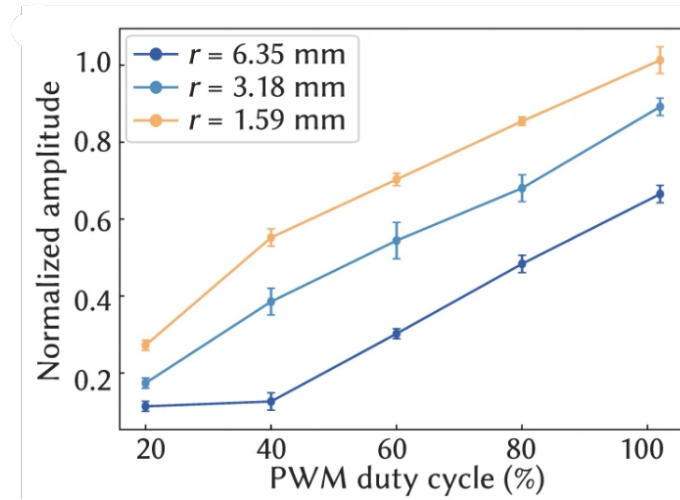


Figure 7-9: **Vibration amplitudes of the vibrotactile units.** Vibration amplitudes of the vibrotactile unit increase with its sizes and the input PWM duty cycle.

Furthermore, the displacement of the vibrotactile haptic units can be captured and quantified through a high-speed camera. The vibrotactile displacement increases with the rise of the input PWM duty cycle and with the decrease of permanent magnet size, which obtains higher magnetic field-to-weight ratios (Figure 7-9). Figure 7-10 presents the normalized vibration amplitudes of typical vibrotactile haptic units with different radii across various left-out fabric link angles (α) and alternating input frequencies, effectively

highlighting the resonant frequencies of different designs. Notably, as the fabric link angle decreases, the vibration amplitude intensifies, while the resonant frequency concurrently decreases.

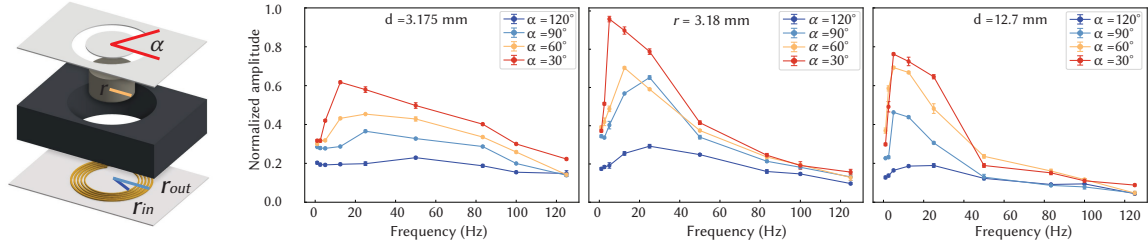


Figure 7-10: **Resonant frequency of vibrotactile haptic units.** Resonant frequency of vibrotactile haptic units of different designs.

7.4 Readout and Driving Circuits

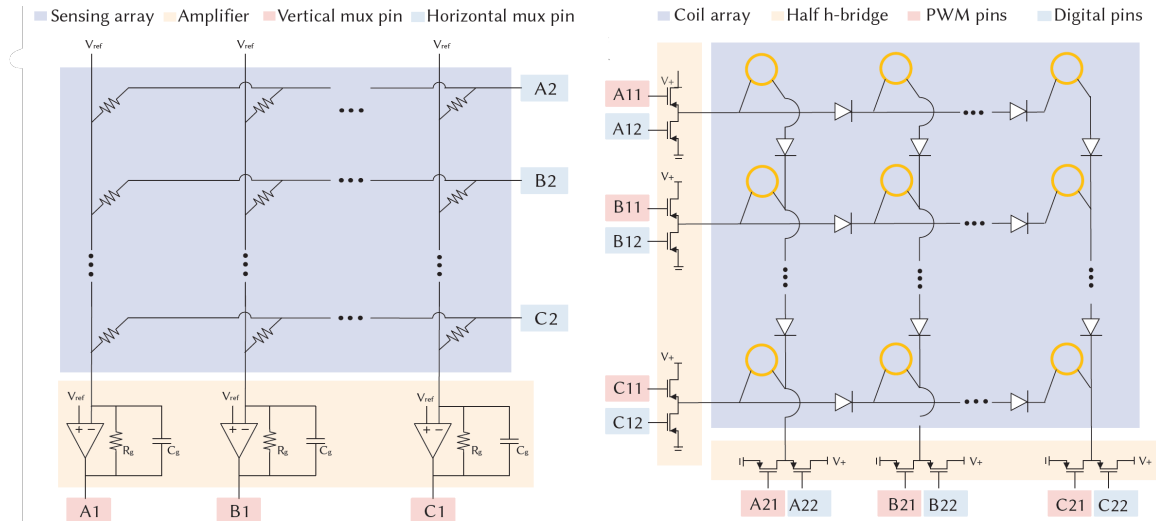


Figure 7-11: **Sensing readout and vibrotactile driving circuit.** Left: A modified electrical-grounding-based isolation circuit architecture for passive sensing array readout. Right: A matrix-based vibrotactile driving circuit.

Both tactile sensors and vibrotactile haptic units are serialized in a matrix-based form factor to minimize the number of connecting wires (Figure 7-11).

7.4.1 Readout Circuit for Tactile Sensing Matrix

The tactile sensors were serialized through an electrical-grounding-based circuit architecture in a matrix form factor [22]. A reference voltage V_{ref} of 2.5 V was applied to each column. An amplifier was added to each column with the gain resistor R_g of 1 k Ω . A capacitor of 10 μ F was added in parallel with each gain resistor to reduce noise. Controlled by Arduino Nano, each row (A2, B2, C2) was grounded at a time while each column (A1, B1, C1) was multiplexed through for signals from individual sensors (Figure 7-11 left). Measurements were transformed into a 10-bit digital signal and transmitted serially to a computer.

7.5 Driving Circuit for Vibrotactile Haptic Matrix

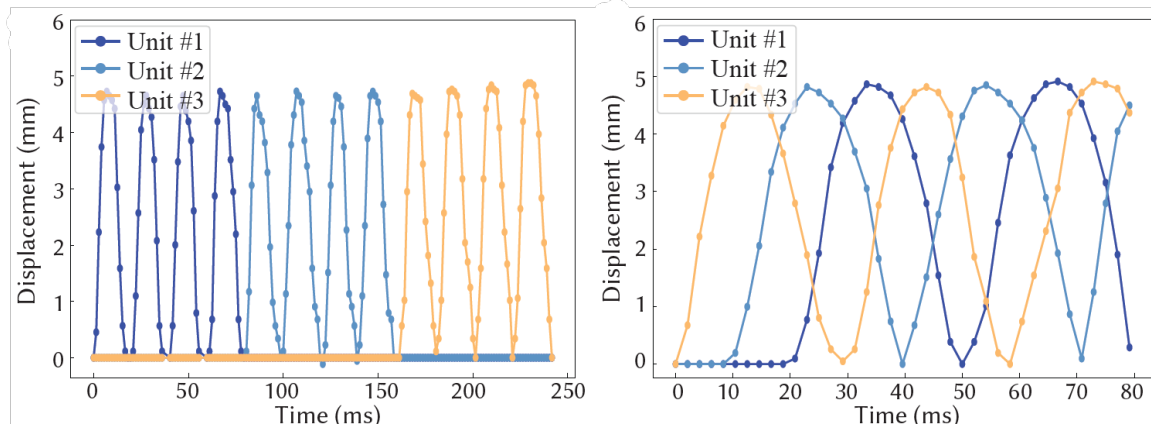


Figure 7-12: **Vibration displacement of neighboring haptic units.** Vibration displacement of neighboring haptic units when driven in a sequential (left) and multiplexed manner (right).

The vibrotactile haptic units were controlled with a customized circuit mounted on a microcontroller board. Our circuit consists of a matrix of five H-bridges, Schottky diodes, and connectors for interconnection between haptic units (Figure 7-11 right). Each haptic unit was driven by an H-bridge matrix, where each row and column was connected to a half-bridge circuit architecture, respectively. The half H-bridge circuit comprised of two N-MOSFETs (IRLB8721PbF, Infineon Technologies) connected in series. Forming a full H-bridge using specific pairs of horizontal (e.g. A11 and A12) and vertical (e.g. A21 and A22) half H-bridges, the defined vibrotactile haptic units (e.g. top-left coil) can be activated

in a multiplexed manner. All half H-bridges were controlled by a microcontroller board (Arduino Mega 2560 Rev3) through pulse-width modulation (PWM) pins (e.g. A11 and A21) and digital pins (e.g. A12 and A22). Coils were driven by square wave input. Each coil was separated by a low turn-on voltage diode (Part number) to prevent cross-talks. External power was supplied by a portable lithium-ion polymer battery (3.7 V, 2500 mAh) to drive the coils. The intensity and frequency of the vibrations are fully programmable. The direction of displacement and the polarity of generated magnetic flux is determined by the direction of current flowing through the coil, which is controlled by the switches of the H-bridge. The intensity of the vibration relies on the average voltage and current delivered to the coil, which is controlled via PWM. The vibration displacement of three neighboring vibrotactile units shows a consistent displacement with minimal interference between each unit when activated sequentially and alternatively (Figure 7-12).

7.6 Perception of Vibrotactile Haptic Feedback

Our experiments with human subjects were approved by the Committee on the Use of Humans as Experimental Subjects (COUHES) at the Massachusetts Institute of Technology (MIT, 2210000769). Participants were recruited through verbal advertisements and voluntarily participated in the studies without receiving any compensation.

7.6.1 Pilot Study

We first investigated users' perception of vibrotactile feedback with different input AC amplitudes and frequencies. We recruited 10 human subjects, who were provided with haptic feedback under different input modulation (PWM duty cycle of 100%, 40%, 20%, 10%, 5% at a frequency of 100 Hz) amplitude and frequency ($f = 250, 100, 50, 25, 12.5, 5$ Hz at 100% PWM duty cycle). Participants then provided quantitative feedback based on the amplitude of sensations. All participants were right-handed. In a randomized order, different AC inputs were continuously applied to participants' index fingertips on left hands until they provided corresponding quantitative ratings. Figure 7-13 shows their resulting ratings of perceived amplitude. In general, users perceive the feedback more strongly with

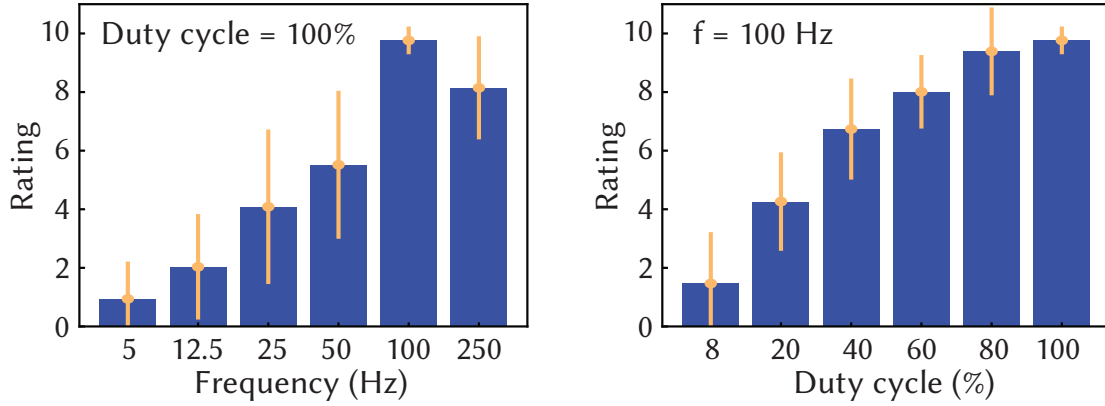


Figure 7-13: **Perception of vibrotactile haptic feedback of different amplitudes and frequencies.** Left: Normalized user ratings on a scale of 0 to 10, indicating the perceived strength of haptic feedback for various amplitudes and frequencies. Right: A rating of 0 represents no perception, while a rating of 10 signifies the strongest perception.

higher input amplitudes and at a frequency of 100 Hz.

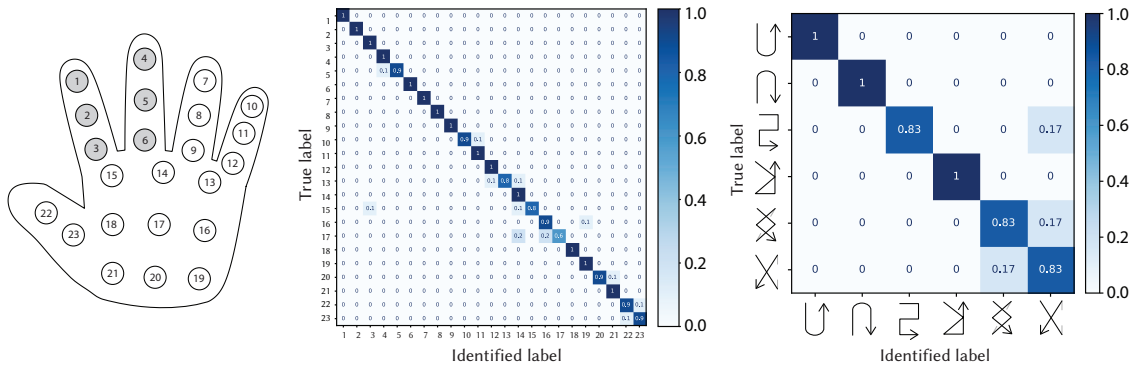


Figure 7-14: **Perception of vibrotactile haptic feedback of different spatial and temporal patterns.** Left: Illustration showcasing the placement of vibrotactile units on a smart glove for studying users' perception. Middle: Confusion matrix summarizes users' identification of activated vibrotactile haptic unit. Right: Confusion matrix on users' identification on the temporal activating patterns. The temporal activating patterns are demonstrated as the confusion matrix labels, which happen at the vibrotactile units on the thumb and index finger, colored in gray.

In addition, tests were performed to explore whether users could identify where haptic feedback is being applied on the hand, and whether they can distinguish between temporal patterns of activation. In this experiment, 10 recruited participants were asked to wear a vibrotactile haptic glove with 23 integrated vibrotactile units (Figure 7-14 Left). We activated one random unit at a time and asked the participants to identify the location

of their sensations (23 trials per participant). We investigated the interference effect by repeating the same experiment with one of the haptic units continuously activated (23 trials per participant). Furthermore, we activated 6 vibrotactile haptic units along the index and middle finger with some defined temporary sequence and asked the participants to classify the spatial and temporal pattern (10 trials per participant). Each sequence is around 3 seconds. Classification accuracy is reported in Figure 7-14 middle and right. All vibrotactile haptic units were activated with 100% PWM at 100 Hz.

7.6.2 Tactile Interaction Transfer for Tactile Occlusion Alleviation



Figure 7-15: **Transfer physical tactile interaction for one person.** Left: Photograph of an outer sensing glove to capture tactile cues and an inner haptic glove to transfer tactile cues under tactile occlusion. Right: Accuracy of classification of single contact points under tactile occlusion, with and without the haptic feedback. Error bars indicate the standard deviations (SD) across measurements.

The sense of touch is essential for delicate manipulation tasks, but it can be significantly hindered when occluded by gloves. This is particularly evident in situations where astronauts and technicians must wear thick personal protection equipment for dangerous tasks, resulting in a considerable reduction in tactile perception. Such tactile occlusion could be alleviated by transferring the physical sense of touch from the glove's outer contact area to the human skin on the glove's inner surface. This would allow users to regain their perception of the external environment, which is crucial for dexterous manipulation tasks. Leveraging the textile-based smart gloves with integrated tactile sensing and vibrotactile haptic capabilities, we demonstrate the transfer of coarse pressure-based tactile interaction to alleviate tactile

occlusion.

We develop a double-glove interface (Figure 7-15 Left) by augmenting a hand-shaped piece of fabric with 23 tactile sensors, then attaching this to a thick protective glove for animal handling. We then fabricate a glove with 23 vibrotactile units whose positions correspond to the sensor locations, and insert this actuated glove into the sensorized protective glove. The completed system can capture tactile interaction outside the protective glove and transmit it to the human skin via the inner haptic glove in real time.

We asked 2 recruited participants to wear double gloves, which consist of an outer thick animal handling glove (RAPICCA) with mounted tactile sensors, and an inner regular-sized haptic glove. The tactile sensors capture the pressure information, which was converted to the corresponding vibrotactile haptic feedback (PWM duty cycle of 100% at 100 Hz) based on threshold clipping (the corresponding haptic units were activated if the tactile sensing reading exceeded 50% in weighted amplitudes) in real time at the frame rate of 40 Hz. We then applied a force stimulus to a specific area on the animal handling glove and asked participants to locate the stimulus with and without the vibrotactile feedback. Accuracy is reported in Figure 7-15 right.

7.7 Adaptive Tactile Interaction Transfer across Users

7.7.1 Method

Leveraging our textile-based wearables, we are able to capture the real-time tactile interactions from an individual user and then reproduce and transfer such interactions to another user via haptic instructions. For example, we ask a piano teacher to play a certain rhythm and capture the corresponding tactile sequence (T_{target}). We then derive the haptic instruction sequence (H) based on the captured data and display it to a student through a haptic glove. Based on the haptic instruction, the student is expected to reproduce the rhythmic sequence of the teacher.

We measure the difference between the students' reproductions and the target tactile sequence to evaluate the transfer efficacy. We assume two users achieve the same performance

for a given task when they produce the same tactile signals during the interaction; a smaller difference between a student's reproduced tactile sequence (T) and the teacher's (T_{target}) indicates a more effective transfer.

A challenge is that simply producing an H that directly copies or linearly maps T_{target} will not result in a faithful reproduction since each person reacts differently to the same haptic sequence. Moreover, a single person may also react differently to haptic signals at different hand locations and with different timings. Therefore, to ensure the effectiveness of tactile interaction transfer, the haptic instructions must be adaptively optimized across time, subjects, and task requirements.

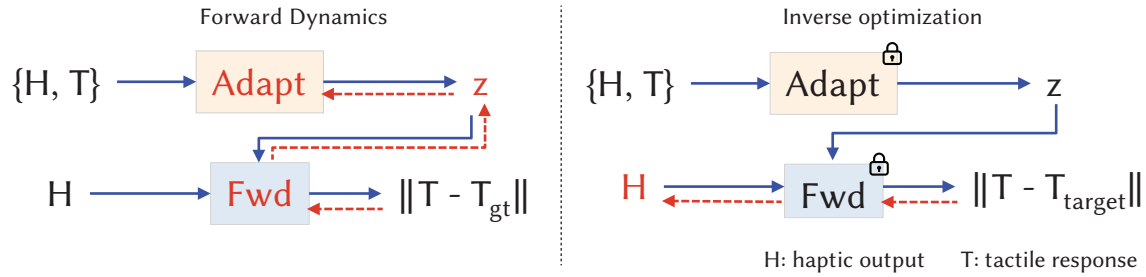


Figure 7-16: **An overview of the pipeline for human model learning and inverse haptics optimization.** The pipeline incorporates a forward dynamics model with an adaptive module (left) and an inverse optimization procedure (right). The vibrotactile haptic output is denoted as H , and the tactile response as T . Backward propagation is represented by the red dashed arrows.

To address this challenge, we develop an adaptive human model learning and inverse haptics optimization pipeline to derive personalized vibrotactile haptic instructions [132]. It outputs an optimized haptic signal (H) given an input target tactile sequence (T_{target}). The pipeline comprises a forward dynamics model and an inverse optimization process, as illustrated in Figure 7-16. The forward dynamics model simulates a user's reaction to the haptic instruction by taking in a sequence of haptic signals (H) and predicting the resultant tactile sequence (T). Given a trained forward dynamics model, the inverse optimization process aims to minimize the difference between the predicted tactile sequence (T) and the target tactile sequence (T_{target}) by optimizing the parameters of the haptic sequence H using gradient descent.

To adapt the pipeline to individual users without dedicated calibration routines, we

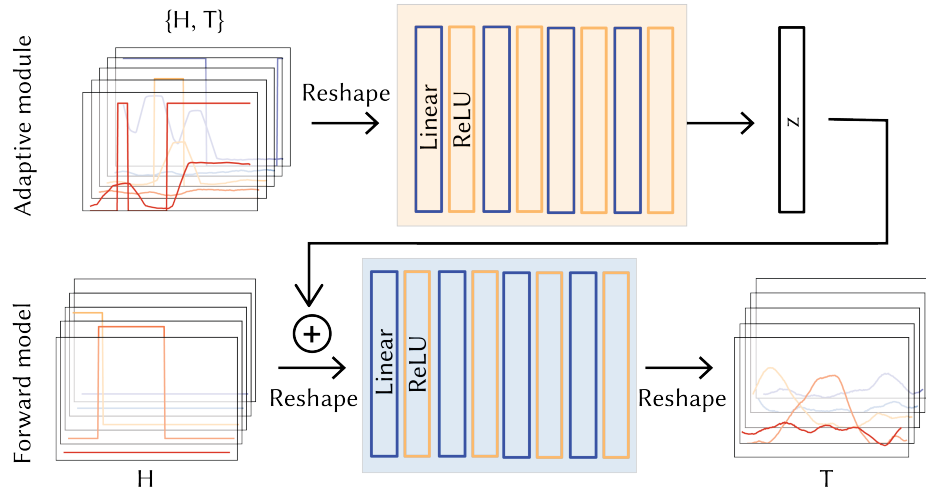


Figure 7-17: **Illustration of the forward model.** Illustration of the forward model featuring an adaptive module.

include an adaptive module that takes in a combined series of haptic instructions and tactile responses ($\{H, T\}$) and generates a user-specific latent feature vector (z). This latent encoding may represent information such as reaction time and finger dexterity (Figure 7-17). The feature vector (z) is then provided to the forward dynamics model together with the haptic sequence. By including the adaptive module, our pipeline learns to adapt to the individual user’s response to the haptic instructions and optimizes the haptic sequence output for individuals given a specific tactile sequence goal. This enables an adaptive, automatic, and accurate conversion between tactile and haptic signals. This process can occur dynamically, allowing the interface to improve in real time.

7.7.2 Data Collection

Using finger pressing as a concept-proofing task, we collected data from 12 participants (IRB by MIT 2210000769). Participants wore our designed smart glove, where 5 tactile units were located at the fingertips and 5 haptic units were located at the inner side of each finger (Figure 7-1). Participants were informed about the basic rule, which was to press the corresponding finger whenever they perceived vibration on one of the five fingers. We played randomly generated haptic instructions, where the 0-1 haptic unit was activated for a random duration. The vibrotactile haptic units were activating at full modulation at the

frequency of 100 Hz. The sensing response from the participant’s pressing was captured in real time. More than 150,000 frames were collected (around 5 minutes of continuous pressing per participant). We split data from each individual participant as train, validation, and test sets with a ratio of around 6:2:2.

7.7.3 Experiments

Forward dynamics model. The forward model took in a sequence of haptic sequence (H , 200 frames, around 4 seconds) and output a sequence of predicted tactile signals (T) with the same length. The model was implemented in PyTorch, composed of 4 fully connected layers, each of which was followed with a ReLU activation function (Figure 7-17). Mean squared error (MSE) was computed and minimized between the predicted tactile signal (T) and ground truth tactile signal (T_{gt}) from the participant’s pressing sequence during data collection (Figure 7-16). The adaptive module took in a concatenated sequence of haptic sequence and tactile sequence ($\{H, T\}$, 800 frames, around 15 seconds) from an individual user and output an adaptive feature (z) with a length of 1000. It was composed of 4 fully connected layers, each of which was followed with a ReLU activation function. The adaptive feature was then input into the forward model together with the haptic sequence. We trained individual forward models using the dataset from each participant, and a universal forward model without the adaptive module using the dataset from all participants as baselines. All models were trained with a learning rate of $1e^{-4}$, weight decay of $1e^{-4}$, and batch size of 32.

Inverse haptics optimization. Given a target tactile sequence (T_{target}), the inverse optimization outputs the optimized haptic instructions by interactively performing gradient descent over and minimizing the MSE between the predicted tactile sequence (T) and the target tactile sequence (T_{target}), which was output by the pre-trained forward dynamics model using the present haptic sequence as input (Fig.7-16). The initialization of the haptic sequence was extracted from the target tactile sequence by straightforward thresholding (the corresponding haptic units would be activated if the tactile signal exceeds a normalized threshold of 0.3). Gradient descent was performed with a learning rate of $1e^{-3}$, and weight

decay of $1e^{-3}$.

7.7.4 Results

As a baseline, we trained a forward model for each subject individually. Then we trained a universal forward model that omits a selected subject, and evaluated its performance both with and without an adaptive module. As shown in Figure 7-18 left, using an adaptive module reduced the mean-squared error (MSE) and even achieved comparable performance to the per-subject baseline model. Compared to baseline models trained for individual users, our adaptive model allows generalization and adaptation to new users with 15 seconds of user data.

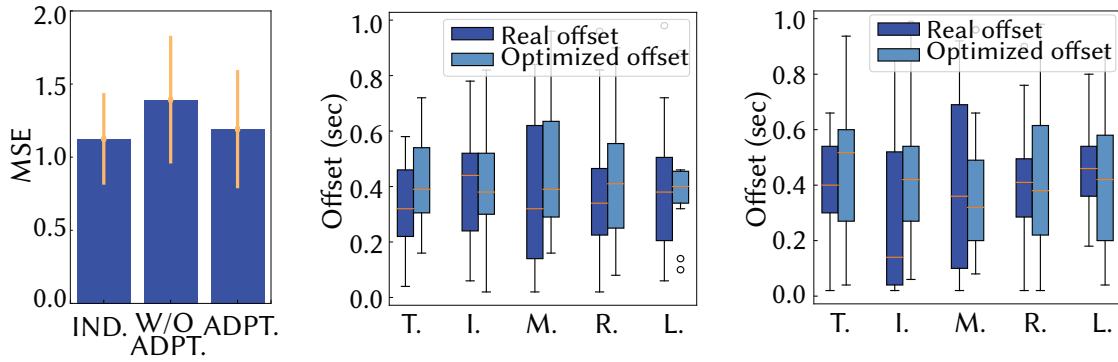


Figure 7-18: **Offline validation of haptic output optimization.** Left: Quantitative comparison of the accuracy of the individually-trained forward model (IND.), universal model without adaptation module (W/O ADPT.), and universal model with adaption model (ADPT.). Middle: The forward dynamics model is able to predict the time offset for individual user's perception and reaction toward the haptic instructions. Right: The inverse optimization pipeline predicts the time offset of the vibrotactile haptic feedback for each individual user's optimal performance. The labels along the x-axis indicate five individual fingers.

We apply this learning and optimization pipeline to piano playing, rhythmic gaming, and racing games (Figure 7-19). In the piano-playing scenario, users are asked to play a specific sequence that can be achieved without moving their hand to new keyboard locations on a digital piano (YAMAHA P-125) with 5-finger control. Performance is evaluated by comparing the tactile response from the users to the target tactile response captured from a piano expert. In the rhythmic game, users are expected to follow a designed track and bump into the goal area (green dot) by left-clicking the mouse to switch the moving line (blue line)

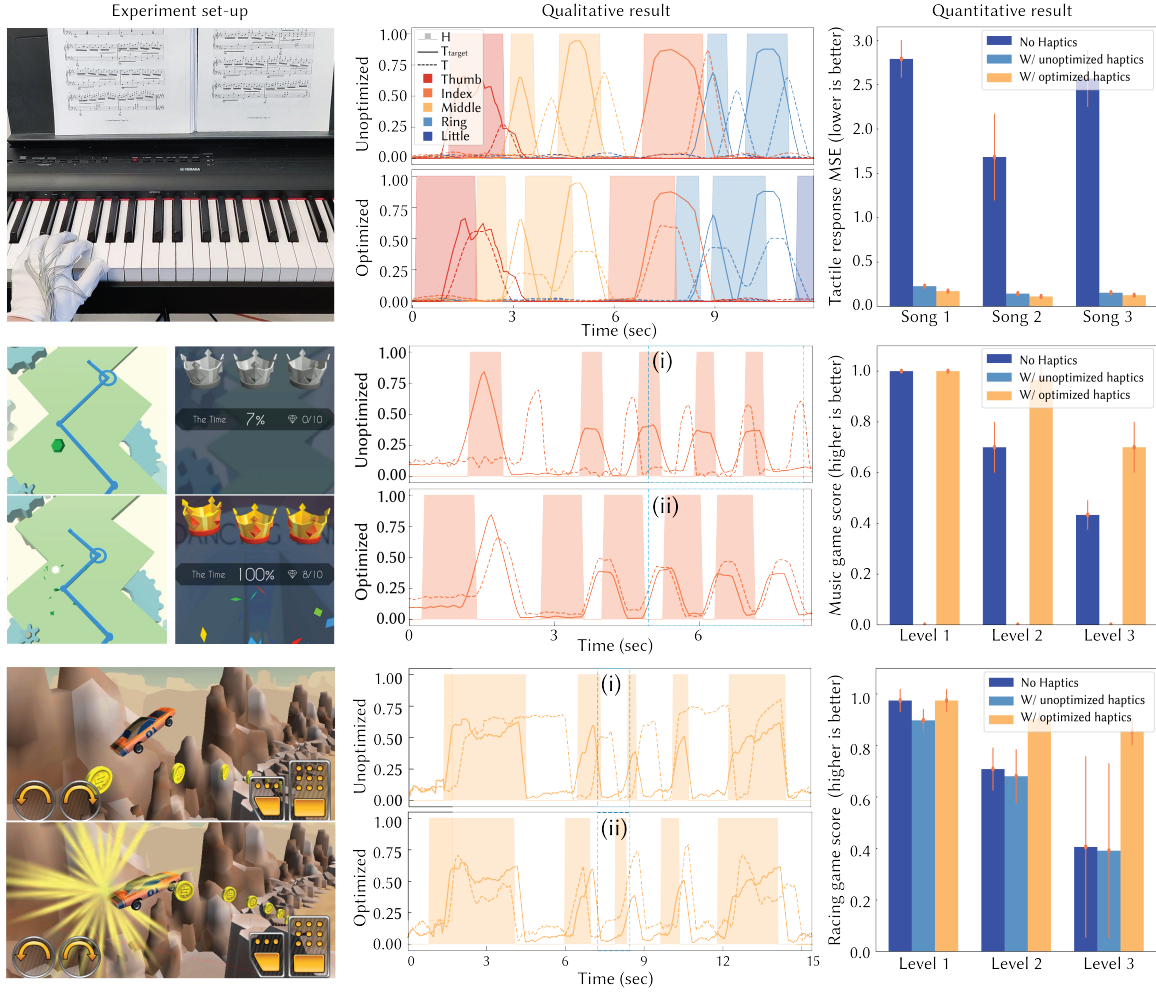


Figure 7-19: **Illustration of the forward model featuring an adaptive module.** Using our pipeline, we demonstrate improved performance in piano playing (top), rhythmic gaming (middle), and racing gaming (bottom) by transferring tactile interactions from expert users. The experimental images (left column) were captured during the time intervals indicated by the dashed light blue boxes depicted in the qualitative results plots (middle column). Error bars indicate the standard deviations (SD) across measurements.

direction. Users need to stay on the route (light green area) and are scored based on how many goals they bump into. In the racing game, users are asked to reach the finish and collect coins along the way by controlling the balance of the car. Performance is evaluated with the number of collected coins. In all scenarios, we first record the tactile response sequence from a high-performance player's finger pressing; taking the recorded tactile sequence as input, the optimization pipeline outputs the optimized haptic instruction for a specified user. We record and compare the performance of that specific user with optimized haptic instructions, unoptimized haptic instructions, and a baseline that does not provide any haptic instructions. Validation and comparison of the effectiveness of our optimization pipeline were performed three times on two users. To eliminate bias, users were asked to get familiar with the validation scenarios before the experiments and to perform the tasks first with optimized haptic instructions, then with unoptimized haptic instructions, and lastly without any haptic instructions. Tactile information was recorded at 50 Hz and haptic instructions were generated at 100 Hz.

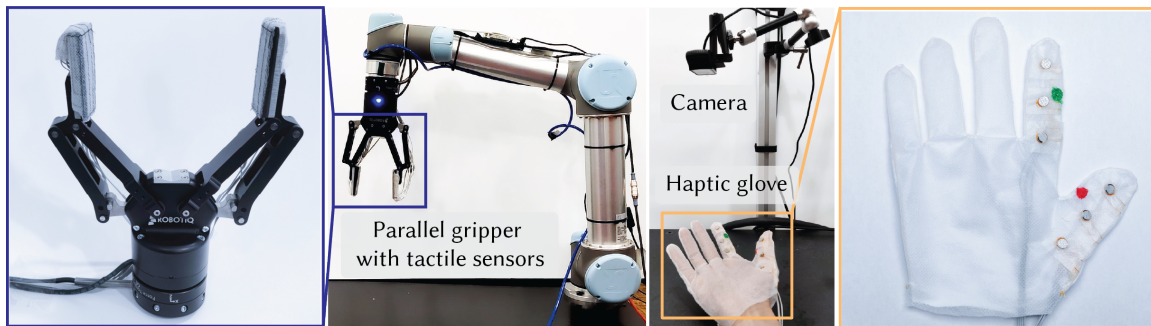


Figure 7-20: **Overview of the teleoperation experiment setup.** A parallel gripper is equipped with tactile sensors and a user wearing a full-sized glove integrated with vibrotactile units on the thumb and index finger. The visual system tracks embroidered green and red color blocks for distance measurement purposes.

The qualitative results shown in Figure 7-19 demonstrate that given the adaptively optimized haptic instructions, users are able to reproduce a similar tactile interaction with aligned timing based on the target tactile interaction sequence. In general, for simpler levels, users tend to have comparable performance regardless of optimized haptic guidance. However, as tasks get harder, users perform better when the optimized haptic guidance is provided. In time-sensitive scenarios, e.g., the rhythmic game, we observe that unoptimized

haptic instruction confuses users and thus lowers users' performance. Additionally, users tend to fail levels more easily with unoptimized haptic instructions since their errors accumulate over time. Adaptive optimization of haptic instructions, on the other hand, improves users' performance by guiding their actions at the right time during harder levels.

7.8 Tactile Transfer for Teleoperation

7.8.1 Setup

Sharing physical tactile interactions between humans and robots plays a critical role in intuitive human-robot collaboration and interactive teleoperation. This is especially important when visual information is occluded, which often happens in real-world scenarios. We demonstrate that our textile-based smart gloves integrated with tactile sensing and vibrotactile haptic capabilities enhance teleoperation performance for fragile and soft object grasping by transferring the physical interaction captured from a parallel robotic gripper to the user's hand in real time. We equip a parallel robotic gripper (Robotiq, UR5 arm) with a textile-based tactile sensing array (3 sensing areas on each side). Then, we ask the user to wear a designed haptic glove with integrated vibrotactile units at the corresponding locations along the thumb and index finger. We embroider colored markers on the haptic glove, which enable the tracking of the distance between the thumb and index finger with a camera in real time. This estimated distance is used to control the separation of the robot's parallel gripper (Figure 7-20).

In our teleoperation setup, users controlled a parallel gripper (Robotiq 2F-140) by moving their thumb and index finger. The distance between the two fingers was tracked by two embroidered color blocks, which were captured by the camera (Logitech C930e 1080p) and extracted by color thresholding using OpenCV [92]. The distance was converted to a command for the parallel gripper through linear mapping. Each of the parallel grippers was covered by a 3 by 6 pressure sensing matrix, which was averaged as 3 sensing read-out values. The participant wore a glove with 3 vibrotactile units along the thumb and 3 vibrotactile units along the index finger, which correspond to the individual sensing area

on the parallel gripper. During the experiment, the contact interactions between the gripper and the object were captured by the tactile sensors in the form of 10-bit ADC output from the data acquisition circuit. We applied a threshold to the tactile signal at 25% of the full ADC output, meaning that any tactile signal exceeding this threshold was converted into haptic feedback and transferred to the user through the vibrotactile haptics. We asked the participants to adjust the distance between his/her thumb and index finger according to the haptic feedback they believed a stable grasp of the specific object was achieved. Such procedure was performed when the participant was blinded and when the participant was offered a real-time view of the grasping process. Tactile information was recorded at 50 Hz and haptic instructions were generated at 100 Hz with full PWM modulation.

7.8.2 Results

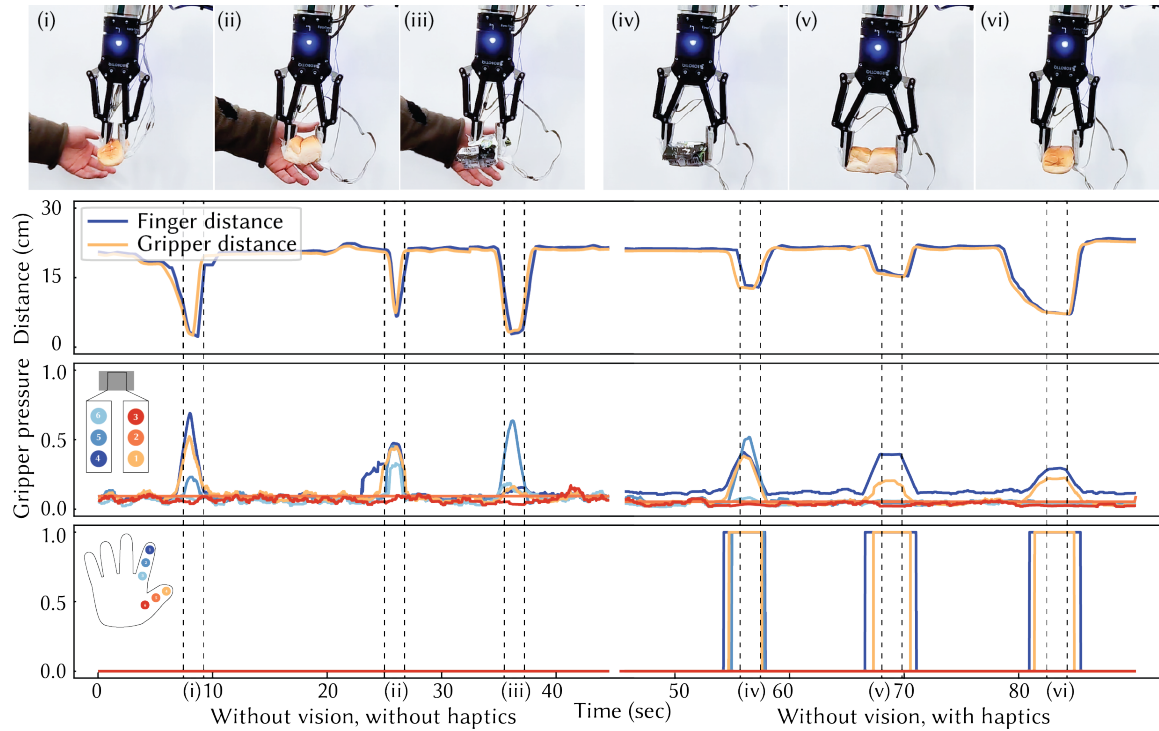


Figure 7-21: Teleoperated grasping with optional tactile information transferring through haptic feedback. The plots show the synchronized distance measurement of users' finger manipulation and parallel gripper control, normalized pressure captured from the parallel gripper, and mapped haptic feedback to the user. With haptic feedback, the user tended to teleoperate the gripper such that objects were securely grasped with reduced pressure and smaller deformations.

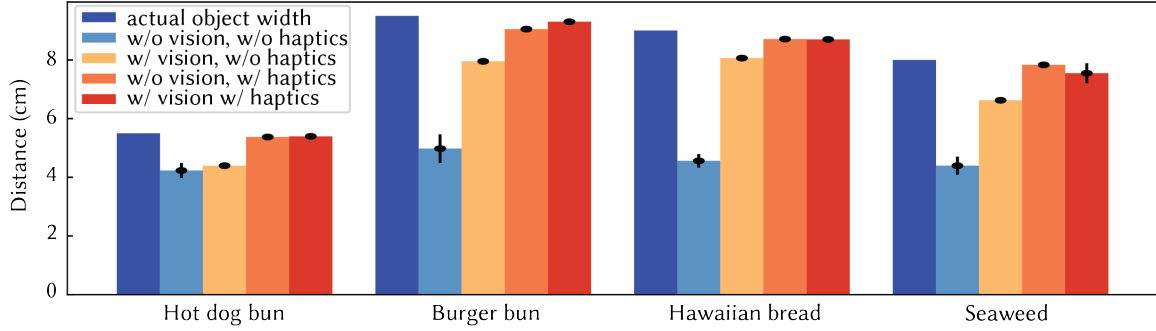


Figure 7-22: **Quantitative evaluation of teleoperated grasping** . Quantitative measurements of the actual width of objects and the distance between grippers during tele-grasping under different scenarios. Gripper distances, which are smaller than the actual object width, imply deformation of the object. Error bars indicate the standard deviations (SD) across measurements.

To evaluate our approach, we tele-grasp a hot dog bun, a burger bun, a Hawaiian bread, and a seaweed plastic box. When visual feedback is available, the user is generally able to perform relatively optimal grasps, where the soft objects only deform slightly to an average of 87% of the natural object width regardless of whether haptic feedback is provided (Figure 7-21). In this process, the user infers the grasp quality from the visual deformations of the objects. On the other hand, when visual information is obscured, we observe that haptic feedback significantly improves the tele-grasping quality.

In the absence of visual and haptic feedback, the user has no information about the grasp and tends to apply strong grasps, resulting in the objects being squeezed to an average of 58% of the natural object width. In contrast, when real-time haptic feedback is provided, the user is able to perceive whether the grasp is good enough through the vibrotactile feedback, even without visual indications of which object is being grasped. This allows the user to control the gripper for a more optimal grasp, securing the object with relatively minimal deformation to an average of 95% of the natural object width (Figure 7-21 and 7-22).

7.9 Discussion

Our work focuses on developing a scalable, customizable, wearable textile-based human-machine interface for capturing, displaying, and adaptively transferring physical tactile interactions. The tactile sensing array and vibrotactile haptic array are digitally designed

and fabricated, and seamlessly integrated into smart gloves. Experiments demonstrate applications for reproducing coarse tactile interactions between humans and the environment, allowing people to share tactile sequences, and enriching robotic teleoperation.

The integration of sensing and haptic actuation happens within the same fabrication cycle in a scalable and customizable manner. We are able to construct smart gloves integrated with tactile sensing and vibrotactile haptic capabilities in a modular way to accommodate different users or task specifications. Furthermore, we present a learning-based approach to adaptively optimize haptic output for individual users, without relying on manual calibration periods. We demonstrate a proof of concept of this behavior modeling and adaptive control approach for guiding users to perform touch sequences. In piano playing, rhythmic gaming, and racing gaming scenarios, we demonstrate that our interface and optimization pipeline are effective for adaptive tactile interaction transfer across users.

Given that humans are most sensitive to haptic feedback on their hands, our system only focuses on tactile interactions on the hands so far. However, with the scalable and customizable digital design and fabrication pipeline, we can extend the system to other wearables, such as socks and jackets, to provide haptic feedback to other body parts.

It is also worth noting that the movement of hands can affect users' haptic perceptions, and metal objects may interfere with the vibrotactile haptic units. These limitations can be addressed by fabricating more conformal and tight wearables with additional insulating layers. Currently, our adaptive optimization pipeline does not consider the AC input amplitudes and frequencies because users' perception of vibration amplitude varies significantly over time; it instead focuses on the users' reaction times. Nevertheless, by collecting more data on users' behavior, the pipelines can be expanded to include parameters on the amplitudes, frequencies, and temporal patterns of vibration, resulting in a larger design space.

In general, our textile-based human-machine interface offers a scalable and adaptive approach for exchanging and transmitting physical tactile interactions across people and time. We demonstrate that such tactile interaction transfer alleviates tactile occlusion, promotes skill and task performance, and facilitates robot teleoperation. The potential applications of our work are wide-ranging and extend beyond the lab, including use in training programs for various skilled professions such as surgeons, pilots, and engineers.

This textile-based wearable human-machine interface could also be integrated into virtual reality and augmented reality systems, providing users with a more immersive and tactile experience. Furthermore, the interface's ability to adaptively transfer tactile information between humans and machines could be used in industries such as manufacturing, where robots and humans can work collaboratively with increased safety and efficiency. We envision that our system will enable physical tactile interactions to persist across space and time and be accessible simultaneously to multiple users.

Part III

Intelligent Textiles for Robotics

THIS PAGE INTENTIONALLY LEFT BLANK

Chapter 8

Digitally Embroidered Impedance Sensors for Liquids Manipulation

8.1 Overview

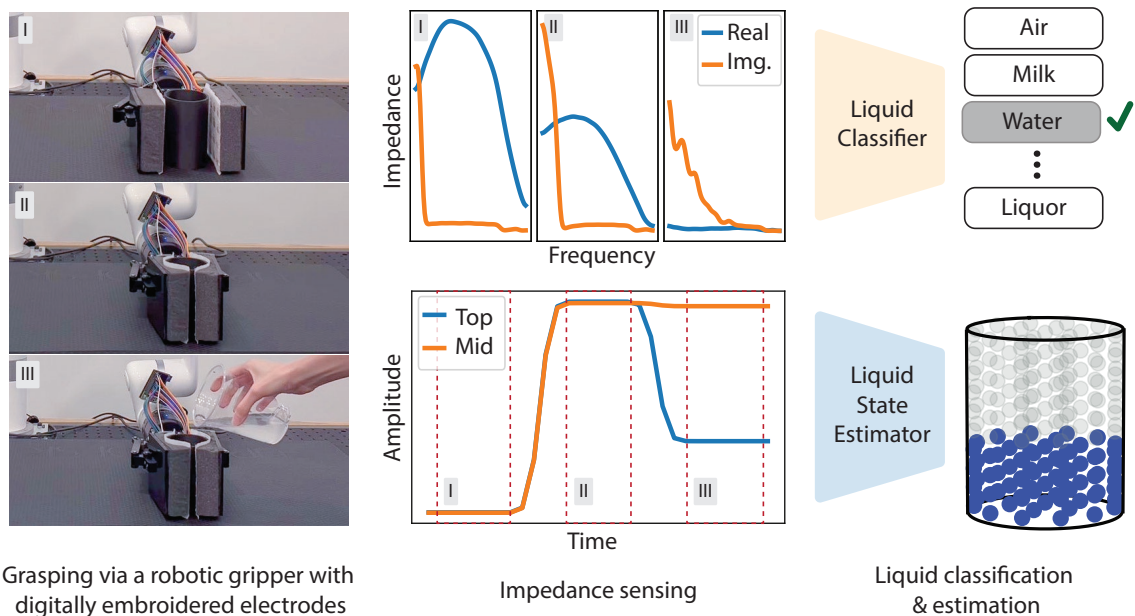


Figure 8-1: **System overview.** We functionalize a parallel robotic gripper with a digitally embroidered impedance sensing array.

Robot manipulation has advanced dramatically thanks to the rapid development of computer vision and machine learning technologies. These breakthroughs empower robots

to comprehend, anticipate, and engage with physical objects and their environments [21, 71, 137, 136]. Despite these strides, liquid manipulation continues to present challenges for conventional vision-based approaches. This is particularly evident when dealing with opaque containers, transparent liquids, splashes, and occlusions generated by the robot’s own manipulative actions, where capturing visual information becomes inherently complex [128, 103].

To address these challenges, researchers have explored alternative sensing modalities, including vibration sensors [76], force sensors [17], infrared reflectance spectroscopy [32], and high-resolution tactile sensors [41, 145] for liquid manipulation. Despite the effectiveness of liquid identification and dynamics estimation, most of the introduced sensors require intricate and complex fabrication processes and are challenging to customize and scale up. In contrast, impedance-based sensing mechanisms, exemplified by electrical impedance tomography (EIT) and impedance spectroscopy, present a promising alternative. These methods leverage readily manufacturable electrodes, offer non-contact sensing capabilities, exhibit geometry-independent versatility, and can be scaled up through the addition of electrodes or sensor re-layout.

In this work [146], we present the leverage of impedance sensing via low-cost, scalable, customizable embroidered electrode arrays for liquid classification and state estimation (Figure 8-1). We digitally designed and automatically fabricated two distinct 4×4 electrode arrays using a digital embroidery machine. These electrode arrays are affixed to a parallel robotic gripper and serve as an impedance sensing matrix. We collected responses across swept frequencies and electrode pairs while manipulating and rotating containers filled with various liquids. We developed integrated models for liquid classification and liquid state estimation. We showcase the effectiveness of our framework with an accuracy of 93.33% in classifying 9 different types of liquids (8 liquids + air), and 97.65% in estimating the state of liquid. Our approach obtains potential for robotics manipulation of liquids, serving as a complementary sensing modality with well-established sensing systems, e.g., vision, for robots handling liquids with precision and efficiency.

The following sections describe details of the system, experiments, and results. The contributions are summarized below.

- We develop a digital design and fabrication pipeline for low-cost, scalable, customizable impedance sensing.
- We apply the digitally fabricated impedance sensing array on robot grippers for liquid identification and manipulation.
- We perform technical evaluations on the performance and effectiveness on the robotics manipulation tasks.

8.2 Design and Fabrication

8.2.1 Embroidered Electrode Array

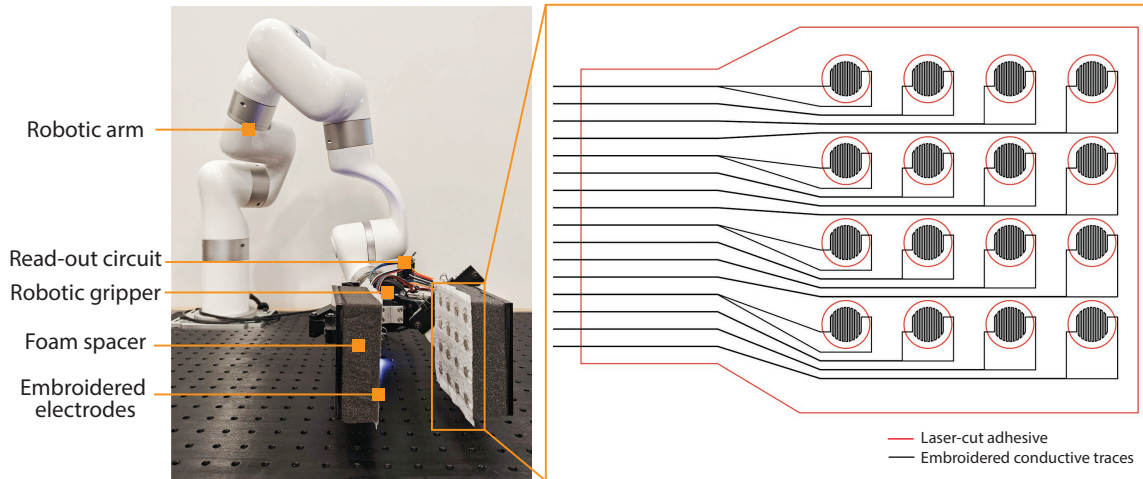


Figure 8-2: **Embroidered impedance sensing matrix.** A 4×4 embroidered electrode array was affixed to each parallel gripper, with a foam spacer in between to enhance conformity during grasping. All electrode connections were routed to the edge for a convenient connection to the read-out circuit.

Our impedance sensing matrix consists of two layers: a bottom layer with embroidered electrodes and connecting traces, and a top fabric layer with selective laser-cut spaces (Figure 8-2). These spaces were designed to reveal the electrodes, allowing them to be in contact with the grasped objects, as well as to minimize cross-talk caused by the contact between the connecting traces and the objects. Our electrode matrices and the connecting traces were digitally designed and fabricated via digital embroidery (Taijima). To optimize impedance reading and minimize noise from the container, each electrode was embroidered

with silver-plated polyamide thread (Madeira HC40) with a 10 mm diameter, 1 mm pitch, and 14 mm spacing from each other. The connection to each electrode was traced via conductive stitches to the side with a placement pitch of 2 mm. Such designs effortlessly interface with the read-out circuit via pre-fabricated connectors. Each of the electrode arrays obtained a 4×4 electrode matrix and was mounted to each side of the gripper with foam in between for conformal contact. With our fabrication pipeline, 4×4 electrode matrix takes less than 5 minutes to fabricate, which provides an opportunity for automated and scalable fabrication of such sensors. Our digital fabrication pipeline provides a remarkable advantage, allowing personalized adjustments in electrode sizes and placement to the unique geometries of robotic operators and meet the specific requirements of users.

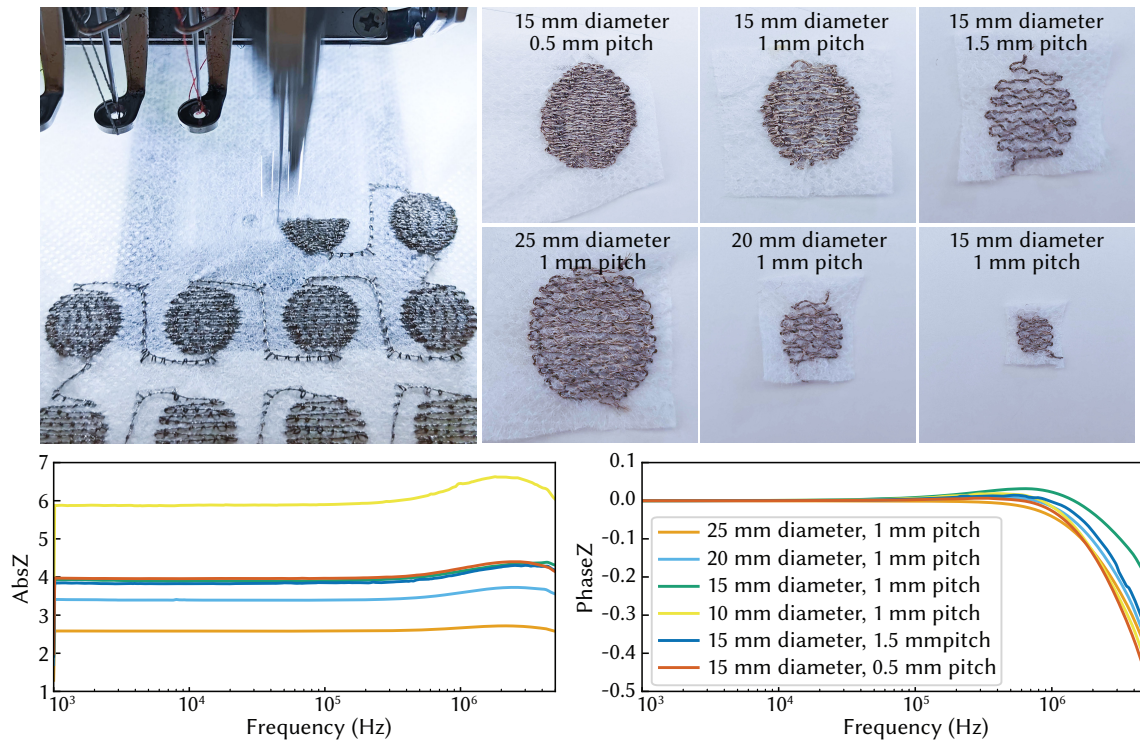


Figure 8-3: **Embroidered electrode designs and characterization.** Impedance measurements were conducted across various frequencies using embroidered electrodes featuring distinct sizes and stitch spacing.

We characterized the embroidered electrode using an impedance analyzer (Zurich Instruments MFIA) with a frequency sweep between 1 kHz and 5 MHz (500 steps). As demonstrated in Figure 8-3, the impedance across frequencies decreases as the electrode sizes increase. However, the impedance remains stable despite an increase in embroidery

itches, which indicates that the density of conductive traces has minimal effect on the signal transmission. We employed the embroidered electrode with 1 mm pitch and 10 mm diameter in our final design for the gripper, featuring a 4×4 sensing electrode matrix. The 10 mm diameter was chosen due to the constraints in the gripper geometry and the conservative wire spacing of 3 mm with our fabrication resolution. The 1 mm pitch was chosen to expedite the fabrication process while maintaining stable electrical performance.

8.2.2 Read-out Circuit

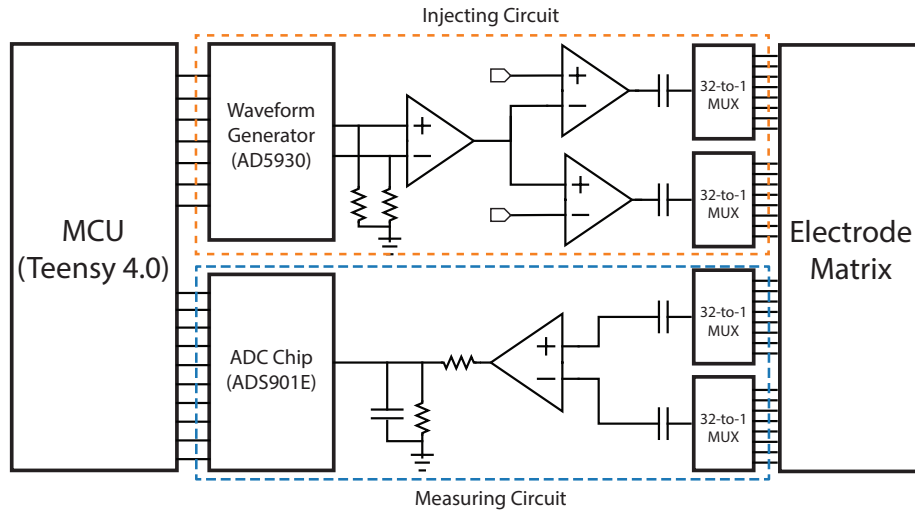


Figure 8-4: **Read-out circuit diagram.** The read-out circuit consists of a current injecting and voltage response measuring components.

For better integration with the robotic grippers, we implemented a BLE-enabled customized impedance sensing board (4cm×6cm), which is built around a Teensy 4.0 microcontroller, and responsible for injecting the AC signal and measuring the resulting voltage response via a 4×8 electrode matrix. The board has two modes: swept frequency sensing mode at pre-selected electrodes, and frequency-specific impedance measuring mode rotating through all connecting electrode pairs. As shown in Figure 8-4, the impedance sensing board consists of two main parts: a current drive circuit for injecting the AC signal, and a voltage response measurement circuit for measuring the voltage output (i.e., signal amplitude and phase) from the current drive. On top of them, there is an additional control circuit built around the microcontroller that assigns the output of current injecting circuit & the input of

voltage response measuring circuit to corresponding electrodes and processes the collected data.

Current injecting circuit. The current injecting circuit is composed of a signal generator, an adjustable instrumentation amplifier, and a voltage-controlled current source (VCCS). Specifically, the signal generator (AD5930) serves as a voltage source and generates a small, constant-amplitude, differential sine waveform at predefined frequencies based on frequency range and steps (frequency sweep mode), or at predetermined injection frequency (single frequency mode). The waveform is subsequently fed into the instrumentation amplifier (AD8220) and modulated by a digital rheostat (AD5270) to directly drive the VCCS. The resulting current output is differential and centered around 0, connected to a 4×8 electrode matrix via two separate 32-to-1 multiplexers (ADG731).

Voltage response measuring circuit. The voltage response measuring circuit takes differential input from the 4×8 electrode matrix via two separate 32-to-1 multiplexers (ADG731). It is composed of two input buffers, an adjustable instrumentation amplifier, and a 10-bit analog-to-digital converter (ADC). Each of the two input buffers employs an op-amp (ADA4841) configured for unit-gain, followed by an RC high-pass filter with a 350Hz cutoff frequency. These buffers feed into the instrumentation amplifier (AD8220) followed by modulation from a digital rheostat (AD5270). The output voltage is scaled down from 5V to 3.3V and then passed through an RC band-pass filter with cutoff frequencies at 1kHz and 1MHz. Finally, the ADC chip (ADS901E) samples such filtered output at 20MHz and outputs voltage at 10 bits.

8.3 Liquid Classification

8.3.1 Data Collection

All data was collected by mounting our embroidered sensing matrix to a robotic gripper (Robotiq 2F-140), which was installed on a robotic arm (UFACTORY xArm). Data collection was conducted with two measurement setups: a swept frequency sensing mode

with pre-selected electrodes, and a frequency-specific impedance measuring mode sampling across all connecting electrode pairs.

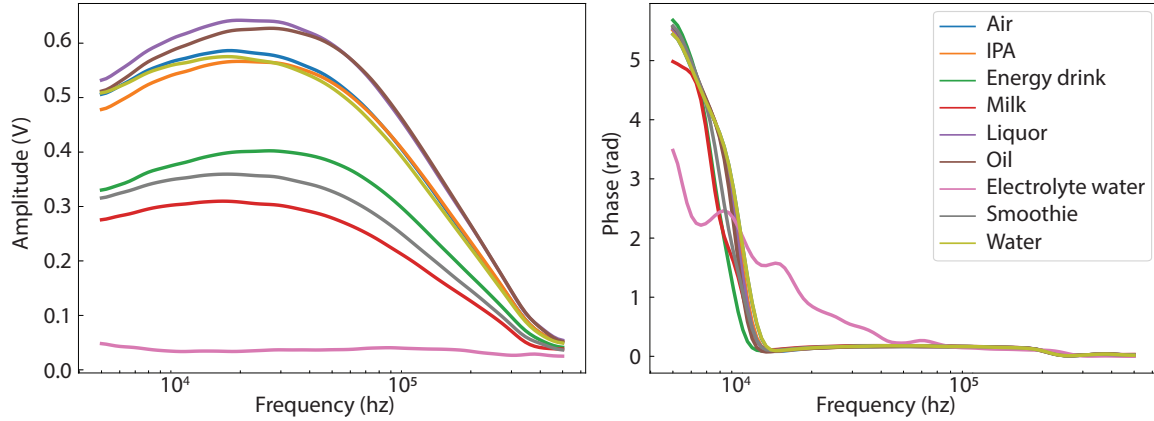


Figure 8-5: **Sample impedance spectroscopy data for liquid classification.** The amplitude (left) and phase (right) responses were recorded from different liquids.

With a swept frequency sensing setup, we captured impedance signals with 4 electrodes (2 injecting electrodes and 2 measuring electrodes). The injecting electrode pair generated waveforms with a frequency sweeping from 5 kHz to 500 kHz (100 steps), and the measuring electrode pair recorded both the signal amplitude and phase shift. We conducted data collection while the sensorized gripper grasped an empty mug (representing the absence of liquid, i.e., air), as well as with 8 different liquids: water, electrolyte water, milk, energy drink, isopropanol (IPA), liquor, oil, and smoothie. In total, we collected 900 full swept-frequency data samples in 90 rounds over 3 days. We split the data in a conventional 80/20 manner for the training and validation of the liquids classifier. Representative impedance spectroscopy data is demonstrated in Figure 8-5.

8.3.2 Model

Our liquid classifier takes in a frequency-swept impedance sensing sequence and outputs the probabilities of each liquid class. The input of this model is a two-dimensional vector with the size of $[100, 2]$, which corresponds to amplitude and phase shift readings in 100 steps of frequency sweep impedance measurements (between 5 kHz and 500 kHz). The liquids classifier consists of two fully-connected layers, with 32 and 9 neurons each. The first layer

uses ReLU as the activation function, and the second layer uses soft-max for generating the classification results. Both layers use L1 regularization with a 0.01 regularization factor. The model was trained by minimizing categorical cross-entropy loss using Adam optimizer with a learning rate of 0.001. Both models were implemented in TensorFlow [75].

8.3.3 Results

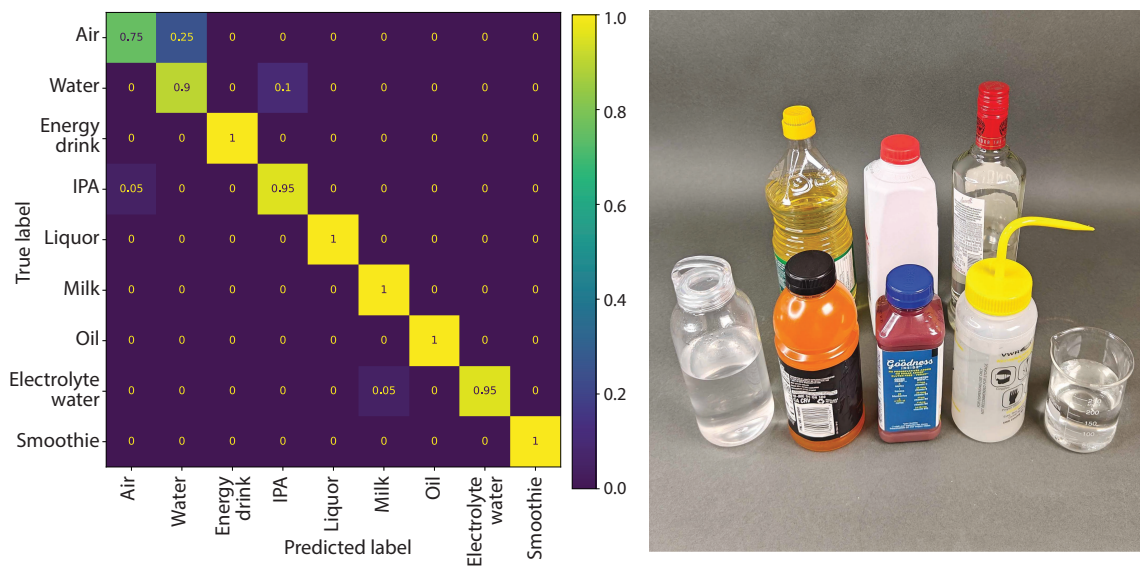


Figure 8-6: **Results of liquids classification.** Confusion matrix on liquids classification.

Our liquid classification model identifies 9 liquid classes, including air, water, electrolyte water, milk, energy drink, IPA, liquor, oil, and smoothie in a grasped container with an accuracy of 93.33%. Based on the confusion matrix (Figure 8-6), the most confusing cases occur between air (i.e., empty mug) and water. This is likely because we used deionized water with little to no free electrons in it, which is verified by the resistance measurement in Megaohms ranges via a DC multimeter. During impedance sensing, water behaves akin to air over its real component, like an insulator. Consequently, distinctions between the two primarily manifest in the imaginary component, in contrast to other liquid types that exhibit disparities in both real and imaginary readings.

8.4 Liquids Manipulation

8.4.1 Data Collection

With a frequency-specific impedance measuring setup, we collected impedance responses from all pairs of electrodes at 50 kHz. Using a 4 x 8 electrode matrix, we captured 256 readings in one full scan at the frame rate of 10 Hz. The measurements were taken layer by layer (4 layers in total). Each adjacent electrode pair within one layer was rotating as the AC signal injecting pair. The impedance responses were measured and recorded by all other adjacent pairs (8 injecting electrode pairs $\times$ 8 measuring electrode pairs = 64 measurements per layer). Our data collection process involved the sensorized gripper securely holding a mug containing water. To introduce variations in the liquid's state, we systematically rotated the mug along different axes, covering a diverse set of angles. These rotations were carried out using a known rotation matrix, which was employed to generate the mathematical ground truth for the liquid state. In total, we collected 6600 data samples with 110 different rotation matrices (evenly distributed among 8-point compass roses) over 5 days. We randomly chose data from 88 rotations to train the liquid state estimator and used the remaining data from the unseen 22 rotations as validation and test sets. Representative data frames are demonstrated in Figure 8-7.

8.4.2 Ground Truth Generation

Ground truth generation for liquid state estimation is calculated mathematically based on the known rotation of the robotic arm, the geometry of the container, and the volume of the introduced liquid. The robotic arm's interface gives the axis-angle representation of the pose, which can be converted into the rotation matrix R between the initial position and the rotated position of the container. The normal vector of the liquid surface at the initial position is defined as $\vec{n}_1 = (0, 0, 1)$ in the xyz coordinates such that the liquid surface is parallel to the world xy -plane and the height of the liquid along the z axis (Figure 8-8.I). The center of the liquid surface is denoted as O . When the robotic gripper grasps the liquid container and rotates (Figure 8-8 II), the liquid state changes while the liquid surface still remains parallel

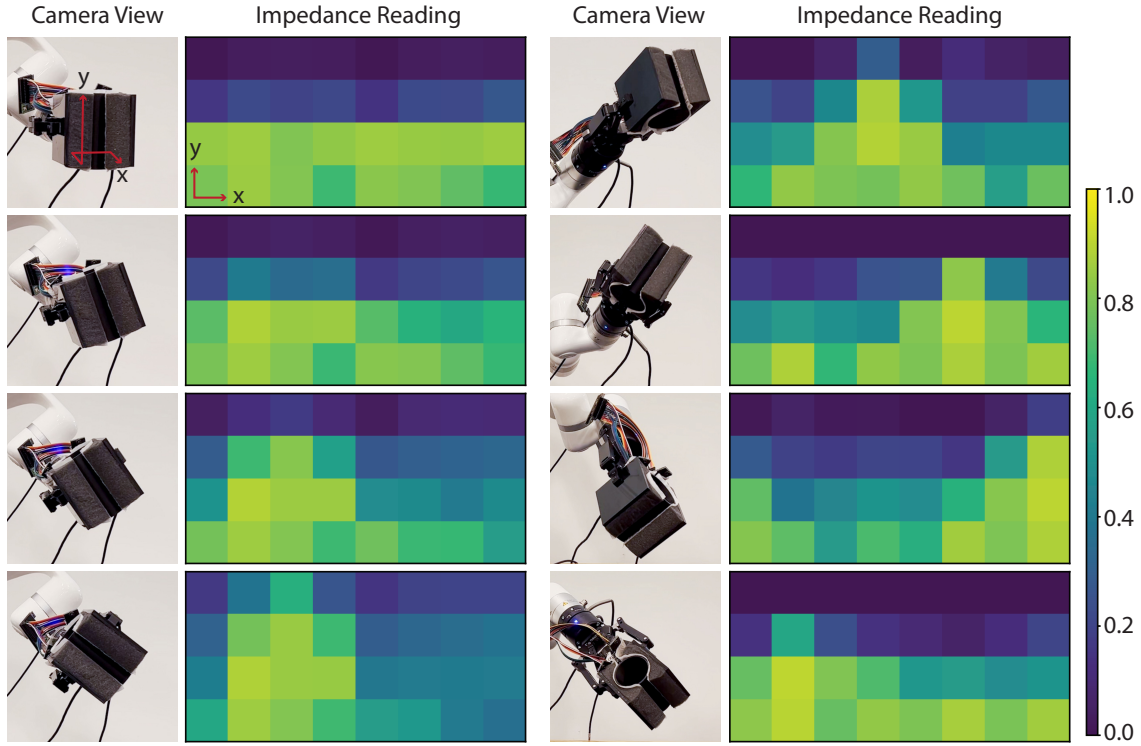


Figure 8-7: **Representative impedance responses for liquid state estimation.** Impedance responses were captured by the embroidered electrode arrays while a mug with 100 mL water was grasped and tilted towards various angles. The average impedance responses captured with each of the injecting electrode pairs is mapped to a pixelized heatmap.

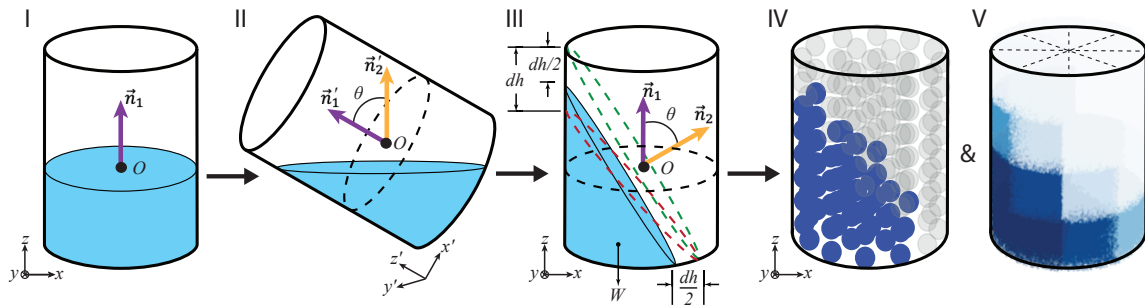


Figure 8-8: **Ground truth generation.** The liquid states at the initial position (I) and tilted angles (II) are shown in sky blue. The liquid state is projected to the initial frame (III), where the ground truth was sampled and generated (IV & V). Normal vectors and calculated parameters are indicated.

to the world xy -plane to form a cylindrical segment. The normal vector of the liquid surface at the rotated position can be defined as $\vec{n}'_2 = (0, 0, 1)$ in the xyz coordinates. We project the rotated liquid to the xyz coordinates by applying the inverse of the rotation matrix between the initial xyz coordinates and the rotated $x'y'z'$ coordinates. Then, the normal vector of the rotated liquid surface can be calculated as $\vec{n}_2 = R^T \vec{n}'_2$ (Figure 8-8.III). With $\vec{n}_1$ and $\vec{n}_2$, the angle of a rotation can be calculated as:

$$\theta = \arccos \left(\frac{\vec{n}_1 \cdot \vec{n}_2}{|\vec{n}_1| |\vec{n}_2|} \right) \quad (8.1)$$

The liquid surface can be defined as the plane $Z_{water}(x, y)$ with respect to the normal vector of the rotated liquid surface $\vec{n}_2$, and the center of the liquid surface at the initial position (O), using the scalar equation of the plane [28].

This model overestimates both the total liquid volume and the heights of the liquid surfaces when the rotation angles surpass a certain threshold when the liquid does not entirely fill the base of the container and form a cylindrical wedge W (shown as a dashed green circle in Figure 8-8 III). To compensate for this overestimation and refine the heights of the liquid surfaces, the derived equation of the plane of the liquid surface should be shifted. The z -intercept is first adjusted by decreasing dh such that the volume of (W) is the same as the volume of the introduced liquid (i.e., 100 mL) while keeping the base-intercept unchanged (shown as a dashed red circle). dh can be derived from the equation on the volume of the cylindrical wedge [34].

Since dh is a relatively small value, we assume that θ remains constant after the adjustment. In other words, the shifts in the z - & base- intercept approximately contribute equally to the overall volume change. Therefore, the liquid surface plane $Z_{water}(x, y)$ is shifted by $\frac{dh}{2}$ along $-z$ axis. This adjustment reduces the root-mean-squared error (RMSE) of volume estimation from 2.860 to 0.265 mL in a 100 mL liquid volume case, yielding a better liquid state estimation.

Given the liquid surface plane $Z_{water}(x, y)$, ground truth are generated in both binary and continuous forms. We first generate sample points (S_b) in the volume, for example, 152 points evenly along 8 height layers with 19 evenly distributed points within each height

layer. We then assign binary values representing the existence of water (0 as "no-water-present" and 1 as "water-present") by comparing the Cartesian coordinates (x_b, y_b, z_b) of each sampled point with the height of the liquid surface $Z_{water}(x_b, y_b)$.

We also generate continuous ground truth data representing the water composition within various regions of the volume, by slicing the volume of the container into 4×8 wedges (corresponds to the 4×8 electrode array) and sample 1000 uniformly distributed random points (S_p^i , where i corresponds to the count of sliced wedges) within each wedge. The Cartesian coordinate (x_p^i, y_p^i, z_p^i) of each sampled points is compared to the liquid surface plane $Z_{water}(x_p^i, y_p^i)$. We then allocate the points percentage located beneath the liquid surface to each wedge with continuous values (from 0 to 1), representing the amount of liquid present within each wedge.

8.4.3 Model

Our liquid state estimation model takes in a scan of impedance reading across all electrode pairs (256 measurements) and predicts the probability of the presence of water at the sampled location. The input of the model is a three-dimensional vector with the size of $[8, 8, 4]$, which represents 8 impedance measurements from each of the 8 different injecting electrode pairs, along 4 individual electrode layers. The output of the model is a 1D vector with a size of sampled ground truth. Our model has two 2D convolutional layers, followed by a fully connected layer after flattening. The entire model has 196,214 parameters, a suitable size for on-device inference. Each of the convolutional layers uses 8 and 16 3×3 kernels and zero padding to keep the dimension the same, with ReLU as the activation function. The model was trained by minimizing the mean-squared error (MSE) via Adam optimizer [55] with a learning rate of 0.001 and a batch size of 128.

8.4.4 Results

In general, we performed liquid state estimation with both a classification setup and a regression setup. In the classification setup, the model was supervised by ground-truth labels in the form of an 8×19 binary array. The model was expected to categorize each

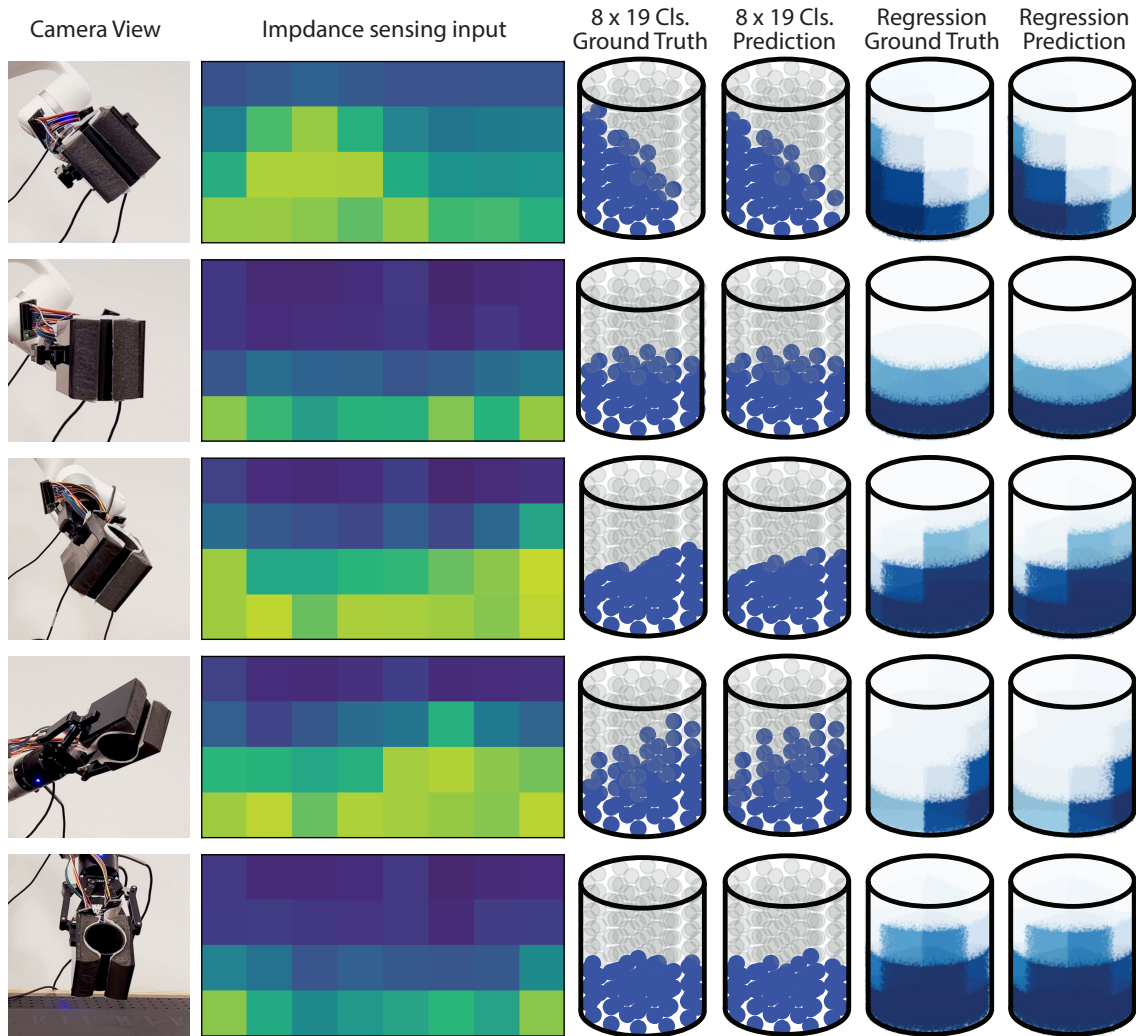


Figure 8-9: **Results on liquid state estimation.** From left to right columns: camera view of gripper and liquid container tilting degrees, EIT sensing raw signal, 8×19 binary classification ground truth and prediction results, 32-wedge (4×8) regression ground truth and prediction results.

of the 8×19 data points into one of two categories: either "water-present" or "no-water-present." In this configuration, our model achieved a classification accuracy of 97.65%. On the other hand, in the regression setup, the model was supervised by 32 continuous numerical values, representing the percentage of water presence in each of the 4×8 wedges. Our model obtained a mean-squared error (MSE) of $7.46e-5$. The corresponding camera views, impedance sensing inputs, and ground-truth values are generated from mathematical analysis.

We investigated the effectiveness of our impedance sensors and modeling pipeline with respect to the sampled resolution along the circular, height, and inner/outer directions. More specifically, we supervised the model with ground truth that was sampled with various resolutions along the circular direction and the height direction (Figure 8-10 left). We trained models using ground truth data sampled at various height layers, ranging from 4 (i.e., a number of layers in our sensor electrode matrix) to 16. A consistent configuration with 19 evenly distributed points within the circular plane at each height layer were maintained. The model demonstrates robust performance with data sampled up to 8 sampled height layers but experiences a significant accuracy drop when moving to 16 layers. Likewise, we trained models with ground truth sampled with 10, 19, and 38 evenly distributed points within the circular plane at 8 individual height layers. No discernible performance difference was observed between models trained with 10 and 19 points along the circular direction, which indicates the capability of our sensors and models. A significant drop in accuracy appeared with further resolution increases along a circular direction to 38 points.

It is noteworthy that models trained with ground truth data sampled using varying radii (8×19 V), where points were uniformly distributed across each layer plane with most points not in direct contact with the sensing patch, and models trained with a single fixed radius (8×19 S), where all points were distributed along the circumference and in direct contact with the sensing patch, yield remarkably similar accuracy results (less than 0.4%). This similarity suggests that despite our impedance sensing electrodes being affixed only to the exterior of the mug, they are capable of effectively extracting data points located within inner circular regions, all without requiring direct contact or connecting traces to the electrodes. Also, we achieved an accurate state estimation with a resolution up to 8×19 ,

effectively doubling the resolution of our impedance sensing matrix (4×8) in both circular and height directions. This increase in resolution can be attributed to the continuous flow of the liquid, enabling the model to effectively interpolate between neighboring sampled points. Additionally, it underscores the inherent capability of impedance sensing to comprehensively capture information across entire planar surfaces.

8.4.5 Ablation Study

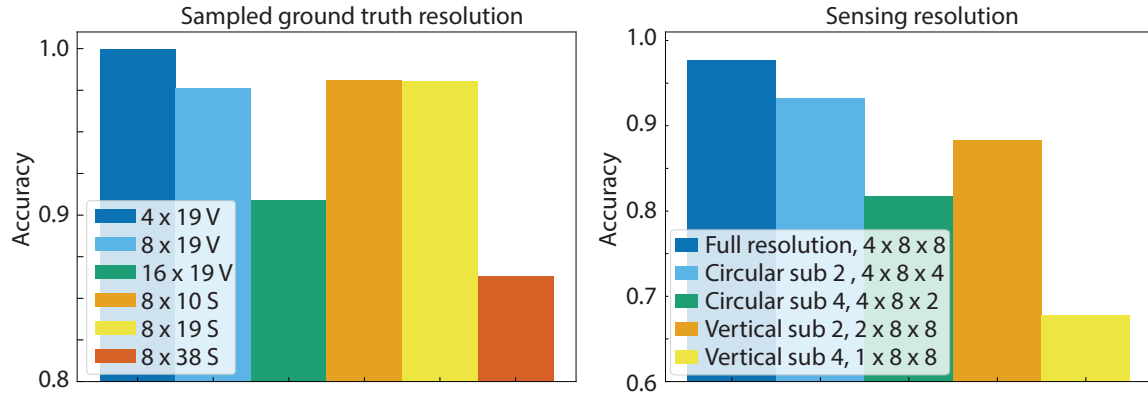


Figure 8-10: **Model evaluation and ablation study.** Left: Model effectiveness regards to prediction resolution along circular and height directions. Right: Ablation study on effective impedance sensing resolution along circular and height directions. V represents points sampled along various radii and S represents points sampled along a single radius.

We performed an ablation study on the sensing resolution of the impedance sensing array. More specifically, to ablate the impedance sensing resolution, we reassign values in every two or four cells with the average of their values. We reduced the effective sensing resolution from $4 \times 8 \times 8$ to $4 \times 8 \times 4$ and $4 \times 8 \times 2$ along the circular direction, as well as from $4 \times 8 \times 8$ to $2 \times 8 \times 8$ and $1 \times 8 \times 8$ along the vertical height direction. We then applied the same training pipeline to derive the predictions, as shown in Figure 8-10 right. Overall, our sensing resolution is more robust along the circular direction, as indicated by the 81.81% accuracy with only 2 effective sensor readings per height layer, and can be more delicate along the vertical height resolution for liquid state estimation.

8.5 Discussion

In this study, we introduce a novel approach for liquid type identification and state estimation using impedance sensing. We devised scalable, customizable embroidered electrode arrays, seamlessly integrated with a portable impedance sensing board compatible with various robot grippers. Our dataset comprises over 900 swept-frequency liquid type measurements and 110 degrees of liquid state data. We developed machine learning models for liquid identification (93.33%) & state estimation (97.65%). Additionally, we evaluated sensor effectiveness, sensing array resolution, conducted an ablation study, and discussed system limitations and future prospects.

Limitation. Currently, our data collection primarily focuses on scenarios involving static liquid conditions. Specifically, we programmed the robotic arm to rotate and pause at a series of pre-defined angles. Although we tried to cover as many different degrees as possible along the 8-point compass roses based on the rotation resolution of the robotic arm, we did not include scenarios involving vigorous liquid movements. Such movements would introduce intricate liquid dynamics and sloshing, which were not part of our data collection approach. We focused on static scenarios at the current stage because our generative models encompass various liquid types, and incorporating liquid sloshing would introduce numerous additional parameters related to fluid properties, arm movement dynamics, and container geometries. Also, in order to capture the impedance reading of all electrode pairs for liquid sloshing states at a reasonable temporal resolution for model training, we estimated the impedance sensing data acquisition frame rate should be around 100Hz based on previous works [65], while we can only achieve a maximum frame rate of 15.62 Hz with the current setup.

For future work, we are planning to extend our approach to containers with more diverse geometries via our customizable and adaptive sensor designs. We plan to improve the impedance sensing frame rate to capture inter-degree liquid behavior, which will enable the capturing of fine-grained liquid movement and dynamics. Moreover, we plan to integrate our pipeline with physics-based liquid simulations, such as voxel method and fluid simulation, which will offer quick and rich data collection featuring fine details, including liquid sloshing and splashing. This will help with the development of a more delicate liquid state

estimation model. We will also expand our liquid classification techniques to analyze the liquid properties such as viscosity and temperature. We are aiming to combine our liquid classification and state estimation pipeline with closed-loop control algorithms to provide real-time sensing feedback and liquid state estimation to facilitate real-world robotics manipulation tasks.

THIS PAGE INTENTIONALLY LEFT BLANK

Chapter 9

Multi-Modal Digitally Embroidered Sensors for Tactual Perception

9.1 Overview

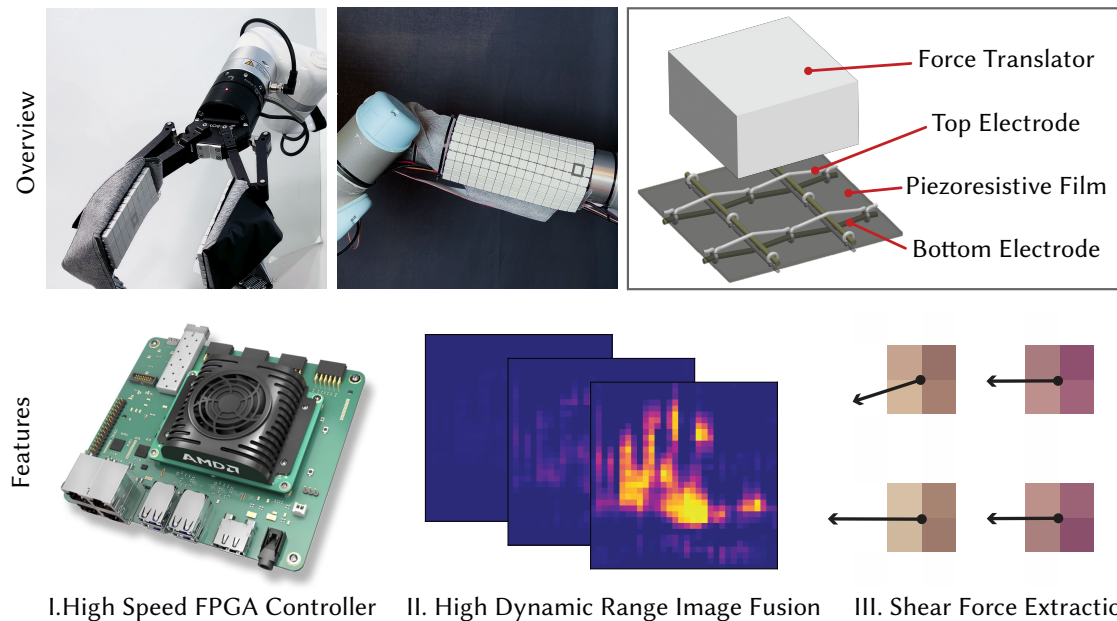


Figure 9-1: **Overview of multimodal tactile sensors.** Top: Our multimodal tactile sensing matrices serve as a full-sized tactile skin for robotic grippers and arms. Bottom: Our multimodal tactile sensors enable high-framerate readout for vibration sensing, high dynamic range image fusion for enhanced resolution, and shear force sensing for more comprehensive interaction data.

Humans rely on multi-modal tactual feedback from their skin’s mechanoreceptors to understand and interact with objects in their surroundings. Our skin is a comprehensive sensory system with a complex topological structure that responds to a wide range of tactile stimuli [63]. The different sensing modalities at our disposal help us recognize and interact with objects as humans grasp and touch them [57]. Normal and shear force feedback allows us to attain feedback about when we have made contact with an object and if we have a sufficient grasp to hold it. Sensing vibrations is useful for detecting surface textures and the moving of objects [100, 93, 106]. Furthermore, humans possess the capability of sensing forces over a wide range of magnitudes, allowing us to complete the manipulation of small objects and large ones [48]. To allow robots to interact with the environment and manipulate objects in a similar manner to humans, cost-effective tactile sensing systems are important, but remain challenging to design and fabricate.

In this work, we present a scalable multi-modal tactile sensing system that is capable of normal force, shear sensing, and vibration sensing with a wide dynamic range, which can be easily integrated into current robotic designs and wearable applications (Figure 9-1). We achieve this by harnessing the capability of machine embroidery, a textile manufacturing process, to fabricate thin flexible piezoresistive sensing arrays in an automated fashion. To extend the capability of shear force sensing, we install a force translator on top of the embroidered tactile sensing array. This force translator is directly 3D printed using a thiol-ene polyurethane-based elastomer [10] and, by comparing and processing adjacent sensor readings, the shear force direction could be estimated. We also present a FPGA-based circuit and coupled algorithms for high-speed sensing matrix (32 by 32) reading over a wide dynamic range, which enables vibration sensing up to 500 Hz. Furthermore, we introduce an automatic calibration pipeline that uses a robotic system to capture and characterize individual sensor performance and convert each measurement to its physical units in a fully automated manner. Finally, we show how this sensing can be used in robotics and wearable device applications alike.

The following sections describe details of the system, evaluation, and application scenarios. The contributions are summarized below.

- We utilize machine embroidery to fabricate thin, flexible piezoresistive sensing arrays.

- We enhance shear force sensing with a 3D-printed force translator.
- We implement an FPGA-based circuit for high-speed sensing matrix readout over a wide dynamic range.
- We create an automated calibration pipeline using a robotic system.
- We perform technical evaluations on the systems and demonstrate their applicability in robotics and wearable devices.

9.2 Design and Fabrication

9.2.1 Tactile Sensing Matrix

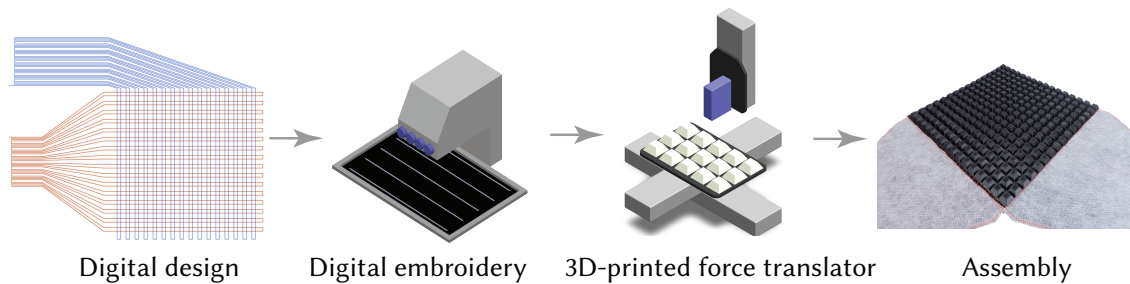


Figure 9-2: **Design and fabrication of multimodal tactile sensors.** The multimodal tactile sensors are fabricated via digital embroidery and 3D printing.

We present a new tactile sensor that is able to sense normal force, shear force, and vibrations. The sensor is comprised of three main parts: the embroidered force resistor sensor array, a force translator, and an FPGA-based sensor reading circuit. The embroidered force resistor array is used to capture information about changes in force on the surface of the sensor. The force translator is used to extract the directionality of the applied force. The embroidered force resistive array and force translators are tiled over the desired surface area.

We manufacture our multi-modal tactile sensors by the use of two highly automated manufacturing processes, machine embroidery, and 3D printing. Utilizing these manufacturing processes can greatly reduce the manual processing needed to make a sensor, reducing that overall cost. As shown in Figure 9-2, our piezoresistive tactile sensor is manufactured with machine embroidery, and our force translators are manufactured with 3D printing. The two parts are then affixed to each other, and the sensor is finished.

The embroidered force resistor sensor array is comprised of a resistive sheet, an array of electrically conductive threads located on both sides of the sheet, non-conductive passive threads used to interlock the electrically conductive threads through the sheet, and an electrical connector board that interfaces with sensing electronics. The resistive sheet, electrodes, and the interlocking passive thread is then sandwiched by a non-conductive fabric to protect the sensing array from environmental hazards and shorting. In operation, the electrodes are used to measure the resistance of the resistive sheet at the specific point where a pair of top and bottom electrodes intersect. The resistance of the resistive sheet reacts to external changes in force. The electrodes are placed to sense the resistance change at various locations on the resistive sheet and create an electrical connection to a set of connection points that interface with sensing electronics. To place the electrodes, a series of sewing switches are used to affix the electrode to the resistive sheet. During the stitching process, the electrode is interlocked with a thread that is resistive or non-conductive.

9.2.2 FPGA-Enabled High-Speed Readout Circuit

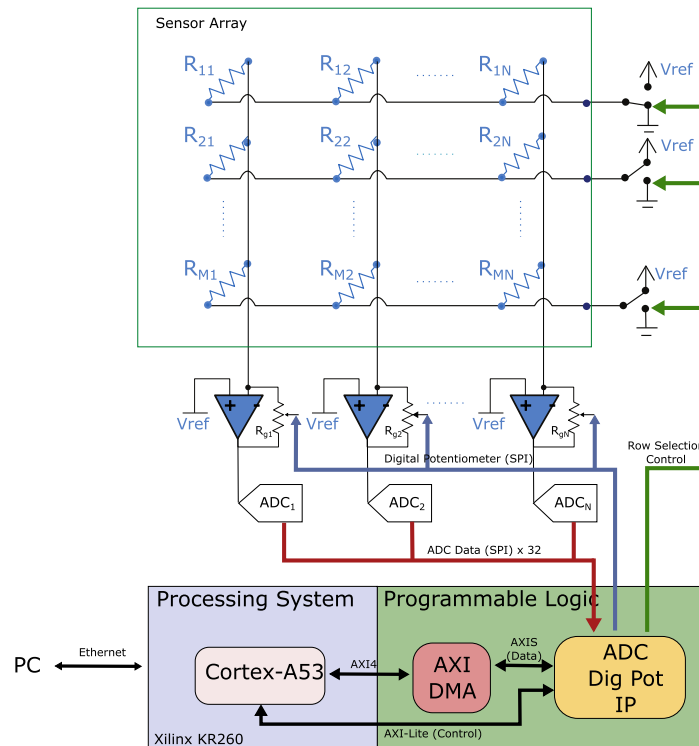


Figure 9-3: FPGA-based readout circuit diagram.

High framerate tactile sensing is crucial for the rapid capture and processing of dynamic interactions between a robot and its environment. This capability ensures that the robot can detect and respond to subtle forces and vibrations in real-time, enhancing its ability to perform complex actions with greater accuracy and reliability. As a result, the robot becomes more effective in a wide range of applications, from industrial automation to human-robot interaction. To achieve this, we implement an FPGA-based sensor readout circuit for high-speed reading of the force resistive sensors (Figure 9-3).

Extending from the electrical-ground circuit [115], we implement our system based on Xilinx Kria KR260 Robotics Starter Kit. Each column in the signal array has a digital potentiometer to set the gain of the signal, op-amp for signal conditioning and an ADC. The signals controlling digital potentiometers and ADCs are implemented using the programmable logic (PL) part of the FPGA.

For each readout, we set the value of the digital potentiometers, select a row, and read the ADC output of all columns simultaneously. We then select another row and repeat the operations until it is finished. The data from ADCs is sent to a DMA controller using AXI-stream. We exposed control registers for setting ADCs sampling time, frame rate and potentiometers with AXI-Lite. We use the ARM processing system of the FPGA based on Ubuntu for controlling AXI-Lite, DMA and data capturing to a flash memory or through Gigabit Ethernet.

9.2.3 Quantization Error Reduction

A common problem faced by converting pressure signals to electronic readings is the quantization error induced by the preset gain values. As demonstrated in Figure 9-4, the analog-to-digital converter (ADC) signals are more distributed and utilize the full 14-bit resolution when a higher gain value is applied. However, with larger forces, the signals can quickly saturate at higher gain levels, leading to a loss of information. Higher pressures benefit from lower gain values, whereas higher gain values are suitable for lower pressures. Large quantization error can occur as gain values are preset without knowing the pressure range beforehand. We propose to tackle this challenge by fusing signals serialized from

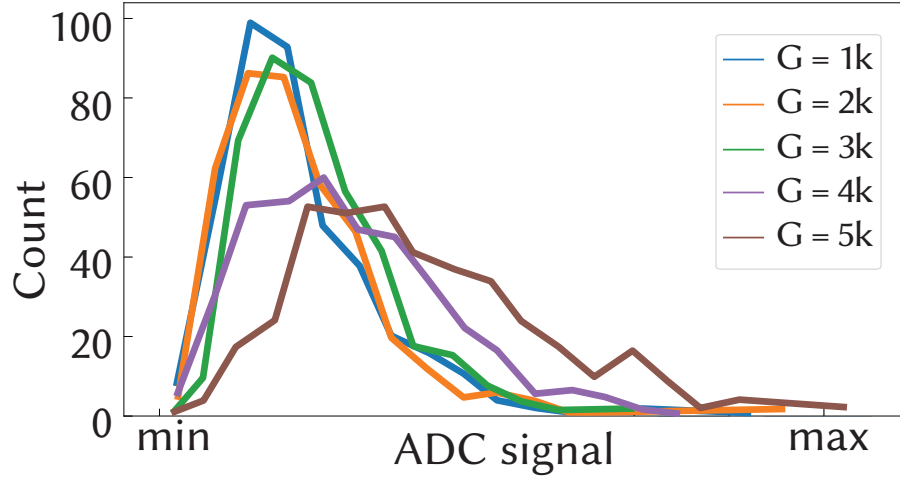


Figure 9-4: **ADC signal distribution over different gain values.** As gain values increase, ADC signals quickly saturate under high pressure but fully utilize the 14-bit resolution with higher signal resolution under low pressure.

different gain values to create a tactile map that minimizes quantization errors and improves accuracy.

Our method takes inspiration from photographic High-Dynamic-Range (HDR) techniques, specifically, the Debevec [24] HDR method, which is known for reducing quantization errors. Originally designed for reconstructing high-dynamic-range radiance maps from conventional photographs, the Debevec method combines multiple images with varying exposures to compute an imaging response function. This function is then used to fuse the images into a single high-dynamic-range image. The effectiveness of HDR methods relies on the proximity of image content in the source low-dynamic-range (LDR) images, often requiring a pre-processing step to spatially align pixel regions across different exposures. In contrast, our approach benefits from the fact that our sensors operate at extremely high speeds (up to 8000 Hz), ensuring inherent spatial alignment of sensor readouts.

Directly applying the Debevec algorithm to tactile sensor arrays presents several challenges. First, force magnitudes and voltage responses vary per pixel, making it difficult to fit the original response curve accurately. Second, even if we assume that differences between response curves can be ignored, computing the response curve for tactile readings is computationally intensive due to the 14-bit precision of the data, which is much finer than 8-bit image data. Third, it is uncertain whether the linear weighting objective used in the

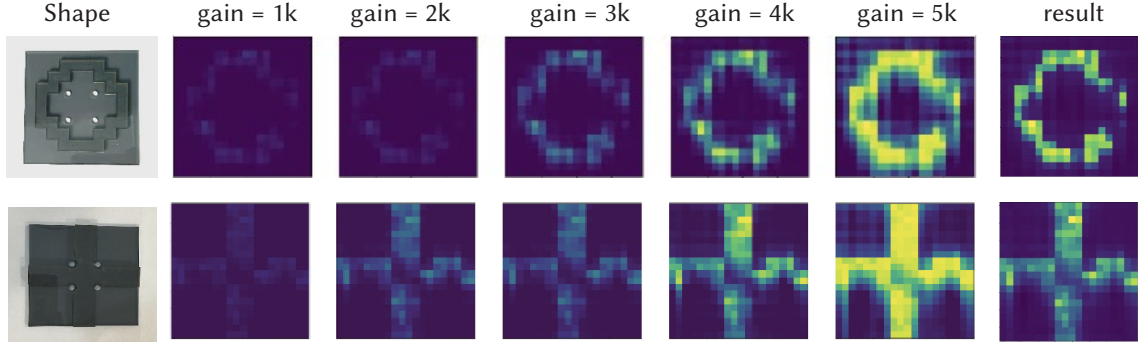


Figure 9-5: **Results on quantization error reduction.** Our quantization error reduction algorithm leverages the high dynamic range of signals for enhanced signal responses and ADC readout resolution.

Debevec algorithm is suitable for our specific task.

To address the first two issues, we begin by calibrating our tactile sensors using an automatic calibration procedure (Figure 9-8). After calibration, we apply AutoGain fusion, which operates directly with force values and eliminates the need for runtime response curve computation. For the third challenge, we evaluate various weighting schemes to determine their effectiveness. An ideal weighting scheme should account for force magnitude and be robust against noise. Inspired by the Debevec algorithm, we use a weighting scheme defined as $E_i = \sum_{j=1}^g w_j(E_{i,j})$, where g denotes the number gain values in the readouts, and i denotes the pixel index in the tactile readout. As shown in Fig. 9-5, our quantization error reduction algorithm generates tactile images with clearer signals and higher resolution compared to the raw readings.

9.3 Evaluation

9.3.1 Shear Sensing

The resistance profile of a typical tactile sensor is measured by a multi-channel datalogger (BK Precision DAS220) under a programmed normal force loading up to 6N at the speed of 2 mm/min (Shimadzu) with the contact area of 4 mm². A cycle test was performed with 1000 cyclic normal force load-unload (0-20N at speed 5mm/min).

To measure the sensing performance under shear force, a shear sensing module (made

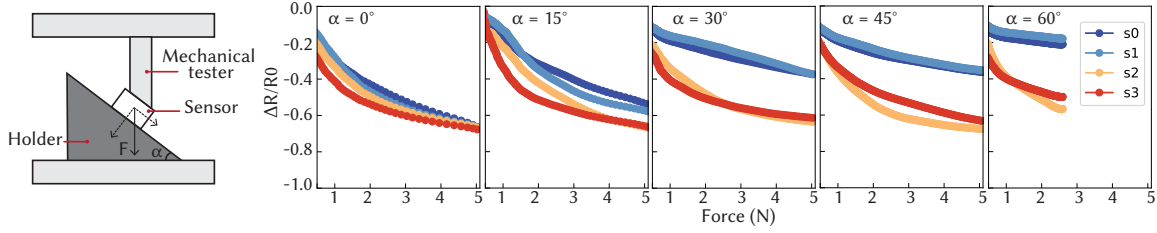


Figure 9-6: **Characterization on shear force sensing.** Shear forces are measured as the difference between sensors s0, s1 and sensors s2, s3. As the tilt angle α increases, the shear forces also increase for the same applied normal force. This is reflected in the growing difference between the two sets of sensors.

of 4 individual tactile sensors) attached with the force translator was mounted on the customized 3D-printed stands of the angles of 15, 30, 45, and 60 degrees (Figure 9-6. During characterization, a normal force (up to 6N at the speed of 2 mm/min) was applied in the middle of the force translator, which generated both normal and shear force towards the sensing units. With a constant applied normal force from the mechanical tester, increasing the tilt angle α results in larger shear forces experienced by the shear sensing module. The normal pressure is captured by the continuous decrease in resistance across all four sensors. In contrast, shear forces are calculated by measuring the difference between the sensor pairs on the left and right sides.

9.3.2 Vibration Sensing

To assess the performance of our sensors in measuring vibration, we mounted a 2060E Modal Shaker (The Modal Shop, Cincinnati, Ohio, USA) on top of a 16×16 multi-modal sensing array. The modal shaker applied a vibratory force with a peak sinusoidal amplitude of 60 pounds-force, ramping linearly from 0 to 700 Hz over 60 seconds. We recorded the piezoresistive sensor array readings using our high-speed readout circuit at a rate of 5000 frames per second. The data was then processed using a fast Fourier transform algorithm, and the resulting spectrogram is shown in Figure 9-7. The frequency was accurately captured up to 500 Hz.

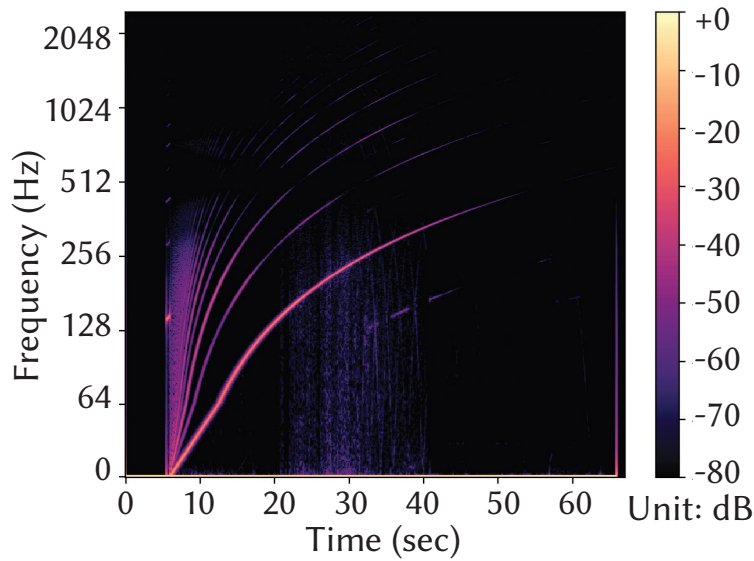


Figure 9-7: **Example responses on vibration sensing.** A spectrogram from Fourier transform of the tactile sensing data, with the dominant vibration frequency highlighted.

9.3.3 Automatic Sensor Calibration

As we scale up the coverage area and density of our tactile sensors, variations among individual sensing units are inevitable. Traditional approaches often address this issue through manual calibration on individual sensors. However, such method is impractical and doesn't scale well. To overcome this challenge, we have developed an automatic sensor calibration pipeline using a robot arm.

We program the robot arm to perform poking actions at various angles on each sensor. A torque sensor integrated into the arm measures the actual applied force, while the corresponding tactile sensor readings are captured by the readout circuit. By synchronizing these signals, we establish an accurate one-to-one mapping between each sensor's output and the applied physical force. This automated calibration process ensures precise measurements and scales efficiently with larger sensor arrays. Figure ?? illustrates the calibration results, demonstrating the precise correspondence between applied forces and individual sensor responses.

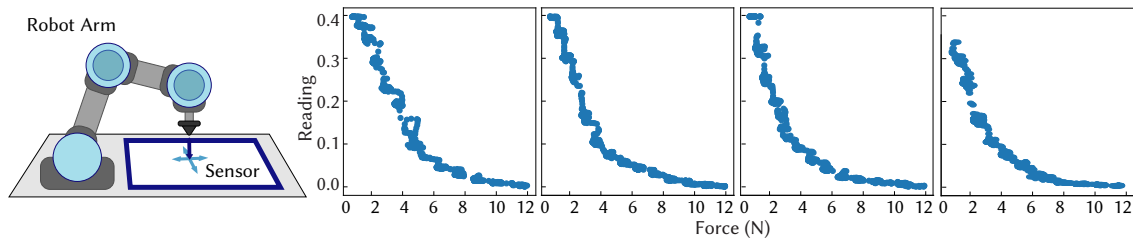


Figure 9-8: **Automatic sensor calibration via a robot arm.** Left: Automatic calibration setup using a robot arm. Right: Example of calibration results.

9.4 Application

9.4.1 Tactile Sensing Shoe Sole

We design a set of wearable insole sensors capable of measuring both normal and shear forces exerted by a person while standing, as shown in Figure 9-9. Our sensors not only capture the normal pressure distribution, but also capture the static shear forces, which were not possible with traditional resistive tactile sensors. As the user stands on a slope and shifts in different directions, the sensors precisely detect the resulting variations in shear forces. This capability allows for detailed analysis of how changes in body orientation and weight distribution affect shear forces, providing valuable insights for applications such as ergonomic assessments, motion analysis, and the design of adaptive support systems.

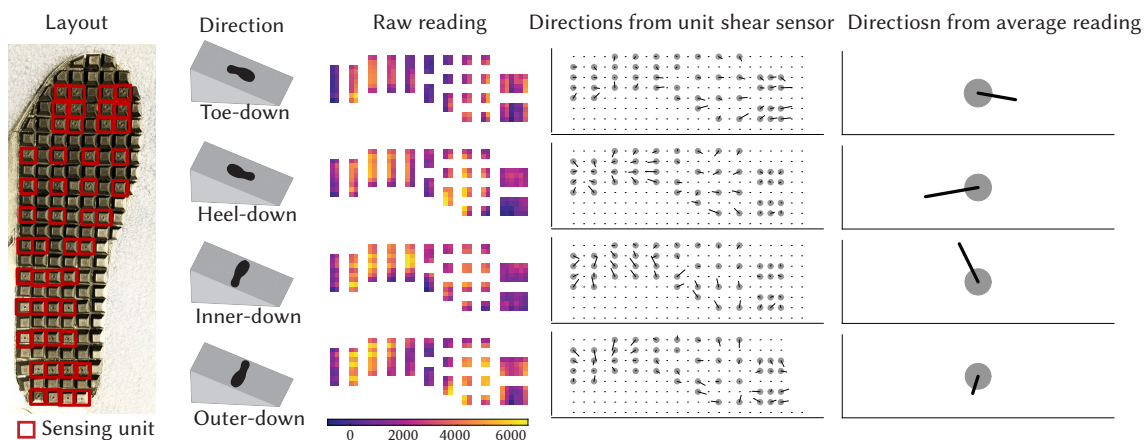


Figure 9-9: **Shoe sole with integrated normal and shear pressure sensors.** As the user stands on a slope in different directions, the sensors accurately capture the corresponding changes in shear forces.

9.4.2 Two-Finger Grippers with Integrated Tactile Sensors

We design a set of robotic grippers capable of measuring both normal and shear forces during object manipulation. Each jaw of a parallel gripper (Robotiq, Levis, Canada) was equipped with two multimodal tactile sensors, as shown in Figure 9-10. Each gripper, measuring 48 mm by 108 mm, features 36 (4x9) multimodal sensors on its surface. The sensors were strategically arranged to achieve the desired density, with electrodes routed to connection points on the back of each gripper. We capture pressure distributions as the grippers grasp a variety of objects. By analyzing these pressure distributions, we can enhance robotic systems' ability to handle different object types and shapes, leading to more accurate and efficient grasping. Applications include advanced robotic systems in manufacturing, automated packaging, and prosthetics, where precise grip control is essential for effective operation.

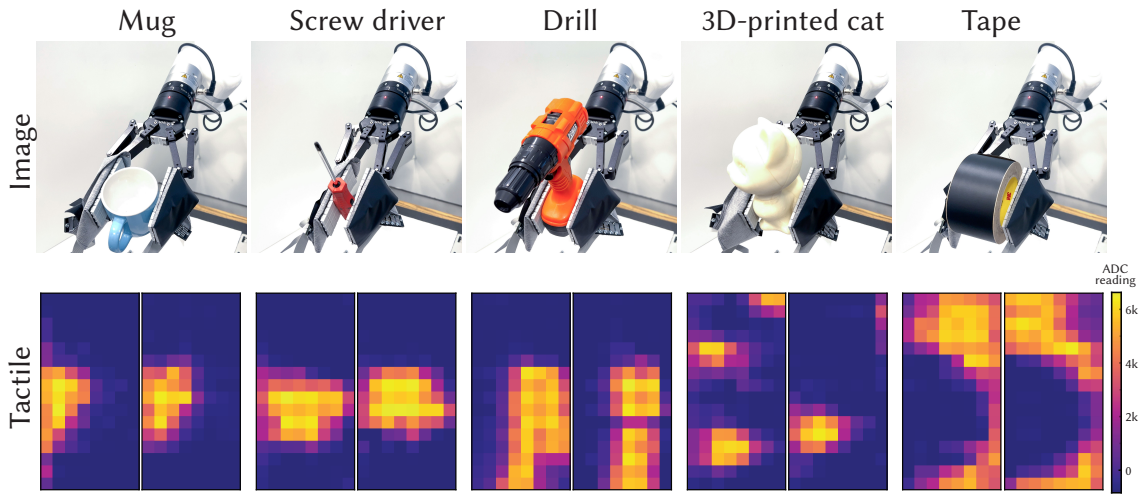


Figure 9-10: **Tactile sensors for two-finger grippers.** Tactile responses captured by the sensors during the grasping of various objects.

9.4.3 Tactile Sensors for Robot Arm

With the digital design and fabrication pipeline, we create a full-sized robot arm cover that captures a wide range of human-robot interactions. Our multimodal sensors capture both normal and shear forces, as demonstrated in Figure 9-11. This comprehensive sensing

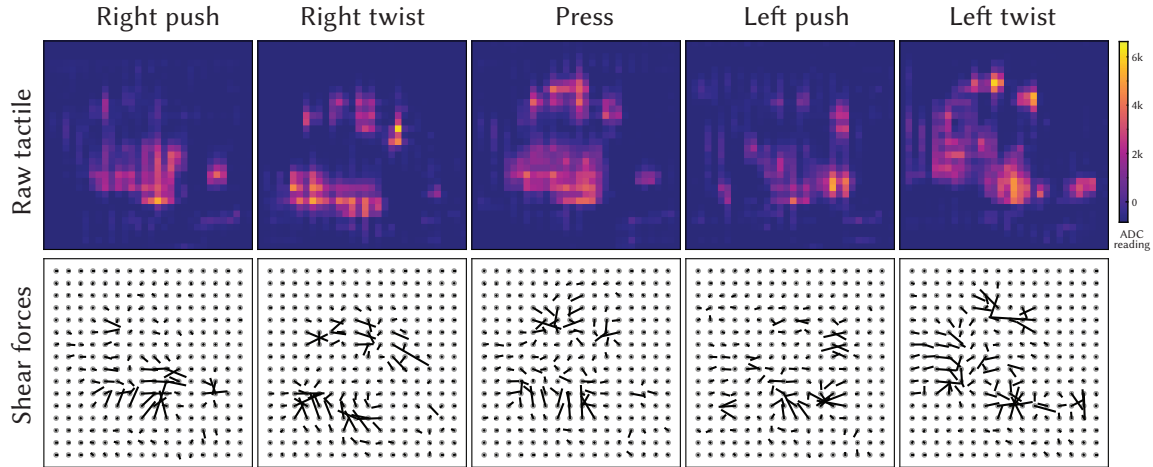


Figure 9-11: **Tactile sensors for robot arm.** Normal and shear force responses captured by the full-sized robot arm’s tactile skin during diverse human-robot interactions.

capability enables the robot arm to interact more effectively with various objects and environments in a scalable manner. Applications include improving human-robot collaboration in manufacturing and assembly tasks, enhancing robotic precision in delicate operations, and developing advanced assistive devices that adapt to complex interactions with users.

9.5 Discussion

In summary, to address the challenge of replicating human-like tactile feedback in robotics, we develop a scalable multi-modal tactile sensing system that integrates normal force, shear force, and vibration sensing. Our method employs machine embroidery to fabricate thin, flexible piezoresistive sensing arrays, which are combined with 3D-printed force translators to extend shear force sensing capabilities. The system utilizes an FPGA-based circuit for high-speed readout, enabling precise measurement of vibrations up to 500 Hz and a wide range of forces. Additionally, we introduce an automated calibration pipeline that leverages a robotic system to ensure accurate sensor performance and conversion of measurements to physical units. This advancement provides a more practical and cost-effective alternative to existing tactile sensing systems, enhancing robotic dexterity and interaction.

Chapter 10

Conclusion and Future Work

This dissertation presents my extensive research on intelligent textile-based systems for capturing, modeling, and augmenting physical human-environment interactions. Leveraging digital design and fabrication pipelines, I successfully constructed scalable, customizable, and seamless wearables embedded with integrated functionalities, such as tactile sensors, pneumatic actuators, and vibrotactile haptics. These advancements have enabled the comprehensive capturing and augmentation of pervasive and prolonged physical interactions between humans and their external environment. Additionally, I leveraged the power of machine learning to establish an intelligent and adaptive computation pipeline, effectively modeling and enhancing diverse and subjective physical human-environment interactions.

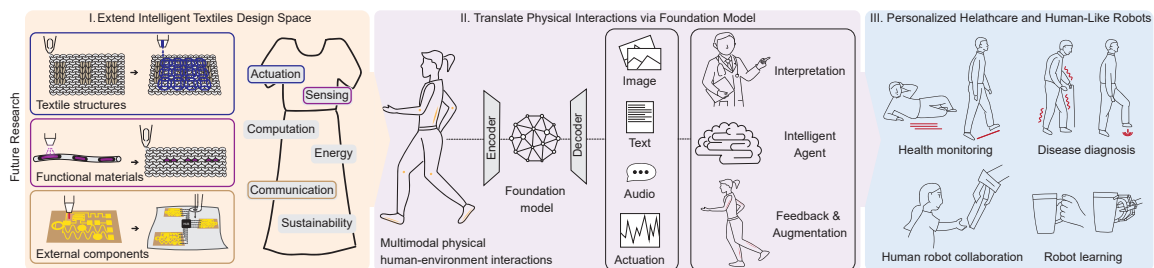


Figure 10-1: **Future directions.**

Looking ahead, future work (Figure 10-1) will build upon the solid foundations established in this dissertation, as outlined below.

Expanding intelligent textiles design space. To extend the design space and resolve the limitation in resolution and complexity inherent in prior attempts, I aim to develop integrated digital fabrication platforms that combine established computational prototyping methods, e.g. 3D printing, and laser cutting, with digital textile fabrication [71, 67]. Examples include inkjet printing on machine-knitted fabric for structural reinforcement, digital deposition onto individual fibers for diverse functional materials integration, and digitally embroidering conductive traces over pre-fabricated flexible PCBs with intricate circuits for interconnected, distributed functional systems. This synergy between additive fabrication and digital textile manufacturing will unlock a new level of potential for scalable, seamlessly integrated, and customizable intelligent textiles by increasing the spatial resolution of functional components, enriching functionalities, increasing fabrication efficiency, maintaining customization freedom, and minimizing fabrication intricacies. I aim to integrate multimodal functionalities, e.g. sensing, actuation, energy harvesting, sustainability, and computation capabilities, in textiles as a full system. Such implementation will extend the application and impact of intelligent textiles.

Translating physical interactions via foundation model. Recent advancements in foundation models are revolutionary but are currently limited to well-studied modalities like text and images. The next-generation foundation model is envisioned to be multimodal, with an understanding of real-world physical interactions. This enables previously elusive physical interactions to be interpreted and shared by a broad audience. Extending from my previous endeavors on large-scale multi-sensory data capturing and learning frameworks [71, 69, 25], I propose a translation between physical human-environment interactions and well-established modalities through foundation model. This involves creating a specialized encoder-decoder system to translate multimodal interactions into compressed yet expressive tokens and query rich and diverse output from the foundation model. This system establishes a seamless connection between complex physical interactions and easily understandable modalities. For example, the physical interactions can be translated into text to help non-experts interpret the data, into tokens for the down-streamed model to learn, and into optimal actuation signals to provide feedback for users.

Democratized yet personalized healthcare. Following Don Norman’s principle of designing for the 10%, I aim to enable cost-effective, personalized health monitoring and delivery for a broad and diverse population. Building upon our digital design and fabrication pipeline of full-sized intelligent garments [71, 72, 68, 72], we will be able to deliver personalized sensing and assistive garments for those beyond the standard product users, e.g., individuals with extreme sizes, or physical or congenital differences. These garments can be tailored to individual preferences and needs, e.g., functional component arrangements, sizes, and appearance, making them suitable for everyday wear with seamlessly integrated intelligent capabilities. Using personalized datasets, we can further customize training models for adaptive delivery to users. These advancements will enable continuous, unobtrusive, and personalized healthcare to every day and everyone. With combined efforts from clinical institutes, these will facilitate the monitoring, diagnosis, and rehabilitation of a broad set of motion-related diseases, e.g., Parkinson’s disease, and muscle or gait disorders.

Towards human-like robots. Modern robots are still far from ideal for real-world practical deployments, with huge performance gaps compared to humans, e.g., perception, planning, and control. Creating intelligent agents that mimic human behavior not only opens up new capabilities for robots, but also fosters natural human-robot collaboration and interactions. My focus lies in developing such agents from two perspectives. Firstly, by capturing and modeling physical human-environment interactions, we enable robot imitation learning, allowing agents to learn from human demonstrations and perform tasks requiring dexterity and natural interaction. Secondly, equipping robots with sensors for perceiving interactions with the physical environment akin to humans sensory enhances their ability to execute tasks and engage in human-like interactions.

THIS PAGE INTENTIONALLY LEFT BLANK

Bibliography

- [1] Ilge Akkaya et al. “Solving rubik’s cube with a robot hand”. In: *arXiv preprint arXiv:1910.07113* (2019).
- [2] Ernar Amanov, Thien-Dang Nguyen, and Jessica Burgner-Kahrs. “Tendon-driven continuum robots with extensible sections—A model-based evaluation of path-following motions”. In: *The International Journal of Robotics Research* 40.1 (2021), pp. 7–23.
- [3] OpenAI: Marcin Andrychowicz et al. “Learning dexterous in-hand manipulation”. In: *The International Journal of Robotics Research* 39.1 (2020), pp. 3–20.
- [4] Myra A Aud et al. “Smart Carpet: Developing a sensor system to detect falls and summon assistance”. In: *Journal of gerontological nursing* 36.7 (2012), pp. 8–12.
- [5] Leticia M Avellar et al. “POF smart carpet: a multiplexed polymer optical fiber-embedded smart carpet for gait analysis”. In: *Sensors* 19.15 (2019), p. 3356.
- [6] Shaojie Bai, J. Zico Kolter, and Vladlen Koltun. “An Empirical Evaluation of Generic Convolutional and Recurrent Networks for Sequence Modeling”. In: *arXiv:1803.01271* (2018).
- [7] Sofien Bouaziz et al. “Projective Dynamics: Fusing Constraint Projections for Fast Simulation”. In: *ACM Trans. Graph.* 33.4 (July 2014). ISSN: 0730-0301.
- [8] Sofien Bouaziz et al. “Shape-Up: Shaping Discrete Geometry with Projections”. In: *Comput. Graph. Forum* 31.5 (Aug. 2012), pp. 1657–1667. ISSN: 0167-7055.
- [9] Albert S Bregman. “Auditory scene analysis: the perceptual organization of sound”. In: *MIT press* (1990).
- [10] Thomas J. K. Buchner et al. “Vision-controlled jetting for composite systems and robots”. In: *Nature* 623 (7987 Nov. 2023), pp. 522–530. ISSN: 1476-4687. DOI: 10.1038/s41586-023-06684-3. URL: <https://doi.org/10.1038/s41586-023-06684-3>.
- [11] Leah Buechley et al. “The LilyPad Arduino: using computational textiles to investigate engagement, aesthetics, and diversity in computer science education”. In: *Proceedings of the SIGCHI conference on Human factors in computing systems*. 2008, pp. 423–432.
- [12] Zhe Cao et al. “OpenPose: realtime multi-person 2D pose estimation using Part Affinity Fields”. In: *arXiv preprint arXiv:1812.08008* (2018).

- [13] Zhe Cao et al. “Realtime multi-person 2d pose estimation using part affinity fields”. In: *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2017, pp. 7291–7299.
- [14] Leonardo Cappello et al. “Exploiting textile mechanical anisotropy for fabric-based pneumatic actuators”. In: *Soft robotics* 5.5 (2018), pp. 662–674.
- [15] Leslie Casas, Nassir Navab, and Stefanie Demirci. “Patient 3D body pose estimation from pressure imaging”. In: *International journal of computer assisted radiology and surgery* 14.3 (2019), pp. 517–524.
- [16] Kabalan Chaccour et al. “Smart carpet using differential piezoresistive pressure sensors for elderly fall detection”. In: *2015 IEEE 11th International Conference on Wireless and Mobile Computing, Networking and Communications (WiMob)*. IEEE. 2015, pp. 225–229.
- [17] Sachin Chitta et al. “Tactile sensing for mobile manipulation”. In: *IEEE Transactions on Robotics* 27.3 (2011), pp. 558–568.
- [18] Hyung Woo Choi et al. “Smart textile lighting/display system with multifunctional fibre devices for large scale smart home and IoT applications”. In: *Nature communications* 13.1 (2022), p. 814.
- [19] Henry M Clever et al. “3d human pose estimation on a configurable bed from a pressure image”. In: *2018 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE. 2018, pp. 54–61.
- [20] Henry M Clever et al. “Bodies at Rest: 3D Human Pose and Shape Estimation from a Pressure Image using Synthetic Data”. In: *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*. 2020, pp. 6215–6224.
- [21] Jinda Cui and Jeff Trinkle. “Toward next-generation learned robot manipulation”. In: *Science robotics* 6.54 (2021), eabd9461.
- [22] Tommaso D’Alessio. “Measurement errors in the scanning of piezoresistive sensors arrays”. In: *Sensors and Actuators A: Physical* 72.1 (1999), pp. 71–76.
- [23] Ravinder S Dahiya et al. “Tactile sensing—from humans to humanoids”. In: *IEEE transactions on robotics* 26.1 (2009), pp. 1–20.
- [24] Paul E. Debevec and Jitendra Malik. “Recovering High Dynamic Range Radiance Maps from Photographs”. In: *SIGGRAPH 97* (Aug. 1997). URL: <http://www.debevec.org/Research/HDR/debevec-siggraph97.ps.gz>.
- [25] Joseph DelPreto et al. “ActionSense: A Multimodal Dataset and Recording Framework for Human Activities Using Wearable Sensors in a Kitchen Environment”. In: *Advances in Neural Information Processing Systems* 35 (2022), pp. 13800–13813.
- [26] Tao Du et al. “DiffPD: Differentiable Projective Dynamics”. In: *ACM Trans. Graph.* 41.2 (Nov. 2021). ISSN: 0730-0301.
- [27] Scott Elrod and Eric Shrader. *Smart floor tiles/carpet for tracking movement in retail, industrial and other environments*. US Patent App. 11/236,681. Mar. 2007.

- [28] *Equation of a Plane - Wolfram Demonstrations Project* — [demonstrations.wolfram.com. https://demonstrations.wolfram.com/EquationOfAPlane/](https://demonstrations.wolfram.com/EquationOfAPlane/). [Accessed 15-09-2023].
- [29] *FEMM (Finite Element Method Magnetics)*. <https://www.femm.info/wiki/HomePage>. [Online; accessed 16-February-2023]. 2023.
- [30] Ross Girshick et al. “Rich feature hierarchies for accurate object detection and semantic segmentation”. In: *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2014, pp. 580–587.
- [31] Jayavardhana Gubbi et al. “Internet of Things (IoT): A vision, architectural elements, and future directions”. In: *Future generation computer systems* 29.7 (2013), pp. 1645–1660.
- [32] Nathaniel Hanson et al. “SLURP! Spectroscopy of Liquids Using Robot Pre-Touch Sensing”. In: *2023 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE. 2023, pp. 3786–3792.
- [33] Christian Harito et al. “The Development of Wearable Polymer-Based Sensors: Perspectives”. In: *Journal of The Electrochemical Society* 167.3 (2020), p. 037566.
- [34] J W Harris. ““Obliquely Cut Circular Cylinder” and “Segment of a Cylinder.””. In: *Handbook of Mathematics and Computational Science*. Ed. by HEditor Stocker. Springer-Verlag, 1998, pp. 103–104.
- [35] Vincent Hayward et al. “Haptic interfaces and devices”. In: *Sensor Review* 24 (Mar. 2004), pp. 16–29.
- [36] Chuan He et al. “Smart floor with integrated triboelectric nanogenerator as energy harvester and motion sensor”. In: *ACS Applied Materials & Interfaces* 9.31 (2017), pp. 26126–26133.
- [37] Kaiming He et al. “Mask R-CNN”. In: *Proceedings of the IEEE International Conference on Computer Vision (ICCV)*. Oct. 2017.
- [38] Jean-Michel Hoc. “From human–machine interaction to human–machine cooperation”. In: *Ergonomics* 43.7 (2000), pp. 833–843.
- [39] Colin Honigman, Jordan Hochenbaum, and Ajay Kapur. “Techniques in Swept Frequency Capacitive Sensing: An Open Source Approach.” In: *Proceedings of the International Conference on New Interfaces for Musical Expression*. London, United Kingdom: NIME, 2014, pp. 74–77.
- [40] Yuanming Hu et al. “Chainqueen: A real-time differentiable physical simulator for soft robotics”. In: *2019 International conference on robotics and automation (ICRA)*. ACM New York, NY, USA: IEEE, 2019, pp. 6265–6271.
- [41] Hung-Jui Huang, Xiaofeng Guo, and Wenzhen Yuan. “Understanding dynamic tactile sensing for liquid property estimation”. In: *arXiv preprint arXiv:2205.08771* (2022).
- [42] Zhenlong Huang et al. “Three-dimensional integrated stretchable electronics”. In: *Nature electronics* 1.8 (2018), pp. 473–480.

- [43] Josie Hughes et al. “A Simple, Inexpensive, Wearable Glove with Hybrid Resistive-Pressure Sensors for Computational Sensing, Proprioception, and Task Identification”. In: *Advanced Intelligent Systems* 2.6 (2020), p. 2000002.
- [44] Daniel P Huttenlocher, Gregory A. Klanderman, and William J Rucklidge. “Comparing images using the Hausdorff distance”. In: *IEEE Transactions on pattern analysis and machine intelligence* 15.9 (1993), pp. 850–863.
- [45] Eldar Insafutdinov et al. “Arttrack: Articulated multi-person tracking in the wild”. In: *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2017, pp. 6457–6465.
- [46] Ahmad Jalal, Shaharyar Kamal, and Daijin Kim. “A depth video sensor-based life-logging human activity recognition system for elderly care in smart indoor environments”. In: *Sensors* 14.7 (2014), pp. 11735–11759.
- [47] Roland S Johansson and J Randall Flanagan. “Coding and use of tactile signals from the fingertips in object manipulation tasks”. In: *Nature Reviews Neuroscience* 10.5 (2009), pp. 345–359.
- [48] Lynette A. Jones and Susan J. Lederman. “Tactile Sensing”. In: *Human hand function*. Oxford University Press, 2007.
- [49] Thorsten Karrer et al. “Pinstripe: Eyes-Free Continuous Input on Interactive Clothing”. In: *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. CHI ’11. Vancouver, BC, Canada: Association for Computing Machinery, 2011, pp. 1313–1322. ISBN: 9781450302289.
- [50] Kasman Kasman and Vasily G Moshnyaga. “New technique for posture identification in smart prayer mat”. In: *Electronics* 6.3 (2017), p. 61.
- [51] Alexandre Kaspar et al. “Knit sketching: from cut & sew patterns to machine-knit garments”. In: *ACM Transactions on Graphics (TOG)* 40.4 (2021), pp. 1–15.
- [52] Shian-Ru Ke et al. “Real-time 3D human pose estimation from monocular view with applications to event detection and video gaming”. In: *2010 7th IEEE International Conference on Advanced Video and Signal Based Surveillance*. IEEE. 2010, pp. 489–496.
- [53] Dae-Hyeong Kim et al. “Epidermal electronics”. In: *science* 333.6044 (2011), pp. 838–843.
- [54] Seungsu Kim, Ashwini Shukla, and Aude Billard. “Catching objects in flight”. In: *IEEE Transactions on Robotics* 30.5 (2014), pp. 1049–1065.
- [55] Diederik P Kingma and Jimmy Ba. “Adam: A method for stochastic optimization”. In: *arXiv preprint arXiv:1412.6980* (2014).
- [56] Roger Koenker and Kevin F Hallock. “Quantile regression”. In: *Journal of economic perspectives* 15.4 (2001), pp. 143–156.
- [57] Susan J Lederman and Roberta L Klatzky. “Hand movements: A window into haptic object recognition”. In: *Cognitive Psychology* 19.3 (1987), pp. 342–368. DOI: 10.1016/0010-0285(87)90008-9.

- [58] Dangwei Li et al. “Pose guided deep model for pedestrian attribute recognition in surveillance scenarios”. In: *2018 IEEE International Conference on Multimedia and Expo (ICME)*. IEEE. 2018, pp. 1–6.
- [59] Dengfeng Li et al. “Miniaturization of mechanical actuators in skin-integrated electronics for haptic interfaces”. In: *Microsystems & nanoengineering* 7.1 (2021), p. 85.
- [60] Dengfeng Li et al. “Touch IoT enabled by wireless self-sensing and haptic-reproducing electronic skin”. In: *Science Advances* 8.51 (2022), eade2450.
- [61] Yiming Liu et al. “Electronic skin as wireless human-machine interfaces for robotic VR”. In: *Science advances* 8.2 (2022), eabl6700.
- [62] Gabriel Loke et al. “Computing fabrics”. In: *Matter* 2.4 (2020), pp. 786–788.
- [63] Jack M Loomis and Susan J Lederman. “Tactual perception”. In: *Handbook of perception and human performances* 2.2 (1986), p. 2.
- [64] Alan Lukežič et al. “Discriminative Correlation Filter Tracker with Channel and Spatial Reliability”. In: *International Journal of Computer Vision* (2018).
- [65] Xihai Luo et al. “A machine learning-based characterization framework for parametric representation of liquid sloshing”. In: *Results in Engineering* 18 (2023), p. 101148. ISSN: 2590-1230. DOI: <https://doi.org/10.1016/j.rineng.2023.101148>. URL: <https://www.sciencedirect.com/science/article/pii/S259012302300275X>.
- [66] Yiyue Luo et al. “Adaptive tactile interaction transfer via digitally embroidered smart gloves”. In: *Nature Communications* 15.1 (2024), p. 868.
- [67] Yiyue Luo et al. “Adaptive tactile interaction transfer via digitally embroidered smart gloves”. In: *Nature Communications* 15.1 (2024), p. 868.
- [68] Yiyue Luo et al. “Digital fabrication of pneumatic actuators with integrated sensing by machine knitting”. In: *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems*. 2022, pp. 1–13.
- [69] Yiyue Luo et al. “Intelligent carpet: Inferring 3d human pose from tactile signals”. In: *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*. 2021, pp. 11255–11265.
- [70] Yiyue Luo et al. “KnitUI: Fabricating interactive and sensing textiles with machine knitting”. In: *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*. 2021, pp. 1–12.
- [71] Yiyue Luo et al. “Learning human–environment interactions using conformal tactile textiles”. In: *Nature Electronics* 4.3 (2021), pp. 193–201.
- [72] Yiyue Luo et al. “MagKnitic: Machine-knitted Passive and Interactive Haptics Textiles with Integrated Binary Sensing”. In: *Proceedings of the 36th Annual ACM Symposium on User Interface Software and Technology*. UIST ’23. Association for Computing Machinery, 2023. ISBN: 979-8-4007-0132-0/23/10. DOI: 10.1145/3586183.3606765. URL: <https://doi.org/10.1145/3586183.3606765>.

- [73] Andrew D Marchese, Robert K Katschmann, and Daniela Rus. “A recipe for soft fluidic elastomer robots”. In: *Soft robotics* 2.1 (2015), pp. 7–25.
- [74] David Marr. “Vision: A computational investigation into the human representation and processing of visual information”. In: *MIT press* (2010).
- [75] Martín Abadi et al. *TensorFlow: Large-Scale Machine Learning on Heterogeneous Systems*. Software available from tensorflow.org. 2015. URL: <https://www.tensorflow.org/>.
- [76] Carolyn Matl, Robert Matthew, and Ruzena Bajcsy. “Haptic perception of liquids enclosed in containers”. In: *2019 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE. 2019, pp. 7142–7149.
- [77] Margaret W Matlin and Hugh J Foley. “Sensation and perception”. In: *Allyn & Bacon* (1992).
- [78] David Matthews et al. “Virtual-reality applications give science a new dimension”. In: *Nature* 557.7703 (2018), pp. 127–128.
- [79] Pauline Maurice et al. “Human movement and ergonomics: An industry-oriented dataset for collaborative robotics”. In: *The International Journal of Robotics Research* 38.14 (2019), pp. 1529–1537.
- [80] Alex Mazursky et al. “MagnetIO: Passive yet Interactive Soft Haptic Patches Anywhere”. In: *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*. CHI ’21. Yokohama, Japan: Association for Computing Machinery, 2021. ISBN: 9781450380966.
- [81] James McCann. *The “Knitout” (.k) File Format*. [Online]. Available from: <https://textiles-lab.github.io/knitout/knitout.html>. 2017.
- [82] James McCann et al. “A compiler for 3D machine knitting”. In: *ACM Transactions on Graphics (TOG)* 35.4 (2016), pp. 1–11.
- [83] Keyu Meng et al. “A Wireless Textile-Based Sensor System for Self-Powered Personalized Health Care”. In: *Matter* (2020).
- [84] M-Marsel Mesulam. “From sensation to cognition.” In: *Brain: a journal of neurology* 121.6 (1998), pp. 1013–1052.
- [85] GRS Murthy and RS Jadon. “A review of vision based hand gestures recognition”. In: *International Journal of Information Technology and Knowledge Management* 2.2 (2009), pp. 405–410.
- [86] Anusha Nagabandi et al. “Deep dynamics models for learning dexterous manipulation”. In: *Conference on Robot Learning*. PMLR. 2020, pp. 1101–1112.
- [87] Ibrahim Al-Naimi and Chi Biu Wong. “Indoor human detection and tracking using advanced smart floor”. In: *2017 8th International Conference on Information and Communication Systems (ICICS)*. IEEE. 2017, pp. 34–39.
- [88] Vidya Narayanan et al. “Visual knitting machine programming”. In: *ACM Transactions on Graphics (TOG)* 38.4 (2019), pp. 1–13.

- [89] A.M. Okamura. “Methods for haptic feedback in teleoperated robot-assisted surgery”. In: *Industrial Robot: An International Journal* 31 (6 2004), pp. 499–508. ISSN: 0143-991X. DOI: 10.1108/01439910410566362.
- [90] Nuria Oliver and Fernando Flores-Mangas. “HealthGear: a real-time wearable system for monitoring and analyzing physiological signals”. In: *International Workshop on Wearable and Implantable Body Sensor Networks (BSN’06)*. IEEE. 2006, 4–pp.
- [91] Aaron van den Oord, Yazhe Li, and Oriol Vinyals. “Representation learning with contrastive predictive coding”. In: *arXiv preprint arXiv:1807.03748* (2018).
- [92] OpenCV. *Image Thresholding - OpenCV*. 2018. URL: https://docs.opencv.org/3.4/da/d97/tutorial_threshold_inRange.html (visited on 02/19/2023).
- [93] Tamás Oroszi et al. “Vibration detection: Its function and recent advances in medical applications”. In: *F1000Research* 9 (2020), p. 619. DOI: 10.12688/f1000research.22649.1.
- [94] Robert J Orr and Gregory D Abowd. “The smart floor: A mechanism for natural user identification and tracking”. In: *CHI’00 extended abstracts on Human factors in computing systems*. 2000, pp. 275–276.
- [95] Adam Paszke et al. “Pytorch: An imperative style, high-performance deep learning library”. In: *Advances in neural information processing systems*. 2019, pp. 8026–8037.
- [96] Ivan Poupyrev et al. “Project Jacquard: interactive digital textiles at scale”. In: *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems*. 2016, pp. 4216–4227.
- [97] Blaine Reeder and Alexandria David. “Health at hand: A systematic review of smart watch uses for health and wellness”. In: *Journal of biomedical informatics* 63 (2016), pp. 269–276.
- [98] David J Reinkensmeyer, Jeremy L Emken, and Steven C Cramer. “Robotics, motor learning, and neurologic recovery”. In: *Annu. Rev. Biomed. Eng.* 6 (2004), pp. 497–525.
- [99] Shaoqing Ren et al. *Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks*. 2016. arXiv: 1506.01497 [cs.CV].
- [100] Edith Ribot-Ciscar. “Cutaneous and Muscle Mechanoreceptors: Sensitivity to Mechanical Vibrations”. In: *Manual of Vibration Exercise and Vibration Therapy*. Ed. by Jörn Rittweger. Cham: Springer International Publishing, 2020, pp. 87–107. ISBN: 978-3-030-43985-9. DOI: 10.1007/978-3-030-43985-9_6. URL: https://doi.org/10.1007/978-3-030-43985-9_6.
- [101] Alice A Robie et al. “Machine vision methods for analyzing social interactions”. In: *Journal of Experimental Biology* 220.1 (2017), pp. 25–34.

- [102] José-Luis Rodríguez et al. “Active and Passive Haptic Perception of Shape: Passive Haptics Can Support Navigation”. In: *Electronics* 8.3 (2019). ISSN: 2079-9292. URL: <https://www.mdpi.com/2079-9292/8/3/355>.
- [103] Ricardo Sanchez-Matilla et al. “Benchmark for human-to-robot handovers of unseen containers with unknown filling”. In: *IEEE Robotics and Automation Letters* 5.2 (2020), pp. 1642–1649.
- [104] Munehiko Sato, Ivan Poupyrev, and Chris Harrison. “Touché: enhancing touch interaction on humans, screens, liquids, and everyday objects”. In: *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. 2012, pp. 483–492.
- [105] Domnic Savio and Thomas Ludwig. “Smart carpet: A footstep tracking interface”. In: *21st International Conference on Advanced Information Networking and Applications Workshops (AINAW’07)*. Vol. 2. IEEE. 2007, pp. 754–760.
- [106] Julien Scheibert et al. “The role of fingerprints in the coding of tactile information probed with a biomimetic sensor”. In: *Science* 323.5920 (2009), pp. 1503–1506.
- [107] Qiongfeng Shi et al. “Deep learning enabled smart mats as a scalable floor monitoring system”. In: *Nature Communications* 11.1 (2020), pp. 1–11.
- [108] Shima Seiki. *SDS-ONE Apex3*. [Online]. Available from: http://www.shimaseiki.com/product/design/sdsone_apex/flat/. 2011.
- [109] Kyoseung Sim et al. “Metal oxide semiconductor nanomembrane-based soft unnoticeable multifunctional electronics for wearable human-machine interfaces”. In: *Science advances* 5.8 (2019), eaav9653.
- [110] Amarjot Singh, Devendra Patil, and SN Omkar. “Eye in the sky: Real-time Drone Surveillance System (DSS) for violent individuals identification using ScatterNet Hybrid Deep Learning network”. In: *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops*. 2018, pp. 1629–1637.
- [111] Gaurav Singh and Girish Krishnan. “A constrained maximization formulation to analyze deformation of fiber reinforced elastomeric actuators”. In: *Smart Materials and Structures* 26.6 (2017), p. 065024.
- [112] Mélina Skouras et al. “Designing Inflatable Structures”. In: *ACM Trans. Graph.* 33.4 (July 2014). ISSN: 0730-0301.
- [113] Matteo Stoppa and Alessandro Chiolerio. “Wearable electronics and smart textiles: a critical review”. In: *sensors* 14.7 (2014), pp. 11957–11992.
- [114] Zhongda Sun et al. “Augmented tactile-perception and haptic-feedback rings as human-machine interfaces aiming for immersive interactions”. In: *Nature Communications* 13.1 (2022), p. 5224.
- [115] Subramanian Sundaram et al. “Learning the signatures of the human grasp using a scalable tactile glove”. In: *Nature* 569.7758 (2019), pp. 698–702.
- [116] K Song Tan et al. “Real-time vision based respiration monitoring system”. In: *2010 7th International Symposium on Communication Systems, Networks & Digital Signal Processing (CSNDSP 2010)*. IEEE. 2010, pp. 770–774.

- [117] Jenny Underwood. “The design of 3D shape knitted preforms”. PhD thesis. Fashion and Textiles, RMIT University, 2009.
- [118] Dongkai Wang and Shiliang Zhang. “Unsupervised person re-identification via multi-label classification”. In: *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*. 2020, pp. 10981–10990.
- [119] Mark Weiser. “The Computer for the 21st Century”. In: *SIGMOBILE Mob. Comput. Commun. Rev.* 3.3 (July 1999), pp. 3–11. ISSN: 1559-1662.
- [120] Mark Weiser. “The computer for the 21st century”. In: *ACM SIGMOBILE mobile computing and communications review* 3.3 (1999), pp. 3–11.
- [121] Irmandy Wicaksono et al. “A tailored, electronic textile conformable suit for large-scale spatiotemporal physiological sensing in vivo”. In: *npj Flexible Electronics* 4.1 (2020), pp. 1–13.
- [122] Kax Wilson. *A history of textiles*. Routledge, 2021.
- [123] David A Winter. “Human balance and posture control during standing and walking”. In: *Gait & posture* 3.4 (1995), pp. 193–214.
- [124] Hao-Yu Wu et al. “Eulerian video magnification for revealing subtle changes in the world”. In: *ACM transactions on graphics (TOG)* 31.4 (2012), pp. 1–8.
- [125] Kui Wu et al. “Stitch Meshing”. In: *ACM Trans. Graph. (Proceedings of SIGGRAPH 2018)* 37.4 (July 2018), 130:1–130:14. ISSN: 0730-0301.
- [126] Kui Wu et al. “Wearable 3D Machine Knitting: Automatic Generation of Shaped Knit Sheets to Cover Real-World Objects”. In: *IEEE Transactions on Visualization & Computer Graphics* 1.01 (Feb. 2021), pp. 1–1. ISSN: 1941-0506.
- [127] Yuanzhao Wu et al. “A skin-inspired tactile sensor for smart prosthetics”. In: *Science Robotics* 3.22 (2018), eaat0429.
- [128] Zhou Xian et al. “Fluidlab: A differentiable environment for benchmarking complex fluid manipulation”. In: *arXiv preprint arXiv:2303.02346* (2023).
- [129] Wei Yan et al. “Advanced multimaterial electronic and optoelectronic fibers and textiles”. In: *Advanced materials* 31.1 (2019), p. 1802348.
- [130] Yiran Yang and Wei Gao. “Wearable and flexible electronics for continuous molecular monitoring”. In: *Chemical Society Reviews* 48.6 (2019), pp. 1465–1491.
- [131] Ruiyang Yin et al. “Wearable sensors-enabled human–machine interaction systems: from design to application”. In: *Advanced Functional Materials* 31.11 (2021), p. 2008936.
- [132] Yiyue Luo. *yiyueluo/adaptTacTransfer: adaptTacTransfer*. <https://zenodo.org/doi/10.5281/zenodo.10246885>, Zenodo. 2023.
- [133] Aifang Yu et al. “Large-Scale Smart Carpet for Self-Powered Fall Detection”. In: *Advanced Materials Technologies* 5.2 (2020), p. 1900978.
- [134] Tianhong Catherine Yu and James McCann. “Coupling programs and visualization for machine knitting”. In: *Proceedings of the 5th Annual ACM Symposium on Computational Fabrication*. 2020, pp. 1–10.

- [135] You Yu et al. “All-printed soft human-machine interface for robotic physicochemical sensing”. In: *Science Robotics* 7.67 (2022), eabn0495.
- [136] Andy Zeng et al. “Learning synergies between pushing and grasping with self-supervised deep reinforcement learning”. In: *2018 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE. 2018, pp. 4238–4245.
- [137] Andy Zeng et al. “Robotic pick-and-place of novel objects in clutter with multi-affordance grasping and cross-domain image matching”. In: *The International Journal of Robotics Research* 41.7 (2022), pp. 690–705.
- [138] Wei Zeng et al. “Fiber-based wearable electronics: a review of materials, fabrication, devices, and applications”. In: *Advanced materials* 26.31 (2014), pp. 5310–5336.
- [139] Qiang Zhang et al. “Dynamic modeling of hand-object interactions via tactile sensing”. In: *2021 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE. 2021, pp. 2874–2881.
- [140] Mingmin Zhao et al. “RF-based 3D skeletons”. In: *Proceedings of the 2018 Conference of the ACM Special Interest Group on Data Communication*. 2018, pp. 267–281.
- [141] Mingmin Zhao et al. “Through-wall human pose estimation using radio signals”. In: *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*. 2018, pp. 7356–7365.
- [142] Shengdong Zhao et al. “Earpod: Eyes-Free Menu Selection Using Touch Input and Reactive Audio Feedback”. In: *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. CHI ’07. San Jose, California, USA: Association for Computing Machinery, 2007, pp. 1395–1404. ISBN: 9781595935939.
- [143] Clement Zheng et al. “Mechamagnets: Designing and Fabricating Haptic and Functional Physical Inputs with Embedded Magnets”. In: *Proceedings of the Thirteenth International Conference on Tangible, Embedded, and Embodied Interaction*. TEI ’19. Tempe, Arizona, USA: Association for Computing Machinery, 2019, pp. 325–334. ISBN: 9781450361965.
- [144] Zhihao Zhou et al. “Single-layered ultra-soft washable smart textiles for all-around ballistocardiograph, respiration, and posture monitoring during sleep”. In: *Biosensors and Bioelectronics* 155 (2020), p. 112064.
- [145] Fan Zhu et al. “Visual-tactile sensing for Real-time liquid Volume Estimation in Grasping”. In: *2022 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE. 2022, pp. 12542–12549.
- [146] Junyi Zhu et al. “Liquids Identification and Manipulation via Digitally Fabricated Impedance Sensors”. In: *2024 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE. 2024, pp. 18164–18171.