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Efficient Data Driven Algorithms for Tactile Data Processing in Embedded and Wearable Systems

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DITEN DIPARTIMENTO
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EFFICIENT DATA DRIVEN ALGORITHMS FOR TACTILE DATA PROCESSING IN EMBEDDED AND WEARABLE SYSTEMS

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I would like to dedicate this thesis to my loving parents ...

Declaration

I hereby declare that, except where specific reference is made to the work of others, the contents of this dissertation are original and have not been submitted in whole or in part for consideration for any other degree or qualification in this or any other university. This dissertation is my own work and contains nothing which is the outcome of work done in collaboration with others, except as specified in the text and Acknowledgements. This dissertation contains fewer than 65,000 words, including bibliography, footnotes, tables, and equations, and has fewer than 150 figures.

Mohamad Yaacoub

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Abstract

Human interaction with the physical world relies heavily on the sense of touch, which provides information essential for manipulation and perception. Artificial tactile sensing systems have therefore emerged as a promising technology to enhance human-machine interaction, with growing interest in applications ranging from wearable devices to robotics and prosthetics. These systems typically consist of artificial tactile sensors that generate signals in response to physical contact, followed by embedded algorithms running on resource-constrained devices for signal acquisition and processing. However, achieving efficient tactile data processing on embedded and wearable platforms remains a challenge due to limitations in memory footprint, execution time, and power consumption.

This thesis explores the development of data-driven algorithms and embedded implementations for efficient tactile data processing across multiple use cases. The first part focuses on processing signals generated by our piezoelectric-based tactile sensors. First, the thesis outlines the analysis of the sensor response behavior, in which we integrated a setup comprising an array of piezoelectric sensors and interface electronics. Indentation experiments were performed with variations in load and speed. Signal processing techniques were developed to detect contact events and reconstruct normal forces under controlled indentation. A lightweight machine learning model was then introduced for force estimation using a shallow artificial neural network trained on time-domain features extracted from the sensor signals. The trained neural network was deployed on a microcontroller to demonstrate real-time estimation of the peak of the normal force, confirming the efficiency of the proposed algorithm, with performance degrading at higher forces. The complete processing pipeline was evaluated on embedded hardware, achieving a total inference time of ≈ 6.23 ms and a total energy consumption of ≈ 528 μ J per inference.

In parallel, modeling of the sensing system, including the transducer and the soft protective layer, was carried out to characterize its electromechanical behavior, aiming to generate tactile simulated data to train the algorithms with a wide range of forces and test the network experimentally, thereby reducing dependence on extensive experimental datasets and minimizing resource usage. The results indicated that the system exhibits a derivative-like response with resonance peaks above 350 Hz, likely originating from the soft cover layer. Accordingly, a phenomenological lumped-parameter model was developed to fit the sensor response function under indentation.

The second part of this work addresses object recognition through the development of low-cost multisensory wearable gloves that combine tactile and proprioceptive sensors. Embedded machine learning techniques, including TinyML workflows for processing time-series data, were implemented to enable real-time recognition of twenty-eight daily-life objects. The results demonstrate that the system achieved high accuracy, with an inference time of 8.147 ms while consuming only ≈ 0.4875 mJ per inference. Furthermore, hardware-aware neural architecture search was applied to automate the design of the learning algorithms, thereby reducing resource usage. The results indicated an energy reduction of $\approx 27.92\%$ without compromising performance.

The glove was subsequently upgraded with a battery-powered embedded system, enabling fully portable operation and real-time classification of 3D-printed objects spanning different categories of shape, size, and stiffness. The system was built using cost-effective components and validated through on-device experiments. The results demonstrated reliable object-recognition performance, with an estimated battery lifetime of ≈ 26.5 hours under continuous operation.

Keywords: Deep learning, Embedded machine learning, Electronic skin, Data-driven computation, Force reconstruction, Haptic, Multisensory wearable system, Object recognition, Piezoelectric, Resource-constrained devices, Sense of touch, Tactile sensors, TinyML.

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Notations

$\mathbb{R}$	Set of real numbers
$\mathbb{Z}$	Set of integer numbers
$\emptyset$	Empty set
N	Normal load or normal force (Newtons)
v	Indentation speed (mm/s)
t	Time (seconds)
f	Frequency (Hz)
V	Voltage (Volts)
Var	Variance of a signal
Σ	Summation operator (used in cumulative sum)
R	Correlation coefficient
RMSE	Root Mean Square Error

Acronyms

AI	Artificial Intelligence
CNN	Convolutional Neural Network
DAQ	Data Acquisition
DL	Deep Learning
EE	Embedded Electronics
e-skin	Electronic Skin
FEB	Feature Extraction Block
FCB	Feature Classification Block
FEM	Finite Element Model
FBG	Fiber Bragg Grating
GUI	Graphical User Interface
HW-NAS	Hardware-Aware Neural Architecture Search
IB	Input Block
KNN	K-Nearest Neighbors
LCD	Liquid Crystal Display
ML	Machine Learning
OA	Overall Accuracy
OCCR	Onset of Contact or Contact Release
OFET	Organic Field-Effect Transistor
OSM	OpenStreetMap
PCB	Printed Circuit Board
PCA	Principal Component Analysis
PDMS	Polydimethylsiloxane
P(VDF-TrFE)	Poly(vinylidene fluoride–trifluoroethylene)
PVDF	Polyvinylidene Fluoride
RF	Random Forest
RMSE	Root Mean Square Error
SVM	Support Vector Machine
STIET	Science and Technology for Electronic and Telecommunication Engineering
TinyML	Tiny Machine Learning
UART	Universal Asynchronous Receiver-Transmitter

CHAPTER 1

Introduction

1.1 Motivation

The somatosensory system endows humans with touch perception, enabling them to explore, perceive, and engage with their environment. This system operates through the activation of primary sensory units known as mechanoreceptors in the skin [3], particularly in the glabrous regions, which convert detected mechanical actions into electrical signals. These signals are then transmitted to the central nervous system (CNS), through the peripheral nerves, where they are processed, decoded, and interpreted [4].

To guide motor control, the brain employs tactile afferent information related to the temporal progression, magnitude, direction, and spatial distribution of frictional contact forces as well as contact shapes [5]. Tactile feedback control operates through interconnected neural loops. Reflexive tactile control [4, 6], which operates through spinal reflexes or subcortical pathways, e.g., cerebellar, provides rapid (within 20-50 ms), automatic responses to tactile or proprioceptive stimuli, without cortical processing. This rapid pathway ensures immediate motor responses to unexpected stimuli, such as pulling away from a hot surface. The slow cognitive tactile control loop ≈ 300 ms engages cortical processing, allowing conscious perception and intentional movement correction based on tactile feedback.

Inspired by the human skin, there has been substantial progress toward mimicking the sense of touch artificially, driving the development of artificial tactile sensing systems, commonly referred to as electronic skin (e-skin) [7, 8, 9, 10]. Biomimetic design principles have led to advanced sensing solutions that capture spatially distributed mechanical interactions, including sophisticated stretchable structures capable of sustaining large strains (e.g. [11]) and soft interfaces embedding tactile sensors [12, 13]. e-skin is a technology that uses artificial mechanoreceptors, capable of detecting contact within a certain range of frequencies, ideally covering the entire spectrum of human tactile perception, from static contact to dynamic contacts at kilohertz frequencies [14, 15]. The e-skin operates through

a distributed sensing matrix, allowing it to capture tactile data with high spatial resolution, particularly in the hand. Combined with advanced signal processing and interpretation techniques, the tactile sensing system is capable of handling non-trivial stimulus patterns and interpreting contact characteristics [16, 17].

There has been a longstanding effort in developing algorithms to reconstruct various aspects of the mechanical contact on the skin surface. Contact forces, induced skin displacements, and spread rate of contact area are key tactile cues for haptic perception through soft artificial skins [18, 19, 20]. However, despite significant research on sensors and tactile data processing, current technological solutions still fall short of human capabilities [21].

Recent advances in artificial intelligence (AI), particularly Deep Learning (DL) [22], have significantly enhanced the ability of the sensing system to extract high-level tactile information that model-based data processing methods struggle to capture, thereby paving the way for data-driven approaches that bypass the need for a detailed understanding of the complex mechanical system [23, 24]. These AI-driven approaches might have the potential to provide predictions of tactile features that mimic or even occasionally surpass human capabilities [25, 26, 27]. In the era of ubiquitous computing, the volume of tactile data to be collected and processed in human-machine interface applications is rapidly increasing [28]. Near-sensor computing presents an attractive solution where acquisition, processing, and decision-making are performed locally on the embedded electronics, so-called interface electronics, thereby improving efficiency and reducing latency [29].

Embedding AI directly within tactile systems marks a vital advancement achieved through interface electronics, leading to the emergence of so-called smart tactile sensing systems [30]. The overall architecture of the smart tactile sensing system is illustrated in Figure 1.1. Such systems typically involve preprocessing of raw data collected from e-skin, extracting relevant patterns or features. Popular preprocessing techniques include filtering, downsampling with a sliding window, dimensionality reduction, baseline removal, and normalization [31]. Following this stage, AI algorithms are employed to achieve specific learning objectives, whether as supervised or unsupervised learning, classification, regression, discriminative modeling, or generative modeling, for the purpose of identifying and categorizing these extracted patterns, a process broadly referred to as pattern classification [32, 23].

Smart tactile systems are capable of performing a variety of intelligent and important tasks, including detecting slippage and touch events [33, 34], discriminating texture levels [35, 36], classifying static and dynamic touch modalities [37], reading Braille letters

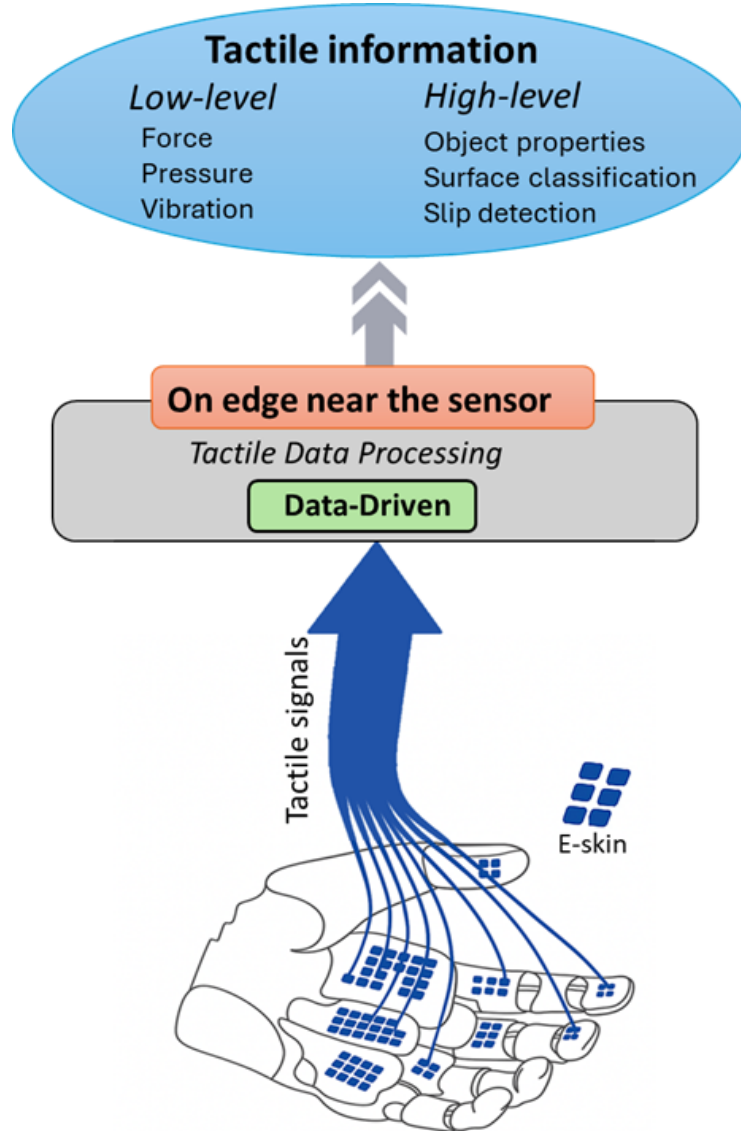


Figure 1.1: Smart Tactile Sensing System: A Data-Driven Pipeline Transforming Distributed e-Skin Measurements Into Low- and High-Level Tactile Perception Through Near-Sensor Computing

[38, 39], recognizing the haptic properties of the contact object e.g. hardness level [40, 41, 42] and the shape [43, 44] of random objects. Nevertheless, significant limitations in the hardware resources of digitally embedded units (interface electronics) hinder the implementation of intelligence at the edge. This is related mainly to the limited power budget, memory footprint, and processing time speed of the devices [45, 46, 47].

The central challenge, therefore, is designing computationally efficient algorithms that maintain high performance under severe resource constraints. Consequently, the develop-

ment of processing approaches that are inherently lightweight and tailored for resource-constrained embedded platforms while still accomplishing the intended intelligent tasks becomes essential. Accordingly, this thesis focuses on embedded and wearable tactile sensing systems for human-machine interaction, addressing both contact force reconstruction and object property recognition under strict constraints on power consumption, latency, and computational resources.

1.2 Objectives

In the perspective of the stated motivation, the primary objective of this thesis is to develop an end-to-end, lightweight, data-driven approach for extracting both low-level working at the contact level and high-level tactile information e.g., haptic properties of the contact object (refer to Figure 1.1) from time-series data. To achieve this, the thesis focuses on the implementation and evaluation of a tactile sensing system that combines advanced sensor technologies with embedded intelligence for real-time, resource-efficient operation.

This overarching aim is addressed through the following specific objectives:

- 1. Tactile sensing system characterization:** Several experimental campaigns were carried out with the e-skin, in which the e-skin was mechanically simulated through indentation. The tactile sensing system has been chosen for its capability of covering a wide range of frequencies with high sensitivity. The collected tactile signals have been analyzed to validate the capability of the system to detect contact information (i.e., normal and tangential forces).
- 2. Lightweight Algorithms for Force Reconstruction:** The tactile signal has been processed leveraging the power of data-driven algorithms to extract contact force information. The focus of the thesis is to prioritize algorithms designed to function within embedded device constraints.
- 3. Wearable Glove for Object Recognition:** A wearable glove integrating cost-effective sensing technology has been developed for object recognition. The focus was to develop a low-cost wearable glove integrated with embedded preprocessing and machine learning to infer high-level haptic properties.

1.3 Contributions

In this perspective, the main contributions of this thesis are summarized as follows :

1.3.0.1 Force Reconstruction from PVDF-Based Tactile Sensing System

This part focuses on validating the capability of a dynamic tactile sensing system to encode tactile information and, through data processing, extract low-level cues such as normal force, load variations, and contact events.

- A custom tactile sensing system based on PVDF piezoelectric sensors was employed. An 8-tixel, fully screen-printed PVDF/P(VDF-TrFE) array was integrated with custom interface electronics supporting high-bandwidth acquisition (2 kHz). The system was evaluated in a controlled environment upon indentation while modulating forces and speeds.
- Time-domain signal processing methods have been developed to extract low-level tactile information. Algorithms for detecting contact onset, release, and load variations are proposed, enabling the extraction of normal indentation characteristics directly from sensor outputs. These methods allow for a first assessment of the dynamic behavior and suitability of the sensing system for haptic applications.
- A machine-learning framework is proposed for normal force estimation. Tactile signals are processed to extract discriminative time-domain features. A lightweight shallow neural network is trained for peak force estimation, demonstrating accurate performance while meeting embedded system constraints. The trained model is deployed on a microcontroller to validate real-time feasibility.

1.3.0.2 Modeling and Simulation of the PVDF-Based Tactile Sensing System

To reduce experimental dependency, this thesis introduces modeling for the tactile sensing system:

- A measurement system and a controlled interface electronics were built to characterize the electromechanical behavior of the tactile sensors based on PVDF to indentation and compute the response function. The experiment involved modeling the PVDF sensor along with the protective layer on top for use in real-world scenarios
- A lumped-parameter electromechanical model is formulated and fitted to the experimentally computed transfer function. The model captures both the mechanical and electrical dynamics of the sensor, reproducing its frequency response across the

full bandwidth (1–1 KHz), including the resonance peaks revealed in the response function.

1.3.0.3 End-to-End Wearable Glove System for Embedded Object Recognition

This contribution concerns the design, hardware implementation, and on-device evaluation of multisensory wearable gloves for high-level haptic perception.

- A low-cost multisensory wearable glove integrating tactile and proprioceptive sensors is developed. The system is designed to collect time series interactions with daily life objects. Embedded machine-learning models, including TinyML pipelines, are implemented for real-time object recognition across multiple classes. In addition, a hardware-aware neural architecture search (HW-NAS) strategy was later integrated to automatically design efficient 1D-CNN models that satisfy the strict memory and latency constraints of the embedded processor.
- An upgraded, fully portable glove system is developed using off-the-shelf components. A battery-operated version of the glove is built, incorporating an embedded processor, onboard preprocessing, and an LCD interface. The system is designed for low-cost, real-time operation. Embedded ML models for shape, size, and stiffness recognition are implemented and evaluated. Classical machine learning and lightweight neural networks are deployed and compared directly on the embedded hardware. Performance metrics, including accuracy, latency, and resource usage, demonstrate that the proposed system achieves reliable on-edge classification within strict hardware constraints.

1.4 Thesis Outline

The structure of this thesis is as follows:

- **Chapter 2** provides an in-depth literature review, beginning with a survey of tactile sensing technologies and transduction mechanisms. It examines data-driven approaches for interpreting tactile signals, with particular emphasis on force estimation and object classification. Finally, the gaps found in the literature are addressed, which motivate our proposed methods.

- **Chapter 3** presents our initial study to investigate the response of piezoelectric tactile sensors, with a focus on their response to controlled indentation. The study explores the detection of fundamental tactile events such as contact onset, release, and variations in applied load, evaluating methods for event detection and force reconstruction. These findings provide a basis for understanding the suitability of our customized piezoelectric sensors for capturing low-level tactile information.
- **Chapter 4** introduces a machine learning framework for contact force estimation, using the dataset acquired in the previous study. The chapter specifically covers the framework, architecture, and learning algorithm used. Time features were extracted from the PVDF response and then selected based on the most informative features through PCA Biplot. A shallow neural network was trained and tested on the extracted features, with performance assessed with different evaluation matrices. Finally, discussions and conclusions are added to highlight the future steps.
- **Chapter 5** introduces the modeling of the sensing system, aiming to generate simulation data to train the network in the previous study. The chapter describes the experimental setup, interface electronics, and circuit designs used. Then it presents results that highlight the electromechanical characteristics of piezoelectric sensors along with the response function to indentation over the full bandwidth. The chapter ends with a discussion and recommendations for future work.
- **Chapter 6** presents an end-to-end solution for object recognition by detailing the design and development of a multisensory wearable glove endowed with embedded machine learning. The system is equipped with tactile and motion sensing units; the glove is used to collect data from everyday objects, and embedded machine learning algorithms are implemented for real-time object recognition. The chapter reports classification results and evaluates on-device performance, demonstrating the potential of the wearable multisensory system.
- **Chapter 7** presents the enhancement of the glove developed in the previous study. The updated glove is developed using off-the-shelf components to enable recognition of higher-level object properties such as shape, size, and stiffness. The glove is also integrated with a battery and LCD screen to provide a battery-operated system in real time. The chapter provides an evaluation of classification performance alongside resource efficiency, concluding with a discussion of findings and future directions.

- **Chapter 8** concludes this thesis, summarizes the major contributions, and presents possible research directions for further investigation.

CHAPTER 2

Literature Review

Drawing inspiration from the complexity of the human skin, artificial tactile sensing systems have been developed to replicate some of its physiological functions through advanced materials, innovative transduction mechanisms, and processing methods [48, 49, 50]. While biomimicry offers significant inspiration, it is often approached through practical simplification, allowing for reduced complexity in design and control to exactly replicate the appearance or dexterity of the human hand. As noted in [19], simplifying this process makes it possible to build systems that are both feasible and effective.

Research in this field has mainly developed in two directions. The first concerns sensor materials and transduction mechanisms that mimic mechanoreceptor responses, operating over a wide frequency range up to around 1 kHz [51]. Recently, increasing attention has been directed toward soft tactile sensors, devices fabricated from thin, flexible, and stretchable materials. These soft sensors represent an emerging class of technologies [52] that hold great potential for endowing robotic systems with the mechanical conformability of the natural human tissue. The second concerns algorithms for tactile data interpretation, where signal processing and machine learning methods are applied to extract meaningful information from raw sensor outputs, supporting tasks such as force estimation, texture classification, or object recognition [53, 54, 55, 56]. These two research directions underscore the importance of balancing sensing accuracy with computational efficiency, especially in resource-constrained embedded systems.

In this context, the goal of this chapter is to offer an overview of the advancements in tactile sensing systems and tactile data processing methods, and their applications. The chapter will conclude with a discussion highlighting current limitations, which have driven the direction of our research.

2.1 Sensing Systems

Several reviews have been published on tactile sensors, focusing on artificial skin design strategies and transduction mechanisms [57, 58, 59, 60]

Tactile sensors can be broadly categorized based on the transduction principle they utilize. Some of the most common types of tactile sensors include [61, 62, 63]:

- **Piezoelectric sensors:** Piezoelectric sensors exploit the direct piezoelectric effect, generating charge in response to mechanical stress [64]. They are highly sensitive and have an excellent frequency response, allowing them to capture fast, dynamic tactile events such as vibrations or slips. Their inherent flexibility enables integration into soft and conformable substrates, making them suitable for wearable systems and robotic skins. Various piezoelectric materials can be used for constructing piezoelectric tactile sensors. Piezoelectric tactile sensors frequently use polyvinylidene fluoride (PVDF) layers embedded into a rubber cover as they provide chemical stability [65], mechanical flexibility, high piezoelectric coefficients, formability into very thin sheets (5 μm), and a relatively low price. Another promising piezoelectric material is zinc oxide (ZnO) nanotransducer because of its high flexibility and biocompatibility [66, 67]. ZnO is proposed to be a good candidate material for a pressure and temperature sensor to be applied to prosthetic limbs. Despite these advantages, piezoelectric sensors are less effective than piezoresistive sensors at detecting static or slowly varying forces because their signal decays under constant loading. Their bandwidth can also be limited depending on the material used, and charge leakage over time reduces accuracy for long-duration contacts.
- **Piezoresistive sensors:** Piezoresistive sensors measure force through changes in electrical resistance of a material when mechanical stress is applied [68]. They are attractive for their low fabrication cost, simple readout circuitry, and compatibility with flexible substrates. These sensors are particularly suitable in applications where affordability and compact integration are priorities. However, they generally provide lower sensitivity than capacitive or piezoelectric sensors and suffer from large hysteresis [69], meaning the sensor's output may not immediately return to its original state after a change in pressure or force, which can cause inaccuracies in measurements. Their low-frequency response also makes them less suitable for detecting rapid or transient tactile events. Additionally, their long-term durability is limited due to material fatigue [70].

- **Capacitive sensors:** Capacitive tactile sensors measure changes in capacitance between conductive plates as they deform under applied force [71, 72]. They are widely used due to their high sensitivity [73], capability to detect both normal and tangential forces, and long-term stability. In addition, they exhibit fast response time and can detect subtle pressure variations across a wide frequency range. Their scalability and ease of miniaturization make them attractive for large-area tactile skins. Capacitive sensors have been deployed for multi-axis force measurement for gripping and object manipulation [74], texture recognition [75], shear sensing [59], and touch screen applications [76], etc. Another capacitive tactile sensor was presented for gripping force measurement with a sensor range of 0-3000 mN [77]. However, their performance can be affected by hysteresis and stray capacitance, often requiring complex electronic circuits for compensation. They are also prone to electromagnetic noise and can be expensive to implement at high resolutions.
- **Optical Sensors:** Optical tactile sensors detect variations in light intensity or transmission caused by deformation of optical paths under applied force. Typically, photo detectors measure the light intensity generated by an array of light transmitters, for example, LEDs, which is proportional to the magnitude of the pressure applied [78]. Moreover, some optical sensor designs are sensitive to shear forces [79] and multi-degree-of-freedom forces [80]. They offer extremely high sensitivity and immunity to electromagnetic interference [59], making them robust in noisy environments. They can also achieve a wide dynamic range, detecting both small and large forces. Nevertheless, their main limitations stem from their relatively large size and structural complexity, which hinder integration into compact wearable devices. Power consumption [49] and alignment stability can also pose challenges for long-term or portable applications.
- **Triboelectric Sensors:** Triboelectric tactile sensors convert mechanical energy into electricity through contact electrification and electrostatic induction between two dissimilar materials. They have been explored in several modes—single-electrode, sliding, vertical contact-separation, and independent-layer configurations [81, 82]. Their advantages include low cost, high sensitivity to dynamic interactions, and suitability for flexible substrates [83]. They are particularly useful in detecting tapping, sliding, or vibration, where repeated contact cycles regenerate charges [84]. However, their performance strongly depends on surface properties, and material wear can degrade reliability with prolonged use. Furthermore, they are less effec-

tive for static force detection and can suffer from variability due to environmental conditions such as humidity [85].

Among the sensors listed in this paragraph, piezoelectric sensors feature high sensitivity, wide frequency bandwidth, and accuracy; however, their high cost limits their usage. Piezoresistive sensors offer good spatial resolution at a low cost, but they are subject to hysteresis and temperature sensitivity. Capacitive sensors stand out for their high spatial resolution and sensitivity, but they have disadvantages such as hysteresis and crosstalk. Optical sensors provide rapid response speed, high spatial resolution, and immunity to electromagnetic interference, but like piezoresistive sensors, they are also sensitive to temperature, which might affect the relevant information. Finally, Triboelectric sensors have the advantage of low cost and efficiency, but they have limited precision, making them more suitable for dynamic measurements. Table 2.1 outlines the advantages and disadvantages of each type of sensor discussed herein. In addition to these common sensor types, several other types of tactile sensors have been developed, such as ultrasonic sensors, Hall effect sensors, and microwave-based sensors [86].

In conclusion, the selection of a sensing transduction technology for e-skin development depends strongly on the requirements of the target application and should consider a trade-off between the advantages of each sensor type against their limitations to achieve optimal performance. However, while this overview presents general sensor characteristics, it is essential to relate these observations to the sensing technology primarily employed in this thesis. The tactile sensing system is based on PVDF piezoelectric films, which provide an effective compromise between dynamic response, sensitivity, flexibility, and mechanical robustness. PVDF-based tactile sensors are widely used for dynamic tactile applications; for example, [87] demonstrated high-bandwidth texture discrimination using PVDF fingertips, and [88] reviewed PVDF films for contact-force and slip detection. These studies highlight that PVDF reliably captures dynamic mechanical events that are challenging for quasi-static technologies such as capacitive or resistive sensors.

Although each sensing technology provides capabilities, the integration of multiple sensing mechanisms, combined with real-time processing, is necessary for e-skin to function effectively in dynamic environments.

Table 2.1: Comparison between Sensing materials and technologies.

Tactile Sensors	Advantages	Disadvantages
Piezoelectric Sensors	- High sensitivity - High accuracy - Wide range of frequencies - Wide dynamic range	- High cost - Circuit complexity - Not suitable for static measurements
Piezoresistive Sensors	- High spatial resolution - High robustness - Low cost - Simple design	- Hysteresis - Energy consumption - Temperature sensitivity - Low sensitivity - Low spatial resolution
Capacitive Sensors	- High spatial resolution - High sensitivity - Wide dynamic range - Temperature independent	- Hysteresis - Crosstalk - Sensitivity to noise - Parasitic effects
Optical Sensors	- High spatial resolutions - Fast response speed - Wide detection range - Good reliability	- Dimensions - Temperature sensitivity - High cost
Triboelectric Sensors	- Low cost - High-performance capabilities - Simple design - Self-sufficient	- Sensitivity to wear - Limited precision - Only detect dynamic forces

2.2 Tactile Data Processing

Signal conditioning constitutes the first stage in processing tactile sensor data, as raw outputs often contain noise, distortions, or irrelevant information. The objective of signal conditioning is to transform sensor outputs into a form suitable for subsequent analysis and interpretation by algorithms [89]. This process typically begins with amplification, where low sensor responses, such as small variations in resistance or capacitance, are amplified

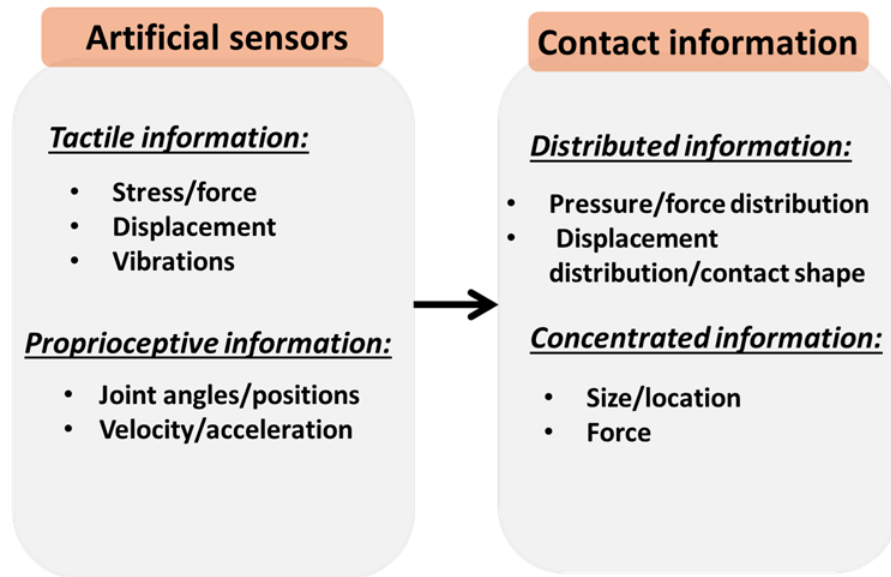


Figure 2.1: Flowchart Illustrating Information Flow from Sensor Measurements to Contact-Level Representations [1].

to levels appropriate for processing. Filtering is then usually applied to remove noise and interference, ensuring that the remaining signals accurately represent relevant tactile information. After filtering, analog-to-digital conversion (ADC) may be performed to translate continuous analog signals into discrete digital values, enabling reliable computational analysis.

Following signal conditioning, sensory data are rarely used in raw form, as they usually require preprocessing to extract meaningful features for further analysis. The flow of information in artificial tactile sensing systems, showing the transformation from raw tactile signals to contact-level representations, is summarized in Figure 2.1. Proprioceptive and tactile information, such as stress, displacement, and vibrations, is directly measured by the artificial transducers. The data can then be processed in two main ways. Distributed information refers to capturing spatial details, or reconstructing pressure maps, force distributions, or displacement distributions. Concentrated information is represented in a synthetic form through a single value targeting specific features such as the contact size, location, or force magnitude, offering a simpler but less detailed representation of the contact.

Building on the previous steps, the processed signals can be used to derive higher-level information. The full pipeline from sensory input to haptic representation is illustrated in Figure 2.2. Haptic representation involves reconstructing object properties such as

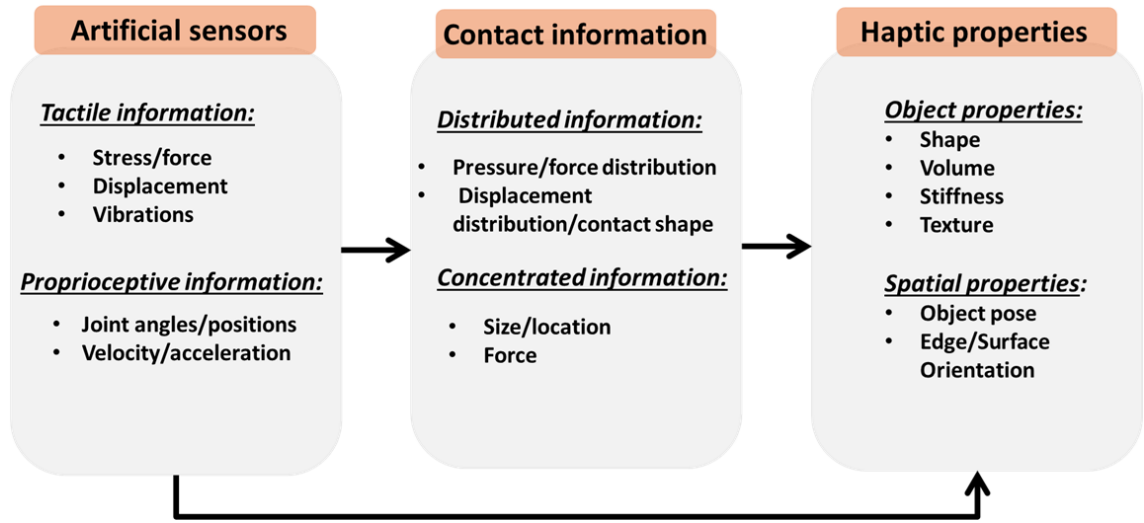


Figure 2.2: Flowchart illustrating the transformation of sensory input into contact information and haptic representation through data processing [1].

shape, stiffness, volume, or texture, along with spatial attributes like edges and surface orientation. Depending on the application, this stage may rely on either distributed or concentrated sensing data. The pathway from artificial sensing to higher-level representations can be approached in two ways. In sequential processing, low-level contact information is first extracted, such as the distribution of forces or displacements [90], before being transformed into higher-level haptic representations. Alternatively, higher-level properties can be inferred directly from raw sensor data using machine learning techniques, thereby bypassing intermediate steps. Neural networks, for example, have been applied to infer object properties such as texture [91, 92] and stiffness [93] from tactile data, offering increased processing efficiency compared to traditional feature-extraction methods and enabling more advanced functionality by handling complex tactile data, facilitating applications like adaptive manipulation.

Among the various types of contact information and haptic representations that can be derived from the output signals of artificial tactile sensing systems, this thesis specifically focuses on the reconstruction of the contact force and of some specific object properties, i.e., shape, size, and stiffness.

Regarding force reconstruction, data-driven algorithms were used to investigate the output signals from a tactile sensing system, with particular attention to the constraints imposed by embedded electronics.

Object properties recognition was addressed through the development of a battery-operated multisensory glove, integrating embedded machine learning to process time-series data in real time. The design emphasized low-cost hardware implementation while maintaining reliable performance in shape, size, and stiffness recognition tasks.

2.2.1 Force Reconstruction

The reconstruction of contact forces is a crucial requirement for effective object manipulation [94]. However, the signals produced by artificial tactile sensors do not directly encode the full force acting on the contact surface. Instead, they provide transduced responses, such as charge variation in piezoelectric films, resistance changes in piezoresistive elements, or capacitance variation in capacitive sensors that capture only certain aspects of the interaction. High-bandwidth sensors, such as optical, piezoelectric, and triboelectric devices, are well-suited for detecting dynamic forces but are unable to reliably represent forces that are static or slowly varying in time. In the case of dynamic sensors, these raw outputs require dedicated processing techniques to extract force-related components before they can be meaningfully interpreted. Conversely, capacitive and piezoresistive sensors can capture static forces but often suffer from limited bandwidth, hysteresis, or drift, reducing their effectiveness in dynamic scenarios. To address these limitations, artificial intelligence methods can be employed to reconstruct static or quasi-static force components from the outputs of sensors, thereby extending their applicability in practical manipulation tasks.

Several state-of-the-art approaches have leveraged AI to extract contact force information. In [95], a machine learning-based approach was proposed to estimate both the contact force and location from a tactile sensing system driven by biomimetic soft skin. This system incorporates photonic fiber Bragg grating transducers that emulate the functionality of human Ruffini mechanoreceptors, all embedded within a flexible polymeric matrix. An FEM of the sensor was built and validated. A deep learning algorithm utilizing a shallow neural network trained on FEM simulated data interprets the outputs from these sensors, enabling the experimental estimation of both the magnitude and localization of contact forces on the skin's surface. The results demonstrated the effectiveness of the methodology, achieving correlation coefficients of $R = 0.97$ for the magnitude of the normal load and $R = 0.99$ for location. Building on this, [96] introduced a bio-inspired large-area tactile-sensitive skin designed for safe human–robot interaction. The system consisted of a soft polymeric matrix embedding fibre Bragg grating (FBG) transducers, mimicking the

diffuse and overlapping receptive fields of Ruffini mechanoreceptors. A CNN was used to reconstruct the force magnitude, while a multigrid neuron integration process decoded the contact localization. Extensive testing on curved robot forearm surfaces demonstrated robust performance, with median errors of 35 mN for force prediction and 3.2 mm for localization. In another approach, [97] employed machine learning algorithms to reconstruct contact position, contact force, and contact diameter from their Electrical Resistance Tomography (ERT) based tactile sensor. The methodology integrates two deep neural networks: Transfer-Net, a network with multiple fully connected layers that mitigates the gap between simulation and reality, and Recon-Nets, a deconvolutional network that reconstructs contact forces from voltage measurements. The proposed pipeline achieved an average error of 74.4 mm in contact position (approximately 13% of the sensor width), a 17.2% error in force estimation, and a 9.3% error in contact diameter prediction. Authors in [98] proposed a tactile sensor based on chirped fiber Bragg gratings (CFBGs) assisted with a convolution neural network to extract force magnitude and position in the 2-D area of the conformable contact surface. The results showed that the prediction accuracy of the force was $\approx 99.925\%$ with a test root-mean-square error (RMSE) of ≈ 0.08 N and an RMSE of ≈ 0.01 cm for extracting 2-D force position. Force reconstruction for soft continuum manipulators was addressed in [99], where capacitive e-skins were combined with deep learning. Their approach addressed the challenge of distinguishing contact-induced forces from self-deformation signals inherent to soft robots. The system achieved force prediction accuracy of 99.9% and a mean localization error of 2.9 mm, demonstrating reliable contact force estimation even under significant structural deformation. Likewise, [100] proposed a soft optical fiber tactile sensing pad for simultaneous reconstruction of contact position and force magnitude. The system consisted of a single Mach–Zehnder interferometer (MZI) optical fiber embedded in a PDMS matrix, with spectral outputs processed by a random forest algorithm. The sensor achieved over 98% accuracy in contact localization across 81 positions and 100% accuracy in force classification within 0.1–0.5 N at 0.1 N resolution. For fine-scale force recognition between 0.11–0.15 N at 0.01 N resolution, the accuracy remained above 98%. More recently, [101] proposed a machine-learning framework for tactile sensor-based estimation of grasp force and contact state with soft fingers. The system consisted of two pneumatic PneuNet fingers, each embedding twelve dielectric elastomer pressure sensors and one dielectric elastomer strain sensor. Capacitance signals were sampled at 100 Hz and processed using a GRU network trained on data from a force/torque sensor. The method achieved a 16% error in total force

estimation under single contact patch conditions, with normal forces showing the highest accuracy.

2.2.2 Object Properties Recognition

Humans recognize objects through touch, a process that relies on the brain's interpretation of sensory input. This ability is fundamental for daily living and working and requires two capacities: first, the acquisition of data from objects through physical contact, and second, the cognitive ability to process and interpret this information [102].

To replicate this capability artificially, it is essential to design sensing systems that can capture multiple physical quantities and process tactile information in real time [103]. A key outcome of such systems is object recognition, which represents a critical haptic function [104]. Although several approaches have been proposed to address this challenge [105], many rely primarily on visual sensing capabilities [106]. Vision-based methods, however, face limitations when dealing with transparent or reflective objects and are inherently unable to capture intrinsic material properties such as stiffness, hardness, and texture.

Tactile sensors, by contrast, overcome these limitations by acquiring information through direct physical interaction with objects. Their relatively low data dimensionality compared to visual sensors also makes them particularly suitable for real-time processing in embedded systems [107]. Leveraging advances in tactile sensing technologies and machine learning, a variety of wearable glove prototypes have recently been developed to support object recognition tasks.

In [43], a wearable glove was introduced featuring 548 piezoresistive sensors arranged in a dense matrix for object recognition, weight estimation, and tactile pattern analysis while grasping 26 objects. The sensor data were transformed into image representations and processed with a convolutional neural network (CNN). While high classification accuracy was achieved, the massive volume of data generated by the dense sensor array imposes difficulty for real-time, low-cost computation, resulting in significant power consumption. Similarly, in [108], a wearable glove equipped with a multimodal array of piezoresistive and thermal sensors was developed to classify 20 objects. Analog signals were converted into distributed pressure and thermal images, which were subsequently processed using CNNs. The system achieved a classification accuracy of 94.2%, but the bottleneck of converting time-series signals into image-based representations still persists. In [109], the authors proposed a glove incorporating five resistive flex sensors mounted on the fingers.

Data collected during the grasping of three object shapes, sphere, cuboid, and cylinder, were classified using a support vector machine (SVM), achieving an accuracy of 91.88%. However, neither inference time nor power consumption was reported, limiting insights into its real-time applicability. A different approach was presented in [110], where a glove with force and bending sensors was used to collect a dataset of interactions with kitchen objects. Multiple machine learning models, including K-Nearest Neighbors (KNN), Decision Trees (CART), AdaBoost (AB), Random Forest (RF), and a hybrid CNN-LSTM architecture, were evaluated. Random Forest achieved the highest reported accuracy of 97%. Nevertheless, the study did not include a hardware evaluation to demonstrate real-time recognition feasibility. Despite promising results, the bulky form factor of many glove systems or their high power consumption remains a critical challenge for portable and continuous use. In [111], a tactile glove based on a flexible capacitive pressure sensor array fabricated with interdigital electrodes and a porous $BaTiO_3$ PU dielectric layer was introduced. The glove integrated 137 sensing units distributed across the hand to capture high-resolution pressure map images during grasping. Using an improved CNN architecture with multibranch fusion and channel attention mechanisms, the system achieved recognition of nine differently shaped objects with an accuracy of 95.14%. However, the reliance on image conversion as input poses challenges for embedded, real-time implementation. More recently, in [112], a haptic glove integrating flexible piezoresistive sensors made of graphene and polyurethane sponge was proposed. The glove was designed to identify object shapes and textures using machine learning methods. Specifically, the authors developed a distributed sensor network embedded into the glove to capture both pressure distribution and deformation patterns during interaction with objects. The signals were processed using multiple learning algorithms, including SVM, RF, and KNN, ResNet, LeNet, and LSTM classifiers, to compare performance across tasks such as object shape classification and texture recognition. The system achieved robust recognition accuracy above 95% using ResNet-18 while preserving flexibility, breathability, and durability due to the sponge–graphene composite. However, no evaluation of real-time latency or energy efficiency was reported, leaving uncertainty about its scalability for portable, embedded applications.

2.3 On-Edge Tactile Data Processing

Embedding machine learning (ML) in resource-limited and battery-powered tactile sensing systems necessitates meeting stringent constraints, including minimal hardware area, low inference latency, and reduced energy consumption. The efficiency of such embedded solutions is mainly determined by (i) the computational complexity of the algorithms and (ii) the capabilities of the hardware platform on which they are deployed [113, 114].

Several studies have addressed these challenges by tailoring deep learning and classical ML methods to embedded or edge platforms for tactile applications. To name a few, authors [115] presented a smart tactile sensing system based on an embedded CNN for 22-class object recognition on a robot. Their approach optimized input data size across three resolutions and evaluated inference time and energy efficiency across multiple GPU- and CPU-enabled edge devices. In contrast, authors [116] implemented a lightweight CNN on a Cortex-M microcontroller for classifying touch modalities on an electronic skin. Through layer fusion and buffer reuse, the optimized CNN achieved real-time performance with lower energy consumption, outperforming conventional ML methods.

Beyond CNNs, classical ML approaches have also been widely explored for edge tactile sensing. Authors in [117] proposed a low-cost Arduino-based platform for real-time, highly accurate texture classification using a RF classifier across 12 texture classes. To enable efficient deployment, they introduced a memory-efficient feature extraction strategy that outperformed Fourier-based methods in speed and power consumption. Similarly, in [118], multiple algorithms, including SVM with tensorial kernels, kNN [119], and CNNs [120] were compared for touch modality classification, highlighting trade-offs between accuracy, complexity, and computational feasibility.

Hardware accelerators have also been investigated for tactile data processing at the edge. Authors in [121] proposed an FPGA-based SVM accelerator on Virtex-7 capable of classifying input touch modalities of size $4 \times 4 \times 20$ within 250 ms while consuming only 285 mJ. A k-NN accelerator on the Zynqberry platform achieved classification of 4×4 touch inputs within 26 μ s at 236 mW [122]. More recently, authors in [123] deployed a 1D-CNN on the Arduino Nano BLE 33, performing real-time classification of $4 \times 4 \times 100$ tactile inputs in 26 ms (float) and 128 ms (int8 quantized).

Recent reviews [124, 125] underline that efficient edge tactile data processing requires co-optimization of algorithms, hardware platforms, and energy-aware design strategies. With the rise of TinyML [126], model compression, quantization, and hardware-software

co-design have become essential to enable real-time, low-power tactile perception in robotics, prosthetics, and human–machine interfaces.

2.4 Discussion and Conclusion

This chapter offers a literature review of tactile sensing technologies and their significant progress in mimicking aspects of human touch. Multiple transduction mechanisms have been explored, each offering distinct advantages: capacitive sensors provide high sensitivity and spatial resolution, piezoelectric and triboelectric sensors excel in capturing dynamic response, while piezoresistive and optical sensors offer simplicity or robustness in specific scenarios. In addition, relevant processing techniques for force reconstruction and object recognition were reviewed, with particular attention to wearable glove systems in the context of object recognition.

At the processing level, considerable advances have been made through machine learning methods, enabling the extraction of high-level tactile information directly from raw sensor output. Both physics-based modeling and data-driven approaches have contributed significantly to advancing this research field. Mechanical modeling provides physical interpretability and can simulate conditions difficult to reproduce experimentally, while machine learning offers flexibility in handling complex, nonlinear data. Recent studies indicate that combining simulation data from physical models with learning-based methods can outperform each approach in isolation, yielding more accurate and robust force estimation. This highlights the importance of integrating physical modeling with machine learning algorithms to fully exploit their complementary strengths.

Despite this progress, important limitations remain. Many existing approaches are tailored for high-end computational platforms, often ignoring the constraints of embedded systems, including limited power budgets, memory capacity, and real-time operation requirements. Furthermore, large-scale sensor arrays, while capable of generating rich data, also produce high-dimensional signals that increase computational complexity and hinder energy-efficient deployment.

At the application level, wearable glove prototypes have demonstrated promising recognition accuracy, yet they often rely on dense sensor arrays, computationally expensive processing pipelines, or bulky hardware, factors that limit their suitability for portable and continuous use. In addition to the lack of end-to-end systems where the learning

algorithms are deployed in edge devices, particularly resource-constrained devices such as microcontrollers.

Moreover, while high-bandwidth dynamic sensors such as piezoelectric devices cover the tactile frequency spectrum of human skin (up to 1 kHz) and provide versatility across applications, they do not directly deliver a complete representation of the force field. Dedicated processing is required to reconstruct static or quasi-static force components from their outputs, highlighting the need for advanced algorithms that can compensate for these limitations.

Driven by all of these, this thesis will focus on 1) investigating how dynamic PVDF/P(VDF-TrFE) sensors encode force information and developing lightweight processing and machine-learning methods capable of estimating contact forces on resource-constrained embedded hardware. 2) Designing an end-to-end system based on a multi-sensory wearable glove, low-cost, integrated with embedded machine learning and optimization pipeline for real-time recognition of object properties such as shape, size, and stiffness. Together, these two directions aim to bridge the gap between advanced tactile sensing capabilities and the practical constraints of embedded and wearable systems.

CHAPTER 3

Reconstruction of the normal indentation force

This chapter presents an initial study on extracting force information from our sensing system based on PVDF piezoelectric materials. The objective was to validate the potential of the PVDF-based sensing system for force detection. To this end, the system was subjected to an indentation action using a Cartesian robot. The chapter describes the data collection process, the applied processing algorithms, and the preliminary results.

3.1 Introduction

Extensive research has been devoted to developing tactile sensors based on piezoelectric polymers [127] due to their interesting features. They exhibit high sensitivity, fast dynamic response, and a large operating frequency range (up to 1 KHz) covering the whole frequency bandwidth of the human skin [51], except for measuring slowly varying stimuli. Those materials proved to be good candidates for flexible tactile sensors, suitable for dynamic tactile sensing and to be integrated into artificial electronic skins[128, 129, 88].

Among the piezoelectric polymers, polyvinylidene fluoride (PVDF) and its trifluoroethylene copolymer (P(VDF-TrFE)), are particularly attractive due to their exceptional sensitivity, flexibility, and stable piezoelectric, pyroelectric, and ferroelectric properties. The advantages of P(VDF-TrFE) as a tactile sensing material were first discussed in [130], while [131] demonstrated fully screen-printed tactile P(VDF-TrFE) sensor arrays for robotic applications. In [132], the strain sensitivity of PVDF arrays on flexible substrates was experimentally validated, and [133] explored multimodal sensing capabilities using P(VDF-TrFE)-gated OFETs for simultaneous pressure and temperature detection. Nevertheless, cross-sensitivity between temperature and pressure in ferroelectric materials (including PVDF) can pose challenges; thus, separating the piezoelectric and pyroelectric effects is often advantageous [134].

PVDF is a semi-crystalline polymer synthesized via the polymerization of the $\text{H}_2\text{C}=\text{CF}_2$ monomer. Its copolymer, poly(vinylidene fluoride–trifluoroethylene) or P(VDF-TrFE), is ferroelectric and does not require mechanical stretching of its molecular chains along a transverse axis, which simplifies fabrication. Several fabrication techniques have been reported for P(VDF-TrFE)-based sensors, including spin coating, electrospinning, sol-gel processing, chemical vapor deposition, micromold transfer, and inkjet printing [135]. However, common methods such as spin coating and inkjet printing face challenges in process speed and alignment accuracy in multilayer structures. Although inkjet printing offers high lateral resolution, patterning large areas often demands repeated droplet deposition, resulting in nonuniform layer thickness and edge irregularities. Moreover, patterning after spin coating typically requires photolithography, increasing fabrication complexity. By contrast, screen printing offers a more cost-effective and scalable approach for fabricating large-area sensors, making it a promising alternative [88].

Piezoelectric polymers generate electrical signals in response to applied stresses. Electrical signals produced in the form of output voltages have been analyzed to evaluate the sensing performance [136]. However, most of the existing research has focused on the sensor fabrication side [137, 138, 139]. Nevertheless, what is important in real applications where sensor signals are expected to drive sensory feedback for motor control is to interpret the time response of the whole sensing system to extract contact information [140]. As a matter of fact, the transduction of the applied mechanical stimuli into electrical signals is the result of how the structural and functional (PVDF piezoelectric polymers, in this case) components of the sensing system are integrated into a very specific electromechanical sensing structure [141]. Only a few papers presented studies to interpret the electrical response of piezoelectric-based devices to mechanical stimuli. To give an example, in [142], the e-skin is composed of two polyimide films sandwiching a sensor array built of a single PVDF film with a few top electrodes and a common bottom electrode. Sensor signals are interpreted as a function of how the sliding motion over the e-skin surface affects the strain profiles over time, driving sensor outputs. In [90], contact force distributions are reconstructed from PVDF sensor signals, although the study is static.

To start addressing the difficult task of the reconstruction of time-varying contact forces from sensor outputs, in this chapter, we focus on a specific type of stimulus, i.e., indentation of the sensing structure with a soft indenter. This can be seen as a first step towards studying haptic interactions of sensorized soft fingers with objects. A Cartesian robot has been used to indent a single sensor at different combinations of normal forces

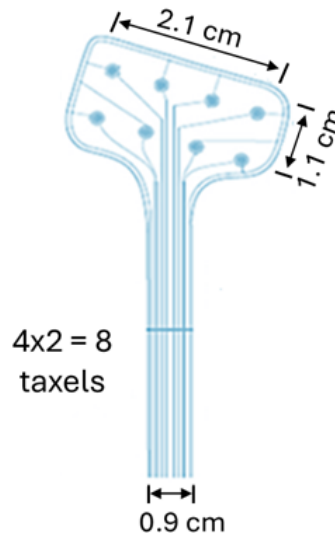


Figure 3.1: PVDF sensor array layout.

and speeds. We have implemented a method based on well-known signal processing techniques in the time domain to study the sensor output as a function of the applied normal load and its speed.

3.2 Materials

3.2.1 Tactile sensing system

The tactile sensing system utilized in this experiment was previously presented in [143]. It is composed of two parts: the piezoelectric sensing array (i.e., the electronic skin patch) and the Embedded Electronics (EE). The fully screen-printed, flexible sensor array comprises 8 taxels (Figure 3.1) fabricated using P(VDF-TrEE) poly(vinylidene fluoride-trifluoroethylene) piezoelectric polymer sensors, a copolymer well known for its strong piezoelectric coefficients, flexibility, and chemical stability. The sensors were shielded following the protocol described in [144].

The EE, previously detailed in [145], is based on a charge amplifier. Figure 3.2 shows the Printed Circuit Board (PCB) and the interface electronics design block diagram. The

The content of this chapter has been published in the following paper:

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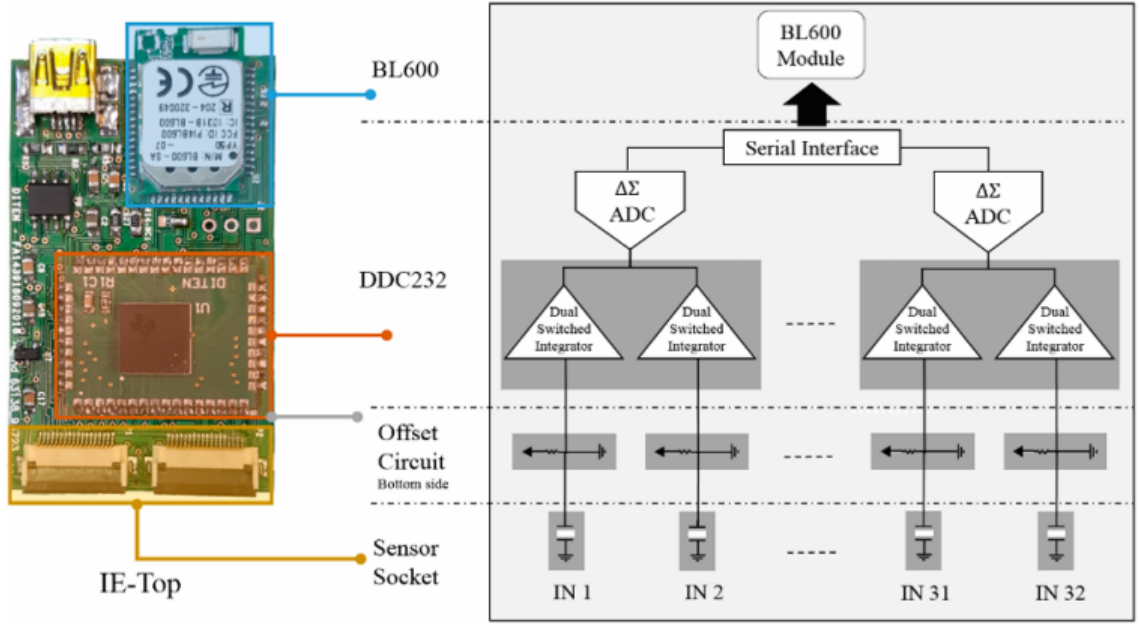


Figure 3.2: Interface Electronics For PVDF Signal Conditioning [2]

circuit incorporates two primary off-the-shelf components: the BL600 module (Laird Connectivity, US) for Bluetooth connectivity and the DDC232 [146] (Texas Instruments, US) current-input analog-to-digital converter. Additionally, the PCB is equipped with digital integrated circuits for power management (e.g., voltage regulator) and a USB interface for wired data transfer (e.g., FTDI232). The design supports up to 32 sensors via two sockets, each with 16 input channels. Both sockets are connected to an offset circuit to adjust the baseline of the bipolar signals generated by the sensors, enabling the DDC232 to process both positive and negative signal polarities. The DDC232 chip includes multiple current-to-voltage integrators and delta-sigma analog-to-digital converters. It is configured for 16-bit resolution and covers the maximum input charge response. The device architecture allows for simultaneous sampling of the 32 input channels with a configurable sampling rate of up to 6 kHz. Data acquired by the DDC232 is transmitted to the BL600 module via UART. The BL600 features an ultra-low-power microcontroller based on an ARM Cortex M0 chip, which reads, processes, and transmits the sensor data. The USB connection powers the PCB and provides a serial interface for data transfer across the system [144]. The interface electronics have been preliminarily validated in [2].

In this work, the EE was configured to collect and process tactile data from 8 sensors at 2 K samples/s. The 2 kHz sampling rate was used to capture the full bandwidth of the sensor working in thickness mode (up to 1 kHz), which is beneficial for detecting

discrete events corresponding to contact onset/release that are characterized by a steep increase/decrease in the sensor signal [145].

3.2.2 Experimental Setup & Protocol

The single skin patch, including 8 sensors, was tested using the experimental setup shown in Figure 3.3. The skin patch was coupled to a rigid plate for sensors working in thickness mode [51] and then fixed on a strain gauge load cell (Tedea Huntleigh, Model 1042), faced upside. To study the response of the sensing system in a controlled environment, a 3-axis Cartesian robot was used to perform a series of indentation actions on a single sensor through the z-axis. The z-axis is driven by a stepper motor and is controlled by modulating the z-coordinates and indentation speed. To modulate the load on the surface of the skin patch gradually, a 700 g weight was mounted on the z-axis and hung from a spring as shown in Figure 3.3. A soft spherical indenter with a radius of 1 mm fixed on the bottom of the weight (see Figure 3.3) was used to indent the surface of the skin patch in a position corresponding to the epicenter of a single sensor on the outer surface. The force stimulus was processed and conditioned using a DAQ (NI, US), while the PVDF sensor response was conditioned by the EE. Data acquisition, visualization, collection, and control of the Cartesian robot were implemented using a graphical user interface (GUI) developed with NI LabVIEW on a host PC.

The aim of this work is to study the sensor response to a change in the applied load (max 700 g) at different indentation speeds to characterize the overall viscoelastic behavior of the whole sensing system and set the basis to reconstruct time-varying normal contact forces from sensor outputs. Before each test, the experimenter adjusted the x-y coordinates of the Cartesian robot to align the indenter with the sensor. Therefore, a sequence of mechanical inputs was applied, and the electrical response of the stimulated sensor and the output of the reference load cell were measured continuously. The indentation procedure comprised the following steps: indent (initial load: 3.7 N), increase the load to a target value (target load), decrease the applied load, then release the indenter. The aforementioned sequence was repeated for 7 target loads (N) {4.5, 5.5, 6.5, 7.5, 8.5, 9.5, 10.5} each repeated at 7 indentation speeds (mm/s) {2.4, 3.2, 4.02, 4.8, 5.6, 6.4, 7.2} therefore generating a dataset composed of 49 combinations of target loads and indentation speeds. Figure 3.4.a shows an example of the indentation sequence at an indentation speed of 7.2 mm/s and a target load of 10.5 (N) and Figure 3.4.b shows the corresponding PVDF sensor response.

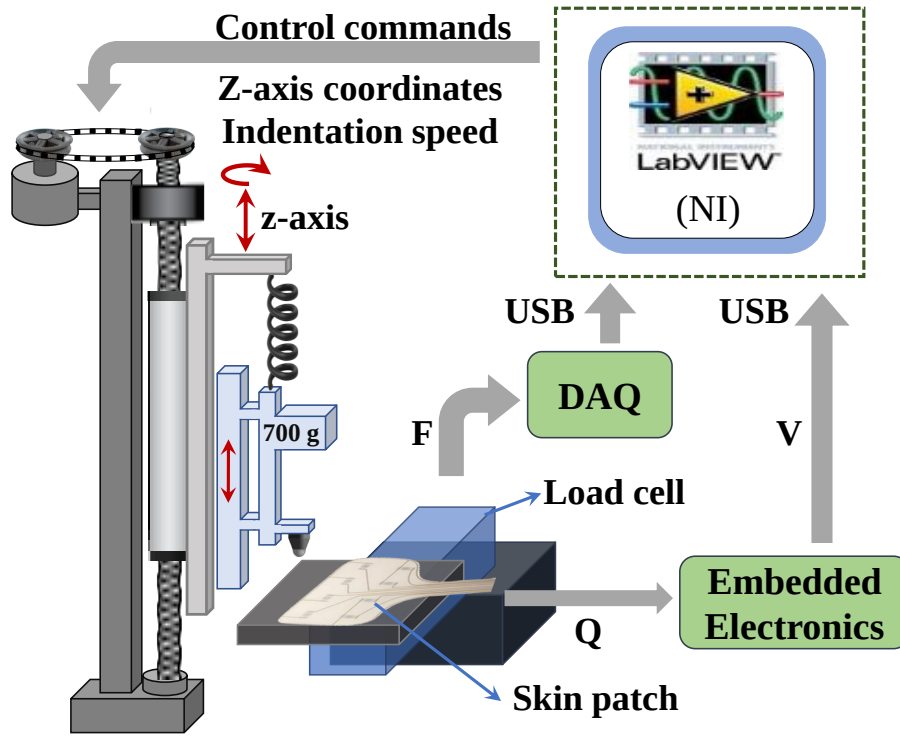


Figure 3.3: Block diagram of the experimental Setup.

3.3 Methodology

As mentioned, the experiment involves indenting on the surface of the skin patch with a soft indenter aligned with the axis of a single sensor at a certain combination of speed and target load. Each of the combinations was repeated for 10 trials. The analysis was performed by averaging the 10 trials for each of the aforementioned combinations. It should be noted that the load cell alone was first solicited by indentation in order to identify the frequency of spurious vibrations coming from the environment (172, 2 Hz), which was removed from the dataset using a notch filter implemented in MATLAB.

3.3.1 Event detection: Onset of contact and contact release

Due to their high cutoff frequency, the main potential of such PVDF sensors is to be capable of instantaneously detecting abrupt changes in contact forces, eg, discrete events like the "onset of contact or contact release" (OCCR). The goal of analyzing peaks in the sensor response (Figure 3.4.b.) is to determine how information about the applied load and speed is coded therein. On the contrary, slow changes in contact forces - as

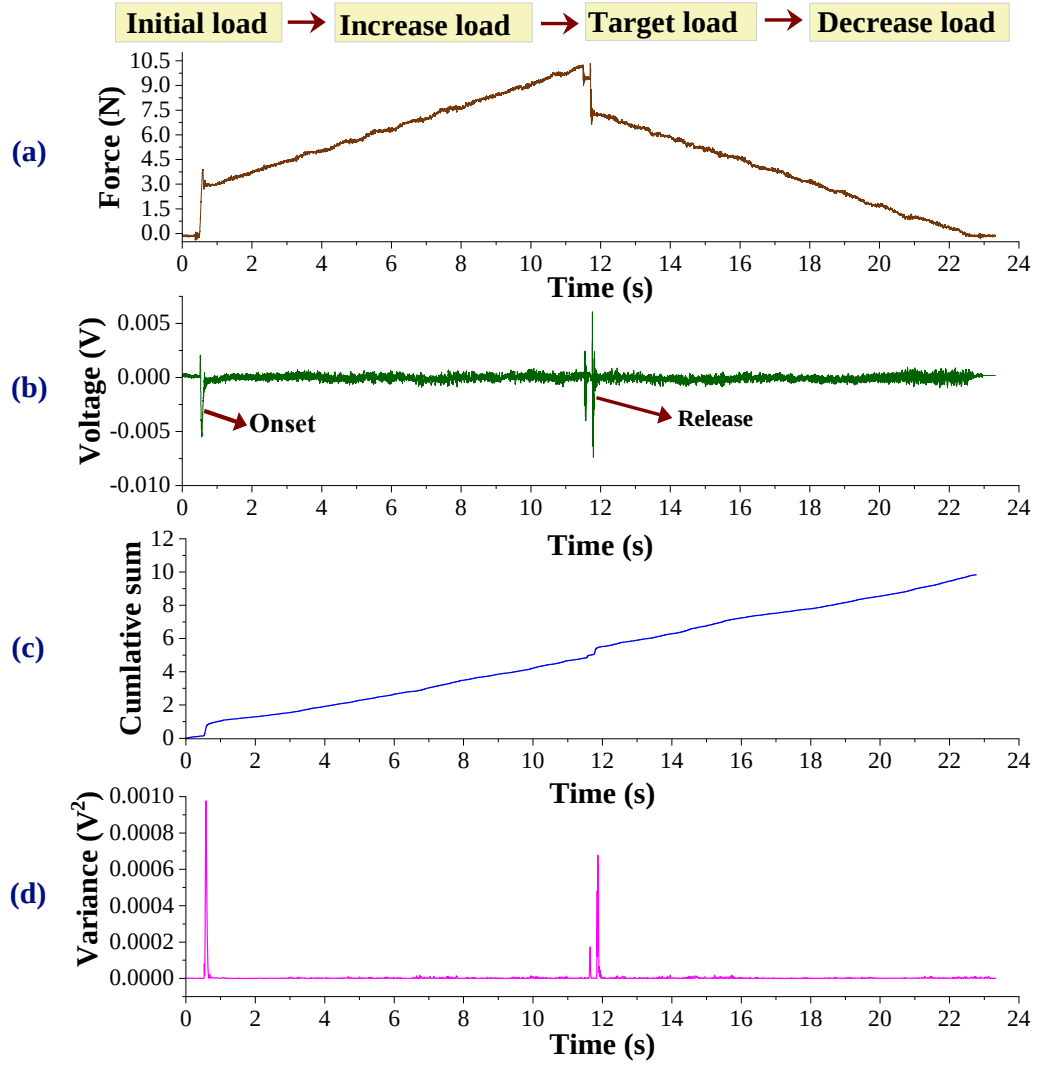


Figure 3.4: Response of (a) the reference load cell (input force) and (b) PVDF sensing system output to an indentation sequence at a target load of 10.5 *N* and indentation speed of 7.2 *mm/s*. (c) The absolute value cumulative sum of the PVDF signal. (d) The Variance of the Cumulative sum shown in (c).

in between the OCCR events - are not detected by PVDF sensors if they are associated with frequencies lower than their low cutoff frequency (around 0.5 Hz). Two quantities are used to automatically detect an OCCR event, to further retrieve information about the time behavior of the load on time scales where the sensors are not sensitive to contact information, i.e., in between the onset and release peaks. The first one is the cumulative

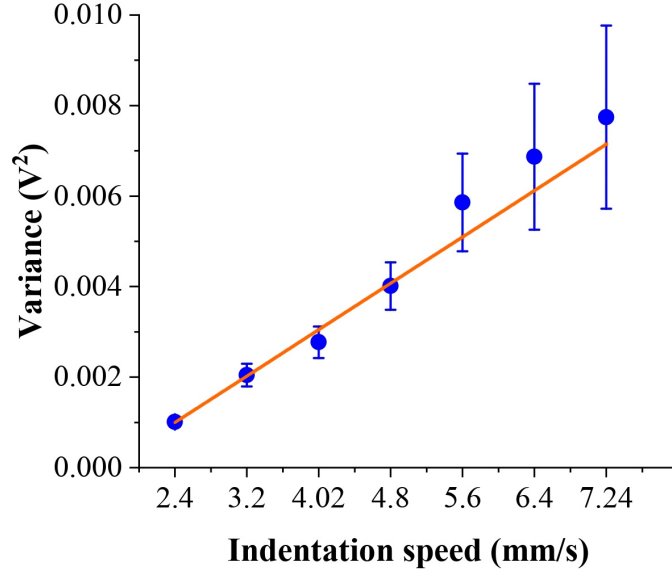


Figure 3.5: Variance of the Press event vs the indentation speed.

sum computed as in (3.1):

$$S_k = \sum_{i=0}^k |x_i| \quad (3.1)$$

where S_k is the cumulative sum, x_i is the i_{th} sample of the sensor signal. Steeper increases in S_k indicate abrupt changes in the signals corresponding to the OCCR events, as illustrated in Figure 3.4.

The second is the variance applied to the windowed cumulative sum and computed as in (3.2):

$$Var_j = \frac{1}{w} \sum_{i=(j-1)*w}^{j*w-1} (S_i - \mu_j)^2 \quad (3.2)$$

where w is the window size, $j = 1, 2, \dots, \frac{N}{w}$ is the index of the window and N is the number of samples in x , S_i is the i_{th} element of the cumulative sum and μ_j is the mean of the j_{th} window. This last quantity detects the steeper changes in the cumulative sum as depicted in Figure 3.4.d, allowing us to identify the OCCR events in the tactile sensor data and in the cumulative sum by a simple thresholding mechanism.

3.3.2 Load Analysis

In order to assess how the PVDF sensor response could be compared to the behavior of the load cell, a linear regression was applied on the increasing and decreasing phases of

the load cell response (Figure 3.4.a). and of the cumulative sum of the sensor response (Figure 3.4.c), located between the OCCR events extracted with the methodology described above. Since the cumulative sum was computed using the absolute values of the signals, the resulting slopes are positive. Therefore, we also considered the absolute values of the slopes for the decreasing behavior of the load cell signal. The resulting slopes were compared to assess if the load cell and sensors showed similar trends at different indentation speeds.

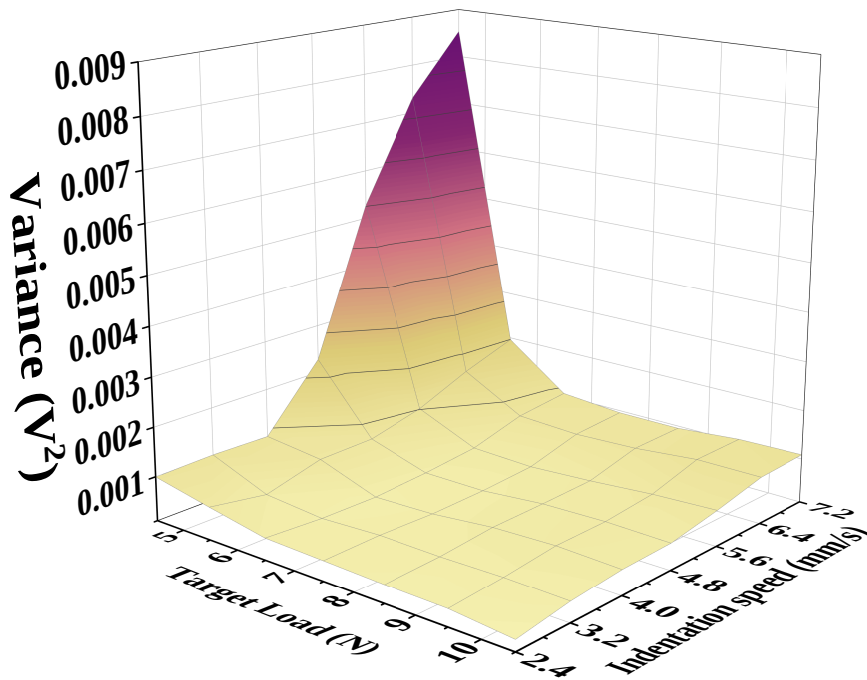


Figure 3.6: Variance of the release event vs target load and indentation speed.

3.4 Results and Discussion

The approach outlined in section 3.3.1 detects the OCCR events using the variance outcomes. The first analysis is based on evaluating the relationship between the indentation speed and the variance of the onset of the contact event. Figure 3.5 shows that an increase in the indentation speed results in a linear increase of the variance amplitude, leading also to an increase in the standard errors.

The second analysis examines the effect of the target load and indentation speed on the variances of peaks related to contact release. Figure 3.6 shows a 3D presentation of

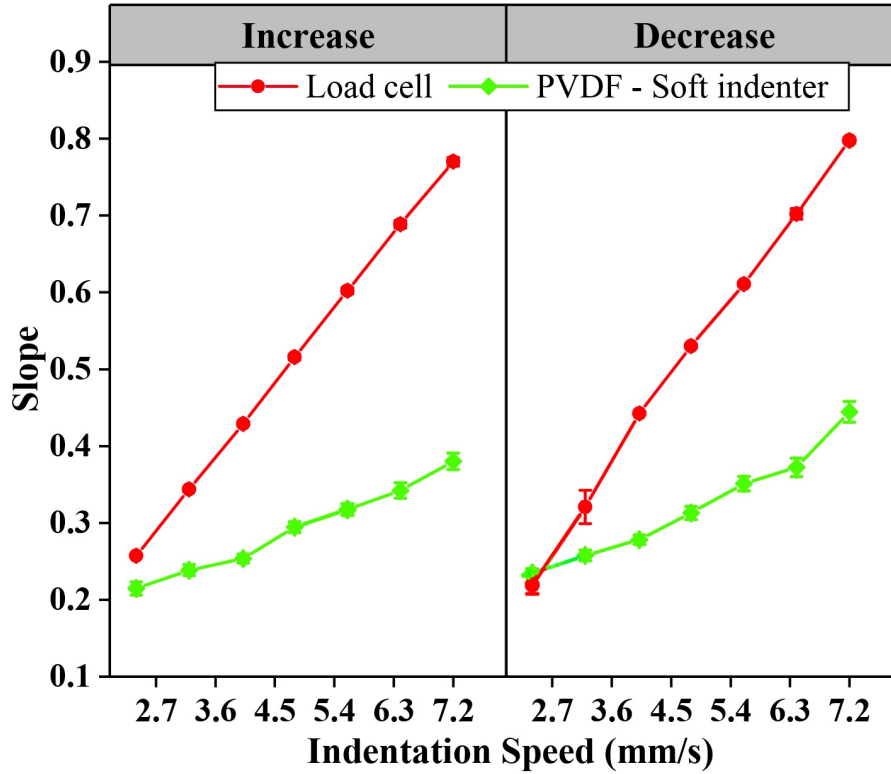


Figure 3.7: Slopes of Increase in load (Left) and decrease in load (Right) vs indentation speed.

the variance of the contact release event as a function of the indentation speed and target load. The 3D plot demonstrates that at a fixed target load, an increase in the indentation speed results in an increase in the variance. On the other side, the relation between the variance peak amplitude and the target load is non-linear and inversely proportional, i.e., at fixed indentation speed, an increase in the target load leads to a decrease in the variance amplitude.

The last analysis consists of assessing the similarity in the response of the load cell and the PVDF-based sensing system to a change in the applied load, as described in section Luc3.3.2. The results presented in Figure 3.7 show that the PVDF sensor and the load cell present a similar increasing behavior in the slope while the indentation speed is increasing.

3.5 Conclusions and Future Work

In this chapter, signal processing techniques were used to study sensor response to indentation stimuli at a variable indentation speed and load. Such preliminary results characterized

the response of the PVDF sensor to a change in the indentation speed and a change in the load, proving the ability of the sensor to detect such information. Moreover, the variance of the release event is an interesting feature towards reconstructing information on the time-varying normal force. Although more extensive experimentation is needed to reconstruct meaningful information from sensor data, our preliminary experiments and analysis can be considered as a first step towards extracting high-level time-varying tactile information from PVDF sensors (e.g. Force and slippage). Moreover, the work proposed in this chapter paves the way towards developing real-time processing techniques due to the simplicity of the employed algorithms to be implemented in the Embedded electronics of the sensing system.

CHAPTER 4

Machine Learning Based Contact Force Estimation Using a PVDF Tactile Sensing System

This chapter presents the development of a machine learning–based approach for estimating the maximum normal force from the data collected, following the validation of the sensing system’s capability to detect contact forces in chapter 3. The processing pipeline, learning algorithms, and experimental results were presented to validate the effectiveness of the proposed methodology.

4.1 Introduction

Touch plays a critical role in human interactions with the surrounding environment, encoding information about contact forces and haptic properties of the touched object (such as compliance, texture, and shape). Information is gathered from multiple receptors in the human skin, in particular in hands and fingers [147, 148]. Over the last decades, researchers have drawn inspiration from the properties of the human skin to mimic the sense of touch artificially, driving the development and advancement of electronic skins [8]. There has been a longstanding effort to develop algorithms to reconstruct various aspects of the mechanical contact on the skin surface. Contact forces, induced skin displacements, and the spread rate of contact area are key tactile cues for haptic perception through soft artificial skins [19]. However, despite significant research on sensors and tactile data processing, current technological solutions still fall short of human capabilities [21].

Typically, the overall sensing system is provided with a soft interface, which allows it to conform to touched objects, while mimicking the appearance of the human skin [149, 13]. Such a layer mediates the transmission of the applied load to the embedded transducers. The choice of the transducer material is pivotal in defining the potentiality

of the sensing systems to reconstruct contact information. Piezoelectric polymers, such as Polyvinylidene fluoride (PVDF) and its copolymers, have received a lot of interest. These materials possess outstanding characteristics, including high sensitivity, flexibility, and a broad frequency range that covers the entire bandwidth of human skin, except for measuring static information[51]. While such transducers are only sensitive to changes in the contact forces, it is possible to process sensor signals to retrieve the peak force in an indentation process. Indentation tests are often used as a simplified model to study localized contact mechanics, offering valuable insights into how soft materials respond to point loads. An indentation process can serve as a simplified model for more complex interactions, such as a multi-fingered grasp by an actuated artificial hand with tactile sensors embedded in the fingers. In such scenarios, while reconstructing the full temporal force profile is important for real-time control, the peak force value can be useful for establishing safe operating thresholds or for calibrating the actuator. However, interpreting the output signals of such sensors to extract peak contact forces can be quite challenging due to the complex mechanical structure in which these transducers are embedded. While the viscoelasticity of these specific transducers seems to be negligible [51], the soft outer layer is expected to exhibit viscoelastic behavior, meaning that stress transmission to the transducers might depend on the speed of the applied contact force. This renders model-based force reconstruction more complex.

To this end, the recent development of artificial intelligence (AI), particularly Deep Learning (DL), has significantly enhanced the ability of the sensing system to extract high-level tactile information that model-based data processing methods struggle to capture, thereby paving the way for data-driven approaches that bypass the need for a detailed understanding of the complex mechanical system. These AI-driven approaches might have the potential to provide predictions that mimic or even occasionally surpass human expertise [25].

4.2 Background

Recent studies have demonstrated the potential of artificial intelligence (AI) methods for extracting contact force information from tactile sensors of different modalities. For instance, Authors in [95] applied machine learning to a fiber Bragg grating (FBG)-based tactile system, achieving correlation coefficients of $R = 0.97$ for force magnitude and $R = 0.99$ for contact location. Authors in [97] employed deep learning with an Electrical

Resistance Tomography (ERT)-based sensor, combining Transfer-Net and Recon-Nets to reconstruct contact position, force, and diameter. Their approach achieved errors of 17.2% for force estimation and 9.3% for contact diameter. More recently, authors in [98] introduced a chirped FBG (CFBG)-based tactile sensor assisted by a convolutional neural network, obtaining force prediction accuracy of $\approx 99.93\%$ with a root-mean-square error (RMSE) of ≈ 0.08 N and a positional RMSE of ≈ 0.01 cm.

Inspired by these advances, this chapter explores a machine learning approach tailored to PVDF-TrFE-based tactile sensors, which combine high sensitivity, flexibility, and a broad dynamic range. Specifically, we address the challenge of extracting the peak (maximum) normal force during indentation, a key reference quantity for understanding contact mechanics and enabling safe and reliable tactile interactions. To this end, we designed a preliminary PVDF-TrFE sensor prototype coated with a thin, rigid layer and indented using a soft probe under seven discrete force levels. Statistical time-domain features were extracted from the voltage signals and ranked via Principal Component Analysis (PCA). The selected features were then used to train and test an artificial neural network (ANN) for estimating peak forces from sensor outputs. This study focuses on normal indentation as a foundational contact type, serving as a reference case for the future extension of AI-based force extraction to more complex tactile scenarios.

The main contribution of this chapter can be summarized as follows:

- A machine learning-based algorithm for estimating the maximum normal force peak from a PVDF-TrFE tactile sensing system.
- Demonstration of the approach's effectiveness, achieving a correlation coefficient of $R = 0.92247$ and a mean absolute percentage error (MAPE) of 16.41%.

The content of this chapter has been published in the following paper:

M. Yaacoub, R. Khalifeh, C. Gianoglio, A. Ibrahim and L. Seminara, "Machine Learning Based Contact Force Estimation Using a PVDF Tactile Sensing System," 2025 23rd IEEE Interregional NEWCAS Conference (NEWCAS), Paris, France, 2025, pp. 430-434.

4.3 Material

4.3.1 Sensing system & Dataset

The dataset collected in [150] was employed in this study. The whole setup is illustrated in Figure 4.1. The piezoelectric sensing system comprised eight P(VDF-TrFE) sensors, screen-printed on a flexible substrate and shielded according to the procedure outlined in [144]. The sensing system was covered by a UV-curable lacquer layer (protective later in Figure 4.1) for overall sensor protection.

The fully screen-printed sensor array was coupled to a rigid plate for sensors working in thickness mode[141] and then fixed on a strain gauge based load cell (Tedea Huntleigh, Model 1042) to measure the force stimulus. Embedded Electronics (EE) described in [145] was used to condition the sensor signals. The tactile signals from a single sensor were acquired using the EE, configured with a sampling rate of 2 kHz to cover the full bandwidth of the PVDF sensor when used for tactile applications (≤ 0.5 Hz -1 kHz).

To collect sensor data, a 3-axis Cartesian robot was used to perform a series of normal indentation actions on a single sensor with a soft spherical indenter through the z-axis (Figure 4.1). Each indentation began with an initial load of 3.7 N, followed by increasing the force to a target value, decreasing the applied force, and finally releasing the indenter. The electrical response of the stimulated sensor was measured throughout the entire indentation process. Seven maximum forces F of {4.5, 5.5, 6.5, 7.5, 8.5, 9.5, 10.5} (N) were targeted. Each indentation process, defined by a specific maximum (target) force, was repeated 65 times at seven different indentation speeds {2.4, 3.2, 4.02, 4.8, 5.6, 6.4, 7.2} (mm/s). The data acquisition, visualization, and control of the Cartesian robot were implemented using a graphical user interface (GUI) developed with NI LabVIEW on a host PC. The collected dataset can be formulated as follows: $\mathcal{D} = \{(\mathcal{X}_i, y_i) \mid \mathcal{X}_i \in \mathbb{R}^{N_s \times N_c}, y_i \in \{f1, \dots, f7\}, i = 1, \dots, 490\}$, where $N_c = 1$ is the number of sensors and N_s corresponds to the number of samples. The collection time varied across the trials, depending on the target forces and speeds.

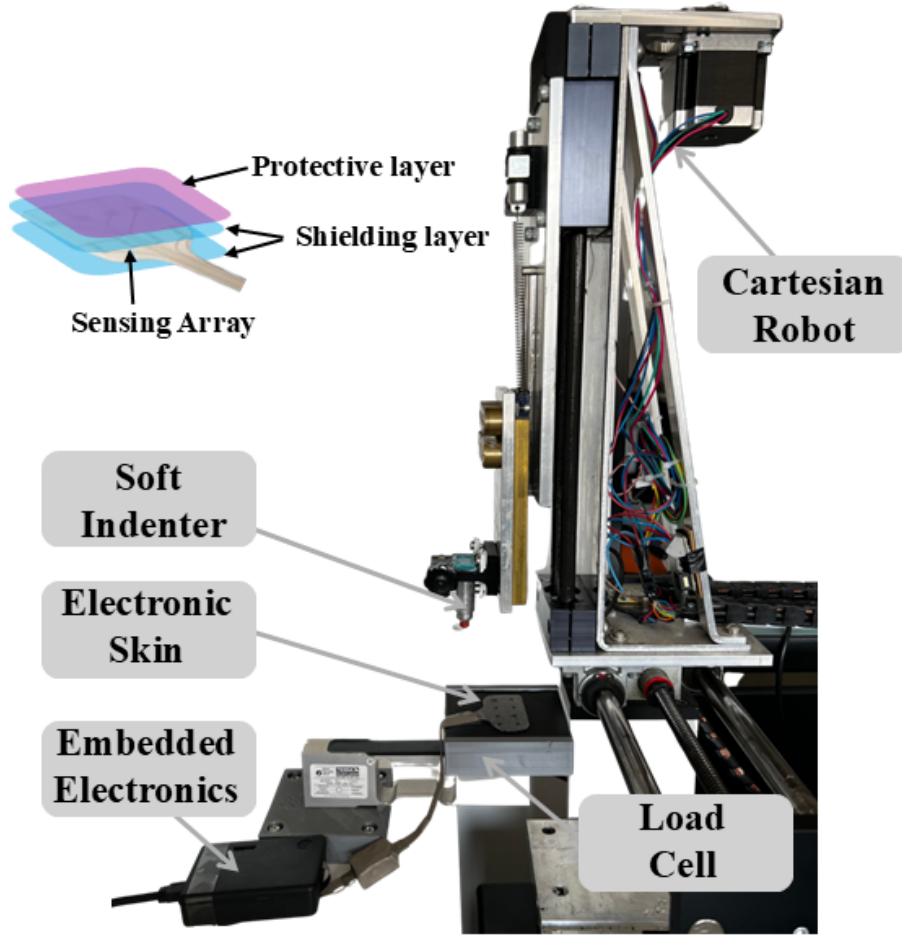


Figure 4.1: Experimental setup for indentation.

4.4 Methodology

4.4.1 Pre-Processing

Variations in the indentation speed led to different durations of the indentation process. More specifically, each trial in the dataset corresponds to a complete indentation cycle — from the onset of contact to the release of the indenter — at a preset peak force. For each given peak force, multiple trials were conducted at different speeds. Since the indentation speed affects the time required to complete the indentation process, and specifically to reach the peak (or maximum) force, the number of acquired samples per trial varied within the collected dataset $\mathcal{D}$. Simple statistical features were thus extracted from each trial to provide a representative dataset for the machine learning (ML) algorithm described in section 4.4.2.

Inspired by work done in [151, 152, 153], eight time-domain statistical features from each $\mathcal{X}_i \in \mathcal{D}$ were extracted, including Standard Deviation (STD), Skewness (SK), Kurtosis (KT), Energy (En), Minimum (Min), Maximum (Max) and Peak-to-peak (PP), Zero-Crossing (ZC), Variance (Var), and Median. Considering that algorithms are capable of operating more efficiently with low-dimensional data, a PCA biplot method [154] was applied to extract the most informative features, thus reducing the dataset dimension. The PCA biplot displays points to represent the scores of the observations, showing their projection onto the principal components (PC1, PC2), and vectors to represent the coefficients of the variables (features), indicating their contribution to the principal components. The length of the feature vectors and the angles between the lines reflect the relevance and the correlation of the represented features. Longer vectors indicate a stronger contribution to the PCs, while smaller angles between vectors represent a higher positive correlation. Features were ranked by multiplying the biplot coordinate values of each feature by the corresponding component explainability, providing a quantitative measure of their importance. Figure 4.2 highlights the ranked feature contributions, from the most important to the least. Consequently, only the two most informative features, SK (eq. 4.1) and KT (eq. 4.2), were selected based on their ranking in this analysis. The rationale behind this selection was to reduce the dimensionality of the dataset, while retaining the most critical information.

$$\text{SK} = \frac{\frac{1}{n} \sum_{i=1}^n (\mathcal{X}_i - \mu)^3}{\left(\frac{1}{n} \sum_{i=1}^n (\mathcal{X}_i - \mu)^2 \right)^{\frac{3}{2}}} \quad (4.1)$$

$$\text{KT} = \frac{\frac{1}{n} \sum_{i=1}^n (\mathcal{X}_i - \mu)^4}{\left(\frac{1}{n} \sum_{i=1}^n (\mathcal{X}_i - \mu)^2 \right)^2} \quad (4.2)$$

where n is the total number of samples, $\mathcal{X}_i$ is the value of the i_{th} sample, and μ is the mean of the data.

This generated a new dataset, where each $\mathcal{X}_i \in \mathcal{D}$ was transformed into $\hat{\mathcal{X}}_i \in \hat{\mathcal{D}}$. The dataset could be formalized as follows: $\hat{\mathcal{D}} = \{(\hat{\mathcal{X}}_i, y_i) \mid \hat{\mathcal{X}}_i \in \mathbb{R}^{2 \times 1}, y_i \in \{f1, \dots, f7\}, i = 1, \dots, 490\}$, where 2 refers to the number of features and 1 refers to the number of sensors. This dataset was normalized using the min-max scaling technique [155]. Additionally, the dataset was split into 80% for training, 10% for validation (for network selection), and 10% for testing (to estimate generalization performance).

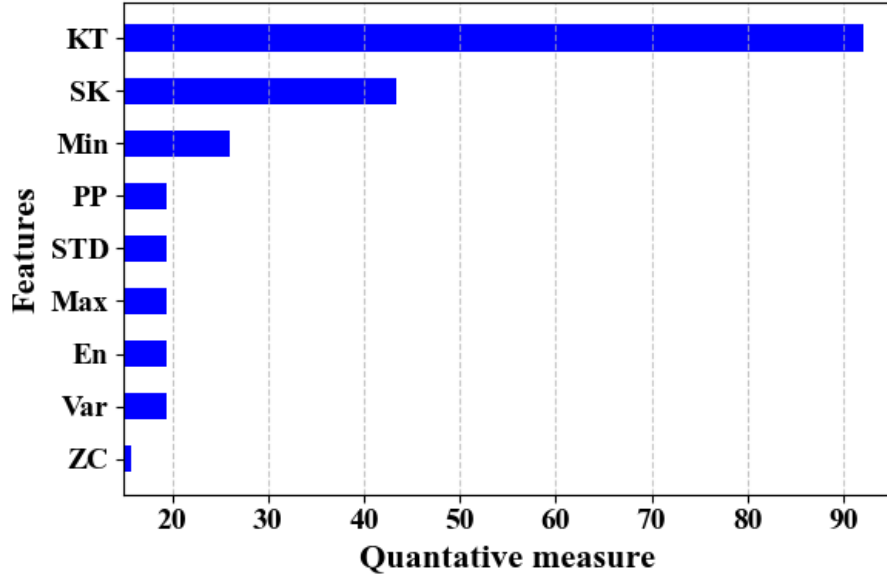


Figure 4.2: Quantitative measure for feature ranking.

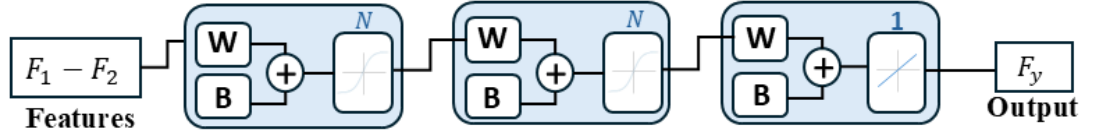


Figure 4.3: Graphical view of the network connectivity.

4.4.2 ML Algorithm

To estimate the peak normal force from sensor output, an artificial neural network (ANN) was designed. The architecture, illustrated in Figure 4.3, consisted of three layers: two hidden layers, each comprising N neurons with sigmoid activation functions (eq. 4.3), followed by an output layer with a single neuron employing a linear activation function.

$$S(x) = \frac{1}{1 + e^{-x}} \quad (4.3)$$

The network was trained with the following configuration: using the Adam optimizer, which is known for its efficiency in handling sparse gradients, the mean square error (MSE) was employed as the loss function to minimize the discrepancy between predicted and actual values, with a batch size of $b = 3$ and number of epochs $e = 100$. An early stop criterion on the validation loss was implemented with a patience value of $p = 5$ to prevent

over-fitting. A grid search was performed to optimize the network hyperparameters. The network was trained and tested using the time features represented by the dataset $\hat{\mathcal{D}}$.

The performance of the neural network was assessed by the means of the correlation coefficient (R) between output and target, alongside the mean absolute percentage error (MAPE).

4.4.3 Hardware Implementation

The STM32F401RE microcontroller is utilized in this study to host the neural network and perform real-time estimation of normal force peaks. The STM32 board integrates an Arm Cortex-M4F processor operating at 84 MHz, with 512 kB of flash memory and 96 kB of SRAM, running at 3.3 V. This board was selected for its low power consumption, which makes it well-suited for low-power, edge-based computation applications.

After completing the neural network training, the feature extraction stage was implemented in C++, and the trained model was quantized to 8-bit integers (Int8) using post-training quantization to ensure compatibility with the microcontroller. The conversion to an MCU-compliant format was achieved via the TensorFlow Lite API. Both the preprocessing module and the quantized network were deployed on the STM32 using STM32CubeIDE, where the flash memory stores the program code and model parameters, and the RAM holds the test samples for inference.

The real-time inference performance was evaluated using two metrics: latency and energy consumption per inference. The microcontroller was configured to operate at its maximum clock frequency, with a 16-bit internal timer used to measure inference time. Power consumption was recorded using the X-NUCLEO-LPM01A power measurement board, and energy consumption was calculated as the product of the measured power and inference time.

Table 4.1: Performance evaluation on hardware of the feature extraction and neural network.

Processing Pipeline	Inference Time (ms)	Power Consumption (mW)	Energy Consumption (μJ)
Feature extraction	6.078	86.1	520
Model	0.1481	54.15	8.019

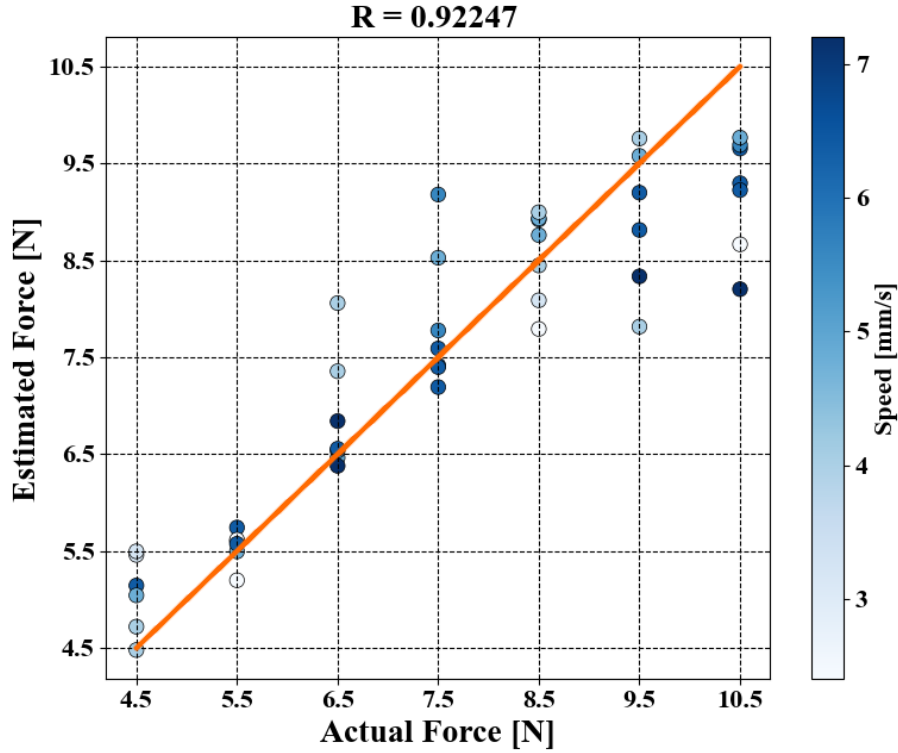


Figure 4.4: Accuracy in sensing the force exerted by means of the proposed neural network.

4.5 Results and Discussion

Following the model selection process based on the validation loss to tune the hyperparameters, the best-performing network was identified with $N = 32$ neurons in each of the two layers.

The accuracy in reconstructing the maximum indentation force by means of the proposed neural network is reported in Figure 4.4. The graph shows the estimated force (at different speeds) through the neural network (dots), namely the output of the neural network, as a function of the actual force represented by the orange line. The preliminary results show a high correlation with $R = 0.92247$ on the testing set, with a mean absolute percentage error (MAPE) of 16.41%. Notably, this high correlation is achieved despite variations in indentation speed, which introduce additional complexity in interpreting the sensor output, hence challenging the neural network's ability to accurately extract the maximum force.

Regarding hardware performance, Table 4.1 presents the evaluation metrics of the pre-processing stage and the neural network deployed on the STM32F401 microcontroller.

Table 4.2: Comparison of embedded tactile normal-force reconstruction systems.

Reference	Sensor	Metric	Value	Latency	Power
[156]	Tactile stress array	Normal-force error	12.6%	58.7 ms	0.87–0.98 W
[157]	Tactile stress array	Normal-force error	3.66%	6.7 ms	0.98 W
This work	PVDF tactile sensor	Normal-force error (MAPE)	16.41%	6.2261 ms	85 mW

For feature extraction, which was computed based on the average input length due to variations in sequence size, the inference time was 6.078 ms, with a power consumption of 86.1 mW, resulting in an energy consumption of 520 μJ per inference. In comparison, the network stage achieved an inference time of 0.1481 ms, consumed 54.15 mW, and required 8.019 μJ per inference without affecting the network performance after quantization. To better interpret the embedded performance of the proposed force-reconstruction pipeline, Table 4.2 compares the proposed embedded force-reconstruction system with two recent FPGA-based tactile force-reconstruction implementations. While FPGA systems achieve lower normal-force reconstruction error (12.6% and 3.66%), they require close to 1 W of power. In contrast, the proposed TinyML-based PVDF tactile system operates with a total inference latency of 6.2261 ms and an average power consumption of approximately 85 mW, computed over the full processing pipeline including both feature extraction and neural network inference. This total latency is lower than that of both FPGA implementations (58.7 ms and 6.7 ms), while the power consumption is more than one order of magnitude lower. Although the reconstruction error is higher (MAPE = 16.41%), the proposed system offers a highly favorable accuracy–energy trade-off, making it well-suited for low-power and wearable tactile sensing applications.

The above results support the idea that Machine Learning is a viable tool to estimate the peak force in real time. Further work will be needed to achieve the ultimate goal of real-time force detection. However, potential improvements could be adopted to enhance the performance of the sensing system. One key improvement involves redesigning the sensor by embedding the PVDF transducers inside a soft protective layer, replacing the current shielding layer. Dragon Skin, a soft material known for its low delamination and high flexibility, is a suitable candidate for this purpose. Widely used in robotic applications,

such as the skin of robotic forearms [95], Dragon Skin could serve as a novel protective layer for the PVDF-based e-skin. Mimicking the characteristics of the human skin, the soft layer distributes the mechanical stimulus onto the transducer array below, while protecting the transducers themselves, thus making the skin system compliant, robust, and able to interact safely with the environment[158].

Nevertheless, limitations in the experimental setup constrained the lower force threshold to 4.5 N due to the capabilities of the Cartesian robot. To expand the range of pressure studied, more systematic measurements are needed using different indenter sizes. This approach would allow for a broader investigation, including low-force interactions, which are relevant for gentle manipulation tasks and affective touches.

Additionally, incorporating a finite element method (FEM) numerical model to simulate the PVDF-TrFE-based e-skin will reduce the need for extensive experimental data collection. In this approach, the simulation data from FEM would be used exclusively to train the machine learning algorithm while the experimental data would be reserved for testing, thereby mitigating reliance on extensive experimental datasets. Furthermore, leveraging the potential of sim-to-real transfer learning could yield more accurate predictions compared to both a physics-based model and end-to-end learning approaches [97].

4.6 Conclusion

In this chapter, we presented a machine learning-based methodology for extracting the peak normal force during indentation on a PVDF-TrFE-based tactile sensing system. The proposed approach demonstrated promising results in estimating the peak force from the sensor output voltage, achieving a correlation coefficient of $R = 0.92247$ and a mean absolute percentage error (MAPE) of 16.41%. The system achieved an inference time of 6.2261 ms while consuming only 528.019 μJ , opening up an interesting perspective towards real-time hardware deployment to perform online force estimation. Furthermore, this advancement could potentially enhance the versatility of piezoelectric sensors in tactile applications, particularly in complex, dynamic environments where a sensitive and rapid response to tactile stimuli is crucial.

CHAPTER 5

Frequency Domain Analysis and Modeling of the Indentation Response of a Soft PVDF-Based Tactile Sensor

This chapter introduces the investigation of the sensor response to model the frequency behavior of the whole sensing system, including the interface electronics. This approach was motivated by empirical hints at the system derivative characteristics, although these were not systematically observed. The complexity of such work lies in the fact that it requires strongly interdisciplinary expertise, spanning mechanical aspects, electromechanical transducer behavior, and electronic design and implementation. Moreover, the development of a comprehensive model demanded designing a new experimental setup and performing extensive experimental campaigns. As highlighted in the literature (see Chapter 2), a major appeal of such model-based approaches is that they can provide simulated data useful to train and guide learning-based algorithms.

5.1 Introduction

The sensing apparatus must be capable of detecting time-varying contact information up to frequencies exceeding 500Hz [159]. Furthermore, a soft skin interface enables human-like haptic interactions and offers increased contact areas, conforming to the irregular shapes of objects.

The choice of the transducer material is pivotal in defining the potentiality of such sensing systems (refer to Chapter 2). As highlighted, piezoelectric polymers such as polyvinylidene fluoride (PVDF) and its copolymers offer a remarkable set of characteristics, including high sensitivity, flexibility, and a wide frequency range that covers the entire frequency bandwidth of human skin, except for the measurement of static information [51]. However, despite these advantages, interpreting the output signals from the

sensing system can be quite challenging due to their complexity. Model-based approaches require a clear understanding of the interplay between functional elements (transducers) and structural components (substrate and cover layer) of the sensing system.

Existing models in the literature exhibit certain limitations. In [160], a sensing system based on PVDF was modeled by an equivalent circuit featuring a charge generator in parallel with a capacitance. Although this configuration (sometimes with a parallel resistor) is commonly used to model PVDF sensors operating in thickness mode, it does not account for the presence of a protective layer. An equivalent model for lossy piezoelectric polymers and its SPICE implementation was presented in [161]. The model includes the viscoelastic/mechanical, dielectric/electrical, and piezoelectric/electromechanical losses by using complex elastic, dielectric, and piezoelectric constants obtained from the measured impedances of PVDF and PVDF-TrFE samples. The equivalent circuit parameters are derived from analogies between a lossy electrical transmission line and acoustic wave propagation. However, the study focuses exclusively on the bare polymeric layer and does not consider any protective layer. Furthermore, the frequency range analyzed (600 kHz to 30 MHz) is suitable for the high-frequency behavior of PVDF but is far beyond the bandwidth of interest in this work, which is limited to frequencies below 1 kHz. Therefore, the model is not applicable to low-frequency applications or configurations that include protective layers. In a previous study [162], we presented a circuit design for a PVDF-based tactile sensing system featuring a different elastomeric cover layer. While this model accounts for the presence of a protective layer on top of the PVDF transducer, the system response was evaluated at only three discrete frequencies (12 Hz, 162 Hz, and 362 Hz), without any systematic frequency analysis. Moreover, the role of the elastomer appears to be limited to static force transmission to the transducer below, with its dynamic response being neglected.

Publications on this topic and :

- M. Yaacoub, Y. Abbass, C. Micheli, D. D. Caviglia, M. Valle, L. Carassale, and L. Seminara, "Frequency Domain Investigation of the Indentation Response of a Soft PVDF-Based Tactile Sensor," 2025 32nd IEEE International Conference on Electronics, Circuits and Systems (ICECS), Accepted, to be published.
- M. Yaacoub, R. Testa, A. Ibrahim, D. D. Caviglia, and M. Valle, "Interface Electronics for PVDF-Based Tactile Sensor," 2025 International Conference on Bio-inspired Adaptive Tactile Sensing (BATS), Accepted, to be published.
- M. Yaacoub, C. Micheli, D. D. Caviglia, M. Valle, L. Carassale, and L. Seminara, "Modeling the indentation response of a soft PVDF-based tactile sensor," to be published.

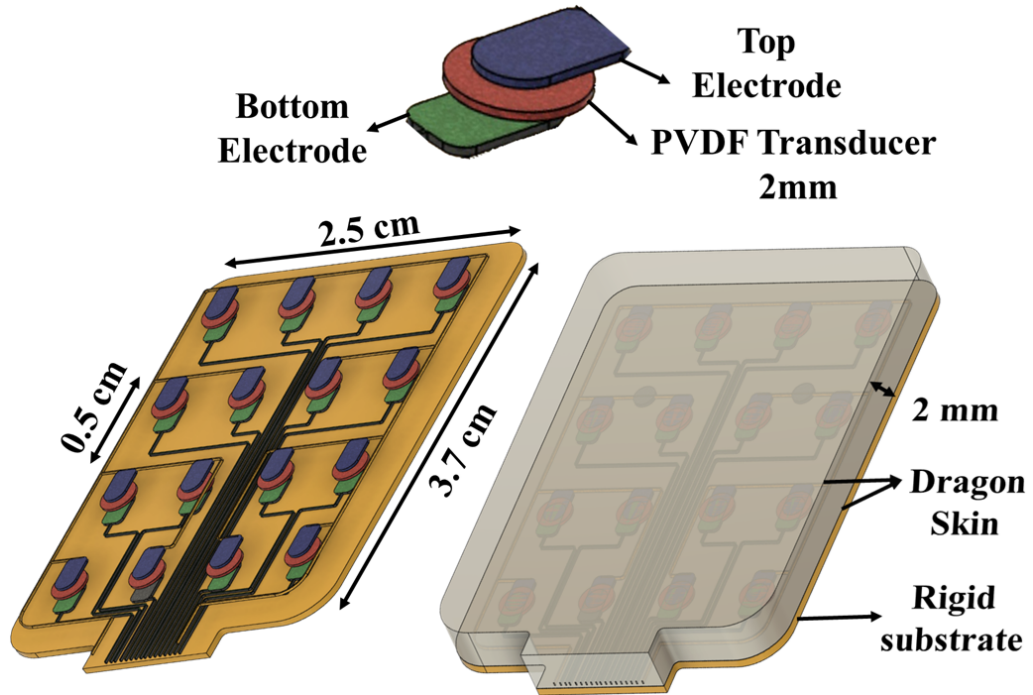


Figure 5.1: The top illustration shows the structure of a single PVDF-based tactile sensor. PVDF (in red) is sandwiched between the two electrodes. The bottom left depicts the layout of the sensor array integrated on a rigid substrate. The bottom right shows the full sensor array, including the soft cover (Dragon skin) and the rigid substrate.

In this work, we focus on a single tactile sensor within a soft tactile sensing array. A key aspect is to interpret and model the electromechanical behavior of such a soft PVDF-based sensor on the basis of its mechanical structure. Our high-level, longer-term objective is to assess how a complex tactile sensor array encodes contact force information.

5.2 Materials

5.2.1 Piezoelectric Tactile sensor

The sensor used in this study belongs to a fully screen-printed, flexible sensor array based on piezoelectric polymer technology, fabricated by JOANNEUM RESEARCH [163]. The manufacturing process involves screen printing P(VDF-TrFE) poly(vinylidene fluoride trifluoroethylene) (piezoelectric polymers) repeated units on a flexible PCB. Figure 5.1 shows the structure of a single sensor and the layout of a 4x4 sensing array. The bottom electrode is screen-printed on a flexible PCB (100 μm thick). A ferroelectric polymer

P(VDF-TrFE) layer (5.1 μm thick) is then printed onto the bottom electrodes, followed by the top electrodes (PEDOT: PSS). A UV-curable lacquer layer is then deposited on top for overall sensor protection. Finally, the poling procedure aligns with the thickness direction of randomly oriented dipoles in P(VDF-TrFE) crystallites.

The latter was rigidly coupled to a rigid substrate and covered by the Dragon Skin elastomer layer [164] (Dragon Skin 10 Medium, Smooth-On Inc., Macungie, Pennsylvania, USA). The Dragon Skin is formulated for safe contact with the human skin (certified Skin Safe, for more information [165]) and its mechanical properties fit those of the human skin. The PVDF transducer measures dynamic contacts covering the entire frequency range of all human mechanoreceptors [166]. The PVDF orthotropic symmetry and small layer thickness (5.1 μm) enable operation in thickness mode when mounted on a rigid substrate [167]:

$$Q = d_{33} \overline{T_3} \pi r_t^2 \quad (5.1)$$

Here, Q is the total charge on the transducer surface orthogonal to the film thickness, $\overline{T_3}$ is the average normal stress on that transducer surface, d_{33} is the piezoelectric coefficient, and r_t is the transducer radius. Therefore, in thickness mode, this transducer directly transforms the received pressure into an electrical charge. Using a quasi-static approach for contact forces varying slowly over time, a linear elastic model proved to be sufficiently predictive for force values and soft layer thicknesses as those employed in the current study [158].

5.2.2 Interface Electronics

The proposed circuit for signal conditioning is presented in Figure 5.2. The interface electronics converts the charge developed by PVDF, as a result of the applied stress, to a voltage signal. The circuit consists of a TIA with a fully differential structure, chosen to eliminate external common-mode noise sources. The first stage consists of two ideally identical inverting topologies based on the OPA350 rail-to-rail CMOS operational amplifiers from Texas Instruments [168] (OP1 and OP2), which feature a very low bias input current, with a typical value of ± 0.5 pA. Each op-amp has a feedback resistor ($R_1 = R_2 = R_f = 1 \text{ M}\Omega$) defining the gain, with a feedback capacitor ($C_1 = C_2 = C_f = 15$) pF in parallel, used to reduce high-frequency noise. These values in the feedback loop yield a cutoff frequency set at approximately 10 kHz, sufficiently higher than the frequency range of interest.

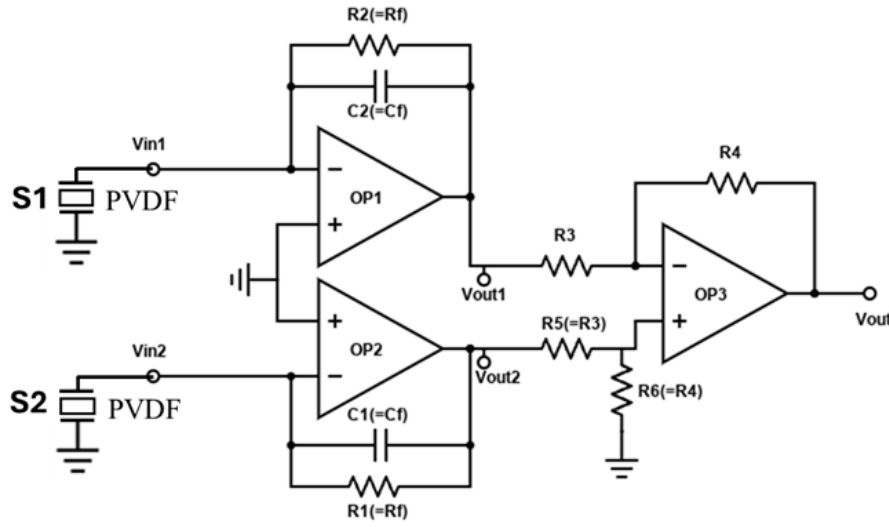


Figure 5.2: Proposed electronic circuits for processing the output voltage of PVDF piezoelectric sensor.

The second stage is a conventional differential amplifier for differential-to-single-end conversion, implemented using the same type of operational amplifier (OP3). The resistors $R_3 = R_5 = 5k\Omega$ and $R_4 = R_6 = 10k\Omega$ determine the gain and common-mode rejection ratio (CMRR). For optimal performance, it is essential that $R_3 = R_5$ and $R_4 = R_6$. This ensures a balanced gain and minimizes the amplification of common-mode signals, thereby enhancing the CMRR and reducing noise. The total transimpedance gain is therefore 126 dB Ω . The interface electronics converts the current generated by the PVDF (i.e., the time derivative of the charge), resulting from the applied stress, to a voltage signal.

5.2.2.1 LTspice simulation of the electronic circuits

To validate the theoretical design, the proposed architecture circuit was simulated using the LTspice software [169]. The simulation circuit was constructed as shown in Figure 5.3. The OPA350 amplifier module was included in the LTSpice project with a symmetric DC supply voltage of ± 2.5 V, this will let the IE handle bipolar signals, as piezoelectric sensors are bipolar charge-output sensors, that is, they generate both positive and negative charge when stimulated. The resistance and capacitance values were set according to the circuit specifications defined in Section 5.2.2. For the input, a current generator supplied a 10 Hz sine wave signal to the circuit. Additionally, two mirror current generators, I_2 and F_2 , were connected as illustrated in Figure 5.3 to introduce a 50 Hz noise component to the signals feeding the first-stage inverting topologies. The output voltages of these two

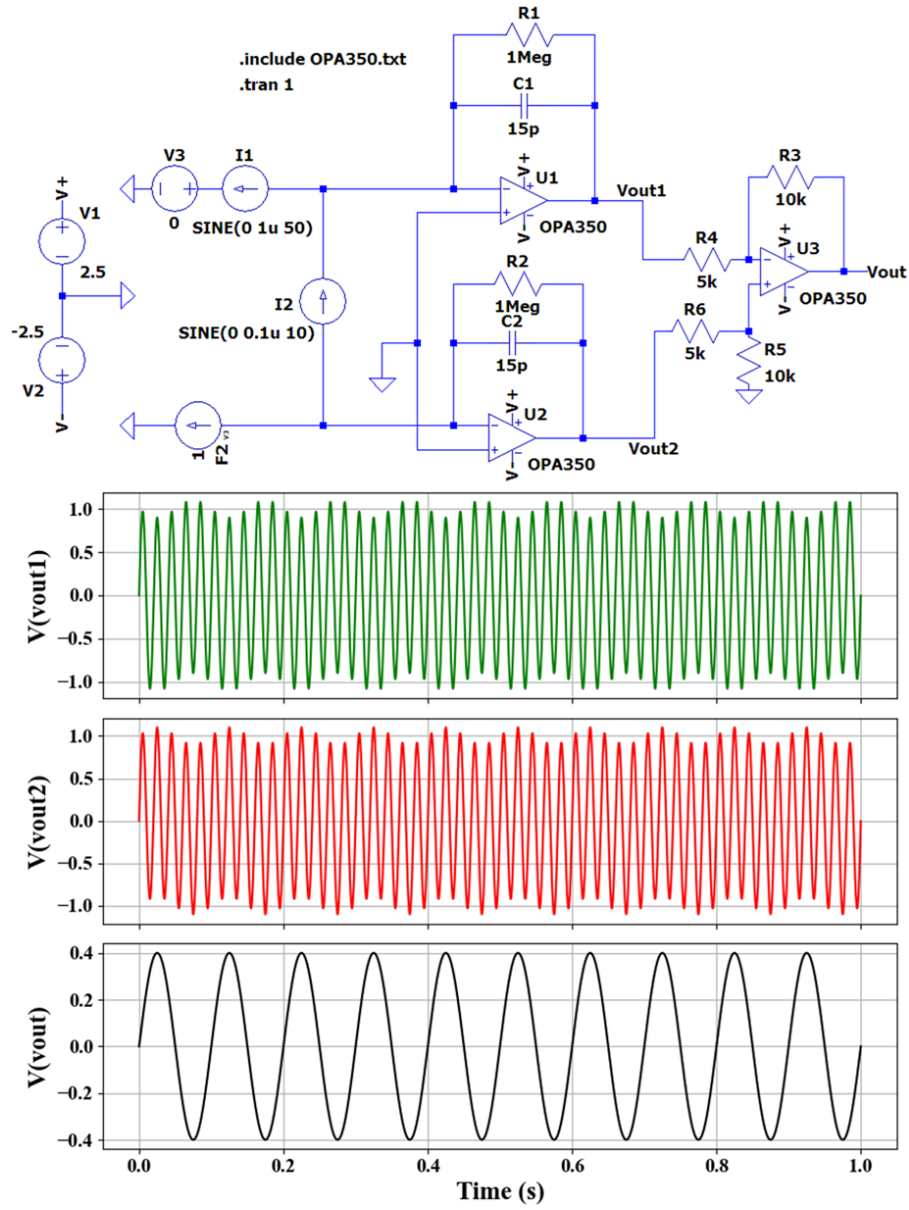


Figure 5.3: Circuit Schematic and Simulation: The upper part shows the circuit schematic; the bottom part displays the circuit simulation.

operational amplifiers, V_{out1} and V_{out2} , are shown in the lower section of Figure 5.3, where the influence of the 50 Hz noise is clearly visible. The figure also presents the final output voltage of the proposed architecture, V_{out} , demonstrating that the noise component has been successfully eliminated from the signal.

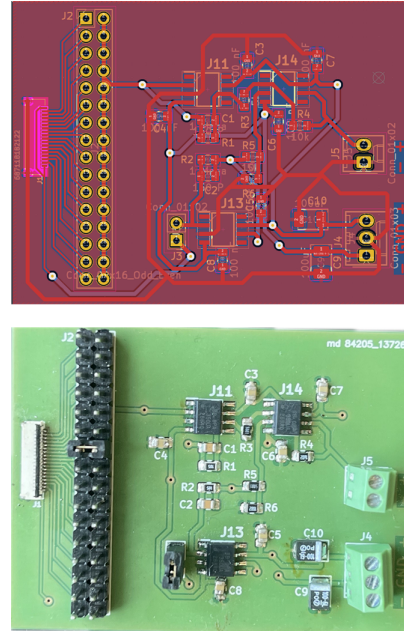


Figure 5.4: Top: the final layout of electronic circuits for signal conditioning; Bottom: The fabricated PCB.

5.2.2.2 PCB design and Fabrication

In order to evaluate the geometry requirements of the proposed electronic circuits for signal conditioning, the final layout is realized and shown at the top of Figure 5.4 (KiCad 8.0 [170], KiCad Project). The area of the proposed circuit is $58.76mm \times 44.39mm$, making it well-suited for integration into tactile sensor applications where space is a critical constraint. Following the layout phase, to evaluate the effectiveness of the proposed interface electronics, a physical prototype was fabricated using COTS components to validate the feasibility of the design in hardware. The assembled board is shown at the bottom of Figure 5.4. This board was used to characterize the sensing performance under indentation; the details are presented in section 5.3.1.

5.3 Methodology

5.3.1 Experimental Setup & Protocol

A DMA (Dynamic Mechanical Analysis) experimental setup [51] was used to characterize the sensor response to indentation (normal forces, Hertzian distribution). Figure 5.5 illustrates the employed experimental setup, the tactile sensor array was coupled to a rigid

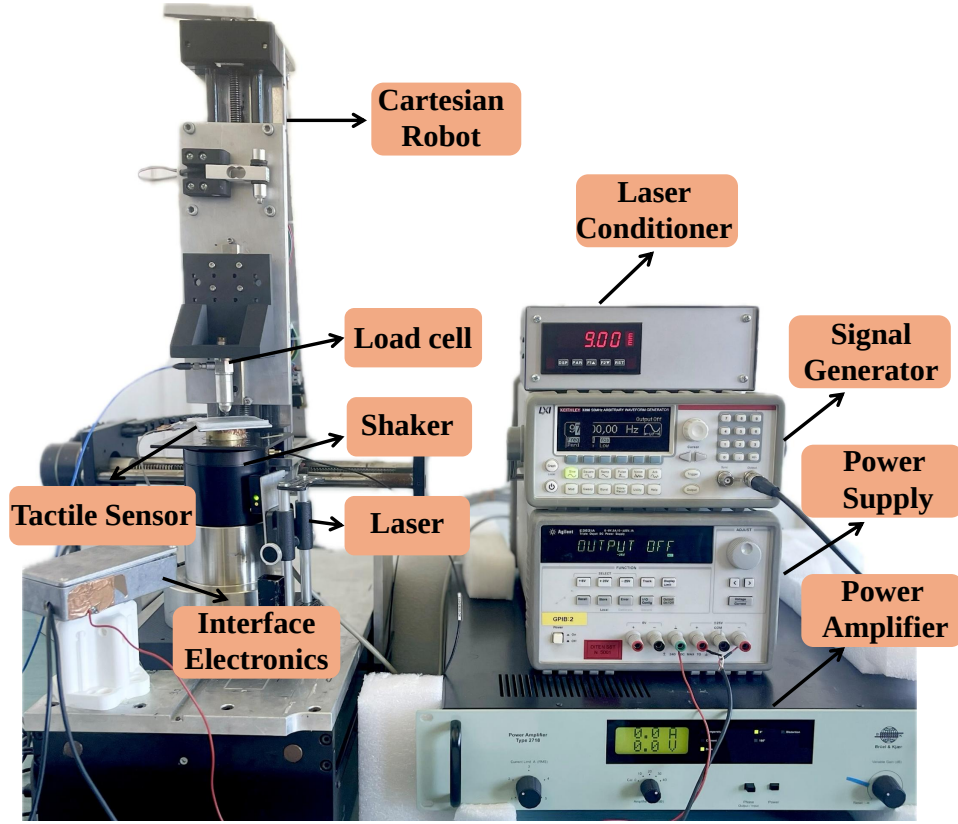


Figure 5.5: Experimental Setup employed to characterize the frequency response of PVDF-based tactile sensor to indentation.

plate for PVDF transducers working in thickness mode, while the dragon skin soft cover was mechanically solicited by a rigid spherical indenter ($R = 4 \text{ mm}$), ensuring Hertzian distribution for the contact force. The tactile sensor array was rigidly coupled to the moving head of an electromechanical shaker (Brüel and Kjaer, Minishaker Type 4810 from HBK company, Germany). A load cell (Model 208C01, PCB Piezotronics, MTS system) was added on top of the mechanical chain for force measurement.

During testing, a mechanical input (force) was applied to a single sensor from the sensor array, while the PVDF response was measured through a voltage output (output 2 in Figure 5.6). A preload of $PL = 1 \text{ N}$ was applied to ensure continuous contact between the indenter and the dragon skin surface throughout the test. The preload value was controlled using a laser displacement sensor (Waycon LAS TM10). For each test, a single-frequency sine wave signal was provided to the electromechanical shaker by a signal generator. The signal was amplified using a power amplifier (Brüel and Kjaer, Power Amplifier, Type 2718 from HBK company, Germany). Sinusoidal forces in the $1 \text{ Hz} - 1 \text{ kHz}$

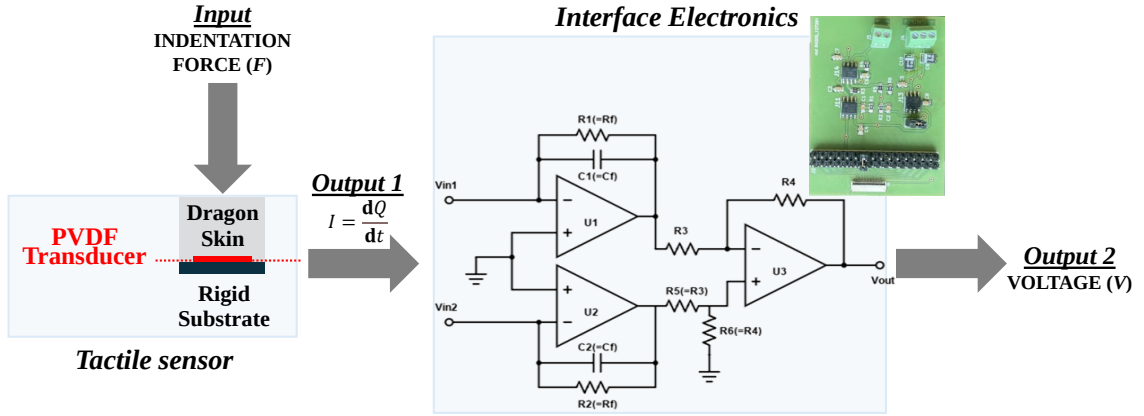


Figure 5.6: Overview of the whole measurement system. Left: Indentation force (input) on the PVDF tactile sensor (output 1: current). Right: The interface electronics (output 2: voltage).

frequency range were applied. The signal from the load cell (stimulus) was conditioned using the PCB Sensor Signal Conditioner (482C54), while the charge output from the PVDF transducer was processed using the proposed interface electronics. The interface electronics were powered by a $\pm 2.5V$ supply and shielded within a grounded metal box to reduce environmental noise. The outputs of both conditioning circuits were routed to an NI DAQ board. Data acquisition, visualization, and collection were implemented using a graphical user interface (GUI) developed with NI LabVIEW on a host PC.

5.4 Results and Discussion

Figure 5.7 (right) shows the response function of the PVDF-based tactile sensor over the 1 Hz - 1 kHz frequency range, illustrating both the amplitude and the phase (in radians). This transfer function represents the relationship between the indentation force (Input in Figure 5.6) and the voltage output from the interface electronics (Output 2 in Figure 5.6). Each point on the resulting curves (amplitude $|H|$ and phase in Figure 5.7) is computed from the mean amplitude and phase of the input and output sinusoids evaluated over 10 oscillations at each specific frequency. Measurement uncertainties due to systematic and random effects are included in the figure. All uncertainties except for the first point are smaller than the point extension. As the interface electronics exhibited a flat transfer function between Output 2 and Output 1 (see Figure 5.6), the overall system response primarily reflects the response function of the tactile sensor itself, from force Input to

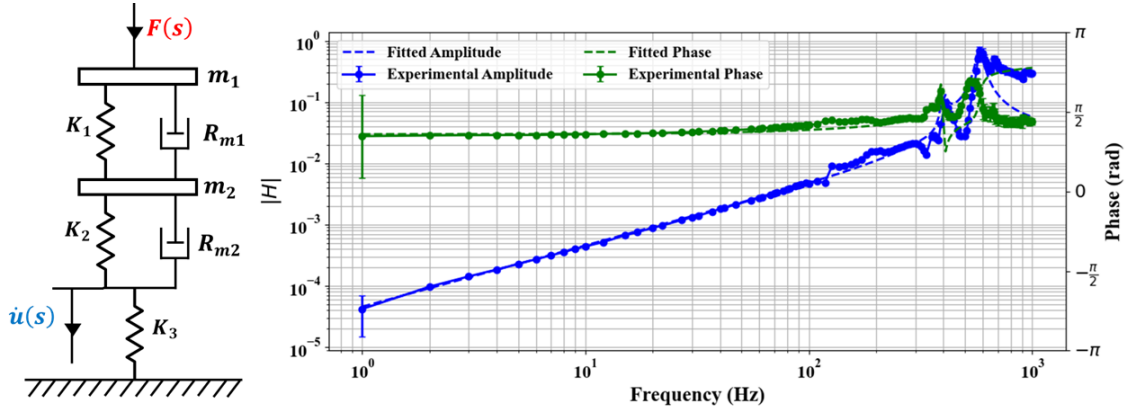


Figure 5.7: Left: Schematics of the current lumped-parameter model, Right: Frequency Response Function (experimental and fitted) of the PVDF-based tactile sensor to indentation.

sensor output current (Output 1). The log-log plot shows a linear trend with approximately 20 dB/decade slope, indicating a first-order linear relationship (proportional to frequency), i.e., a derivative behavior in the linear domain. This is supported by the phase profile of the transfer function, confirming that the tactile sensor mechanically behaves as a velocity sensor, suggesting a derivative relationship between the indentation force and the output current (or the derivative of the displacement $u(s)$, i.e. a velocity $\dot{u}(s)$, in the mechanical analogy - see Figure 5.7 (left)).

Driven by these findings, a lumped-parameter mechanical model has been proposed in Figure 5.7 (left) to fit the experimental Frequency Response Function in Figure 5.7 (right). This phenomenological model replicates the experimental dynamic behavior of the tactile sensor. The overall derivative behavior of the tactile sensor is attributed solely to the PVDF layer. This is consistent with findings reported in [51], where the PVDF transducer showed a flat frequency response in its d_{33} coefficient, with no significant resonances. However, in that study, the PVDF response was proportional (not derivative) because the signal was acquired via a charge amplifier, measuring charge directly rather than current. Therefore, the derivative behavior seen in our system (with the current readout circuit) aligns with the PVDF expected dynamic behavior in current mode and excludes high-frequency resonances.

Nonetheless, Figure 5.7 (right) reveals the presence of resonance peaks in the 300–700 Hz frequency range. These peaks are expected to be attributed to high-frequency mechanical resonances introduced by the soft protective layer covering the PVDF transducer. To verify this hypothesis, additional experimental tests were conducted using a setup simi-

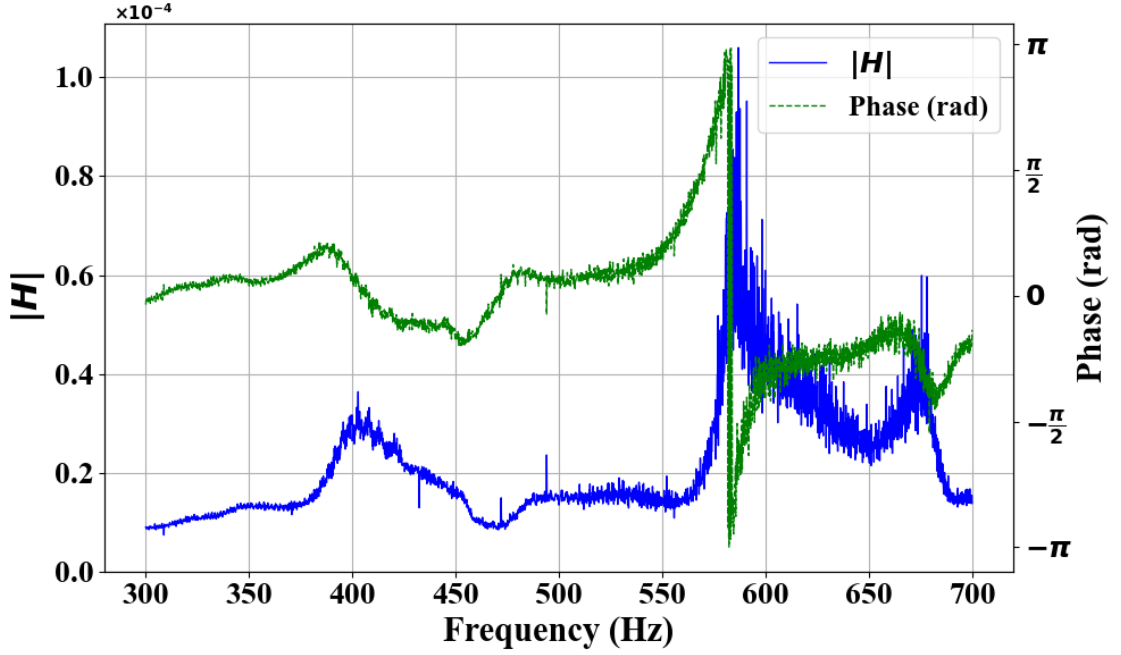


Figure 5.8: Mechanical response function of the dragon skin soft cover layer in the 300 - 700 Hz frequency range.

lar to Section 5.3.1, equipped with a laser displacement sensor. This setup enabled the measurement of displacement and the derivation of the mechanical response function for the soft protective layer. The measurements presented in Figure 5.8 consistently revealed two dominant resonance peaks in the expected frequency range, supporting the attribution of the observed high-frequency peaks to the soft cover layer rather than to the PVDF transducer or the readout circuit. Further investigation is necessary to verify the origin of these resonance peaks and to distinguish the relative contributions of geometric and material effects. Although these preliminary results exhibit additional peaks likely caused by system-level vibrations, the two major resonances attributable to the soft material were reliably reproduced.

5.5 Conclusions

This chapter presents a measurement system for characterizing the dynamic response of a PVDF-based tactile sensor. Indentation forces have been applied to the sensor surface in the 1 Hz to 1 kHz frequency range, and the system response function was extracted. The results revealed in which frequency range the sensor exhibits pure derivative behavior,

dominated by the PVDF layer, and the range where the mechanical resonances of the soft protective layer are non-negligible. These findings indicate that the sensor behaves as a velocity sensor within a certain bandwidth, while deviations at higher frequencies are due to structural resonances. A phenomenological 2-dof lumped-parameter model has been proposed to provide a compact and physically interpretable representation of the sensor dynamic behavior. This model is based on a basic idealization of the continuous behavior of the protective layer and is sufficient to reproduce the resonance peaks that appear in the amplitude of the FRF. However, the phase behavior is not well reproduced after the first resonance, indicating a discrepancy likely related to the tridimensionality of the local deformation. A refined design of the protective layer could shift or damp the observed resonances, extending the bandwidth over which the sensor behaves as an ideal derivative device. This would enable direct integration of the PVDF output current to reconstruct the indentation force profile, representing a basic signal processing step for force reconstruction. Additionally, this refinement would lead to the generation of simulation data to be used for the previously illustrated machine learning algorithm for force estimation and reconstruction.

5.6 Model Refinement and Extended Experimental Validation

To further investigate the observed behavior and enhance the previously developed model for the PVDF-based tactile sensor, a new experimental setup was developed.

5.6.1 Experimental Setup & Protocol

To improve the precision, repeatability, and control of the indentation process, an updated setup was designed, as shown in Figure 5.9. In this configuration, the indenter applies a controlled mechanical stimulus to the sensor surface, while the z-axis position is manually adjusted using a geared mechanism. This modification provides higher precision and reliability compared to the robot's motorized control, thereby reducing vibration. This assembly was rigidly coupled to the moving head of the electromechanical shaker. The assembly comprising the indenter and the load cell used for force measurement remained unchanged with respect to the previous setup (refer to Section 5.3.1).

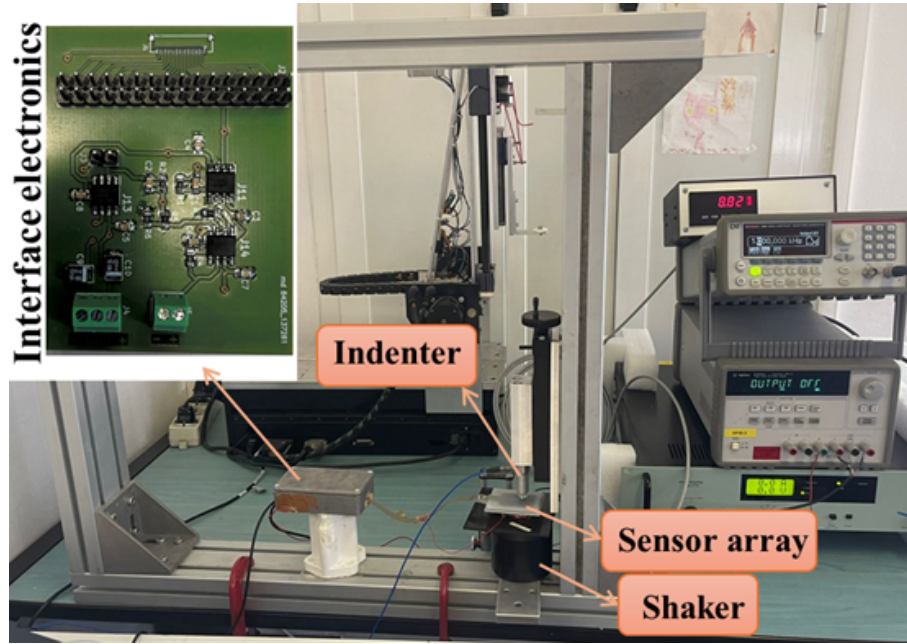


Figure 5.9: Experimental setup to characterize the electromechanical behavior of a PVDF-based tactile sensing system.

A square metallic support structure was incorporated to minimize unwanted vibrations and mechanical resonances transmitted through the system, which may have contributed to the resonance observed in the response function (see Figure 5.6). This modification ensures a more stable and uniform excitation during testing. The same interface electronics described in Section 5.2.2 have been employed to condition the PVDF output signals. Overall, the updated setup enables synchronized mechanical excitation and signal acquisition, providing enhanced stability and accuracy in the experimental data that will be used to refine the PVDF sensor model.

During testing, a mechanical input (force) was applied to a single sensor within the array, while the PVDF response was recorded as a voltage output. Three different preload levels ($PL = 0.7, 1.0, \text{ and } 1.2 \text{ N}$) were applied to ensure continuous contact between the indenter and the Dragon Skin surface throughout each test, additionally to test the linearity of the system. The preload values were controlled using a laser displacement sensor (WayCon LAS-TM10).

For each experiment, a single-frequency sinusoidal signal was generated using a signal generator and supplied to the electromechanical shaker. The excitation signal was amplified through a power amplifier (Brüel and Kjaer, Type 2718, HBK Germany). Sinusoidal forces were applied in the $1 \text{ Hz} - 1 \text{ kHz}$ frequency range. The signal from the

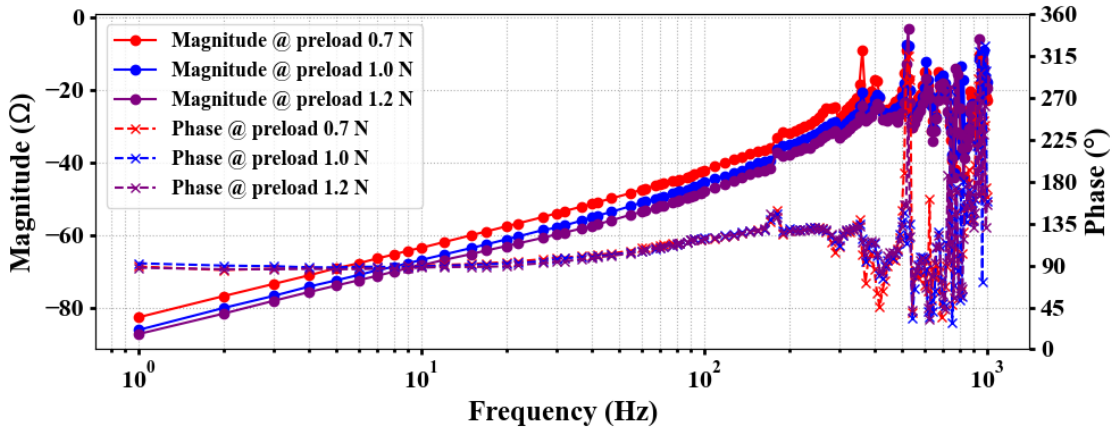


Figure 5.10: Response function of the PVDF tactile sensor in the 1–1000 Hz frequency range under three different preload levels.

load cell (stimulus) was conditioned using Signal Conditioner (Model 482C54), while the charge output from the PVDF transducer was processed through the proposed interface electronics.

The outputs of both conditioning circuits were routed to an NI DAQ board. Data acquisition, visualization, and storage were managed through a custom graphical user interface (GUI) developed in NI LabVIEW on a host PC.

5.6.2 Results

Figure 5.10 presents the experimental results showing the response function of the PVDF-based tactile sensor for three different preload levels applied during the experimental protocol. The figure displays both the amplitude (in dB) and the phase (in degrees) of the sensor's response over the 1–1000 Hz frequency range.

Each curve corresponds to a specific preload level, as indicated in the legend. The response function characterizes the relationship between the applied indentation force and the voltage output from the PVDF sensor through the interface electronics. Each data point represents the mean amplitude and phase of the input and output sinusoidal signals, averaged over ten oscillation cycles at each frequency.

Because the interface electronics exhibited a flat transfer function in the analyzed frequency range, the measured response primarily reflects the intrinsic electromechanical behavior of the PVDF sensor and its cover layer. In other words, the output mainly

characterizes the force-to-current conversion of the PVDF element integrated on its rigid substrate and covered by the protective layer.

The log–log amplitude plot reveals an approximately 20 dB/decade slope, consistent with a first-order linear system, indicating derivative-like behavior. The phase profile supports this observation, confirming that the PVDF tactile sensor behaves mechanically as a velocity sensor, with an output proportional to the rate of change of the applied force. Additionally, the response functions obtained under three different preload conditions were highly repeatable and consistent with the findings from the previous experiment.

However, the results obtained with the new setup still exhibit noticeable vibration components and a more pronounced resonance region above approximately 350 Hz. This suggests that, although the updated configuration improves mechanical control, alignment, and measurement repeatability, it may also introduce additional structural vibration modes due to coupling effects between the shaker, the metallic support, and the sensor assembly. Further refinements of the setup are therefore necessary to mitigate these parasitic resonances and achieve a smoother, more stable frequency response. In addition, further optimization of the cover layer is required to shift the main resonance outside the frequency band of interest (up to 1 kHz). A complete description of the electromechanical modeling framework, parameter identification, and extended experimental validation of the PVDF-based tactile sensor is provided in the corresponding journal submission [171].

CHAPTER 6

Multisensory Wearable Glove for Object Recognition Based Embedded Machine Learning

This chapter presents the development of a multisensory wearable glove integrated with embedded machine learning, addressing the second main objective of this thesis. The glove is designed to enable haptic representation, with a particular focus on object recognition. By combining multiple sensing modalities with lightweight, real-time processing, the system aims to provide an affordable and compact solution for recognizing object properties in practical scenarios.

6.1 Introduction

The human skin is the primary interface for interacting with the surrounding environment. In particular, the somatosensory system embodies haptic perception, enabling the detection of various physical properties of objects [172]. Researchers have been motivated by the features of the skin to replicate the sense of touch, resulting in the development and advancement of artificial tactile sensing systems [141]. These systems exhibit promising capabilities in endowing, to a certain measure, artificial tactile perception, which is involved in many robotics [40], prosthetic [144], and wearable devices applications [173].

Considerable efforts have been made to exploit these sensory signals to perform intelligent tasks through Machine Learning (ML) algorithms. These efforts contributed to developing the so-called smart tactile sensing systems, that are capable of conducting smart tasks such as texture classification [174], object shape recognition [175], and braille letter reading [176]. Nevertheless, this domain is restricted by many constraints when considering real-time applications. These limitations involve the bulky material and components of the sensing system and the high computational cost of signal preprocessing

and classification (ML classifiers). Thereby, the challenge lies in developing hardware-friendly systems in terms of scalability and portability, besides the low computational cost of the processing algorithms due to the resource constraints of hosting devices.

Several state-of-the-art solutions proposed wearable glove systems for object recognition. For instance, authors in [43] proposed a wearable glove featuring 548 piezo-resistive sensors arranged in a dense matrix for object recognition, to estimate object weight, and to explore tactile patterns that emerge while grasping objects. Despite the high reported classification accuracy, dealing with massive data collected by a large number of sensors imposes difficulty in performing low-computational cost processing of data, besides the high power consumption required during data collection. In [108], the authors introduced a wearable glove with a multimodal sensor array based on piezoresistive and thermal transducers to classify 20 objects. The authors transformed the analog signals into pressure and thermal distributed images, followed by a deep convolutional neural network to classify these images into their corresponding objects. Although the high reported classification accuracy of 94.2%, converting time-series signals into images introduces delays making the system not suitable for real-time applications that require rapid responses. Additionally, the authors in [177] proposed a glove that features a fusion of visual-tactile sensing for object recognition using deep learning algorithms. Nevertheless, the bottleneck of converting time series signals into images persists. Overall, most solutions adopt either bulky systems in terms of hardware resources, or high computational cost processing algorithms. Besides these limitations, there is a lack of hardware deployment of these processing algorithms on edge devices to perform real-time inferences and assess the overall performance.

The main contributions of this chapter can be summarized as follows:

- Establishing a low-cost glove equipped with commercial sensors covering the fingertips to record data while interacting with daily objects.
- Development of a 1D-CNN to process time series spatio-temporal data for object recognition. A classification accuracy of 99.29% has been achieved.
- Deployment of the 1D-CNN classifier on a low-cost STM32F401-RE for real-time inferences. The system is evaluated in terms of classification accuracy, latency, power, and energy consumption. A latency of 8.147 ms, and power and energy consumption of 59.85 mW and 0.4875 mJ, respectively, have been reported.

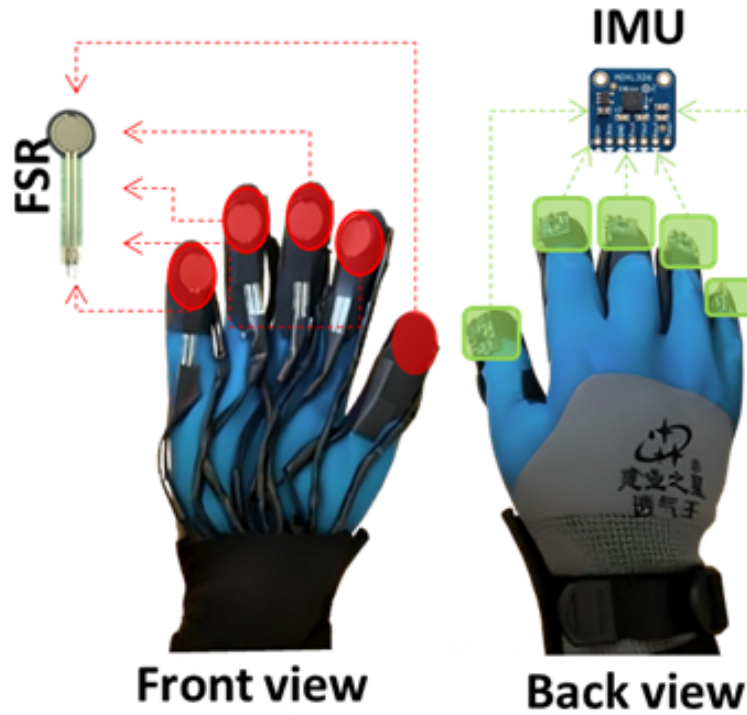


Figure 6.1: The developed multisensory wearable glove: Front and back view of the glove developed for the experiment

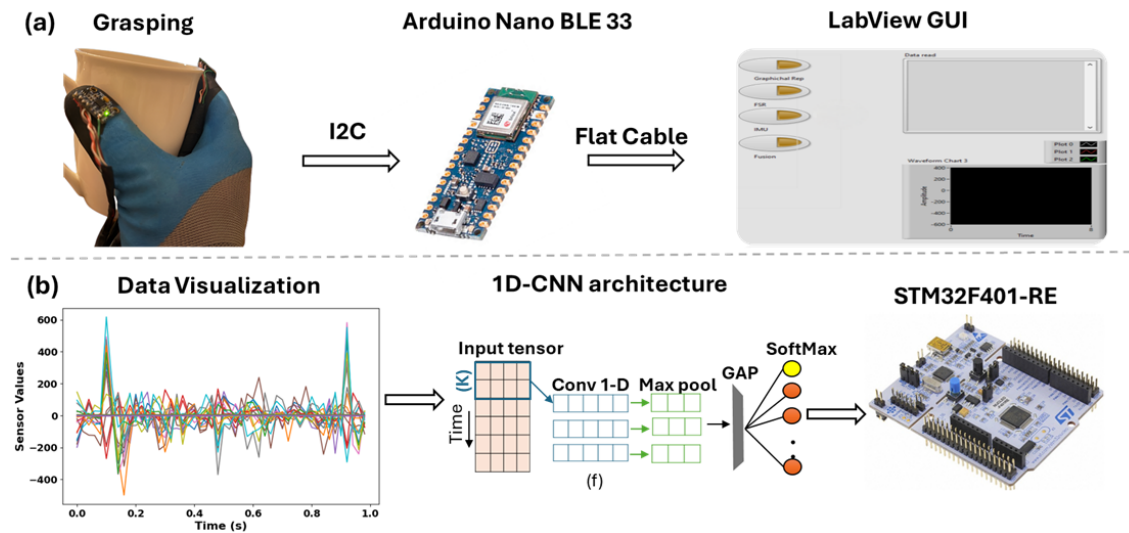


Figure 6.2: The end-to-end system for object recognition: (a) Data acquisition board and the LabVIEW GUI for data collection. (b) An example of collected data, followed by the architecture of the 1D-CNN used in this work for identifying objects and the board used for performing real-time inference.

This chapter aims to overcome these limitations by introducing an end-to-end framework that utilizes a low-cost multisensory glove equipped with commercial piezoresistive force sensors (FSRs) and inertial measurement units (IMUs), alongside an embedded shallow one-dimensional convolutional neural network (1D-CNN) for object recognition. The proposed system performs online recognition of 28 daily objects by directly dealing with raw signals in the form of time series.

6.2 Materials and Methods

This section describes the proposed wearable glove along with the data collection procedure. Then, we discuss the employed 1D-CNN for classification. Finally, the deployment of the classifier on the edge device is presented.

6.2.1 Sensing system

A commercial textile glove (≈ 5 USD) is employed in this work as the supporting structure for the sensing system. The glove hosts five FSR402 pressure sensors [178] (≈ 7 USD per item) mounted on the front of the distal phalanx of the finger, along with five IMUs (MPU6050) [179] (≈ 15 USD per item) fixed on the back of the same area (see Figure 6.1). The 3 axes (x, y, and z) of both the accelerometer and gyroscope embedded in the IMUs are considered in this work. Therefore, our system constitutes a total of 35 input channels (5 FSR402 + 5 IMUs (3-axis $\times$ 2 embedded sensors)). The rationale for this sensorization architecture is to partially emulate the coverage area of the biological mechanoreceptors that are particularly present in the fingers. The FSRs detected the touch by measuring applied forces, providing tactile information [180], while the IMUs captured finger position (proprioceptive data [181]). A custom-designed PCB is fabricated to connect the sensors to an Arduino Nano 33 BLE (≈ 25 USD) through the I2C connection protocol. The signals of the sensors were conditioned by the Arduino board with a sampling rate of 200 samples/second. Data acquisition and collection were implemented using a graphical user interface (GUI) developed with LabView on a host PC. Overall, the proposed wearable glove costs around 140 USD.

The content of this chapter has been published in the following paper:

M. Yaacoub, H. Al Haj Ali, C. Gianoglio, M. Valle, and A. Ibrahim, "Multisensory Wearable Glove for Object Recognition Based Embedded Machine Learning," 2024 31st IEEE International Conference on Electronics, Circuits and Systems (ICECS), Nancy, France, 2024.



Figure 6.3: Employed 28 daily life objects.

6.2.2 Dataset

A dataset including haptic information provided by the sensing system when grasping 28 daily life objects (see Figure 6.3) has been collected through the proposed wearable glove, as shown in Figure 6.2(a). Five subjects have been involved in this experiment. Each subject was asked to wear the glove, grasp the objects for 1 second, and then release it. Each subject performed 10 trials for each object, resulting in 50 trials per class. The dataset is formalized as: $\mathcal{D}_{Fusion} = \{(\mathcal{X}, y)_i; \mathcal{X}_i \in \mathbb{R}^{200 \times 35}; y_i \in \{Object1, Object2, \dots, Object28\}; i = 1, \dots, 1400\}$, where 35 represents the input channels (5 FSR + 5 IMUs) and 200 are the time steps (considering a sampling frequency of 200 Samples/ second). To investigate the influence of the two types of sensors used in this study, the dataset was further split into two separate datasets. The first dataset contains only IMU data, formalized as follows: $\mathcal{D}_{IMU} = \{(\tilde{\mathcal{X}}, y)_i; \tilde{\mathcal{X}}_i \in \mathbb{R}^{200 \times 30}\}$. The second dataset contains only FSR data, formalized as follows: $\mathcal{D}_{FSR} = \{(\hat{\mathcal{X}}, y)_i; \hat{\mathcal{X}}_i \in \mathbb{R}^{200 \times 5}\}$. Overall, we aim to study the suitable sensor configuration for the object shape recognition application, attempting to study the versatility of our system for future experiments.

6.2.3 Classifier

A 1D-CNN network is employed in this study to process the spatio-temporal nature of the raw signals. Such networks are able to capture temporal dependencies in the signals without requiring hand-crafted features. Furthermore, the compact nature of 1D-CNNs, which mainly involves scalar multiplications and additions, makes them suitable for real-time implementation on low-cost hardware[182].

Figure 6.2(b), illustrates the architecture of the 1D-CNN. It embeds one convolution layer that processes a 2-D input tensor, one dimension corresponding to the number of sensors, and the second dimension is the time information (time samples). The convolution

layer comprises f 2-D kernel (k) with the same geometry as the input tensor. These kernels slide along the time axis creating f feature vectors through the scalar product operation. Rectified Linear Unit (ReLU) is used as an activation function, followed by a batch normalization layer. The Max pooling performs a maximum pooling operation with dimension 2×1 . The global average pooling layer (GAP) condenses all the feature maps from the previous layers into a single one by averaging each feature map. The resulting vector is fed to the last layer consisting of 28 neurons with Softmax activation function to perform prediction (corresponding to the 28 objects).

6.2.4 Training strategy

The training process involves two steps: data preparation and network selection. During data preparation, each signal is standardized to ensure a consistent scaling range for both the FSR and IMU, accounting for their different ranges. For each collected trial, this involves adjusting the signals to have a mean of zero and a standard deviation of one, using the following equation:

$$\mathcal{X}_{\text{standardized}} = \frac{x - \mu}{\sigma} \quad (6.1)$$

where $\mathcal{X}_{\text{standardized}}$ is the standardized signal and x is the original signal.

The network selection phase involves a grid search performed after standardization using different combinations of filters (f) and kernel sizes (k) to select the best-performing network, as follows:

$$f = \{4, 8, 16, 32, 64\}.$$

$$k = \{2, 3, 4, 5\}.$$

A total of 20 1D-CNN configurations are evaluated based on the proposed k and f values. We first investigate the best-performing network on $\mathcal{D}_{\text{Fusion}}$ dataset based on the grid search. Following this, the architecture of the best network is chosen to perform the training on the two other datasets $\mathcal{D}_{\text{IMU}}$ and $\mathcal{D}_{\text{FSR}}$. In each training experiment, the dataset is split into 80% for training, 10% for a validation set (for network selection), and 10% for testing (to estimate generalization performance). The networks are all implemented in Python by using the TensorFlow framework [183] with the following settings: Adam optimizer [184] with a learning rate of 10^{-3} , batch size of 32, and number of epochs $ep = 300$. We implement the early stop criterion on the validation loss with a patience value of $p = 5$ to prevent over-fitting.

6.2.5 Hardware Deployment

The STM32F401-RE[185] is employed in this study to host the 1D-CNN and perform online object recognition. The STM32 board features an Arm Cortex-M4F processor clocked at 84 MHz, equipped with 512 kB of flash memory, and 96 KB of SRAM, operating at 3.3 V. The motivation for selecting this board lies in its low power consumption, making it ideal for a wide range of low-power computations at the edge. This ensures that the overall computational cost of the proposed system remains minimal.

Upon the training completion, the network is converted into an MCU-compliant format through the API made available by the TensorFlow Lite library to export the int8 network format (i.e. compressed network size for light computations). The quantized network is loaded on the microcontroller using the STM32CubeIDE software [186], where the flash memory hosts both the code and network parameters, and RAM stores the testing sample for inference. We evaluate the real-time inference through four evaluation metrics: classification accuracy ($\mathcal{ACC}$), latency ($\mathcal{T}_{inf}$), power ($\mathcal{P}$) (static and dynamic), and energy consumption ($\mathcal{E}$) per inference (sample). The microcontroller is configured with the maximum clock frequency and a 16-bit internal timer to measure the $\mathcal{T}_{inf}$ (network execution time). The $\mathcal{P}$ values are measured by using the X-NUCLEO-LPM01A extension board [187]. Finally, The $\mathcal{E}$ is computed using the following equation:

$$\mathcal{E} = \mathcal{P} \times \mathcal{T}_{inf} \quad (6.2)$$

6.3 Results and Discussion

This section presents the $\mathcal{ACC}$ of the 1D-CNN network on the test datasets. Consequently, we report the evaluation metrics of the hardware deployment through the metrics presented in section 6.2.5.

6.3.1 Classification accuracy

Figure 6.4 reports the $\mathcal{ACC}$ values of the best performing 1D-CNN on the three datasets. The x-axis represents the datasets, and the y-axis reports the $\mathcal{ACC}$. We found that the best-performing network on the $\mathcal{D}_{Fusion}$ includes a convolutional layer with a filter dimension $f = 64$ and a kernel size $k = 2$, with a $\mathcal{ACC}$ of 99.29%. This $\mathcal{ACC}$ dropped by $\approx 36.43\%$ when considering only the five FSR sensors. However, when considering the 5 IMUs, the $\mathcal{ACC}$ dropped only by $\approx 0.25\%$. This behavior implies that

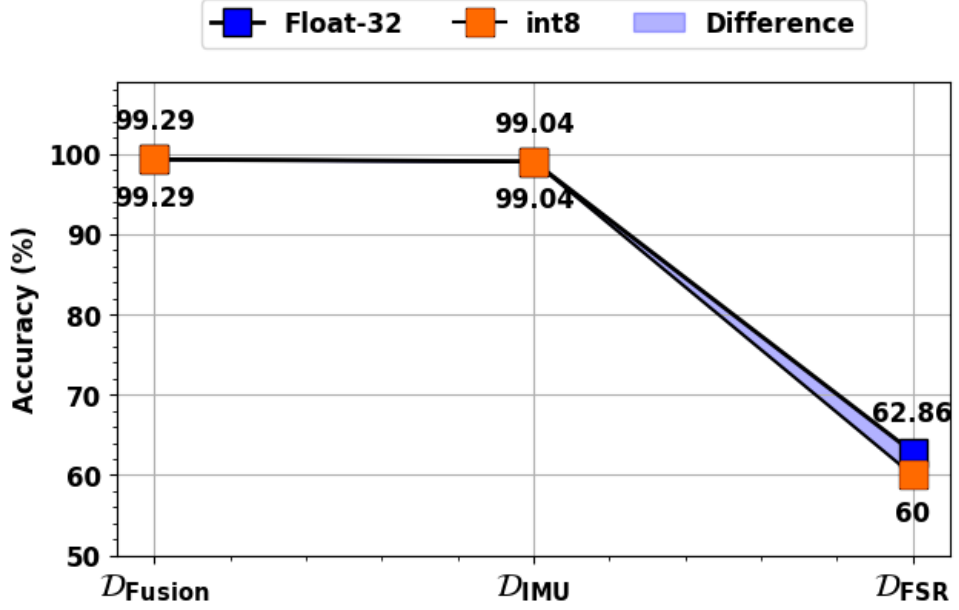


Figure 6.4: Summary of the 1D-CNN classification accuracy on the three datasets. Float-32 (before quantization) is color-coded in dark yellow and int-8 (quantized) is in dark blue. The shaded areas highlight the accuracy differences between the float-32 and int8 formats.

IMU sensors, through the 3 axes of both the accelerometer and gyroscope, contribute mainly to conveying the primary information of the objects such as the kinematics of the glove’s fingers when grasping the object, instead of the contact information. Overall, the classification outcomes indicate a low significance of the data acquired from FSR sensors in identifying objects. Conversely, they underscore the criticality of the IMU sensors, affirming that proprioceptive information is more valuable for such applications.

6.3.2 Hardware evaluation

Starting with the $\mathcal{ACC}$ of the int8 network, a minor drop $\approx 2.86\%$ is found when training on $\mathcal{D}_{FSR}$. This can be attributed mainly to the so-called quantization error (i.e., difference in format precision). The performance of the evaluated models in terms of accuracy, memory footprint, and inference time is summarized in Table 6.1. The 1D-CNN trained on $\mathcal{D}_{Fusion}$ exhibited a $\mathcal{T}_{inf}$ of 8.147 ms, which is higher compared to the network trained on $\mathcal{D}_{IMU}$ and $\mathcal{D}_{FSR}$, with $\mathcal{T}_{inf}$ of 6.944 ms and 3.133 ms, respectively. This disparity is attributed mainly to the difference in input size (i.e., 35 input channels for $\mathcal{D}_{Fusion}$, 30 channels for $\mathcal{D}_{IMU}$, and 5 for $\mathcal{D}_{FSR}$). Regarding $\mathcal{P}$ values, the $\mathcal{D}_{Fusion}$ network consumed 59.85 mW, slightly higher than the networks of $\mathcal{D}_{IMU}$ and $\mathcal{D}_{FSR}$ which consumed 59.4

Table 6.1: Performance metrics of different models.

1D-CNN			
Dataset	latency (ms)	Power (mW)	Energy (mJ)
$\mathcal{D}_{Fusion}$	8.147	59.85	0.4875
$\mathcal{D}_{IMU}$	6.944	59.4	0.412
$\mathcal{D}_{FSR}$	3.133	57.45	0.179

mW and 57.45 mW, respectively. Finally, $\mathcal{E}$ followed the same trend of $\mathcal{T}_{inf}$ with a 0.4875 mJ in $\mathcal{D}_{Fusion}$, 0.412 mJ in $\mathcal{D}_{IMU}$ and 0.179 mJ in $\mathcal{D}_{FSR}$.

6.4 Conclusion

The chapter proposes a low-cost multisensory wearable glove (≈ 140 USD) for object recognition. The glove includes commercial FSRs and IMUs sensors to collect haptic information when grasping daily life objects. A shallow 1D-CNN was implemented to deal directly with the time-series data and perform subsequent object recognition. The implemented 1D-CNN is deployed on a low-cost STM32F401-RE edge device to perform real-time inferences. Through the chapter, we investigated the contribution of each sensor in recognizing the objects. We found that IMU sensors exhibited an accuracy of 99.04% while consuming only 0.412 mJ per inference, making it favorable for object recognition. The fused sensors achieved a slightly higher accuracy of 99.29%, while consuming 0.4875 mJ per inference. Overall, the proposed system is considered a suitable candidate for performing efficient online inferences. Future research will involve design optimization along with dynamic signal analysis, such as texture recognition, to extend the applicability of the proposed system across diverse tasks and scenarios.

6.5 Glove Optimization

Building on the baseline 1D-CNN glove framework introduced in the previous sections, this part focuses on optimizing the manually designed neural network architecture, aiming

to reduce the resource usage of the embedded hardware. Deep neural networks (DNNs) [22] are computationally distributed models capable of learning representations from raw data through a structure of hierarchical layers, similar to how the brain processes and interprets information. Their generalization and learning capabilities, overcoming the limitations of traditional statistical approaches, offer an optimal solution for such applications. However, designing the most effective DNN model is a function of the problem under analysis and requires advanced expertise, which most end users lack. Nevertheless, DNN architectures are often highly dependent on data distribution, necessitating a re-design when the data changes. Additionally, as highlighted in Chapter 2, in the context of wearable and edge devices, the deployment of DNNs introduces additional challenges due to the constraints imposed by the embedded hardware on power consumption, memory capacity, and computational efficiency [188]. Traditional cloud-based inference solutions are impractical in scenarios requiring real-time processing and low-latency decision-making. Instead, near-sensor computing allows DNNs to operate directly on resource-constrained hardware, minimizing energy consumption while enhancing response times and communication efficiency [189].

To address these challenges, hardware-aware Neural Architecture Search (HW-NAS) [190] automates DNN architecture design, reducing the need for expert intervention and enhancing adaptability to different data distributions. Additionally, it integrates hardware constraints to optimize architectures for deployment on wearable and edge devices. This work integrates Hardware-Aware Neural Architecture Search (HW-NAS) with the multisensory glove developed in section 6.2.1, extending the results presented in section 6.3 by applying neural architecture search to develop an energy-efficient multisensory glove. To the best of our knowledge, this is the first work to implement HW-NAS for wearable devices in the context of object recognition. The main contribution of this work can be summarized as follows:

- Employing HW-NAS to design and deploy CNNs for object recognition based on signals acquired from a multisensory wearable glove.
- Demonstrating that HW-NAS enables the design of efficient CNNs that generalize well on resource-constrained edge devices for real-time object recognition.

6.5.0.1 Hardware-Aware Neural Architecture Search

HW-NAS automates neural network design by identifying optimal architectures for a given hardware target. Once the execution device is specified, HW-NAS searches for a network

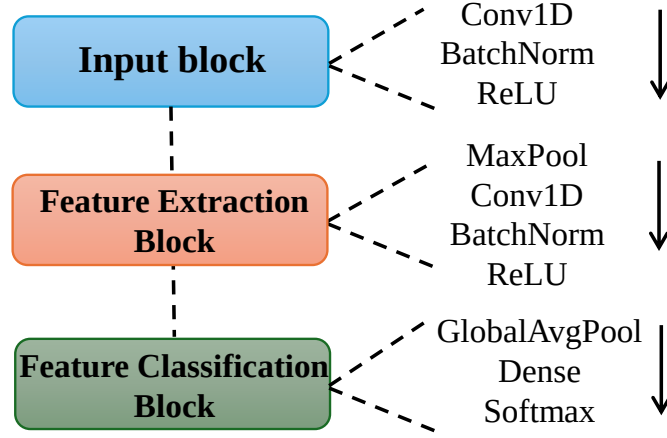


Figure 6.5: Search space of the proposed NAS.

design that runs efficiently on the chosen hardware while maximizing performance on the given dataset. HW-NAS has outperformed human-designed neural networks on several TinyML benchmarks [191], achieving state-of-the-art results in computer vision, signal processing, and anomaly detection [192, 126, 193]. On the other hand, a state-of-the-art HW-NAS as MnasNet requires 40,000 GPU hours [194], while MCUNet demands 300 GPU hours [192]. Recently, Garavagno et al. [195] proved that one can reduce the search cost (e.g., 1.14 GPU hours) while still obtaining state-of-the-art results for tiny computer vision on ultra-low-power microcontrollers. Accordingly, this paper aims to show that last-generation HW-NAS provides a convenient way to automate the design of neural networks for real-time object detection in multisensory wearable gloves. This approach ensures compliance with strict hardware constraints while achieving satisfactory generalization performance.

6.5.0.2 Proposal

One-dimensional convolutional neural networks (1D-CNNs) demonstrate strong potential in processing time-series spatiotemporal data, while maintaining a lightweight architecture suitable for hardware deployment [182]. In this work, we propose an HW-NAS framework to optimize 1D-CNNs for object recognition, considering the constraints of the device where the networks are executed.

In general, every NAS has three hallmarks: the search space, i.e., the set of rules used to build candidate neural networks; the search strategy, which defines how the NAS explores the search space; and the evaluation strategy, i.e., the logic adopted to pick the

Algorithm 1 Search Strategy

```

 $n = 1$                                 ▶ minimum number of kernels of the first layer
 $(b, score) = BestBlock(n)$                 ▶ find best block
repeat
     $reference = score$ 
     $n = n * 2$                                 ▶ increase number of kernels
     $(b, score) = BestBlock(n)$                 ▶ find best block
until  $score > reference$                 ▶ stop if no improvement
return  $n, b$ 
procedure BESTBLOCK( $n$ )
     $best = 0, \Delta = 0$ 
     $b = MaxBlocks(n)$                                 ▶ get maximum number of blocks
    repeat
         $train\ CNN(n, b)$                                 ▶ train the new candidate
         $score = f(n, b)$                                 ▶ get score of new candidate
         $\Delta = score - best$                                 ▶ check if score is increasing
        if  $\Delta > 0$  then
             $best = f(n, b)$                                 ▶ update best
             $b = b - 1$                                 ▶ remove a block
        else
             $b = b + 1$                                 ▶ restore best block
        end if
    until  $\Delta > 0$ 
    return  $b, best$ 
end procedure
procedure MAXBLOCKS( $n$ )
     $b = -1$ 
    repeat
         $b = b + 1$ 
        check feasibility of  $CNN(n, b)$                 ▶ check HW constraints
    until  $CNN(n, b)$  is feasible
    return  $b$ 
end procedure

```

best neural network among the explored candidates. The **search space** of the adopted NAS is inspired by "ColabNAS: Obtaining lightweight task-specific convolutional neural networks following Occam's razor" [193] builds candidate neural networks by stacking fixed architectural blocks. Figure 6.5 shows the search space: each candidate always starts with an input block (IB) and ends with a feature classification block (FCB), with a variable number of feature extraction blocks (FEB) placed between. The **IB** is composed of a mono-dimensional convolutional layer, followed by batch normalization and a rectified linear unit; while the **FEB** is composed of a mono-dimensional max pooling layer with pool size 2 and stride 2, followed by a mono-dimensional convolutional layer, a batch

normalization layer, and a rectified linear unit. The **FCB** applies global average pooling to extracted features, which are then classified by a single dense layer having a softmax activation function. The number of kernels k_i adopted in the i -th convolutional layer, i.e. in the i -th FEB, is defined by the following equation: $k_i = k_{i-1} + k_{i-2}/2 + k_{i-3}/2 + \dots$ with $i \geq 0$ and $k_0 = n$. All the kernels have a fixed length equal to 3. Each candidate neural network can be identified by $CNN(n, b)$, where n is the number of kernels adopted in the first convolutional layer and b is the number of feature extraction blocks adopted. The **search strategy** starts with the lowest possible number of kernels, i.e., $n = 1$, and generates a neural network that has the maximum possible number of FEBs. Then, it starts removing a FEB at a time, until the evaluation score decreases. The candidate generated before the evaluation score drop is taken as a reference for the next iteration. During the next iteration the parameter n is doubled, and the process of searching for the candidate having the minimum number of FEBs while offering the best evaluation score is repeated. The reference is compared with the new candidate found: if the reference has a better evaluation score, the algorithm stops, otherwise, the new candidate becomes the reference, and the algorithm continues. Eventually a candidate not improving the reference is found, and the algorithm stops. The algorithm 1 provides a pseudo-code for the proposed search strategy. The **evaluation strategy** f gives a score to candidates based on the best validation accuracy shown during 100 training epochs. A negative score is assigned to candidates that do not meet the constraints imposed by the hardware target. In detail, the RAM and Flash occupation, as the number of multiply and accumulate instructions of each candidate are evaluated for testing the deployability on the target hardware.

6.5.0.3 Results and Discussion

The HW-NAS was run independently on the three datasets described in Section 6.2.2. A detailed comparison of the evaluation metrics across different deployment configurations is provided in Table 6.2, which compares the performance of the proposed HW-NAS approach with the CNN manually designed in [196]. The comparison is based on key metrics, including classification accuracy, memory consumption (RAM and Flash), latency, and energy consumption for networks deployed on low constraint devices, STM32-F401 featuring an Arm Cortex-M4F processor clocked at 84 MHz, equipped with 512 kB of flash memory, and 96 KB of SRAM, operating at 3.3 V. The networks designed in [196] for the two datasets have the same architectures (with a different input size based on the sensors used), consisting of one convolutional layer (64 filters, kernel size 2), followed

by batch normalization, max-pooling, global average pooling, and a fully connected layer with softmax activation function).

The network trained on $\mathcal{D}$ consists of the IB (the convolutional layer has 8 filters) and the FCB. The network achieves a slight improvement in accuracy of 0.23 % compared to [196]. However, this small gain is accompanied by significant reductions in resource usage, including a 17.97% decrease in RAM and a 33.89% reduction in Flash memory requirements. Additionally, latency is reduced by 23.18%, while energy consumption decreases by 27.92%. The network trained on $\mathcal{D}_{IMU}$, which utilizes only IMU sensor data, has the same architecture as the previous one. It achieves a comparable accuracy with a slight improvement of 0.24% while demonstrating significant gains in resource efficiency. RAM usage is reduced by 23.72%, and flash memory utilization decreases by 34.28%. Additionally, latency is lowered by 12.31%, and energy consumption is reduced by 17.71%. For the FSR sensors, the network trained on $\mathcal{D}_{FSR}$ consists of the IB, two FEB with 8 and 12 filters respectively, and the FCB. It achieves an accuracy of 76.57%, surpassing previous work but remaining lower than the results obtained with sensor fusion and IMU sensors. Nonetheless, it improves resource efficiency, with RAM usage reduced by 9.6% and Flash memory by 14.32%. However, despite these resource savings, the network exhibits increased latency and energy consumption, rising by 33.9% and 26.5%, respectively.

Overall, the results demonstrate that the proposed method consistently outperforms previous work in terms of computational efficiency and energy consumption, while maintaining comparable accuracy. The improvements observed in both networks highlight the potential of the proposed approach for deployment in real-time, resource-constrained environments, where energy efficiency and low latency are crucial. However, the network trained solely on FSR data achieved the lowest accuracy, highlighting the inherent challenge of relying exclusively on force information for human-object interaction. This limitation explains why HW-NAS could not achieve satisfactory accuracy when using only FSR data.

Compared to other works that propose sensorized gloves for object recognition, our approach offers an alternative solution by automatically designing a classifier that not only achieves a high accuracy of 99.52% but also has an architecture deployable on a low-power microcontroller, enabling real-time classification. For instance [43], achieved 89.4% accuracy with manually designed CNN processing image sequences, but its architecture is unsuitable for microcontroller deployment. Similarly, [108] obtained 94.2% accuracy with a CNN trained on pressure maps, yet microcontroller deployment was not feasible. while

Table 6.2: Comparison of evaluation metrics.

Sensor	Ref.	Acc. (%)	RAM (KB)	Flash (KB)	Latency (mS)	Energy (μ J)
Fusion	[196]	99.29	13.02	29.62	8.147	487
	This work	99.52	10.68	19.58	6.258	351
IMU	[196]	99.04	12.73	28.99	6.944	412
	This Work	99.28	9.71	19.05	6.089	339
FSR	[196]	60.00	7.57	27.39	3.133	179
	This work	76.57	6.82	23.74	4.194	226

[109] used an SVM on time-series data and achieved 91.88% accuracy, their model required five seconds of manipulation per prediction and was not deployed on a microcontroller. lastly, [110] reached 97% accuracy with an RF model trained on one-second time features, but deployment was not in the scope of the study. Our work addresses this limitation by achieving both high classification accuracy and efficient real-time deployment on low-power microcontrollers.

6.5.0.4 Conclusion

This work presents a multisensory wearable glove integrating FSRs and IMUs for object recognition. It leverages HW-NAS to automate the design of DNN architectures, specifically 1D-CNNs, for real-time time-series processing. The HW-NAS was evaluated on three datasets: FSR-only, IMU-only, and a combined FSR-IMU dataset. The optimized models were deployed on a low-cost STM32F401-RE edge device for real-time inference. A classification accuracy of 99.52% was achieved using the combined FSR-IMU data, with a significant reduction in resource consumption, including up to 27.92% lower energy consumption compared to previous work. These results highlight the effectiveness of the proposed methodology as a robust framework for designing processing pipelines in wearable systems. Furthermore, integrating automated network design with the wearable system opens new perspectives for on-board training, particularly for fine-tuning models to adapt to new objects.

CHAPTER 7

Wearable Multisensory Glove for Shape, Size, and Stiffness Recognition Based on Off-the-Shelf Components

This chapter presents an upgraded version of the glove prototype developed in the previous chapter. The new design integrates a battery module to enable fully portable, battery-operated real-time operation. Additionally, the glove's supporting structure was redesigned to be more compact. To further increase the complexity of the recognition task, three object characteristics, shape, size, and stiffness, were incorporated into a new set of 3D-printed test objects.

7.1 Introduction

Interactions of human with the environment are enabled through their so-called somatosensory system. This system includes a network of senses that relays information about bodily states and physical interactions, with a particular focus on the hands [197]. The sense of touch, originating from the skin, conveys contact information, while proprioception provides essential information about finger position and the movement of the hand. The mechanoreceptors in the skin and deeper tissues convert mechanical deformations into neural signals [172]. These signals are interpreted and decoded by the central nervous system [4], enabling the detection of various physical properties of objects.

Addressing sensory deficits prevalent in conditions such as post-stroke outcomes necessitates the development of artificial tactile sensing systems that emulate the sensing capabilities inherent in the human hand. There has been a long-standing effort to develop advanced sensing solutions [8, 173]. Given the hands' critical role in interacting with and manipulating our environment, this gained the interest of researchers to develop wearable

gloves integrated with these advanced sensing systems [198]. In addition to the advancements in the development of wearable gloves, the integration of these gloves with artificial intelligence (AI) leverages the outcome of handling complex functions such as texture classification [199], object recognition [43], and hardness discrimination [42], to name a few.

To this end, several state-of-the-art solutions have proposed wearable gloves for object recognition. The authors in [43] presented a wearable glove equipped with 548 piezoresistive sensors arranged in a dense matrix for object recognition, weight estimation, and tactile patterns analysis while grasping 26 objects. The collected sensor data was transformed into an image format and processed using a convolutional neural network (CNN). Although the system achieved high classification accuracy, processing the massive data collected by a large number of sensors imposes difficulty for real-time processing with low computational cost processing, in addition to the requirement for high power consumption. Similarly, in [108], authors developed a wearable glove featuring a multimodal sensor array based on piezoresistive and thermal transducers to classify 20 objects. The analog signals were converted into pressure and thermal distributed images, then classified using CNN into corresponding objects. While the system achieved a high classification accuracy of 94.2%, converting time-series signals into images introduced latency, rendering the system unsuitable for real-time applications requiring a fast response. Authors in [109] propose a glove equipped with five resistive flex sensors attached to the finger hands. A support vector machine (SVM) was trained to classify the data transmitted from the sensors while grasping three object shapes: sphere, cuboid, and cylinder. The system demonstrated a high classification accuracy of 91.88%, but with restricted system usability due to the introduced delays from its reliance on the PC. Overall, most state-of-the-art solutions adopt highly computational-demanding algorithms. This often limits their deployment in resource-constrained environments or edge devices. Furthermore, these systems typically rely on custom-built components, making it difficult to implement solutions using off-the-shelf hardware for real-time inference. As a result, scalability, cost-effectiveness, and ease of integration into practical applications are often compromised.

This chapter attempts to overcome these limitations by proposing a wearable multisensory glove based on shelf components, equipped with commercial force piezoresistive sensors (FSRs) and inertial measurement units (IMUs). A dataset was collected from 16 3D-printed objects, encompassing differences in three distinct categories: shape, size, and stiffness. Three tiny machine-learning models were evaluated for processing the dataset and performing online recognition. These models include a one-dimensional con-



Figure 7.1: Front and back views of the developed multisensory glove, highlighting sensor locations.

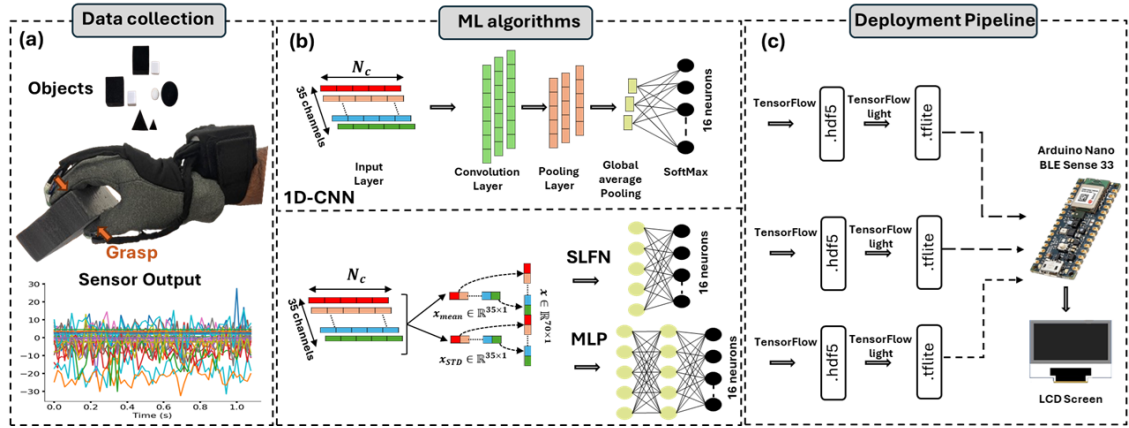


Figure 7.2: End-to-end System: (a) the glove grasping an object, with a photograph of the printed objects alongside an example of the collected data, (b) the preprocessing techniques and the architecture of the machine learning algorithms, and (c) the deployment pipeline.

volutional neural network (1D-CNN) that operates directly on raw signals, a single-layer feed-forward neural network (SLFNN), and a multilayer perceptron (MLP), both trained on representative features extracted from the raw data.

The main contribution of this chapter can be summarized as follows:

- Developing a wearable multisensory glove equipped with commercial sensors based on off-the-shelf components.
- Implementing shallow machine learning algorithms to classify objects based on three categories: shape, size, and stiffness.

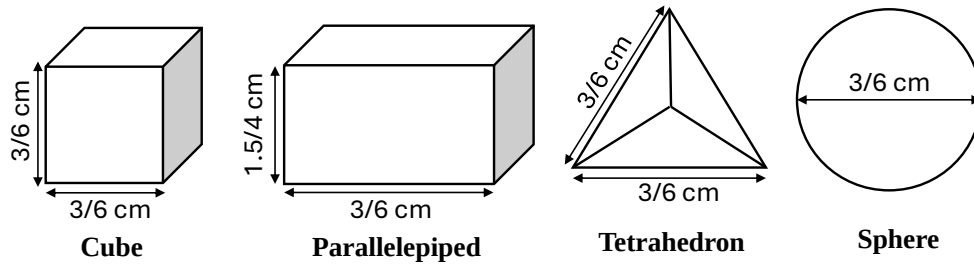


Figure 7.3: Dimensions of the printed objects.

- Deploying the pre-processing and ML models, on a resource-constrained device, specifically the Arduino Nano 33 BLE Sense.

7.2 Materials and Methods

7.2.1 Experimental setup

This section presents the fabricated glove and the printed object used for data collection.

7.2.1.1 Fabrication of the multisensory glove

A scalable commercial textile glove was developed as the supporting structure for the sensing system. This glove is equipped with five Force Sensing Resistors (FSR402) on the fingertips and five 6-axis Inertial Measurement Units (MPU6050) placed on the posterior distal phalanges Figure 7.1 . The rationale behind this sensorization is attempting to replicate the human somatosensory system by providing both tactile and proprioceptive information. The FSRs detect the touch by measuring applied forces, while the IMUs provide the finger position information, enabling applications such as shape discrimination and stiffness estimation [200, 201]. All sensors are connected to an Arduino Pro Mini board with an ATmega328 microcontroller, featuring 2 KB SRAM and 32 KB flash memory, operating at 3.3V. The signals are then transmitted to an Arduino Nano 33 BLE

The content of this chapter has been published in the following paper:

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for recognition. A lithium polymer battery (3.7V, 2000 mAh) powers the system, while an LCD screen connected to the Arduino Nano 33 BLE displays the predicted class.

7.2.1.2 Printed objects

To evaluate the capability of the proposed system in capturing useful data, we 3D-printed 16 objects in four distinct shapes: cube (C), parallelepiped (P), tetrahedron (T), and sphere (S) (Figure 7.3). Each shape was produced in two sizes: large objects (L) and small objects (S). Additionally, each shape includes one hard (H) and one soft (S) version, providing a range of stiffness for evaluation. This combination of shape, size, and stiffness results in the following object set $objects = \{PLH, PLS, PSH, PSS, CLH, CLS, CSH, CSS, TLH, TLS, TSH, TSS, SLH, SLS, SSH, SSS\}$.

7.2.2 Dataset and Pre-Processing

In the experiment, five subjects were asked to wear the glove and interact with each object by grasping, holding, and releasing. In particular, the participants grasped the objects randomly, without controlling the speed and velocity of their grasp; however, they were asked to act within 1 s. This action sequence was repeated 30 times per person per object, resulting in a dataset of 2400 trials. Figure 7.2 (a) depicts the sensor outputs and the grasping mechanism. The dataset can be formalized as follows: $\mathcal{D} = \{(\mathcal{X}, y)_i, \mathcal{X}_i \in \mathbb{R}^{N_C \times N_S}, y_i \in \{PLH, PLS, \dots, SSS\}; i = 1, \dots, 2400\}$. where $N_C = 35$ denotes the number of channels, with each FSR sensor contributing one channel and each IMU contributing six channels (3 for the accelerometer and 3 for the gyroscope sensor). $N_S = 200$ represents the time dimension of the acquired data (200 samples/s).

Features were extracted from $\mathcal{D}$ to find a suitable data representation for the algorithms presented in section 7.2.3. To keep low the computational cost related to the features extraction procedure [40], two simple statistical features, i.e. the mean and standard deviation, were calculated for each channel in $\mathcal{X}_i \in \mathcal{D}$ (Figure 7.2 (b)). This transformation converts each $\mathcal{X}_i \in \mathbb{R}^{35 \times 200}$ into a 1-D array $\tilde{\mathcal{X}}_i \in \mathbb{R}^{70 \times 1}$, where the 70 elements are the concatenated mean and standard deviation values for each of the 35 channels. The resulting dataset, capturing the time features, can be formalized as: $\tilde{\mathcal{D}} = \{(\tilde{\mathcal{X}}, y)_i, \tilde{\mathcal{X}}_i \in \mathbb{R}^{70 \times 1}, y_i \in \{PLH, PLS, \dots, SSS\}; i = 1, \dots, 2400\}$. After feature extraction, the datasets were normalized to have a mean of zero and a standard deviation of one, preventing scale differences from affecting algorithm performance.

7.2.3 Machine learning algorithms

Three ML algorithms are employed to classify the objects: Single-Layer Feed-forward Neural Network (SLFNN), Multi-Layer Perceptron (MLP), and One-Dimensional Convolutional Neural Network (1D-CNN). These algorithms have demonstrated significant success in numerous real-world classification tasks [182, 202, 203, 204].

7.2.3.1 Single-Layer Feed-Forward Neural Network

The SLFNN comprises an input layer with 70 neurons, matching the size of $\tilde{X}$; a hidden layer with N neurons utilizing the ReLU activation function; and an output layer with 16 neurons, corresponding to the number of classes, using the softmax activation function. The optimal network configuration was determined by testing four hidden layer sizes: $N = \{4, 8, 16, 32\}$.

7.2.3.2 Multi-layer Perceptron

The MLP takes the same input as the SLFNN, with two hidden layers using the ReLU activation function and containing N_1 and N_2 neurons, respectively. The output layer is identical to that of the SLFNN, utilizing the softmax activation function to classify the data. Six different combinations of neurons for the first hidden layer N_1 and the second hidden layer N_2 were evaluated: $[N_1, N_2] = \{[4, 8], [8, 16], [16, 16], [16, 32], [32, 16], [16, 8]\}$.

7.2.3.3 One Dimensional convolution neural network

The 1D-CNN processes a 2D input tensor $X \in \mathbb{R}^{35 \times 200}$ representing a time series, normalized using a standard scaler along the channels. The architecture embeds a single convolutional layer comprising $f = \{4, 8, 16, 32\}$ filters, with 2D kernels of sizes $k_s = \{(35, 2), (35, 3), (35, 4), (35, 5)\}$ that slide along the time dimension. The combination of different filters and kernel sizes results in a total of 12 distinct networks to be optimized. The layer employs the ReLU activation function, followed by batch normalization applied to the feature maps, and a max pooling layer reduces the dimensionality by a factor of two. Finally, a global average pooling layer is followed by a dense layer with 16 neurons, utilizing the softmax activation function for classification.

For the training procedure, the datasets $\mathcal{D}$ and $\tilde{\mathcal{D}}$ were split into 80% for training, 10% for validation to select the best network configuration, and 10% for testing, maintaining

class balance throughout. SLFNN and MLP were trained using the time features represented by $\tilde{\mathcal{D}}$, while the 1-D CNN was trained on raw data from $\mathcal{D}$. All networks were implemented in Python using the Keras API, with the following settings: Adam optimizer (learning rate 10^{-2}), a batch size of 32, and 300 epochs. Early stopping based on validation loss, with a patience of $p = 5$, was employed to prevent overfitting.

Table 7.1: Summary of the networks evaluation metrics.

Models	1D-CNN	SLFNN	MLP
Accuracy	0.992	0.938	0.908
Precision	0.992	0.941	0.915
Recall	0.992	0.938	0.908
F1 Score	0.992	0.937	0.908

7.2.4 Embedded Deployment

The deployment was achieved via the following pipeline. First, the trained networks were converted into an MCU-compliant format using the TensorFlow Lite (TFLite) API for deployment on the embedded device (Figure 7.2(c)). Next, the Edge Impulse API was utilized to transform the TFLite models into an Arduino-compatible library. The models were then deployed on the Arduino Nano BLE Sense 33, which operates with a CPU clock frequency of 64 MHz, 1 MB of flash memory, 256 KB of SRAM, and a 3.3 V power supply. This device was chosen for its excellent power management features and compact size, making it an ideal microprocessor for such applications. The real-time inference was evaluated using three metrics: inference time, memory usage, and energy consumption per inference. Energy consumption was calculated by multiplying the power consumption measured through a USB multimeter by the inference time.

7.3 Results and Discussion

Following the model selection process on the validation loss, the best-performing networks identified are the SLFNN with $N = 32$, the MLP with $N_1 = 16$ and $N_2 = 16$, and the

Table 7.2: Summary of the network’s evaluation metrics on board.

Models	1D-CNN	SLFNN	MLP
Inference time (ms)	167	2	1
RAM (kB)	17.7	1.6	1.5
Flash size (kB)	46.2	22.3	18
Energy consumption (<i>mJ</i>)	2.9	0.035	0.017

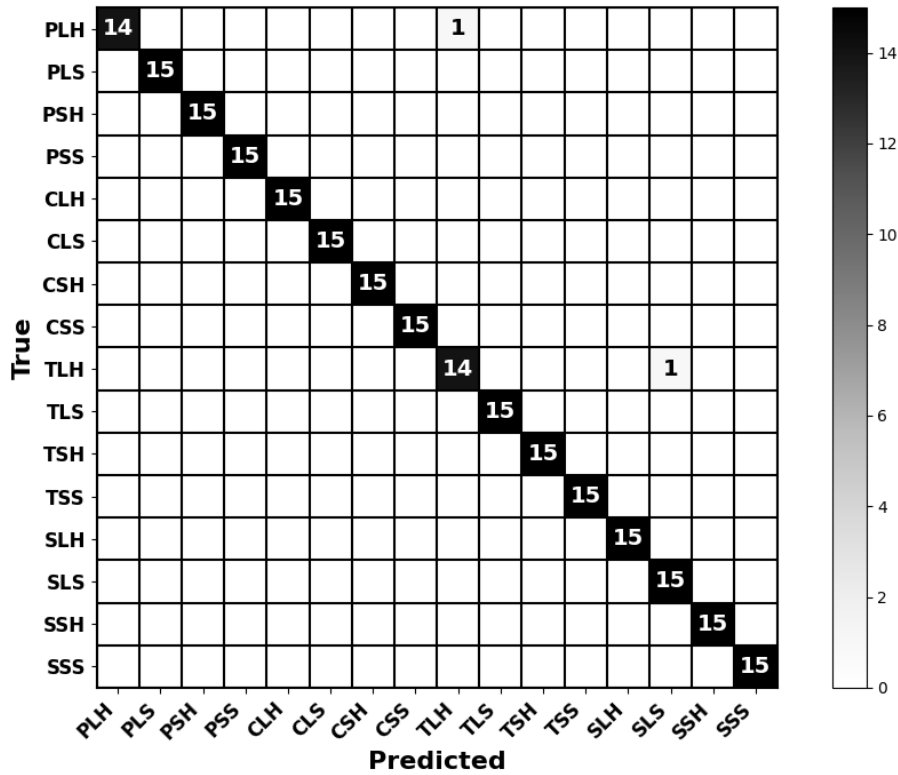


Figure 7.4: Confusion matrix for 1D-CNN with combined subjects.

1D-CNN with $f = 16$ and $k_s = 2$. The overall classification performance of the evaluated neural networks is summarized in Table 7.1 which reports the accuracy, precision, recall, and F1-score for each model. The results demonstrate that the 1D-CNN exhibits the highest classification accuracy of 99.2%, outperforming the SLFNN at 93.8% and the MLP at 90.8%, with respective accuracy drops of 5.4% and 8.4%. This trend is consistent

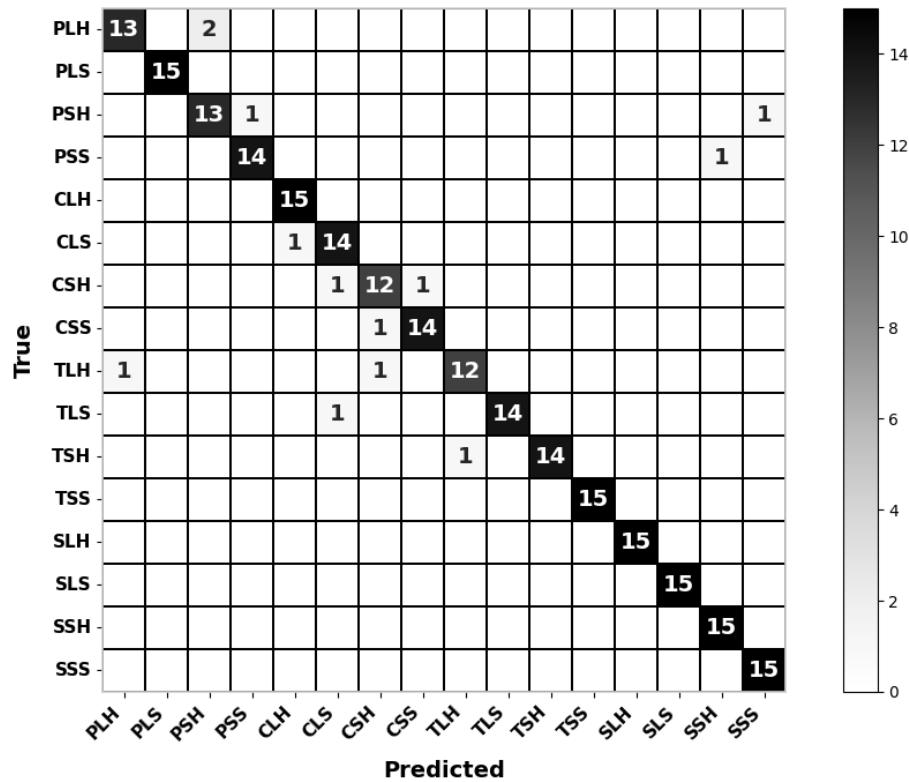


Figure 7.5: Confusion matrix for SLFNN.

across other metrics, where the 1D-CNN surpasses the SLFNN by $\approx 5\%$ and the MLP by $\approx 8\%$.

Figure 7.4 illustrates the confusion matrix of the 1D-CNN, as it has been identified as the best-performing model. The 1D-CNN shows a minor misclassification between the shape of a parallelepiped and a tetrahedron, as well as between a tetrahedron and a sphere, indicating a satisfactory identification of three object categories. In contrast, in Figure 7.5 the SLFNN demonstrates a higher miss classification rate, misidentifying more shapes (eight instances). For instance, it classifies a small soft cube as large, a small hard tetrahedron as large, and a small hard cube as large. Additionally, the SLFNN correctly identifies both shape and size in four cases, such as misclassifying a small hard parallelepiped as a large cube, a large soft cube as a small parallelepiped, a small hard cube as a large tetrahedron, and a large hard tetrahedron as a small cube. MLP in figure 7.6 exhibited the lowest classification accuracy, but it is noteworthy that out of the 22 misclassified data, the network incorrectly classified 14 shapes, 6 stiffness, and 2 both shapes and stiffness. This suggests that the MLP primarily struggles with shapes, while it performs relatively well with size and stiffness.

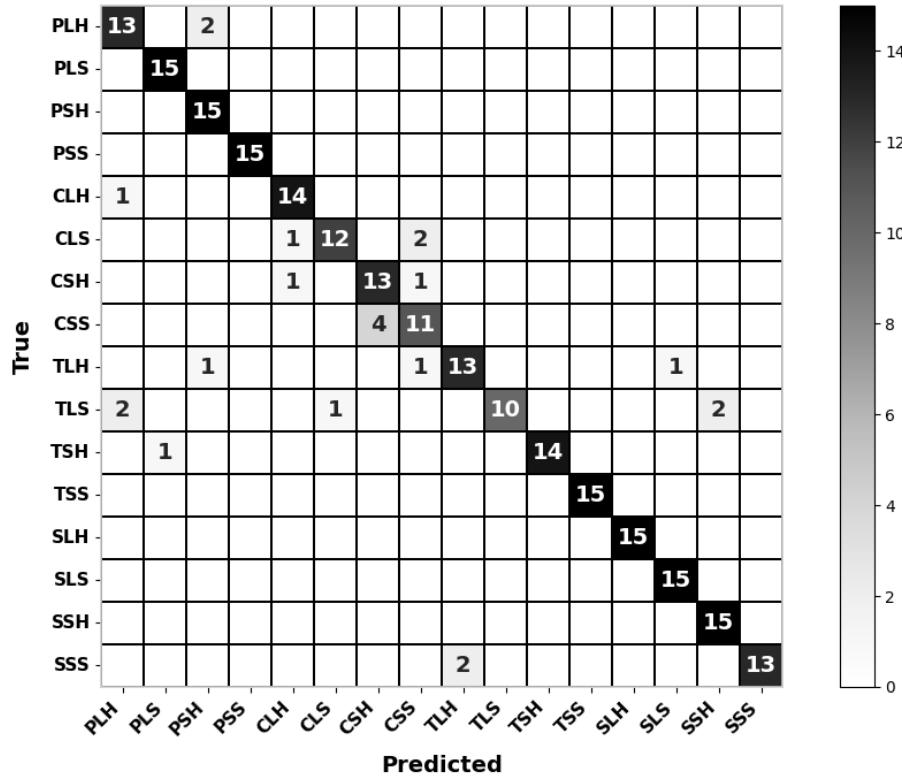


Figure 7.6: Confusion matrix for MLP.

Additionally, to evaluate the generalization performance of the proposed system, data from one subject, out of the five involved in the dataset, was reserved for testing. In contrast, the remaining subjects' data were used to train and validate the same 1D-CNN network configuration. Although the subject-independent setup made the task more difficult and caused more misclassifications (Figure 7.7), the 1D-CNN still achieved an accuracy of 94.58%, demonstrating its effectiveness in handling inter-subject variability.

Regarding the hardware performance, the on-board execution metrics, including inference latency and resource usage, are reported in Table 7.2, which summarizes the performance of the networks deployed on the Arduino Nano device.. As expected, the 1D-CNN has the longest inference time at 167 ms, which is 82.5 $\times$ and 165 $\times$ slower than the SLFNN and MLP, respectively. Regarding RAM usage, the 1D-CNN requires 17.7 kB, which is 11.1 $\times$ and 11.8 $\times$ larger than the SLFNN and MLP, respectively. For flash memory, the 1D-CNN occupies 46.2 kB, whereas the SLFNN and MLP require 2.1 $\times$ and 2.6 $\times$ less space, respectively. Regarding energy consumption, the 1D-CNN consumed 2.9 mJ per inference, while the SLFNN and MLP consumed 0.035 mJ and 0.017 mJ, respectively. Additionally, the inference time of the pre-processing stage (i.e., feature extraction)

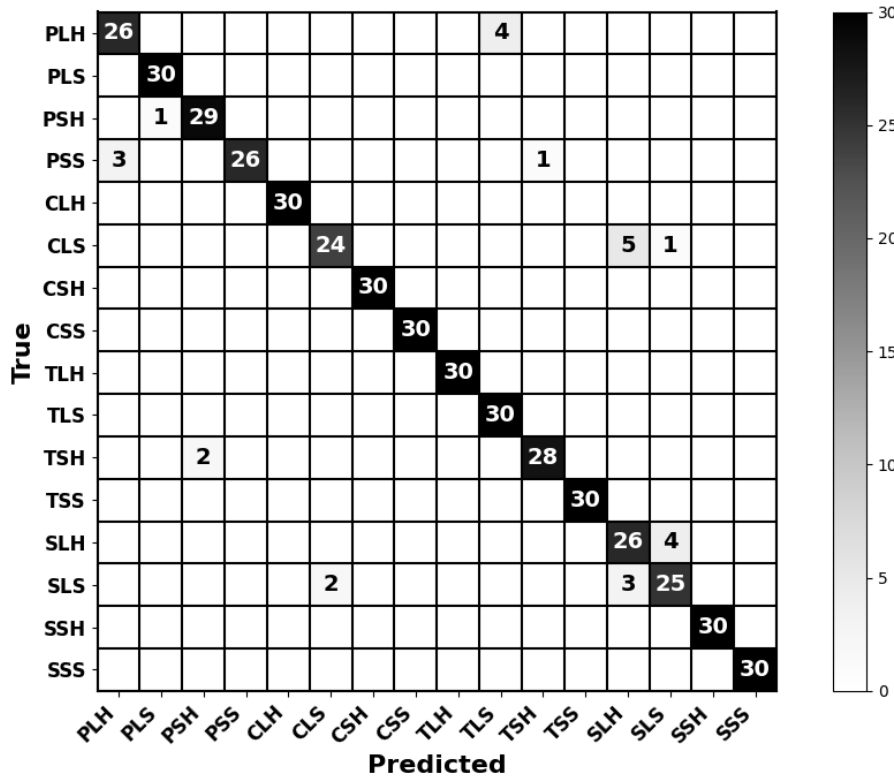


Figure 7.7: Confusion matrix for 1D-CNN with separated subjects.

was measured by deploying the process in Arduino format on the board. This stage has an inference time of $350 \mu s$, thus contributing negligibly to the overall inference time.

Despite the higher resource demands, driven by the difference in the input and the size compared to the SLFNN and MLP, the 1D-CNN offers the best classification accuracy. Furthermore, when estimating the total energy consumption of the system over the lithium battery lifetime, the system will last ≈ 26.5 hours. The energy consumed by the networks shows minimal impact on the overall consumption, allowing for confident use of the 1D-CNN due to its satisfactory accuracy, despite its higher resource usage.

A comparison between the proposed method and relevant state-of-the-art approaches for object recognition is presented in Table 7.3, which highlights the contributions of the proposed system relative to existing solutions. While relying on fewer commercial sensors than typical in the literature, the system effectively extracts valuable information and achieves high accuracy, using similar models adopted in the state of the art. Notably, this work addresses the three physical properties of objects, which are either comparable to or more complex than those used in existing solutions. Moreover, the incorporation

Reference	Sensors & Sensor Number	Classification Method	Accuracy (%)	Number of Objects	Data Type	Hardware Implementation
[43]	Piezoresistive, 548	CNN	89.4	26	Image	No
[108]	Pressure, 80 & Temperature, 32	CNN	94.2	20	Image	No
[109]	Resistive Flex, 5	SVM	91.88	3	Time Series	No
This Work	FSR, 5 & IMU, 5	CNN	99.2	16	Time Series	Yes

Table 7.3: Relevant methods for object recognition.

of time-series data offers a significant advantage for real-time deployment, a feature not considered in previous solutions.

7.4 Conclusion

This chapter proposes a wearable multisensory glove based on off-the-shelf components for object recognition. The glove features commercial sensors, including FSRs and IMUs for haptic information extraction. The system was used to collect a dataset from 16 3D-printed objects categorized by size, shape, and stiffness. Time-domain features extracted from this dataset were used to train two ML algorithms (SLFN and MLP) while 1D-CNN was trained directly on the raw data. The 1D-CNN achieved the highest accuracy of 99.2% CNN and was deployed on a low-cost Arduino Nano BLE Sense 33 to perform real-time inference. Results demonstrate that the system exhibited an inference time of 167 ms while consuming 2.8 mJ of energy. The developed wearable glove with its real-time object recognition capability could be useful for sensory restoration in post-stroke patients or as a high-fidelity rehabilitation system.

CHAPTER 8

Conclusions and Future Directions

8.1 Conclusions

This thesis addressed the development of efficient, data-driven approaches for tactile data processing in embedded and wearable systems, with a focus on achieving intelligent, low-power, and real-time operation for resource-constrained devices. The research journey began with the analysis of the behavior of our piezoelectric-based tactile sensors, proceeded through signal processing, and machine learning-based signal interpretation. What is important in real applications is to interpret the time response of the whole sensing system to extract contact information is expected to drive sensory feedback for motor control.

The first stage of my research focused on characterizing and validating the response of a customized and distributed PVDF-based tactile sensing system with high sensitivity and a wide frequency range (i.e., 1 Hz - 1 KHZ). Through controlled indentation experiments, it was demonstrated that the system exhibits strong sensitivity to dynamic tactile events, such as contact onset and release, across a wide range of frequencies. The analysis of the signal using signal processing techniques confirmed the sensor capability to detect discrete events and variations in load, thereby establishing its suitability for capturing low-level tactile information. Building on these results, the second stage introduced a machine learning framework for contact force estimation. Time-domain features were extracted from the PVDF signals, specifically the skewness and kurtosis of the signal distribution, as these statistics are computationally lightweight to compute and therefore suitable for implementation on resource-constrained embedded devices. These features were processed using lightweight neural networks, optimized for embedded implementation. The results showed that the proposed data-driven model could reconstruct normal contact forces with good accuracy, validating the feasibility of learning-based force estimation for real-time tactile sensing. The third stage extended to the modeling of the PVDF-based tactile sensor. An electromechanical model was developed to simulate sensor behavior under various loading conditions, providing a complementary tool for generating syn-

thetic datasets. This approach effectively reduced the need for extensive experimental testing, minimizing fatigue-induced degradation of the PVDF material, and deepened the understanding of its mechanical–electrical coupling. The resulting response function was fitted to a lumped-parameter model; however, several resonance peaks were observed that require further experimental investigation to identify their source. Refining this model will improve its predictive accuracy and enhance its applicability for generating simulated data to train the developed machine learning algorithms.

The final part of the thesis focused on developing a multisensory wearable glove prototype for object recognition. Two types of sensors were integrated to provide tactile and proprioceptive information: Force Sensing Resistors (FSRs) and Inertial Measurement Units (IMUs). FSR sensors were employed as the primary sensing elements. This choice was driven by their simplicity and affordability, which made them well-suited for rapid prototyping and validation of embedded data-driven algorithms. FSRs offer a stable and easily interpretable response to static and quasi-static loads, enabling the system to capture contact pressure information necessary for object and material recognition. Their integration also facilitated the real-time implementation of lightweight machine learning models on embedded hardware, allowing the study to focus on algorithmic performance and system integration without the additional complexity of piezoelectric signal conditioning. The multisensory glove was developed and tested using embedded ML algorithms for classifying objects. The glove was later enhanced using off-the-shelf components in a battery-operated configuration. The system demonstrated reliable accuracy and efficiency, indicating that low-cost wearable tactile platforms can support intelligent human–machine interaction and assistive applications.

Overall, this thesis contributed to the advancement of tactile data processing on edge devices by bridging sensing modalities and embedded artificial intelligence. The developed methods and systems illustrate how lightweight, data-driven algorithms can be effectively deployed in controlled environments to endow artificial skins and wearable interfaces with real-time perception capabilities.

8.2 Future Directions

The work presented in this thesis opens several promising directions for future research. We outline the following future steps to address the current limitations:

- Based on the results presented in Chapter 5, the computed response function indicates that the system exhibits a derivative-type behavior. Future work should focus on identifying the source of the observed resonance peaks and determining whether they are linked to the Dragon Skin encapsulation layer. If so, adjusting the layer thickness could be an effective strategy to shift the resonant frequencies outside the frequency bandwidth of interest. A more detailed analysis will also help to define the frequency range over which the system behaves derivatively and where deviations occur. This insight will be valuable for signal processing, enabling integration of the sensor output to reconstruct the relative contact force from the complex dynamic response. In parallel, this analysis will support the refinement of the lumped-parameter model, improving its capability to generate simulation data for training data-driven algorithms. Given that piezoelectric sensors are expensive and prone to fatigue under extensive experimental testing, the ability to simulate sensor responses will significantly reduce resource consumption and extend system longevity. Furthermore, an additional line of research could investigate the use of neural networks to reconstruct the complete force distribution across all taxels in the distributed array. Such an approach would enable the creation of tactile heatmaps from sensor outputs, providing detailed spatial information that could enhance performance in dynamic tactile applications, including slippage detection [205].
- The processing algorithms for the normal peak force developed in this dissertation were evaluated under controlled experimental conditions, specifically the speed and the target load during touch (Chapter 4). However, in real-world scenarios, these parameters are often unknown and uncontrolled. As a future direction, the proposed system will be evaluated in an uncontrolled environment to better simulate real-world applications. For instance, the system could be mounted on a prosthetic arm [144, 206] or integrated into a tactile glove [199]. Subsequently, the methods proposed here will be repeated and adjusted to adapt to these new uncontrolled conditions
- Based on Chapters 6 and 7, while FSRs effectively demonstrated the feasibility of embedded tactile intelligence, they remain limited in their ability to capture dynamic and transient tactile events. Future work will therefore focus on replacing the FSRs with PVDF-based piezoelectric sensors, once the previously defined goal of achieving accurate force reconstruction from the PVDF system has been met. This

transition will simplify signal processing while enabling richer and more dynamic tactile feedback. Additionally, extending the number of integrated IMUs could further enhance the glove's proprioceptive sensing capabilities, resulting in a more versatile wearable platform adaptable to multiple applications. The extended system would leverage time-series data for real-time operation, reinforcing its suitability for embedded tactile intelligence across diverse use cases.

Publication record

1. International Journal Papers

- [1] M. Yaacoub, A. Ibrahim, F. Khansa, L. Hammadi, and C. Gianoglio, "Wearable Multisensory Glove for Shape, Size, and Stiffness Recognition Based on Off-the-Shelf Components," in *IEEE Sensors Letters*, vol. 9, no. 4, pp. 1-4, April 2025, Art. no. 6003904, doi: 10.1109/LSSENS.2025.3548264.
- [2] M. Yaacoub, C. Micheli, D. D. Caviglia, M. Valle, L. Carassale, and L. Seminara, "Modeling the indentation response of a soft PVDF-based tactile sensor," To be submitted to a Q1 journal.
- [3] H. Al Haj Ali*, M. Yaacoub*, C. Gianoglio, Y. Abbass, and M. Valle, "On-Edge Tactile Signal Processing: Assessing Neuromorphic and Machine Learning Methods for Texture Classification," *IEEE Transactions on Circuits and Systems for Artificial Intelligence*, to be submitted (equal contribution).
- [4] R. Khalifeh, M. Yaacoub, C. Gianoglio, M. Saleh, M. Valle, and Y. Abbass, "A Soft Piezoelectric-based Tactile Sensing System Enables Object Recognition Using Machine Learning," *IEEE Sensors Journal*, submitted.
- [5] S. Awada, O. Audi, M. Yaacoub, O. Aiello, and A. Ibrahim, "Energy Efficient Optimization of Tiny Machine Learning Models for Microcontroller: A Novel Approach", *IEEE Transactions on Consumer Electronics*. (To be submitted)

2. International Conference Papers

- [1] M. Yaacoub, Y. Abbass, C. Micheli, D. D. Caviglia, M. Valle, L. Carassale, and L. Seminara, "Frequency Domain Investigation of the Indentation Response of a Soft PVDF-Based Tactile Sensor," 2025 32nd IEEE International Conference on Electronics, Circuits and Systems (ICECS), Accepted, to be published.
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Participation in Research Projects

Intelliman (Horizon 2022 EU)

Description of the research project:

This project focuses on the question of “How a robot can efficiently learn to manipulate in a purposeful and highly performant way”. IntelliMan range from learning individual manipulation skills from human demonstration to learning abstract descriptions of a manipulation task suitable for high-level planning to discover an object’s functionality by interacting with it, to guarantee performance and safety. IntelliMan aims at developing a novel AIpowered manipulation System with persistent learning capabilities, able to perceive the main characteristics and features of its surrounding by means of a heterogeneous set of sensors, able to decide how to execute a task in an autonomous way and able to detect failures in the task execution in order to request new knowledge through the interaction with humans and the environment. IntelliMan further investigates how such AI-powered manipulation systems are perceived by the users and what factors enhance human acceptability. My main contribution was in developing algorithms for tactile data processing and high-level information extraction.

Teaching and other activities

Teaching support activities for the course of Sensors (Cod. 114750) (laboratories), Electronic Engineering (DITEN), University of Genoa, Italy, 2024/2025.

Reviewing activity for the following international journals

- Journal of Circuits, Systems, and Computers.

Reviewing activity for the following international Conferences

- The IEEE International Symposium on Circuits & Systems (ISCAS) in Singapore, 2024.
- The IEEE International Conference on Electronics, Circuits and Systems in Marrakech, 2025.

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Efficient Data Driven Algorithms for Tactile Data Processing in Embedded and Wearable Systems

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