

Enhancing Robotic Manipulation of Liquid Using a Digitally Fabricated Intelligent Wearable Device

by

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ABSTRACT

Despite recent exponential advances in computer vision and reinforcement learning, it remains challenging for robots to interact with liquids due to visual obstructions, transparent liquids, and fine-grained splashes. Yet, a substantial opportunity exists for robotics to excel in liquid identification and manipulation, given its potential role in chemical handling in laboratories and various manufacturing sectors such as pharmaceuticals or beverages. Recent advancements in electronic wearables, designed to replicate or surpass the functions and attributes of human skin, and their convergence with machine learning have provided opportunities to enhance the capabilities of robotic systems. Here, we present a novel approach for liquid class identification and position estimation with the robotic wearable device that can ‘see through’ the container, leveraging electrical impedance sensing. We design and mount a digitally embroidered electrode array to a commercial robotic gripper. Coupled with a customized impedance sensing board, we collect data on liquid manipulation with a swept frequency sensing mode and a frequency-specific impedance measuring mode. Our developed learning-based models achieve an accuracy of 93.33% in classifying 9 different types of liquids (8 liquids + air) and 97.65% in estimating the liquid position in the cup without any vision system present. We investigate the effectiveness of our system with a series of ablation studies. These findings highlight our work as a promising solution for enhancing robotic manipulation in liquid-related tasks.

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Chapter 1

Introduction

Robot manipulation has advanced dramatically due to the rapid development of computer vision and machine learning technologies, enabling robots to comprehend, anticipate, and interact better with physical objects and their environments [1–4]. However, mimicking human-like proficiency in manipulation with conventional vision-based approaches remains a formidable challenge for robots.

Recent advancements in soft intelligent wearable devices and their convergence with machine learning have provided opportunities to enhance robotic systems’ capabilities that rely solely on conventional vision-based information. Intelligent wearable devices are flexible and stretchable electronic devices designed to mimic the properties and functions of human skin. The initial concept of intelligent wearable devices was introduced in the 1970s [5, 6] to replicate human skin’s sensing capabilities by integrating electronic components with flexible materials. The available materials and fabrication processes constrained their initial developments. However, the emergence of epidermal electronics [7] in the early 21st century established a foundation for advanced electronic with a wide range of potential applications in robotics [8–10], prosthetics [11–13], wearable health monitoring and therapeutic devices [14–16], and human-machine interfaces [17–19]. As such, intelligent wearable devices can be broadly categorized into two types according to their intended uses: 1) robotic wearables for

robotics and prosthetics, which aim to replicate or restore the functions of human body parts, and 2) biomedical wearables, which collect physiological data in real-time for prevention and diagnosis of various diseases and provide immediate therapeutic interventions when possible. For the scope of this thesis, only robotic wearables will be discussed. For robotic wearables, the focus has been on precisely imitating the functions of human skin, such as sensing capabilities including but not limited to tactile (pressure and strain), temperature, vibrations, and humidity [20–22]. Flexible and stretchable sensors, capable of multi-modal sensing with high-resolution and large-area coverage, have been extensively investigated. Robotic systems with such robotic wearables can obtain information about their surroundings to execute complicated tasks.

Despite these strides, liquid manipulation continues to present challenges. 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 [23, 24]. To address these challenges, researchers have explored alternative sensing modalities, including vibration sensors [25], force sensors [26], infrared reflectance spectroscopy [27], and high-resolution tactile sensors [28, 29] 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 thesis, we present a low-cost, scalable, customizable robotic wearable system capable of impedance sensing for liquid classification and liquid position estimation [30]. We digitally designed and automatically fabricated two distinct 4×4 electrode arrays with a digital embroidery machine. These textile-based flexible 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 position 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 position of liquid inside the container without the vision system. 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 remainder of the thesis is structured as follows: Chapter 2 covers the background and related work on robotic wearable devices and their integration with machine learning, as well as liquid manipulation and impedance sensing in robotics. Chapter 3 details the fabrication and specifications of the system components, along with the computational pipeline, including data collection, ground truth generation, and the model architectures used for liquid classification and position estimation. Chapter 4 presents the experimental characterization, model performance results, and findings from ablation studies. Finally, Chapter 5 provides a summary of the research and outlines potential directions for future work.

Chapter 2

Background and related work

In this chapter, we first provide an overview of intelligent robotic wearables and their integration with machine learning and a literature review of the state-of-the-art technologies for machine learning-integrated intelligent robotic wearables. Then, we introduce previous approaches for liquid manipulation and work on impedance sensing for robotics applications.

2.1 Design and fabrication strategies for robotic wearables

Recent advancements in soft, intelligent wearable devices have led to the development of human-like devices that reproduce or surpass the skin’s functions and physical attributes. This section describes technological breakthroughs in state-of-the-art wearable devices, emphasizing technologies that achieve skin-like properties.

High mechanical compliance is required for robotic wearable devices to ensure safer, more efficient human-machine interaction and seamless interaction with complex geometries [31, 32]. The functional electronic devices that constitute wearables, such as sensors, actuators, data storage and transmission modules, and energy devices, should adapt to the body’s dynamic shapes and movements without compromising their functionalities and performance. Early research in wearables focused on imparting stretchability to individual devices, especially sensor devices, aiming for high sensitivity and durability over repeated use cycles [33–36].

Among various strategies, structural engineering of device designs [37, 38] has proven to be highly effective in simultaneously achieving high performance and mechanical freedom. This approach utilizes well-established yet rigid inorganic materials with crystallinity for their high performance and geometrically engineered designs to achieve stretchability. Typical designs include island-bridge configurations [39, 40], serpentine/honeycomb routing designs [41, 42], and kirigami-inspired stretchable designs [43, 44].

Functional electronic devices can be fabricated on geometrically engineered supports that tolerate applied strains, such as bio-inspired or serpentine structures. For instance, functional electronic devices are designed as separated island arrays for the island-bridge configurations, which are then connected by strain-tolerant interconnects. Applied strain is effectively dissipated through the stretched interconnects, leaving the functional devices on the rigid islands unaffected, which can thus be constructed from rigid crystalline materials for enhanced performance. Soft wearable devices employing this island-bridge configuration have been deployed in multifunctional wearables for temperature display and strain sensing [45], and wearables embedded with biomimetic mechanoreceptors [46]. Conductive electrodes combining patterned honeycomb and butterfly structures or fabrication of stretchable electrodes with serpentine designs have been also reported. The stretchable electrodes have been used as skin-mounted devices for articular thermotherapy or as epicardial devices to monitor cardiac activities and provide thermal therapy [47, 48]. Similarly, by forming strategical openings (i.e., kirigami structures) in the elastic supports, the mechanical stress applied can be effectively alleviated through the torsional deformation of the kirigami structures. A recent report demonstrated the fabrication of multifunctional wearable based on kirigami structured liquid metal paper electrodes, capable of effectively monitoring various electrophysiological signals due to its robust mechanical properties [49].

Despite the high performance of wearable devices based on rigid crystalline materials and stretchable device designs, various technical issues exist. First, the device density is restricted due to stretchable interconnects or geometrical device designs, resulting in low

spatiotemporal resolution. Complex device designs and fabrication methods lead to higher production costs, which are undesirable for mass production. These functional electronic components also struggle to recover from mechanical failures, making component replacement challenging and often unfeasible.

Hence, developing wearable devices with intelligent textiles has gained significant interest because of their compatibility with daily human activities and well-established industrial textile manufacturing technologies [50]. Such manufacturing technologies utilize machines to knit, sew, and embroider desired yarns, fibers, garments, etc. Generally, intelligent textile-based wearables are created by mechanically attaching pre-fabricated sensor arrays to the textile [51] or using functional fibers [52] with the machines as mentioned above. Araromi et al. demonstrated a strain gauge integrated in a textile-based sensor sleeve fabricated using conventional textile construction techniques like machine sewing [53]. The strain gauge employs strain-induced contact in an anisotropically resistive structure to achieve compliance while enabling highly sensitive strain detection with robust mechanical durability. Their textile-based sensor sleeve can identify hand movements and gestures by sensing subtle deformations in the arm associated with its muscle contractions. Luo et al. reported a digitally embroidered glove integrated with piezoresistive sensors and vibrotactile haptic units for tactile interaction transfer [54]. Tactile sensing electrodes and electromagnetic coils are patterned onto the textile using a digital embroidery machine, and the piezoresistive layer and magnets are affixed on the glove.

Nevertheless, the performance of textile-based wearables remains generally inferior to those based on rigid crystalline materials due to their susceptibility to noise induced by daily activities and their inherent limitations in material properties. Consequently, while convergence with machine learning has unlocked new potentials for textile-based wearables, investigating novel fabrication techniques and materials technologies is required for more advanced and diverse features in intelligent textile-based wearables.

2.2 Functionalities of robotic wearables

In this section, robotic wearables based on different stretchable device fabrication strategies are reviewed, focusing on the state-of-the-art technologies that grant them skin-like properties and functionalities.

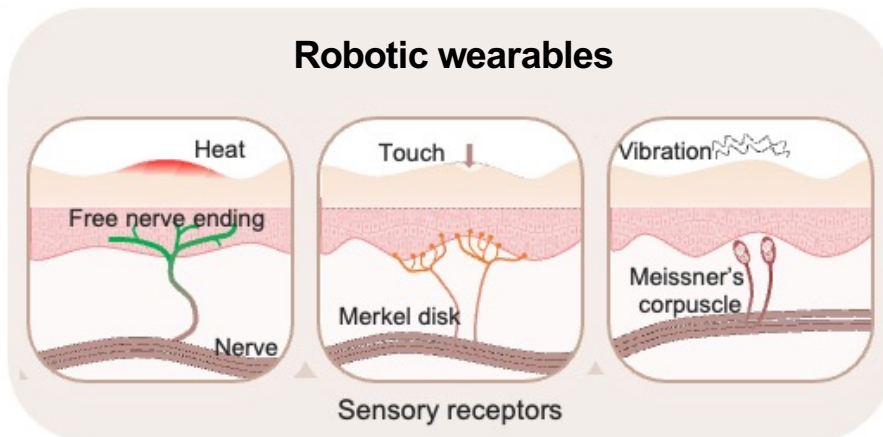


Figure 2.1: Requirements of robotic wearables. Mimicking sensory receptors of skin with robotic wearable devices [55].

The primary purpose of the robotic wearables, as highlighted earlier, is to mimic or surpass the functions of human skin. Achieving this necessitates understanding the intricate features of our skin: it not only acts as a protective barrier but also serves as a sophisticated sensory interface, enabling tactile sensations, temperature regulation, and even pain detection. Robotic wearables must incorporate a range of sensory, actuating, and protective devices to emulate these complex functionalities. This ensures refined control when these skins are used in robotic devices. When integrated into prosthetics or robots, such devices aim to restore, assist, or even replace certain human functionalities. Several characteristics are desirable to accomplish these goals. For prosthetics, they must integrate seamlessly with the human body to minimize discomfort, requiring high mechanical compliance [56]. To this end, biomimetic wearable devices should have sensor arrays with stretchable features and high spatiotemporal resolution across expansive areas. Additionally, they should support multimodal sensing, akin

to various sensory receptors of human skin (Fig. 2.1). These receptors detect and differentiate stimuli, such as humidity, temperature, vibration, and tactile information. Consequently, wearable devices with multimodal sensing have become a research focus in recent years. Table 2.1 lists the various modalities that robotic wearables aim to sense and actuate for different applications.

Table 2.1: Sensing and actuation modalities

	Modality		Information / Function
Sensor	Pressure		Heart beat, heart rate, tactile, breath, intraocular pressure
	Strain		Body motion, wound monitoring, heart beat, breath
	Acoustic		SCG, respiration, swallowing, voice
	Temperature		Body and ambient temperature
	Ultrasonic		Deep tissue imaging, blood pressure
	Optical		Oximetry, PPG
	Electrical		ECG, EMG, EEG
	Chemical		Electrolyte, metabolite, metals, drug, stress, UV exposure
Actuator	Vibrotactile		Tactile feedback
	Pneumatic		Exoskeleton, tactile feedback
	Thermal		Thermal transfer, drug delivery trigger
	Ultrasonic		Neuromodulation
	Electrical		Stimulation, tactile feedback
	Electromagnetic		Power harvesting and transfer
	Drug Delivery		Drug delivery

Jung et al. reported the development of a flexible tri-modal sensor adept at detecting pressure, temperature, and airflow [57]. To closely mimic the human skin’s structure, varied sensors were vertically stacked in a multilayered formation without disturbing the electrical contacts. This was achieved by placing an insulating layer between the sensors, minimizing interference and differentiating input-response between the sensors. In another study by Lee et al., the capability to discriminate materials and recognize texture was accomplished using fingerprint-inspired elastic designs made from composites of hybrid nanomaterials and elastomeric matrices [58]. Their wearable could successfully distinguish multiple stimuli combinations by utilizing different electrical properties of piezoelectricity, triboelectricity, and piezoresistivity. When the wearable was applied to a robotic hand, it exhibited capabilities similar to human tactile perception. Chen et al., through a straightforward in situ reduction and solvent casting approach, fabricated wearable sensors capable of detecting strain, temperature, and humidity [59]. Uniformly dispersing nanoparticles and charged ions in an elastomeric matrix resulted in high stretchability (about 600% strain) and optical transparency (transmittance of 90%), which are ideal features for prosthetic devices.

To ensure optimal performance, robotic wearables must adhere firmly to the dynamic surfaces of robots or prosthetic devices. While complete contact with electronic devices is not always imperative for performance enhancement, the wearables must conform to their host structures’ dynamic environments for precise functionalities. Traditional chemical adhesives might degrade over time or be physically and chemically compromised by environmental conditions. A promising alternative is bio-inspired adhesives that excel in wet and dry environments. Such structures, constructed from chemically inert materials, can serve as interfacial adhesive layers and efficient tools for reversible adhesion without damaging the target or themselves.

Drawing inspiration from the suction cups of octopuses, Baik et al. devised a simple solution-based method to create patterned structures mimicking an octopus’ architecture [60]. The base polymer’s low air permeability enhanced suction behaviors and exhibited reversible

and highly repeatable adhesion to various surfaces in both wet and dry conditions. This group further innovated by combining features of the octopus' sucker with a hierarchical micro-channel network seen in tree frogs [61].

This section listed recent developments of robotic wearables that were aimed at mimicking or surpassing the functionalities of real human skin, not only in terms of making them perceptible but also making them more durable. The technological advancements described in this section and continuous efforts to develop novel materials and device techniques are expected to accelerate the growth of intelligent robotic wearables for soft robotics and prosthetics.

2.3 Machine learning for robotic wearables

More recently, machine learning (ML) has enhanced device control accuracy and data processing efficiency. This section reviews machine learning methods adopted for control optimization and pattern recognition.

With the continual advancement of wearable technology, capturing better conformality, resolution, and modality, robotic wearables can now acquire and process data at an unprecedented scale. This data offers significant potential in enhancing embodied intelligence in devices and robots [2, 62]. Within this context, ML, a subset of AI, serves as a powerful tool for effectively organizing and extracting meaningful insights from voluminous data in an interpretable and practical manner (Fig. 2.2). ML's iterative algorithmic procedures effectively extract intricate statistical connections within the input data. They also elucidate highly nonlinear relationships between acquired signals and desired outcomes. These characteristics are often prevalent in physiological signals and real-world interactions. Ultimately, ML constructs a comprehensive model capable of predicting outcomes for new inputs with precision and computational efficiency. ML encompasses three primary categories of algorithms, each serving distinct purposes: supervised learning, unsupervised learning, and reinforcement

learning.

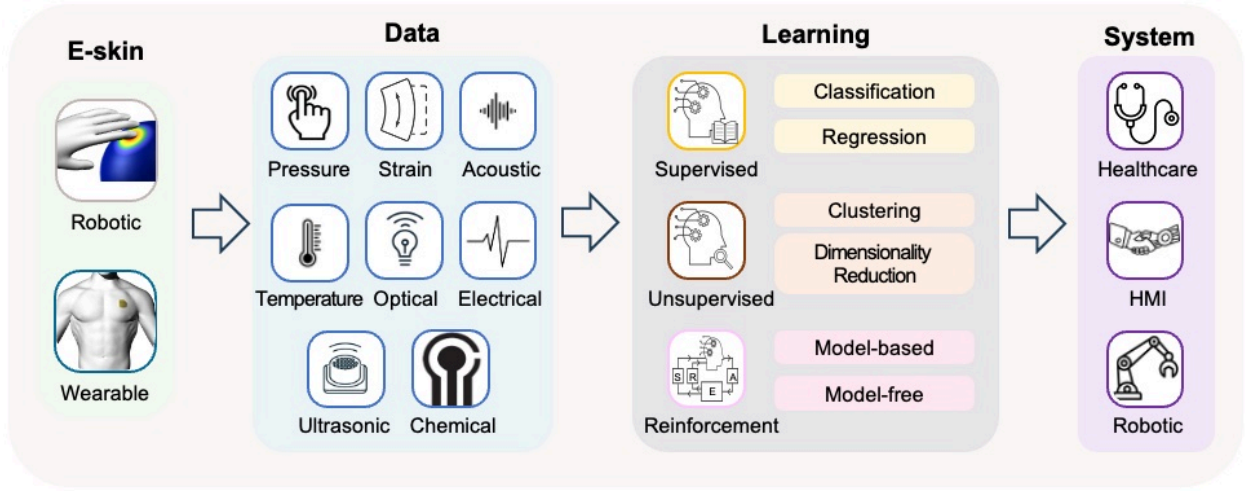


Figure 2.2: Flowchart for integrating wearables, various sensing modalities, ML, deployable system, and their applications in healthcare, human-machine interface (HMI), and robotics systems [55].

Supervised learning involves establishing relationships within labeled datasets, facilitating the prediction of output values based on given inputs. It is widely adopted in ML due to its predictive accuracy. In supervised learning, two common tasks are regression and classification, where it predicts continuous output values and categorizes inputs into discrete classes, respectively. Algorithms such as Support Vector Machines (SVM) [63], k-Nearest Neighbors (kNN) [64], Decision Trees (DT) [65], and Random Forests (RF) [66] are often applied in classification tasks. In contrast, regression tasks often apply linear regression, Bayesian regression, DT, and RF. A major drawback of supervised learning is the necessity for labeled data, which can be expensive and time-consuming to obtain and may potentially introduce biases and errors if not carefully curated.

Unsupervised learning focuses on extracting valuable features from unlabeled datasets. Data clustering and dimensionality reduction are two common tasks in unsupervised learning. Algorithms such as k-Means clustering [67], and Hierarchical clustering [68] are commonly used for clustering tasks. In contrast, Principal Component Analysis (PCA), Singular Value

Decomposition (SVD), and t-Distributed Stochastic Neighbor Embedding (t-SNE) [69, 70] are commonly used for dimensionality reduction tasks. Unsupervised learning is suitable when exploring and discovering hidden patterns or structures within data and providing scalability to handle large datasets without the need for labeling. Nevertheless, evaluating the quality of results can be challenging in unsupervised learning due to the absence of clear objectives or metrics for validation. Moreover, as datasets grow larger, handling high-dimensional data becomes computationally expensive.

Reinforcement learning represents a distinct paradigm centered around optimizing cumulative reward functions. In this approach, a reward function quantifies the success of each decision or action taken, and the algorithm refines its decision-making process through iterative optimization. Some examples of reinforcement learning methods include Markov-Decision Process (MDP) [71], Deep Model Predictive Control (MPC) [72], Q-learning [73], State-Action-Reward-State-Action (SARSA) [74], and Deterministic Policy Gradient (DPG) [75]. While inference follows the training in supervised and unsupervised learning, reinforcement learning adapts in real-time to enhance the model’s performance. However, reinforcement learning often requires numerous interactions with the environment without explicit objectives, which can reduce sample efficiency and introduce high dimensionality, leading to computational challenges. Furthermore, in reinforcement learning, where agents must navigate stochastic environments, it is crucial to design systems to manage probabilistic outcomes and reward functions meticulously. This approach aims not only to optimize agent behavior but also to uphold ethical and responsible agent conduct.

Recent advancements in sensing technology have combined wearables and ML across a broad spectrum of applications. However, the integration of wearables with ML-reinforced control policies remains relatively underexplored. As ML methods for control systems further mature, there is immense potential for leveraging them with ML-reinforced wearables, creating a closed-loop system. Such a system could revolutionize patient-specific therapies in healthcare, presenting personalized interactions in human-machine interfaces, and intelligent

autonomous manipulations (Fig. 2.3).

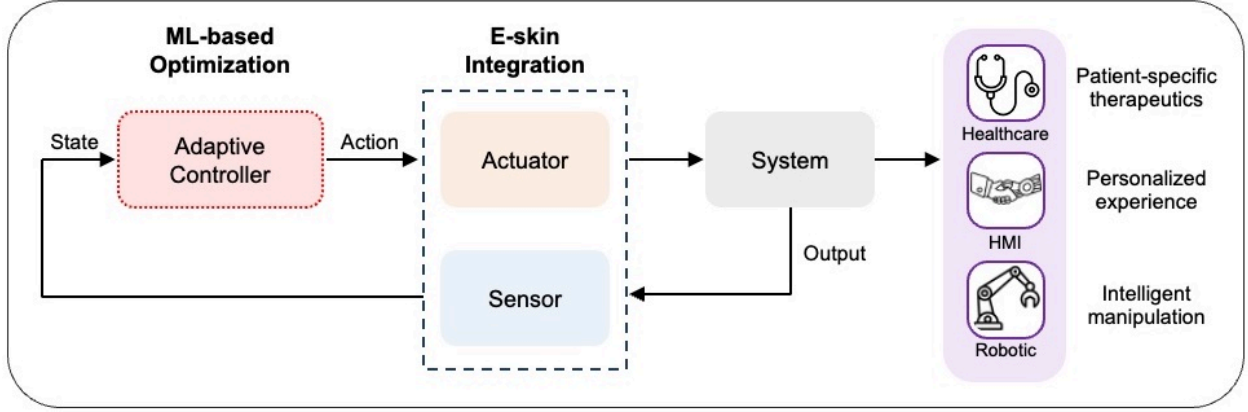


Figure 2.3: Closed-loop system of ML-reinforced controller, ML-reinforced wearable actuator and sensor, and the system for healthcare, HMI, and robotics [55].

For instance, DPG has been effectively employed in robotic insertion tasks, addressing tactile-based policy optimization problems [76] (Fig. 2.4a). In this work, the pipeline incorporates both simulated and real tactile sensor data as the observation input to a neural network policy, ultimately generating precise pose adjustments for subsequent steps. In applications of human-machine interfaces (HMI), data-driven deep MPC has been utilized for adaptive human model learning and inverse haptics optimization pipelines [77] (Fig. 2.4b). Here, the pipeline can generate personalized vibrotactile haptic instructions, ensuring the faithful reproduction of target tactile information while accommodating individual variabilities in tactile response. Despite notable advancements in robotics and HMI, the application of ML-reinforced control policies in biomedical wearable remains an unexplored and still challenging area to study. This is due to the highly stochastic and nonlinear nature of biological systems and the requirement for rigorous validation of control policies to ensure safety and responsibility. Further research and development in this area are essential to unlock the full potential of integrating ML-reinforced control policies with wearables.

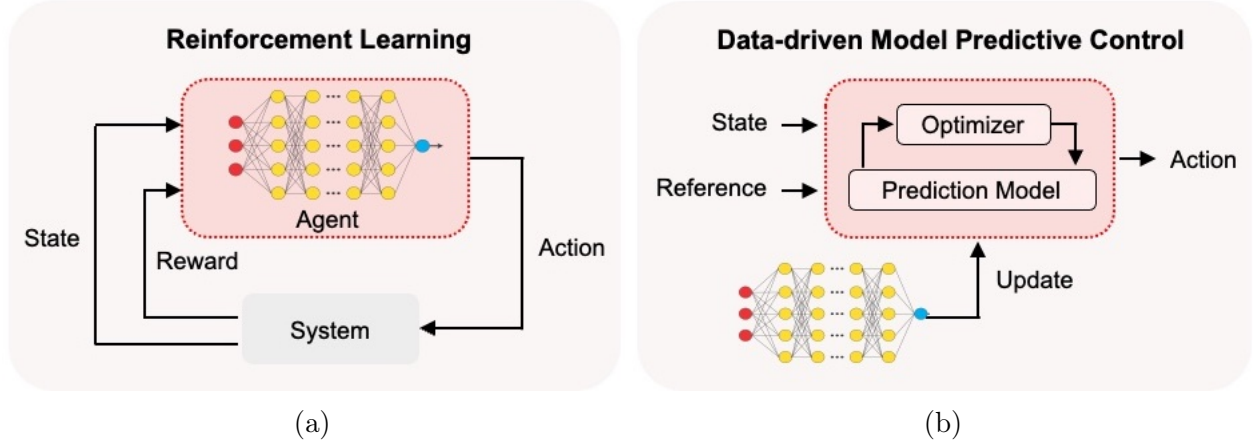


Figure 2.4: Integration scheme of wearables with ML-reinforced control policy. (a) Diagram of the reinforcement learning (RL) system. (b) Diagram of the data-driven model predictive control (MPC) system.

2.4 State-of-the-art ML-reinforced robotic wearables

The convergence of wearable technologies with machine learning is promoting their translation into robotics applications. This section introduces practical applications that converge the two technologies.

Fig. 2.5 illustrates a combined timeline of ML and soft robotic wearables, presenting their development and the recent emergence of ML-equipped intelligent wearables [7, 78–86]. The interdisciplinary research bridging soft robotic wearable devices and ML algorithms is expected to accelerate the translation of related technologies into industrial applications.

Despite remarkable advancements in computer vision and machine learning technologies, achieving precise and dexterous interaction for robots and machines with objects and environments akin to human capabilities remains a formidable challenge. This challenge is particularly pronounced when dealing with visual information that is occluded or inherently complex. In response to these challenges, researchers have explored alternative sensing modalities, namely somatosensory perception, facilitated by integrating robotic wearable into robotics, prosthetics, and human-machine interfaces [87–89]. The primary objective is to

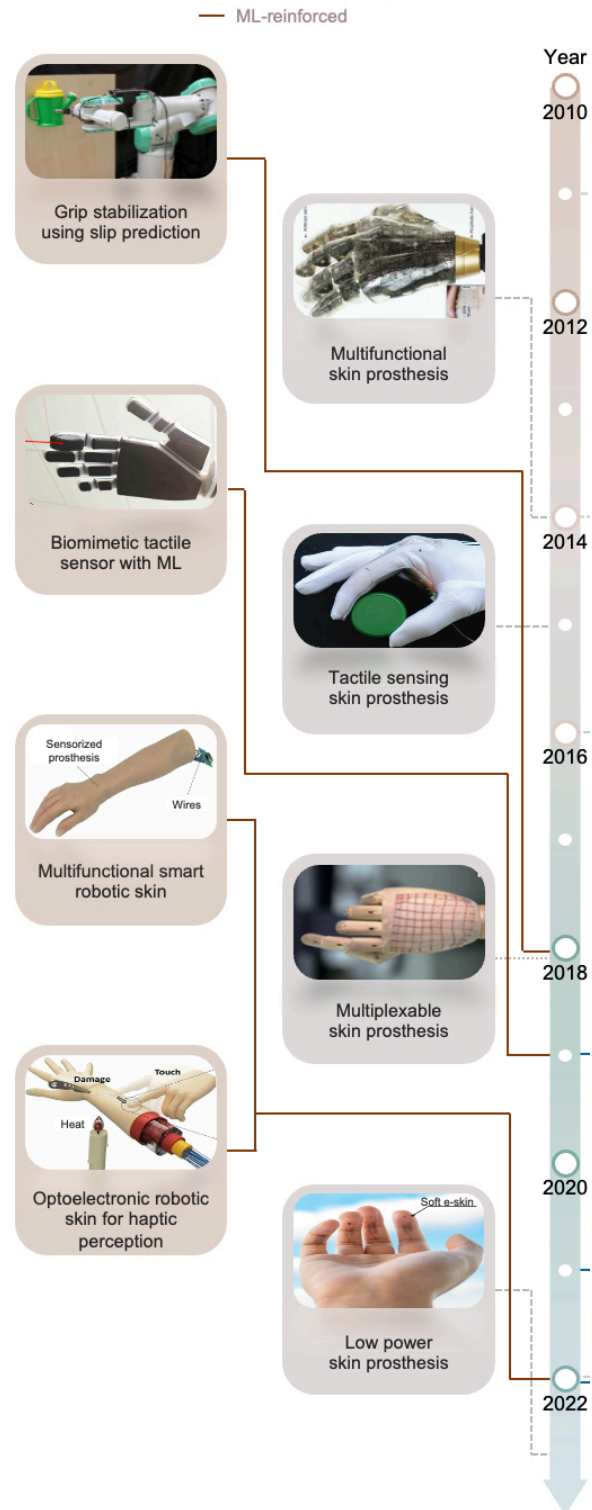


Figure 2.5: Timeline showing advancements in intelligent wearable technologies (dashed lines) along with their recent integration with ML for intelligent e-skins (solid lines).

enable closed-loop control mechanisms guided by this sensory feedback.

Among these alternative sensing modalities, tactile sensing has received significant attention, as it allows for robots and machines with embodied AI agent to learn from their body interfaces. To impart this ability, robotic wearable systems often adopt the form of 2D arrays of tactile sensing units. Interestingly, there are noteworthy parallels in the principles of shape perception between the tactile and visual domains. This similarity suggests that the processing of signals from arrays of tactile sensors can benefit from analogous techniques, where sets of sensor readings are encoded within their spatial relationships to form an image-like representation effectively. By associating sensor readings in an array and image classification tasks, robotic wearable systems exhibit the capability to classify dynamic tactile information.

Barreiros et al. have reported on an elastomeric, optoelectronic robotic skin capable of sensing touch, temperature, and damage using a complementary metal-oxide semiconductor (CMOS) image sensor [82] (Fig. 2.6a). This robotic skin incorporated layers of functional elastomers, such as thermochromic layers for temperature sensing and a stretchable optical fiber embedded layer that samples and projects light onto a CMOS image sensor. To address the intricacy of the interactions between light and materials such as reflection, refraction, transmission, coupling, and losses, various supervised learning frameworks were applied for feature extractions: SVM for touch location and gesture classification, linear regression for force sensing, and DT regressor for temperature sensing.

In addition to various supervised learning frameworks to analyze image-like representation, a convolutional neural network (CNN) stands out as the most prominent algorithm, as it enables human-level performance across a diverse range of visual tasks [91–93]. In tactile sensing, CNN architecture takes the raw pixel data from the tactile sensors as inputs and learns to extract distinctive tactile features, ultimately inferring the nature of the object they interact with. In the work by Park et al., a biomimetic elastomeric robotic skin was developed capable of sensing deep pressure that induces skin deformation, as well as various dynamic touch modalities [81] (Fig. 2.6b). This robotic skin utilizes conductive hydrogels and an array

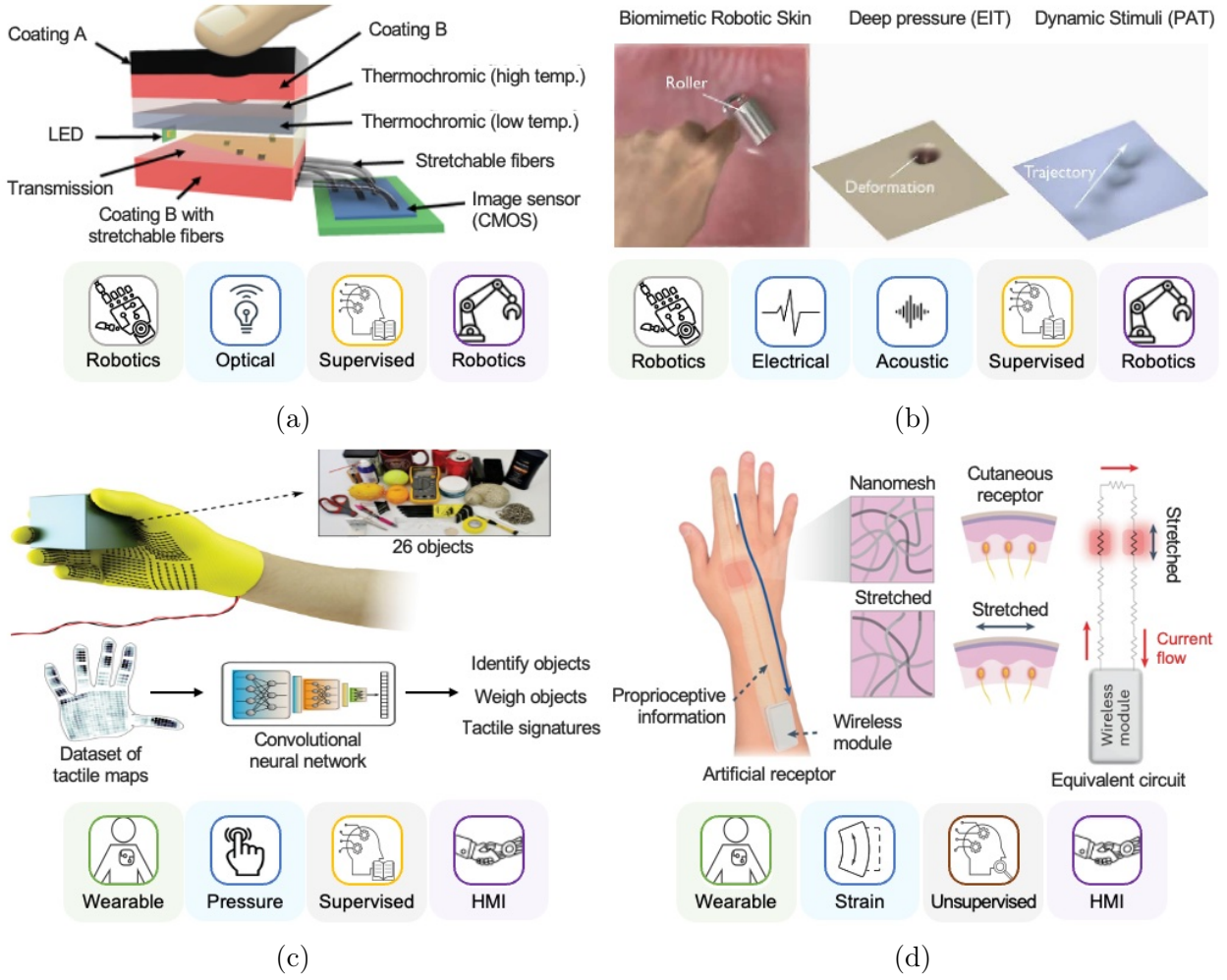


Figure 2.6: Diagrams and examples of ML-reinforced robotic wearables. (a) An elastomeric, optoelectronic robotic skin for sensing touch, temperature, and cuts [82]. (b) A biomimetic, elastomeric robotic skin capable of sensing pressure and light touch [81]. (c) A piezoresistive sensing array integrated wearable glove for exploring the tactile signatures of the human grasps [51]. (d) A sensory intelligent robotic skin system for learning and adapting to human tasks through biocompatible nanomesh cutaneous receptors [90].

of electrodes to create electrical impedance tomography (EIT) using CNN architecture to generate image reconstruction for various shape deformations from deep pressure. Moreover, the robotic skin employs an array of microphones to map the spatiotemporal pattern of the vibrations, which are then analyzed using CNN architecture to classify four touch modalities (pat, tickle, stroke, and wind blow). In the context of human-machine interfaces, Sundaram

et al. reported tactile wearable integrated into a glove that learns the signature of the human grasp with objects [51] (Fig. 2.6c). Here, a hand-shaped 32×32 piezoresistive passive matrix consisting of encapsulation layers, conductive threads, and force-sensitive film recorded a dataset of 135,198 tactile maps during interactions with 26 objects. This recorded data was subsequently analyzed using CNN architecture to weigh and classify objects with tactile information and study cooperativity among different hand regions during manipulation.

When integrating robotic wearables into real-world applications in robotics and human-machine interfaces, it becomes evident that the tasks encountered are extremely diverse and signals generated are often subject to interpersonal and temporal variability. To address these variabilities, Kim et al. introduced an innovative approach by incorporating unsupervised learning into their nanomesh robotic wearable for recognizing and adapting to human hand tasks by measuring strain on the skin during such tasks [90] (Fig. 2.6d). In this work, an unsupervised learning method known as the contrastive learning technique was applied to uncover the underlying structure of the data by instructing the model to discern similarities and differences between different examples. This application generated a general latent feature space (MFS), which allowed the system to identify new user’s hand gestures, even when these gestures exhibited signal patterns distinct from those found in the training data. This work introduced a novel approach named TD-C learning, which leverages temporal features to create MFS from unlabeled hand motion data by augmenting sensor signals based on a sliding time window, encouraging the model to identify similarities between diverse hand motions based on their temporal characteristics.

The utilization of these ML advancements and seamlessly integrated robotic wearable technologies outlined in this section represents a significant stride forward not only in enhancing the accuracy of dynamic signature sensing at robots, prosthetics, and human interfaces but also in promoting generalizability across a spectrum of tasks and users. As a result, these developments will promote the evolution of AI-powered intelligent machines tailored for specific applications.

2.5 Liquid manipulation for robotics

Mimicking human-like proficiency in household tasks is a formidable challenge for robots, particularly when these tasks involve handling liquids. Extensive research has been dedicated to liquid manipulation, employing model-based control [94] or data-driven approaches [95, 96], where particular setup was built to avoid the complexities associated with fluid measurement during experiments. Accurate fluid measurement is critical for robots to autonomously execute pouring tasks with precision. Vision-based methods have been developed for flowing liquids detection, such as [97, 98], which provided useful information for robots to control liquid flow. To precisely control and transfer liquid between containers, the volume estimation could be helpful in building a feedback control loop. To this end, however, vision-based solutions (e.g., [99]) are limited due to the common occlusion in daily-life containers.

Taking inspiration from the way humans interact with their environment, the properties of liquid within a container can also be estimated using vision-based tactile sensors [28] and light-based spectroscopy [27]. These contact-based methods eliminate the challenges posed by visual occlusion, thus offering a significant advantage over vision-based feedback and ensuring more robust measurements. In addition, it has been shown that tactile sensors can be easily integrated into customized gripper designs [100]. This inspired our development of impedance-based sensing solutions for liquid measurement that can be directly mounted on a gripper.

2.6 Impedance sensing for robotics

Impedance sensing encompasses electrical impedance tomography (EIT) and electrical impedance spectroscopy (EIS). EIT noninvasively estimates the internal resistivity distribution based on the measured boundary voltage–current data [101]. It has been commonly used for medical applications such as lung function monitoring [102] and muscle engagement

monitoring [103, 104], as well as industrial processing monitoring [105]. Recently, EIT has been extensively investigated as artificial skins for robotics due to its advantages of high versatility, low power consumption, and high sensitivity range [106]. Examples include single-layer rubber with conductive carbon particles as tactile sensing skins [107, 108], EIT-based flexible tactile sensing gloves for capturing human-object interactions [109], as well as using EIT as input for robotic prosthesis control [110]. On the other hand, EIS has been widely explored for material property detections [111] and battery characterization [112] in material science, and then the robotics community, such as via capacitive proximity sensor [113] and integrating with the robotic gripper for solid object material detection [114]. More recently, it has also been investigated for object and user behavior detections, which enables complex configurations of human hands and users' body recognition [115, 116].

In this work, we extend the benefits of low-cost and salable by digitally designing and integrating impedance sensing electrodes via digital machine embroidery. We leverage the inherent "see-through" capability of EIT and high versatility and wide frequency range impedance spectroscopy sensing for liquid type classification and position estimation.

Chapter 3

Method

This chapter presents the details of our hardware and software development. We first discuss our sensor fabrication and coupled read-out circuit design. We then describe our data collection pipeline, ground truth generation, and model development for liquid classification and position estimation.

3.1 Sensor Fabrication

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 (Fig. 3.1). These spaces were designed to reveal the electrodes, allowing them to be in contact with the grasped objects and 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 electrode array obtained a 4×4

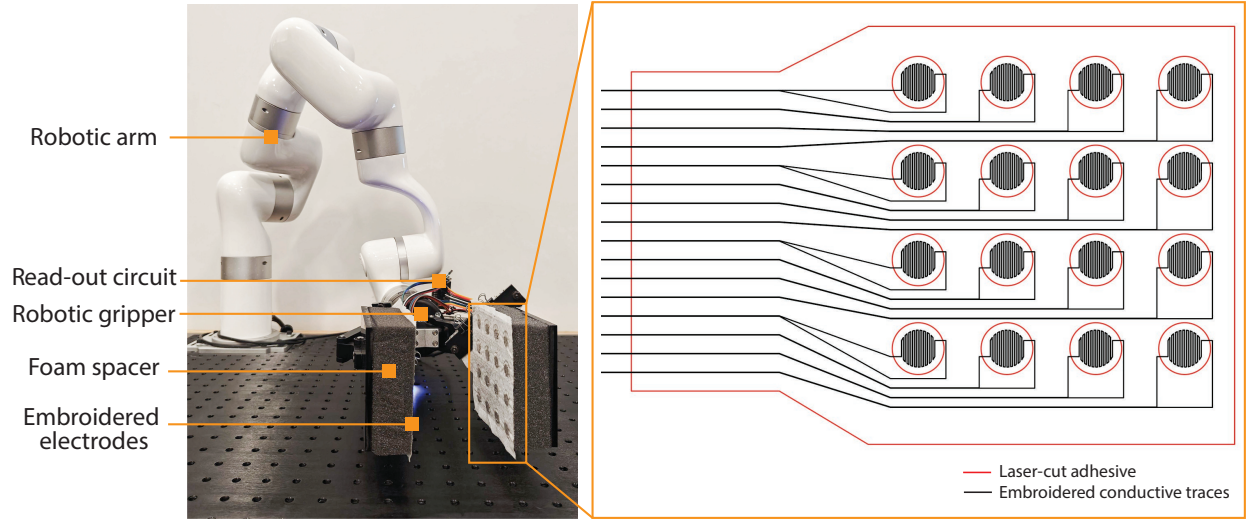


Figure 3.1: Embroidered impedance sensing matrix. A 4×4 embroidered electrode array was affixed to each parallel gripper, with a foam spacer in between to enhance conformity during grasping. All electrode connections were routed to the edge for a convenient connection to the read-out circuit.

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 users' specific requirements.

3.2 Impedance Sensing Board

For better integration with the robotic grippers, we implemented a BLE-enabled customized impedance sensing board ($4\text{cm} \times 6\text{cm}$), 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 Fig. 3.2, the impedance sensing board consists of

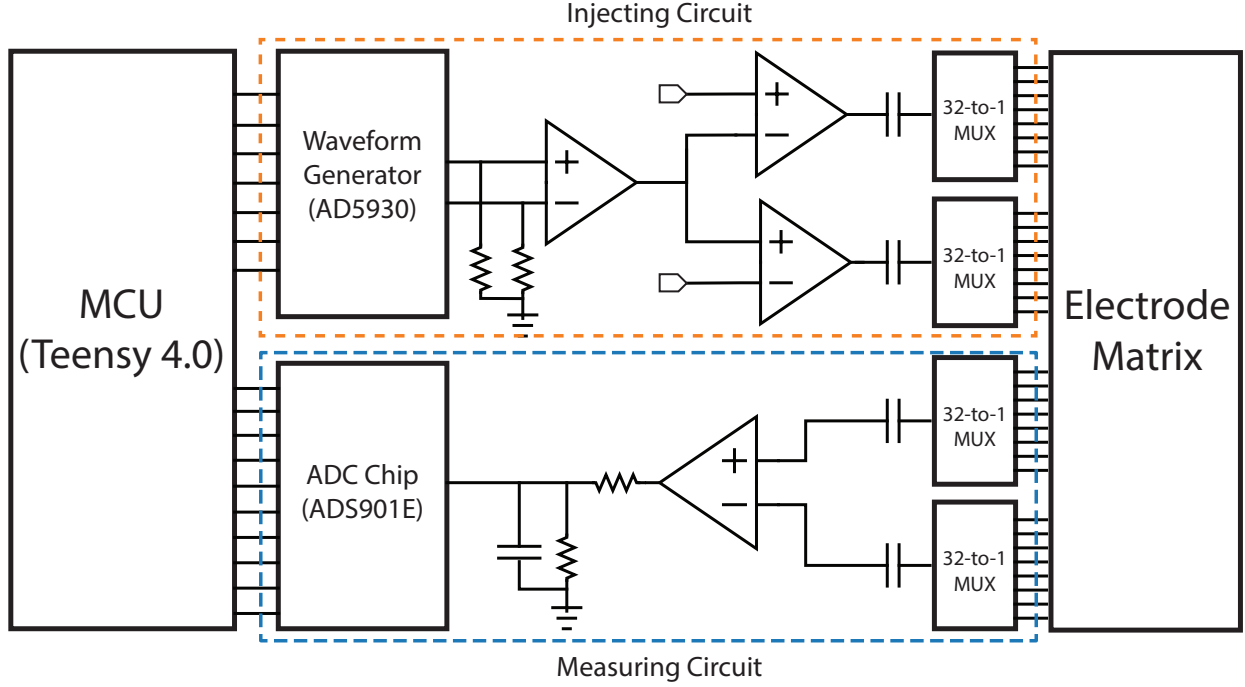


Figure 3.2: Read-out circuit diagram.

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 the current injecting circuit & the input of the voltage response measuring circuit to corresponding electrodes and processes the collected data.

3.2.1 Current Injecting Circuit:

The current injecting circuit comprises a signal generator, an adjustable instrumentation amplifier, and a voltage-controlled current source (VCCS). Specifically, the signal generator (AD5930) serves as a voltage source. It 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 drive the VCCS directly. The resulting current output is differential and centered around 0. It is connected to a 4×8 electrode matrix via two separate 32-to-1 multiplexers (ADG731).

3.2.2 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 comprises two input buffers, an adjustable instrumentation amplifier, and a 10-bit analog-to-digital converter (ADC). Each input buffer 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 have filtered outputs at 20MHz and output voltages at 10 bits.

3.3 Data Collection

All data was collected by mounting our embroidered sensing matrix to a robotic gripper (Robotiq 2F-140) 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.

With a swept frequency sensing setup, we captured impedance signals with 4 electrodes (2 injecting 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),

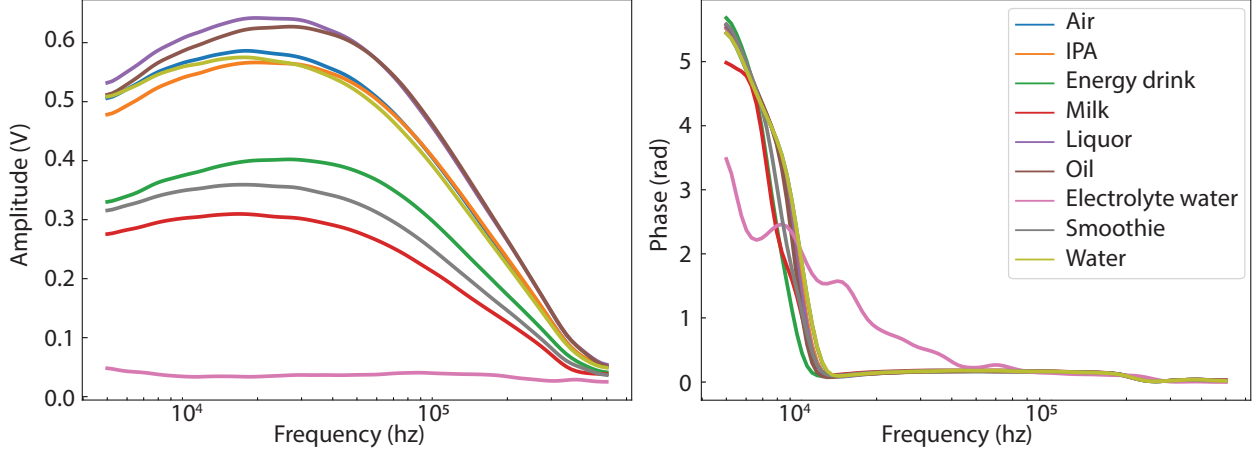


Figure 3.3: Sample impedance spectroscopy data for liquid classification.

as well as with 8 different liquids: water, electrolyte water, milk, energy drink, isopropanol (IPA), liquor, oil, and smoothie. We collected 900 total swept-frequency data samples in 90 rounds over 3 days. We split the data in a conventional 80/20 manner to train and validate the liquids classifier.

We collected impedance responses from all pairs of electrodes at 50 kHz with a frequency-specific impedance measuring setup. 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 rotated as the AC signal injecting pair. All other adjacent pairs measured and recorded the impedance responses (8 injecting electrode pairs $\times$ 8 measuring electrode pairs = 64 measurements per layer). Our data collection process involved the sensorized gripper securely holding a water container. To introduce variations in the liquid’s position, we systematically rotated the container along different axes, covering various angles. These rotations were carried out using a known rotation matrix, which was employed to generate the mathematical ground truth for the liquid position. 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 position estimator and used the remaining data from the unseen 22 rotations as validation and test sets.

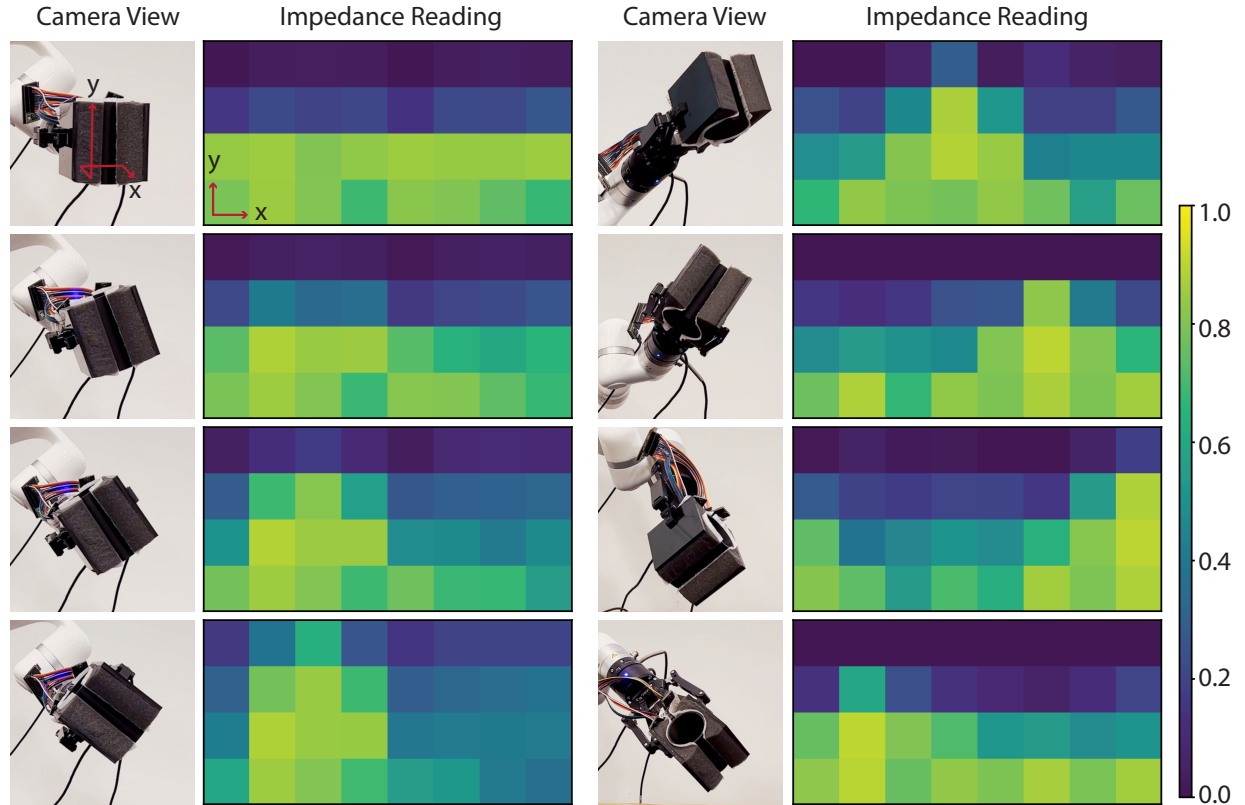


Figure 3.4: Representative impedance responses for liquid position estimation. Impedance responses were captured by the embroidered electrode arrays while a container with 100 mL water was grasped and tilted towards various angles. The average impedance responses captured with each injecting electrode pair is mapped to a pixelized heatmap.

3.4 Ground Truth Generation

Ground truth generation for liquid position 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.

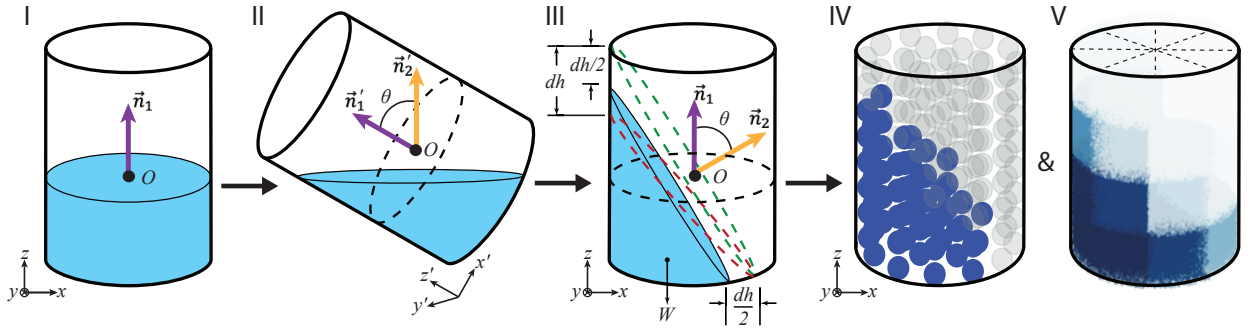


Figure 3.5: Ground truth generation. The liquid positions at the initial position (I) and tilted angles (II) are shown in sky blue. The liquid position is projected to the initial frame (III), where the ground truth is sampled and generated (IV & V). Normal vectors and calculated parameters are indicated.

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 (Fig. 3.5.I). The center of the liquid surface is denoted as O . When the robotic gripper grasps the liquid container and rotates (Fig. 3.5 II), the liquid position changes while the liquid surface remains parallel 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 $\vec{n}_2 = R^T \vec{n}'_2$ (Fig. 3.5.III). With $\vec{n}_1$ and $\vec{n}_2$, the angle of a rotation can be calculated as:

$$\theta = \arccos \left(\frac{\vec{n}_1 \cdot \vec{n}_2}{|\vec{n}_1||\vec{n}_2|} \right). \quad (3.1)$$

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:

$$Z_{water}(x, y) = -\frac{a(x - x_0) + b(y - y_0)}{c} + z_0, \quad (3.2)$$

where $\vec{n}_2 = (a, b, c)$, $[x_0, y_0, z_0] = [r, r, \frac{V_l}{\pi r^2}]$, r is a radius, and V_l is the volume of liquid.

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 3.5 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). Derived from the equation of the volume of the cylindrical wedge [117], dh is defined as:

$$dh = \frac{3(V_w - V_l)}{r^2} \left(\frac{1 - \cos \phi}{3 \sin \phi - 3\phi \cos \phi - \sin^3 \phi} \right), \quad (3.3)$$

where h is the height of the cylindrical wedge, V_w is the volume of the cylindrical wedge without the adjustment in the base intersection, r is the radius of the container, and ϕ is the end angle of the base circular wedge.

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 position estimation.

Given the liquid surface plane $Z_{water}(x, y)$, ground truth is generated in 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 $Z_{water}(x_b, y_b)$.

$$s_b = \begin{cases} 1 & \text{if } z_b < z_{water}(x_b, y_b) \\ 0 & \text{if } z_b > z_{water}(x_b, y_b) \end{cases} \quad \text{where } s_b \in S_b \quad (3.4)$$

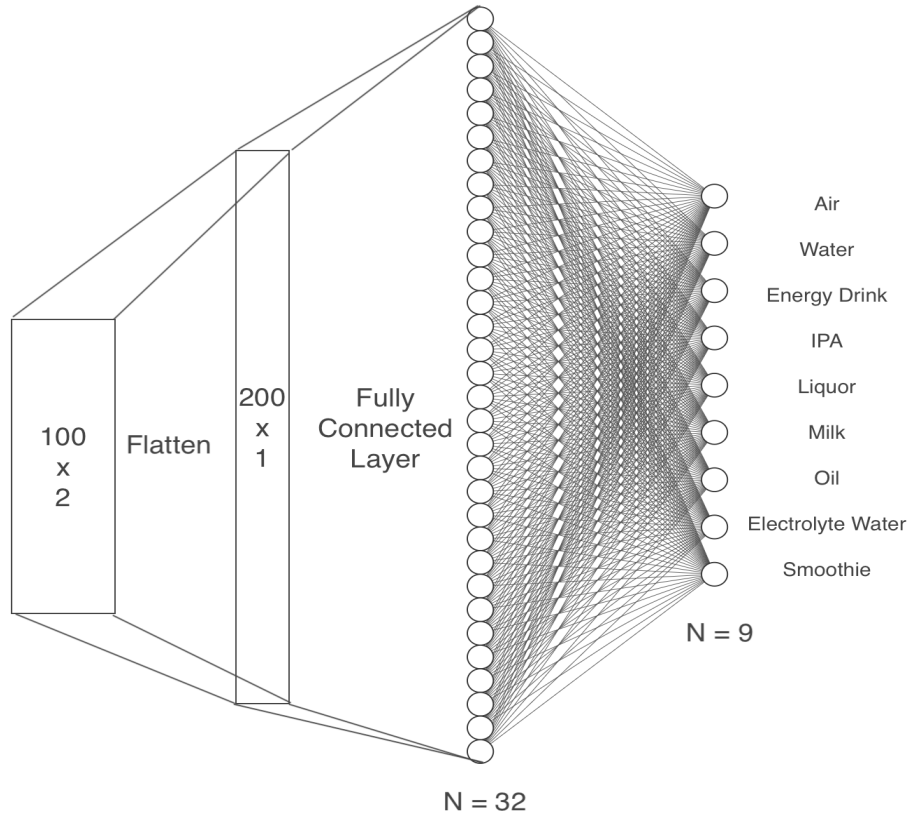
We also generate continuous ground truth data representing the water composition within various volume regions. To achieve this, we slice the volume of the container into 4×8 wedges (which correspond to the 4×8 electrode array) and sample 1000 uniformly distributed random points (S_p^i , where i corresponds to the count of sliced wedges) within each wedge. Similar to the binary scenario, the Cartesian coordinates (x_p^i, y_p^i, z_p^i) of each sampled point are compared to the height of the liquid position given 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.

3.5 Model Architecture

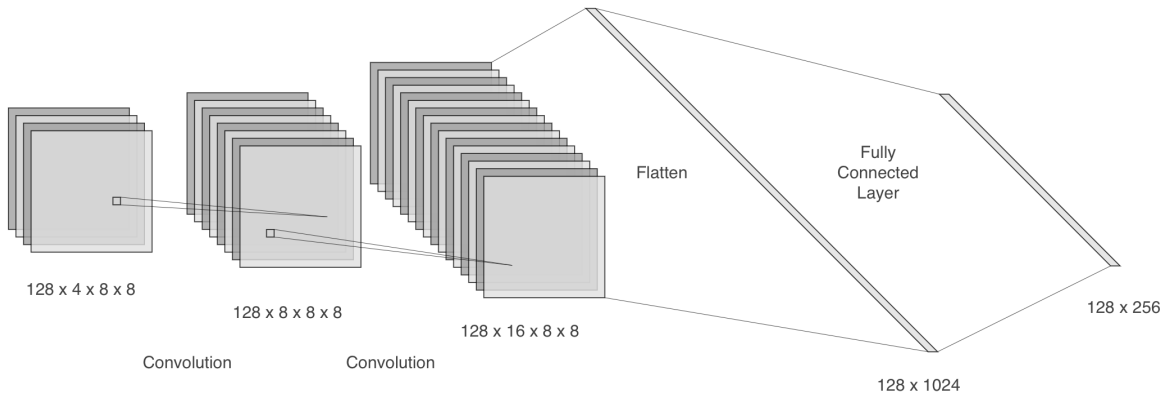
Our liquid position estimation model takes in a scan of impedance reading across all electrode pairs (256 measurements, more details in Chapter 4, Section C) and predicts the probability of the presence of water at the sampled location (Fig. 3.6a). The input of the model is a three-dimensional vector 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 [118] with a learning rate of 0.001 and a batch size of 128.

Similarly, our liquid classifier takes in a frequency-swept impedance sensing sequence and outputs the probabilities of each liquid class. (Fig. 3.6b) 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 [119].



(a)



(b)

Figure 3.6: Diagrams of model architectures used to train (a) liquid type classification model and (b) liquid position estimation model.

Chapter 4

Results

In this chapter, we present results on embroidered electrode characterization, the model’s performance on liquids classification and position estimation, and results on a series of ablation studies to evaluate our framework’s effectiveness.

4.1 Embroidered electrode characterization

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 Fig. 4.1, the impedance across frequencies decreases as the electrode sizes increase. However, the impedance remains stable despite an increase in embroidery pitches, which indicates that the density of conductive traces minimally affects signal transmission. In our final design for the gripper, we employed the embroidered electrode with 1 mm pitch and 10 mm diameter, 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.

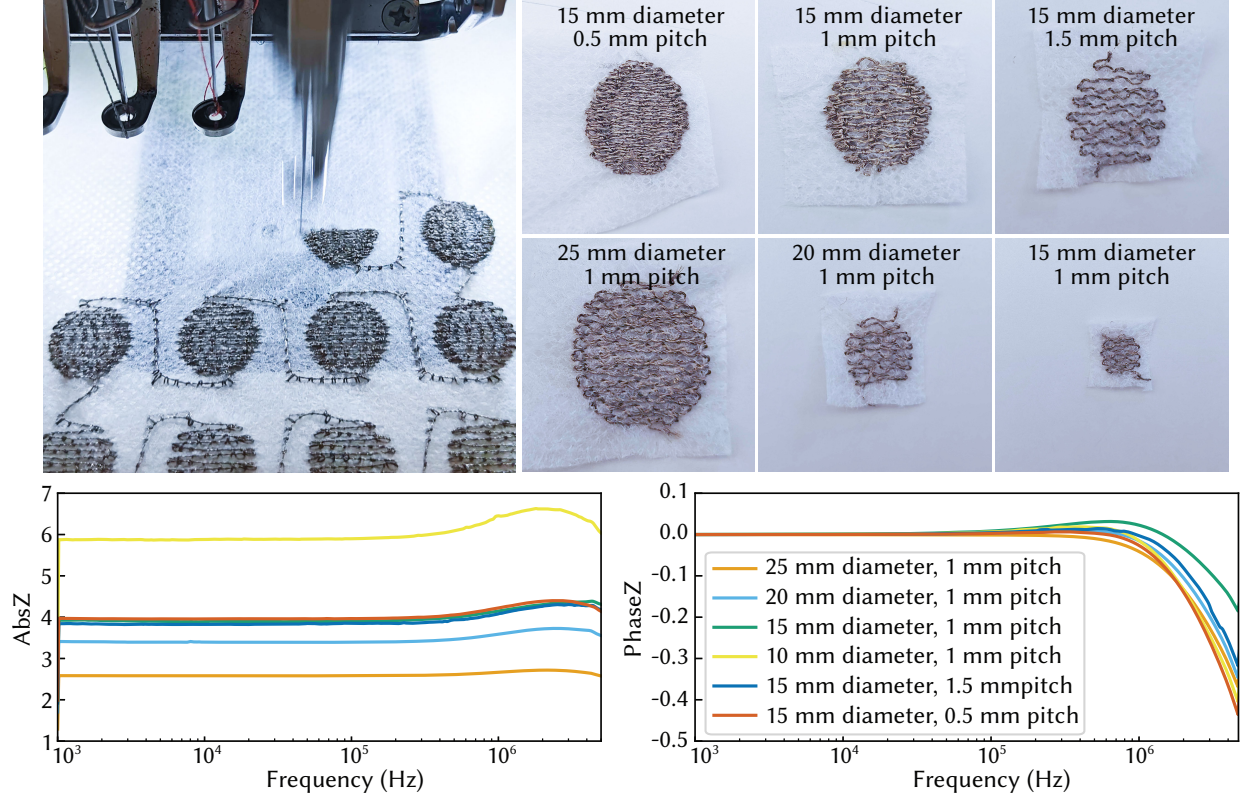


Figure 4.1: Embroidered electrode designs and characterization. Impedance measurements were conducted across various frequencies using embroidered electrodes featuring distinct sizes and stitch spacing.

4.2 Liquid 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 (Fig. 4.2), the most confusing cases occur between air (i.e., empty container) and water. This is likely because we used deionized water with little to no free electrons, 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 real and imaginary readings.

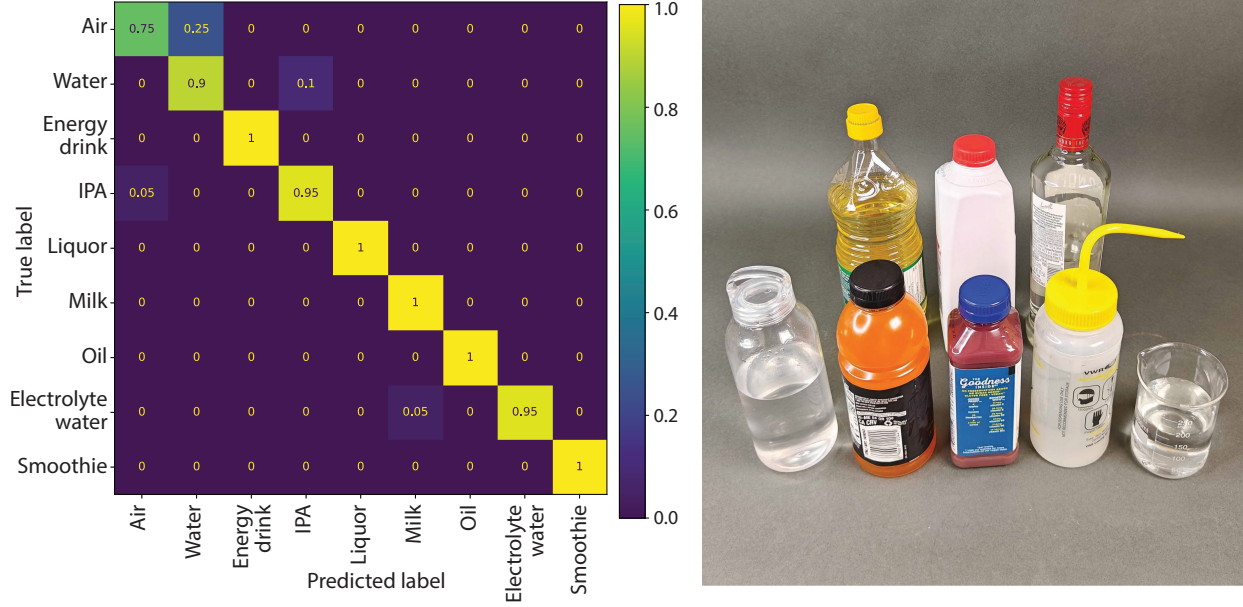


Figure 4.2: Confusion matrix on liquids classification.

4.3 Liquid position estimation

In general, we performed liquid position estimation with both a classification and regression setup. In the classification setup, the model was supervised by ground-truth labels in an 8×19 binary array. The model was expected to categorize each of the 8×19 data points into one of two categories: "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 (Figure. 4.2).

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 (Fig. 4.4 left). We trained models using ground truth data sampled at various height layers, ranging from 4 (i.e., a

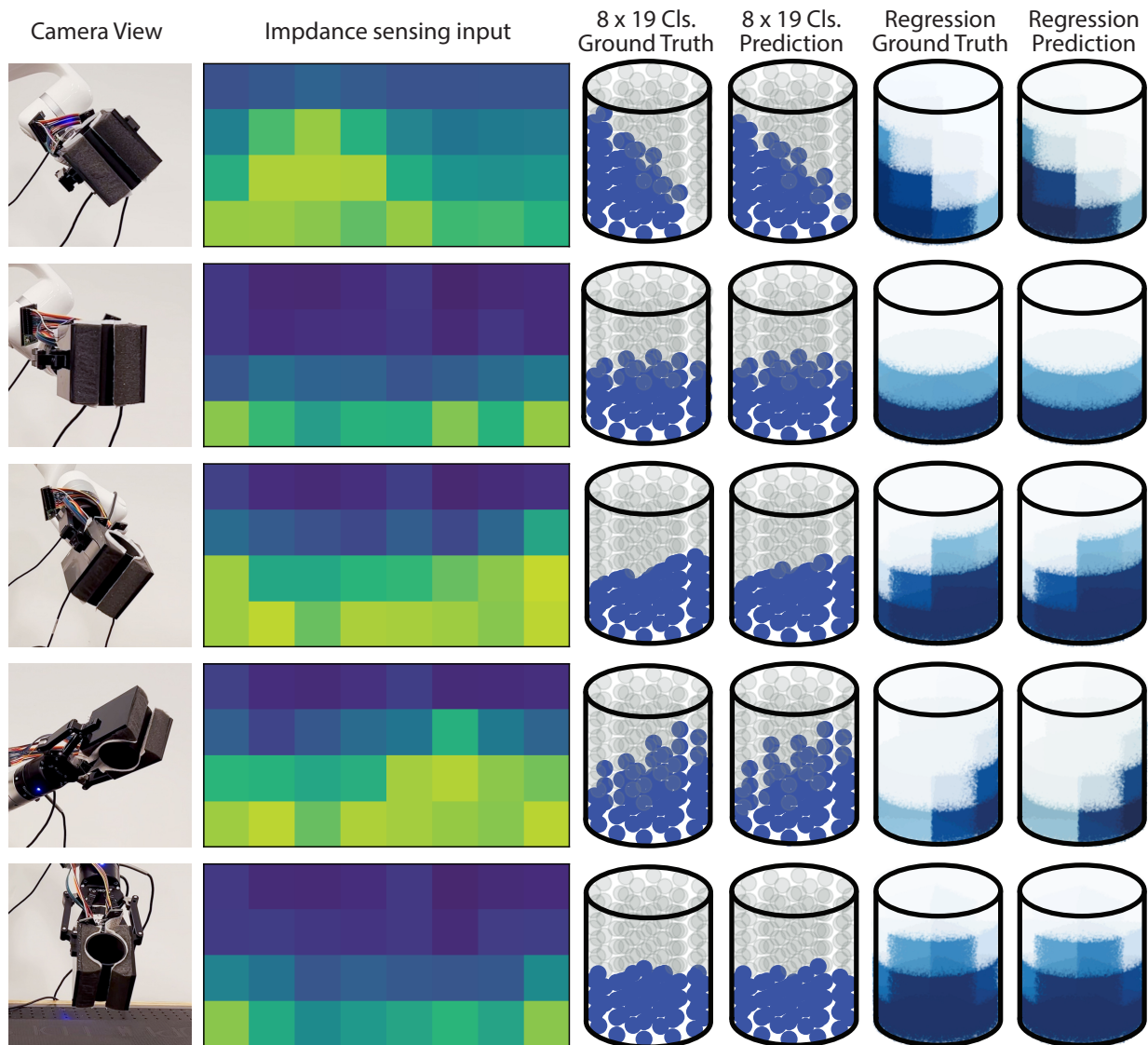


Figure 4.3: Results on liquid position estimation. From left to right columns: camera view of gripper and liquid container tilting degrees, EIT sensing raw signal, 8×19 binary classification ground truth and prediction results, 32-wedge (4×8) regression ground truth and prediction results.

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 was 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 container’s exterior, they can effectively extract data points located within inner circular regions, all without requiring direct contact or connecting traces to the electrodes. Also, we achieved an accurate position 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 interpolate between neighboring sampled points effectively. Additionally, it underscores the inherent capability of impedance sensing to capture information across entire planar surfaces comprehensively.

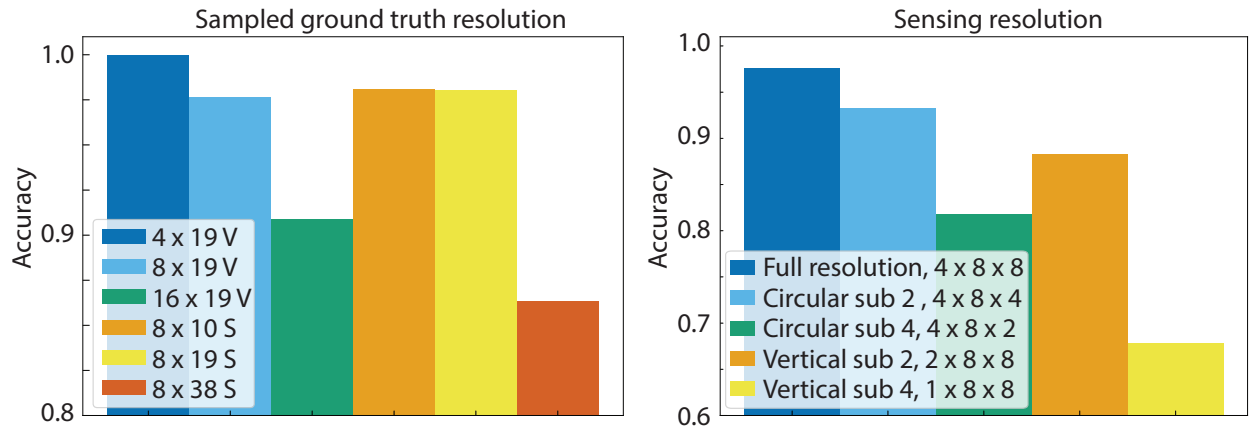


Figure 4.4: Model evaluation and ablation study. Left, model effectiveness regards prediction resolution along circular and height directions. Right, Ablation study on effective impedance sensing resolution along circular and height directions. V represents points sampled along various radii, and S represents points sampled along a single radius.

4.3.1 Ablation study

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 Fig. 4.4 right. Overall, our sensing resolution is more robust along the circular direction, as indicated by the 81.81% accuracy with only 2 active sensor readings per height layer, and can be more delicate along the vertical height resolution for liquid position estimation.

Chapter 5

Conclusion

In conclusion, this thesis introduces a novel approach for liquid type identification and state estimation using impedance sensing, grounded in a thorough exploration of related work in robotic wearable devices, machine learning, and liquid manipulation, as discussed in Chapter 2. By developing scalable, customizable embroidered electrode arrays integrated with a portable impedance sensing board, this research offers a flexible solution adaptable to various robotic grippers. The dataset, comprising over 900 swept-frequency liquid type measurements and 110 degrees of liquid position data, supported the creation of machine learning models that achieved high accuracy in liquid identification (93.33%) and state estimation (97.65%). This thesis also detailed the system’s fabrication and the computational pipeline, covering data collection, ground truth generation, and the model architectures used for classification and estimation, as presented in Chapters 3 and 4. Experimental results and ablation studies further demonstrated the system’s effectiveness while underscoring areas for improvement.

However, there are several limitations to the current approach. The data collection process focused primarily on static liquid conditions, avoiding scenarios with dynamic liquid movements like sloshing, which introduces complex parameters related to fluid dynamics and container geometries. Additionally, the current sensing setup is limited by a frame rate of 15.62 Hz, which restricts our ability to capture finer liquid dynamics, such as sloshing, at the

desired temporal resolution of 100 Hz.

Future work will address these limitations by extending the system to cover dynamic liquid manipulation and diverse container geometries. Enhancing the impedance sensing frame rate to capture inter-degree liquid behavior better and incorporating physics-based simulations, such as voxel method and fluid simulation, will provide richer data featuring fine details, including sloshing and splashing. This will help develop a more delicate liquid position estimation model. Additionally, developing the liquid classification model to include properties such as viscosity and temperature can expand the model’s utility to more accurately estimate liquid types, capture their positions, and provide valuable information for specific use cases. Integrating closed-loop control with our liquid classification and state estimation pipeline will provide real-time feedback and the system’s utility in real-world robotics manipulation tasks. These improvements aim to create a more comprehensive and robust framework for liquid manipulations in dynamic environments.

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