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FIBER BRAGG GRATING-BASED ARTIFICIAL SKIN FOR ROBOTIC TACTILE PERCEPTION

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Fiber Bragg grating-based artificial skin for
robotic tactile perception

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A thesis submitted in partial fulfilment of the requirements for
the degree of Doctor of Philosophy

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LEONG Chern Yang (Name of student)

*For the version of myself that I lost along the way,
for the version I found,
and for the version I will become.*

“...it’s always most important that you’re happy with what you see in the mirror and you’re honest to yourself, because what’s the point in trying to fake or pretend being something else, someone else? You are always the first one to notice, you’re always the first one to know if you are cheating yourself.”

—*Sebastian Vettel*

Abstract

Tactile perception is crucial for dexterous object manipulation in humans, and its adaptation in robotics is crucial for safe and effective interaction in unstructured environments. Despite significant progress, achieving sufficient sensitivity, robust and multimodal tactile sensing while ensuring integrability and scalability remains a challenge. This thesis explores the development of a biomimetic, tactile-sensitive artificial skin based on Fiber Bragg gratings (FBGs) to replicate human perceptual capabilities on robots.

The research begins with fabrication of custom single-mode ZEONEX polymer optical fibers (POFs) with an in-house built POF drawing tower. The fabricated POFs offer superior flexibility, fracture toughness and strain sensitivity compared to silica fibers. Allowing seamless integration into soft, conformable skins on complex surfaces such as robotic fingers.

First, an artificial skin with an array of four FBGs was developed for high-precision contact force measurement and localization on fingertips. The artificial skin withstood pressures up to 955 kPa without damage. Assistance by a random forest algorithm, the skin measured and located forces with mean absolute errors (MAEs) of 0.07 N and 0.24 mm, respectively, outperforming human tactile spatial acuity.

Second, the capability to recognize object hardness was investigated. An artificial skin with four embedded FBGs captured unique strain signatures when pressed against objects of different hardness. An artificial neural network (ANN) processed these signatures, achieving a force estimation correlation of 0.96 and hardness classification accuracy of 92%, demonstrating excellent capability in simultaneous force estimation and hardness recognition capabilities.

Next, an artificial skin with three-FBGs array and a biomimetic fingerprint-like pattern was developed for multidirectional force and vibration sensing. Normal force of up to 10 N and shear forces of up to 4 N were tested on the skin. A self-developed multi-input-multi-output convolutional neural network (MIMO-CNN) estimated applied forces with correlation of 0.96 and distinguished between 20 fabric samples with 94% accuracy via slip induced vibrations.

Finally, a skin with thermal-based object recognition capability was developed. It utilized cobalt-doped photothermal fiber for heating and FBGs for temperature sensing. By monitoring heat transfer upon contact, an ANN classified metal, glass and wood with 100% accuracy within 5 seconds providing a complementary recognition modality to physical sensing.

This thesis establishes a comprehensive framework for polymer fiber Bragg grating (POFBG)-based artificial skin, demonstrating exceptional performance in force localization, hardness discrimination, texture recognition and thermal material identification. This work also validates the combination of POFs and machine learning as a viable and scalable platform for advanced robotic tactile perception.

Publications

Journal Papers

1. **C. Y. Leong**, X. Cheng, J. Cui, D. S. Gunawardena, and H. Y. Tam, “Artificial Skin Based on Polymer Optical Fiber Bragg Grating Arrays for Robotic Tactile Perception,” *J. Light. Technol.*, vol. 42, no. 8, pp. 3022–3029, 2024, doi: 10.1109/JLT.2023.3343833.
2. **C. Y. Leong**, J. Cui, X. Cheng, L. Htein, and H. Tam, “Tactile-Sensitive Artificial Skin for Multiaxial Force Detection and Texture Recognition,” *J. Light. Technol.*, pp. 1–10, 2025, (Early Access), doi: 10.1109/JLT.2025.3634683.

Conference Papers

1. **C. Y. Leong**, J. Cui, X. Cheng, and H.-Y. Tam, “Artificial skin using photothermal optical fibers for material identification,” in *29th International Conference on Optical Fiber Sensors*, 2025, p. 410. doi: 10.1117/12.3062711.

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List of Abbreviations

A

AI	Artificial intelligence
ANN	Artificial neural network

C

CNN	Convolutional neural network
-----	------------------------------

D

DoF	Degree of freedom
-----	-------------------

E

EMI	Electromagnetic interference
-----	------------------------------

F

FBG	Fiber Bragg grating
FFT	Fast Fourier transform

I

IR	Infrared
----	----------

M

MAE	Mean absolute error
MIMO-CNN	Multi-input-multi-output convolutional neural network
MLP	Multilayer perceptron
MWCNT	Multi-walled carbon nanotube

N

NN	Neural network
----	----------------

P

PDMS	Polydimethylsiloxane
POF	Polymer optical fiber
POFBG	Polymer fiber Bragg grating
PTFE	Polytetrafluoroethylene
PU	Polyurethane
PVDF	Polyvinylidene fluoride
PZT	Lead zirconate titanate

R

RI	Refractive index
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S

SMPOF

Single-mode polymer optical fiber

T

TENG

Triboelectric nanogenerator

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Chapter 1. Introduction

1.1 Background and Research Motivation

Tactile perception, or the sense of touch, is a fundamental aspect of human experience. It plays a significant role in human interaction with others and the surrounding environment. The ability to perceive and respond to touch serves both physiological and psychological functions which influence social communication, emotional bonding, and practical interaction with surrounding objects.. Research indicates even infants demonstrate sensitivity to pleasant touch, suggesting that tactile engagement is crucial for bonding with caregivers. This sensitivity facilitates emotional connection, laying the groundwork for affectionate relationships later in life [1]. Furthermore, the capacity of touch to convey emotion, including comfort and support, fosters trust and prosocial behaviours, which are essential for societal cohesion [2], [3].

Tactile perception is intrinsic to the human ability to interact with physical objects and navigate the surrounding environment effectively. Perceptual properties such as roughness, temperature, and texture enable individuals to make informed decisions regarding object manipulation even when vision is obstructed, which is fundamental for daily tasks. For instance, judgments related to material compositions based on tactile feedback can inform choices about grip force when handling objects, thereby enhancing manual dexterity [4]. Mechanoreceptors in the skin respond to various tactile stimuli, aiding in the perception of nuanced physical interactions, essential for both practical activities and social communication [5]

Technological advancements in robotics and haptic devices have begun to integrate principles of human anatomy and tactile perception to enhance human-robot-object interaction. Humanoid robots are robots designed to imitate human appearance and behaviour [6], replicating functions such as perception, decision-making and interaction. These robots are characterized by their bipedal locomotion [7], [8], dexterous manipulation capabilities, and the ability to interact with their environment in a human-like manner. Due to their great adaptability and flexibility [9], the demand for humanoid robots has increased across different sectors, including healthcare and industrial applications [6], [8], [10]–[13]. As industries strive for greater efficiency and precision, robots equipped with advanced manipulation capabilities are required, capable of fine motor skills to perform delicate operations such as assembling intricate components or performing surgical procedures where safety and precision are paramount [14]. Grasping is one of the most essential functions for anthropomorphic robotic

hands [15], enabling interaction with a wide range of objects in dynamic environments. However, effective grasping strategies heavily rely on tactile perception for grip force adjustments, slippage detection, and object property recognition, which are major factors for stable and adaptive manipulations [16]–[19]. Despite advances in software techniques for grasp planning and control [8], their performance remains limited by the accuracy and responsiveness of sensory systems, which can constrain real-time performance and adaptability.

The main development goal is to create a humanoid robot capable of learning and adapting to unstructured environments, ultimately benefitting individuals, increasing the quality of life and facilitating human-robot collaboration [20]. As robots are integrated into everyday environments, humanoid robots are envisioned to assist humans in a shared environment [21], [22], enhancing productivity by taking on repetitive and trivial tasks, or replacing human altogether in environments deemed too dangerous or impractical for humans [23], [24]. Under such circumstances, not only are they required to navigate themselves across an open environment [6], but they are also required to interact with surrounding objects designed for humans in a natural manner [20], [21].

Artificial skin is a class of device developed to mimic the functions and aesthetics of human skin. Due to its flexible and conformable nature, artificial skin can be applied or molded onto various robotic and prosthetic surfaces without interfering with the structure and movement mechanics of robots and prostheses [25], effectively replacing bulky sensor housing and equipment. By integrating tactile sensors within the artificial skin, the skin material serves as a protective material to prevent excessive wear on the sensing elements due to prolonged contact and abrasion, enabling functionality under various environmental conditions. Furthermore, with properties of artificial skin closely mimicking a human skin, machines are capable of perceiving touch in a human-like manner, facilitating safe and intuitive interaction with their surrounding environment.

As the hands are the first point of contact for most object interactions [26], dexterous robotic hands with object manipulation capabilities and adaptability are particularly important for effective robot-object manipulation. Designed to replicate the functionality of human hands, humanoid robots are generally equipped with multi-fingered hands which typically feature multiple degrees of freedom (DoF), enabling execution of intricate and dexterous movements such as grasping, rotating, and various in-hand manipulations which require precision and real-time adaptability [27]. However, the increased number of DoF brings more complex problems

in control planning, dynamics, and kinematics, posing higher challenges for practical applications [9]. Hence, it is particularly important to equip robotic hands and grippers with tactile perception to ensure reliable tactile feedback in real time during object interaction.

Fiber Bragg gratings (FBGs) are emerging as a significant technology being utilized as tactile sensors for artificial skin applications. Their unique properties, such as immunity to electromagnetic interference, high sensitivity, compactness, and, most importantly, the ability to multiplex multiple sensors along a single fiber, make them a promising candidate for mimicking human tactile perception. This capability holds significant implications for the development of intelligent robotic systems and advanced prosthetics capable of human-like interaction with surrounding objects. With multimodal sensitivity and excellent multiplexing capability, multiple FBGs can be fabricated along a single optical fiber, with each FBG can be tuned to specific tactile responses, thereby addressing the diverse tactile perceptions required in practical applications. Additionally, the small size and flexible nature of optical fiber allow for easy integration into artificial skins without compromising sensing performance [28].

As carriers of FBGs, optical fiber can be broadly classified into glass-based fibers and polymer-based fibers, both of which have properties suited for different sensing applications. Glass-based FBGs are more common due to the availability of silica optical fibers and well-developed fiber-optic communication industry. They offer advantages such as low transmission loss, high mechanical strength, and excellent UV photosensitivity for FBG inscription. These benefits have contributed to their success in large-scale, long-distance sensing applications such as structural health monitoring, transportation, and aviation applications. On the other hand, polymer optical fibers (POFs), although less common compared to silica optical fibers, are particularly suitable for sensing applications that demand high elasticity and low Young's modulus. These traits allow FBGs inscribed on POFs to exhibit much higher in strain sensitivity and better performance in measuring large deformations compared to glass-based FBGs. Consequently, POF-based FBGs are ideal for applications requiring high flexibility and conformability, such as biomedical devices, wearable devices, as well as distributed tactile sensing.

In this thesis, the development and implementation of a biomimetic artificial skin utilizing FBGs inscribed in a custom-made POF is comprehensively studied and presented. The research establishes a complete fabrication pipeline, from drawing custom ZEONEX POFs to molding functional skin prototypes. A series of artificial skins is developed, each demonstrating a

specific advanced tactile function. Throughout this work, the unique advantages of POFs are leveraged to overcome the limitations of silica optical fibers for robotic skin applications. Furthermore, the integration of machine learning algorithms, including random forest and various neural network architectures, is consistently employed to translate the complex FBG responses into accurate and robust tactile perceptions, demonstrating performance that rivals or even surpasses human tactile acuity in specific metrics.

1.2 Research Objectives

Considering the merits offered by POFs and their complementary characteristics to FBG for tactile sensing, this thesis explores the development of polymer optical fiber Bragg grating (POFBG)-based artificial skin for robotic tactile perception. The specific objectives of this study are:

1. To establish a scalable fabrication technique for tactile-sensitive artificial skin, encompassing the production of POFs and POFBGs through to the final POFBG-based tactile-sensitive artificial skin.
2. To implement and characterize a POFBG-based artificial skin with force measurement and localization capabilities.
3. To develop an artificial skin and explore its functionality in the recognition of object hardness via contact pressure.
4. To explore the application of artificial skin in object texture recognition via multidirectional force, vibration measurement, and slip detection.
5. To investigate and analyze the object material recognition capability of artificial skin based on thermal characteristics.

1.3 Structure of thesis

This thesis documents the development and characterization of FBG-based artificial skins for robotic tactile perception, with focus on utilizing POFs to overcome the limitations of conventional silica optical fibers. The research is presented in eight chapters, each building upon the previous to form a comprehensive study from fundamental fabrication to advanced multimodal sensing. The structure is outlined as follows:

Chapter 1 establishes the context and motivation for the research. It begins by highlighting the importance of tactile perception for dexterous robotic manipulation in human-centered environments. The limitations of current robotic tactile sensing technologies are discussed,

leading to the introduction of FBGs and POFs as a promising solution. The chapter outlines the research objectives and contributions of this work and concludes with this overview of the thesis structure.

Chapter 2 provides the necessary knowledge foundation for the thesis. It begins with a brief overview of the human skin's structure and physiology, which serves as the biological inspiration for artificial skin design. The essential characteristics for evaluating tactile-sensitive artificial skins are then defined and discussed. A review of state-of-the-art tactile sensing technologies, including capacitive, piezoresistive, piezoelectric, triboelectric, and fiber-optic sensors, is presented, highlighting their respective advantages and limitations. An overview of FBGs, including their working principles and primary fabrication techniques, is then outlined. Finally, the advantages of using polymer fiber materials, particularly the ZEONEX cyclo olefin polymer, for robotic tactile applications are discussed.

Chapter 3 details the core fabrication processes developed for this research. It describes the “pull-through” method for molding ZEONEX single-mode preforms. The design, construction, and operation of an in-house built POF drawing tower are then elaborated upon, with emphasis on its key components, including the preform feeder, infrared furnace, capstan, and integrated process monitoring and control system.

Chapter 4 presents the implementation of POFBG-based artificial skin. It covers the fabrication of the FBG array, the design of a tactile-sensitive artificial skin molded onto a fingertip model, and a two-step molding process. The skin's performance in measuring and localizing contact points is characterized. A random forest regression model is developed and validated, demonstrating high-precision force and localization estimation that surpasses human tactile spatial acuity.

Chapter 5 explores the artificial skin's capability to perceive a higher-level object property: hardness. The design and characterization of an artificial skin with a stiffness gradient are presented. The distinct strain signatures captured by the embedded FBG array when pressed against objects of different hardness are analyzed. A dual-branch artificial neural network (ANN) is developed to simultaneously estimate multidirectional forces and classify object hardness with high accuracy.

Chapter 6 advances the functionality of the artificial skin to dynamic tactile sensing. A skin featuring a biomimetic fingerprint-like pattern is developed to facilitate vibration generation

during slip. The sensitivity of the artificial skin towards multidirectional forces and its response to slip-induced vibrations are thoroughly characterized. A multi-input-multi-output convolutional neural network (MIMO-CNN) is implemented to simultaneously estimate 3-axis forces and recognize textures from twenty different fabric samples based on their vibrational signatures.

Chapter 7 introduces a novel sensing modality by investigating thermal-based object recognition. An artificial skin incorporating photothermal fiber for heat generation and FBGs for temperature sensing is developed. The skin's ability to distinguish materials (metal, glass, and wood) by monitoring the heat transfer dynamics upon contact is demonstrated. An ANN is employed to achieve perfect classification accuracy within seconds of contact.

Chapter 8 concludes the thesis by summarizing the key achievements and contributions of the research, reaffirming the viability of POFBG-based artificial skin as a high-performance platform for robotic tactile perception. It also provides a forward-looking perspective by outlining specific and actionable recommendations for future work. These recommendations are directed at key areas such as full integration of multimodal sensing, real-world robotic validation, scalability for large-area coverage, the development of advanced specialty POFs, and the creation of more efficient and adaptive machine learning algorithms.

Chapter 2. Background of tactile sensors for artificial skin

2.1 Introduction

Humans have five primary senses: vision, hearing, smell, taste, and touch. These senses collect information from the surroundings and transmit them into the brain, allowing humans to perceive and understand the surrounding environment. The sense of touch, or tactile perception, is fundamental to human interaction with the physical environment. While other senses are localized to specific organs, the skin, being the largest organ of the human body, serves as a continuous, distributed sensory interface that envelopes the entire body. This system allows humans to perceive a vast spectrum of tactile information, from light brushes and subtle pressure to texture, vibration, and temperature, enabling not only the perception of the immediate environment, but also complex, dexterous manipulation of objects. The intricate, multi-layered biological sensing capability of humans serves as the ultimate blueprint for the development of artificial tactile systems, driving the development of artificial skins that seek to emulate the sensitivity, adaptability, and intelligence of human touch.

Substantial progress has been made in the development of tactile sensing technologies for replicating robotic tactile perception. However, an artificial skin with sufficient spatial resolution, sensitivity, and multimodal sensing capabilities to fully replicate the complex functionality of human skin remains an unrealized goal, highlighting a significant challenge in the field of robotics and prosthetics. This chapter will therefore consolidate and review recent developments in tactile sensors to identify the underlying reasons behind the underdevelopment of tactile sensing technologies and to indicate future development directions.

This chapter is organized as follows: First, the structure and physiology of the human skin will be briefly discussed as it serves as an important inspiration for the development of artificial skins. Second, the characteristics of tactile-sensitive artificial skin, in terms of sensing and physical parameters, will be outlined and discussed. Third, various tactile sensors for artificial skin will be reviewed with emphasis on the ones that represent the current state-of-the-art. Fourth, an overview of FBGs and POFs is provided, detailing their working principle as well as the primary fabrication techniques that enable their use as high-performance, multiplexable tactile sensing elements in artificial skin. Fifth, a summary of the chapter will be provided.

2.2 Brief overview of the human skin

The human skin is the largest organ in the human body, covering the entire body and serving as a barrier against pathogens, harmful substances as well as providing protection against mechanical damage. The skin is also an important sensory organ, allowing humans to perceive various tactile sensations such as touch, pressure, temperature, and pain. With perception and comprehensive understanding of the perceived sensations, humans are able to acquire higher-level features of an object such as texture and hardness. These features, combined with human motor skills, allow humans to effectively interact with surrounding objects and tools via grasping and in-hand manipulation.

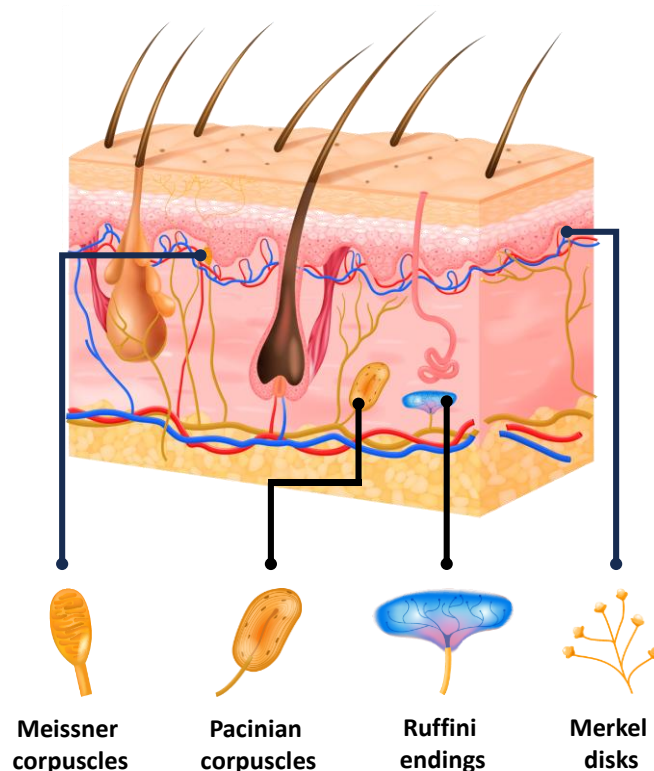


Figure 2.1: Illustration of human skin structure.

The human skin is primarily composed of three layers, namely the epidermis, dermis, and hypodermis. Located at the outermost layer, the epidermis is typically 0.02-0.4 mm in thickness [29], [30]. It contains Merkel cells within its basal layer, which are closely associated with sensory afferents, forming Merkel disks that extend into the dermis. The Merkel disks respond to light touch and continuous pressure, exhibiting slow-adaptation characteristics which facilitates detection of sustained contact with an object, thus enabling perception of fine details, textures, and hardness. Their small and localized receptive fields play a crucial role in shape and texture discrimination, contributing to sensory acuity [31]. The epidermis is mainly

composed of keratinocytes, which not only function as a protective barrier, but also amplify transmitted stimuli before activating sensory neurons [32]–[34].

Underneath the epidermis lies the dermis, a layer typically 1–4 mm thick across different body regions [35] that hosts various mechanoreceptors such as Ruffini endings, Meissner corpuscles, and Pacinian corpuscles, each specialized for distinct tactile stimuli. Ruffini endings respond to skin stretch and sustained pressure. They are located deep within the dermis and provide information related to force and motion, contributing to proprioception, which is the awareness of body position and movement in space [36]. They exhibit slow-adapting characteristics, continuously firing tactile signals as long as stimuli such as pressure and stretch remain. Meissner's corpuscles, on the other hand, are fast-adapting mechanoreceptors located in the upper dermis. They respond to quick and fine changes in touch and vibrations, allowing detection of textures and movements across the skin surface [36]. Their fast-adapting characteristics allow rapid response to stimuli but firing of tactile signals is only sustained when the stimulus is changing. Pacinian corpuscles, located deep within the dermis, are fast-adapting mechanoreceptors responsible for detection of high-frequency vibrations and transient pressures [37] which are critical for vibrational texture recognition. They also play a critical role in object interaction and proprioception, as they detect object slippage, which is essential for grip force adjustments. Furthermore, the dermis is composed of collagen and elastin fibrils, which are viscoelastic in nature. When the skin is subjected to external pressure, it deforms and the strain within the skin is transmitted to the mechanoreceptors, triggering tactile signals to the central nervous system. The physical properties of the dermis dictate the transmission mechanism of forces and pressures to the sensory receptors [38] where higher skin elasticity facilitates larger skin deformation and hence greater receptor response.

The hypodermis, the deepest skin layer, consists mainly of adipose tissue and collagen fibers which serve as a mechanical support to the dermis [39] and mechanical buffer that modulates pressure transmission to mechanoreceptors [40]. Being the softest layer within the skin [39], the hypodermis exhibits low-pass filter characteristics, dampening high-frequency vibrations while allowing sustained pressure to reach Ruffini endings. Its viscoelastic properties assist in distributing mechanical forces across larger skin areas, enhancing sensitivity to gentle pressure and texture. By anchoring the dermis to underlying structures, the hypodermis ensures proper tension in the skin, which is essential for mechanoreceptors to effectively and accurately detect stretch and deformation.

The interplay between the epidermis, dermis, and hypodermis effectively filters and transforms mechanical stimuli, affecting how touch is sensed and perceived. The stiffer epidermis acts as a high-pass filter, localizing deformations to amplify high-frequency vibrations while shielding deeper layers from minor perturbations [34]. The viscoelastic dermis distributes forces, amplifying light touches while transmitting sustained pressure and stretch to deeper mechanoreceptors. The hypodermis, on the other hand, functions as a low-pass filter, dampening high-frequency vibrations while allowing sustained pressures to propagate, in addition to providing cushion and mechanical support to stabilize grip via redistribution of shear and pressure. This hierarchical mechanical gradient, from firmer epidermis to compliant hypodermis, serves as the fundamental mechanism for tactile acuity and overall sensory experience [41].

2.3 Characteristics of tactile-sensitive artificial skin

To comprehensively evaluate the performance of a tactile-sensitive artificial skin, several important characteristics shall be outlined. These characteristics are critical for successful implementation of tactile-sensitive artificial skin on robots. As tactile-sensitive artificial skin is inherently a tactile sensor by nature, many of the features are adapted from conventional sensor performance metrics while some characteristics are exclusive to artificial skins. It is important to note that the following list includes only a subset of many characteristics that must be considered during the design phase. Moreover, these features are usually interdependent as optimizing one typically requires compromising others. Consequently, there is no single “best” artificial skin suitable for all applications, rather each skin must be tailored for its specific use.

2.3.1 Sensing range

The sensing range refers to the specified span between the minimum and maximum input values that a sensor is capable of accurately and reliably measure. It defines the operation limits within which the sensor performs within specifications. A larger sensing range often comes with a trade-off as sensing resolution is often reduced with increased sensing range. For tactile sensitive artificial skin, softer skin materials enable lower minimum pressure detection but may sacrifice high-range robustness, while stiffer skin materials offer the opposite compromise. The design of the sensing range depends heavily on application requirements. For robotic hands, where fine gripping and dexterous manipulation are critical, tactile-sensitive artificial skin often prioritizes low minimum force detection over extended maximum force range.

2.3.2 Sensitivity

Sensitivity refers to the relationship between the sensor response and the measurand. It is a measure of how much the sensor output varies per unit change in the measurand, where higher sensitivity indicates stronger response to small changes. In most cases, linear sensors are generally preferred due to simpler calibration, though many artificial skin materials are viscoelastic, resulting in non-linear response. Sensitivity of an artificial skin is mainly determined by the mechanical properties, in which materials with lower stiffness results in higher sensitivity. However, softer skin material usually comes with a trade-off, resulting in higher hysteresis and lower spatial resolution.

2.3.3 Hysteresis

Hysteresis generally refers to the dependency of sensor output on its immediate past state [42], often manifesting as lag or memory effects in sensor response to variations in measured stimulus. This results in output discrepancies between loading and unloading [43], where different outputs occur for the same input, depending on the direction of change, complicating the interpretation of sensor data. In artificial skins, hysteresis arises from material viscoelasticity, where softer materials deform slower and require longer recovery time after stimulus is removed, often requiring mitigation through calibration and signal processing.

2.3.4 Response time

Response time is the amount of time required for the sensor output to reach a certain percentage, usually 63% or 90% of its final value after a step change in the input [43]. It is a measure of how fast a sensor reacts to dynamic changes in the measured parameter. This is critical for tactile perception applications requiring rapid feedback, such as responding to potential stimuli. Furthermore, fast response time enables higher frequency response for detection of dynamic forces and vibrations. However, extremely soft materials may incur slow response time due to material viscoelasticity.

2.3.5 Size and form factor

A thin artificial skin is crucial for robotic applications as it enables better integration with robotic surfaces. A thin profile allows the skin to conform to complex surfaces such as fingers and palms without adding bulk or restricting movement. Achieving thin profiles requires miniaturization of embedded tactile sensing elements. As the thickness of the skin is determined by the height of the tactile sensors, reducing the sensor size not only ensures a low-profile design, but it also facilitates high spatial resolution and compact integration for multi-

modal sensing. This allows localized detection of pressure, temperature and vibration, enabling comprehensive tactile feedback.

2.3.6 Spatial resolution

Spatial resolution refers to the minimum distance between two point-stimuli that a sensor can resolve as two distinct entities [44]. It serves as a measure of a sensor's ability to resolve fine spatial details, typically expressed in units of length. For artificial skins, this is crucial for interpreting fine mechanical features such as textures and edges. A typical adult human finger has a two-point threshold of around 1.6 mm [45]. For artificial skin with dense tactile sensor array, the spatial resolution is determined by the distance between adjacent tactile sensors, though increased sensor density raises multiplexing demands. A well-optimized spatial resolution enables precise mapping and localization of contact forces, shapes and surface textures, which is essential for dexterous object interactions. It is also worth mentioning that extremely soft materials may spread pressure induced deformations over a larger area, deteriorating the spatial resolution and hence the skin's ability to distinguish fine details.

2.3.7 Multi-modal sensing capability

Multi-modal sensing enables comprehensive environmental interaction via seamless integration of multiple sensory inputs such as multi-directional force, temperature and vibration into a unified structure. This enhances adaptability in dynamic environments, allowing robots to perform complex tasks with human-like dexterity such as slip prevention via vibration and shear sensing. However, the implementation of multi-modal tactile sensing in robots may face challenges related to sensor interference and data processing complexity. Overcoming these challenges requires advanced data processing algorithms, alongside optimization of skin design with emphasis on sensor miniaturization and multiplexing.

2.3.8 Multiplexing capability

Multiplexing capability refers to a system's ability to simultaneously acquire and process signals from multiple sensors using shared hardware resources such as transmission media and data acquisition units [46]. This capability reduces the weight, cost, and size of the sensor system making it particularly important for large area or high-resolution tactile sensing in robots. As the number of tactile sensors increases, so does the number of wires required to power and access their respective tactile data. This poses physical challenges such as routing of wires across articulated joints, and competition for limited space with other pre-existing components such as actuators and onboard electronics, requiring optimization of system

efficiency for effective implementation of tactile systems. However, multiplexing in most tactile systems involves a fundamental trade-off between efficiency and performance. While simplifying hardware requirements, multiplexing may limit sampling speed, degrade signal quality, or increase system complexity. Hence design considerations have to be taken to balance system efficiency and performance based on application needs.

2.3.9 Flexibility and conformability

Flexibility is the material's ability to bend or adapt to shape changes without breakage. Flexibility is somewhat related to how conformable a material is and is complementary to stiffness and rigidity. These characteristics are essential for artificial skins to cover arbitrarily curved robotic surfaces, facilitating better integration. Flexibility is often achieved either via inherent elastic properties or structural design. Soft materials such as elastomers offer good flexibility while some rigid materials, such as polyimide and silicon, can also exhibit a certain degree flexibility when they are sufficiently thin. When considering the characteristics of human skin, its flexibility arises from both the elastic properties of the skin and its structural composition along with factors such as thickness and moisture content.

2.3.10 Compliance

Compliance refers to the material's ability to deform under applied force. It quantifies the degree which the shape of a material changes in response to applied force, where higher compliance indicates greater deformation for a given force. For artificial skin, compliance facilitates safe robot-human interaction [14] and a larger contact area for better acquisition of contact information. However, high compliance skin material may introduce positional uncertainty, degrading spatial resolution. Therefore, achieving optimal performance requires careful balance of compliance and precision. Compliance can be introduced by embedding tactile sensors into elastic materials such as silicone or polyurethane rubbers, mimicking the presence of tactile receptors at different depths within the human skin. Furthermore, encapsulation of tactile sensors within elastic materials also provides protection to the tactile sensors from abrasion due to prolonged contact.

2.3.11 Stretchability

Stretchability refers to how much a material can be stretched (and recover) without experiencing permanent deformation or breakage. This is critical for robotic applications where the skin endures repeated mechanical stress especially on dynamic joints such as the knees and elbows while ensuring functional and structural integrity. Skins in these areas experience

frequent stretch during operation, requiring materials with sufficient stretchability to accommodate such movements without compromising performance. Human skin experiences a maximum stretch of around 44.6% at the knee joint for a full range of motion (flexion and extension) [47], serving as a benchmark for artificial skins.

2.3.12 Durability

Durability refers to a material's ability to withstand wear, deformation, or damage over time. Industrial robots, depending on their use, typically last for 7 to 20 years [48]. As artificial skin is being the primary contact point with various stimuli during interaction and each physical interaction will induce some form of wear. A durable skin can better withstand repetitive stresses while maintaining functionality and material properties, reducing the need for replacements and maintenance. Furthermore, enhanced durability also allows robots to operate reliably in harsh environments, ensuring consistent performance across diverse environmental conditions. While stiffer materials are generally more durable compared to softer materials, they often compromise sensitivity, stretchability, and conformability. Therefore, optimizing skin longevity requires balancing the skin material stiffness with other critical properties of the skin.

2.4 Artificial skin-based tactile sensors

Tactile perception while being indispensable for humans to interact with surrounding objects, remains as one of the main barriers preventing robots to perform human-like tasks. Many tactile sensing approaches have been reported, yet achieving the sensitivity, adaptability, and robustness of human touch remain a significant challenge. Current robotic systems often struggle with fine texture discrimination, real-time force modulation and accurate multidirectional force sensing. These functions are pivotal for robots to replicate effective interaction with fine and fragile objects. Taking inspiration from the human skin, development of artificial skin for robotics and prostheses aims to replicate functions such as pressure detection, texture recognition and contact localization while providing protection against damage. Various tactile sensing mechanisms have been reported, out of which capacitive, resistive, piezoelectric, triboelectric and fiber optic sensors are among the common transduction mechanisms for tactile sensors. Recent breakthroughs in materials science, bioinspired engineering, and artificial intelligence (AI) have accelerated progress in this field, leading to highly sensitive, durable, and multifunctional artificial skins. This subchapter provides a comprehensive review of primary tactile sensing technologies developed for robots,

focusing on their operation principles, key advancements, and inherent challenges. While significant progress has been made, replicating the full sensitivity, adaptability and robustness of human touch remains a challenge. This subchapter covers five major sensing mechanisms: capacitive, piezoresistive, piezoelectric, triboelectric and fiber-optic sensors.

2.4.1 Capacitive tactile sensors

Capacitive tactile sensors are generally recognized for their high spatial resolution, excellent frequency response, and broad measurement range. With well-established design and fabrication techniques, integration of capacitive sensors into high spatial resolution sensor arrays is relatively straightforward. However, achieving high density integration remains a challenge due to signal crosstalk caused by parasitic capacitance and electromagnetic interference (EMI) between neighbouring sensors. Furthermore, each sensing element typically requires individual connections, leading to complex routing and high pin counts in large arrays. Researchers have explored various electrode configurations, dielectric layers, and sensor structures, resulting in diverse architectures tailored for artificial skin applications.

One notable recent advancement was presented by Boutry et al. in 2018, who reported a bioinspired electronic skin (e-skin) capable of detecting and distinguishing both normal and shear forces in real time, mimicking the tactile sensing abilities of human skin for robotics [49]. The e-skin features a hierarchical design inspired by the interlocked dermis-epidermis interface in human skin, with a bottom layer featuring molded hills that mimics the morphology of human stratum spinosum layer. The top and bottom sensor layers are distributed with carbon nanotubes electrodes embedded in a polyurethane matrix. With such a biomimetic sensor structure, the e-skin achieves high sensitivity, fast response time, and robust performance over 30,000 cycles. This biomimetic structure, incorporated with a densely packed capacitive sensor array, enables precise directional force discrimination by monitoring deformations on different functional layers, allowing robots to perform delicate tasks such as handling fragile objects such as raspberries or preventing slippage of lightweight items.

Building on the demand for multifunctional tactile sensing, Ge et al. developed a dual-functioned capacitive tactile sensor featuring pressure measurement as well as proximity detection [50] to enhance grasping accuracy for prosthetic hands. The sensor comprises of copper foil ring electrodes with a pyramid-structured polydimethylsiloxane (PDMS) dielectric layer, utilizing self-capacitance for proximity detection and mutual capacitance for force measurement. The sensor demonstrates high sensitivity towards approaching objects, detecting

conductor, insulator and human finger from up to 100 mm away while measuring pressures up to 700 kPa with segmented sensitivities of 2.05, 0.03, and 0.015 MPa⁻¹ for 0–40, 40–180 and 180–630 kPa respectively. When integrated onto a prosthetic hand, the sensor enabled compliant control, collision detection and prevention as well as precise force tracking, representing a significant advancement towards human-like dexterous motion in prosthetics.

With bioinspiration in mind, Guo et al. presented a skin-like flexible capacitive tactile sensor with incorporated microstructures inspired by octopus' suckers [51] within the dielectric layer designed to enhance tactile sensitivity and linearity of the tactile sensor. The dielectric layer is sandwiched between two flexible electrode layers, forming a flexible capacitive sensing unit. The tactile sensor unit achieved a high sensitivity of 0.636 kPa⁻¹ and a wide sensing range of 8–500 kPa. Besides, it also exhibits a rapid response time of around 40 ms towards tactile perturbations. The tactile sensitive skin was applied to a robotic hand for grasp monitoring and human bodies to monitor joints and muscle movements. Such demonstrations highlight its potential for electronic skins in healthcare and intelligent robotics.

2.4.2 Piezoresistive tactile sensors

Piezoresistive sensors are one of the promising candidates for artificial skin applications as their resistance changes in response to deformation, allowing easy and straightforward measurement. To mimic the conformability of human skin, compliant piezoresistive material are generally used as the active layer, where applied forces change the conductive pathways within the material, altering its resistance. Due to their simplicity, piezoresistive sensors often require simple readout mechanisms and their compatibility with flexible substrates makes them more appealing for robotic and prosthetic tactile sensing. However, they also come with several shortcomings such as non-linear response and hysteresis, limiting their consistency. Furthermore, maintaining uniform response across a large sensor array often requires tailored material composition [52] or specialized calibration procedures. Although these challenges have yet to be overcome, the advantages offered by piezoresistive sensors allow them to remain one of the versatile solutions for tactile sensing in artificial skins.

Sun et al. presented a flexible piezoresistive tactile sensor array utilizing multi-wall carbon nanotubes (MWCNT)/PDMS composite as the active layer [52]. The active layer is molded with an anomalous surface structure, which enhances the sensitivity and linearity of the sensor towards applied pressure. A 6 × 8 array of sensors was fabricated and the sensor array achieved sensitivities up to 16.9 kPa⁻¹ for pressures below 0.1 kPa, 5.41 kPa⁻¹ at 0.3 kPa, and 1.05 kPa⁻¹

at 1.3 kPa while demonstrating fast response time of around 40 ms. In addition, the durability of the sensor array was verified with stable performance after 1,000 cycles at a pressure of 10 kPa. The sensor array features a low form factor with a thickness of around 530 μm while maintaining flexibility and conformability to various surfaces. Paired with a self-developed readout circuit, real-time pressure mapping was demonstrated, highlighting its potential in prosthetics and robotics.

Similarly, using MWCNT/PDMS composite as the piezoresistive material, Wang et al. presented a skin-inspired, multilayer tactile sensor with the ability to detect object hardness in addition to pressure sensing [53]. The sensor combines a central hole gradient-structured pressure sensor with a planar strain sensor, mimicking SA-I and SA-II receptors in the human skin to measure applied pressure and stretch respectively. The dual-layered sensor structure enables simultaneous measurement of applied pressure and object deformation, evaluation of hardness through differences in response between the strain and pressure sensors. For example, softer objects induce larger deformation (higher planar strain) under the same pressure, and vice versa. The sensor achieved a sensitivity of 10.55 kPa^{-1} and a linear range of 0–1,000 kPa. When applied to a robotic hand, the sensor demonstrates human-like grasping adaptability, adjusting force based on object hardness.

Yang et al. presented a conformable piezoresistive pressure sensor with tactile feedback and self-healing capabilities for electronic skin, robotics and human activity monitoring [54]. The sensor comprised of a spinosum-structured MXene/polyurethane (PU) sensitive layer stacked on MXene-based interdigital electrodes. The sensor was fabricated on a cellulose membrane, allowing conformability while the PU enables self-healing via hydrogen bonding, retaining functionality after mechanical damage. With the aid of the incorporated spinosum structure, the sensor demonstrated high pressure sensitivity of up to 509.8 kPa^{-1} . It also achieved fast response and recovery time of 67.3 and 44.8 ms, respectively. Multiple pressure sensors were integrated to form a sensor array with pressure mapping capabilities, enabling tactile feedback in robotics.

2.4.3 Piezoelectric tactile sensors

Piezoelectric sensors are also widely used as tactile sensors for robotic applications. Exploiting the piezoelectric effect, by which mechanical stress is converted into electrical signals, piezoelectric sensors do not require an external power source. Furthermore, they generally exhibit high sensitivity, fast response time, and large bandwidth, making them promising for

real-time, dynamic tactile sensing applications. However, they come with limitations as signals generated are only responsive to changing pressure, limiting their ability to detect and measure static pressures. Due to this limitation, they usually underperform in sustained and slow-evolving tactile sensations, a significant drawback. Furthermore, despite self-powering capability, piezoelectric sensors usually require additional amplifying and signal conditioning circuits to ensure signal quality, increasing integration complexity. Various sensor designs have been reported to improve sensing performance while retaining structural robustness.

In 2022, Zhang et al. demonstrated a piezoelectric tactile sensor array featuring a biomimicry force transmission layer [55]. The layer consists of rigid pillars encapsulated in soft polymer, mimicking the soft-rigid structure of a human finger, consisting of bones and muscle tissues. The soft-rigid layer is positioned on top of a polyvinylidene fluoride (PVDF) film and a soft substrate. The sensor achieves a large operating bandwidth of 5–600 Hz and multidirectional force sensitivity by analyzing responses of multiple units. The rigid pillar design amplifies in-plane stress, enabling high force sensitivity, peaking at 345.5 pC/N at 30 Hz. It also exhibits a linear force range of 0.009–4.3 N while maintaining high durability. This soft-rigid architecture enhances the flexibility-sensitivity trade-off.

Wang et al reported an alternative approach to material design for a piezoelectric tactile sensor capable of multidirectional force detection [56]. The sensor design combines PVDF as the active material and a conductive sponge serving as substrate and electrode concurrently. The porous structure of the conductive sponge effectively enhances PVDF deformation in response to pressure, amplifying voltage output while reducing charge transfer loss. The sensor unit was tested under normal forces up to 15 N and shear forces of up to 10 N, achieving a low shear direction error of $4.54 \pm 1.53^\circ$. The sensor exhibits a nonlinear but highly correlated response, fitted with a fourth-order polynomial and features a fast response time of 48 ms. When applied onto robotic gripper, it enabled real-time detection of slip and grip transition, highlighting its potential for robotic tactile feedback.

He et al. reported a flexible tactile sensor with active layer composed of lead zirconate titanate (PZT) nanofibers dispersed in PDMS [57], sandwiched between copper electrodes. A 3×3 sensor array was fabricated, and optimization of PZT weight ratios results in high pressure sensitivity of $9.5 \text{ mV}/10^5 \text{ Pa}^{-1}$ with 75 wt% PZT. The sensor maintained stable sensing operation after 1600 pressure cycles demonstrating high durability. Compared to PVDF, PZT exhibits higher piezoelectric coefficient, resulting in higher sensitivity when used as the active

material for tactile sensor. However, PZT is brittle in nature, limiting its application in artificial skin applications which requires conformability. Utilization of PZT nanofibers enable high pressure sensitivity while retaining sensor flexibility, providing an alternative active material to overcome limitations of conventional piezoelectric tactile sensors.

2.4.4 Triboelectric tactile sensors

With similar characteristics to piezoelectric sensors, triboelectric tactile sensors have emerged as one of the promising technologies for artificial skin applications due to their ability to generate electrical signals from mechanical perturbations such as touch, pressure and vibration. Leveraging the triboelectric effect, where electrical charge is generated when two dissimilar materials come into contact and separate, these sensors usually exhibit high sensitivity, especially to small mechanical movements, enabling detection of subtle pressures and vibrations. Triboelectric sensors do not require external power and their simple fabrication, cost-effectiveness as well as compatibility with biomaterials favours them for wearable electronics and soft robotics. However, environmental factors such as humidity and surface contamination may affect signal stability, while material wear from repeated abrasion degrades sensor performance over time. Although exhibiting self-powering capability, they require complicated signal processing techniques as triboelectric sensors generate AC signals, increasing the complexity of the system. Ongoing research focuses on optimizing sensor design, material selection and hybrid sensing mechanisms to improve sensor reliability and performance.

In 2020, Cai et al. reported a flexible tactile sensor based on triboelectric nanogenerator (TENG) comprised of PDMS/MXene composite [58]. The design and material selection of the tactile sensor focused on enhancing the sensor sensitivity. MXene were selected to enhance triboelectric performance by introducing oxygen-containing functional groups. To increase the contact area, which enhances charge generation, wrinkles were introduced on the PDMS surface via simultaneous stretching and UV ozone exposure. It is worth noting that UV-ozone treatment oxidizes the PDMS surface, increasing hydroxyl group (-OH) content while enhancing charge adsorption. These combined modifications resulted in a high sensitivity of 0.18 V/Pa from 10–80 Pa and 0.06 V/Pa from 80-800 Pa. When layered on a human finger, the tactile sensor demonstrated grasp monitoring capabilities.

Also in the year 2020, Yao et al. reported a bioinspired artificial skin based on TENG for tactile sensing in robotics and prosthetics [59]. The artificial skin is designed to maximize charge

generation which enhances sensor sensitivity. The triboelectric layers of the artificial skin consist of PDMS with surface microstructured cones mimicking the surface of *Calathea zebrina* leaf to increase contact area. In addition, the surface of the microstructured tribo-negative layer is also incorporated with submicron polytetrafluoroethylene (PTFE) burrs to enhance charge transfer efficiency. The surface microstructure of both active layers facilitates layer interlock, maximizing frictional contact and charge generation. As a result, the artificial skin achieved a linear pressure sensitivity of 127.22 mV/kPa up to 50 kPa, a 14-fold increase compared to non-microstructured sensors. The artificial skin was attached to a bionic hand, achieving excellent pressure mapping, gesture tracking as well as object recognition capabilities.

Later in 2022, Liu et al. presented a flexible bimodal smart skin to facilitate intuitive interaction between human and soft-robots [60]. It integrates TENGs as triboelectric proximity sensor, and liquid metal as a piezoresistive pressure sensor, of which the former is sensitive to both approaching objects and pressure while the latter is only sensitive to contact pressure. When an object with different electron affinity compared to the dielectric layer approaches, contact electrification occurs where electrons transfer between them, resulting in equal but opposite charge on each. If the object reapproaches, the electric field is distorted, causing free electron flow between the electrode and ground. As TENGs respond to both proximity and contact, distinguishing them requires an additional piezoresistive pressure sensor, which is only sensitive to contact pressure. By cross-referencing the response between the two sensors, detection and distinguishing of tactile and touchless stimuli in real time is possible.

2.4.5 Fiber optic and FBG based tactile sensitive artificial skin

Fiber-optic sensors, although not as widely adopted compared to electronic sensors, are rapidly growing for robotic tactile sensing applications due to their high resolution, distributed sensing capability, flexibility and durability. Unlike conventional electronic sensors, fiber-optic sensors utilize light-based transmission and detection, which is immune to electromagnetic interference (EMI), ensuring reliable operation. Furthermore, optical fibers enable remote sensing through low-loss and long-distance signal transmission, which architecturally mimics the human nervous system. For instance, optical fibers are routed throughout the robot body, interconnecting multiple tactile sensors, similar to human sensory nerves, while a centralized processing unit, analyzes the sensor output, analogous to the human brain. Fiber optic tactile sensors typically measure changes in optical intensity [61]–[65] or wavelength [14], [66], [67]

in response to mechanical stimuli such as pressure, strain and deformations across the skin surface.

Jiang et al. developed a finger-skin-inspired optical sensor for force sensing and slip detection [62]. Mimicking human fingerprint and tissues, it features parallel ridges and a multilayer design with varied stiffness by utilizing elastic resin and PDMS sandwiching an optical microfiber, taper-drawn to $\sim 1.2 \mu\text{m}$ from a standard optical fiber, acting as a sensory element. The optical fiber detects mechanical stimuli via changes in light transmission, which demonstrates high sensitivity in normal force measurement of $5.4\% \text{ N}^{-1}$ below 1 N, and $1.6\% \text{ N}^{-1}$ up to 10 N, in addition to slip detection and object recognition capabilities. Utilization of a microfiber instead of standard optical fiber enhances mechanical flexibility of the skin while improving sensor sensitivity, making it suitable for detecting small forces and applications that require sensor conformability. When integrated onto a robotic gripper, measurement of grasping force and slip detection as well as object stiffness recognition was achieved.

In 2022, Massari et al reported a large-area tactile-sensitive artificial skin for collaborative robots [14]. It consists of 16 serially connected FBGs embedded within silicone rubber, exploiting the multiplexing capability of FBGs. The skin is molded onto a robotic forearm in which 16 FBGs are distributed across the forearm at varying density, mimicking the innervation of the human forearm and the functionality of human Ruffini mechanoreceptors. A neural network framework, combining convolutional neural network (CNN) and multilayer perceptron (MLP) was developed for force estimation and contact localization, achieving high accuracy with median errors of $\sim 0.8 \text{ N}$ and $\sim 3 \text{ mm}$. This biomimetic design leverages the single-hotspot receptive field of FBGs embedded within an elastomer, enabling tactile feedback over large, curved surface with minimal integration complexity. Demonstrated on a robotic arm, the system shows great potential in robotic applications, facilitating safe human-robot interaction in unstructured environment.

2.5 Overview of FBGs and POFs

2.5.1 Working principle of FBGs

FBGs are wavelength-selective optical devices characterized by their periodic modulation of refractive index in the core of an optical fiber. FBGs function as narrowband reflectors which selectively reflect light at a specific wavelength while transmitting others. This unique property arises from constructive interference of back-reflected light that satisfies the Bragg condition,

while other wavelengths destructively interfere and pass through. The reflected wavelength, known as the Bragg wavelength, λ_B , is determined by:

$$\lambda_B = 2n_{eff}\Lambda \quad (2.1)$$

where n_{eff} is the effective refractive index of the optical fiber, and Λ is the grating period. This relationship indicates that any change in either the effective refractive index, or the grating period will result in a shift in Bragg wavelength and Figure 2.2 depicts the optical characteristics of FBG and its response to external perturbations.

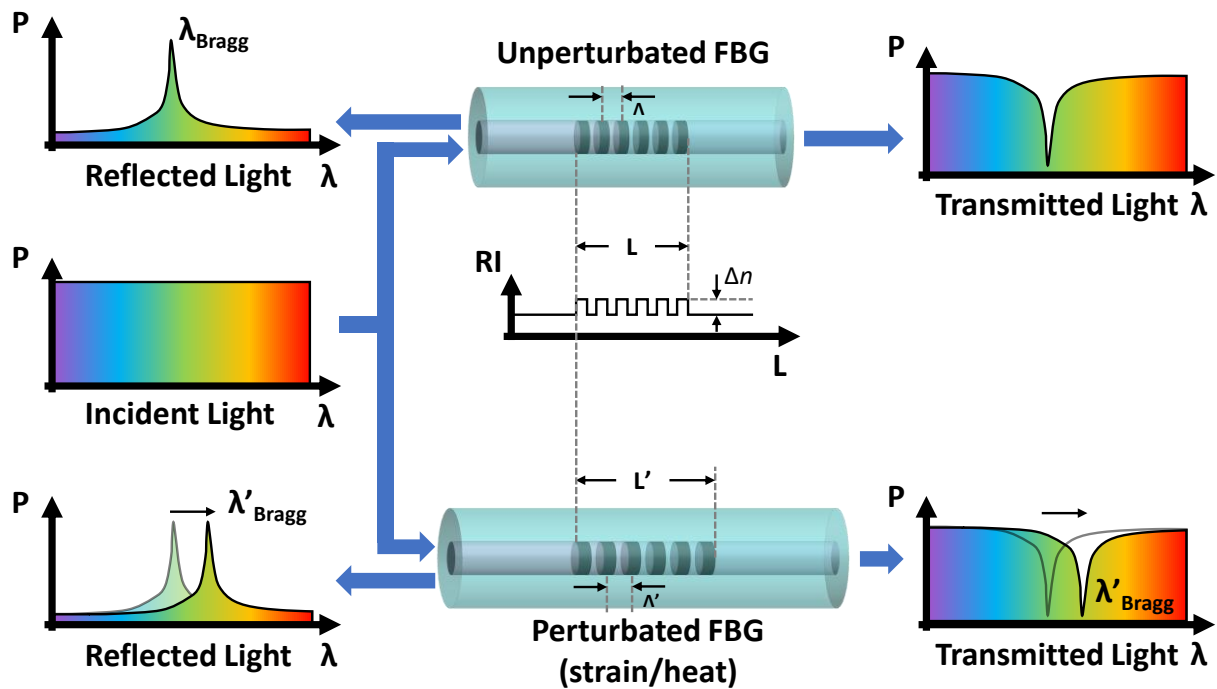


Figure 2.2. Working principle of FBG, optical characteristics and responses. (P: power, λ : wavelength, L: length, RI: refractive index)

The dependency of λ_B on both effective refractive index and grating period allows FBGs to be utilized in sensing applications as both axial strain and temperature perturbation results in shifts in the wavelength. The change in wavelength with corresponding applied strain $\Delta\epsilon$ under constant temperature is expressed as:

$$\frac{\Delta\lambda_B}{\lambda_B} = \left\{ 1 - \left(\frac{n^2}{2} \right) [\nu(P_{11} + P_{12})] \right\} \Delta\epsilon \quad (2.2)$$

where P_{11} and P_{12} are the photoelastic coefficients, ν is the Poisson's ratio, and n is the refractive index. The wavelength shifts for a unit-change of temperature ΔT under constant strain is expressed as:

$$\frac{\Delta\lambda_B}{\Delta\lambda} = (\alpha + \xi)\Delta T \quad (2.3)$$

where α is the thermal expansion coefficient and ξ is the thermo-optic coefficient.

2.5.2 Fabrication of FBGs

The fabrication process of FBGs involves permanent periodic modification of refractive index in the optical fiber core. The capacity of an optical fiber to have its refractive index modified physically or chemically via light exposure is known as photosensitivity. Photosensitivity was first discovered by Hill et al. in 1978 [68], when a 488-nm argon-ion laser was launched into a germanium-doped silica fiber, and a standing wave was formed due to the interference between the incoming laser beam and the back-reflected beams from the fiber end. This periodic pattern induced a modulated refractive index change in the fiber core where the intensity pattern of the standing wave was “imprinted” on the fiber core in the form of modulated refractive index, which was later termed the Hill grating.

Later in 1989, Meltz et al. reported a holographic formation of gratings via transverse exposure of UV laser beams onto the optical fiber [69] and Figure 2.3 illustrates the free-space interferometer for FBG inscription. The fabrication process involves splitting of the laser beam into two paths, which are recombined at an angle, causing interference between two incident beams where the period of interference pattern is dependent on the angle of recombination. By placing an optical fiber at the point-of-interference, the interference pattern can be imprinted onto the optical fiber, forming an FBG on the optical fiber core. The period of FBG (Λ) is expressed as:

$$\Lambda = \frac{\lambda_{UV}}{2 \sin \theta} \quad (2.4)$$

where λ_{UV} is the wavelength of the inscription laser, and θ is the angle of recombination. With adjustable recombination angle, this technique allows FBGs of different pitches to be fabricated at selected sections of an optical fiber. Although having drawbacks such as complex alignment procedures and sensitivity to vibrations, this technique still revolutionized FBG fabrication technology for being a more practical and controllable method for writing strong, wavelength-tunable, and location-selective FBGs. Despite being less utilized nowadays, the two-beam interferometric technique served as a foundation for modern holographic FBG fabrication techniques such as the phase mask technique.

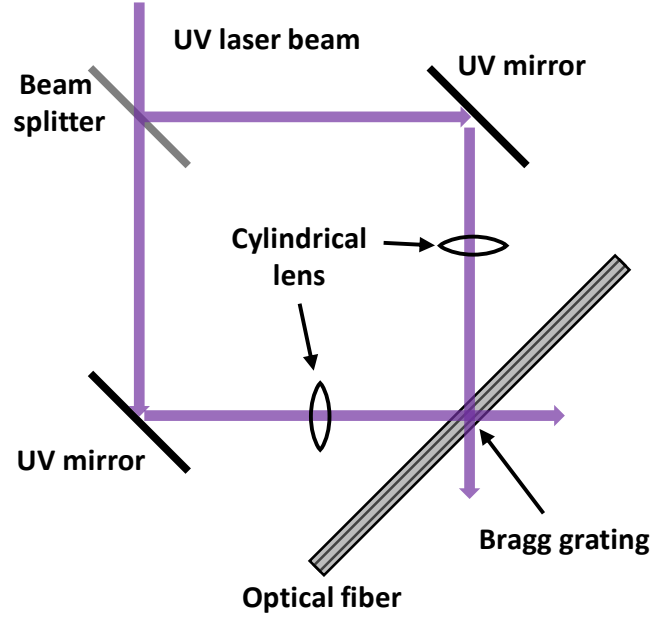


Figure 2.3: Illustration of transverse holographic method [69].

1993 marks another pivotal year for FBG fabrication in which phase masks were utilized for FBG fabrication. The phase mask is a silica plate with a surface-relief grating structure designed to diffract incoming light into specific orders, typically ± 1 orders while suppressing other modes. One of the techniques involving a phase mask for FBG fabrication was the Talbot interferometer [70], where the ± 1 order beams are split by a phase mask of desired grating pitch, reflected and recombined at a distance. Figure 2.4 presents the typical Talbot interferometer for FBG fabrication. Upon recombination, an interference pattern is generated that projects the grating and the distance between the phase mask and the point of combination is known as the Talbot distance, expressed as:

$$Z_T \approx \frac{2d^2}{\lambda} \quad (2.5)$$

where Z_T is the Talbot distance, d is the period of the phase mask, and λ is the laser wavelength. Compared to the transverse holographic method [69], this technique is capable of producing a more precise and repeatable grating pattern. Furthermore, this configuration is also less sensitive to fiber misalignment and beam phase difference, and compensation is much simpler compared to the transverse holographic method as the Talbot interferometer relies on the self-imaging properties of coherent beams.

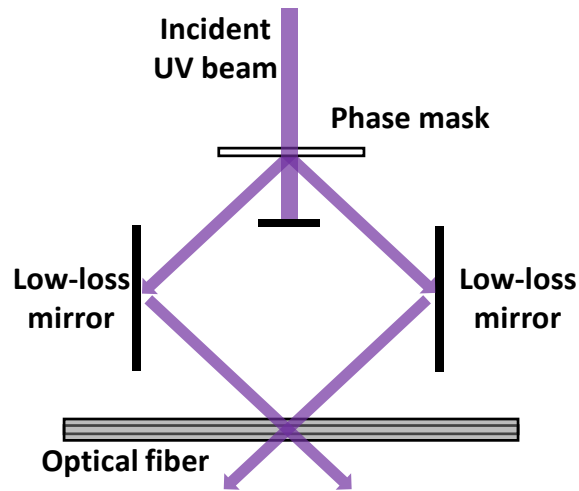


Figure 2.4: Illustration of a typical Talbot interferometer for FBG inscription.

Also in 1993, the phase mask technique was introduced independently by Anderson et al.[71], [72] and Hill et al.[73], where the near field interference between ± 1 order diffraction beams is utilized to produce a periodic intensity pattern. By placing a photosensitive fiber near the phase mask surface, the interference pattern is imprinted onto fiber core, forming an FBG. Figure 2.5 illustrates the typical inscription setup for FBG fabrication using the phase mask technique. One of the main advantages of the phase mask technique is its reliability and stability. It eliminates complex interferometric setups, simplifying the optical alignment process while being less sensitive to surrounding vibrations. Due to the reduced need for precise optical alignment, a scanning beam can be employed by attaching optical components on a translation stage, allowing fabrication of continuous gratings with lengths beyond the laser beam width. Furthermore, the phase mask technique also offers high reproducibility as the grating period is determined by the phase mask. The phase mask technique remains one of the primary techniques for mass production of FBG today.

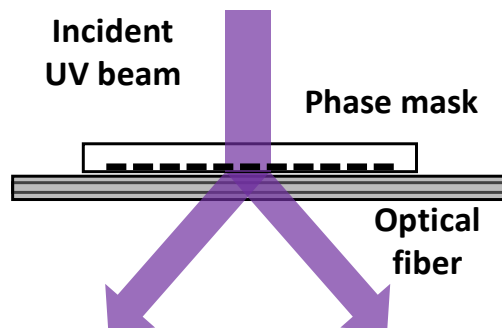


Figure 2.5: Illustration of phase mask technique.

Another alternative technique, the laser direct writing technique, pioneered by Malo et al. [74] in 1993, is a flexible and precise method for fabricating FBGs by locally modifying the refractive index in the fiber core. Figure 2.6 presents a simplified illustration of laser direct writing for FBG fabrication. The process involves scanning a focused laser beam along the fiber core in a point-by-point or line-by-line manner, which allows maskless fabrication of FBGs with customized parameters. Since the refractive index modulation is directly controlled by the laser power, scan speed, and beam-focus, it allows for dynamic real-time adjustments during fabrication. This method is particularly advantageous for producing specialized grating structures such as apodized and chirped gratings. Another advantage of the laser direct writing technique is its independence from phase masks, as one phase mask is proprietary to only one grating structure. This significantly reduces fabrication costs and enables rapid prototyping of novel FBG designs. Although first demonstrated with UV laser beams [74], this technique is now more commonly used incorporated with femtosecond lasers, which eliminates the requirement of photosensitivity on the optical fiber.

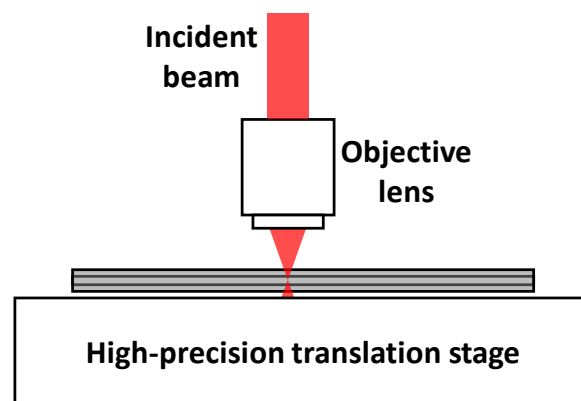


Figure 2.6: Laser direct writing setup.

2.5.3 Polymer optical fibers

Silica-based optical fibers have long been a proven sensing modality for structural sensing [75], [76] and long-haul communication [77]. However, their inherent brittleness, low fracture toughness and mechanical stiffness [78] render them unsuitable for integration into artificial skins where conformability and bendability are indispensable [46]. When embedded within an artificial skin, the optical fiber is subjected to repeated bending and localized stresses during manipulation, causing fiber breakage or delamination from the skin material. This mechanical

incompatibility limits the reliability and the overall feasibility of creating a skin-like tactile sensor array.

Polymer optical fibers (POFs), due to their lower Young's modulus, present a potential alternative sensing medium for artificial skin applications, offering high flexibility and bendability. Their lower stiffness minimizes stiffness mismatch between the embedded POF and artificial skin material, ensuring efficient strain transfer and minimizing fiber-skin delamination, which ensures robust integration into curved and complex surfaces. These characteristics render them ideal for the dynamic interaction required in robotics. While polymethyl methacrylate (PMMA) is the most common POF material, it is usually less suitable for sensing applications due to its material drawbacks such as high moisture absorption, viscoelastic creep and low thermal stability. These drawbacks eventually lead to signal drifts and reduced long-term stability, which are detrimental in applications demanding precise and repeatable sensing performance.

Consequently, our research is steered towards alternative polymer material, namely the ZEONEX, a cyclo-olefin polymer (COP). ZEONEX directly addresses the disadvantages of both silica and PMMA in tactile sensing applications as it exhibits negligible water absorption, ensuring FBG signal stability in a humid environment and a much higher glass transition temperature, resulting in greater thermal stability. In addition, ZEONEX materials possess intrinsic UV photosensitivity which is crucial for FBG fabrication with UV lasers [79]. These characteristics allow ZEONEX POF to fit well within the ecosystem, ensuring robustness, signal fidelity and mechanical compatibility, enabling practical implementation of reliable, multimodal artificial skins.

2.6 Summary

In summary, this chapter provides a comprehensive framework for the development of tactile-sensitive artificial skins, beginning with an analysis of the human skin's multi-layered structure and specialized mechanoreceptors as the fundamental biological inspiration. The essential characteristics of an artificial skin are then outlined and the inherent trade-offs between different characteristics are discussed, serving as a guideline for artificial skin design. Several major sensing technologies, including capacitive, piezoresistive, piezoelectric, triboelectric, and fiber-optic sensors are then reviewed, highlighting their respective advantages and limitations. The working principle and the fabrication of FBGs are outlined, followed by discussion of their advantages and compatibility with robotic tactile sensing. The discussion

focus then pivots to the material choice for FBG sensing medium, highlighting the limitations of conventional silica fibers and common PMMA polymer optical fiber for artificial skins, particularly issues related to brittleness, moisture sensitivity and signal drift. Finally, the selection of ZEONEX COPs as the optimal material is justified. Their unique combination of flexibility, low moisture absorption, high thermal stability as well as their intrinsic UV photosensitivity is presented as the key for robust and reliable FBG-based artificial skin for robotic applications.

Chapter 3. Fabrication of polymer optical fiber

3.1 Fabrication of ZEONEX single mode preforms and optical fibers

The fabrication of ZEONEX single-mode POF (SMPOF) involves the production of ZEONEX optical fiber preform, followed by the fiber drawing process. The preform was fabricated using the “pull-through” method [79]–[81], which consists of separate casting processes for two different grades of ZEONEX materials, namely E48R and 480R for core and cladding, respectively. The combination of material grades was selected due to their compatibility in refractive indices and glass transition temperatures [82]. Both materials exhibit glass transition temperature of ~ 138 °C, which enables homogeneous melting of the core and cladding during thermal drawing process. The core material, ZEONEX E48R has a refractive index of 1.531, slightly higher than that of the cladding material, ZEONEX 480R, at 1.525, which facilitates light guidance in the fabricated optical fibers. As both ZEONEX E48R and 480R comes in the form of pallets, the main objective of the “pull-through” method is to consolidate both materials into homogeneous rods via melting and solidification cycles in a predetermined molds for assembly and thermal drawing in subsequent processes.

Figure 3.1 illustrates the “pull through” method which begins with filling core and cladding material pallets into separate glass tubes with an inner diameter of 32 mm. In the glass tube with cladding material, a polytetrafluoroethylene (PTFE) wire of 2 mm diameter was suspended vertically through the center of the glass tube. The melting of both materials was done in a vacuum oven where a vacuum was applied, and the oven was gradually heated to 245 °C over 1 hour, and the temperature was maintained for 30 hours before the oven was cooled naturally to ambient temperature. After cooling, and solidification, both materials were demolded and the PTFE wire was removed from the cladding preform, leaving behind a hole through the center. The core preform was then thermal drawn into rods with a diameter around 2 mm, matching the diameter of the hole along the cladding preform. The core rods were then inserted into the cladding, completing the single-mode POF preform with a cladding to core ratio of 125:9. The POF preform was again thermally drawn to a diameter of 125 μm , forming the single-mode POF with a core diameter of 9 μm .

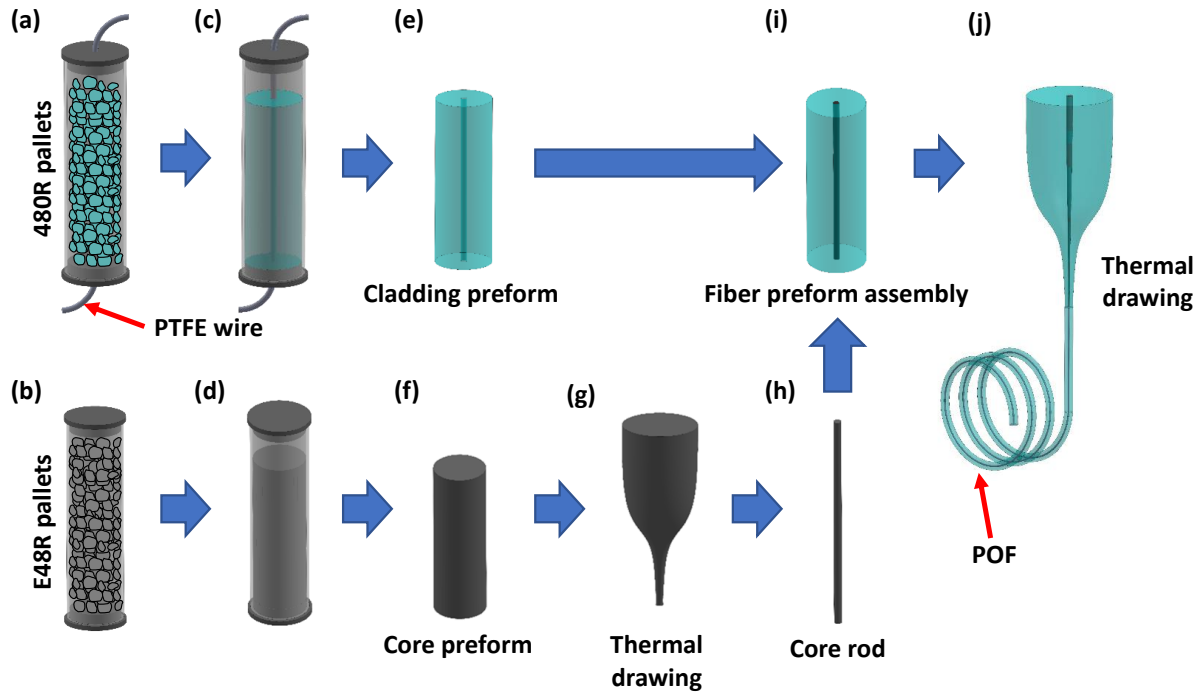


Figure 3.1: Overview of the ‘pull-through’ POF fabrication process. Two separate glass tubes are filled with (a) cladding material, ZEONEX 480R and (b) core material, ZEONEX E48R pallets with a PTFE wire suspended vertically through the cladding glass tube. (c-d) both tubes of material are melted and cast into a solid rod. (e-f) The glass tubes and PTFE wire are removed, leaving behind the (e) cladding and (f) core preforms. (g) The core preform is drawn into (h) core canes of smaller diameter. (i) The core cane is inserted to the cladding preform (where the PTFE wire was), completing the single-mode POF preform. (j) The preform is then drawn into POF of smaller diameter.

3.2 Polymer optical fiber drawing tower

The thermal drawing process of optical fiber serves as the foundation of the fiber fabrication process where a large-scale structured preform is reduced to fiber dimensions through precisely controlled heating and stretching. However, the commercial availability of a fiber drawing towers optimized for the thermal drawing of POFs is limited, hence, a custom POF drawing tower was built in-house with strong reference to a conventional drawing tower for silica optical fibers. Resorting to an in-house built drawing tower allows great flexibility in terms of functions and components based on the desired optical fiber, ZEONEX POFs in our case, while retaining potential expandability in the future. The structure of the fiber drawing tower is illustrated in Figure 3.2.

Standing at 4 meters in height, the POF drawing tower integrates several functional units into a cohesive system. The system begins with a preform feeder that consistently feeds the POF preform into the furnace. The furnace consists of infrared (IR) heating elements, emitting

radiant heat, the energy from which is directly transferred to the preform. This direct heating process is less susceptible to airflow and turbulence within the furnace, leading to rapid and uniform heating which is essential for a controlled thermal profile and improved stability. When the preform temperature reaches its glass transition temperature, the preform is carefully stretched downwards, reducing in diameter, while being guided to the capstan. The capstan constantly draws the softened fiber while applying tension to the preform, maintaining a constant drawing process. Upon achieving the desired fiber dimensions, the optical fiber is reeled and collected into an optical fiber spool. Complementing these core units, multiple process monitoring modules continuously measure drawing parameters such as the fiber diameter, drawing tension and spool tension. These functional units are all mounted on extruded aluminium frame, ensuring modularity and structural rigidity.

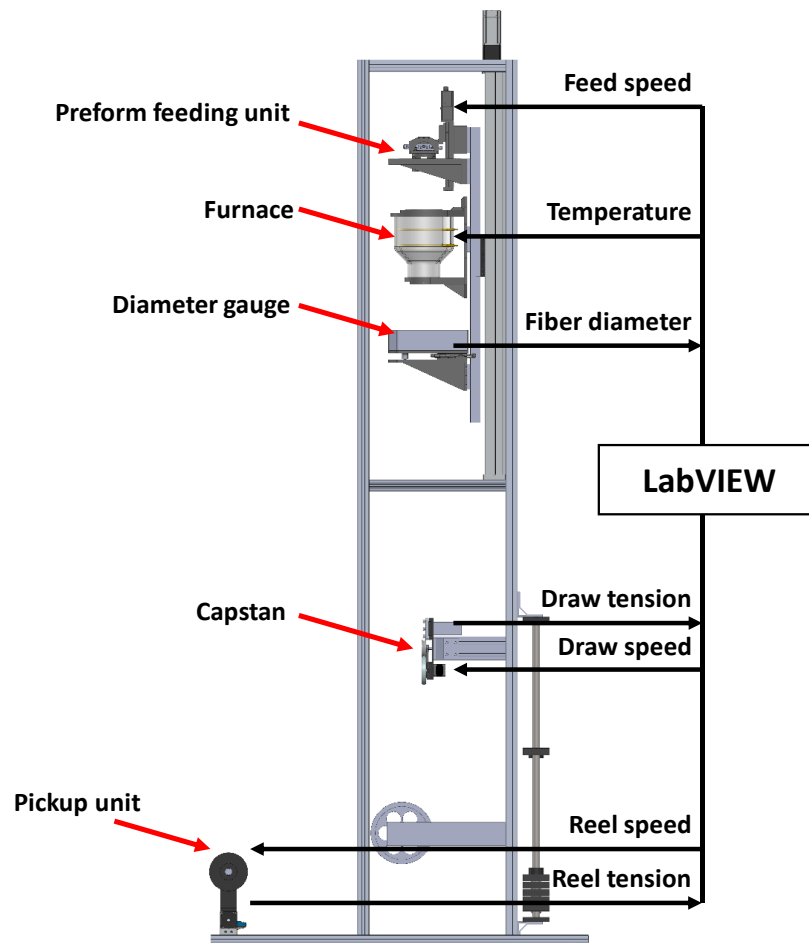


Figure 3.2: Structure of POF draw tower.

3.2.1 Preform feeder

A reliable preform feeder is critical for ensuring stable feeding of the preform for a clean and repeatable draw. Key qualities of a reliable preform feeder include precise speed and feed control to ensure uniform preform delivery to the furnace with minimal fluctuations. The feeder should also exhibit high mechanical stability and rigidity to maintain preform alignment throughout the fiber drawing process while damping vibrations that could disrupt fiber formation. The preform holder, on the other hand, should exert a gentle yet secured grip on the preform, enough clamping force to prevent slipping without stressing or damaging the preform, while offering positional adjustability, ensuring preform concentricity with the furnace.

The structure of the preform feeder of the in-house built POF drawing tower is as shown in Figure 3.3. Vertical motion of the preform feeder is provided by an electronic translation stage (Zaber Technologies X-LSQ150A) with a 150 mm travel range, designed for a typical preform length of 100 mm. A stepper motor drives a precision lead screw (1.27 mm pitch), which in turn moves a platform along linear guide rail. The translation stage features a wide speed range of 0.000061 to 53 mm/s with a resolution of 0.000061 mm/s, providing great adjustability while having ample speed overhead for both fast and slow feeding requirements. In terms of structural rigidity, the stage exhibits high tilt stiffness of 150, 225, and 150 N·m/° in pitch, roll, and yaw, respectively, which is more than enough to withstand the weight of a POF preform. The preform holder is attached to the translation platform via lateral stages for lateral adjustability of preform-furnace concentricity. To reduce torsional load on the translation platform, counterweights were installed to counteract the weight of the preform holder, minimizing creep and ensuring the longevity of the translation stage.

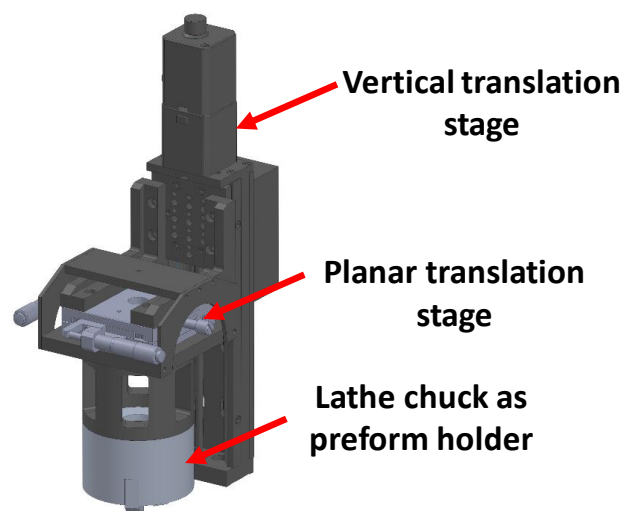


Figure 3.3: Illustration of preform feeder.

3.2.2 Furnace

The fiber drawing process, where a macro-scaled preform is reduced to fiber dimension occurs in the furnace. The preform is fed into the furnace at a constant rate, allowing the temperature of the polymer to increase sufficiently beyond its glass transition temperature (T_g), decreasing its viscosity to a level where the polymer can be readily deformed. As the heated material is drawn, a tapered neck-down region forms, where rapid change in preform diameter occurs. The neck-down region is an important indicator for the drawing process, its shape is dictated by several drawing parameters including the dimensions and heating intensity of the furnace, the feed and draw rate as well as the thermal properties of the preform material, particularly the temperature dependence of the viscosity of the preform material. Generally, the neck-down region should be smooth and continuous, free of abrupt changes in diameter and shape to avoid stress points and defects. The slope of the taper should ideally be gentle, and the length of the neck-down should be proportional to the heated zone, typically around 30 mm long, so that the preform experiences a gradual softening and elongation rather than abrupt necking. Furthermore, a radially uniform heat profile is also essential for consistent heating across the cross-section of the preform, preventing asymmetry which could cause uneven stress distribution that eventually causes polarization and concentricity issues.

The shape of the deforming preform within the neck-down region is critically important for precise translation of the preform design into fiber structure upon drawing, especially for microstructured fibers. Hence, the furnace design and operation are key considerations for fabricating high-quality optical fiber. The furnace of the in-house built POF drawing tower features IR heaters, which heat the preform via radiation rather than convection. Four ring-shaped IR heaters are stacked above one another, each spaced 15 mm apart as illustrated in Figure 3.4. One major advantage of radiative heating is enhanced heat transfer from the surface into the interior of the preform. As ZEONEX is generally opaque at the emission wavelengths of the IR heaters [83], most of the heat generation occurs at the external surface of the preform. However, several windows of partial transparency exist within the emission spectrum, allowing considerable thermal radiation to penetrate through and be absorbed beyond the preform surface [84]. With sub-surface heat generation, not only can the temperature of the inner portion of the preform can be elevated more quickly, but it also promotes a more uniform radial temperature profile. This is a key objective from a fabrication perspective, as it helps to minimize deformation and facilitate laminar, axisymmetric material flow during fiber drawing. With multiple IR heaters stacked above one another, the heated zone is effectively lengthened,

and the temperature profile can be adjusted by individually controlling the output power of each IR heater. A thermal camera is integrated into the furnace to monitor the preform temperature and heating conditions, providing an alternative way to observe and monitor the neck-down region during the thermal drawing process.

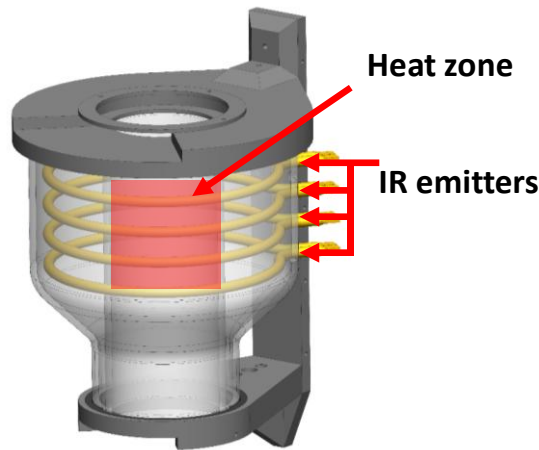


Figure 3.4: Illustration of furnace.

3.2.3 Capstan

The capstan is the main driver of the fiber drawing process, pulling the fiber strand from the melted preform in the neck-down region. It serves as the primary mechanism to regulate fiber diameter and tension by controlling the draw speed based on real-time feedback from the diameter gauge and tension meters. Located between the neck-down region and the spooler, the capstan decouples the neck-down region from the spooler, preventing fluctuations and vibrations from the winding process from affecting the neck-down region, ensuring stable production of high-quality optical fiber. The structure of the capstan for the in-house built POF drawing tower is as shown in Figure 3.5. The capstan consists of a pair of clamp wheels, in which one is directly driven by a servo motor (active) and the other is free spinning (passive). The free-spinning wheel is attached to a horizontal translation stage, realizing a clamp-like structure that allows the passive wheel to be pushed towards the active wheel. This allows adjustment of the distance and clamping pressure to cater for both fiber drawing and cane drawing. The draw rate is dictated by the rotation of the active wheel, while the passive wheel applies clamping pressure on the drawn fiber, firmly engaging it to the active wheel. Both wheels are lined with 5-mm thick silicone rubber to increase traction and to prevent the drawn fiber from slipping.

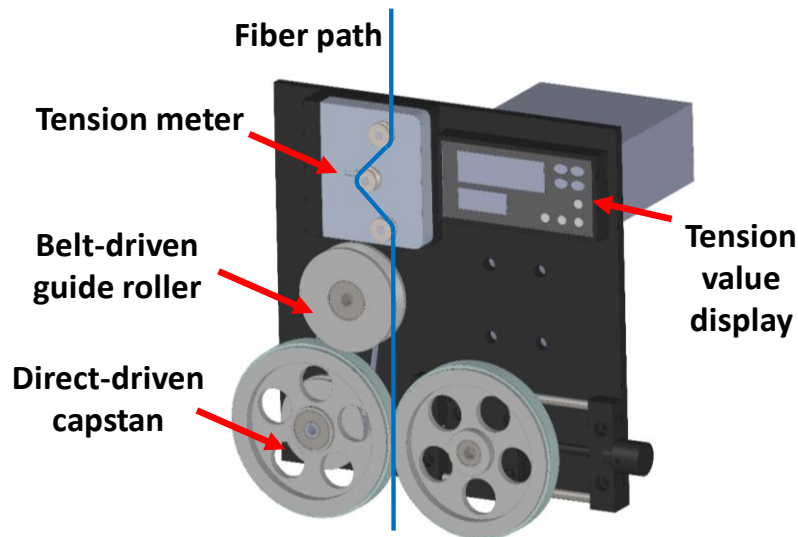


Figure 3.5: Illustration of capstan.

3.2.4 Process monitoring and control

The process control for fiber drawing generally aims to precisely control the diameter of the drawn fiber while regulating the drawing tension to be within a specific tolerance in real time, ensuring consistent quality, performance and reliability. Real-time diameter and tension feedback provide insight towards the drawing parameters, allowing immediate process control while ensuring the drawn fibers are within specifications. In most cases, the drawing speed is controlled to regulate the fiber diameter while the drawing temperature, which is proportional to the viscosity of the melted polymer is varied to regulate the draw tension.

The diameter of the drawn fiber is measured in real time using an optical-based diameter gauge (Ridee, LDM-10XY) at a frequency of 1.8 kHz. The diameter gauge features a resolution of 1 μm and a measuring range of 0.1 to 10 mm, making it compatible for both fiber and cane drawing. In addition, the diameter gauge is also capable of measuring diameter across two orthogonal directions, which provides an indication on the circularity of the drawn fiber or cane. After the diameter measurement, the fiber is passed through a three-wheel tension meter (JN JZHL-T1) before with engaging to the capstan. The tension meter monitors the drawing tension at a resolution of 0.1 N and is capable of measuring tension up to 10 N. In addition, an identical tension meter is employed before the fiber spooler to monitor the spooling tension, and the spool rate is regulated to prevent excessive tension on the spooled fiber, potentially causing fiber creep and deformation. The integrated feedback and controls of the fiber drawing tower are implemented using LabVIEW.

3.3 Summary

This chapter has detailed the foundational fabrication process established for this research work, focusing on the production of custom POFs which is essential for the development of high-performance tactile sensors. The process began with the successful fabrication of single-mode ZEONEX preforms using the “pull-through” method, which enabled the precise co-axial integration of core (ZEONEX E48R) and cladding (ZEONEX 480R) materials.

A significant contribution of this work was the design, construction and operation of a custom, in-house built POF drawing tower. The drawing tower integrates several critical functional units, which include a precision preform feeder for controlled material delivery, an infrared furnace for rapid and uniform radiative heating, a servo-driven capstan for tension-controlled drawing, and an integrated process monitoring system for real-time diameter and tension control. The operation of these components, governed by a self-developed LabVIEW program, ensures the production of high-quality, tailored ZEONEX POFs.

The successful establishment of this scalable fabrication pipeline from raw polymer pellets to single-mode POFs is a critical foundation for subsequent work in this thesis.

Chapter 4. Artificial skin with contact force measurement and localization capabilities

4.1 Introduction to contact localization

Tactile perception relies heavily on contact force and contact localization for effective object interaction. Contact force perception determines how forces are applied during object manipulation such as grasping and squeezing. It allows precise feedback on grip strength to maintain grip stability, prevent slip, and avoid excessive pressure that could potentially damage delicate objects. Contact localization, a vital auxiliary information for object manipulation [85], identifies the position of stimuli on the skin, allowing real-time mapping of touch locations and fine adjustments during interaction. Together, these elements enable strategic movement planning during grasping where finger adjustments, manifested in the form of grip force and joint angles [86], are heavily dependent on the feedback related to force magnitudes and contact location.

Human hands, particularly the fingertips, serve as the primary contact point for most object interactions to provide reliable tactile feedback. For robots to achieve similar dexterity, they must be equipped with fingertips or grippers capable of high spatial acuity tactile perception [87] during object manipulation and exploration [88], [89]. FBGs are excellent candidates for tactile sensing due to their compact size, fast response, and excellent multiplexing capability. Multiple FBGs can be inscribed along a single optical fiber with customizable Bragg wavelengths, grating lengths and positions. Furthermore, FBGs also inherit the advantages of optical fibers including immunity to EMI, small form factor and flexibility.

Previous studies have investigated the characteristics of FBG-based tactile sensitive elastomeric membranes in planar configuration [90]–[93], demonstrating their ability to resolve force magnitude and location. However, real-world applications often require these membranes to conform to complex robotic surfaces while maintaining tactile functionality. To better correlate the application of such devices to practical realization, researchers have implemented FBG-embedded artificial skin on robotic surfaces such as the arms [14], fingers [94]–[96] and grippers [97] to replicate tactile perception. These approaches, however, are based on silica optical fibers which are often unsuitable for sensing on small areas with high spatial acuity of touch, such as the fingertips. Routing of silica fibers in such spaces requires intricate pathways with tight bends, increasing the risk of fractures due to material brittleness.

Since all FBGs are serially multiplexed, a single fiber breakage disables all downstream sensors. In addition, silica fractures may also release hazardous micro-sized shards, which can be detrimental to the skin material or even robotic components.

POFs could potentially play a significant role in enabling the placement of multiple FBGs in confined areas such as robotic fingertips, as their lower Young's modulus allows superior flexibility and fracture toughness compared to silica fibers of comparable diameter. This allows POFs to be routed on smaller areas such as robotic fingertips without breakage while inheriting all of the aforementioned merits offered by conventional silica FBGs [79], [98], [99]. In addition, the lower Young's modulus of a POFs enhances the strain sensitivity of embedded FBGs [79], reducing the required sensor density for effective tactile coverage. Recently, the demonstration of FBG inscription in ZEONEX optical fibers made of two different grades, namely, grades E48R and 480R [100] unveiled several traits such as low affinity to water and resilience to most chemicals [79], further expanding the potential applications of polymer optical fiber Bragg gratings (POFBGs) for artificial skins, particularly for tactile sensing in open or harsh environments.

FBG arrays, due to their fiber optic nature, are inherently limited to quasi-distributed sensing configurations. In such a setup, the sparse distribution of sensors complicates the detection of forces and contact location as the contact point may not be directly above the sensing element. Consequently, extrapolation techniques based on the responses from multiple sensors are required to determine the force magnitudes and locate the point of contact. While mathematical models for elastic materials can ideally resolve both measurands [101], practical implementation still faces challenges. The curvature of the covered surface and the elasticity of the skin membrane introduce non-linearities, causing the mapping of contact-induced deformations to be highly intricate and extremely sensitive to the position of the sensors. Furthermore, these models require precise knowledge of sensor positions, imposing strict fabrication tolerance on sensor positions. To overcome these limitations, data-driven models are employed in quasi-distributed sensing, in both electronic-based and fiber optic-based configurations, to resolve for contact location, eliminating the necessity of knowing the exact positions of the sensors [102], [103]. These approaches eliminate the need for precise sensor positioning, simplifying the fabrication of artificial skin by accommodating position tolerances and other systematic errors [104].

In this chapter, a POFBG-based tactile sensitive artificial skin is developed and tested on a fingertip model. The POF is encapsulated in a silicone layer, forming a skin-like membrane that is ~2 mm thick and could be molded to fit any surface. Due to the bending resilience of the POFs, four FBGs were placed closely together with the presence of tight fiber bending without affecting the functionality of the FBGs when the POF was routed on small areas such as a fingertip. A 3D-printed indenter with a diameter of 2 mm was used to indent the surface of the artificial skin, applying forces up to 3 N, which corresponds to a pressure of 955 kPa, double the pressure pain threshold of a typical human index finger [105] with no damage to the skin observed. A random forest machine learning model was implemented to estimate the magnitude and location of the applied force by considering the responses of all FBGs when force was applied.

4.2 Fabrication of POFBG and design of tactile sensitive artificial skin

4.2.1 FBG array inscription

The fabrication of FBG arrays was performed using the phase mask technique with a 248-nm excimer laser. In addition, a load cell is installed at one of the fiber holders to measure the tension applied to the POF during FBG inscription, and Figure 4.1 illustrates a simplified FBG fabrication setup. One of the characteristics of POFs is their lower Young's modulus of POF compared to silica optical fibers, which results in much larger wavelength tunability of FBGs inscribed in POFs. By pre-tensioning the POF during the FBG inscription process [106], a wide variety of FBGs wavelengths can be obtained by precisely controlling the fiber tension and the tunability depends on the wavelength-to-tension response as well as the maximum applicable tension before the POF yield point or degradation of FBG quality.

The optical setup for FBG fabrication is illustrated in Figure 4.1. The setup consists of a mirror, a cylindrical lens and a vertical aperture mounted on a motorized translation stage (Newport). The laser beam is reflected by the mirror, focused by the cylindrical lens and horizontally truncated by the vertical aperture. The focused laser beam is directed to a phase mask while a POF, with both ends secured on fiber holders, is placed at the beam focus, in close proximity to the phase mask. Both fiber holders and the phase mask holder are mounted on 3-axis translation stages to ensure optical alignment. A load cell (Simbatouch) is installed on one fiber holder to monitor tension applied on the secured fiber, which is adjusted by laterally translating the fiber holder, stretching the secured POF.

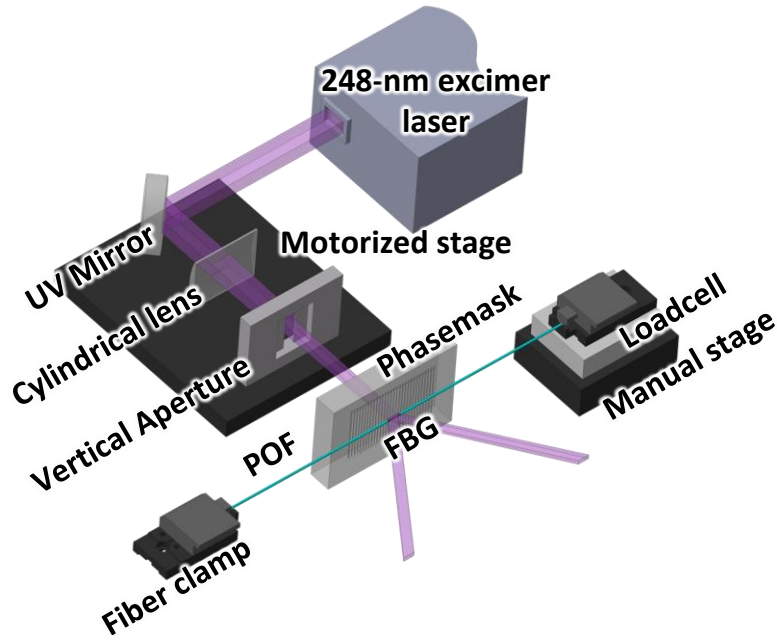


Figure 4.1: Inscription setup for FBG fabrication.

4.2.2 Design of artificial skin

The artificial skin was designed to encapsulate an FBG array with a silicone layer over a 3D-printed fingertip support, mimicking the mechanical properties of human skin with force detection and localization capabilities. The fingertip model was designed using the dimensions of an adult index finger, as illustrated in Figure 4.2(a). It is comprised of an in-house fabricated single-mode ZEONEX POF [28] with four cascading FBGs inscribed along the POF embedded within a silicone layer, mimicking the human skin. The cross-section of the POF is depicted in the inset of Figure 4.2(a). The POF features a core and cladding diameter of $9\text{ }\mu\text{m}$ and $125\text{ }\mu\text{m}$ respectively and the propagation loss of the POF was found to be 1 dB/cm at 1550 nm . The POF was routed in such a way that the FBGs are parallel to the finger. The reflection spectra of the FBG array before and after being embedded in the artificial skin are shown in Figure 4.2(b). The FBG-array was interrogated from the fiber end closer to FBG4 and it was observed that the induced loss after embedding is negligible as indicated by the blue curve of FBG3 and FBG4. However, light reflected by FBG1 and FBG2 passed through the bend (radius of curvature $\sim 4\text{ mm}$) twice and experienced a bending loss of about 10 dB . Although the drop in the intensity of FBG1 and FBG2 is relatively large, the functionality of the FBGs is not affected as only their Bragg wavelengths are considered. Each FBG is 2 mm long and spaced 7 , 12 , and 7 mm apart along the POF, as depicted in Figure 4.2(c). Credited to the robustness of POF, the thickness of the artificial skin is only 2-mm thick, allowing it to be utilized on robotic surfaces

without significant modifications on the robotic structure. The design of the artificial skin structure involves suspension of the POF within the silicone membrane to undergo sufficient deformation when pressure is applied to the skin.

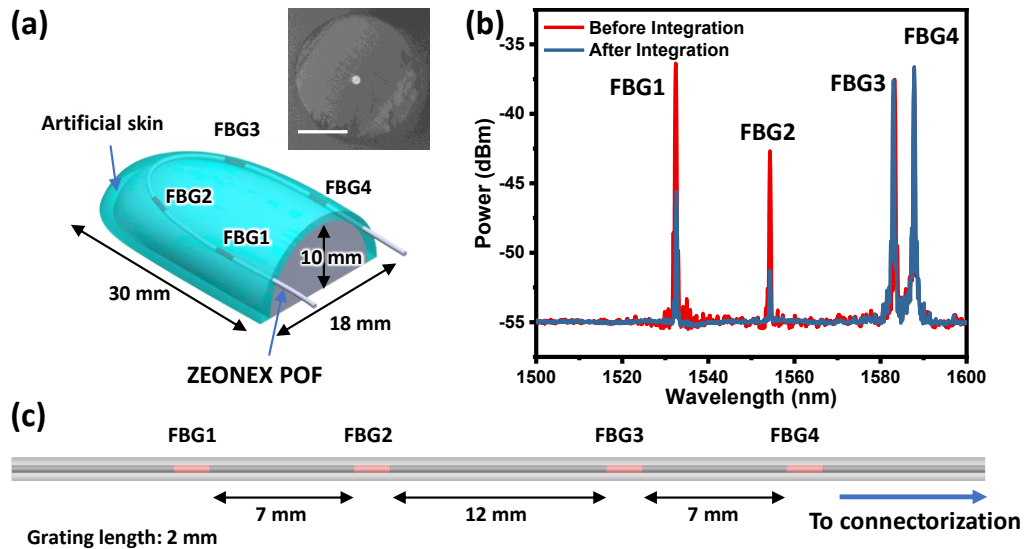


Figure 4.2: (a) Schematic illustration of fingertip model encapsulated with 2-mm thick tactile sensitive artificial skin (inset: Cross-section of the in-house fabricated SMPOF, scale: 50 μm). (b) Reflection spectra of the FBG array before and after integration. (c) Locality of FBGs along ZEONEX POF.

4.3 Molding process of artificial skin

To ensure the POFBG array is suspended within the artificial skin, a two-step molding process, as illustrated in Figure 4.3, was used. Several customized 3D-printed molds were incorporated, and prior to molding, both the fingertip support and the POF inscribed with FBGs were treated with a silicone primer (DOWSIL™ 1200 OS Primer) to improve adhesion to silicone. The treated POF has shown excellent adhesion to the molded silicone rubber, as pulling the embedded POF to fiber breakage results in no observable slippage. The first silicone layer was molded with the routed and adhered POF on the mold wall (Figure 4.3(a)), followed by pouring liquid silicone through a gap in the mold to fill the void of the fingertip model (Figure 4.3(b)). After curing and demolding, the routed POF with four FBGs was transferred to the silicone surface through strong bonding between POF and the silicone membrane (Figure 4.3(c)). Then an encapsulating layer was molded with a mold with larger spacing (Figure 4.3(d)) and liquid silicone was poured into the void (Figure 4.3(e)) to fully embed the POF within the silicone membrane. Upon curing, the complete artificial skin is molded on the fingertip model (Figure 4.3(f)).

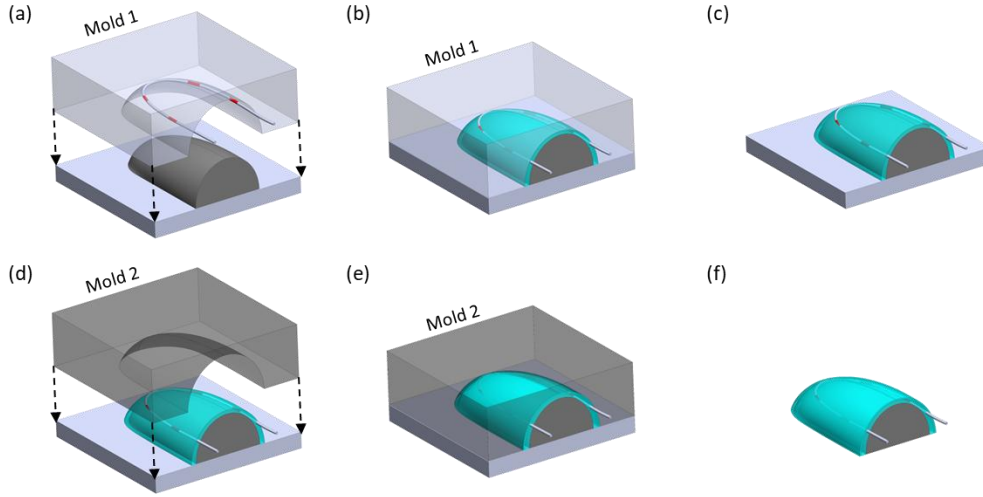


Figure 4.3: Molding process of tactile sensitive artificial skin. (a) Mold 1 assembly, fingertip support attached to bottom mold and FBG inscribed POF adhered to top mold. (b) Liquid silicone poured into opening of mold 1, forming base layer. (c) Demold, POF transferred to cured silicone. (d) Mold 2 assembly, larger mold opening for encapsulating layer. (e) Liquid silicone poured into opening of mold 2, forming encapsulation layer. (f) Demold and detachment of fingertip from mold.

4.4 Characterization of tactile sensitive artificial skin

The experimental setup for exerting force onto the FBG-based artificial skin is presented in Figure 4.4. It consists of a 4-axis electronic platform that employs a load cell with a 3D-printed indenter of 2 mm in diameter and three orthogonally placed translation stages (FUYU Technology) to allow horizontal and vertical movements (X-, Y-, and Z-axes), while a motorized rotator (LAIPER) with the axis of rotation parallel to the Y-axis enables rotational movement (θ -axis). Due to the freeform shape of the artificial skin, the lateral-medial direction of the fingertip was oriented in parallel to the X-axis of the platform, allowing perpendicular force measurements at different positions of the artificial skin. The responses of the FBGs, including both reflection spectra and Bragg wavelength shifts were simultaneously recorded with an FBG interrogator (Micron Optics, HYPERION si155) with an acquisition rate of 10 Hz. In addition, a customized LabVIEW user interface was utilized for integrated control and data acquisition.

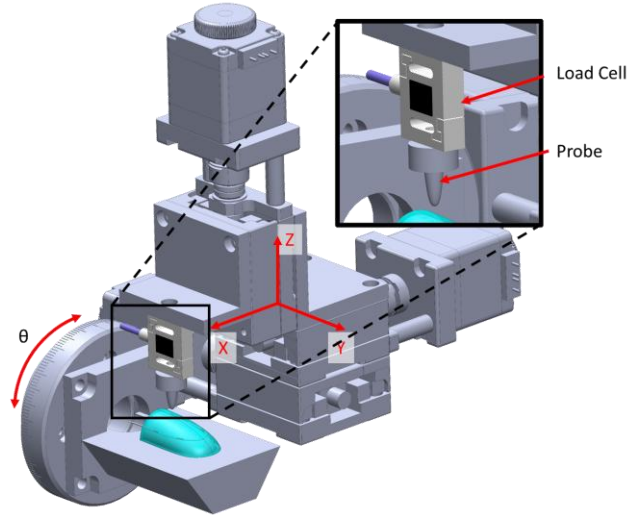


Figure 4.4: Electronically controlled, 4-axis platform for force exertion onto the skin surface.

To evaluate the performance of the proposed artificial skin, a total of 49 force-controlled indentations were conducted across a 7×7 grid on the fingertip surface. The origin of the indentation grid was located at the center of the fingertip surface, and the indentation points were evenly spaced 2 mm apart. The indentations were carried out using a 3D-printed indenter. Each indentation was repeated for three cycles and at each indentation point, the indenter was lowered at a speed of 0.1 mm/s up to a force value of 3 N, double the pain threshold of the human index finger, followed by retraction at a speed of 0.1 mm/s. During the indentation process, the force response on the load cell, the wavelength responses of all FBGs as well as the location information were recorded at a rate of 10 Hz.

4.5 Force and contact location sensitivity of the artificial skin

Figure 4.5 represents the force responses of all embedded FBGs for 3 of the 49 tested locations, namely Point 1, Point 2 and Point 3. Based on Figure 4.5, all FBGs generally exhibit a logistic response to forces applied across the fingertip surface, displaying linear-like growth before reaching saturation, which is attributed to the silicone material being fully displaced by the applied force. As depicted in Figure 4.5(a), the indenter is indented on Point 1 which is located closest to FBG1 compared to the other three FBGs. Since the indentation is located on the side of the fingertip close to FBG1 and FBG2, only FBG1 and FBG2 are responsive towards the indentation, showing a wavelength shift of 6.61 and 1.66 nm respectively at a tested force of 3 N, whereas FBG3 and FBG4 exhibit negligible responses.

As shown in Figure 4.5(b), the force indentation is located at the midpoint between FBG3 and FBG4, resulting in wavelength shifts of 0.48 and 0.27 nm for FBG3 and FBG4, respectively at 3 N of applied force while negligible responses are observed for FBG1 and FBG2. Similarly, when indentation is applied on the center of the finger, as depicted in Figure 4.5(c), the indentation is distanced similarly apart from each of the four FBG centers, resulting in similar responses for FBG1 and FBG3, each having wavelength shifts of 0.12 and 0.11 nm, respectively while wavelength shifts of FBG2 and FBG4 are 0.25 and 0.07 nm, respectively at 3 N indentation. To better visualize the sensitivities of each FBG on force indentations applied on different locations, linear curve fitting was performed on the linear regime, and Table 4.1 summarizes the initial linear force sensitivities of each FBG when subjected to forces at Point 1, Point 2, and Point 3, respectively.

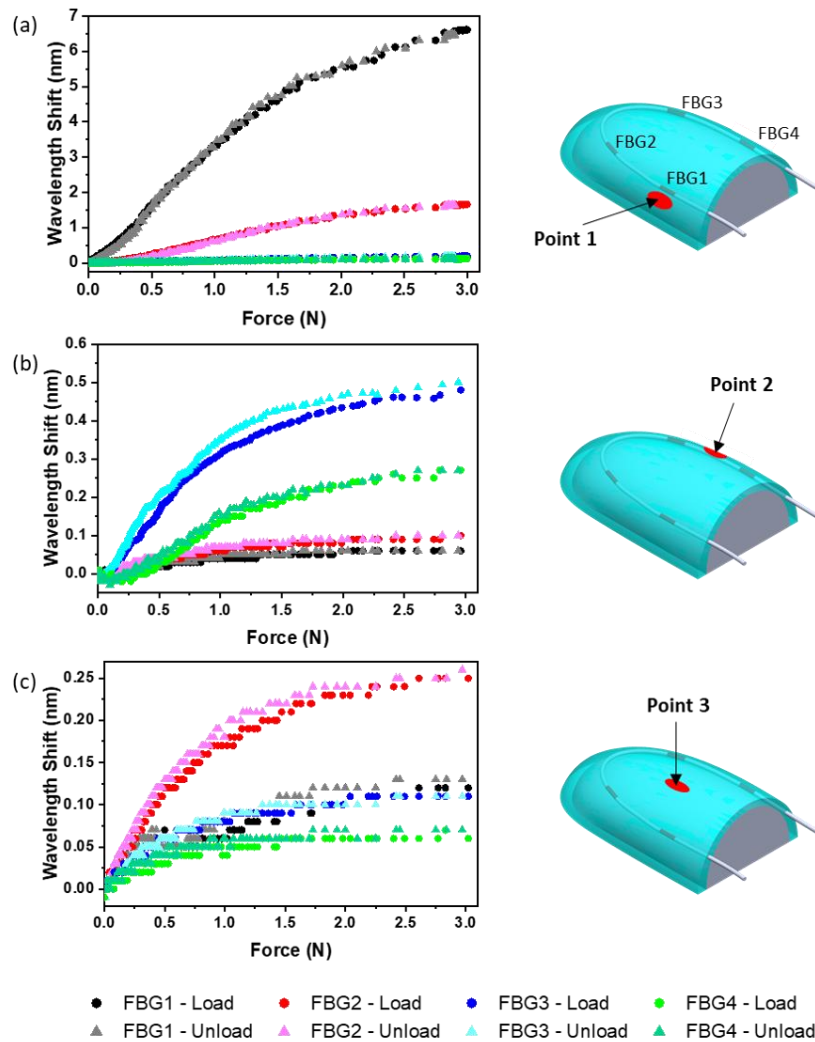


Figure 4.5: Force responses of fabricated artificial skin when force is applied at three different locations on the fingertip (a) Point 1, (b) Point 2, and (c) Point 3.

In addition to assessing the force sensitivity at various locations on the proposed artificial skin, the force receptive region [14] of an FBG sensor serves as another useful parameter for characterizing its performance, quantified by the sensitivity level as the reciprocal of the force required to induce a 0.1 nm wavelength shift. By knowing the force receptive region, optimization of FBG position can be performed to determine the maximum distance between adjacent FBGs while ensuring overlapping force receptive regions, resulting in the least amount of FBGs required for a given area.

Table 4.1: Linear force sensitivities for FBG array towards force indentations at Point 1, Point 2, and Point 3.

Indentation Location	Point 1		Point 2		Point 3	
Linear Fit Region	0-1.5 N		0-1.25 N		0-0.5 N	
	Linear Sensitivity (nm/N)	R^2	Linear Sensitivity (nm/N)	R^2	Linear Sensitivity (nm/N)	R^2
FBG1	3.29	0.996	0.04	0.954	0.15	0.970
FBG2	0.81	0.997	0.07	0.971	0.19	0.979
FBG3	0.08	0.979	0.35	0.956	0.12	0.959
FBG4	0.05	0.963	0.19	0.973	0.07	0.925

Figure 4.6 depicts the normalized spatial sensitivity of the embedded FBGs where darker points indicate greater sensitivity. It is observed that the embedded FBGs possess a force receptive region that is centered around the FBG element and is more sensitive towards the FBG center, with sensitivity gradually decreasing as the position moves away from the FBG. For instance, the response of FBG2 (Figure 4.6 (top left)) peaked at $(-6 \text{ mm}, -6 \text{ mm})$, which is reduced by 35% when the force indentation is shifted 2 mm away from the FBG center along Y-axis, to $(-6 \text{ mm}, -4 \text{ mm})$. As a result, by incorporating FBGs within the skin membrane, their force receptive regions intersect, enabling simultaneous determination of the force intensity and position of the applied force based on the cross-sensitivity between multiple FBGs.

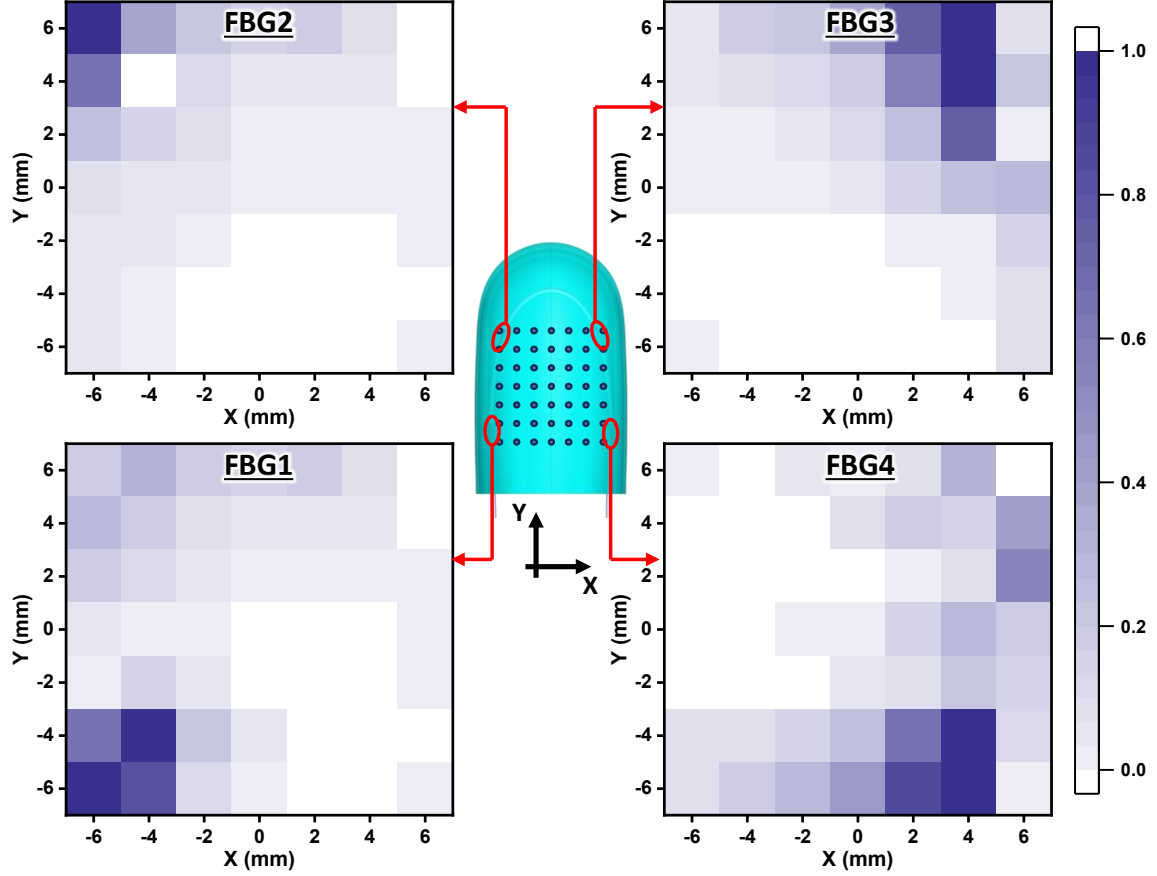


Figure 4.6: Normalized spatial sensitivity of embedded FBGs across the fingertip surface.

4.6 Random forest regression for force magnitude and contact localization

As previously mentioned, the contact force and contact location can be calculated with precisely known sensor location. However, it may not be practical or robust for determining deformations in a continuous elastic medium due to its non-linearity and sensor position sensitivity. Instead, machine learning algorithms can be used to construct a model based on underlying patterns within the training dataset. The model effectively maps the output directly to the input FBG signals, while treating all intermediary decoding process as a “black box”², allowing the model to adapt to the positions of the FBGs. Therefore, machine learning algorithms enable a direct correlation between FBG responses, force magnitudes and contact locations, without requiring the precise knowledge of the position of each FBG within the system. In other words, the model characterizes the response of the artificial skin as a whole, negating the necessity for individual sensor calibration.

Random forest is one of the supervised machine learning algorithms comprised of bagging algorithm with a tree model as the base model [107]. It utilizes an ensemble technique where multiple independent decision trees are constructed in parallel, and the combined output of all

decision trees are considered to achieve an accurate prediction. During the training process, bagging is performed on the data set where a random subset of the training set is sampled with replacement to train a decision tree model, this process is also known as bootstrapping [108]. To ensure model diversity, randomization, data sampling and training are repeated for every decision tree, resulting in multiple independent trees specific to the allocated training data sample (bootstrap sample). The average output of all decision trees is taken to reach a single result for a regression task. These processes allow the random forest algorithm to perform well within a noisy dataset with a reduced variance due to data randomization and accurate estimations due to the averaging process [107].

In this work, a random forest regression model was developed using the scikit-learn library in Python to estimate the force magnitudes and contact locations simultaneously. Since random forest is a supervised learning algorithm where labelled data are required, a dataset comprising of 65,971 data samples was used to train and test the model, with the wavelength shifts of four FBGs as input variables and their corresponding force values as well as contact locations (X- and Y-coordinates with respect to the fingertip surface) as output variables. Prior to the learning process, 70% of the dataset was randomly selected for model training while the remaining 30% were reserved for validation. A simplified block diagram of the algorithm is shown in Figure 4.7 where k is set to 300, in other words, 300 trees were utilized within the model.

It is worth mentioning that only data samples with non-zero force values were incorporated in the training and validation process as position values corresponding to a no-touch situation are irrelevant. During the testing process, input filtering was performed to bypass the machine learning model when wavelength shifts of all four FBGs were zero, indicating that no contact has occurred, and hence a zero force and no position information would be displayed.

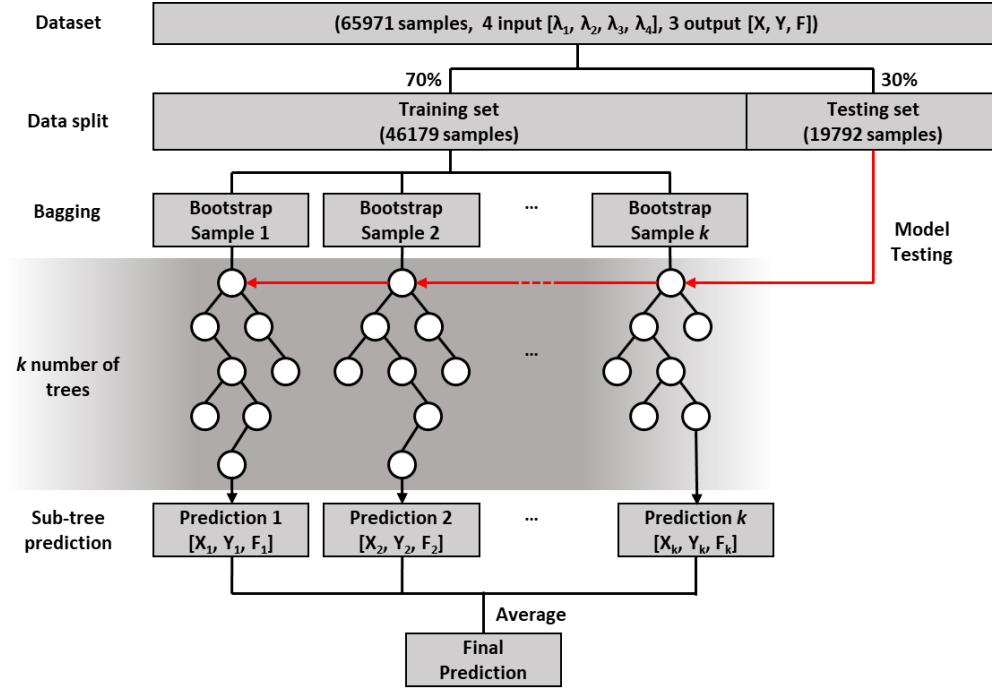


Figure 4.7: Block diagram of the random forest regression algorithm.

4.7 Validation of random forest regression model

The R^2 value of the constructed random forest regression model was calculated to be 0.964 and the MAE was found to be 0.07 N for force predictions up to 3 N, and localization MAE values of 0.24 and 0.21 mm in X- and Y-axes for a tested area of $12 \times 12 \text{ mm}^2$, respectively. The absolute error maps of the three prediction outputs are shown in Figure 4.8.

According to the performance of the estimation model, it is demonstrated that the proposed sensing approach is capable of resolving touch across a surface with a considerably higher resolution than the separation between two adjacent FBGs. Through combining this sensing configuration with machine learning algorithms, it is possible to determine the corresponding force magnitudes and contact location information without requiring precise knowledge of the position and orientation of the sensing FBGs.

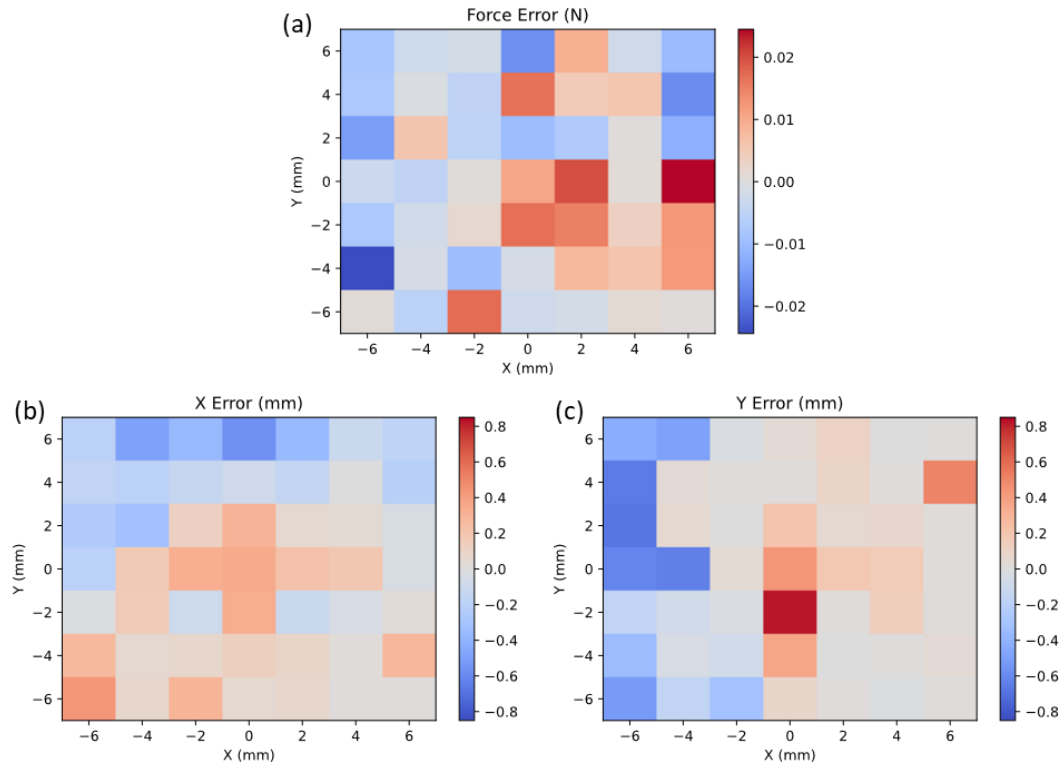


Figure 4.8: Absolute error maps of force and localization estimations. (a) Force estimation error. Error distance along (b) X-axis and (c) Y-axis.

4.8 Summary

In summary, an artificial skin with tactile sensing capability is presented. The skin consists of a silicone membrane embedded with a single-mode ZEONEX POFBG array that contains four FBG elements. The POFs are capable of withstanding tight bends and being routed on small areas, demonstrated with a fingertip surface, without breakage due to their low Young's modulus. Skin characterization and data collection were achieved based on a 4-axis electronic platform with a motorized force indentation. The proposed artificial skin is capable of extracting force magnitudes and contact locations on curved and potentially complex surfaces based on cross-sensitivity between multiple FBGs with the use of a data-driven model. Random forest regression was utilized for force detection and contact localization for normal forces up to 3 N across the fingertip surface. MAE for estimating the magnitude of forces was determined to be 0.07 N while contact localization yielded errors of 0.24 and 0.21 mm for X- and Y-axes over a $12 \times 12 \text{ mm}^2$ area, respectively. By utilizing a data driven model, the precise location information of each FBG is no longer required to resolve for force magnitudes and contact location, hence simplifying the fabrication process. Table 4.2 summarizes the key metrics of several reported artificial skins in comparison to human fingertip. Overall, our proposed artificial skin demonstrates a balance of biomimetic and practical engineering features. With four sensors, the artificial skin achieved spatial acuity of 2 mm, which is comparable to the spatial resolution of human fingertip. Furthermore, the design matches the human fingertip's thin profile with thickness of around 2 mm, facilitating seamless integration without hindering other structures of the robotic systems. With the help of machine learning, the artificial skin operates effectively without requiring prior knowledge of precise sensor location. In addition, only one POF is required to serially connect the 4 FBGs and with the multiplexing capability of FBGs and POF, many more FBG can ideally be connected serially, offering excellent scalability for large-area sensing, and presenting excellent potential for full body sensorization on robots.

Table 4.2: Comparison of performance metrics of different artificial skin compared to human fingertip

Modality	Spatial Acuity (mm)	No. of sensors	Known sensor location?	No. of connections	Skin area (mm ²)	Skin Thickness	Reference
Human Fingertip	1.6-3	~500	No	-	~35 × 35	~2 mm	[45], [109], [110]
ERT*	6.6 ± 3.5	30	Yes	31	290 × 240	-	[111]
Capacitance	0.5	30	Yes	11	96 × 138	15	[112]
Magnetic	0.1	9	Yes	-	54 × 54	5	[113]
Magnetic	1.2	16	Yes	-	148 × 148	12	[114]
Triboelectric	0.3	81	Yes	18	3 × 10	-	[115]
Fiber Optic	2	4	No	1	25 × 35	2	Ours

* ERT: electrical resistance tomography

Chapter 5. Object hardness recognition with tactile sensitive artificial skin

5.1 Introduction

Humans' ability to recognize objects is an important trait for effective interaction with the surroundings. During object interaction, continuous stream of tactile information such as texture, compliance and temperature is acquired and analyzed [116], allowing humans to perform intelligent tactile interaction, for example, judging the ripeness and freshness of fruits by assessing their firmness via gentle squeezing [117]. This cognitive intelligence is critical for manipulating tools, performing delicate tasks, as well as safely and effectively navigating in open environments [14]. This profound ability has inspired the development of robots with similar tactile perception capability. For robots to operate autonomously in a human-centered environment, they must be equipped with a similar capacity to perceive and understand objects through physical interaction. While computer vision provides spatial awareness, it is inherently limited as vision alone is unable to ascertain the physical properties of an object, which is crucial for safe and effective manipulation. Under such circumstances, contact-based tactile recognition becomes indispensable, allowing robots to identify properties that are hidden from vision such as material compliance. The ability to identify object compliance is not only an additional feature to object interaction, but also a crucial prerequisite for safe and dexterous manipulation. It is an important control parameter that allows robots to determine necessary force for reliable grip, preventing slip without causing damage due to excessive grip force.

Development of tactile sensors for this purpose requires high fidelity pressure mapping where FBGs are particularly advantageous. FBGs offer high sensitivity, immunity to EMI, and excellent multiplexing capability where several FBGs can be serially connected. However, conventional silica-based FBGs often underperform in small areas such as the fingertip due to bending limitations, as routing of fibers in confined areas requires tight bending which may result in fiber breakage. In addition, artificial skin applications often require embedment of optical fibers within soft elastomer materials. Under such circumstances, the large stiffness mismatch between silica optical fiber and skin material may result in restriction of skin deformation by the high silica fiber stiffness, reducing tactile sensitivity.

These limitations can be overcome by utilizing POFs as the transmission medium. Due to their significantly lower Young's modulus, POFs allow tighter bends with lower bending losses as

well as lower risks of fiber breakage. Furthermore, they also provide better mechanical compliance with soft elastomer, enabling effective transfer of strain from the skin material to the optical fiber without impeding skin deformation. This results in wider dynamic range and enhanced sensitivity to subtle force gradients which is crucial for compliance discrimination. In addition, their high fracture toughness leads to a robust and durable signal transmission medium, making POFBGs ideal for repeated contacts during robotic manipulations.

In this chapter, the development and characterization of an artificial skin for robotic fingertip, comprised of silicone rubber with embedded array of four POFBGs acting as distributed force sensing elements is outlined. As the skin is pressed onto materials of different stiffness, the embedded POFBGs captures a unique, multi-point strain signature of the interaction, serving as a direct mapping of the material's mechanical response. The wavelength response of the embedded POFBGs is then processed by a neural network (NN) model, which learns to correlate the distinct strain patterns with material stiffness.

5.2 Design and characterization of artificial skin

The schematic illustration of the artificial skin is shown in Figure 5.1(a). It consists of an array of four POFBGs sandwiched within silicone layers of different stiffness. The molding process is outlined in Chapter 4.3, in which an FBG array is molded within a silicone membrane, mimicking the human skin. The base layer of the artificial skin is comprised of softer silicone while the encapsulating layer consists of stiffer silicone material. The stiffness gradient of the artificial skin mimics the hardness distribution of human dermis and epidermis, facilitating human-like skin deformation.

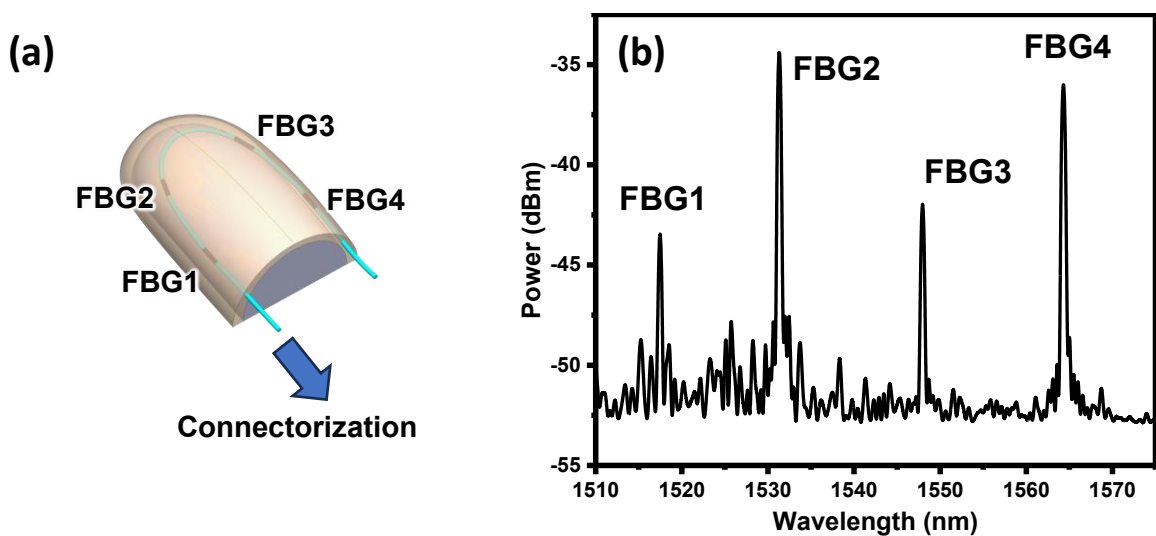


Figure 5.1: (a) Illustration of the artificial skin molded on a fingertip model. (b) The FBG spectrum of the embedded POFBG array.

To characterize the skin response towards materials of different hardness, nine equally sized silicones slabs ($25\text{ mm} \times 25\text{ mm} \times 5\text{ mm}$) of different hardness were molded and their respective hardness, measured with a Shore-A durometer is tabulated in Table 5.1.

Table 5.1: Measured hardness of silicone slabs

Sample no:	Measured Shore-A hardness
1	4
2	8
3	10
4	15
5	21
6	30
7	44
8	50
9	54

To press the artificial skin-molded finger against each silicone slab in a controlled manner, the experiment setup in Figure 4.4(a) was utilized with modification on the end-plate to interchangeably hold each silicone slab. The attached silicone slab was lowered at a speed of 0.01 mm/s and the indentation depth, applied force and wavelength response were recorded simultaneously at a sampling rate of 10 Hz .

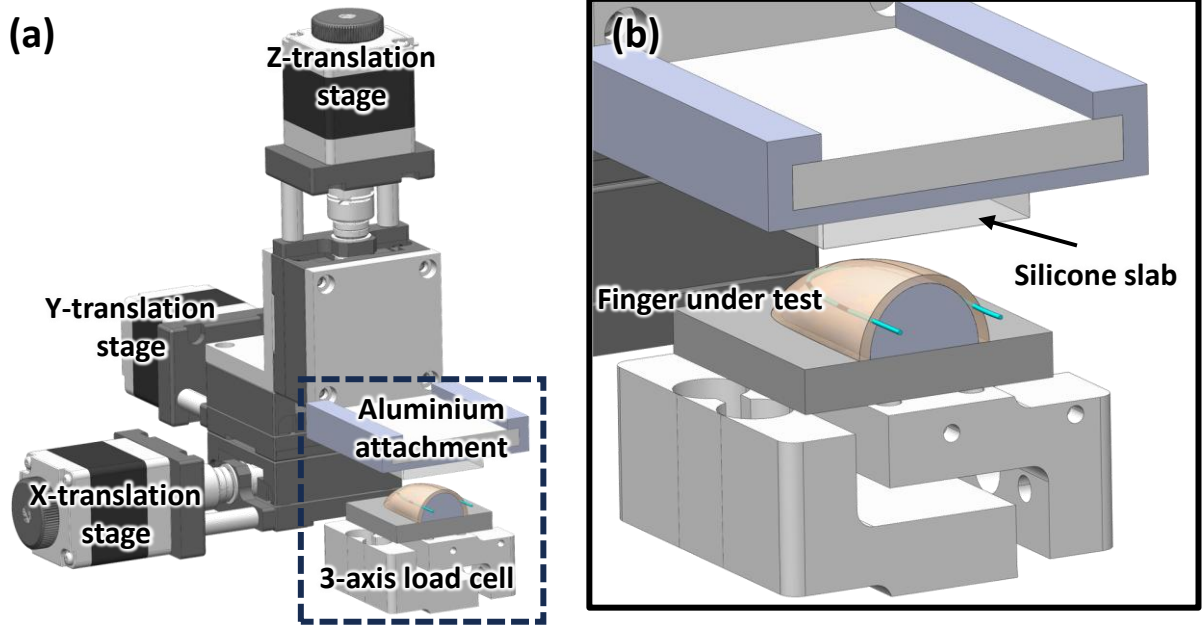


Figure 5.2: Illustration of experimental setup for pressure application over different material stiffness. (a) Setup overview, (b) Zoom-in view.

5.3 Characteristics of artificial skin

Figure 5.3 shows the interaction between the force-applying plate and the artificial skin. Figure 5.3(a) depicts the application of normal force, followed by +X-direction shear force while Figure 5.3(b) shows the application of normal force, followed by -X-direction shear force. The top graphs track the position of the force-applying plate with respect to the fingertip surface, showing controlled loading and unloading motions. The middle graphs present the measured multiaxial force experienced by the skin while the bottom graphs present the transient response of the embedded FBG sensors, demonstrating their sensitivity to mechanical stresses from multidirectional forces. The FBG response reveals a rapid change, indicating their quick adaptation to forces. It is observed that the shear forces overshoot during lateral unloading where the force-applying plate returns to its original position. The overshooting is likely due to slipping which occurs during lateral loading, resulting in a positional offset between the skin contact point and the force-applying plate.

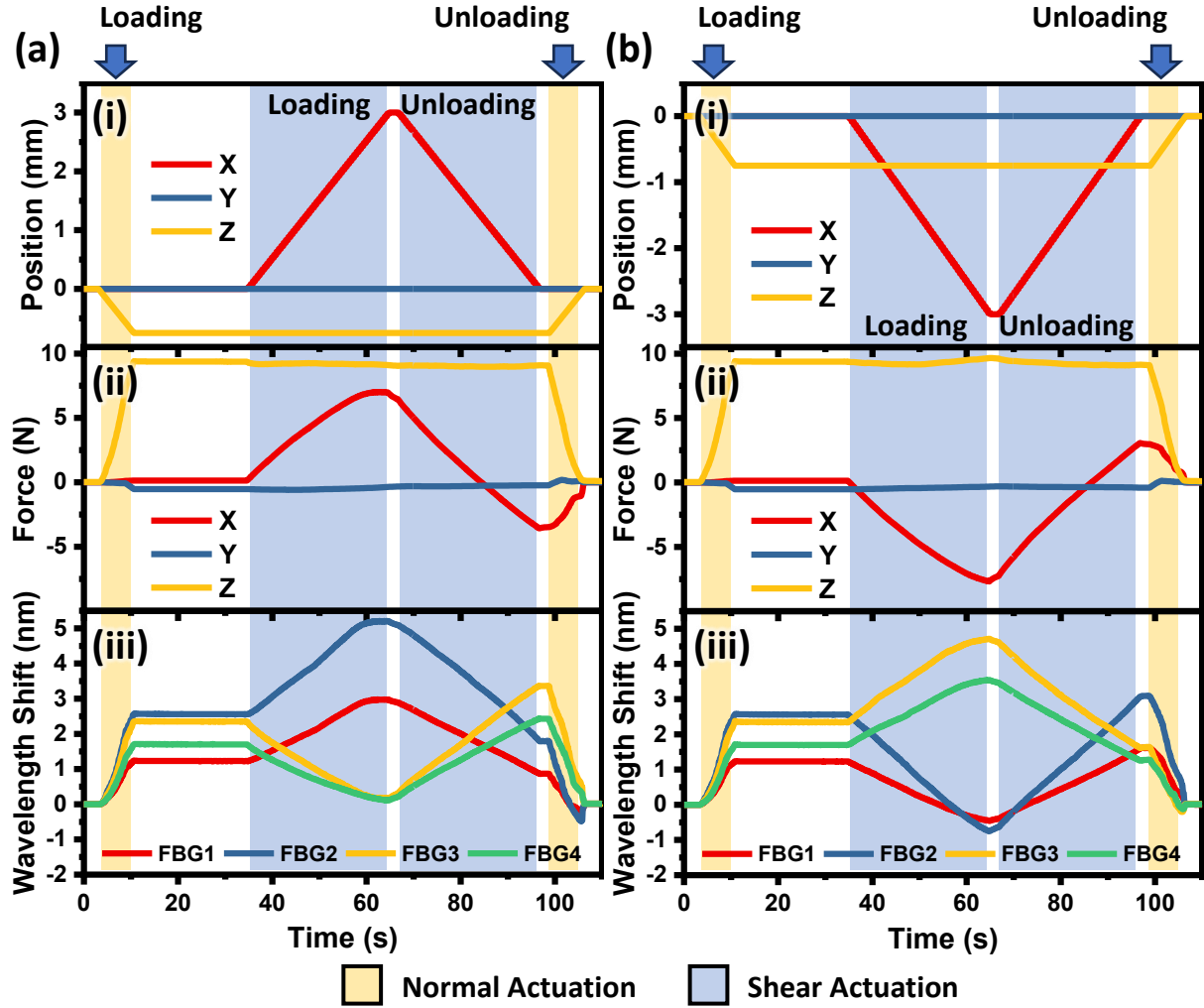


Figure 5.3: Real-time (i) position of the force-applying plate relative to the skin surface, (ii) measured multiaxial force experienced by the artificial skin and (iii) transient response of the embedded POFBG array when (a) normal force, followed by +X-direction shear force and (b) normal force, followed by -X-direction shear force is applied on the molded artificial skin.

Figure 5.4 shows the dynamic response of the embedded FBGs when the artificial skin is loaded with silicone slabs of different hardness at a speed of 0.1 mm/s until a normal force of 10 N is reached. As the silicone slabs have different hardness values, the indentation depths required to reach a normal force of 10 N are different, which is reflected in the varying times required under the same indentation speed for all tested silicone slabs. According to Figure 5.4, it is evident that each FBG exhibits different sensitivity to the applied normal force, as they are located at different locations within the artificial skin.

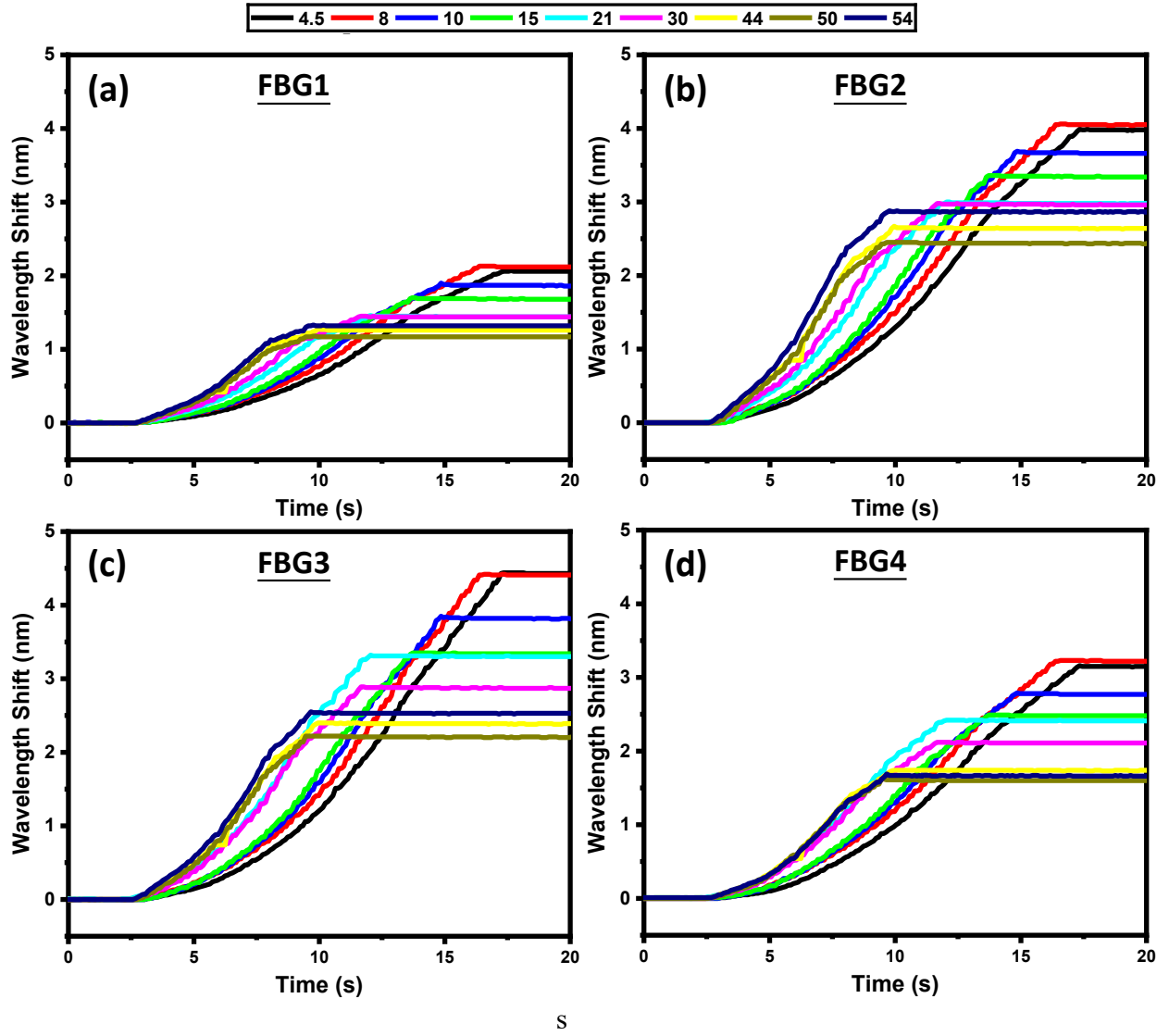


Figure 5.4: Wavelength response of (a) FBG1, (b) FBG2, (c) FBG3, and (d) FBG4 when silicone slabs of different hardness are gradually pressed against the artificial skin up to 10 N at a speed of 0.01 mm/s.

The force responses of the POFBG array when the artificial skin is loaded with objects of different hardness values are plotted in Figure 5.5. Overall, all four FBGs exhibit linear normal force response regardless of the hardness of the loaded silicone slab, with sensitivity decreasing as the hardness increases. The difference in sensitivity highlights the potential for the artificial skin to replicate human-like hardness recognition capabilities. Linear fitting was performed on the loading force response and the sensitivity response is plotted in Figure 5.6. It was found that the embedded FBGs exhibit a decaying sensitivity with increasing, hardness which is due to different deformation mechanics. When a softer material is pressed against the skin, deformation primarily occurs in the soft material, and the skin response is dictated by the soft material. Conversely, when a material much harder than the skin material is pressed against it,

deformation occurs within the skin side, and the sensitivity would be dictated by the skin material. Therefore, it is expected that if harder materials are introduced to the skin, the sensitivity of the FBG remains almost stagnant as the harder material experiences negligible deformation, therefore not affecting the skin response.

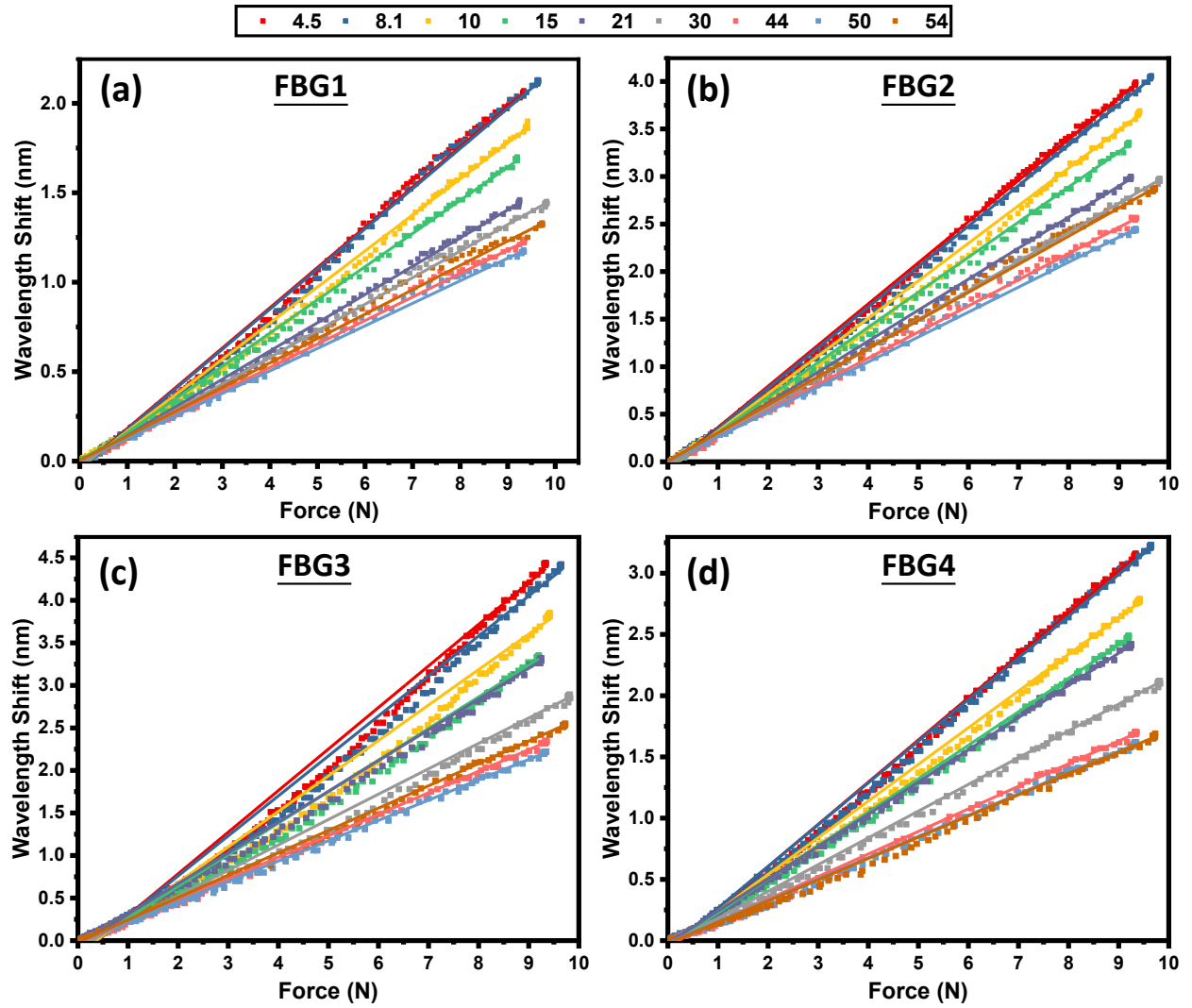


Figure 5.5: Force responses of (a) FBG1, (b) FBG2, (c) FBG3, and (d) FBG4 when silicone slabs of different hardness are pressed against the artificial skin.

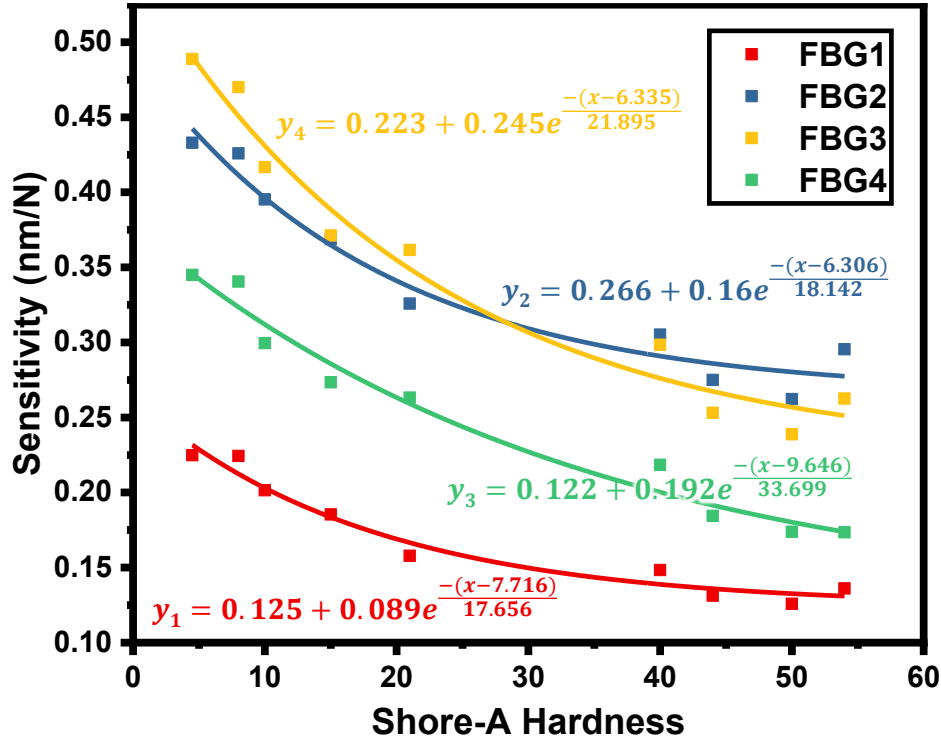


Figure 5.6: Sensitivity response of embedded POFBG array across different object hardness.

5.4 Force estimation and hardness classification

Based on the characteristics of the artificial skin, it was found that it is capable of distinguishing the object hardness based on the force sensitivities of embedded FBGs. To exploit this characteristic, a NN was developed using the Keras library to simultaneously estimate the multi-axial force experienced by the skin as well as the hardness of the object in contact based on the responses of the four embedded FBGs and the NN architecture is outlined in Figure 5.7. The NN consists of four input nodes, each responsible for one FBG signal. The four FBG signals were first fed through a common layer of 128 neurons, which acts as a feature extraction layer, learning a general representation that captures both force-related and hardness-related patterns. From the shared representation, the network branches into two pathways, particularly the force estimation branch and hardness classification branch. The force estimation branch consists of a single hidden layer with 32 neurons, which output three continuous values which correspond to forces along the X-, Y- and Z-directions, effectively mapping strain patterns to physical forces in three directions. In parallel, the hardness classification branch refines the shared features from the common layer via two hidden layers which consist of 32 neurons each, producing ten probability values representing the likelihood of different hardness categories. The highest probability is then selected as the final estimated material hardness. This dual-branch architecture leverages the correlation between force and hardness, allowing the network

to decouple the two parameters and learn more efficiently and generalize better compared to separate models. By taking multiple FBG signals as the input, the system is capable of capturing complex strain distributions, making it highly suitable for tactile perceptions in robotics where force sensing and material property recognition are crucial.

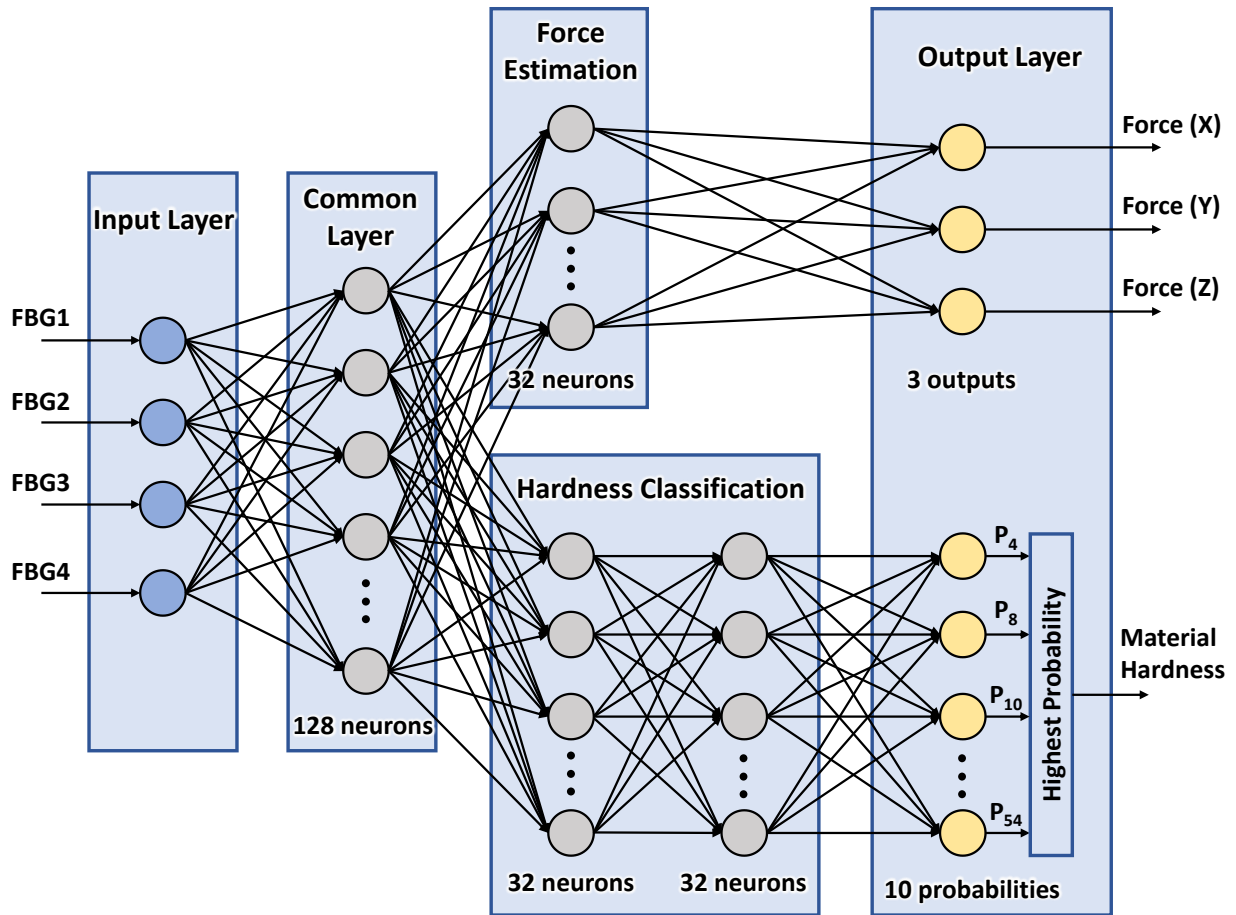


Figure 5.7: Architecture of neural network for simultaneous force and hardness perception.

Figure 5.8 presents the force estimation output in which the estimated force values are plotted against the actual force values. Based on Figure 5.8(a), the estimated normal force shows strong correlation, demonstrating an R^2 of 0.9840 and an MAE of 0.2292, indicating reliable estimation with negligible deviations. Figure 5.8(b) and Figure 5.8(c) on the other hand, highlight the shear force estimation performance of the developed neural network. The estimation of shear force along X-direction is slightly weaker, demonstrating an R^2 of 0.9377 and a higher MAE of 0.3245, suggesting greater variability and reduced precision. On the other hand, the estimation of shear force along Y-direction yields good performance, with an R^2 of 0.9812 and MAE of 0.1496, reflecting excellent agreement between estimated and true forces. The performance mismatch between the two orthogonal shear force directions is due to the

orientation of the embedded FBGs relative to the applied shear force. The conversion of shear force that is perpendicular to an FBG axial axis into axial strain is relatively ineffective compared to that of parallel shear force.

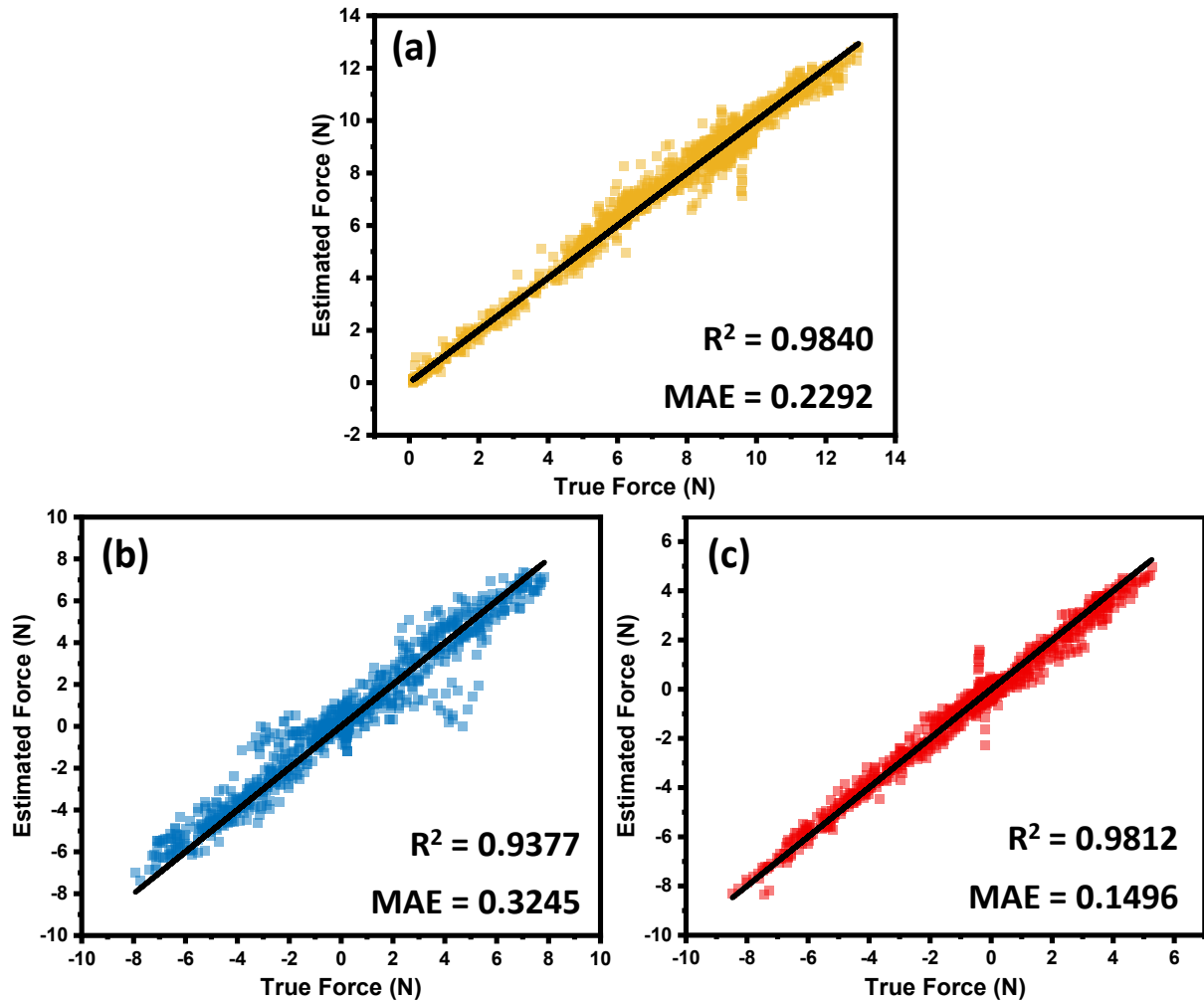


Figure 5.8: Actual force applied on the artificial skin vs. estimated force along (a) Z-direction, (b) X-direction, and (c) Y-direction by the developed neural network.

Figure 5.9 presents the confusion matrix of the NN's hardness classification branch where the estimated hardness is plotted against the actual hardness. With an overall classification accuracy of 92.03%, the model demonstrates robust generalization, successfully capturing subtle strain sensitivity signatures from the embedded POFBGs and reliably translate them into reliable hardness categories. Overall, these estimation outputs confirm that the dual-branch NN architecture is effective in capturing the force induced skin deformation due to multiaxial force and extracting relevant features for material hardness recognition.

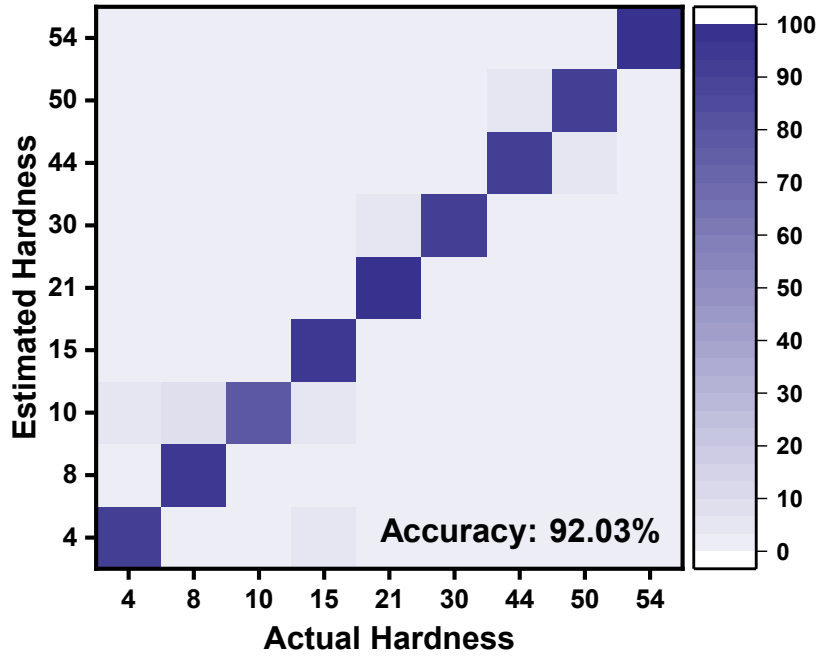


Figure 5.9: Confusion matrix of material classification results based on wavelength response

5.5 Summary

In this chapter, a bio-inspired artificial skin for robots is developed and demonstrated on a fingertip model. The finger features an integrated POFBG within a silicone membrane, enabling force detection and hardness recognition. A dual-branch NN was developed that simultaneously performs multiaxial force estimation and object hardness recognition directly from the embedded POFBG signals, which capture the complex skin deformation due to force application. The sensing system achieved good correlation with R^2 values up to 0.98 for force estimation and high material hardness classification accuracy of 92.03%, reflecting excellent performance. This robust sensing framework allows robots to not only sense interaction forces but also intelligently distinguish material properties, a significant advancement for safe and dexterous manipulation in unstructured environments.

Chapter 6. Artificial skin for multidirectional force, vibration, and texture recognition

6.1 Introduction

Tactile perception, especially at the fingertips, is essential for fine motor control and dexterous object manipulation, enabling reliable interaction with surrounding objects. As the initial point of contact in most interactions, it is important for robotic fingers to have sensory feedback, especially normal and shear forces, with high tactile sensitivity and spatial acuity [87]. Dexterous manipulation requires balancing normal and shear forces between the finger and the object [89]. During human-object interaction, these forces are controlled in real time based on different frictional conditions [118]. For instance, grips are tightened for slippery objects to prevent slipping and loosened for rough, sticky objects. In some cases, slip is intentionally introduced by gently sliding the fingertip across an object's surface to acquire texture information [17]. This multidimensional tactile information, along with other sensory feedback, can be further analyzed to recognize complex features of the object, ultimately enabling robots to mimic human object recognition [17] and develop strategies for effective manipulation.

While multiaxial force sensors are used in robotic joints for load and grip monitoring as well as tactile sensing, they are usually fabricated on rigid substrates [119] and are not optimized for curved and complex surfaces, making them unsuitable for replicating tactile perception in robots, especially at the fingertip. On the other hand, the emergence of soft sensing devices has led to the development of tactile-sensitive artificial skin, a sensor-rich synthetic material designed to mimic the properties and tactile sensing capabilities of human skin. Tactile-sensitive artificial skin for robots and prosthetics has been implemented using various sensing mechanisms such as resistive [120]–[122] and capacitive [123]–[125] sensors. However, electronic sensors are generally susceptible to EMI from the surrounding environments or near power lines within the robot, limiting their use in harsh environments [126]. Furthermore, electronic sensors require a large number of electrical connections as the number of sensing elements increases, limiting their functionality in large-area, high-spatial-resolution tactile sensing.

In this chapter, a tactile-sensitive artificial skin with multiaxial force detection and texture recognition capability is presented. The artificial skin is made of silicone and embedded with a three-element FBG array inscribed along a single-mode ZEONEX POF, which has very low

water-affinity. The artificial skin mimics the thickness of human skin and features a fingerprint-like pattern with a triangular profiled spiral to facilitate vibration generation during slip. A multi-input multi-output convolutional neural network (MIMO-CNN) is developed to simultaneously estimate normal and shear forces from FBG responses and recognize textures from vibrational responses, replicating human-like tactile perception.

6.2 Design and fabrication

The artificial skin consists of three cascading FBGs inscribed along a ZEONEX POF with a core diameter of 8 μm and an outer diameter of 160 μm . The ZEONEX POFBGs are embedded within a 2-mm thick silicone elastomer layer, similar to the thickness of human skin [127], [128], which was molded on a fingertip model, as shown in Figure 6.1(a). The artificial skin mimics the depth-wise hardness gradient of the human skin using a bilayer silicone structure, where a soft base layer (Shore-A 0) mimics the dermis and a stiffer encapsulating layer (Shore-A 40) replicates the epidermis [39], [127]. Despite not replicating the exact stiffness of the human skin (Shore-A 13-28) [39], [128], [129], this biomimetic stiffness distribution, where the top layer is harder than the base facilitates slip-induced vibration detection.

Before sensor fabrication, thermal annealing was performed at 90°C for 24 hours to remove residual stress [130] induced during the fiber drawing process. Each FBG was fabricated using the phase mask technique with a single 248-nm KrF excimer laser pulse. The reflection spectrum of the embedded FBG array is shown in Figure 6.1(b) and all three FBGs are 2-mm long and spaced 12.5-mm apart (center-to-center), as illustrated in Figure 6.1(c).

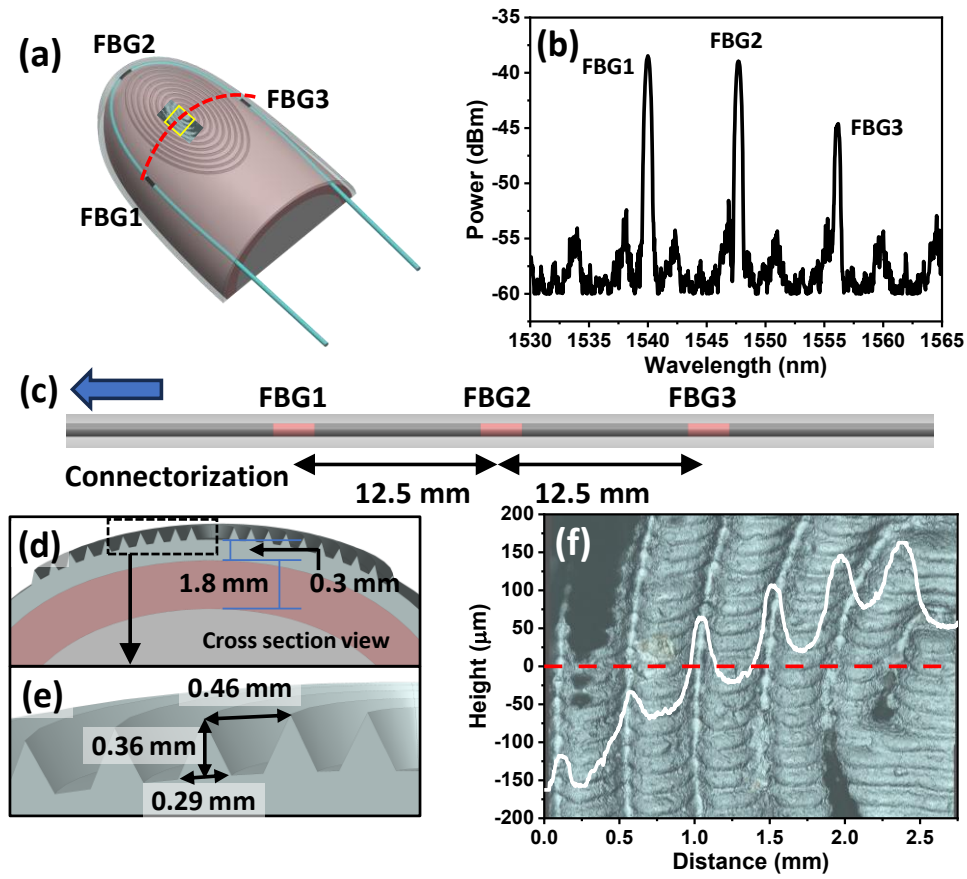


Figure 6.1: (a) Illustration of the fingertip phantom covered with tactile-sensitive artificial skin (b) Reflection spectra of the FBG array embedded within artificial skin. (c) Dimensions and location of the FBG array along ZEONEX POF. (d) Cross-sectional view of the artificial skin along the dotted line in (a). (e) Enlarged view of the triangular profile resembling fingerprint ridges. (f) Laser confocal micrograph of the area highlighted by the yellow box in (a) along with the measured line profile of the fingerprint ridges along dotted line in (a).

The POF is routed so that FBG1 and FBG3 run parallel to the finger, while FBG2 is perpendicular to them, allowing for effective monitoring of deformations in the artificial skin by multidirectional forces. Prior to molding, the POF inscribed with FBGs was treated with a silicone primer (Dowsil™ 1200 OS) to improve silicone adhesion, and a two-step molding process [67] was used, with triangular-profiled spirals incorporated onto the 3D-printed mold surface with printing resolution of 20 μm . As smaller fingerprint ridges allow the detection of smaller distinguishable feature [17], a triangular profile is selected to minimize the tip size and a spiral pattern is employed to introduce varied pitch distances to ensure versatility for different textures. The base width, ridge height and ridge-to ridge distance of the fingerprint are approximately 0.3, 0.4, and 0.5 mm respectively, closely resembling the dimensions of human fingerprint ridges [131] while taking into account the printing resolution of the molds. The dimensions of the artificial skin and the fingerprint are shown in Figure 6.1(d) and Figure

6.1(e), respectively. The laser confocal micrograph highlighting the surface profile of the artificial skin is shown in Figure 6.1(f) with the overlaid plot representing the line profile of the surface along the dotted line. The line profile is measured orthogonally with respect to the fingerprint ridges, indicating the dimensions of the molded fingerprint ridges. Generally, the fingerprint ridges are rounded on the tip due to limitation in 3D-printing resolution and the resulting tip diameter was found to be around 80 μm .

6.3 Characterization of tactile sensitive artificial skin

The experimental setup for applying multidirectional force is shown in Figure 6.2 (a). It consists of a 3-axis electronic platform with three precision stages mounted orthogonally to each other. An L-shaped aluminum attachment is secured to the translation platform, creating a levelled flat contact surface that faces the fingertip for applying normal and lateral forces through the movement of the contact surface.

The platform's contact surface is polished to minimize wear on the artificial skin during lateral force application. Beneath the levelled platform, the fingertip phantom with integrated tactile-sensitive artificial skin is attached to a three-axis load cell (Simbatouch), which captures the forces acting on the fingertip phantom. The load cell has a detection range of 10 N for Z-axis and ± 5 N for X- and Y-axis with resolution of 0.1 N. The reflection spectrum is acquired by an FBG interrogator (Luna, HYPERION si255) and the Bragg wavelength of each FBG is recorded at a rate of 5 kHz. The movements of the 3-axis platform, the load cell response, and the response of each FBG are controlled and recorded simultaneously through an integrated LabVIEW interface. Figure 6.2(b) illustrates movements of contact surface to apply force to the fingertip surface. Generally, applying normal force involves vertical translations of the contact surface while shear force application involves lateral translation of the contact surface relative to the fingertip.

6.3.1 Multidirectional force characterization

As illustrated in Figure 6.2(b), the application of a normal force on the artificial skin involves a Loading phase, followed by Unloading phase. During the Loading phase, the contact platform is lowered at a speed of 0.5 mm/s until a normal force of 10 N is exerted, which is approximately the typical human grip force [132]. The platform's position is then held for 5 seconds before the Unloading phase, where the platform is retracted upwards at the same speed of 0.5 mm/s.

To evaluate the shear force response, the sequence of motions is Loading, Shear loading in the negative direction, Shear loading in the positive direction, and then Unloading. Initially, the contact platform is lowered to apply normal force, allowing shear to be transferred to the artificial skin through friction between the contact surface and the skin. The platform is then moved laterally to apply shear force until slipping occurs between the artificial skin and the contact surface. The lateral movement is then reversed to apply shear force in the opposite direction until slipping occurs again, after which the platform returns to the center, and the contact surface is retracted. These movements are performed on both the $\pm X$ - and $\pm Y$ -directions.

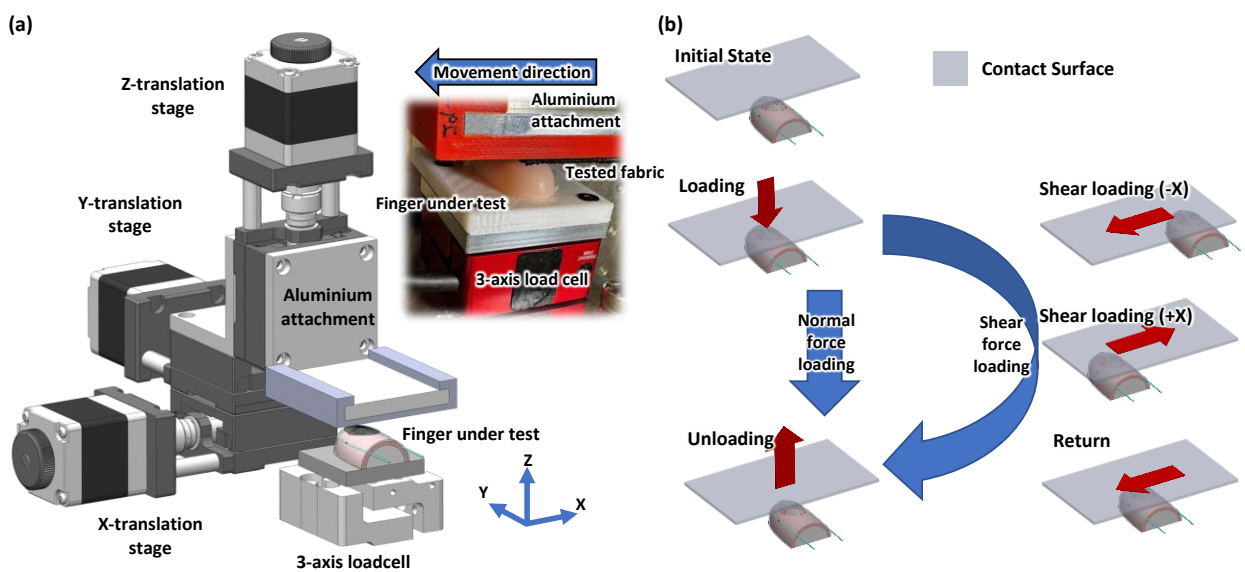


Figure 6.2: (a) Diagram of the experimental setup for characterizing the artificial skin (inset: photograph of fingertip under fabric sliding test condition) and (b) the movement of the contact surface for applying normal and shear force on the fingertip; Initial state: the surface is not in contact with fingertip, and no force is applied; Loading: the surface is lowered until specified normal force is applied to the fingertip; Shear loading: the contact surface is moved laterally (shown in the $\pm X$ -direction) to apply shear force; Unloading: the contact surface is lifted from the fingertip, releasing all forces.

6.3.2 Slip induced vibration acquisition

When the applied shear force exceeds the static friction between the finger and the contact surface while sliding motion is sustained, slip occurs, generating vibrations whose characteristics depend on factors such as surface texture. To capture slip-induced vibrations between the fingertip and various textured surfaces, 20 different fabric samples were prepared, as shown in the photographs in Figure 6.3(a). The surface roughness of all fabric samples was measured using a laser confocal microscope and their respective arithmetic surface roughness

(Ra) and average maximum height (Rz) values are plotted in Figure 6.3(b), where larger values indicate higher surface roughness.

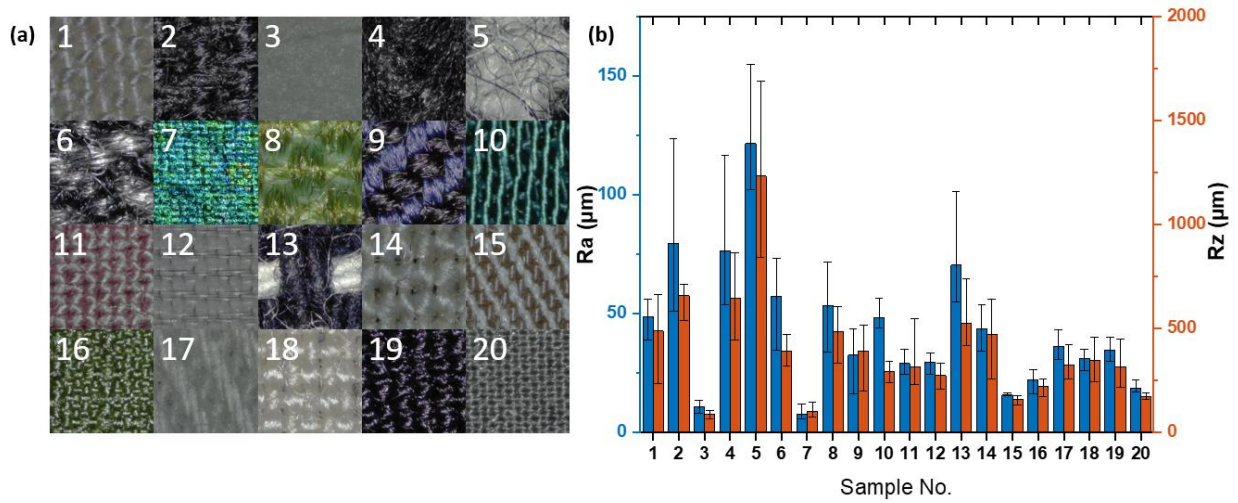


Figure 6.3: (a) Photographs of the 20 fabric samples, each labelled with number on the top left corner. Field of view: 2 mm × 2 mm. (b) Arithmetic average roughness (Ra) and average maximum height (Rz) of the fabric samples, averaged across 10 measurements.

The fabric samples consist of a variety of roughness, with Ra values ranging from 7.8 to 121.6 μm and Rz values ranging from 87.4 to 1234.4 μm. It is also worth mentioning that several fabric samples, particularly sample 11, 12, 17, 18, and 19 have similar roughness values, which is difficult to differentiate if recognition is solely based on surface roughness. Such fabric collection allows thorough investigation of texture recognition performance of the artificial skin. Each fabric sample was attached to the contact surface and lowered onto the fingertip to apply a specified initial normal force. The surface was then laterally translated by 50 mm in both the $\pm X$ - and $\pm Y$ -directions, one after another, to induce slip while maintaining the fingertip's vertical position. The 50-mm lateral translation distance is sufficient to apply shear force beyond the sliding threshold of all fabric samples and the fingertip surface. The sliding tests were repeated three times for each initial normal forces and sliding speeds for all 20 fabric samples, as detailed in Table 6.1.

Table 6.1: Implemented initial conditions of sliding tests

Test no.	Initial normal force (N)	Sliding speed (mm/s)	Sliding distance (mm)
1	1	2	50
2	1	4	50
3	2	2	50
4	2	4	50

6.4 Characteristics of tactile sensitive artificial skin

6.4.1 Multidirectional force sensitivity

Figure 6.4 depicts the force response of all embedded FBGs to normal and shear forces along the X- and Y-directions. As shown in Figure 6.4(a), each FBG exhibits a linear response to normal force up to 10 N, with sensitivities of 218.0, 381.4, and 283.5 pm/N for FBG1, FBG2 and FBG3, respectively. The variation in sensitivities is mainly due to the difference in position and the distance between the load center and each FBG element. This configuration of FBG embedded in an elastomer creates a force receptive region with maximum sensitivity at the center of the FBG, which gradually decreases as the distance between the applied normal force and the FBG increases [67]. Due to the viscoelastic nature of the silicone elastomer, all three FBGs exhibit hysteresis error, quantified as 10.3%, 10% and 11% for FBG1, FBG2, and FBG3, respectively, using Eq. (6.1) [133]. The hysteresis, $H(\%fs)$, expressed as a percentage of maximum wavelength shift, is defined by the ratio between the maximum uncertainty of wavelength shift during loading and unloading at a given applied force, and the full-scale wavelength shift when a maximum force of 10 N is applied.

$$H(\%fs) = \frac{|\Delta\lambda_{load} - \Delta\lambda_{unload}|_{max}}{\Delta\lambda_{max} - \Delta\lambda_{min}} \times 100\% \quad (6.1)$$

The shear force response along X- and Y- directions of the embedded FBG array are depicted in Figure 6.4(b) and Figure 6.4(c), respectively. To apply shear force to the fingertip surface, an initial normal force of 6 N was applied before introducing shear forces. The shear force measurement range of the multiaxial load cell was limited to ± 5 N, and a contact force of 6 N was selected such that that slipping occurs just below 5 N at one of the four shear directions. During the application of shear force, the experiment setup was adjusted so that shear force was applied in only one direction when the aluminum contact surface was moved in the desired direction, with forces on all three axes being monitored and recorded. This adjustment ensured that the FBG response due to normal force during shear force application is effectively cancelled out, making the shear force in the orthogonal direction negligible.

The shear force response in the X-direction is depicted in Figure 6.4(b). It can be observed that FBG1 and FBG3 exhibit a linear response to X-direction shear force with low hysteresis errors of 4.59% and 3.38%, respectively. Linear fitting on FBG1 and FBG3 yield sensitivities of 659.4 and -881.9 pm/N, respectively. However, while FBG2 shows a linear response, its response deviates from linearity when shear forces exceed 3 N in the X-direction, with relatively larger hysteresis error of 14.81%. Similarly, for Y-direction shear, as shown in Figure 6.4(c), FBG1

and FBG3 exhibit larger hysteresis compared to FBG2, which shows a linear response to shear force applied in the Y-direction with a sensitivity of -396.8 pm/N . The hysteresis errors were found to be 28.45%, 5.69%, and 39.57% for FBG1, FBG2, and FBG3, respectively. Overall, the embedded FBGs demonstrated optimal performance, characterized by strong linearity and minimal hysteresis error [134], when shear forces are applied perpendicular to their orientation. The use of a soft skin layer (Shore-A 0) facilitates enhanced sensitivity, despite causing relatively high hysteresis error when shear aligns parallel to the FBGs. For effective measurement of shear in both X- and Y-directions, the embedded POF routes FBG2 orthogonally to FBG1 and FBG3.

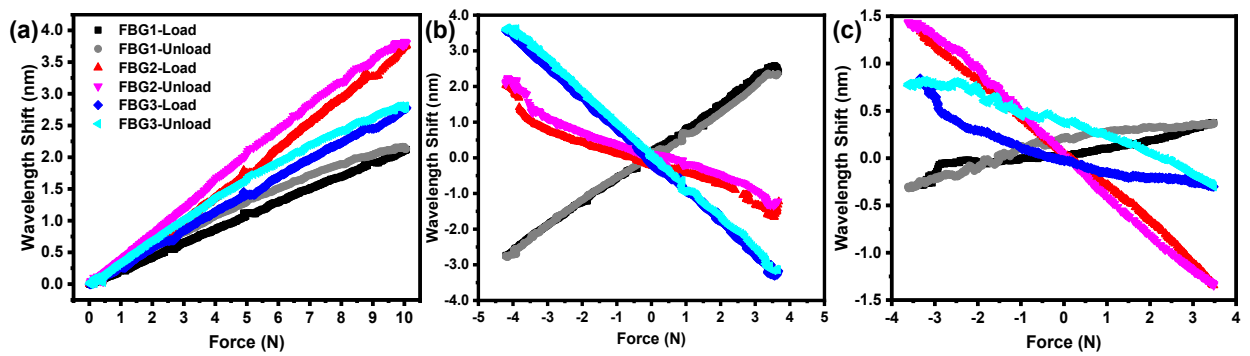


Figure 6.4 Response of embedded POFBG array to (a) normal force, (b) shear force along the X- axis, and (c) shear force along the Y-axis.

6.4.2 Slip-induced vibration characteristics

Figure 6.5(a) shows the transient response of the FBG array, while Figure 6.5(b) illustrates the corresponding forces exerted on the fingertip when fabric sample 17 slides across the fingertip surface at a speed of 2 mm/s . As seen in these figures, the forces experienced by the artificial skin are reflected in the FBG response. During the loading phase, all FBGs experience redshift when a normal force of 1 N is applied to the artificial skin. At $t = 15 \text{ s}$, shear loading is applied, indicated by an increase in the $-X$ direction force. Each FBG responds differently to the applied shear force due to its distinct positions and orientations across the artificial skin. Initially, as fabric sample 17 slides across the artificial skin, the applied shear force rapidly spiked and saturated around -0.7 N as the fabric slips, generating vibrations. This is indicated by the oscillations in the FBG response and the recorded force values. At $t = 60 \text{ s}$, when fabric sample 17 is slid in the $+X$ -direction, a similar response with the shear force saturating around 0.7 N and vibration occurring as slipping continues.

Figure 6.5(c) and Figure 6.5(d) display 5-second windows of the FBG response during slipping in the $-X$ - and $+X$ -directions and their fast Fourier transform (FFT) spectra are as shown in

Figure 6.5(e) and Figure 6.5(f) respectively. These results reveal that sliding fabric sample 17 in both directions at 1.67 mm/s result in similar frequency components, with a prominent frequency of 1.00 Hz. It is noted that FBG1 and FBG3 are more sensitive to slip along X-direction compared to FBG2, as indicated by the vibration amplitude and the peak intensity in their respective FFT spectra.

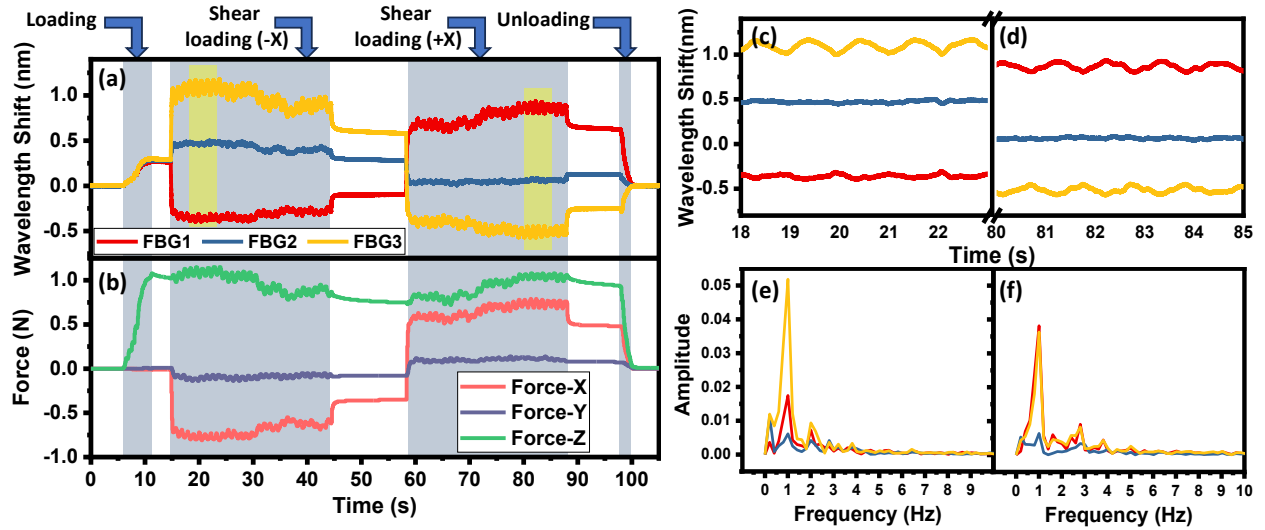


Figure 6.5: (a) Recorded wavelength response of FBG array. (b) multi-axial force experienced by the fingertip during slipping between the artificial skin and fabric sample 17 along the $\pm X$ axis at 1.67 mm/s. (c-d) transient response during slip in the (c) $-X$ and (d) $+X$ direction. (e-f) FFT spectra of the FBG response during slip in the (e) $-X$ and (f) $+X$ direction, with time windows sampled from the regions highlighted in yellow in (a).

Figure 6.6(a) shows the vibration response of FBG1 when the artificial skin slides across fabric samples 3, 5, 7, 10, 13, and 15 at a speed of 2 mm/s towards $+X$ -direction, with their respective FFT spectra shown in Figure 6.6(b). Under the same conditions, the vibration amplitude and frequency generated by each fabric sample differ. Generally, rougher fabrics produce vibrations with larger amplitudes and lower frequencies, and vice versa. For instance, fabric sample 5, the roughest of all 20 samples as indicated by its R_a and R_z values, exhibits a vibration signal with a peak-to-peak amplitude of approximately 0.25 nm and a prominent frequency of 0.7 Hz. In contrast, the vibration generated by sliding across fabric sample 10 exhibit a peak-to-peak amplitude of about 0.06 nm and a prominent frequency of 0.9 Hz as it is smoother than fabric sample 5. Fabric sample 7, the smoothest among all samples, generates virtually no vibration.

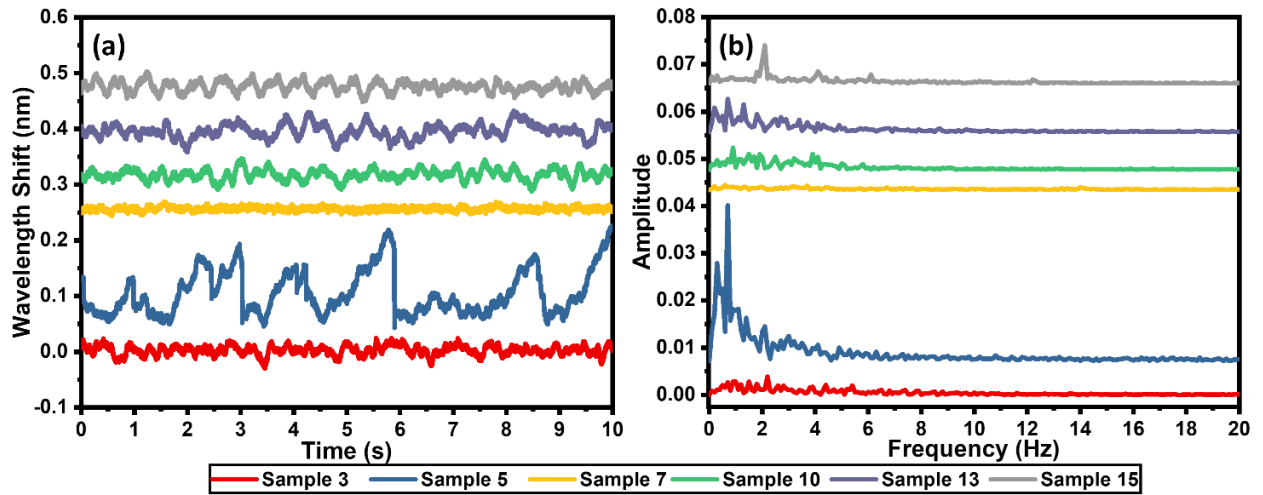


Figure 6.6: (a) Vibration signals acquired by FBG1 from selected fabric samples at a sliding speed of 1.67 mm/s and (b) their respective FFT spectra.

6.4.3 Long-term stability of the artificial skin

The long-term stability of the artificial skin was investigated. Figure 6.7 depicts the cyclic pressure response, where rapid loading and unloading of normal force was applied on the artificial skin over 10000 cycles between 1 and 3 N at a 1-second interval. Throughout the 10000 force cycles, no significant drift nor signal degradation was observed, and the signal maintained a repeatable and stable wavelength response, indicating long-term stability and durability.

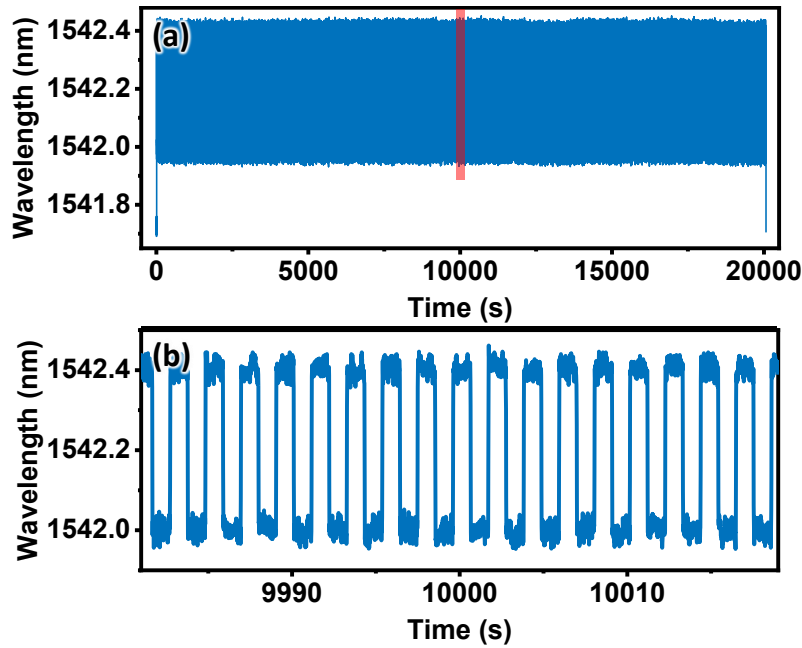


Figure 6.7: (a) Cyclic wavelength response of FBG1 towards 10000 rapid normal force loading cycles between 1 and 3 N at 1-second interval. (b) Zoom-in view of wavelength response from 9980 to 10020 second (highlighted red in (a)).

6.5 Force estimation and texture recognition

Different surfaces interact differently with the artificial skin, producing distinct vibrations during slipping that are unique to each slipping surface. With an algorithm capable of analyzing these vibrational responses, different textures can be recognized and differentiated. While it is possible to numerically estimate the forces applied to the artificial skin, this approach is less practical for tactile-sensitive artificial skin designed for humanoid robots due to the complex curvatures and shapes involved, which led to cumbersome calculations. Additionally, precise knowledge of the position and orientation of the FBGs is required, imposing strict tolerance and necessitating tedious calibration procedure [67]. Furthermore, tactile exploration, especially in an open environment, involves multidimensional stimuli such as pressure, vibration, temperature and pain which are deeply intertwined [135], [136]. Distinguishing these stimuli requires a robust algorithm capable of processing large and complex datasets while learning and adapting to new data in real-time.

Neural networks, especially CNNs [137], [138] are well-suited for decoding tactile stimulus due to their excellent performance in handling large volume, nonlinear and multidimensional data. Being data-driven, CNNs can inherently compensate for fabrication errors and tolerances in the artificial skin. Additionally, CNNs offer inherent robustness to noise and input variations [137]. This allows raw and multidimensional tactile signals, which in our case, consists of intercoupled forces and vibration signals, to be input directly with minimal preprocessing. The CNN internally decouples and extracts individual components from the multichannel sensor signals. They also support transfer learning, allowing pre-trained model parameters to be fine-tuned for new events and stimuli, mimicking human learning by correlating past experiences with new situations.

In this study, a MIMO-CNN was developed using the Keras library to simultaneously estimate the normal and shear forces experienced by the fingertip and classify the contact surface texture based on the vibration signal generated when the artificial skin slips across a surface. The architecture of the MIMO-CNN is shown in Figure 6.8(a). It consists of three input channels, each handling one FBG signal, and two outputs for force estimation and texture classification, respectively. Before preprocessing, the acquired time series from all four sliding experiments (Table 6.1) and their respective repetitions were down-sampled to 100 Hz to reduce the computation load. After down sampling, the time series consisted of 918589 data points which were then segmented into 300 ms intervals using a sliding window method with window length

and stride length of 30 and stride length of 30. The contact and shear force values within the window are averaged across that window and then associated with the force outputs of that particular window. The resulting window-sampled output is formatted as 30×3 wavelength values (per window) as the input, and 3 force values as well as 1 fabric class as the output. After window sampling, 30606 segments were generated. As the window length generally dictates the recognition time, a time window of 300 ms (30×10 ms) was selected such that the recognition time of the sensing system is around 300 ms, comparable to typical human recognition time of different textures of around 400 ms [139]. These segmented time series were fed into convolutional layers where features were identified and extracted. The feature maps produced by the convolutional layer were passed through a max-pooling layer, which effectively reduces spatial dimensions while preserving essential information. This process of convolution and max-pooling was repeated twice, forming a two-layer hierarchal feature extraction approach. The initial convolutional layer extracts low-level, simple features from the input FBG signals, while the subsequent convolutional layer builds upon these to extract higher-level, more complex feature representations. The features were then flattened into a 1D vector and fed into two parallel neural network branches: one for force estimation and the other for texture classification. The shared convolution layers allow the network to learn common features relevant to both tasks, while the separate neural network branches allow for independent optimization of model parameters for each task. This modularity is particularly advantageous for real-world applications where task requirements may evolve independently over time.

Figure 6.8(b) shows the output metrics of the MIMO-CNN for force estimation and texture classification for 9182 test samples, where the estimated force vectors are plotted against the actual force values. The MIMO-CNN model achieved an R-squared value of 0.9618 with mean absolute error (MAE) of 0.025, 0.023, 0.036 N for X-direction shear, Y-direction shear and normal forces, respectively. Figure 6.8(c) depicts the confusion matrix of the MIMO-CNN texture classification branch across 20 different textures at various sliding speeds and normal forces, achieving a classification accuracy of 94.06%. The high classification accuracy and strong correlation between estimated and actual force values demonstrate the MIMO-CNN's effectiveness in identifying features within multi-channel FBG responses and providing accurate force and texture estimations.

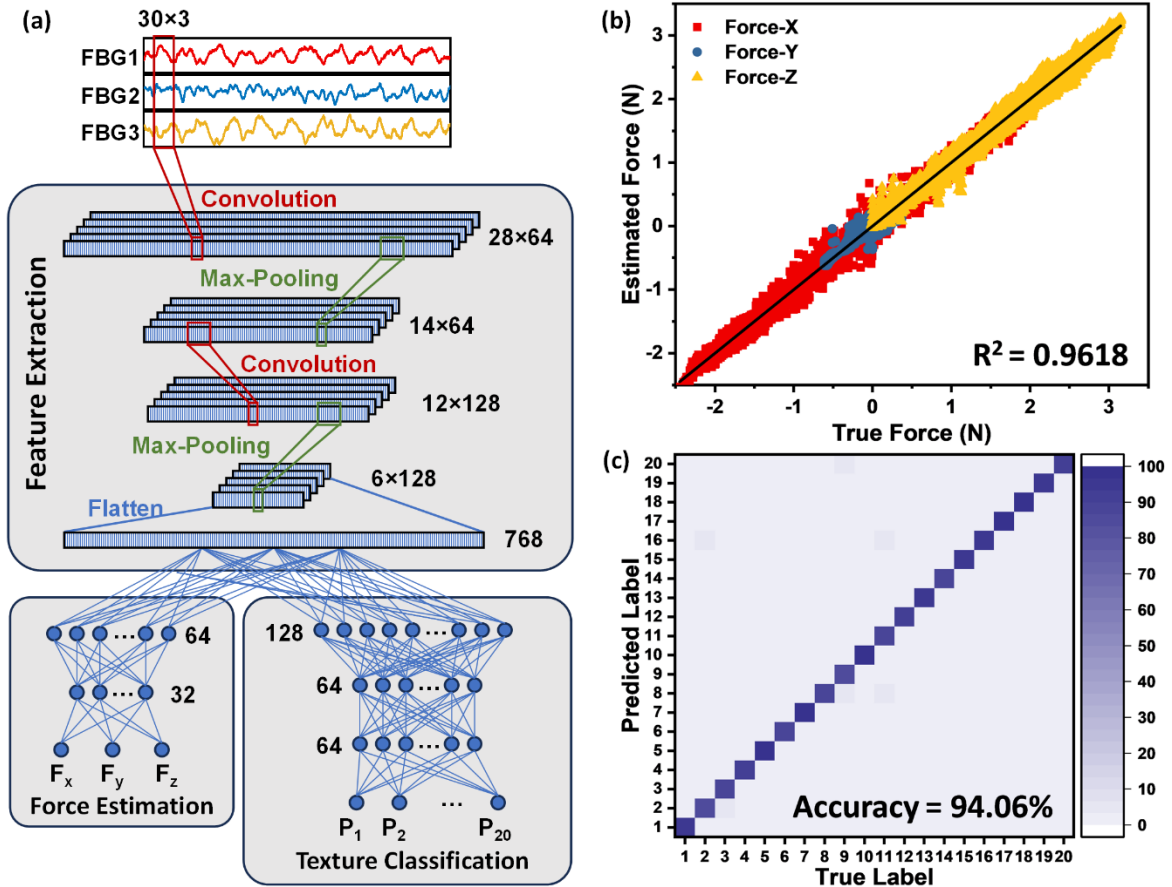


Figure 6.8: (a) Illustration of MIMO-CNN architecture. CNN output metrics showing (b) the comparison between estimated force and true force and (c) the confusion matrix for texture recognition.

6.6 Summary

This study introduces a tactile-sensitive artificial skin designed for robotic tactile applications. The artificial skin is comprised of three FBG elements inscribed along a ZEONEX POE embedded within a silicon membrane. The use of POEs as the transmission medium allows tight bends and high-resolution tactile sensing across small areas without breakage, thanks to their low Young's modulus. The multiplexing capability of FBGs offers the opportunity for large area tactile sensing with minimal fiber paths, and the skin-like form factor facilitates easy application on robotic surfaces without interference with other structures. The tactile-sensitive artificial skin was demonstrated on a fingertip model with dimensions similar to a human index finger, and its static force and slip-induced vibration characteristics were characterized. The collected force and vibrational responses were used to train a MIMO-CNN model, enabling simultaneous multidirectional force sensing and texture recognition. The data-driven nature of the MIMO-CNN model compensates for fabrication and placement errors, reducing the impact of fabrication tolerances. The MIMO-CNN achieved an R-squared score of 0.9618 for force

estimation with tested normal force up to 10 N and shear forces around ± 4 N in both the X- and Y-directions, as well as texture recognition accuracy of 94.06% for 20 tested textures. This robust combination of CNN and FBG array allows excellent scalability for both small- and large-area tactile sensing applications on various robotic surfaces, with potential for expandability to other tactile stimuli and senses for enhanced object recognition. The implications of this work extend to improving human-robot interaction in applications ranging from assistive technology to automated industrial tasks.

Chapter 7. Artificial skin for object recognition based on thermal conductivity

7.1 Introduction

Thermal characteristics, in addition to physical attributes, provides complementary information crucial for touch-based object recognition [140]. The recognition and classification of objects based on thermal properties during touch involve a complex sensory process which involves both mechanoreceptors and thermoreceptors.

This technique employs temperature sensors to monitor heat transfer between the robotic gripper surface and the object during contact. The captured information allows robots to gain valuable insight into the object's temperature profile according to material properties. The thermal information enriches the object recognition process, allowing robots to develop a more comprehensive understanding of the material composition of the objects they interact with, thereby improving their accuracy and intuitiveness in recognizing various objects. As FBGs are inherently sensitive to both thermal and strain variations, seamless temperature sensing with tactile feedback without major modification is possible.

Inspired by the warmth of human skin, generation of heat on the artificial skin plays a critical role in facilitating heat transfer between the skin and the object in contact. When touching a cooler object, the rate of initial heat loss is dependent on the heat capacity of the surface in contact, followed by the temperature conductivity if the contact is maintained. By monitoring the initial heat transfer profile which is unique to each object, material recognition is possible by capturing and analyzing the initial temperature loss due to heat capacity, realizing material recognition within a short duration while providing an alternative recognition method in addition to physical attributes of an object [140].

In this chapter, an artificial skin with thermal-based material recognition capability is developed. A high-attenuation optical fiber serving as the photothermal element while an FBG array consisting of two FBGs fabricated along a 50- μm single mode optical fiber is utilized as the temperature sensing element, both of which are encapsulated within a silicone membrane, forming the artificial skin. The optical fiber acts as a photothermal device, effectively absorbing optical power and converting it into heat through non-radiative processes, increasing the temperature of the optical fiber and as well as the surrounding artificial skin. The material recognition capability of the artificial skin is tested by classifying three materials including

metal, glass, and wood. An ANN is also developed to recognize objects based on their unique heat transfer profiles during contact.

7.2 Structure of artificial skin

The artificial skin consists of a 6-mm long, commercially available high-attenuation optical fiber (Coractive) fusion spliced to a bend-insensitive single mode optical fiber (Silitec G657B) and an FBG array consisting of two FBGs inscribed on a single mode optical fiber (Fibercore SM1500) acting as the temperature sensing elements, each with a length 2-mm in length and distanced 10 mm apart along the optical fiber. The optical fiber has a core and cladding diameter of $4.2\ \mu\text{m}$ and $50\ \mu\text{m}$ respectively. As illustrated in Figure 7.1(a), both optical fibers are embedded within a 2-mm thick silicone membrane. The embedded 50- μm fiber is routed such that each FBG is distanced 5 and 13 mm from the photothermal fiber, involving a 4-mm radius of curvature bend at the section between two FBGs. The reflection spectrum of the embedded FBG array is shown in Figure 7.1(b). Both FBGs are of similar intensity, indicating that a 4-mm radius of curvature induced little to no bending-loss on the 50- μm optical fiber.

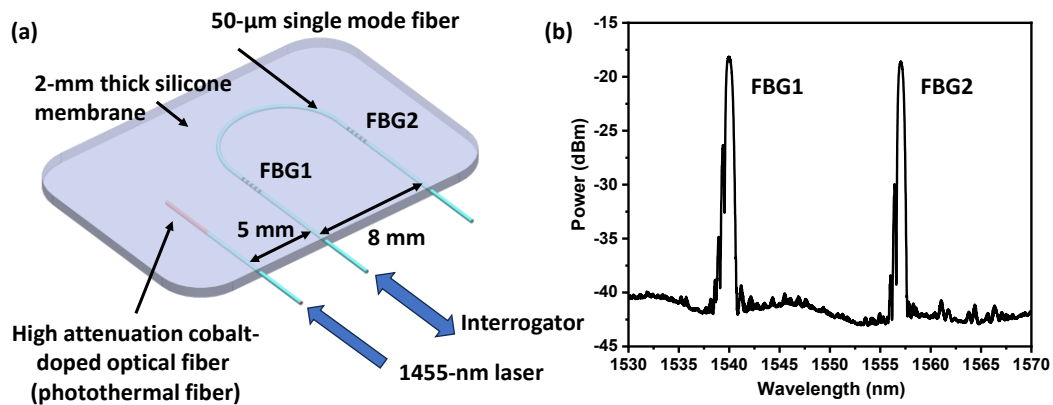


Figure 7.1: (a) Illustration of optical fiber embedded artificial skin. (b) Reflection spectrum of the embedded FBG array.

7.3 Fabrication process of artificial skin

The FBG array is fabricated using the phase mask technique [73] and each FBG is 2 mm in length, distanced 10 mm apart from each other along a 50- μm optical fiber and a photothermal fiber of 6-mm length is fusion spliced to a 125- μm single mode fiber before molded into silicone rubber. After splicing, both the FBG array and the photothermal fiber are treated with silicone primer while a 3D-printed mold is treated with mold release. The mold is designed with protrusions to form grooves on the molded silicone rubber for guiding the optical fiber routes and placements. The molding process for the artificial skin is illustrated in Figure 7.2.

The treated mold is first assembled (Figure 7.2(a)) before liquid silicone is injected into it (Figure 7.2(b)). Upon curing and demolding (Figure 7.2(c)), grooves are formed on the cured silicone rubber. The photothermal fiber as well as the FBG inscribed 50- μm fiber are placed into their respective grooves (Figure 7.2(d)). Then, the groove openings are then filled with liquid silicone to fully embed the optical fibers within the silicone rubber (Figure 7.2(e)), forming the complete artificial skin, as shown in Figure 7.2(f).

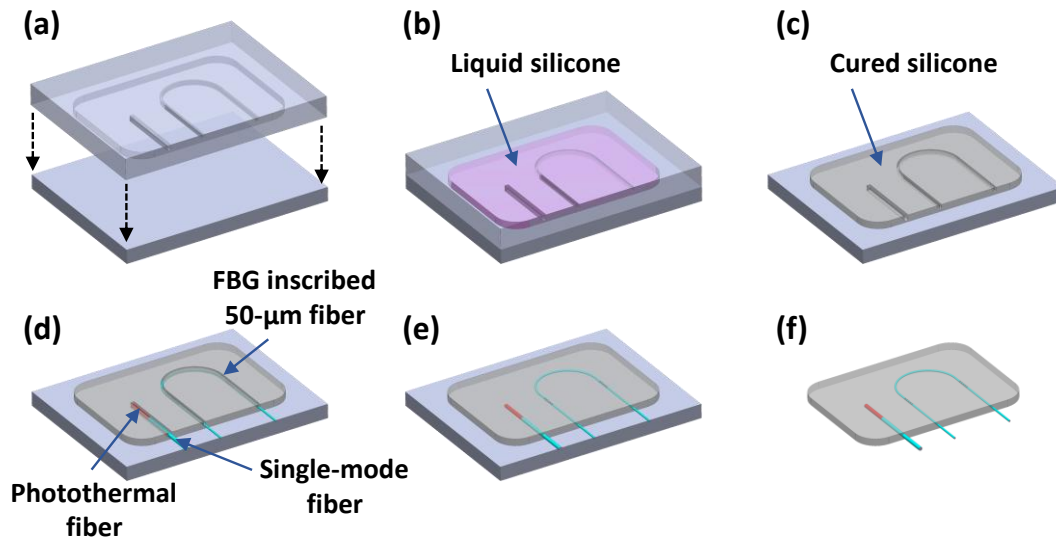


Figure 7.2: Molding process of artificial skin. (a) Mold assembly. (b) Liquid silicone is injected into the mold. (c) Demold, grooves formed on cured silicone rubber. (d) Photothermal fiber and FBG inscribed 50- μm photothermal fiber placed into grooves. (e) Encapsulation layer molded onto groove openings. (f) Molded artificial skin.

7.4 Thermal characteristics of artificial skin

As the FBG array is intended to be used as temperature sensing element, temperature calibration is performed where the artificial skin is placed in a programmable oven and the temperature is increased at 10 $^{\circ}\text{C}$ interval up to 100 $^{\circ}\text{C}$, followed by controlled decrease at 10 $^{\circ}\text{C}$ interval. Each temperature interval is maintained for 60 seconds, sufficient for reaching steady-state response. The steady-state temperature response of FBG1 is as shown in Figure 7.3(a). It is observed that both upcycle and downcycle of temperature exhibit excellent linearity with little to no deviation between them. Linear fitting on the temperature response resulting in temperature sensitivity of 12.18 and 12.4 $\text{pm}/^{\circ}\text{C}$ for upcycle and downcycle respectively, yielding an average temperature sensitivity of 12.29 $\text{pm}/^{\circ}\text{C}$.

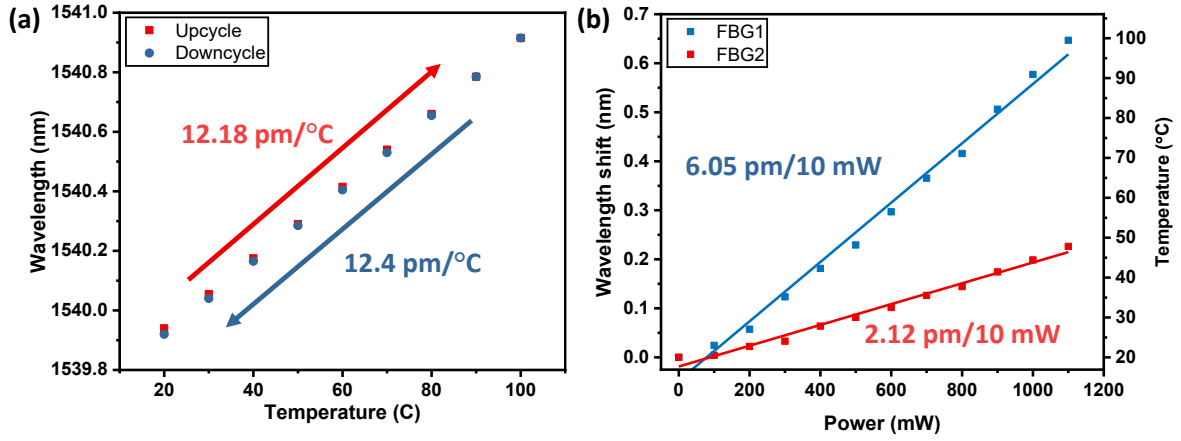


Figure 7.3: (a) Temperature response of FBG1 when heated with programmable oven. (b) FBG temperature response vs. laser pump power to photothermal fiber, temperature deduced from obtained temperature sensitivity of 12.29 pm/°C.

In a typical use case scenario, the photothermal fiber acts as a heat source, increasing the surface temperature of the artificial skin, facilitating heat loss upon contact with objects. To engage heat generation, a 1455-nm laser is emitted into the photothermal fiber. Figure 7.3(b) shows the heat generation performance of the artificial skin in terms of temperature changes experienced by FBG1 and FBG2 in response to varied laser power. Based on Figure 7.3, both FBGs experienced a linear increase in temperature as the pump power is increased. Linear fitting on their response yields the temperature sensitivity of 6.05 and 2.12 pm/10mW for FBG1 and FBG2 respectively. The temperature experienced by FBG1 is much higher compared to FBG2, which is located further away from the photothermal fiber.

7.5 Contact based thermal object recognition with neural network

To verify the thermal-based object recognition capability of the artificial skin, metal, wood, and glass samples of 50 mm × 50 mm × 5 mm were used. The artificial skin was first heated up, with the heat maintained at laser power of 300 mW, where FBG1 and FBG2 experienced temperature increases of around 15 and 4 °C, respectively. Then, the heated artificial skin was placed in contact with the test materials, and the thermal evolutions of both FBG1 and FBG2 were recorded using an optical interrogator (Micron Optics, SM-125) at a rate of 2 Hz. The experiment was repeated for 20 trials for each material. Figure 7.4 shows the wavelength response of FBG1 and FBG2 resulting from the thermal evolution as the heated artificial skin comes into contact with metal, wood and glass samples. Upon contact, both FBGs exhibit an immediate blueshift due to heat loss towards cooler material surface, highlighted in green. The rate of wavelength shift in this regime is mainly dependent on the temperature difference between the artificial skin and the material in contact, as well as the localized heat capacity of

the material. Based on Figure 7.4, the wavelength shift due to initial heat loss is much higher in FBG1 compared to FBG2, as the temperature around FBG1 is higher than that of FBG2. In general, the rate of heat loss upon contact is unique to each material, making it possible to distinguish materials by analyzing the thermal interaction between the artificial skin and objects within the first few seconds of the interaction.

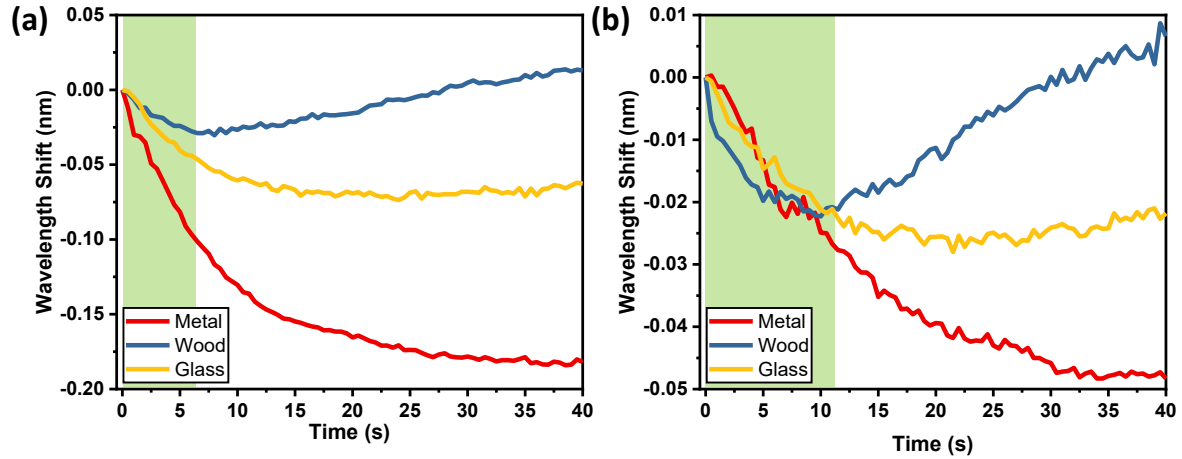


Figure 7.4: Wavelength response of (a) FBG1 and (b) FBG2 due to thermal evolution. (Highlighted region: initial temperature loss due to localized heat capacity)

To realize automated recognition and ensure expandability for different objects, an ANN is developed using the Keras library to classify the contacting object based on the first 5 seconds of both FBG responses due to thermal variations upon contact. Figure 7.5(a) shows the architecture of the developed ANN. The ANN receives the wavelength responses of the FBG array due to thermal variation upon contact and the hidden layers, containing 64 and 32 neurons respectively, processes the input from the previous layer and applies weights and an activation function. The connections between hidden layers allows the network to transform the input data into intermediate representations. They capture detailed features and patterns within the incoming data, which eventually allows classification and recognition of objects based on incoming wavelength patterns. To train the ANN model, 67.7% of the generated dataset, comprising 5 seconds of the wavelength response mapped with their corresponding contacting object, was randomly selected while the remaining 33.3% was reserved for model validation. The trained ANN model is capable of achieving recognition accuracy of 100% using the first 5 seconds of the FBG response, and Figure 7.5(b) shows the confusion matrix of the ANN for material recognition.

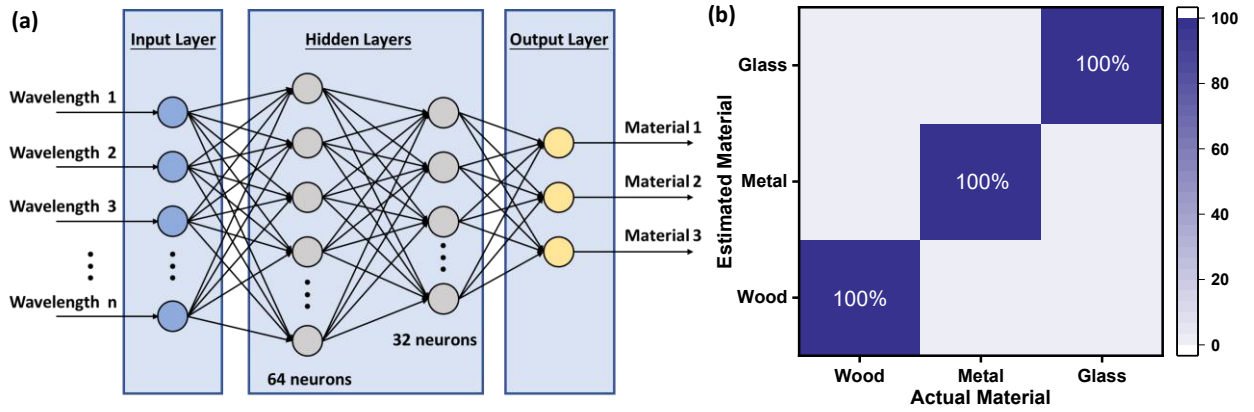


Figure 7.5: (a) Neural network architecture for contact-based thermal object recognition. (b) Confusion matrix for material recognition.

7.6 Summary

In this chapter, the developed artificial skin demonstrates the ability to recognize materials based on their thermal properties by utilizing a cobalt-doped photothermal optical fiber for heat generation and FBG for temperature sensing. The system effectively captures essential thermal information upon contact. The successful classification of metal, glass and wood, realized with an ANN, highlights the potential for high accuracy in material recognition. This research highlights the significance of multi-sensory inputs in robotic tactile perception. Future efforts will focus on combining thermal and physical sensing to enhance robust and reliable object recognition capabilities in robots.

Chapter 8. Conclusion and future work

8.1 Conclusion

This thesis demonstrated the design, fabrication and implementation of a novel biomimetic artificial skin based on POFBGs for advanced robotic tactile perception. The research journey began with the establishment of a foundational fabrication platform, culminating in a series of artificial skins capable of replicating and, in some aspects, surpassing human tactile capabilities.

The core achievement was the development of an in-house POF drawing tower, enabling the production of high-quality, single-mode ZEONEX POFs. The superior flexibility and fracture toughness of these POFs, compared to conventional silica optical fibers, were critical for their successful integration into soft, conformable artificial skins on complex curved surfaces like robotic fingertips.

A series of four distinct artificial skin prototypes were developed, each exploring a key modality of human touch:

1. **High-precision force measurement and localization:** The first skin, embedded with an array of four FBGs, demonstrated the ability to measure contact forces up to 3N and localize them with a MAE of 0.24 mm, outperforming human tactile spatial acuity. The use of a random forest regression model effectively overcame the challenges of quasi-distributed sensing on a curved surface.
2. **Object hardness recognition:** The second skin prototype showcased the capability to perceive a higher-level object property—hardness. By analyzing the distinct strain signatures captured by four embedded FBGs when pressed against objects of varying hardness, a dual branch ANN simultaneously estimated multidirectional forces ($R^2 = 0.96$) and classified object hardness with 90% accuracy.
3. **Multidirectional force and texture recognition:** The third skin prototype incorporated a biomimetic fingerprint-like pattern to facilitate slip-induced vibrations. An array of three FBGs enabled the measurement of normal and shear forces. A MIMO-CNN was developed to simultaneously estimate 3-axis forces ($R^2 = 0.96$) and recognize textures from 20 different fabric samples with 94% accuracy, realizing dynamic tactile sensing.
4. **Thermal-based material recognition:** The final skin prototype introduced a novel sensing modality by incorporating a photothermal fiber for active heating and FBGs for

temperature sensing. The skin successfully distinguished metal, glass, and wood by monitoring the heat transfer dynamics upon contact, achieving 100% classification accuracy with 5 seconds of contact using an ANN.

Different machine learning models, including random forest, dual-branch ANN, a MIMO-CNN and a standard ANN, were selected in this study as optimal architectures for each specific proof-of-concept demonstration. Fundamentally, all tactile tasks demonstrated could ideally be performed using variations of a neural-network framework, which could potentially be integrated for unified multimodal tactile recognition. Realizing a comprehensive sensing system relies on both decoding capability and sensing performance. This work demonstrated the inherent versatility, scalability and multimodal sensing capability of POFBGs, providing a solid physical framework for integrated and intelligent system.

In summary, this thesis established a comprehensive framework for POFBG-based artificial skin, spanning from fundamental fiber fabrication to advanced, intelligent multimodal perception. The work demonstrated that POFBGs' unique physical advantages, including flexibility, high strain sensitivity, and multiplexing capability, combined with powerful machine learning algorithms, create a powerful and scalable platform for equipping robots with a rich, human-like sense of touch. This advancement represents a significant step towards enabling safe, dexterous and intelligent human-robot interaction in unstructured environments.

8.2 Recommendations for future work

The research presented in this thesis opens several promising avenues for future exploration and development.

1. **Integration and system-level integration:** The individual sensing modalities presented (force, hardness, slip, temperature) were characterized in isolation. A critical milestone would be the development of a fully integrated, multimodal artificial skin that combines all these capabilities into a single, unified system. This would involve the creation of a more complex, multi-branch neural network to fuse all sensory data for comprehensive object recognition and manipulation
2. **Development of specialty POFs for enhanced sensing:** The reliance on custom ZEONEX POFs presents a unique opportunity for investigation of application-specific POFs for superior tactile sensing performance. Future work should explore the fabrication and utilization of specialty POFs, such as multi-core POFs, microstructured POFs and elastomeric POFs.

3. **Real-world robotic validation and closed-loop control:** While the artificial skins were demonstrated on fingertip model under controlled settings, their true value will be realized through integration onto a functional robotic hand and implementation in real-world tasks. Future work should focus on closed-loop control experiments, such as using tactile feedback for adaptive grasping of fragile objects, manipulating tools, and object recognition. This will also require robust, real-time signal processing and control algorithms.
4. **Enhancing scalability for large area coverage:** Further investigation into scaling the sensing technology to cover larger areas, such as the entire palm, forearm, or other body parts of a humanoid robots. Research should also explore the optimization of FBG array topologies, multiplexing and more efficient data interrogation techniques to manage increased sensor count without compromising performance.
5. **Algorithmic advancement for efficiency and adaptation:** The machine learning models used, while effective, were trained offline. Future work should investigate online learning and adaptive algorithms that allow robotic systems to continuously learn and adapt to new objects and textures during operations. Furthermore, optimizing the neural network architectures for lower computational cost and power consumption would be essential for deployment on robots with limited onboard processing capabilities.
6. **Exploration of other tactile modalities:** This sensing platform exhibits great potential for expansion into other sensing modalities, such as nociception/pain perception to detect potentially damaging stimuli and trigger reflex actions. In addition, humidity sensing could also be investigated for robots to handle wet objects or liquids.

Ultimately, the realm of tactile-sensitive artificial skin is poised for rapid development as interdisciplinary research fuels innovation. The foundational work of integrating biomimicry, advanced materials, and computational approaches illustrates the complexity and potential of mimicking the human tactile system. As the technology matures, its applications across medical prosthetics, robotics, and human-machine interactions hold the potential for a transformative leap towards more intuitive and responsive systems that can enhance user experiences in everyday environments.

Tactile-sensitive artificial skins represent a frontier that merges biological inspiration with technological advancement. By continuously refining sensor designs, enhancing material

properties, and integrating computational methods, the promising technology of POFBG-based artificial skin can evolve from a sophisticated laboratory prototype into a core component of the next generation of perceptive and dexterous robots.

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